Anwer, S., Li, H., Umer, W., Antwi-Afari, M. F., Mehmood, I., Yu, Y., Haas, C., & Wong, A. Y. L. Identification and Classification of Physical Fatigue in Construction Workers Using Linear and Nonlinear Heart Rate Variability Measurements. *Journal of Construction Engineering and Management*. Accepted Version.

Identification and Classification of Physical Fatigue in Construction Workers Using Linear and Nonlinear Heart Rate Variability Measurements

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Abstract

Several studies have analyzed heart rate variability (HRV) using nonlinear methods, such as approximate entropy, the largest Lyapunov exponent, and correlation dimension in patients with cardiovascular disorders. However, few studies have used nonlinear methods to analyze HRV in order to determine the level of physical fatigue experienced by construction workers. As a result, to identify and categorize physical fatigue in construction workers, the current study examined the linear and nonlinear approaches of HRV analysis. Fifteen healthy construction workers (mean age, 33.2 ± 6.9 years) were selected for this study. A textile-based wearable sensor monitored each participant's HRV after they completed 60 minutes of bar bending and fixing tasks. At baseline, 15, 30, 45, and 60 minutes into the task, participants were given the Borg-20 to measure their subjective levels of physical fatigue. Nonlinear (e.g., RRI variability, entropy, detrended fluctuation analysis) and linear (e.g., time- and frequency-domain) HRV parameters were extracted. Five machine learning classifiers were used to identify and discern different physical fatigue levels. The accuracy and validity of the classifier models were evaluated using 10-fold cross-validation. The classification models were developed by either combining or individualized HRV features derived from linear and nonlinear HRV analyses. In the individualized feature sets, time-domain features had the highest classification accuracy (92%) based on the Random Forest (RF) classifier. The combined features (i.e., the time-domain and nonlinear features) sets showed the highest classification accuracy (93.5%) using the RF classifier. In conclusion, this study showed that both linear and nonlinear HRV analyses could be used to detect and classify physical fatigue in construction workers. This research offers important contributions to the industry by analyzing the variations in linear and nonlinear HRV parameters in response to construction tasks. This study demonstrates that HRV values changed significantly in response to physical work, indicating a change in the relative activity of cardiac autonomic functions as a result of fatigue. Using the ways in which HRV parameters vary in response to increased workloads provides a sensitive marker for contrasting construction workers with and without cardiovascular disease. It also allows the site manager to track how quickly workers fatigue, so that they can switch up their workload to reduce the likelihood that any one worker would get severely exhausted, or to suggest that workers who are already severely fatigued take a break to prevent further injury.

Keywords: Fatigue; Ergonomics; Construction safety; Wearable sensors; Heart rate variability; Machine learning

1. Introduction

Construction work is labor-intensive because it includes both repetitive and physically demanding tasks (NG and Tang, 2010; Darbandy et al., 2020). It is estimated that over 40% of construction workers in the United States have reported experiencing significant fatigue, which can have a negative influence on the employees' safety, physical wellbeing, and overall productivity (Ricci et al., 2007; Rosa, 2017).

Furthermore, the US Bureau of Labor Statistics reported 31 fatalities in 2013 due to outdoor environmental heat exposure, with the construction industry accounting for 45 percent of the fatalities (BLS, 2013). Between 2007 and 2011, newspapers in Hong Kong reported 43 incidents involving heat and stress on construction sites, including 11 fatalities (Chan, 2012). Furthermore, past studies have suggested that extended working hours, inhospitable working conditions, and excessive workloads can aggravate the harmful effects of fatigue (Sluiter, 2006; Hallowell, 2010), resulting in increasingly unsafe human actions and errors (Sluiter, 2006). In addition, construction workers who are too tired may be more likely to have work-related musculoskeletal disorders (Anwer et al., 2021a) and be absent from work (Umer et al., 2018; Anwer et al., 2021a; Yu et al., 2021).

Fatigue is defined as a person's reduced ability to perform at an optimal level of function (Edwards, 1981). Fatigue can be classified as either mental or physical. Mental fatigue refers to a decrease in cognitive and behavioral performance due to prolonged cognitive workload (Boksem and Tops, 2008; Boksem et al., 2005), whereas physical fatigue refers to a reduced capacity and efficiency in performing physical work due to prolonged and intense physical workload (Gawron et al., 2001; Frone and Tidwell, 2015). As a result of the extremely physically demanding nature of construction work, proper assessments, and classifications of fatigue levels in construction workers are essential steps to minimize their risk of physical fatigue.

Since occupational fatigue has a significant impact on wellness, safety, and efficiency in all sectors, including construction, it has consistently been rated as one of the top five health-related risk factors over the years (Lerman et al., 2012; Shortz et al., 2019). Workers in the construction industry are prone to developing fatigue because they often perform physically intensive manual tasks in hot and humid outdoor environments (Anwer et al., 2020, 2021a; Umer et al., 2020). However, it has been discovered that the changes of physical work settings, such as the lowering of noise, optimization of lighting, and working in an indoor environment, can mitigation the adverse effects of work-related fatigue (Kołodziej and Ligarski, 2017). The perception of fatigue may also be lessened at indoor work sites due to less extreme temperature and humidity compared to outdoor settings (Umer et al., 2022). It is known that changes in high environmental temperature increase physiological responses (such as HR) during exercise (Galloway and Maughan 1997). Likewise, as high humidity is associated with increased heart rate (HR) during exercise (Maughan et al., 2012), lower indoor humidity levels may reduce physical stress to the body. Further, Hořínková (2021) suggested that most construction site accidents could have been avoided if work was performed at an off-site factory. Modular construction is believed to reduce accidents by as much as 80 percent when compared to conventional construction practices (Hořínková, 2021). Becker et al. (2003) also found that half of respondents in their survey held the view that modularization was safer than conventional construction. However, no prior empirical study has quantified how off-site construction affects construction workers' fatigue. Fatigue in the workplace is a multifaceted issue that affects workers' productivity (Maman et al., 2017; Shortz et al., 2019). With rising concerns about workers' safety and health, it is more important than ever to keep track of unnecessary physical workloads to avoid worker fatigue, injuries, or accidents in physically challenging environments (Hwang et al., 2016). Therefore, assessments and early detection of physical fatigue are vital to minimize its adverse effects on construction workers (Umer et al., 2017).

There are a few different approaches that have been taken in order to evaluate the level of physical fatigue experienced by construction workers (Anwer et al., 2020, 2021b; Umer, 2022). They can be broken down into two major categories: subjective and objective evaluations. For subjective assessments, self-reported measures (e.g., Fatigue Assessment Scale, Swedish Occupational Fatigue Inventory, etc.) are used to assess physical fatigue. While this approach is cost-effective, it is interruptive and may be subject to recall bias. As a result, many workers cannot recognize their level of exhaustion, as shown by fatigue-related accidents (Gonzalez et al., 2017). Therefore, it is important to use non-invasive and non-interruptive methods to measure fatigue in real time so that we can keep track of the presence or severity of fatigue.

Wearable sensors offer objective assessments and remote monitoring of an extensive range of critical signals, that can help give advanced warning for workers with significant health-related risks (Ananthanarayan and Siek, 2010; Shortz et al., 2019). Professional sports, transportation, and mining industries have been adopting wearable sensors to evaluate fatigue in athletes, drivers, and mining workers, respectively (Ananthanarayan and Siek, 2010; Mardonova and Choi, 2018; Seshadri et al., 2019). However, in the construction industry, the application of wearable sensors to assess fatigue is still in its infancy (Anwer et al., 2021a). Only a few studies have used wearable sensors to measure several physiological metrics, such as HR and heart rate variability (HRV) of workers to uninterruptedly evaluate physical fatigue during construction tasks (Aryal et al., 2017; Umer et al., 2020; Anwer et al., 2021b; Umer, 2022). In another approach, Zhang et al. (2019) attempted to monitor fatigue using wearable inertial motion units to process "jerk" signals related to masons' body motions.

The rate of heartbeat is the most often employed physiological indicator for evaluating fatigue (Kumar et al., 2007). Some researchers examined the association between physical or mental fatigue and HRV. For example, Richter et al. (1998) recruited drivers on rural routes to see if their heart rates reflected how much they experienced physical or mental fatigue. Their results demonstrated that HR and HRV accurately reflect the workload demands placed on individuals and could be used to assess their dependability. Similarly, Mulder et al. (1973) and Veltma et al. (2002) revealed that a higher fatigue level is associated with a higher HR and a lower HRV. Thus, HRV can be a helpful indicator of fatigue levels. It is possible to extract and analyze the HRV signal to use it as an index to evaluate the functioning of the autonomic nervous system (ANS) (Zhu et al., 2019). The HRV signal contains information regarding the regulation of the cardiovascular system. Analytical approaches for HRV indices can be divided into three major groups, namely the time-domain, the frequency-domain, and the nonlinear indices (Bhardwaj and Balasubramanian, 2019). Time-domain analysis and frequency-domain analysis are two linear analysis methods for analyzing the HRV (Chen et al., 2020). Because HRV is a non-stationary signal derived from an electrocardiogram (ECG) signal, it fluctuates in both the time and frequency domains (Elhaj et al., 2016). These approaches can also be used to quantitatively examine the regulatory action of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). Fatigue and workload evaluation using HRV signals was performed by Isler et al. (2007), Xu et al. (2015), and Cinaz et al. (2013). All of these studies chose both time- and frequency-domain analysis indices. However, typical cardiac action has an unsteady dynamic law (Goldberger, 1992). It has been established that the HRV signal is nonlinear (Hao et al., 2022). Since HRV is nonlinear, it cannot be evaluated by time-domain or frequency-domain analyses. The heartbeat is governed by several factors and is prone to alterations. Therefore, a nonlinear approach, as opposed to a linear one, may more accurately portray the global impact of the heart's own autonomic nerve regulation (Karrakchou et al., 1996).

