IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

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To cite this article: S Tang *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **530** 012060

IOP Conf. Series: Materials Science and Engineering **530** (2019) 012060 doi:10.1088/1757-899X/530/1/012060

Running and Cycling Induced Fatigue on Wrapper vs. BLR Feature Selection for IBk Classification

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Abstract. Running and cycling fatigue causes muscle pains, cramps and accidental injuries. Previous studies had considered the importance of tri-axial accelerometer to detect fatigue motion in stability, balance and postural deviation aspects. While tri-axial accelerometer is important, the capability to predict running and cycling fatigue from the biomechanical attributes were unclear. Therefore, the study aims to (i) compare the featured attributes selected from wrapper approach and Binary Logistic Regression (BLR) on running and cycling datasets and (ii) perform IBk classification accuracy comparison on the feature selection attributes. Public running, experimental running and cycling induced fatigue datasets were employed to test the analysis. The most significant attributes identified in the public running was RMS_ML, followed by Range_ML and the cycle frequency in experimental running and cycling respectively. On 10 folds cross-validation classification test using the IBk algorithm in WEKA, accuracies for experimental running and cycling datasets were 93.1% and 90.5% from wrapper method, 65.6% and 76.2% from BLR respectively. Wrapper method performs better than BLR in data overfitting phenomenon. Findings reveal that the mediolateral variation at body trunk motion plays a major impact to predict fatigue running but fatigue cycling shows cycling frequency as the main attribute in fatigue cycling prediction.

1. Introduction

Continuous endurance sports like running and cycling under fatigue state contributes to muscle soreness and cramp. Running and cycling comparisons had been investigated from the aspect of muscle fatigue on peripheral neuromuscular [1]. Cycling is generally better than running considering the low impact and less eccentric muscle motion [2]. Running-induced fatigue attributes included lengthy training duration on muscle damage [3], plantar pressure distribution on different foot structures [4], foot strike pattern for impact force reduction [5] or surface type (treadmill or overground) on acceleration impact [6]. On the other hand, the cycling-induced fatigue attributes as reported in Raymond et al. [7] were riding posture, saddle height, muscle fatigue or cadence.

Identifying significant attributes contributing to running and cycling fatigue were crucially important for injury risk prevention. Past studies have reported tri-axial accelerometers on fatigue detection [8–11], in which, the stability and movement balancing were focused. Knowing the importance of tri-axial accelerometer in fatigue detection, researchers attempted to investigate the posture deviation through acceleration root mean square (RMS) ratio, step frequency, steps and stride regularity and sample entropy [11-12]. Running and cycling are the repetitive nature of activities that involve lower limb motions. However, the comparison between running and cycling using the significant attributes of accelerometry derived quantities and sacral trajectory measurements for fatigue determination was not reported. The accelerometry derived quantities might be redundant as each derived quantity is repeatedly measured in the vertical (VT), mediolateral (ML) and anteroposterior (AP) directions. Sacral trajectory data collection in the three directions is not only tedious but also time-consuming. Thus, feature selection approach to determine the important attributes that differentiate the fatigue levels in running and cycling is pivotal to reduce the data complexity for class prediction.

Therefore, the objectives of this study are mainly i) to compare the featured attributes selected from wrapper approach and Binary Logistic Regression (BLR) on running and cycling datasets and ii) perform IBk classification accuracy comparison on the feature selection attributes. Wrapper method of feature selection with IBk supported classifier was applied to select the attributes in Waikato Environment for Knowledge Analysis versions 3.8 (WEKA) tool. BLR statistical analysis on IBM Statistical Package for the Social Sciences Statistic versions 23 (SPSS) was applied to compare the results. The IBk classification algorithm was used to test the classification performances on selected attributes. Three datasets will be employed for the wrapper and BLR feature selection for the IBk classification analysis: public running, experimental running and experimental cycling.

2. Methodology

2.1. Dataset

Three datasets: public running, experimental running and experimental cycling were used to test the feature selection methods using the wrapper and BLR approaches.

