Linear and Nonlinear Analysis of Photoplethysmogram Signals and Electrodermal Activity to Recognize Three Different Levels of Human Stress

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***Abstract*—All human beings experience different levels of psychological stress during their daily activities, and stress is an integral part of human life. So far, few studies have attempted to identify different levels of stress by analyzing physiological signals. However, it should be noted that developing a practical system for detecting multiple stress levels is a challenging task, and no standard system has been developed for this purpose. Therefore, in the current study, we propose a new detection system based on linear and nonlinear analysis of photoplethysmogram (PPG) and electrodermal activity (EDA) signals to classify three levels of stress (low, medium and high). In the current study, we recorded the physiological signals of EDA and PPG during three trials of a Stroop color word test that induced three levels of stress in 42 healthy male volunteers. Mean, median, standard deviation, variance, skewness, kurtosis, minimum, maximum, and RMS features in the time domain were calculated from physiological signals as linear features. Also, approximate entropy, sample entropy, permutation entropy, Hurst exponent, Katz fractal dimension, Higuchi fractal dimension, Petrosian fractal dimension, detrended fluctuation analysis (DFA), and embedding dimension and time delay parameters from phase space reconstruction of the signals were calculated as nonlinear features. The combination of nonlinear and linear features extracted from both PPG and EDA signals resulted in the highest mean accuracy (88.36%), intraclass correlation (ICC) (98.82%) and F1 (89.24%) values in the classification of three levels of mental stress through multilayer perceptron neural network. Our findings showed that the combination of nonlinear and linear approaches for biological data analysis (PPG and EDA) could help to develop a stress detection system.**

Keywords—Stress detection; biological signal; linear analysis; nonlinear analysis; classification

I. Introduction

All human beings experience different levels of psychological stress during their daily life activities, and stress is an integral part of human life. Stress refers to situations and feelings in which people perceive expectations to be beyond their capabilities [1]. In fact, stress can be defined as the mind or body's response to any need for change [2]. Human stress is controlled by the activation of the limbic system and the hypothalamus-pituitary-adrenal axis, which control the release of adrenaline and cortisol (stress hormones) in the bloodstream [3]. The circulation of these hormones in the human body through the bloodstream leads to different physiological variations. As a result, the heart rate begins to increase relative to the normal condition, increasing blood pumping to the muscles and various organs. Therefore, blood pressure and breathing rate increases [4]–[6]. In addition, adrenaline causes the release of stored fat and glucose into the bloodstream, preparing the body to respond to stress [7]. Furthermore, it has been shown that different areas of the human brain, such as the prefrontal cortex, play an important role in regulating various signs of the body during stress [8]. All this cumulative evidence shows that physiological systems and signals undergo changes during psychological stress.

On the other hand, it should be noted that excessive stress affects people's health. It has been introduced as a risk factor involved in the occurrence of major psychiatric diseases such as schizophrenia, depression and anxiety disorders [9]– [11]. Mental stress affects the ability for problem-solving, creativity, work memory and decision-making in humans. In addition, it can be a risk factor for various physical illnesses such as strokes, diabetes, and cardiovascular diseases [12], [13]. Therefore, determining the level of stress in different situations can help people to control it using stress reduction techniques and avoid the unpleasant consequences of excessive stress on health. Accordingly, in recent years, many pattern recognition methods have been developed to detect different emotions and their levels from biological signals [14]–[16]. Electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), electrodermal activity (EDA), respiratory signal (RSP), blood volume pulse (BVP) and photoplethysmogram (PPG) are among the biological and physiological signals that have been computationally analyzed for this purpose. However, the main challenge in stress detection systems is the fact that each person is unique and shows emotions in different ways. This makes the topic of research hot. Although most studies on emotion recognition used ECG and EEG signals, we attempted to record and analyze PPG and EDA signals in the current study because they can be recorded via two-finger electrodes on the non-dominant hand without compromising privacy and comfort. Moreover, some early studies demonstrated that PPG and EDA are good indicative tools to assess emotions.