As a result, nonlinear methods have been proposed as a potential solution to overcome the shortcomings of linear approaches. Recently, Chen et al. (2020) analyzed the HRV signals using linear and nonlinear dynamics to determine physical fatigue in miners. Based on their results, they suggested that both linear and nonlinear HRV indices can be used effectively and reliably to identify physical fatigue in mining workers. However, the application of nonlinear indices of HRV analysis for fatigue assessment in construction workers has not been studied. Therefore, the current study aimed to use both linear and nonlinear methods to analyze HRV to identify and classify physical fatigue in construction workers. It was expected that the incorporation of linear and nonlinear variables into HRV analysis would result in a more accurate prediction and classification of physical fatigue in construction workers.

The remaining sections of this paper are structured as follows. Relevant literature on the linear and nonlinear HRV analyses is presented in section 2. Section 3 describes the research materials and methodology, which includes multiple subsections describing participants' characteristics, experimental procedures, a description of the wearable sensing device utilized in the current investigation, an overview of the HRV parameters, an explanation of feature selection, application of machine learning classifiers, and evaluation of models. The findings of the suggested technique and algorithm are illustrated in section 4. Section 5 discusses the findings about the use of linear and nonlinear HRV analysis to automatically identify and classify physical fatigue in construction workers, as well as its implications, practical contributions, limitations, and future directions for research. Finally, conclusions of the study are elaborated in section 6.

2. Related research background

The analysis of HRV from ECG signals is considered a promising method to indirectly measure the ANS (Meeusen et al., 2013). The heart is mainly controlled by the vagal nerve, which is a part of the PNS. It is also controlled by the SNS. It is the interplay between these two systems that controls HRV at rest and during activity (**Figure 1**). The resting HR is primarily controlled by parasympathetic activity, and during exercise or stressful activities, the sympathetic system is activated in a reciprocal fashion to increase the HR to accommodate whatever need there may be (Balzarotti et al., 2017). Therefore, HRV can be a surrogate to evaluate whether someone is undergoing physical training or activity at the moment or whether they are recovering from vigorous activity. For example, previous research used HRV to assess physical fatigue or physical responses to training loads among athletes (Schmitt et al., 2015). A previous review indicated that HRV analysis showed promise in detecting both cognitive and physical fatigue (Gonzalez et al., 2017). HRV refers to the variability of the intervals between two heartbeats, which is known as the interbeat interval (IBI) (Shaffer et al., 2014). While an increased HR indicates higher levels of physical activity, a decreased HRV value suggests a higher intensity of physical activity (De Waard and Brookhuis, 1991; Mulder, 1992). Wearable optical heart rate monitors can be used to monitor the myoelectrical activity and HRV of the heart (Schmalfub et al., 2018). Analysis of HRV is regarded as a noninvasive and objective method for analyzing autonomic dysfunction in persons who have chronic fatigue syndrome (Escorihuela et al., 2020). Analysis of HRV can reveal the dynamic shifts in cardiac autonomic function that occur in a matter of minutes (Escorihuela et al., 2020). HRV can be measured using linear and nonlinear analysis. Time-domain recordings can last up to five minutes (short) or more than five minutes (long). Recordings lasting longer than 5 minutes can yield reliable HRV data (Shaffer and Ginsberg, 2017). In the current study, we estimated HRV based on 60 minutes of recording. When fatigue is present, the autonomic nervous system demonstrates sympathetic hyperactivity while the parasympathetic system becomes less active. A shift in the central command pathomechanisms could be the cause of such an imbalance in the ANS (Escorihuela et al., 2020).

2.1. HRV analysis

HRV is a key indicator of neural cardiac function, with high HRV values indicating successful ANS adaptation and identifying a healthy individual, whereas low HRV values indicate abnormal ANS adaptation and are associated with an increased risk of cardiovascular disease (Appelhans and Luecken, 2006; Karavirta et al., 2009). High HRV scores are associated with stress/fatigue management and the ability of a person to cope with stress/fatigue (Appelhans and Luecken, 2006).

2.1.1. Linear analysis: time-domain component

HRV can be analyzed by many methods. Of these, time-domain analysis is the simplest one. Specifically, the time-domain approaches are utilized in order to compute the HR at any given time or the gaps that exist between the occurrences of subsequent normal Q-, R-, and S-wave (often known as QRS complex) in an ECG waveform (Shaffer and Ginsberg, 2017). After the initial dip of the P wave, the first upward deflection of the S wave is the R wave. In physiology, the R wave indicates the beginning of ventricular depolarization. Each R-wave is identified on a continuous ECG record as shown in **Figure 2**. Calculations are made to determine either the instantaneous heart rate or the normal-to-normal (NN) intervals (Shaffer and Ginsberg, 2017). The beat-to-beat interval was expressed in seconds by noting the times of two consecutive peaks and then subtracting the second peak from the first one. Then the instantaneous heart rate in beats per minute was calculated by dividing this number by 60 (Shaffer and Ginsberg, 2017). The NN interval was determined by measuring the time difference between two successive QRS waves. After modifying the RR interval to eliminate outliers, the NN interval was determined. An additional exclusion was an RR interval that exceeded 150 ms different from the average of the 5 preceding intervals (Shaffer and Ginsberg, 2017). The mean HR, the mean NN interval, the difference between the shortest and longest NN interval, as well as other basic time-domain variables can be measured. More intricate analytical time-domain components can be extracted from a series of instantaneous heartbeats, especially those observed over longer periods, typically 24 hours, as shown in supplementary file **Table S1**.

2.1.2. Linear analysis: Frequency-domain component

HRV spectral analysis converts the ECG signal from the time-domain to the frequency-domain (Tarvainen et al., 2014) (supplementary file **Table S1**). The power range of heart rate is divided into three distinct bands. The power spectrum has three distinct peaks: one at very low frequency (VLF), which occurs below 0.05 Hz; one at low frequency (LF), which occurs between 0.06 Hz and 0.15 Hz; and one at high frequency (HF), which occurs between 0.15 Hz and 0.4 Hz (Tarvainen et al., 2014). The VLF is associated with vasomotor and thermoregulatory functions (Kamath and Fallen, 1993). The LF is linked to HR regulation and reflects sympathetic behavior. A parasympathetic response is indicated by the presence of respiratory sinus arrhythmia, which is related with HF (Heathers, 2014). The LF, HF, and LF/HF ratio are three popular frequency-domain characteristics that are used to quantify levels of physical activity (Schmalfub et al., 2018). The LF band can show SNS activity in response to physical activity or stress (Schmalfub et al., 2018). The LF and HF bands indicate the levels of sympathetic and parasympathetic activity, respectively (Heathers, 2014; Quintana and Heathers, 2014). LF fluctuation is caused by both vagal and sympathetic activity, while HF variability is primarily caused by vagal (parasympathetic) activity. In addition, the LF/HF ratio could be a sign of sympathetic or parasympathetic activity, and it's a measure of how well the sympathetic and vagal systems are working together (Schmalfub et al., 2018).

2.1.3. Nonlinear analysis

The nonlinear dynamics properties that characterize complex systems are captured by nonlinear analysis techniques and metrics (Supplementary file **Table S1**). Nonlinear metrics were developed to characterize autosimilarity, fractal time behavior, and time series complexity (Delliaux et al., 2019). For example, RRI time series in HRV are made up of an autonomous mechanism that is part of the human body called the ANS and various environmental factors (Goldberger, 2002). Nonlinear analysis of HRV appears to be more sensitive and accurate than linear analysis in describing cardiac and clinical status and predicting the prognosis of various cardiovascular diseases (Huikuri et al., 2009). In past studies, the nonlinear

Poincaré plot analysis was found to be valid, responsive, and reliable (Mukherjee et al., 2011; Gergelyfi et al., 2015). The most commonly used nonlinear metrics are SD1 (the variance of the instantaneous beat-to-beat RRI calculated as the standard deviation; this variable is the minor axis of the fitted ellipse), SD2 (the principal axis of the fitted ellipse, which represents the standard deviation of the continuous long-term RRI variability), SD1/SD2 ratio (the axis ratio), detrended fluctuation analysis (DFA) $\alpha 1$ and $\alpha 2$ coefficients, Approximate Entropy (ApEn), and Sample Entropy (SampEn) (Hoshi et al., 2013; Delliaux et al., 2019).

