

# Machine Learning Approaches for Exercise Exertion Level Classification Using Data from Wearable Physiologic Monitors

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**Abstract.** This research aimed to develop a model for real-time prediction of aerobic exercise exertion levels. ECG signals were registered during 16-minute cycling exercises. Perceived ratings of exertion (RPE) were collected each minute from the study participants. Based on the reported RPE, each consecutive minute of the exercise was assigned to the “high exertion” or “low exertion” class. The characteristics of heart rate variability (HRV) in time and frequency domains were used as predictive features. The top ten ranked predictive features were selected using the minimum redundancy maximum relevance (mRMR) algorithm. The support vector machine demonstrated the highest accuracy with an F1 score of 82%.

**Keywords.** Machine learning, aerobic exercise, exertion level

## 1. Introduction

This research aims to develop an algorithm to predict exercise exertion levels during cycling exercise using classification algorithms from the given HRV parameters.

## 2. Methods

### 2.1. System and Data Acquisition

We asked ten healthy adults to perform sixteen minutes of pedaling using our previously developed (iBike) system [1]. Each 16-minute session started with two minutes of pedaling with no resistance, followed by four minutes of pedaling with medium resistance, and followed by the last ten minutes of pedaling with full resistance when participants were asked to pedal as fast as they could. At the end of each consecutive minute, users were asked to report the RPE based on a 1-10 Borg RPE scale. We used two wearables to collect physiological signals from the study participants during each exercise session. ECG signal was collected using Actiheart 5. Pulse rate and blood oxygen saturation were collected using a pulse oximeter (WristOx2®, Model 3150).

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## 2.2. Analysis

The ECG data were analyzed with the Kubios HRV software. First, the collected ECG data from each exercise session was divided into eight 2-minute windows. Then for each window, HRV analysis was performed in both time and frequency domains. These parameters were later used as predictor variables for our classification algorithms. Moreover, RPM, oxygen saturation levels, and HR data from the oximeter were averaged for every window and added to the initial list of the predictor variables. Finally, based on the corresponding RPEs, each 2-minute window was assigned to one of two classes: 1 - high exertion (RPE above 3.5), 2 - low exertion (RPE equal or below 3.5).

## 3. Results

A combined dataset of all exercise sessions with different user predictor variables was assembled. Features were ranked for classification using the mRMR algorithm based on the RPE response variables. The top ten predictors were selected for predictive modeling of the two classes of RPEs. The top ten ranked predictors, in order, were: very low frequency (%) using AR spectrum estimate method, high-frequency power (%) Welch's periodogram, Approximate Entropy, Logarithm of very low-frequency power (lo) using AR spectrum estimate method, respiration rate (Hz), high-frequency power (ms<sup>2</sup>) using AR spectrum estimate method, high-frequency peak (Hz) using AR spectrum estimate method, number of successive RR interval pairs (beats) that differ more than 50 milliseconds, minimum heart rate value (bpm), and very low-frequency peak frequency (Hz) using AR spectrum estimate method. Each predictor consisted of eighty values (eight windows for each user, a total of ten users). 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. Table 1 summarizes the classifiers' results.

**Table 1.** Training and testing results using three primary machine learning techniques. Val: Validation.

Model (Classifier)	Val Accuracy	Val F1 Score	Test Accuracy	Test F1 Score
Ensemble (Subspace k-NN)	85%	85%	75%	71%
Kernel (SVM Kernel)	84%	84%	81%	82%
Kernel (naïve Bayes)	84%	83%	75%	77%

## 4. Conclusions

Automated assessment of exercise exertion levels can improve unsupervised home-based exercise safety and efficacy. The developed algorithms must be further evaluated in large representative groups of patients with different chronic conditions over a prolonged period in clinical trials.

## References

- [1] Smiley A, Tsai TY, Cui W, Parvanova I, Lyu J, Zakashansky E, Xhakli T, Cui H, Finkelstein J. Telemonitoring of Home-Based Biking Exercise: Assessment of Wireless Interfaces. *JMIR Biomed Eng.* 2022 Oct;7(2):e41782, doi: 10.2196/41782.