# A Machine Learning Approach for Stress Detection using a Wireless Physical Activity Tracker

B. Padmaja, V. V. Rama Prasad and K. V. N. Sunitha

***Abstract*—Stress is a psychological condition that reduces the quality of sleep and affects every facet of life. This paper provides an effective method for the detection of cognitive stress levels using data provided from a physical activity tracker device developed by FITBIT. The main motive of this system was to use a machine learning approach in stress detection using sensor technology. Individually, the effect of each stressor was evaluated using logistic regression and then a combined model was built and assessed using variants of ordinal logistic regression models including logit, probit, and complementary log-log. This system was used and evaluated in a real-time environment by taking data from adults working in IT and other sectors in India. The novelty of this work lies in the fact that a stress detection system should be as non-invasive as possible for the user.**

***Index Terms*—Physical activity tracker, sleep pattern, working hours, heart rate, smartphone sensor**

## I. Introduction

Stress has become an embedded part of our daily life and is a noticeable concept in public health. Recently, stress has become an integral part of professional life, especially in today's fiercely competitive economy. In the workplace, an individual has to continuously face several situations, such as work overload, job insecurity, lack of job satisfaction, and the pressure to stay up-to-date. The continuous presence of stress can lead to several negative health effects, such as high blood pressure, lack of sleep, susceptibility to infections, and cardiovascular disease. All these situations result in mental stress, which has become the leading cause of many diseases. Such adverse effects not only affect the employees' health and well-being, but also affects workplace productivity and overall profit.

Fig. 1 shows the conceptual model of our research work on stress. The significance of sleep, physical activity, number of working hours and change in heart rate with regard to stress levels are analyzed in this paper.

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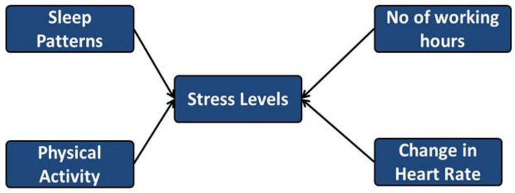


Fig. 1. The conceptual model of STRESS.

Many researchers are working on investigating stress levels among different professionals. We are currently working on studying the stress levels (low, medium, high) among professionals using the data collected from a wireless physical activity tracker developed by FITBIT. Our current research question (Q) and hypotheses (H) are:

**Q: What is the stress level among professionals due to the following factors?**

*H1: Is there any significant relationship between their sleep patterns and stress levels?*

*H2: Is there any significant relationship between their physical activity and stress levels?*

*H3: Is there any significant relationship between number of working hours and their stress levels?*

*H4: Is there any significant relationship between any changes in heart rate and their stress levels?*

## II. Related Work

Day to day job demands lead to psychological and physiological strain among individuals. Every individual experiences strain over time and it is likely to depend on the perceived and real consequences of how they cope with stress. Many personal and environmental resources are involved in coping with stress [1].

Many studies have been conducted in this field. Alireza Bolhari *et al.* (2012) have studied workplace stress [2]. Jong-Ho Kim *et al.* (1992) investigated the social life of college students and highlighted the impact of physical exercises in reducing stress levels [3], [4]. Enrique Garcia-Ceja *et al.* (2016) used smartphones as a potential tool to detect behavior that is correlated with stress levels [5]. Panagiotis Kostopoulos *et al.* (2016) designed a stress detection system, *StayActive*, which uses sleep patterns, physical activities and social interactions to detect stress [6]. Mario Salai *et al.* (2016) have worked on automatic stress detection by measuring the heart rate variability (HRV) using a low cost heart rate sensor and chest belt. They used the galvanic skin response (GSR), electromyography (EMG), skin temperature, electrocardiography (ECG) and skin conductance as the indicators of stress [7], [8]. Vanith *et al.*

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(2014) used a hierarchical classifier to detect mental stress in humans using the HRV measured using ECG [9]. Padmaja *et al.* (2016) worked on human stress using a TreeNet classifier based on smartphone interaction data and social features [10]. Gimpel *et al.* (2015) developed the application, *mystress*, as a stress detection system based on hardware and software sensor data collected using an android application. Hong Lu *et al*. (2012) developed an application called, *stress sense*, a human voice based stress detection system using real-life conversations on smartphones [8], [11].

Besides, stress has negative impact on public health and it plays a major role in behavioral disorders such as depression and anxiety [12]. Oscar Martinez Mozos *et al.* (2017) worked on a machine learning approach for stress detection by combining physiological and sociometric sensors and it accurately discriminated the stressful and neutral situations of an individual [13]. Martin Gjoreski *et al.* (2016) used a machine learning approach for continuous stress detection using a wearable wrist device using the objective and subjective labeling of laboratory and real-life data as well as physiological measurements [14], [15].

TABLE I: AN OVERVIEW OF THE RELATED WORK ON STRESS DETECTION SYSTEMS.

| Related work | Focus group | Data sources | Reference | Year |
|---|---|---|---|---|
| Alireza Bolhari *et al.* | Occupational stress | Questionnaire | [2] | 2012 |
| Jong-Ho Kim *et al.* | physical exercise on stress | Interviews and questionnaire | [4] | 2014 |
| Enrique Garcia-Ceja *et al.* | Occupational stress | Smartphone sensor | [5] | 2015 |
| Gimpel *et al.* | Individuals | Questionnaire, sensors | [8] | 2015 |
| Martin Gjoreski *et al.* | Perceived stress | Questionnaire, sensors | [14] | 2015 |
| Martin Gjoreski *et al.* | Stress in adults | Questionnaire, wrist device | [15] | 2016 |
| Mario Salai *et al.* | Stress in volunteers | Chest belt, heart rate sensor | [7] | 2016 |
| Kostopoulos *et al.* | Stress in professionals | Smartphone sensor data, sleeping pattern | [6] | 2016 |
| Current work | Stress in working professionals | Questionnaire, Fitbit data | - | 2017 |

Table I shows an overview of the related work on stress detection systems reported to date.