3. Materials and Methods

3.1. Participants, Instrumentation, and Experiment

A convenient sampling approach was used to recruit 15 healthy construction workers aged 18 years or older from a construction site. People who had a history of disorders affecting their musculoskeletal system, neurological system, or cardiovascular system were not included. The principles outlined in the Declaration of Helsinki were adhered to throughout the research, and the ethical committee at the institution gave its final approval to the protocol (Reference Number: HSEARS20190824004). Before the data collection, participants signed a written informed consent document.

Figure 3 depicts the methodologic framework of the research process. After receiving written consent, participants were given a self-reported questionnaire to complete in order to collect information on their demographics and medical history. After that, participants were given the instruction to wear the EQ02 system (Equivital Lifemonitor system, Hidalgo, UK) to assess HRV parameters while doing a manual bar bending and fixing task for one hour. The EQ02 is a body-worn device made of textiles that has various sensors that gather and send physiological data (ECG, respiration frequency, and skin temperature). These data are used to display the user's cardiorespiratory and thermoregulatory condition. The EQ02 device is made up of three different parts: (a) a sensor electronic module that is housed inside of a specially constructed vest (four different sizes are available); (b) software called Equivital Manager that is used to manage the sensor electronic module; and (c) an application that is based on smartphones

(**Figure 4**). The sensor electronic module, which is coupled to the textile-based sensors, detects, records, and transmits data through Bluetooth to a laptop or smartphone for the Equivital manager software to be able to remotely monitor those physiological outcomes in real time. To ensure the conduction of bioelectric signals to the textile-embedded electrode, the ECG electrodes were moistened with water. It was recently discovered, through experimental studies, that a textile-based multi-sensor body-worn device (i.e., EQ02) is an accurate and valid tool for measuring physiological parameters while working on a construction site (Anwer et al., 2021b; Umer, 2022).

The bar bending and fixing tasks were performed by participants on a construction site (**Figure 5)**. These tasks were chosen because they represent one of the most strenuous activities in the construction industry in terms of physical exertion, number of hours spent working, and complexity (Wong et al., 2014). Bar bending entails adjusting the length and shape of reinforcement bars by cutting and bending them. Meanwhile, bar fixing entails precisely positioning and layering and spacing the reinforcement bars that have been individually designed for the project. When compared to other construction tasks such as form works, bar bending, and fixing are considerably more physically demanding jobs given the weight of the rebars. To stabilize participants' physiological parameters prior to the data collection, they were asked to sit in a chair for 10 minutes. The baseline (T0) HRV data was measured by the EQ02 system, while the subjective fatigue level was documented by the Borg-20 scale (Borg, 1982). The Borg-20 is a widely used subjective scale to assess the rating of perceived exertion during and after physical activity. It is a 6-to-20-point scale, where 6 indicates "No physical exertion at all" and 20 indicates "Maximal exertion". After the initial assessments were completed (T0), it was requested that each participant carry out one hour of their usual bar bending and fixing tasks (**Figure 5**). Subjective levels of fatigue were assessed using the Borg-20 scale at 15, 30, 45, and 60 minutes of the construction task, and these intervals were designated as T1, T2, T3, and T4, respectively. For features selection, the HRV parameters of ECG signals during the last 5 minutes before each time point (i.e., 15, 30, 45, and 60 minutes of task) as measured by the EQ02 system were used to evaluate fatigue at T1, T2, T3, and T4, respectively. The corresponding linear and nonlinear HRV features of ECG signals were analyzed. The sampling frequency of the ECG signal in EQ02 was 256 Hz.

3.2. Data Analysis and Signal Processing

The raw HRV data was exported from the EQ02 system as a text file, and then it was imported into an HRV analysis software program (Kubios HRV, 2.1, Biosignal Analysis and Medical Imaging Group, Kuopio, Finland) for the purpose of analyzing several HRV parameters, including (1) time domain, (2) frequency domain, and (3) nonlinear dynamics. The HRV was analyzed using the standards that were determined to be acceptable by consensus (Rawenwaaij et al., 1993; Electrophysiology task force, 1996). The R-R intervals series was detrended using the smoothness prior approach with an alpha of 500, and the sampling frequency was set to 300 Hz. To perform an HRV analysis (Alcantara et al., 2020; Tarvainen et al., 2014), we ensured that the following conditions were met: (i) the R-R intervals and the HR distribution graphs were Gaussians; (ii) there were no substantial R-R interval outliers; and (iii) the R-R intervals were equally spaced. Further, we applied all the available Kubios threshold-based artefact correction levels (thereinafter called Kubios filters). Five different Kubios filters were used: a very low (0.45 s), a low (0.35 s), a medium (0.25 s), a strong (0.15 s), and a very strong (0.05 s) (Alcantara et al., 2020; Tarvainen et al., 2014). Notably, HRV parameters were calculated with all the Kubios filters. For instance, the very low Kubios filter was used to obtain HRV values using the same threshold (0.45 s). This study used other Kubios filters (thresholds: low [0.35 s], medium [0.25 s], strong [0.15 s], and very strong [0.05 s]) followed the same logic. The final step was to fix the highlighted artifacts by interpolating between them with a cubic spline (Alcantara et al., 2020). If the R-R interval was not a multiple of 0.45 (very low), 0.35 (low), 0.25 (medium), 0.15 (strong), or 0.05 (very strong) seconds, the Kubios program automatically interpolated it. The HRV was then automatically analyzed in both linear (frequency and time domains) and nonlinear parameters after the IBIs were imported into the Kubios computer program.

3.2.1. Time-domain HRV analysis

Time-domain data were detrended with Smooth priors (lambda: 500), and the average of five beats was used to calculate the average of the Min/Max HR. The threshold for NNxx/pNNxx was set at 50 ms for NNxx/pNNxx. Many time-domain parameters were utilized in order to measure the overall variability, which was shown to originate from both regular and random sources. These include the mean RRI and the mean HR in addition to the standard deviation RRI and the standard deviation HR, the RMSSD, NN50, pNN50, the RRI triangular index, and TINN (details are available in supplementary file **Table S1**) (Billman, 2011).

3.2.2. Frequency domain HRV analysis

In order to determine the periodic oscillations of the examined time series, we used a number of different frequency domain metrics. These metrics were chosen based on the estimated power spectrum that was produced by the Fast Fourier transform and Welch's periodogram technique. These metrics contained the centroid frequency (expressed in *Hz*) and power (expressed in ms^2) in three frequency bands that were of interest: low frequency (LF, 0.04 – 0.15 *Hz*) and high frequency (HF, 0.15 – 0.4 *Hz*). The interpolation rate, points in frequency domain, window width, and window overlap were 4 Hz, 300 points/Hz, 300 s, and 50%, respectively. In addition to this, the power of the LF/HF ratio as well as the total power (TP) were computed. The LF and HF powers were also reported as a percentage of TP (LFperc and HFperc, respectively), as well as in normalized units (LFnu and HFnu, respectively). This was done in order to more accurately depict the sympatho-vagal components of the HRV and were specified as $LFnu = LFpw/(TP - VLFpw) * 100$; $HFnu = HFpw/(TP - VLFpw) * 100$. These factors have been used as a way to measure the total variability of the heart rate. These include the parasympathetic component of the ANS (HFnu), the sympathetic and parasympathetic components of the ANS (LFnu), temperature, and other hormonal influences on the heart rate (VLFpw), as well as the balance between the sympathetic and parasympathetic components of the ANS (LF/HF).

3.2.3. Nonlinear HRV analysis

Four methods were used to examine the nonlinear properties of HRV: (1) Poincaré plot (Brennan et al., 2001; Melillo et al., 2011); (2) Approximate entropy (ApEn) (Richman and Moorman, 2000); (3) Sample entropy (SampEn) (Richman and Moorman, 2000); and (4) Detrended fluctuation analysis (Peng et al., 1995; Penzel et al., 2003). We calculated the SD1 (the variance of the instantaneous beat-to-beat RRI calculated as the standard deviation; this variable is the minor axis of the fitted ellipse), SD2 (the principal axis of the fitted ellipse, which represents the standard deviation of the continuous long-term RRI variability), and the SD1/SD2 of the RRI of rank n + 1 plotted as a function of the RRI of rank n in a lag 1 Poincaré plot (Hoshi et al., 2013). We calculated the detrended fluctuation analysis coefficients $\alpha 1$ and $\alpha 2$ with segment lengths of $n \in (4{,}12)$ and $n \in (13{,}64)$, respectively. SampEn and ApEn estimates of each RRI time series were calculated with r (filtering level) and m (embedding dimension) set to 0.2 SD and 2 of the RRI time series, respectively.