Public running: Dataset were retrieved from Schütte et al. [8] as the benchmark data. Dataset involved 20 athletes (11 males, 9 females, 21.1±2.1 years old, 177±8cm, 66.1±6.2kg) whom participated in continuous fatigue run on a treadmill (until Borg RPE reaches minimum 17) based on individual time-trial speeds [8]. The time-trial speed of each participant was obtained through the recorded time on 3.2km run a day before. A single tri-axial accelerometer (X16-2 wireless accelerometer, 3 axis ±16g, 15-bit resolution, Gulf Coast Data Concepts, MS) was attached to the participants' waists by double-sided tape and elastic straps to measure the acceleration of trunk in three directions: VT, ML and AP during the treadmill run. Running motion was recorded on ten Vicon system cameras (Vicon®, Oxford, Metrics UK) for sacral trajectory measurements.

Experimental running: The study subjects involved were non-athletes, involving 14 males and 6 females (22.5±3.9 years old, 167.0±8.5cm, 62.9±18.6kg) whom were tasked to perform running on a treadmill (Cybex Model 700T). Participants have signed an informed consent at their voluntary basis prior to the experiment. Instruction was first given to run 6km/hr for 6 minutes on the treadmill for familiarization [13]. After some warming up, the treadmill speed was increased by 1km/h every 2 minutes till 70% of maximum heart rate was achieved (Borg RPE scale reaches 13) [14]. The heart rate was monitored on the treadmill throughout the experiment. The similar speed at Borg RPE scale-13 was maintained till 90% of maximum heart rate (Borg RPE scale reaches 17). Participants continued to run at Borg RPE scale-17 for another 2 minutes and the termination time was recorded. An iPhone6 installed with SensorLog versions 2.0 APP (to function like a tri-axial accelerometer) was attached to the back of the body trunk (with a waist bag) throughout the experiment to measure the trunk acceleration. Two cameras (Canon EOS 30D) for sacral trajectory measurements were stationed at the side and the back of the treadmill to capture the participants' motions.

Experimental cycling: There were 16 males and 4 females (26.1±4.3 years old, 168.7±8.9cm, 66.0±12.1kg) participated in the cycling induced fatigue experiment on an ergometer bike (Cateye Upright Bike Model EC-2300). The participants have signed their voluntary consent prior to the experiment. Similar experimental procedure to the experimental running was employed. The experiment began with 6km/h warm up for 6 minutes [13] followed by 1km/h speed increment at every 2 minutes till 70% of maximum heart rate was achieved (Borg RPE scale reaches 13) [14]. The heart rate was monitored on the ergometer bike itself during the experiment. The similar speed at Borg RPE scale-13 was maintained till 90% of maximum heart rate (Borg RPE scale reaches 17). Participants continued the cycling motions at scale-17 for another 2 minutes and the termination time was recorded. An iPhone6 with SensorLog versions 2.0 APP was attached to the back of the body trunk throughout the experiment for acceleration data recording. Two cameras (Canon EOS 30D) were stationed at the side and the back of ergometer bike to record the cycling motions.

The recorded running and cycling data consist of 880 records each (22 attributes along with a class attribute x 40 instances). The 22 attributes describe the accelerometry-derived measures and sacral trajectory measures in three directions: VT, ML and AP. Acceleration root mean square (RMS), ratio RMS, step regularity, stride regularity, step frequency or cycle frequency and sample entropy were attributes of accelerometry measures while the sacral trajectory measures included the mean and range of displacement. There were two predefined class attributes: fatigue and pre-fatigue. Following Schütte et al. [8]**,** the prior 10 seconds motions at Borg RPE scale-17 is identified as pre-fatigue, while the last 10 seconds motions prior to termination is defined as fatigue.

2.2. Feature selection

The data features, which provides the relevant information that enhances classification analysis were considered at this level.

The datasets were tested on the wrapper method of WEKA and BLR using SPSS tool to select the significant attributes. Wrapper method applied Wrapper Subset Evaluator with BestFirst searching method in forward direction. IBk (Instance-bases) learner was selected as the supported classifier which employed the nearest neighbour technique to form the attributes subsets. The importance of the generated subset was evaluated on merit point basis (ranged from 0 to 1) [15]. It was noted that the higher the merit the better will be the subset in distinguishing fatigue and pre-fatigue classes.

