# EFFECT OF RISING HABIT ON HUMAN HEALTH USING ECG SIGNALS

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## ABSTRACT

**Objective:** To find out the effect of rising habit on human health using ECG signals.

**Methodology:** One hundred male individuals (age 20 to 35 years) have been selected for the study. The morning rising habit of these individuals was different. The study was conducted at University of Malakand in collaboration with Ali Clinical Laboratory, Lower Dir. The duration of the study was from August-2015 to November- 2015. The electrocardiogram (ECG) signals were classified to find out patterns in heart rhythm of early and late risers. An artificial neural network based classifier named Multi-Layer Perceptron (MLP) was used for the classification. The ECG signals were obtained and on the bases of ECG patterns, the individuals were classified into two groups i.e. early and late risers. The classifier was trained on 70% samples and was tested on 30% of the data set.

**Results:** The proposed classification shows 83 % accuracy. Late risers have more probability of different abnormalities. The QRS duration was normal for 80% samples of the early risers while it was normal for only 37% samples of the late risers. Similarly, QTc interval was normal for 80% samples of the early risers while it was normal for only 40% samples of the of later risers. There were 20% abnormal values for early risers and 60% abnormal values for late risers in their QTc intervals.

**Conclusion:** Earlier risers are healthier than the late risers based on their ECG pattern as well as on the number of normal ECG features.

**Keyword:** Electrocardiogram, Wakeup behaviour, Early riser, Late riser

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## INTRODUCTION

The early rising habit has been advocated all the times and several researchers and clinicians have described its positive effects on physical, social, academic, and psychological behaviours. It has been investigated that those students who wakeup early in the morning have shown significant academic outcomes and achievements than the late risers[1,2]. The performance of morning-type (MT) students is better in school as compared to evening-type (ET) students[3]. According to sleep experts, if you go to bed early and get up early in the morning, your body will be more in tune with the earth's circadian rhythms[4]. Circadian cycles (circadian rhythm) are the physical, mental and behavioural changes in the human body that occur during 24-hour cycle. Similarly, in the research of early and late rising, scientists have discovered differences between the structures of brain. These differences have the tendency to affect biological and genetic forces.

Electrocardiogram (ECG) is the measurement of electrical activity of the heart in human body[5]. ECG signals carries important information in its structure related to cardiovascular system. ECG signals can be obtained from ear lobe, limbs or by placing electrodes on some specific areas of the body e.g. on chest. It is a wave form of energy generated by heart, and it represents an individual's cardiac features. ECG signals are used in clinics for assessing and analysing electrical and muscular functions of the heart and are used as a diagnostic tool for different diseases and abnormalities[1-3,6].

In the past years, several approaches have been suggested to detect the heart rhythm using ECG signal. McCraty[7] investigated that heart rhythmic feedback technology has broad-based applications in clinical, workplace, and academic settings for the improvement of health and human performance. Thurber et al[8-10] describes that biofeedback training greatly affect mental, emotional and behavioural[9,10] aspects of human. McCraty et al[11] also suggested that positive emotions cause alteration in heart rate variability which may be beneficial for the treatment of several heart related abnormalities. Karlen et al[12,13] presented sleep/wake classification algorithms and described the importance and use of ECG signals in human behaviour. Forbes[14] invented cardiac analyzer system for monitoring physiological indicators of rapid eye movement (REM) sleep, autonomic fluctuations and ischemia. When any of these "indicators" are detected, a full complement of ECG data is recorded from a subject for subsequent analysis. In this system, feature extraction was performed through heart rate variability analysis (HRV) and detrended fluctuation analysis (DFA).

The aim of this study was to find out the effect of rising habit on human health using ECG signals. Features from the ECG signals of early and late risers were used for classification and detection. In this paper, a thorough study was conducted to establish quantitative relationship between early and late risers. We have performed computer-based investigation and detection of wake-up behaviour. This can be extremely useful in the diagnoses of cardiovascular diseases such as left ventricular hypertrophy (LVH) and myocardial infarction.

## METHODOLOGY

The study was conducted on one hundred participants having age between twenty and thirty five years. The participants were healthy and also had no history of any heart diseases. The participants were normal in their daily life activities. All the participants belonged to the Khyber Pakhtunkhwa province of Pakistan. The ECG signals were obtained during 09:00 am and 12:00 pm. The participants were divided into two groups where each group had fifty participants.

