Healthcare Transformation with Informatics and Artificial Intelligence
J. Mantas et al. (Eds.)
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doi:10.3233/SHTI230454

Exercise Exertion Levels Prediction Based on Real-Time Wearable Physiological Signal Monitoring

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Abstract. The real-time revolutions per minute (RPM) data, ECG signal, pulse rate, and oxygen saturation levels were collected during 16-minute cycling exercises. In parallel, ratings of perceived exertion (RPE) were collected each minute from the study participants. A 2-minute moving window, with one minute shift, was applied to each 16-minute exercise session to divide it into a total of fifteen 2-minute windows. Based on the self-reported RPE, each exercise window was labeled as "high exertion" or "low exertion" classes. The heart rate variability (HRV) characteristics in time and frequency domains were extracted from the collected ECG signals for each window. In addition, collected oxygen saturation levels, pulse rate, and RPMs were averaged for each window. The best predictive features were then selected using the minimum redundancy maximum relevance (mRMR) algorithm. Top selected features were then used to assess the accuracy of five ML classifiers to predict the level of exertion. The Naïve Bayes model demonstrated the best performance with an accuracy of 80% and an F1 score of 79%.

Keywords. Aerobic exercise, exertion level, heart rate variability, machine learning

1. Introduction

Unsupervised home-based aerobic exercise may result in unintended consequences in older adults and people with cardiovascular conditions if exercise safety is not monitored in real-time. To enhance exercise safety, real time monitoring of the exercise exertion level needs to be added to the current home-based exercise platforms.

Exercise exertion is associated with sympathetic nervous system (SNS) activity, which is a branch of the autonomic nervous system (ANS) [1]. ANS plays a significant role in regulating HRV [2]. Thus, HRV analysis at rest and during exercise could be used to elucidate the ANS status and, therefore, the level of exertion [3]. This study aimed to build machine learning (ML) algorithms for the automated classification of cycling exercise exertion levels using data from wearable devices. The proposed approach may

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be used for real-time monitoring of exercise exertion.

2. Methods

2.1. System and Data Acquisition

Using our previously developed (iBikE) system [4], ten healthy individuals were asked to perform a pedaling exercise for 16 minutes. For each session, the participants were asked to follow the same protocol for pedaling exercises. The protocol consisted of the first two minutes of pedaling with no resistance and four minutes with medium resistance. It ended with the last ten minutes of pedaling with full resistance when the participants were asked to pedal as fast as they could. The bike resistance was adjusted without interrupting the user's pedaling during each exercise session. Participants were asked to report the "rating of perceived exertion" (RPE) at the end of each consecutive minute of pedaling. The rating was based on the visual, a 1-10 Borg RPE scale [5]. A total of 16 ratings, one for each minute, were collected for each exercise session.

One of our classification features was RPM data collected from the iBikE system. This data was sent from the bike to the customized app installed on a tablet [4]. In addition, participants were asked to wear two wearables for collecting physiological signals during each exercise session. We collected ECG signals using Actiheart 5 [6], a wearable sensor that combines single-lead ECG and an activity recorder. Actiheart 5 has been used in research in multiple application areas and provides full ECG waveform at up to 1024 Hz [6]. In addition to the ECG signal, pulse rate and blood oxygen saturation were collected using a pulse oximeter (WristOx2®, Model 3150) [7]. These collected data from the pulse oximeter and the results of HRV analysis parameters from collected ECG formed additional classification features.

2.2. Analysis

The ECG signal was analyzed using the Kubios scientific HRV software [8]. First, we defined a 2-minute moving window, which was shifted every minute for every 16 minutes of collected data. Therefore, we had a total of fifteen 2-minute windows. HRV analysis was performed in both time and frequency domains for each window—all the extracted HRV features were generated by Kubios HRV software [8]. The extracted results were saved in a MATLAB® (license number: 40477919) MAT-file format and included all the analysis results and analysis parameters and the RR intervals from raw data. We used these parameters as model features for our classification algorithms.

We used the same approach to evaluate the RPM data, oxygen saturation levels, pulse rate data, and self-reported RPE data. A 2-minute moving window was shifted every minute for every 16 minutes of collected data. Then the values of each window were averaged. A total of fifteen averaged numbers were reported for each of the 16 minutes of collected data. Finally, each 2-minute set of predictive features was assigned to one of 2 classes based on the corresponding RPE. Class I: high exertion (RPE >= 3.5), Class II: low exertion (RPE < 3.5). Overall, we extracted 68 predictors from RPM data, oxygen saturation levels, pulse rate data, and HRV analysis in both time and frequency domains.