The BLR approach was later used to compare selected attributes with those featured attributes identified from the wrapper approach. The BLR approach was deemed suitable as the class predicted is categorical (fatigue vs. pre-fatigue). BLR applied the forward stepwise (Wald) method to search the attributes in the forward direction. Wald Chi-Squared forward search method is desirable to ensure the attributes selected in a model are significant. BLR presents the coefficient value (B), standard error (S.E.), Wald statistic (Wald), Sig. value and the odds ratio (Exp(B)) of each attribute selected. The statistical significance of attributes was determined by lower S.E. and Sig. value < 0.5. Meanwhile, Exp(B) examine the relationship of attributes with the fatigue and pre-fatigue classes following [16]:

$$\mathrm{Exp(B)} = 1\text{: no relationship}$$
$$\mathrm{Exp(B)} > 1\text{: positive relationship}$$
$$\mathrm{Exp(B)} < 1\text{: negative relationship}$$

On feature selection approach, both wrapper and BLR approaches returned subsets of data features to be classified using 10 folds cross-validation on IBk algorithm. The significant attribute selections were evaluated by the percentage data classification accuracies in using the IBk algorithm. ZeroR classification results are referred as the baseline classifier to verify informative classification. The classification accuracy must be higher than ZeroR accuracy to ensure informative results obtained, else the results are deemed meaningless for interpretation.

3. Results and discussions

Findings from the study datasets experimented were segregated by the wrapper method, BLR approach and their comparisons at feature selection level. This is followed by classification accuracies to judge the feature selection approaches.

3.1. Feature selection

3.1.1. Wrapper method. The attributes selected of each dataset under evaluation of wrapper subset evaluator with Best First in forward searching method was tabulated in Table 1.

Table 1. Attributes selected from wrapper method

Dataset	Total number of subset		Merit of best subset found		Number of attributes selected		Attribute selected
	N	Percent difference (%)	Merit	Percent difference (%)	N	Percent difference (%)	
Public Running (benchmark)	184	-	0.786	-	5	-	*RMS_AP*, RMS_ML, ***SampEntropy_AP,*** StrideReg_AP, ***StrideReg_VT.***
Experimental Running	214	16.3	0.890	13.2	8	60	Disp_VT, **Range_AP,** Range_ML, ratio RMS_VT, ***SampEntropy_AP,*** **SampEntropy_VT**, StepReg_VT, ***StrideReg_VT.***
Experimental Cycling	216	17.4	0.876	11.5	6	20	CycleFreq, **Range_AP**, ratio *RMS_AP*, RMS_AP, RMS_VT, **SampEntropy_VT**.

bold- similar attribute selected for experimental running and cycling
italic- similar attribute selected for public running and experimental cycling
bold & italic- similar attribute selected for public and experimental running

Table 1 shows that the experimental datasets: running and cycling resulted in higher number of subsets evaluated (Running: 16.3%, Cycling: 17.4%) with the merit of the best subset (Running: 13.2%, Cycling: 11.5%) and number of attributes (Running: 60%, Cycling: 20%) selected as compared to public running data (benchmark). The attributes selected on feature selection approaches differ on datasets basis. The commonly selected attributes were *RMS_AP*, ***SampEntropy_AP*** and ***StrideReg_VT***. *RMS_AP* was similarly selected in public running and experimental cycling while ***SampEntropy_AP*** and ***StrideReg_VT*** were selected for public and experimental running. **Range_AP** and **SampEntropy_VT** were the attributes resulted in experimental running and cycling. However, there was no similar attribute selection from three different datasets.

3.1.2. Binary logistic regression (BLR). On BLR, the attributes were selected using the Wald forward searching method as shown in Table 2. B and Exp(B) indicate the attributes strength and relationship direction with the data class. S.E. is referred as the indicator of coefficient's precision.