3.3. Features selection

The filter method and the wrapper method are both utilized in the feature selection process. Wrapper methods evaluate the usefulness of a subset of features by training a model on those features, whereas filter methods evaluate the significance of features based on their correlation with the variable that is being evaluated (Chandrashekar and Sahin, 2014). Since filter methods do not need the models to be trained, they can complete the process much more quickly than wrapper techniques. Filter methods evaluate a subset of characteristics using statistical methods, whereas wrapper techniques employ cross validation (Preece et al., 2009). The filter approach that was employed in this study selected several cardiovascular features (i.e., time-domain, frequency-domain, and nonlinear-domain indices) that were significantly affected by the level of physical fatigue experienced among construction workers using repeated-measures analysis of variance (ANOVA). The wrapper technique used sequential selection algorithms (i.e., forward selection methods) that began with an empty set and gradually added features to the model, and the performance of the classifier is evaluated regarding each feature. The best performing feature is chosen from among all the features.

3.4. Classification of physical fatigue using Machine learning classifiers

To enable accurate classification of physical fatigue based on the linear and nonlinear HRV analyses, five types of supervised machine learning classifiers are used: (1) K-Nearest Neighbor (KNN); (2) Decision Tree (DT); (3) Random Forest (RF); (4) Support Vector Machine (SVM); and (5) Artificial Neural Network (ANN). Details of these techniques are available elsewhere (Lai et al, 2010; Umer et al., 2020; Karvekar et al., 2021; Antwi-Afari et al., 2020). Although a number of algorithms could be used for our purpose, we decided to utilize these five instead because previous research has proven that they are effective in monitoring physical fatigue. For example, Umer et al. (2022) used several supervised machine learning classifiers including KNN, RF, DT, and ANN for developing a model to monitor physical fatigue. Additionally, Hu and Min (2018) have compared a variety of machine learning classifiers, such as DT, KNN, SVM, and ANN for detecting driver's fatigue. Therefore, in the current study, these supervised machine learning classifiers were chosen to identify the best model parameters to be used for training a specific dataset.

For features selection, HRV parameters of ECG signals collected in the 5 minutes preceding each time point (i.e., baseline, 15, 30, 45, and 60 minutes of task) were used to evaluate fatigue at T0, T1, T2, T3, and T4, respectively. Further machine learning-based fatigue monitoring was performed using a sliding window segmentation approach with a window size of 30 s and 50% data overlap between adjacent windows. This method resulted in a dataset containing 1425 labelled examples for 15 participants. Measured subjective Borg-20 scores at baseline (T0) and at T1, T2, T3, and T4 were evaluated with the corresponding HRV data during 60 minutes of work. After that, the data were divided at random into three separate groups. To be more specific, 70% (999 datasets) of the data was set aside for training, 15% (213 datasets) was used for validation, and the remaining 15% (213 datasets) was used for testing.

3.5. Model Assessments and Validation

There were seven classification models developed using individualized and combined HRV features derived from linear and nonlinear analyses**.** Specifically, models 1, 2, and 3 used only time-domain, frequency-domain, and HRV parameters obtained from nonlinear analysis, respectively. Models 4 to 6 used different combinations of HRV features obtained from linear and nonlinear HRV analysis. Model 7 used all HRV features to identify and classify physical fatigue during the construction task. As a reference, Borg-20 scores were used to classify physical fatigue into four levels: no fatigue (score ≤ 6), mild fatigue (score 7 – 11), moderate fatigue (score 12 – 16), and severe fatigue (score 17 or higher) (Aryal et al, 2017; Karvekar et al, 2021). Additionally, the accuracy and validity of the classifier models were evaluated using 10-fold cross-validation (Antwi-afari et al., 2018). Although there is no universal rule, 5 or 10 is a common choice for k when performing a cross-validation. The size gap between the training set and the resampling subsets decreases as the value of k increases (Esbensen and Geladi, 2010). The bias (the discrepancy between the predicted and observed results) of the method becomes smaller with decreasing difference (i.e., the bias is smaller for k = 10 than for k = 5). Therefore, a 10-fold cross-validation was used in the current study.

This study used the Orange data mining tool (Version 3.27.1, Bioinformatics Lab, the University of Ljubljana, Slovenia), which is an open source data mining software based on Python programming to compare and evaluate the classification algorithms (Demsar et al., 2013; Kukasvadiya and Devecha, 2017). The process of data preprocessing and classification analysis was done using the Orange data mining tool (supplementary file **Figure S1**). The canvas interface of Orange software allows users to create data analysis workflows by dragging and dropping widgets into place. Reading data, displaying a data table, choosing features, training predictors, contrasting learning methods, and visualizing data items are some of the fundamental functions of a widget. The user can interact with the programme to look at visuals and put parts of them into other widgets (Kukasvadiya and Devecha, 2017).

4. Results

Table 1 presents demographic details of the participants. The fifteen male construction workers (mean age, 33.2 $\pm$ 6.9 years) had an average sleep duration of 7.4 hours the prior night. Most of the participants had no physical fatigue at baseline as measured by the Borg-20 rating of perceived scale. Participants reported a gradual increase in their fatigue levels from baseline over the course of a 1-hour construction task. Average fatigue levels at T0, T1, T2, T3, and T4 were 6.1, 9.3, 11.9, 14.4, and 17.8, respectively.

The outcomes of the analyses performed in the time domain, frequency domain, and nonlinear HRV are presented (supplementary file **Figures S2, S3, and S4**, respectively). RRI was significantly reduced from 0.89s at baseline to 0.61s at T4 (**Figure S2)**. The ratio of LF and HF power was increased from 0.63 at baseline to 5.99 at T4 (**Figure S3**). While short-term variability (SD1) significantly decreased from 38.60 ms at baseline to 12.38 ms at T4, long-term variability (SD2) non-significantly decreased from 49.11 ms at baseline to 35.91 ms at T4 (**Figure S4**).

A total of 34 linear (time-and frequency-domain) and nonlinear HRV features were extracted. **Table 2** details the effects of physical fatigue on HRV parameters during the construction task. Based on the repeated measure ANOVA results, 25 statistically significant linear and nonlinear HRV features were selected in the final classification model. Ten, 10, and five features were selected for the time domain, frequency domain, and nonlinear sets, respectively.

For the classification assessments, three different feature sets and their combinations and five machine learning classifiers were used to identify the best feature set and classifier combination to accurately classify physical fatigue in construction workers. **Table 3** presents the evaluation parameters of each model using different classifiers to classify physical fatigue in construction workers. For the comparisons of machine learning classifiers' accuracy, the RF classifier demonstrated the highest accuracy (93.5%) for time-domain and nonlinear features, followed by ANN (92.6%) for time and frequency-domain features, and SVM for time-domain features (88.9%). In general, the RF classifier is the best machine learning model to classify physical fatigue using both individualized and combined feature sets. For the comparisons of the individualized feature sets, the time domain features had the highest accuracy (92%), followed by nonlinear (77.3%), and frequency domain features (74%). Similarly, for the comparisons of the combined feature sets, the time and nonlinear features set showed the highest accuracy (93.5%), followed by the time and frequency domain features set (92.6%), all linear and nonlinear feature sets (91.9%), and frequency and nonlinear features sets (75.8%). Figures 6 and 7 show the confusion matrices for the individualized and combined feature sets using the best classifier. When comparing the accuracy levels of individualized feature sets (i.e., Models 1, 2, and 3), model 1 that included time-domain features showed the highest classification accuracy (**Figure 6**). The comparison of the combined feature set showed that the highest accuracy was noted for model 5 (time-domain and nonlinear domain features), followed by model 4 (combined time-domain and frequency-domain features) (**Figure 7**).

5. Discussion

This study used linear and nonlinear HRV analysis to automatically identify and classify physical fatigue in construction workers. In addition, this study compared linear and nonlinear approaches in analyzing HRV among construction workers in order to detect and classify physical fatigue. The current study discovered that several time-domain HRV measures (including RRI, SDNN, RMSDD, NN50, pNN50, RR triangular index, and TINN) were significantly decreased during the 60-minute construction task. Similarly, various frequency-domain HRV parameters (such as peak, power, log, and percentage of HF band) were sharply reduced during the construction task, indicating that the presence of fatigue affected these features. Conversely, the peak of the LF band, the percentage of VLF and LF bands, and the ratio of LF/HF power all increased substantially during the construction task.

The current findings revealed that various HRV components were sensitive to physical exhaustion, suggesting that HRV measures could be used to predict physical fatigue in construction workers. The HR variations associated with the respiratory cycle are reflected in the HF band, which is also known as the respiratory band (Vuksanovic and Gal, 2007). The HF band is reflective of parasympathetic activity (Vuksanovic and Gal, 2007), and it is characterized by respiratory sinus arrhythmia (RSA) (Kamath and Fallen, 1993). This is most likely what occurred throughout the construction task. Due to the stooping/squatting postures and repeated lifting tasks, oxygen demands increase, which results in an increase in respiratory rate, which reduces the HF component during these tasks (Vuksanovic and Gal, 2007). According to Kamath and Fallen (1993), changes in posture significantly increase the power of the LF band. Similarly, another study found that when physical effort increased, the power of LF bands also increased (Parotala, 2009). Likewise, research revealed that following high-intensity exercise, the LF/HF ratio increased from baseline (Perini and Veicsteinas, 2003; Parotala, 2009; Collins et al., 2005). Collins et al., (2005) found that the LF/HF ratio (a measure of sympathetic activity) was greatly increased, but the HF power (a measure of parasympathetic activity) was significantly reduced during high workload physical activity. These findings supported our observations that the LF/HF ratio increased while the HF power decreased during the construction task. During activities of moderate to high intensity, some authors hypothesized that there was a shift in autonomic interaction toward sympathetic dominance. This was inferred from the observation that HF power decreased, while LF power increased during these activities. As a consequence of this, there was an increase in the ratio of LF to HF (Parotala, 2009).