II. Related Works

Paul Ekman was the first researcher who tried to recognize different emotions through physiological signal analysis [17]. Later, several researchers tried to continue his interesting path by analyzing different physiological signals. However, most studies focused on emotions like joy, fear, sadness, disgust, anger and surprise, and very few studies attempted to detect different levels of mental stress. Healey and Pickard induced three levels of stress (low, moderate, and high) during a driving task and analyzed ECG, EMG, RSP, and EDA signals recorded from healthy participants. They used linear frequency analysis and a linear discriminant analysis (LDA) classifier and reported a good accuracy of 97% for distinguishing three levels of human stress [18]. Shirvan et al. proposed a computational technique based on different linear and nonlinear analyses (including statistical analysis, fractal dimension analysis and detrended fluctuation analysis) of functional near-infrared spectroscopy (fNIRS) signals to detect low and high levels of stress. They used a feature selection method and support vector machine (SVM) classifier at both individual and group settings for stress levels classification and reported an accuracy of 88.72% in this regard [19]. Yannakakis and Hallam induced two levels of fun (low and high) in healthy participants through an interactive game and analyzed the recorded ECG, EDA and BVP signals by linear statistical analysis. They used SVM and Artificial Neural Networks (ANN) in the classification stage and reported 70% accuracy in recognizing two levels of fun [20]. Katsis et al. induced low stress, high stress, euphoria and disappointment in subjects through a driving task and analyzed the linear dynamics of the recorded ECG, EMG, EDA and RSP signals. In the classification stage, they used SVM and a neuro-fuzzy inference system and achieved 79.3% accuracy for the classification of the four states [21]. Valenza et al. induced multiple levels and valence and arousal in healthy volunteers through an international affective picture system and analyzed the nonlinear dynamics of the recorded ECG, EDA and RSP signals. In the classification stage, they used a quadratic discriminant classifier and achieved more than 90% accuracy in affective arousal and valence recognition [14].

As mentioned, few studies have attempted to identify different levels of stress by analyzing physiological signals. However, it should be noted that developing a practical system for detecting multiple stress levels is challenging, and no standard system has been developed for this purpose. Therefore, in the current study, we propose a new detection system based on linear and nonlinear analysis of PPG and EDA signals to classify three levels of stress (low, medium and high).

III. Materials and Methods

A total of 42 healthy male volunteers participated in the research with an average age of 26.31 ± 5.12 years. The research method was first explained to all participants, and informed consent was obtained from them before beginning the experiment. All subjects had a normal or normalized vision. A psychiatric interview was conducted by a psychiatrist to ensure the mental health of all participants to have no symptoms of major psychiatric disorders, cognitive problems, insomnia, anxiety, or social dysfunction. In addition, participants had no history of major physical illnesses, drug or alcohol abuse, and neurological disorders.

A. Stress Induction

In the current study, we utilized the Stroop color word test in a visual basic windows environment to induce three levels of stress in the participants. This test comprises three different experiments: preliminary experiment, congruent or non-conflict experiment, and non-congruent or conflict experiment. In the preliminary experiment, the color of the word appeared black. In the congruent experiment, the color of the work that appeared is similar relative to the color in the written word. In the non-congruent experiment, the color of the word appeared in different colors relative to the written word. Fig. 1 shows the Stroop color word test used in the current study for inducing stress. In each task and experiment, participants should indicate the color of the word. Each experiment lasted three minutes. In all experiments, each trial was displayed for three seconds, and participants were asked to respond to each trial using a mouse. Previous studies have shown that this test can reliably elicit three levels of stress in human subjects. Indeed, the preliminary experiment induces a low-stress level, the congruent experiment induces a medium stress level, and the non-congruent experiment induces a high-stress level [22], [23]. A 16-inch monitor was placed in front of participants at a 70-cm distance from them to perform the Stroop test.

B. Physiological Signal Acquisition

As mentioned, in the current study, we captured the EDA and PPG physiological signals during three experiments of the Stroop color word test. EDA indicates the variations in the electrical properties of the skin because of mentally induced sweat gland activities upon external stimuli. Skin resistance varies with the status of sweat glands in the skin. Sweating is controlled by the sympathetic nervous system, and thus, skin resistance is an indication of psychological arousal [24]. On the other hand, PPG is a simple optical non-invasive method to determine volumetric changes in blood in peripheral circulation that has been shown to be related to affective states [25].

In the current study, the Shimmer3 EDA+ module, along with an optical pulse sensor, was used for recording the EDA and PPG signals. This device is an extensible wireless sensor platform for recording sampled EDA data in real-time. The optical pulse sensor attached to this module also can record a PPG signal from a finger. This module digitized data at a 250 Hz sampling rate and streamed the data to a host PC in real-time. Two dry electrodes, along with the optical pulse probe, were attached to the fingers of subjects' non-dominant hands to record the EDA and PPG signals. The Shimmer3 module has shown to be an accurate and reliable wearable sensor platform for capturing physiological signals, which can be utilized for biomedical research applications [26].