The wake up behaviour detection process consist of a series of steps. These steps consisted of ECG signals acquisition, features extraction, signal classification and analysis (figure 1). In the first step, ECG signals of early and late risers were acquired. In the second step, features extraction was performed using fiducial and morphological method. In the third step the features were classified. The participants of first group (group A) had the habit of getting up early in the morning. They were getting up before dawn and were completing six to eight hours of sleep. The second group (group B) consisted of late risers who were getting up after dawn and were completing six to eight hours of sleep.

Before taking ECG signals of an individual, five to ten minutes were given to each subject for relaxation. ECG signals were obtained through Cardio-Care2000 Bionet machine[15]. The machine was facilitated with 12-channel leads to find accurate heart's electro-magnetic field. During study, every subject was explained about the procedure. The Cardio-Care machine was also configured with computer through local area network (LAN). Similarly, the machine enabled to retrieve ECG print out in 3-chanels, 6-chanels and 12-chanels as well as in soft form. Furthermore, the machine was facilitated to produce the ECG signals in the format of 10 and 60 second duration. The machine was also connected with a PC while an EKG-Plus-II viewer software[15] were installed to visualize different views of ECG signals.

There are different techniques used for features extraction including heart-beat temporal intervals[1], morphological features[3], frequency domain features[16] and wavelet transform coefficients[6]. These techniques are used by different algorithms to extract features from signals i.e. wavelet transform, principal component analysis and Fisher-linear-discriminant[17-20]. In current investigation, fiducial and morphological based method has been used for features extraction[21-23]. Nineteen features were extracted from each ECG signal. These features include heart beats variation or beat per second (BPS), PR interval, QRS duration and amplitude, QT/QTc, P axis, amplitude and duration, T and R orientation, T amplitudes and durations, Q amplitudes and durations and ST amplitude as depicted in figure 2.

The features extraction process consisted of the following steps: In the first step, the R-peak points were detected from the ECG signals. The peak values were computed with setting-up a threshold value. The identification of the peak (R locations) values were further used as a base to find more features including R-amplitude (height). The duration (interval) between the R-wave was measured by calculating the distance between each successive R-peak. Similarly, the skewness was measured by calculating the orientation or angle of R-peaks along the axis. In the same way, each consecutive R-peak was also used as base to calculate the heart beats for each participant. Heart beat was determined as the time between two consecutive QRS complexes. The RR interval is equal to one beat which is further multiplied with 60 seconds and it produces one beat per minute.

The values of R-peaks were also used as a base for calculating the exact location of P, Q, S and T waves. In the ECG signals, P and Q values should be prior to each R-peaks while the S and T values should be coming after R-peaks. Similarly, the amplitude, duration and angle with axis were also calculated for P-wave, Q-wave, S-wave and T-wave. QRS-complex is the combination of Q, R and S wave (figure 3). It is the most complicated and important part of ECG signal. The combination of all these points generates the QRS complex. The angles of P, R and T (skewness of P, R and T) wave along the axis were calculated as depicted in figure 2[24].

In the classification phase, the subjects were classified based on the features extracted from their ECG signals. There are different classification techniques used for ECG patterns, including support vector machine[25], linear discriminant analysis[3] and artificial neural network[2] etc. In this study, we used Multilayer Perceptron (MLP)[26]. MLP is a supervised artificial neural network model that maps sets of input data into a set of appropriate outputs. In the first step, the MLP algorithm was trained to learn the behaviours of input samples. The training of MLP was performed on 70% of the samples and testing on 30% samples. The MLP of the proposed approach consisted of input layer (19 neurons), hidden layer (10 neurons) and input layer (one neuron) as shown in Figure 4.

Kappa statistic expresses greater agreement between the classification and the true classes. Value greater than zero means that the classifier is doing better (than by chance) and predicting significance agreement.

Mean absolute error (MAE) is the average over the verification sample of the absolute values of the differences between forecast and the corresponding observation. Similarly, root mean square error (RMSE) is the measure of average magnitude of the error. It gives the difference between forecast and corresponding observed values. The error is squared and then taken an average for each value. RMSE provides relatively high weight to large errors. MAE and RMSE together used to diagnose the variations in the errors. The difference between MAE and RMSE point to the variance in the individual errors in the sample. Greater the difference between them, greater will be the variance error in the individual error. The lower values for both MAE and RMSE are also better an accurate result. The concerned model is considered good when the value of MAE and RMSE is less than one.

Relative squared error (RSE) takes the total squared error and normalizes it by dividing by the total squared error of the simple predictor. RRSE is obtained by taking the square root of RSE to reduce the error to the dimension as predicted. As the value of RSE approaching to a larger value, it represents greater influence of the classification result.