Table 2. Attributes selected from BLR on three datasets

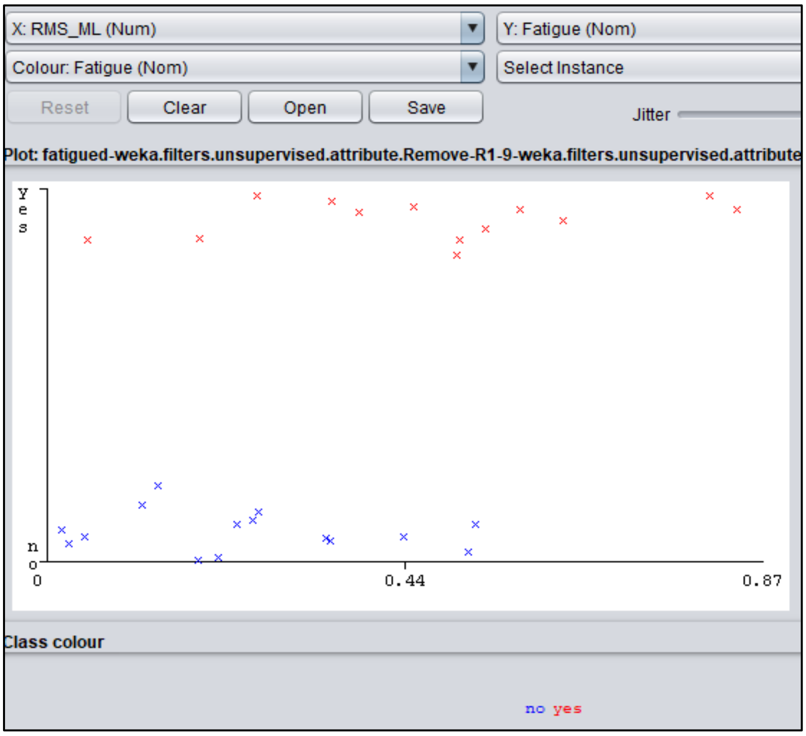
Dataset	B	S.E.	Wald	df	Sig.	Exp(B)	Attribute selected
Public Running	-6.481	2.882	5.056	1	0.025	0.002	RMS_ML
(benchmark)	-5.774	2.909	3.939	1	0.047	0.003	SampEntropy_AP
	5.381	2.060	6.823	1	0.009	217.329	Constant
Experimental	-8.314	4.348	3.657	1	0.056	0.000	StepReg_ML
Running	-0.913	0.443	4.256	1	0.039	0.401	Range_ML
	9.508	3.733	6.489	1	0.011	13472.313	Constant
Experimental	-0.060	0.029	4.274	1	0.039	0.942	CycleFreq
Cycling	7.888	3.799	4.311	1	0.038	2664.600	Constant

There were lesser attributes selected using the BLR approach. Only one to two attributes were identified being important in the three datasets. RMS_ML and SampEntropy_AP were selected in public running, StepReg_ML and Range_ML were seen in experimental running whereas only one single attribute, CycleFreq was selected in experimental cycling. All attributes selected were found statistically significant (*Sig.* < 0.05) except for StepReg_ML.

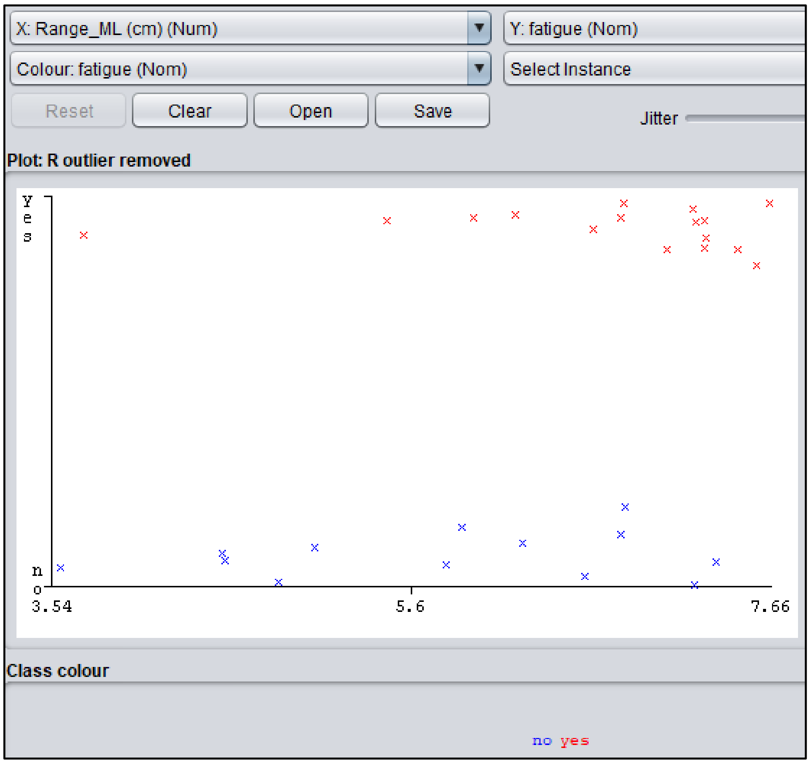
In public running (benchmark), RMS_ML and SampEntropy_AP were statistically significant (*Sig.* < 0.05). RMS_ML demonstrated major impact compared to SampEntropy_AP due to lower S.E. (2.882 < 2.909) and Sig. value (0.025 < 0.047) (Table 2). The RMS_ML showed B value = -6.481<1 indicating the negative relationship exists between RMS_ML with the pre-fatigue class. This is visualized in Figure 1(a), as RMS_ML increases, amount of data belonging to pre-fatigue decreases. The Exp(B)=0.002 in RMS_ML implied that when the RMS_ML increases by 1, probability to have pre-fatigue class reduces by 99.8%.