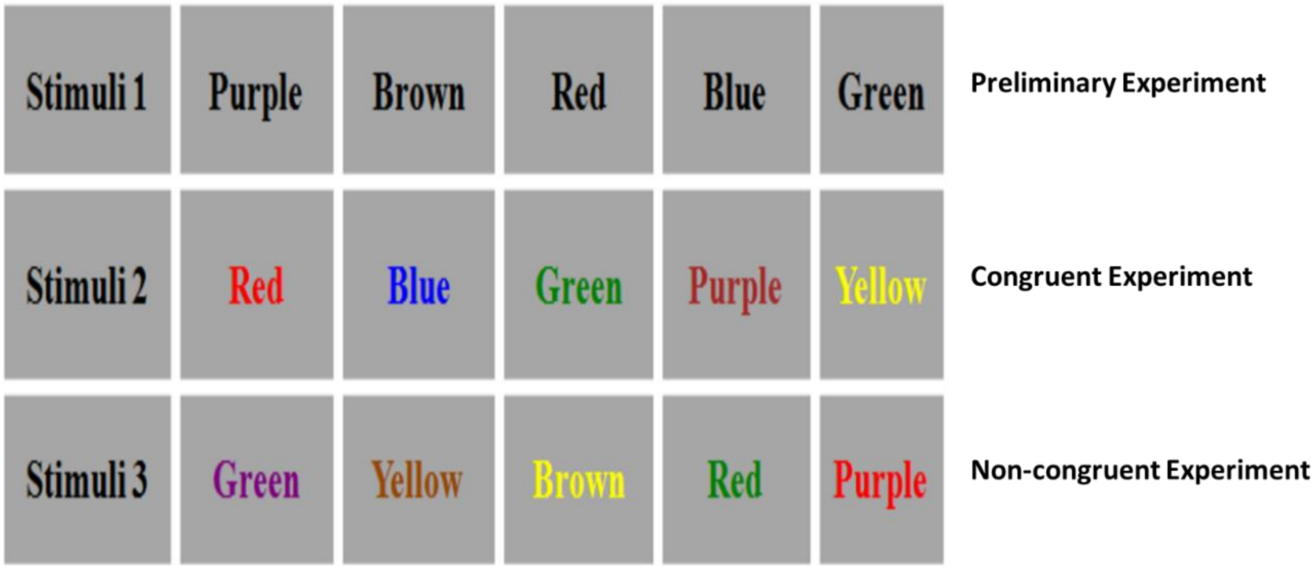

Fig. 1. The Stroop color word test was used in the current study to induce three levels of stress.

C. Linear and Nonlinear Analysis for Feature Extraction

The linear features extracted from EDA and PPG signals include mean, median, standard deviation, variance, skewness, kurtosis, minimum, maximum, and RMS in the time domain. These linear statistical features have a low computational cost which has been shown to be effective in various biomedical research applications. Mathematical definitions of these features and their details can be found in [27], [28]. On the other hand, the nonlinear features extracted from EDA and PPG signals include approximate entropy, sample entropy, permutation entropy, Hurst exponent, Katz fractal dimension, Higuchi fractal dimension, Petrosian fractal dimension, detrended fluctuation analysis (DFA), and embedding dimension and time delay parameters from phase space reconstruction of the signals (see Table I). Mathematical definitions of these features and their details can be found in [29], [30].

TABLE I. LIST OF LINEAR AND NONLINEAR FEATURES EXTRACTED FROM PPG AND EDA SIGNALS

Analysis	Extracted features from PPG and EDA signals
Linear	Mean, median, standard deviation, variance, skewness, kurtosis, minimum, maximum, RMS
Nonlinear	Approximate entropy, sample entropy, permutation entropy, Hurst exponent, Katz fractal dimension, Higuchi fractal dimension, Petrosian fractal dimension, detrended fluctuation analysis, embedding dimension, time delay

IV. RESULTS

Before feature extraction, we first applied a simple segmentation method to the recorded signals through a rectangular window with a length of 45 seconds. Considering the sampling frequency of 250 Hz, each segment contained 11250 data points. Also, each segment had a label to show the individual's stress level. All the above features were extracted from each segment, and the average values extracted for all segments with the same label were defined as the main feature in the classification step. Linear features were first extracted from PPG and EDA time series, and then, nonlinear features were estimated from the signals through the described nonlinear dynamic algorithms. Fig. 2 and Fig. 3 show examples of PPG and EDA signals recorded at three stress levels, respectively. Also, Fig. 4 depicts the histogram of time delays obtained from PPG and EDA signals.