True positive (TP) rate means when the instances were correctly classified and false positive (FP) rate means when the instances were incorrectly classified. Precision is the proportion of instances that are truly of a class divided by the total instances classified as that class. Receiver operating characteristic (ROC) analysis shows that the proposed method produces a more balanced correct classification of early and late risers. The ROC which was produced in this study showed the optimal classifier as the value approaching to 1.

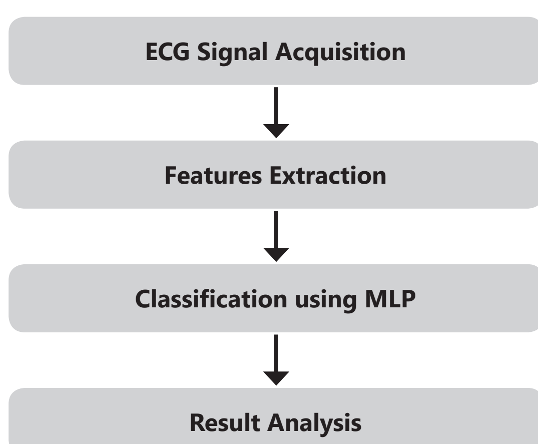
## RESULTS

The statistical results of the analysed data are presented in Table 1 using MLP. These statistics were generated from classification results. The correct classification results were reported 83.33% and incorrect classification was reported 16.67%. There were 30 subjects out of 100 who were used for testing in which 25-subjects correctly and 5-subjects were incorrectly classified.

The detail class accuracy is presented in the Table 2, with TP Rate, FP Rate, precision and recall. The confusion matrix is shown in Table 3. Early riser was represented with ‘a’ and later risers with ‘b’ in the confusion matrix. The values 15 and 5 in first row in the table is the corrected and uncorrected predictions for ‘a’ from total out of ‘20’. Whereas in the second row, the zero means no incorrect prediction while the value 10 means the corrected positive prediction. The first, second, third and fourth cell are associated to false positive (FP), false negative (FN), true positive (TP) and true negative (TN) respectively.

Table 4 shows the occurrence of various diseases in both groups due to the variations in QRS and QTc

**Figure 1: Steps of ECG signals classification**



features. Late risers have more probability of different abnormalities. The QRS duration was normal for 80% samples of the early risers while it was normal for only 37% samples of the late risers. Similarly, we found that the QTc interval was normal for 80% samples of the early risers while it was normal for only 40% samples of the late risers. There were 20% abnormal values for early risers and 60% abnormal values for late risers in their

**Table 1: Summary from the classification results**

| Observed Values | |
|---|---|
| Kappa statistic | 0.6667 |
| Mean absolute error | 0.1677 |
| Root mean squared error | 0.3962 |
| Relative absolute error | 32.1898% |
| Root relative squared error | 75.595% |
| Coverage of cases (0.95 level) | 83.3333% |
| Mean rel. region size (0.95 level) | 50% |

**Table 2: Detailed accuracy by class**

| | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC | Class |
|---|---|---|---|---|---|---|---|---|---|
| Weighted Average | 0.750 | 0.000 | 1.000 | 0.750 | 0.857 | 0.707 | 1.000 | 1.000 | A |
| | 1.000 | 0.250 | 0.667 | 1.000 | 0.800 | 0.707 | 1.000 | 1.000 | B |
| | 0.833 | 0.083 | 0.889 | 0.833 | 0.838 | 0.707 | 1.000 | 1.000 | |

**Table 3: Confusion matrix**

| A | b | Classified as | A | b | Classified as |
|---|---|---|---|---|---|
| 15 | 5 | a=a | False Positive (FP) | False Negative (FN) | a=a |
| 0 | 10 | b=b | True Negative (TN) | True Positive (TP) | b=b |

**Table 4: Probability of diseases in early and late risers based on the ECG records**

| Diseases | Probability % | |
|---|---|---|
| | Group A (Early Risers) | Group B (Late Risers) |
| Left Ventricular Ejection Fraction | 20% | 63% |
| Left Ventricle End-Systolic-Counts | 20% | 65% |
| LV End-Diastolic-Count | 15% | 65% |
| Myocardial Infarction | 15% | 61% |
| Left Ventricular Hypertrophy | 18% | 64% |
| Anterior Infarct | 16% | 63% |
| Wolf-Parkinson-White-Syndrome | 15% | 63% |
| Ventricular-Tachycardia | 19% | 62% |
| Right and Left Bundle-Branch Block | 20% | 63% |
| Ventricular Arrhythmia | 18% | 61% |
| Ventricular Fibrillation | 20% | 64% |
| Hypokalemia | 15% | 63% |
| Myocardial Ischemia | 18% | 62% |
| Hypothermia | 15% | 67% |
| Congenital Long QT Syndrome | 20% | 62% |