While in experimental running, only the Range_ML was statistically significant (*Sig.* < 0.05). Lower standard error (0.443 < 4.348) in Range_ML supports the results that the attribute is significant compared to StepReg_ML to distinguish between fatigue and pre-fatigue classes. The relationship of Range_ML and the pre-fatigue class is negative (B = -0.913, Exp(B) = 0.401). When Range_ML increases by 1cm, the probability to have pre-fatigue class decreases by 59.9%. This can be observed in Figure 1(b), the number of data accumulated at pre-fatigue class decreases as Range_ML increases.

Similar observation was shown in experimental cycling, the relationship between CycleFreq with the pre-fatigue class is negative (B = -0.060, Exp(B) = 0.942). CycleFreq is statistically significant (*Sig.* < 0.05). The probability to have pre-fatigue class reduces by 5.8% when CycleFreq increases in 1 cycle/min (Figure 1(c)).

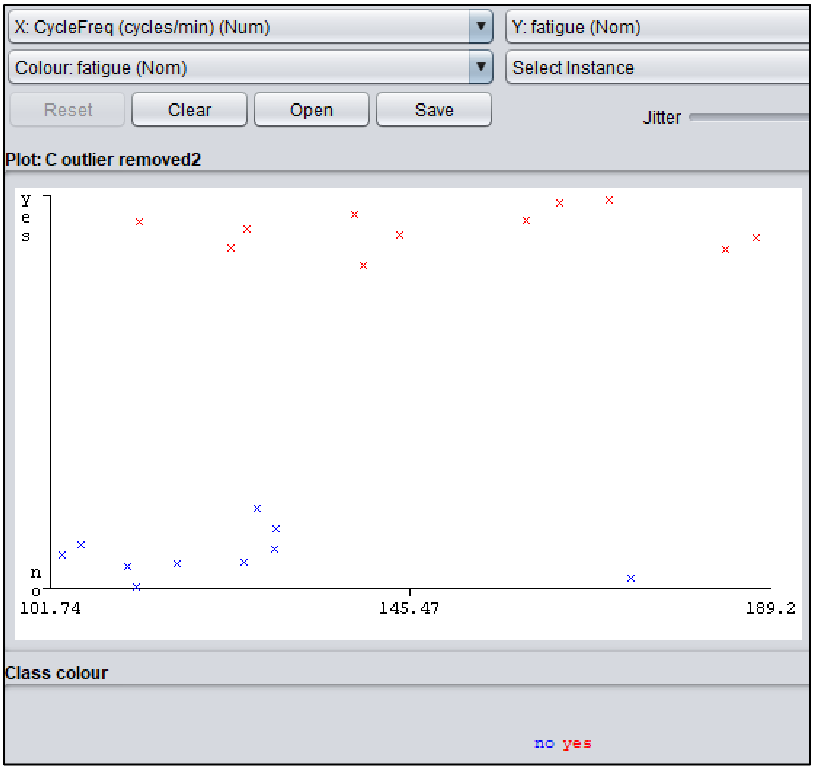

X: RMS_ML (Num)
Y: Fatigue (Nom)
Colour: Fatigue (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: fatigued-weka.filters.unsupervised.attribute.Remove-R1-9-weka.filters.unsupervised.attribute
yes
no
0
0.44
0.87
Class colour
no yes

(a)


X: Range_ML (cm) (Num)
Y: fatigue (Nom)
Colour: fatigue (Nom)
Select Instance
Reset
Clear
Open
Save
Jitter
Plot: R outlier removed
yes
no
3.54
5.6
7.66
Class colour
no yes

(b)

IOP Conf. Series: Materials Science and Engineering **530** (2019) 012060 doi:10.1088/1757-899X/530/1/012060



(c)

Figure 1. The data classes (yes = fatigue, no = pre-fatigue) on (a) RMS_ML (b) Range_ML (c) cycle frequency attributes

3.1.3. Wrapper method vs. BLR. Table 3 compiles the attributes selected using wrapper method and BLR. There were five to eight attributes selected for the three datasets using the wrapper method. Meanwhile, the BLR shows the presence of merely one or two attributes for each dataset that were identified being significantly sufficient (Sig < 0.5) to classify data into fatigue or pre-fatigue classes.