In the classification stage, 70% of features were utilized to train a multilayer perceptron (MLP) neural network, 10% was utilized for model validation, and the remaining 20% was used to test the MLP. In the validation stage, the leave-one-subject-out approach was utilized to estimate the performance of MLP. We investigated different combinations of features and signals (i.e., EDA and PPG) to arrive at the optimal way to detect the stress level. In other words, we utilized various feature combinations for MLP modeling and assessed the classification results of each combination to obtain the best solution for this three-class classification problem. Assessment metrics utilized in the current study for evaluating different strategies were accuracy, intra-class correlation coefficient (ICC) and F1-measure.

Fig. 5 to Fig. 7 show mean classification accuracies, F1-measures and ICC values obtained for each feature combination by MLP classifier. As shown, the best accuracy of 79.5% was obtained by nonlinear features extracted from PPG signals. The best accuracy of 80.42% was obtained by combined features (i.e., linear and nonlinear features) extracted from EDA signals. In addition, the best accuracy of 88.36% was obtained by combining features extracted from PPG and EDA signals. Indeed, the combination of nonlinear and linear features extracted from both PPG and EDA signals resulted in the highest mean accuracy (88.36%), ICC (98.82%) and F1 (89.24%) values in the classification of three levels of mental stress.

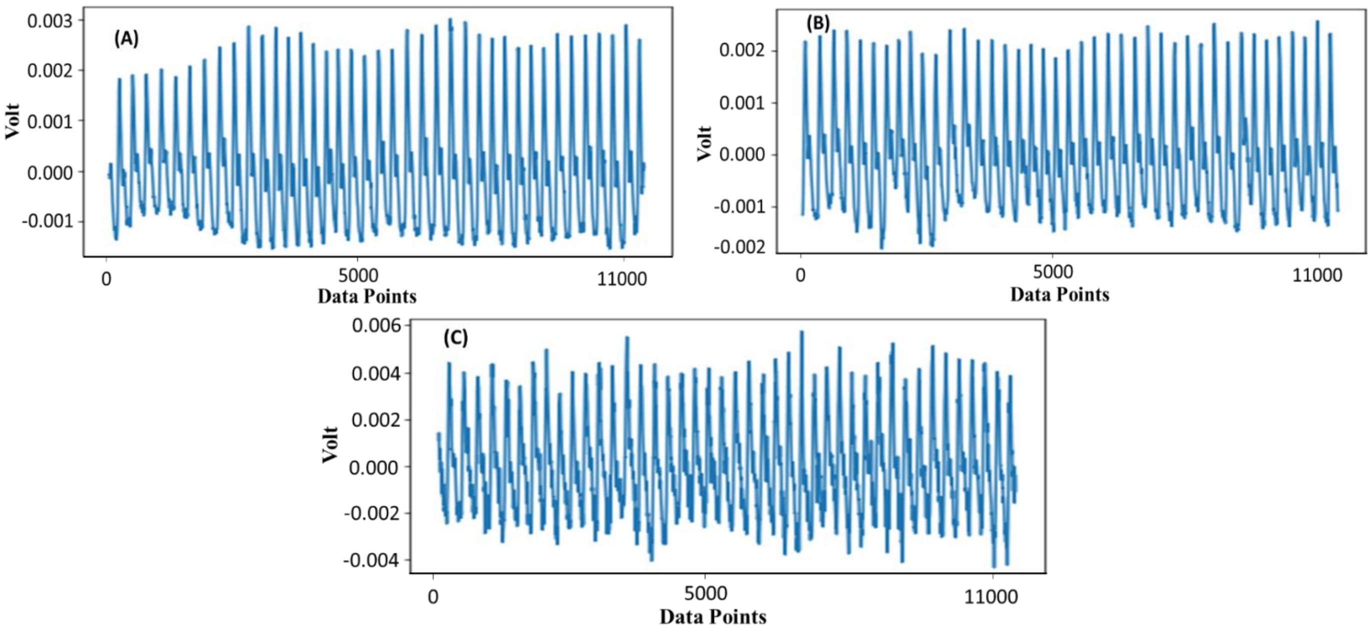

Fig. 2. Example of recorded PPG signals for (A) low-stress level, (B) medium stress level, and (C) high-stress level.