**Figure 2: ECG signal with its intervals (QT, PR,P¯, QRS, R̿, S̿, ST), amplitude (¯R, P̿,¯S,¯Q) and Angle (<P,<R,<T)**

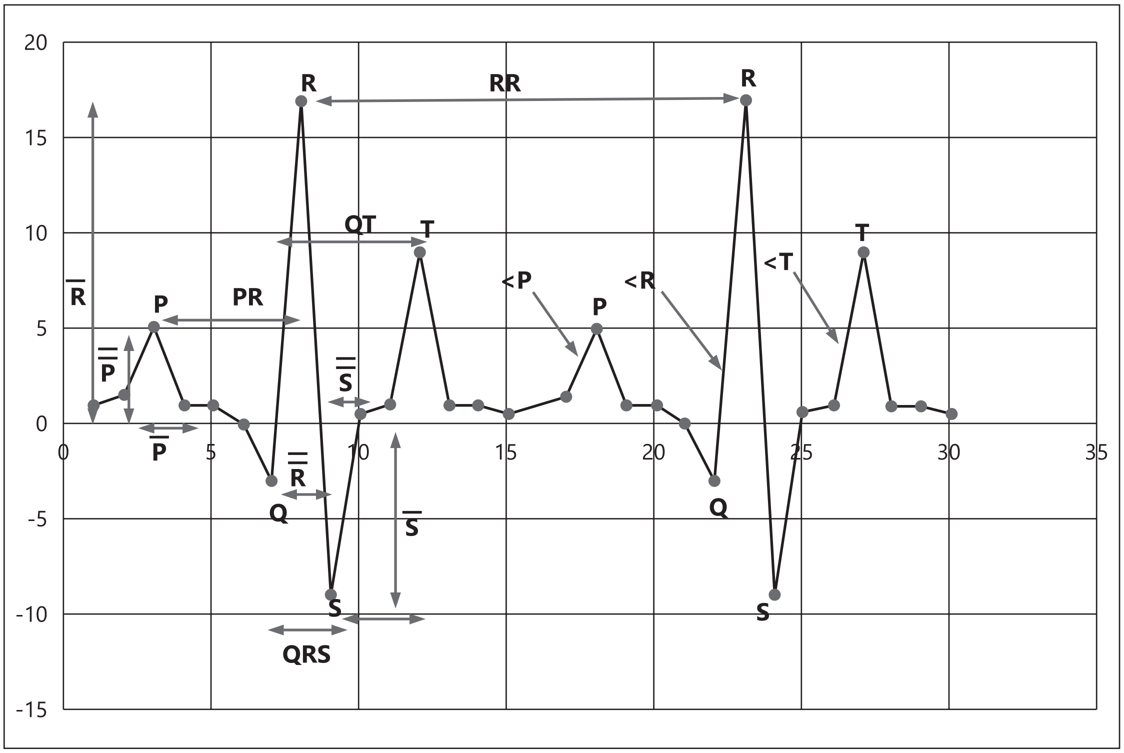



**Figure 3: The set of all points in the range of Q, R and S wave in the ECG signal**

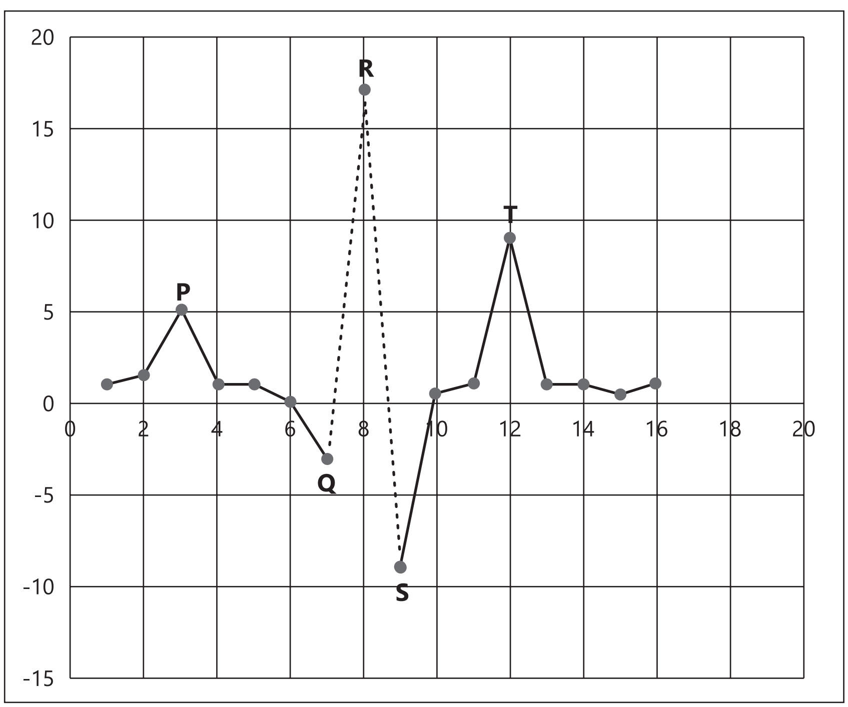
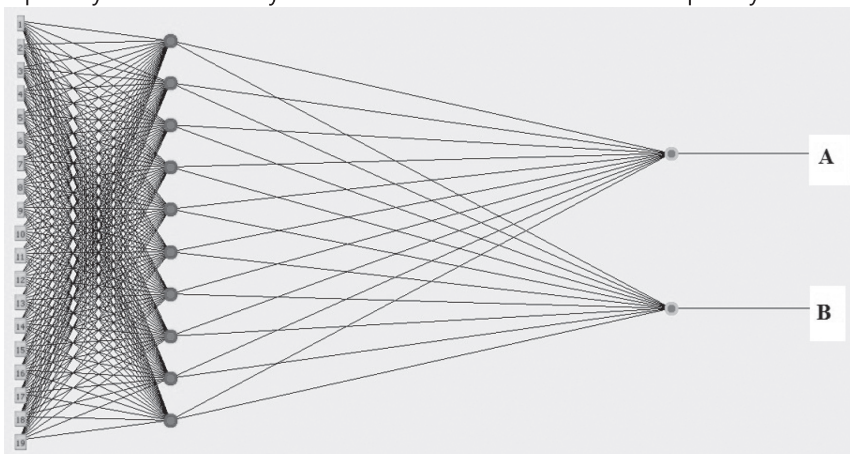


**Figure 4: Multilayer perceptron with input, hidden and output layers**

Input Layer Hidden Layer Output layer




QTc intervals.

## DISCUSSION

The MLP classifier algorithm classifies early and late risers with 83% accuracy to detect the rising behaviour of an individual using ECG signals. The value produced for kappa static was 0.666 (0.6 to 0.8 shows substantial agreement). Mean absolute error (MAE) was 0.1667, root mean square error (RMSE) was 0.3962, relative squared error (RSE) was 32.1898% and root relative squared error (RRSE) was 75.595%).

The confusion matrix comprised of information about actual and predicted classifications performed by a classification system. Performance of classification system was evaluated using the data (early and late risers). The values for false positive (15) and true positive (10) significantly accurate while the other is less accurate. These results point out that classification was precise and significant.

On the basis of ECG signal recording, the earlier risers were found healthier than the late risers. It is obvious that the early risers were less prone to the diseases mentioned in the table. On the other hand, the chances of listed diseases were more in late risers. In the table, the average percentage of the diseases in early risers was 17% while for late riser it was 63%.