Table 3. Selected attributes using *wrapper method and **BLR for three datasets

Selected Attribute	Public Running (benchmark)	Running	Cycling
RMS_VT			*
RMS_ML	* **		
RMS_AP	*		*
Ratio RMS_VT		*	
Ratio RMS_ML			
Ratio RMS_AP			*
StepReg_VT	*	*	
StepReg_ML			
StepReg_AP	*		
StrideReg_VT		*	
StrideReg_ML			
StrideReg_AP			

StepFreq or CycleFreq			* **
SampEntropy_VT		*	*
SampEntropy_ML			
SampEntropy_AP	* **	*	
Disp_VT		*	
Disp_ML			
Disp_AP			
Range_VT			
Range_ML		* **	
Range_AP		*	*

Wrapper method and BLR apply the forward search method for attribute selection. The wrapper is aided by the IBk classifier that applies the nearest neighbour technique to select the most efficient subset containing the relevant attributes. BLR, whereas, selects the significant attributes based on Wald statistics. Findings in Table 3 shows eight attributes (36.36%): Ratio RMS_ML, StepReg_ML, StrideReg_ML, StrideReg_AP, SampEntropy_ML, Disp_ML, Disp_AP, and Range_VT were redundant as the attributes were not selected in both wrapper method and BLR on the three datasets. The public running benchmark data illustrates RMS_ML and SampEntropy_AP were the two similar attributes detected between wrapper method and BLR. Meanwhile, on experimental running and cycling only one similar attribute identified from both feature selection approaches: Range_ML and CycleFreq respectively.

3.2. Classification

The attributes selected from wrapper method and BLR were tested on data classification into two predefined data classes: pre-fatigue and fatigue. This is to investigate the effects of feature selection on the classification accuracy between wrapper method and BLR on the three datasets.

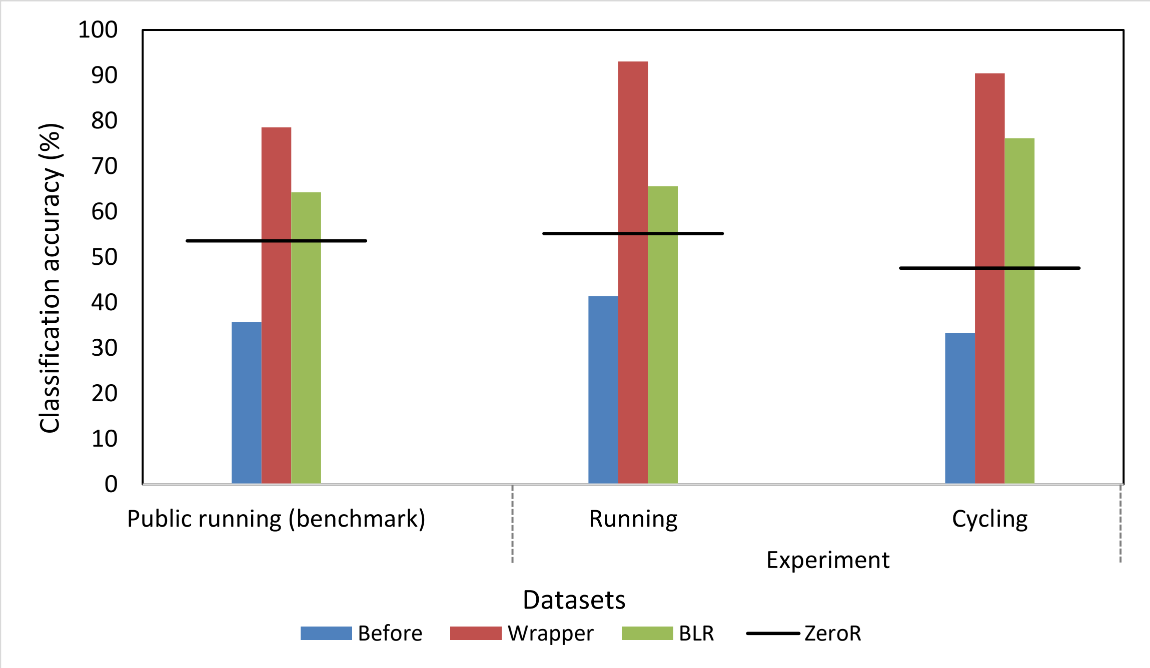


Figure 2. Percentage classification accuracy on three datasets before and after feature selection