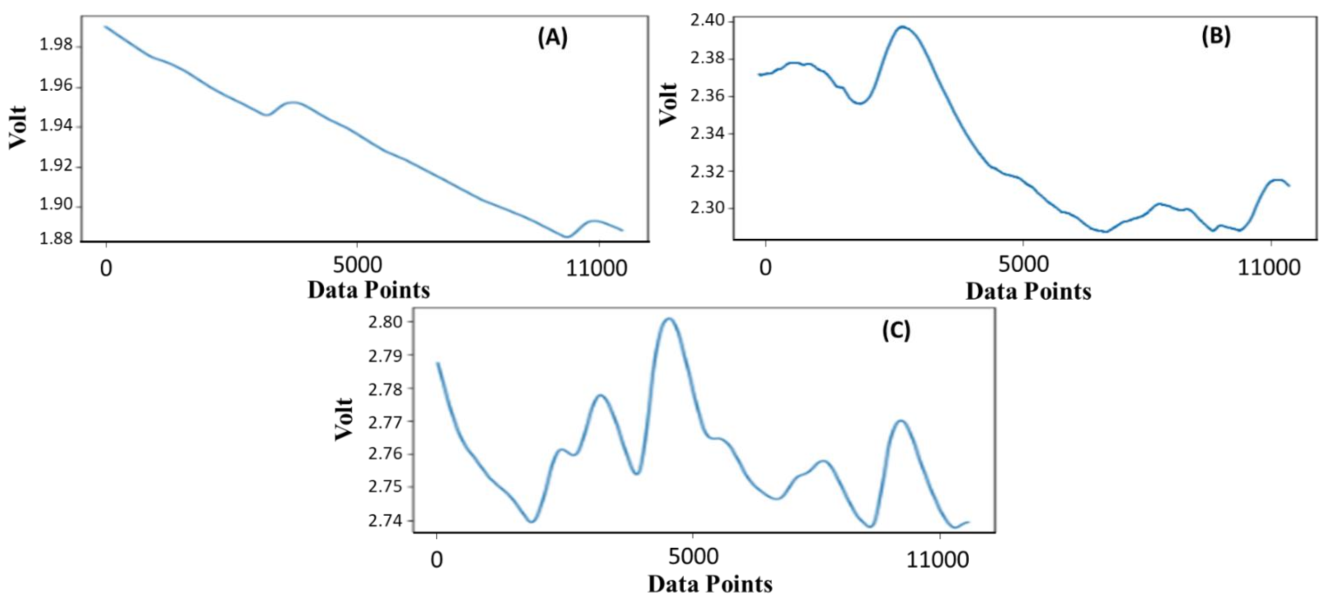

Fig. 3. Example of recorded EDA signals for (A) low-stress level, (B) medium stress level, and (C) high-stress level.

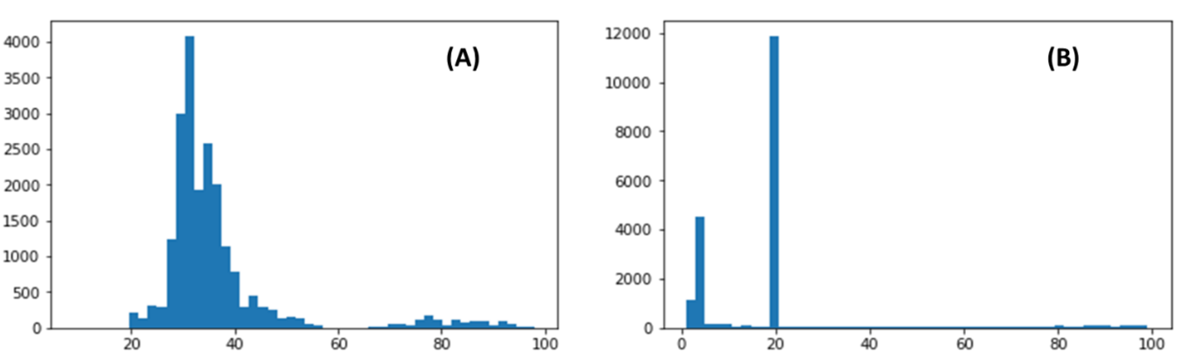

Fig. 4. Histogram of time delays obtained from (A) PPG and (b) EDA signals.