In the current study, nonlinear HRV parameters (e.g., short-term variability (SD_1) and sample entropy) were reduced significantly from baseline, whereas the ratio of SD_2/SD_1, short-term fluctuations ($\alpha 1$), and long-term fluctuations ($\alpha 2$) steadily increased during the construction task. In contrast to SD1, which is a nonlinear measurement of parasympathetic sinus node control, SD2 is a nonlinear index of sinus node control that includes both sympathetic and parasympathetic control (De Vito et al., 2002; Mourot et al., 2004; Delliaux et al., 2019). Although no previous studies have used nonlinear HRV analysis to assess physical fatigue, some researchers have reported adequate sensitivity and reliability of nonlinear HRV analysis in assessing mental fatigue (Mukherjee et al., 2011; Trutschel et al., 2012; Gergelyfi et al., 2015; Delliaux et al., 2019). Therefore, future research is warranted to validate whether nonlinear HRV parameters can be used to evaluate physical fatigue-related cardiac changes. Previous research found that high SD1 and SD2 were reported at the start of the work, but these measurements dropped down during the computerised switching task (Delliaux et al., 2019).

5.1. Classification performance

Because HRV components were found to be responsive to physical fatigue, it is possible that HRV assessments could be used to detect and classify physical fatigue using machine learning classifiers in construction workers. As a result, the linear and nonlinear HRV features were used in this study to identify and categorize the levels of physical fatigue experienced by construction workers. Research has recently used sensor informatics for proactive monitoring of physical exertion among construction workers. While previous research used diverse off-body and on-body sensors, the current study employed a novel and simple strategy to monitor exertion by analyzing HRV features collected from a single ECG sensor. To obtain the best classification performance, machine learning algorithms were adopted in two steps. First, the separate time, frequency, and nonlinear feature sets were used to find the best classifier and ideal selected features for detecting physical fatigue. Second, the combined time, frequency, and nonlinear feature sets were used to find the best classifier and the best features to use for detecting physical fatigue.

The RF classifier demonstrated the highest accuracy (93.5%) for time-domain and nonlinear features. The RF classifier is the best machine learning model to classify physical fatigue using both individualized and combined feature sets. In the current study, the accuracy of using both linear and nonlinear HRV features in classifying physical fatigue outperformed the accuracy of predicting fatigue based on the heart rate during physical exertion (Aryal et al., 2017; Umer et al., 2020). However, these prior investigations required multiple physiological assessments (e.g., skin temperature and breathing rate) in order to attain an accuracy of approximately 82 % (Aryal et al., 2017). The higher classification accuracy of our novel method may be attributed to the choice of physiological features in training the machine learning models. Aryal et al. (2017) trained a model using a small number of features, mainly the time domain obtained from heart rate data and skin temperature. However, our study extracted both linear and nonlinear data from the HRV features. Further, the current study selected the most relevant data based on statistical tests before entering these data into the five machine learning models for training to identify the best model for classifying fatigue.

In the current study, the RF demonstrated the highest accuracy rate among all the tested classifiers for classifying physical fatigue. The results could be attributed to RF's ability to deal with computational complexity by tolerating certain classification errors on the training dataset (Ishaque et al., 2021). The RF is a bagging method that, like Adaboost, uses an ensemble of decision trees to carry out its functionality (Ishaque et al., 2021). Bagging algorithms reduce the amount of variation in a dataset, which both improves accuracy and reduces the amount of overfitting that occurs. This contrasts with many strong learners, which have a tendency to remember data and overfit the data. The performance of most models is significantly improved using features (i.e., time- and frequency-domain) that have linear patterns. On the other hand, the RF is a curve-based method that can adapt to nonlinear parameters in an effective manner (Ishaque et al., 2021). A longer training period is required, as well as a significant amount of computational power, to effectively manage the extensive use of decision trees (Ishaque et al., 2021). In contrast, KNN demonstrated the lowest accuracy rate among all tested classifiers in the current study. This could be ascribed to the inductive bias of KNN. The KNN inductive bias has a correlation with the fundamental assumption of the KNN technique, which categorizes each instance data point I as the class label of most of the other k surrounding instances by measuring the Euclidean distance. This fundamental assumption classifies each instance data point I as the class label of most of the other k surrounding instances. The KNN method determines the distance between two instances by considering all the characteristics of each instance and giving equal weight to each of those characteristics. Because only a very small portion of the entire feature set can be used for discrimination, this may pose a challenge for certain data windows. In addition, the effectiveness of KNN is highly dependent on the characteristics of the noise. Even though we have removed a lot of signal artifacts, it was impossible to remove all of them from HR recordings and HR signals, which were always going to be noisy.

5.2. Study implications and practical contributions

HRV has been known to be a reliable indicator for detecting physiological and psychophysical illnesses. In recent years, HRV has been employed to improve heart rate diagnostics in the general population, including both working and nonworking people (Burns et al., 2016; Sessa et al., 2018). Assessing the impact of work-related physical fatigue on the heart can help predict cardiac illnesses. As such, evaluating HRV has become more important (Gamelin et al., 2006). In the past, accurate evaluations of HRV required high-quality ECG signals. However, the complexity and cost of ECG equipment makes HRV analysis very challenging, particularly in field studies (Kingsley et al., 2005). Wearable sensor development has advanced to the point where HRV parameters can be reliably assessed in field settings (Hinde et al., 2021). The current study adds novel contributions to the field by exploring how linear and nonlinear cardiovascular kinetics vary in response to construction tasks (i.e., bar-bending and fixing). The current study used the Borg-20 rating of perceived exertion scores to explore the relationship between changes in self-perceived fatigue and the HRV parameters. Our findings showed that linear and nonlinear analysis of HRV could quantify work-related changes in cardiac autonomic functions. We showed that physical exertion caused significant changes in HRV parameters, indicating a shift in the relative activities of PNS and SNS in response to physical fatigue. The potential changes in HRV parameters during heavy workloads can be employed as sensitive markers to compare construction workers with and without cardiovascular diseases (CVDs). Additionally, it enables the site manager to monitor how easily a person becomes fatigued and to request that people experiencing severe fatigue take a break to avoid injury or accident. Finally, this algorithm could be integrated into a computer system or a mobile app, allowing the site manager or even individual workers to monitor their level of fatigue and take appropriate breaks. It has the potential to be a vital occupational safety and health (OSH) tool.

5.3. Limitations and future research directions

This study had a few limitations. The duration of the experiments in this study was not a typical half-day of work. Although it was originally planned to collect data continuously for a half or full day of construction work, workers' reluctance to participate forced us to cut the project down to just a 1-hour recording. While the majority of participants mentioned a busy work schedules and data privacy issues (e.g., demographic data) as their reason for declining to participate, others provided no plausible reason. Despite this limitation, our findings demonstrated that the algorithm was sensitive enough to detect even one hour of work-related fatigue. It is a sensitive approach to detect even mild fatigue in workers on a construction site. Future studies should use HRV parameters to continuously monitor fatigue during a whole day construction task. Furthermore, although bar-bending is one of the most physically demanding jobs in construction, construction work involves a wide range of tasks or activities. It is necessary to do additional research to verify the applicability of our findings to other groups of construction workers, such as manual laborers and form workers. Future research should also compare fatigue between workers performing repetitive and non-repetitive tasks. Such large-scale prospective studies can provide appropriate training data for the development of a comprehensive fatigue monitoring system on construction sites. Moreover, although this study lacked objective validation of fatigue (e.g., blood lactate level measurement to support the presence of fatigue), the Borg scale, a common scale for subjective assessment of perceived exertion, was used to determine self-perceived exertion. Although no participants complained about allergic reactions to wearing the textile-based wearable sensor system, prior research reported that some individuals felt irritation and discomfort while wearing this system (Umer et al., 2017). Future research should investigate new textile materials to improve the comfort of wearable physiological monitoring systems. Despite these limitations, the current study developed a reliable classification system that could be applied in future field research to assess construction workers' physical fatigue in real-time.