Figure 2 shows the accuracy of classification on IBk algorithm of the three datasets before and after the feature selection approach using wrapper method and BLR. The baseline classifier (ZeroR) classifies the data into fatigue or pre-fatigue: 53.6% in public running, 55.2% in experimental running and 47.6% in experimental cycling. Before selecting the attributes, the classification accuracies resulted were lower than the baseline, ZeroR (< 47.6%) in the three datasets. This shows that the classification performances obtained are not reliable.

In public running, upon wrapper approach feature selection, the classification accuracy improves to 78.6%, while BLR approach improves to 64.3% classification accuracy (Figure 2). Contrary to the public running (benchmark), experimental running shows eight main attributes selected using wrapper method (Table 3) with 93.1% classification accuracy (Figure 2). However, BLR approach picked only a single Range_ML attribute (Table 3) resulting in 65.6% accuracy (Figure 2).

Experimental cycling, whereas, shows 90.5% classification accuracy on six attributes selected using wrapper method while the BLR selected only a single attribute; cycle frequency with 76.2% accurate classification (Table 3 & Figure 2). The classification accuracy of wrapper and BLR feature selection successfully improves for all datasets classification accuracy. Overall classification accuracy in experimental running and cycling were found higher than public running; showing 14.5% and 11.9% improvement on the wrapper method feature selection but merely 1.3% and 11.9% improvement in BLR approach respectively. The higher classification accuracy enhancement of wrapper indicates that attribute selection approach is critical in not only model complexity reduction but also address to data overfitting phenomenon. The BLR was found to have overfitted data causing the effect of information loss. As compared to the wrapper, BLR loses about 60-87.5% selected data. Thus, BLR is inappropriate for feature selection in the study datasets. However, its statistical significance test helps to identify which attribute having a better impact over the other on classification analysis.

The RMS_ML was the most significant attribute in public running data (Table 2). RMS_ML shows the variability of acceleration in mediolateral trunk motion. The results implied that the variation of acceleration dispersion in mediolateral trunk acceleration has major contribution to predict running fatigue. This finding was agreed in Schütte et al. [8] that the fatigue participants were identified from increased variability in horizontal plane trunk acceleration. In other words, when the value of RMS_ML increases, the participant has a higher tendency to experience the fatigue.

On the other hand, the feature selection approaches indicated Range_ML had a major contribution for experimental running in distinguishing the fatigue classes. However, feature selection on the public dataset confirms RMS_ML being significant for distinguishing fatigue classes. Although the identified attribute differs for two running datasets (public vs. experimental), the main emphasis was similar i.e. the mediolateral variation. Such finding indicates either variability of acceleration in ML or ML deviation of trunk motion displacement is desirable in fatigue run prediction. ML variation is crucially important in fatigue run detection. The variability of ML increases the fatigue tendency, therefore, causing the loss of stability to maintain the running posture.

The feature selection attributes in experimental cycling differ from public and experimental running. CycleFreq was the most significant attribute demonstrated (Table 2). Cycling speed plays a major impact in fatigue classification because fatigue condition causes high-speed motion difficult to sustain. Cycling in a seated position is more stable and balanced, thus ML variation was not identified in this dataset. VT and AP variations of trunk acceleration motion are critical only when body posture change from sitting to standing. Thus, the six attributes: Range_AP, ratio RMS_AP, RMS_AP, RMS_VT and SampEntropy_VT selected from wrapper including CycleFreq are important for cycling fatigue prediction.

4. Conclusion

This study considers the attributes selection comparison between wrapper method and BLR on IBk classification performance. As per the results obtained, the significant attributes selected from wrapper method are found better than the BLR resulting in 93.1% classification accuracy for the experimental running (an improvement of 51.7% from the original dataset) and 90.5% classification accuracy for cycling (an improvement of 57.2% from the original dataset). The most significant attributes resulted in the three employed datasets using wrapper approach verified on BLR showed different significant attributes selected; RMS_ML for public running, Range_ML for experimental running, and CycleFreq for experimental cycling. Conclusively, the fatigue condition in running can be predicted when the mediolateral variation at body trunk increases. Meanwhile, the cycling fatigue level can be determined from the cycling speed impact on lower limb muscles.

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