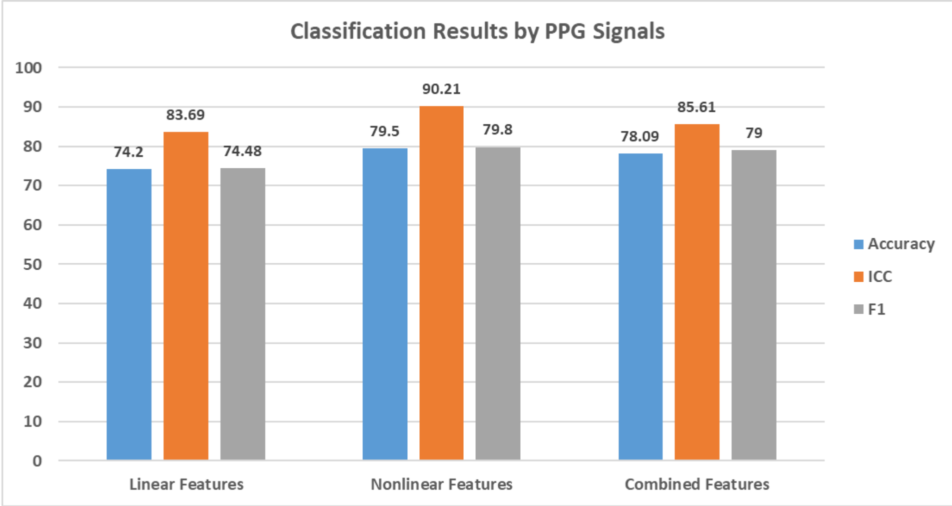

Fig. 5. Averaged classification results were obtained for different features extracted from PPG signals.

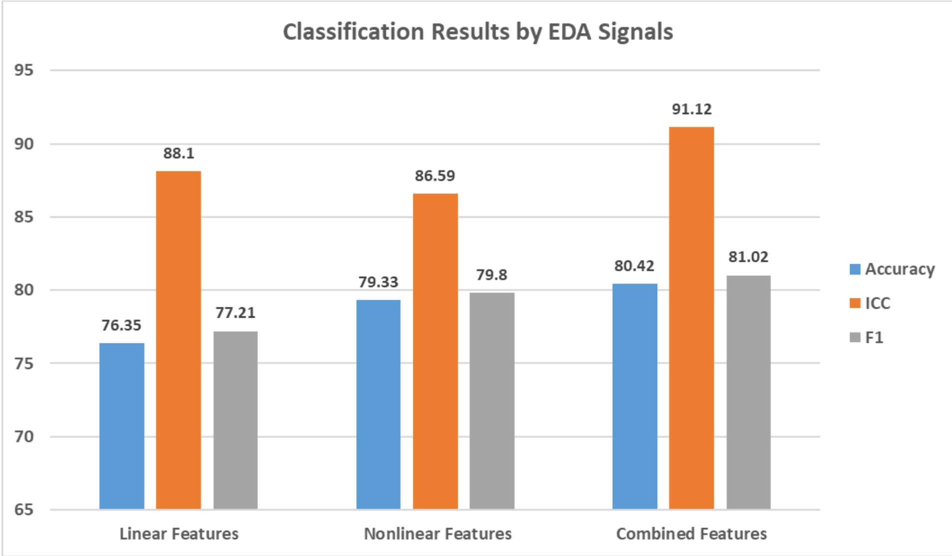

Fig. 6. Averaged classification results were obtained for different features extracted from EDA signals.