6. Conclusions

This is the first study to use linear and nonlinear analytic methods to extract various HRV parameters so as to better categorize different extents of physical fatigue in bar-benders using various machine learning algorithms. We discovered that variations in linear and nonlinear HRV parameters caused by fatigue may be classified using supervised machine learning approaches. The study confirms that the random forest classifier can better predict fatigue in construction workers based on linear and nonlinear HRV parameters. Furthermore, the combined feature set of HRV measures is better than the individual HRV feature set in assessing physical fatigue. Future research is warranted to validate the use of nonlinear HRV measures as a biomarker for monitoring physical fatigue. This study makes unique contributions to the field by examining the possible changes in HRV parameters during excessive workloads, which can be used as sensitive indicators to distinguish construction workers both with and without cardiovascular disease. The proposed method has the potential to reduce work-related musculoskeletal injuries and other fatigue-related risks through enabling continuous monitoring of physical fatigue. Our findings may also be used to develop a monitoring and warning system for severe physical fatigue and to help tailor-make optimal work rest schedules for individual workers. It could facilitate it as ideal occupational safety and health (OSH) technology.

Data Availability Statement

Upon request, the corresponding author of this study will provide access to any and all data that was generated or analyzed in order to support the findings of the study.

Acknowledgements

The authors acknowledged the following two funding grants: 1. General Research Fund (GRF) Grant (BRE/PolyU 152047/19E) entitled “In Search of a Suitable Tool for Proactive Physical Fatigue Assessment: An Invasive to Non-invasive Approach”; and 2. General Research Fund (GRF) Grant (BRE/PolyU 15210720) entitled “The development and validation of a non-invasive tool to monitor mental and physical stress in construction workers”.

Supplemental Materials

Table S1 and Figs. S1–S4 are available online in the ASCE Library (www.ascelibrary.org).

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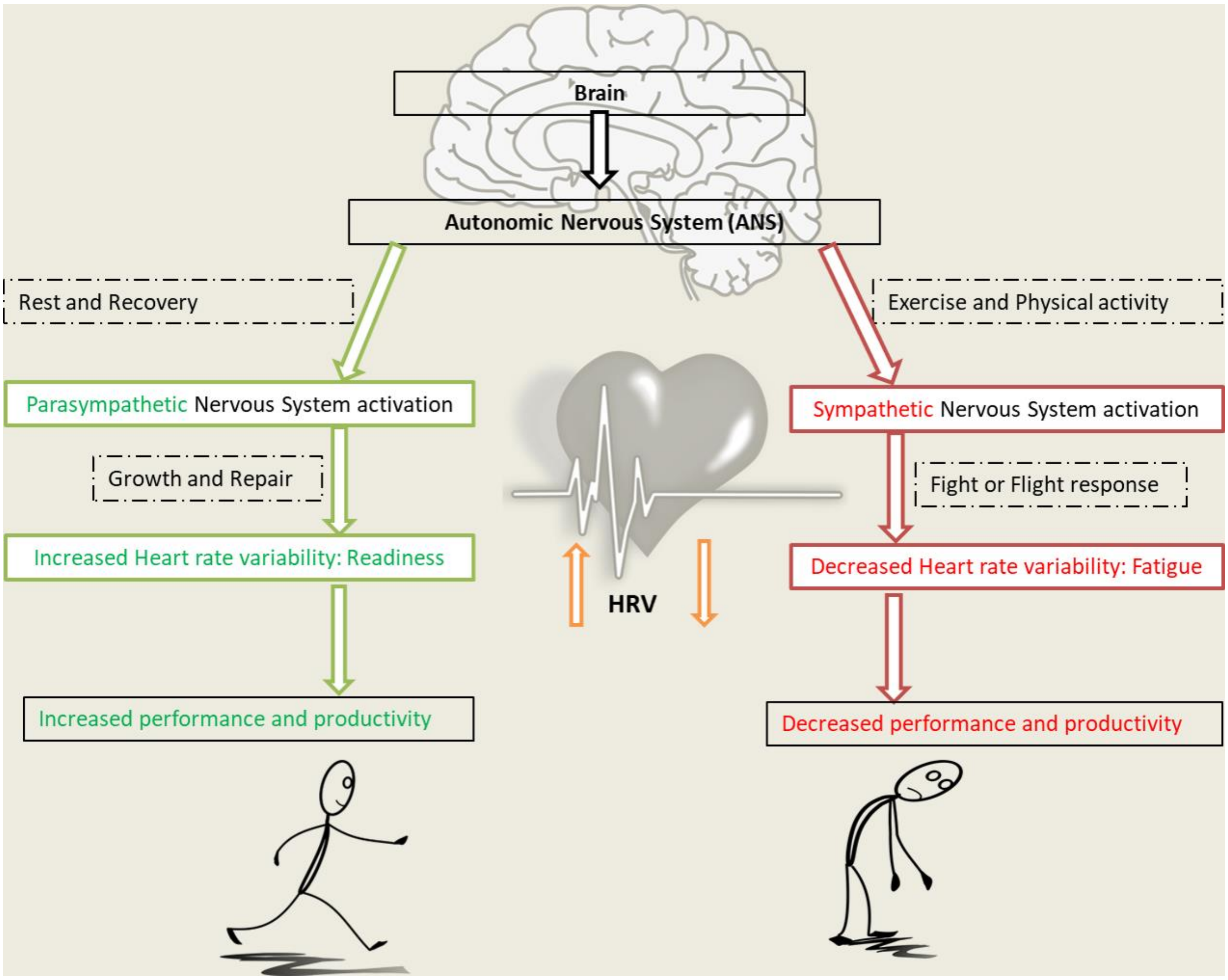

Figure 1. Influence of autonomic nervous system on heart rate variability (HRV) during exercise and rest (Reproduced with permission (Virgile, 2023))

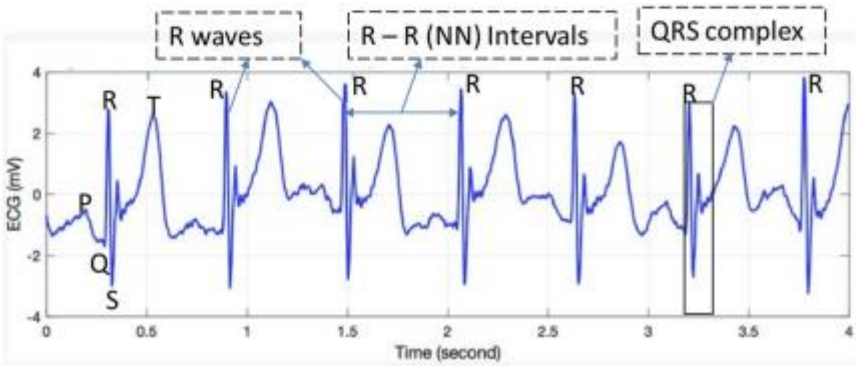

Figure 2. HRV analysis from electrocardiogram (ECG) signals

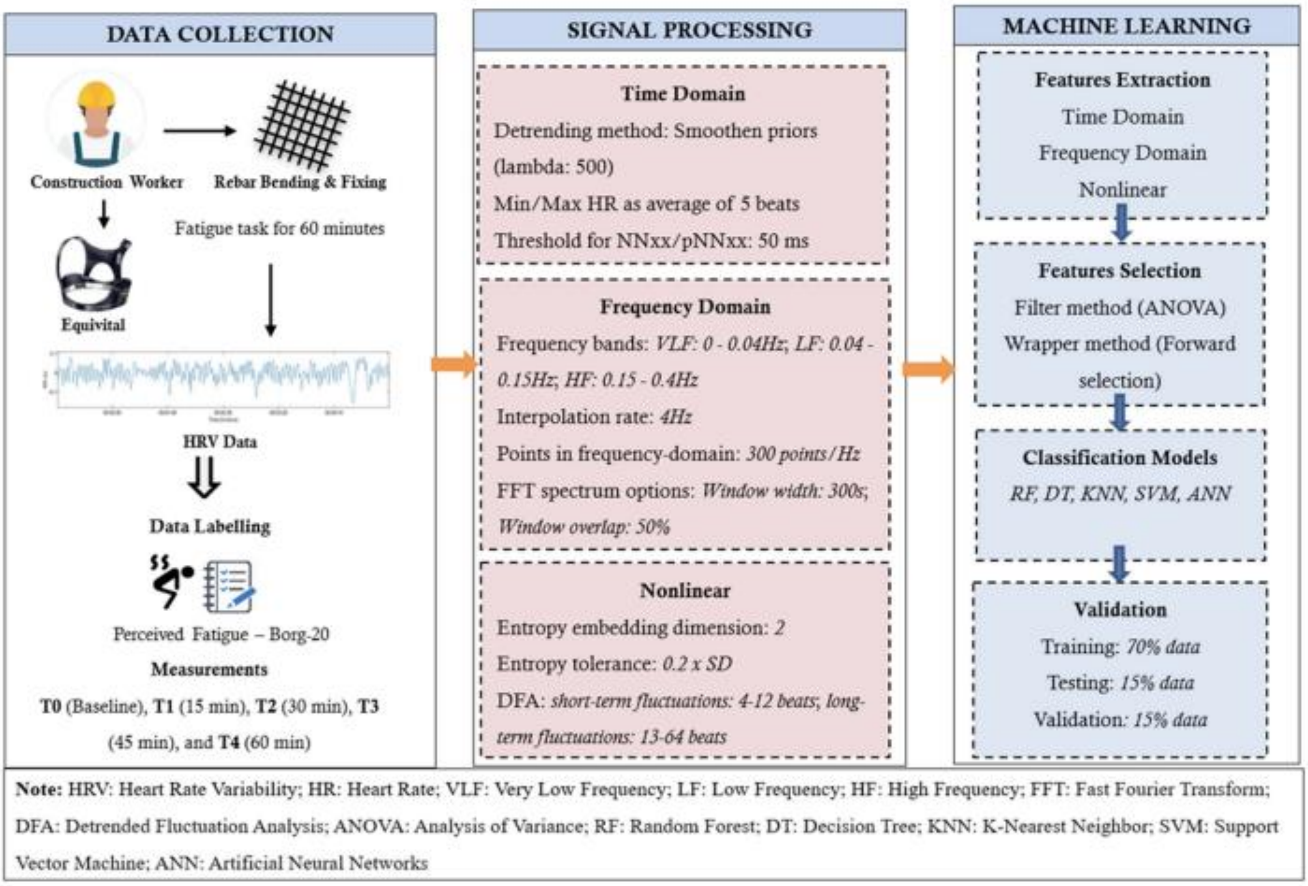

Figure 3. Methodological framework (Part of this figure is reproduced with permission (Anwer et al., 2021b))