A further analysis of the ECG signals of early and late risers showed that late risers have more probability of different abnormalities. The ECG signals of early risers were found normal as compared to late risers. This was done on the basis of QRS and QTc features of the ECG signal. In our investigation, the QRS duration was normal for 80% samples of the early risers while it was normal for only 37% samples of the late risers. Similarly, we found that the QTc interval was normal for 80% samples of the early risers while it was normal for only 40% samples of the of later risers. There were 20% abnormal values for early risers and 60% abnormal values for late risers in their QTc intervals. QRS and QTc variation causes several types of abnormalities such as left ventricular ejection fraction (LVEF)[27], increased left ventricle end-systolic-counts (LV ESCs) and LV end-diastolic-count (LV EDCs)[27], left ventricular hypertrophy (LVH) and myocardial infarction[28-31]. In addition to these abnormalities, late risers were also prone to other diseases like Wolf-Parkinson-White-Syndrome[32] and right and left bundle-branch blocks (RBBB and LBBB)[33]. The chances of these diseases in late risers were doubled than the early risers.

## CONCLUSION

ECG signals showed that rising habit affects the cardiovascular system. Earlier risers are healthier than the late risers based on their ECG pattern as well as on the number of normal ECG features.

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## CONTRIBUTORS

MH conceived the idea, planned the study, and drafted the manuscript. SUR and FA and helped acquisition of data and did statistical analysis. SA and ZA helped in literature search, interpretation of data and critically revised the manuscript. All authors contributed significantly to the submitted manuscript.