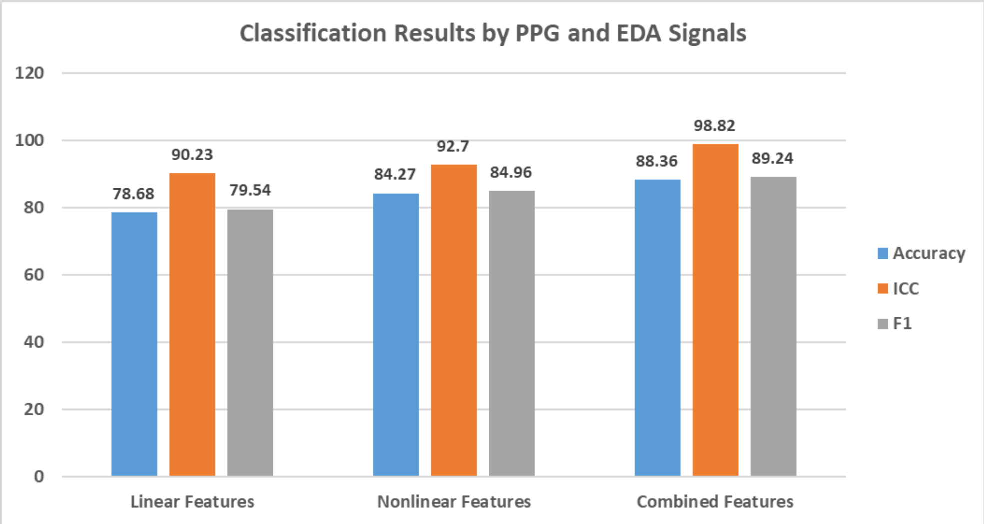

Fig. 7. Averaged classification results were obtained for different features extracted from PPG and EDA signals.

V. Discussion

In the current study, we explored the possibility of detecting and classifying three levels of human stress (low, medium and high-stress levels) in 42 healthy people. Our findings showed that classification with linear and nonlinear features extracted from PPG and EDA signals is a good strategy for achieving an artificial intelligence-based automated system for detecting closed levels of human stress. Therefore, the nonlinear and linear dynamics of biological signals play a vital role in recognizing stress levels. This shows that the biological signals are not purely stochastic and random and follow a deterministic nonlinear behavior in response to different conditions. However, it should be noted that these results were obtained in laboratory conditions. All participants experienced a fixed setup with a noiseless environment, and different stress levels were induced through an executive cognitive task. However, this situation is totally different from real-life situations and the stress of everyday life, and this is the main limitation of this work. The use of wearable devices and virtual reality environments may alleviate this important limitation that future studies should consider.

Moreover, it should be noted that human stress may be unstable and temporary [31]. Therefore, it is very important to design a fast real-time system to detect stress levels in such situations. In addition, emotions and mental stress may be influenced by different physical and mental disorders. However, here, we only worked on healthy subjects. Consequently, our proposed system should be used with caution. On the other hand, our findings can be used in the field of psychiatry and psychology, and future studies should investigate the ability of our system to detect different levels of stress in psychiatric patients. Overall, our proposed automated stress detection system can be used in a wide range of settings to improve safety, health, and performance, including workplace safety, healthcare, education, sports, and transportation. For example, our stress detection system can be used in sports to monitor athletes' stress levels and provide feedback on how to manage stress during competition. This can help improve performance and reduce the risk of injury. Also, our stress detection system can be used in schools to monitor students' stress levels and provide support if necessary. This can help improve academic performance and reduce absenteeism.

Our proposed system showed good performance compared to previous studies. Healey and Picard proposed an automated system to distinguish three stress levels caused by a driving task through EMG, ECG, EDA and RSP signals and achieved an accuracy of 97% for this purpose [18]. However, the variety of biological signals in their work has led to a large increase in the cost of computations and the practical limitation of their proposed system. Zhai and Barreto reported an accuracy of 90% in distinguishing two stress levels using different biological signals and support vector machines [32]. This is despite the fact that we achieved the same accuracy as their work in our three-class problem. Furthermore, our proposed system outperformed the system introduced by Katsis et al., which achieved 79% accuracy in detecting three stress levels [21]. However, an important point that should be mentioned when comparing different systems is the lack of a comprehensive and public database for a more accurate evaluation and comparison of the systems proposed by researchers in this field.

VI. Conclusion

To sum up, we dealt with the crucial stages of an automated recognition system for three levels of human stress using biological signals of EDA and PPG, from signal recording to the classification step, and investigated the results from each stage of this system. Using the proposed system, we achieved a mean detection accuracy of 88%, which provides evidence to show autonomic nervous system differences among different stress levels. A range of biological features from linear and nonlinear analyzes was calculated to obtain the optimum stress-related features. Our findings showed that combining nonlinear and linear approaches for biological data analysis (PPG and EDA) could help develop a stress detection system. At the end, we call to action for a comprehensive, publicly accessible database of physiological signals to evaluate and compare stress detection systems rigorously.

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