Figure 4. EQ02 Life monitor system

Figure 5. Bar bending and fixing tasks

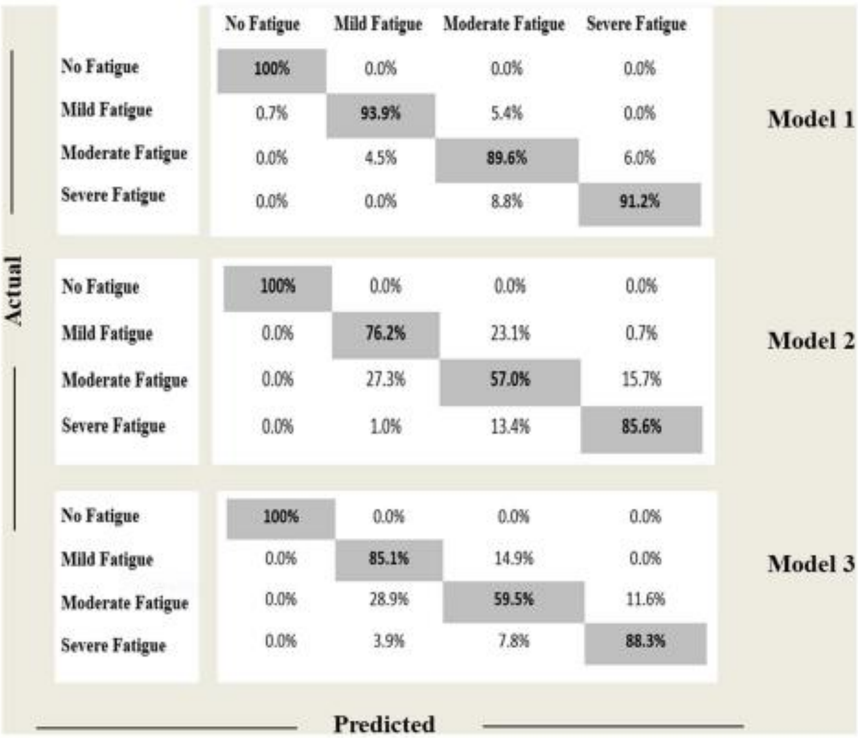

Figure 6. Comparisons of classification accuracy based on the individualized features datasets using the RF classifier. Note: Model 1 (Time-domain features); Model 2 (Frequency-domain features); Model 3 (Nonlinear features)

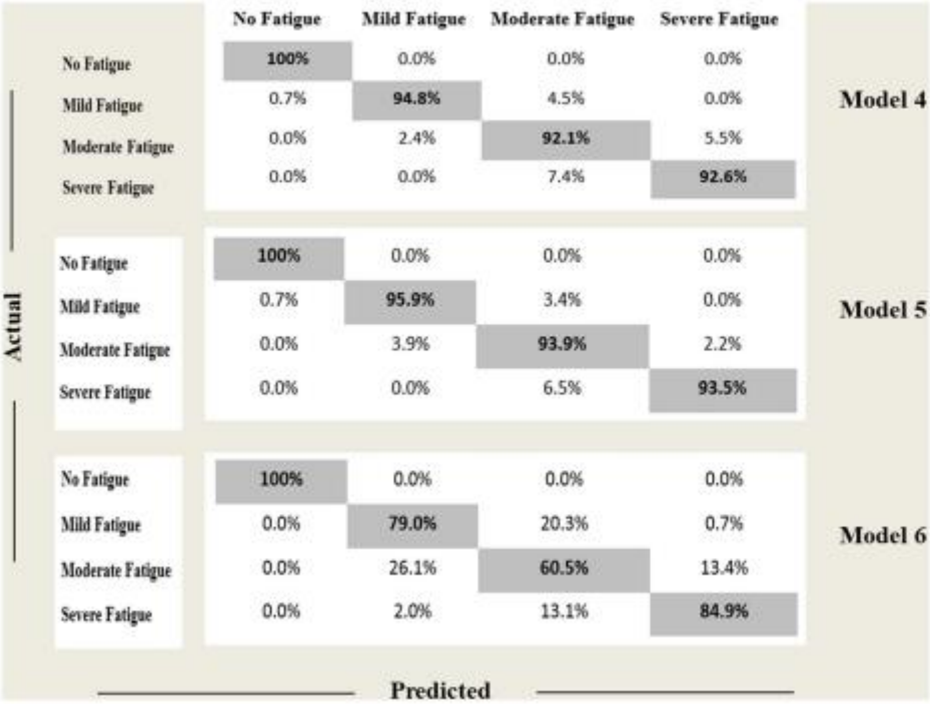

Figure 7. Comparisons of classification accuracy based on the combined features datasets using the RF classifier. Note: Model 4 (Time-and frequency-domain features); Model 5 (time-domain and nonlinear features); Model 6 (frequency-domain and nonlinear features)

Table 1. Descriptive statistics

Variables	Mean	SD
Age (years)	33.2	6.9
Weight (kg)	72.7	12.1
Height (m)	1.7	0.1
Sleep (h)	7.4	0.7
Borg-20 (6 – 20)		
Baseline	6.1	0.4
15-minute	9.3	1.4
30-minute	11.9	1.6
45-minute	14.4	1.4
60-minute	17.8	1.3

Table 2. Effects of physical fatigue on heart rate variability parameters during the construction task

Variables	Baseline	15 min	30 min	45 min	60 min	ANOVA		
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	F	*p	Partial Eta Squared
Time domain								
RRI (ms)	893.15 (80.73)	660.58 (124.86)†	586.14 (58.05)†	572.76 (60.61)†	596.20 (67.97)†	66.02	0.001*	0.86
SDNN (ms)	43.90 (14.66)	30.33 (16.12)	27.72 (16.97)	26.91 (15.53)†	26.95 (16.58)†	9.33	0.002*	0.46
HR (beats/min)	66.70 (10.36)	93.62 (16.34)†	103.33 (10.68)†	105.92 (12.06)†	101.85 (11.67)†	48.43	0.001*	0.82
SD HR (beats/min)	3.80 (1.99)	4.04 (1.65)	4.61 (2.34)	4.72 (2.21)	4.57 (2.51)	1.09	0.351	0.09
Minimum HR (beats/min)	61.14 (7.91)	77.42 (15.14)†	85.52 (14.51)†	85.51 (12.74)†	84.17 (13.95)†	18.65	0.001*	0.629
Maximum HR (beats/min)	83.10 (9.62)	113.73 (13.81)†	121.93 (8.73)†	124.88 (15.49)†	121.84 (15.01)†	35.21	0.001*	0.762
RMSSD (ms)	54.18 (15.16)	24.01 (15.92)†	18.67 (12.89)†	16.47 (10.34)†	17.48 (9.62)†	62.34	0.001*	0.850
NN50 (count)	40.50 (16.99)	7.50 (5.87)†	6.25 (6.70)†	6.08 (7.06)†	3.75 (3.74)†	115.51	0.001*	0.913
pNN50 (%)	44.22 (11.36)	7.83 (12.44)†	3.25 (4.75)†	2.91 (4.45)†	2.59 (3.61)†	146.39	0.001*	0.930
RRI triangular index	12.53 (3.72)	7.43 (3.45)†	6.17 (2.93)†	5.96 (2.55)†	6.13 (2.82)†	34.76	0.001*	0.760
TINN (ms)	214.58 (90.64)	174.83 (78.09)	155.08 (90.51)	158.00 (81.94)	155.17 (86.70)	3.772	0.010*	0.255
Frequency domain								
VLF (Hz)	0.04 (0.01)	0.03 (0.01)	0.04 (0.01)	0.04 (0.01)	0.04 (0.01)	1.809	0.192	0.141
LF (Hz)	0.05 (0.02)	0.06 (0.02)	0.06 (0.01)	0.06 (0.01)	0.07 (0.02)	2.729	0.041*	0.199
HF (Hz)	0.38 (0.04)	0.21 (0.08)†	0.17 (0.03)†	0.16 (0.01)†	0.21 (0.06)†	36.739	0.001*	0.770
VLFpw (ms^2)	74.60 (65.02)	147.34 (153.10)	133.43 (222.44)	123.09 (106.32)	83.14 (91.29)	1.224	0.314	0.100