As there were no health risks and the participants were all authors of this paper, we did not require institutional review board approval. No protected health information was collected, and the resulting analytical data set was fully de-identified. No compensation was provided to the study participants.

3. Results

We made a dataset of all exercise sessions with different user predictor variables. Then, to select the best features, they were ranked for classification using mRMR algorithm in MATLAB® [9]. The mRMR algorithm ranks predictor variables based on the response variables (high exertion vs. low exertion). Figure 1 shows the top-ranked predictor variables.

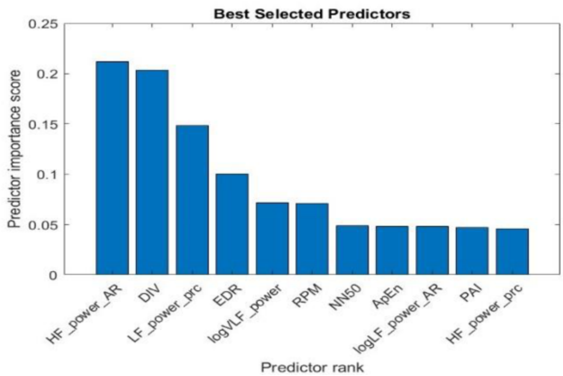

Figure 1. Top ranked predictor variables based on feature selection MRMR algorithm. prc: Percentage; AR: AR spectrum estimate.

Features with higher values in mRMR results give a higher confidence in feature selection. Therefore, we selected the top six predictors which showed the highest values by mRMR to be later used for the predictive modeling of two classes of RPE values. The selected predictors were: 1) HF_power_AR: High-frequency power (ms2), using AR's periodogram estimation methods, 2) DIV: The maximum line length inverse (1/Lmax (beats), the divergence), 3) LF_power_prc: Low-frequency power (%), using Welch's spectrum estimate method, 4) EDR: Respiration rate (Hz), 5) logVLF_power: Logarithm of very low-frequency power (lo), using Welch's spectrum estimate method, and 6) RPM: The bike speed (rotation per minute).

Each predictor consisted of 150 values (fifteen for each user, a total of ten users) for the classification algorithm training. Twenty percent of the total values were randomly chosen for testing the trained algorithms. We used MATLAB® Classification Learner app to train models to classify the data. The app allows generating the algorithm as a function for future evaluation. Five primary machine learning techniques were deployed, including (1) Naïve Bayes technique with Kernel Naïve Baye classifier, (2) Neural Network Technique with Tri-layered Neural Network classifier, (3) Ensemble technique with Subspace Discriminant classifier, (4) Kernel technique with SVM Kernel classifier, and (5) Tree technique with Coarse Tree classifier. Table 1 provides a summary of the classifiers' results. The Naïve Bayes technique with the Kernel Naïve Baye classifier performed best based on the highest accuracy (80%) and F1 score (79%). However, the Ensemble technique with Subspace Discriminant classifier showed the highest Area Under Curve (AUC) value of 0.8.

Table 1. Training and testing of the selected data using machine learning techniques. *AUC: Area Under Curve.

Model	Validation **Accuracy**	Validation **F1 Score**	Validation **AUC***	Test **Accuracy**	Test **F1 Score**	Test **AUC***
Naïve Bayes	78.3%	77%	0.85	80%	79%	0.75
Neural Network	74.2%	74%	0.78	76.7%	72%	0.73
Ensemble	70%	69%	0.81	76.7%	74%	0.83
SVM Kernel	70%	70%	0.69	76.7%	74%	0.77
Tree Classifier	79.2%	79%	0.79	73.3%	75%	0.73

4. Discussion

Our findings demonstrated the potential of our developed algorithms for real-time automated monitoring of the patient's exertion levels during aerobic exercise using physiologic data from wearable sensors. Moreover, data gathered from exercise equipment (RPMs in this example) could be employed as a critical feature in determining exercise exertion based on selecting the top predictors of the mRMR algorithm.

5. Conclusions

A larger sample size could be used to conduct additional validation experiments. Adding more sensors, such as force detectors on the pedals, could add more predicting features to the algorithm and improve the results. In addition, the generated algorithms must also undergo extensive testing in large groups of patients with different chronic conditions over an extended period. The effect of AI-driven exertion level monitoring on exercise adherence, clinical outcomes, and patient safety must be established in randomized clinical trials.

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