LFpw (ms^2)	490.62 (221.05)	615.41 (817.97)	726.71 (945.19)	689.27 (983.91)	639.50 (1020.29)	0.340	0.850	0.030
HFpw (ms^2)	778.79 (390.07)	217.61 (298.38)†	184.39 (357.36)†	122.39 (169.82)†	117.08 (146.39)†	33.129	0.001*	0.751
Total power (ms^2)	1350.56 (228.57)	980.50 (1099.67)	1044.70 (1420.24)	935.04 (1198.39)	839.94 (1236.51)	0.985	0.394	0.082
VLF (log)	4.31 (1.01)	4.41 (1.21)	4.18 (1.23)	4.41 (1.01)	3.83 (1.19)	1.044	0.395	0.087
LF (log)	6.21 (2.03)	5.82 (1.16)	5.81 (1.36)	5.82 (1.26)	5.49 (1.48)	1.307	0.282	0.106
HF (log)	6.66 (1.02)	4.42 (1.59)†	3.97 (1.57)†	3.86 (1.53)†	3.95 (1.47)†	24.344	0.001*	0.689
VLFperc (%)	5.52 (3.11)	17.23 (10.73)†	16.79 (11.48)	19.49 (10.49)†	14.43 (7.23)†	6.727	0.001*	0.379
LFperc (%)	36.33 (6.21)	63.69 (14.73)†	63.28 (7.55)†	68.90 (12.25)†	68.12 (9.02)†	27.007	0.001*	0.711
HFperc (%)	57.67 (10.31)	19.05 (13.19)†	14.14 (7.93)†	11.58 (7.93)†	17.39 (10.52)†	81.822	0.001*	0.881
LFnu (n.u.)	38.45 (8.05)	77.25 (15.33)†	84.14 (7.93)†	85.59 (9.69)†	80.02 (11.24)†	64.321	0.001*	0.854
HFnu (n.u.)	61.04 (9.04)	22.72 (15.33)†	15.84 (7.93)†	14.37 (9.67)†	19.91 (11.18)†	63.172	0.001*	0.852
LF/HF ratio	0.63 (0.05)	5.34 (3.61)†	9.28 (12.58)	8.91 (6.26)†	5.99 (4.44)†	3.941	0.046*	0.264
Nonlinear dynamics								
SD_1 (ms)	38.60 (0.01)	17.01 (11.28)†	13.22 (9.12)†	11.66 (7.32)†	12.38 (6.81)†	65.080	0.001*	0.855
SD_2 (ms)	49.11 (0.01)	39.11 (20.40)	36.79 (22.46)	36.08 (20.91)	35.91 (22.67)	3.079	0.073	0.219
SD_2/SD_1 ratio	1.27 (0.01)	2.64 (0.82)†	3.03 (0.97)†	3.28 (0.92)†	2.99 (0.77)†	19.385	0.001*	0.638
ApEn	1.19 (0.01)	1.14 (0.06)	1.12 (0.16)	1.09 (0.16)	1.11 (0.16)	1.766	0.153	0.138
SampEn	1.84 (0.01)	1.40 (0.29)†	1.23 (0.31)†	1.19 (0.27)†	1.27 (0.33)†	15.550	0.001*	0.586
alpha 1	0.70 (0.01)	1.34 (0.26)†	1.36 (0.17)†	1.46 (0.18)†	1.41 (0.24)†	40.325	0.001*	0.786
alpha 2	0.31 (0.01)	0.68 (0.22)	0.73 (0.21)	0.74 (0.16)	0.69 (0.23)	21.958	0.001*	0.666

Note: The linear and nonlinear dynamics of the cardiovascular parameters during the construction task are presented as the mean (SD) throughout the experiment, i.e., at the baseline and during the 5 min recording at the first, second, third, and fourth temporal quartiles (i.e., 15, 30, 45, and 60 minutes, respectively). RRI: RR Intervals; SDNN: the standard deviation of NN intervals; HR: heart rate; SD HR: standard deviation of HR; RMSSD: root mean square of successive differences; NN50: number of successive RRI that differ more than 50 ms; pNN50: percentage of successive RRI that differ more than 50 ms; TINN: triangular interpolation of RRI histogram; VLF: very low frequency; LF: low frequency; HF: high frequency; pw: power; perc: percentage; nu: normalized units; SD_1: standard deviation of the instantaneous beat-to-beat inter-beat interval variability (semi-minor axis length of Poincaré plot ellipse fitting); SD_2: standard deviation of the long term beat-to-beat inter-beat interval variability (semi-major axis length of Poincaré plot ellipse fitting); alpha 1: short-range scaling exponent; alpha 2: long-range scaling exponent; ApEn: approximate entropy; SamEn: sample entropy;†: significant difference from baseline (adjustment for multiple comparisons, Bonferroni); *Statistically significant at $p<0.05$.

Table 3. Comparison of linear and nonlinear heart rate variability parameters used to classify physical fatigue using supervised machine learning classifiers

Models	**Classifiers**	**Performance indicators (%)**				
		AUC	CA	F1	Precision	Recall
1. Time-domain features*	KNN	96.5	87.8	87.8	87.9	87.8
	DT	90.0	87.6	87.4	87.5	87.6
	SVM	98.0	88.9	88.9	89.3	88.9
	RF	**97.8**	**92.0**	**92.0**	**92.0**	**92.0**
	ANN	98.0	89.9	89.9	89.9	89.9
2. Frequency-domain features**	KNN	82.0	63.0	62.7	62.9	63.0
	DT	78.7	66.8	67.0	67.5	66.8
	SVM	86.6	68.1	68.3	68.8	68.1
	RF	**88.4**	**74.0**	**73.9**	**73.8**	**74.0**
	ANN	87.2	69.7	69.5	69.5	69.7

3. Nonlinear dynamics features* **	KNN	82.6	65.6	65.5	65.6	65.6
	DT	82.4	72.1	71.8	72.0	72.1
	SVM	88.7	72.4	72.6	73.3	72.4
	RF	**90.6**	**77.3**	**77.0**	**77.0**	**77.3**
	ANN	88.9	75.5	75.3	75.4	75.5
4. Time- and frequency-domain features	KNN	95.7	84.8	84.8	85.0	84.8
	DT	92.2	90.0	89.9	89.9	90.0
	SVM	97.9	89.7	89.8	89.9	89.7
	RF	**98.8**	**92.6**	**92.6**	**92.7**	**92.6**
	ANN	98.8	92.0	92.0	92.0	92.0
5.Time-domain and Nonlinear dynamics features	KNN	95.8	83.8	83.9	84.4	83.8
	DT	93.9	91.0	91.0	91.0	91.0
	SVM	98.0	89.2	89.3	90.0	89.2
	RF	**98.4**	**93.5**	**93.5**	**93.6**	**93.5**
	ANN	97.9	88.7	88.7	88.9	88.7
6. Frequency-domain and Nonlinear dynamics features	KNN	83.5	63.9	63.9	64.2	63.9
	DT	79.3	70.6	70.2	70.1	70.6
	SVM	89.9	72.4	72.6	72.8	72.4
	RF	**90.8**	**75.8**	**75.7**	**75.6**	**75.8**
	ANN	90.1	74.2	74.2	74.2	74.2
7. All features	KNN	93.2	81.1	81.3	82.1	81.1
	DT	94.8	93.6	93.6	93.7	93.6
	SVM	97.8	88.5	88.6	88.7	88.5

	RF	**98.2**	**91.9**	**91.9**	**91.9**	**91.9**
	ANN	98.2	90.1	90.3	90.3	90.1

Note: *(RRI: RR Intervals; SDNN: the standard deviation of NN intervals; HR: heart rate; RMSSD: root mean square of successive differences; NN50: number of successive RRI that differ more than 50 ms; pNN50: percentage of successive RRI that differ more than 50 ms; TINN: triangular interpolation of RRI histogram); **(LF: low frequency; HF: high frequency; pw: power; perc: percentage; nu: normalized units); ***(SD_1: standard deviation of the instantaneous beat-to-beat inter-beat interval variability (semi-minor axis length of Poincaré plot ellipse fitting); SD_2: standard deviation of the long term beat-to-beat inter-beat interval variability (semi-major axis length of Poincaré plot ellipse fitting); alpha 1: short-range scaling exponent; alpha 2: long-range scaling exponent; SamEn: sample entropy); AUC (Area under curve); CA (Classification accuracy); F score (weighted average of Precision and Recall); KNN (K-nearest neighbor); DT (Decision tree); SVM (Support vector machine); RF (Random forest); ANN (Artificial neural networks).