Our research aims to develop a novel stress detection mechanism using a physical activity tracker and smartphone. This paper is organized as follows: Section I and II give an overview of stress and its impact on our daily lives. It also covers related research work on stress detection especially using smartphones. Section III contains the data collection, feature selection and model building process used for our data. Section IV includes the validation process for stress detection and results analysis. Finally, we conclude with the pros and cons of our study in Section IV.

## III. METHODOLOGY

Fig. 2 shows the block diagram of steps followed in the stress detection process, which is divided into various steps including data collection, data pre-processing, feature selection, hypothesis building, stress detection model, hypothesis testing, and interpretation of results.

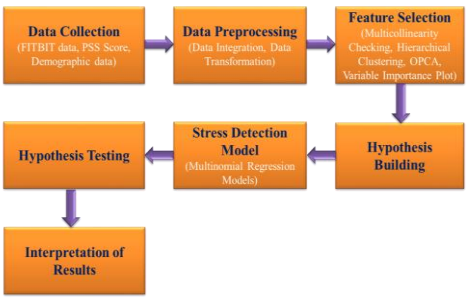


Fig. 2. The block diagram of the stress detection system.

### A. *Data collection*

The methods used in this study to measure stress are the data collected from the various sensors in the FITBIT device and an online perceived stress scale questionnaire (PSS) (Form-based). In this study, 10 users working in IT and other fields participated in the experiment for more than 10 months in the period between July 2016 and the present day. The ages of the individuals vary from 28 to 45 years. The participants were equipped with a FITBIT watch and the app was installed on their smartphone. FITBIT uses various sensors to gather data on an individual's daily physical activity, sleep patterns, movement patterns and heart rate information during sleep and physical activity. The data gathering process from individuals was carried out on a monthly basis. The following are the FITBIT data details: 1. Body related information – Date, weight, BMI, fat; 2. Physical activity information – Date, calories burned, steps, distance, floors, minutes sedentary, minutes lightly active, minutes fairly active, minutes very active, activity calories; 3. Sleep information – Date, minutes asleep, minutes awake, number of awakenings, time in bed; and 4. Heart rate information during physical activity – Date, calories, average_bpm, maximum and minimum heart rate, active minutes, zone, resting heart rate, type_of_activity, heart rate zone. Table II shows the data statistics for the stress detection system.

TABLE II: THE DATA STATISTIC FOR THE STRESS DETECTION SYSTEM.

| | |
|---|---|
| Number of users | 10 |
| Number of days | 300 |
| Number of attributes | 29 |
| Number of records | 3000 |

The perceived stress scale (PSS) is the most preferred psychological instrument used to measure stress. The scale includes a questionnaire, which consists of two parts: A demographic questionnaire and a stress questionnaire. The PSS consists of 10 questions in several categories and the scores are obtained by reversing the responses (e.g., 0 = 4, 1 = 3, 2 = 2, 3 = 1 and 4 = 0). These scores indicate the level of stress with a score of 27–40 indicating very high stress, 14–26 indicating moderate stress and 0–13 indicating low stress. Fig. 3 shows the online PSS questionnaire form used to gather data from the participants.

In addition to the FITBIT data and PSS score, we have used various demographic attributes including name, age, gender, and working hours as well as the maximum heart rate and heart rate level of the participants. The maximum heart rate shows the change in the heart rate of an individual and is computed as follows:

Maximum heart rate = 217 - (0.85 * valid$Age)

The heart rate level indicates how closely our computed maximum heart_rate is with the recorded maximum heart rate (in percentage) and is computed as follows:

Heart rate level = (Recorded maximum heart rate / computed maximum heart rate) * 100

### B. *Feature Selection*

The feature selection aims to choose a set of highly discriminant attributes i.e., those that are capable of discriminating the samples that belong to a completely different class from the data set. A feature $f_i$ belongs to a class $C_j$ if $f_i$ and $C_j$ are highly correlated. In this paper, the steps shown in Fig. 3 were followed in the feature selection.

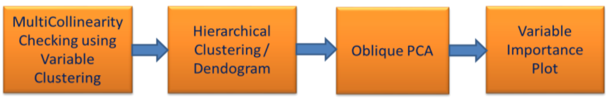


Fig. 3. The steps followed in the feature selection.

The first step involved a multicollinearity checking between the attributes, where variable clustering was carried out using the correlation metric and the variables with high correlation clustered together. In the second step, agglomerative hierarchical clustering was applied on the data set, which builds a cluster hierarchy using a tree diagram called a dendrogram. This initially builds each object in a separate cluster and then at each step, the two clusters that are most similar are joined into a single new cluster. In the third step, oblique principal component analysis for feature selection was carried out, which is superior to the orthogonal results given by PCA and produces cleaner and easily interpreted results based on the cluster distances. In the final step, variable importance plots were built to identify the prominent features required for model building. The variable importance plot is shown in Fig. 4.

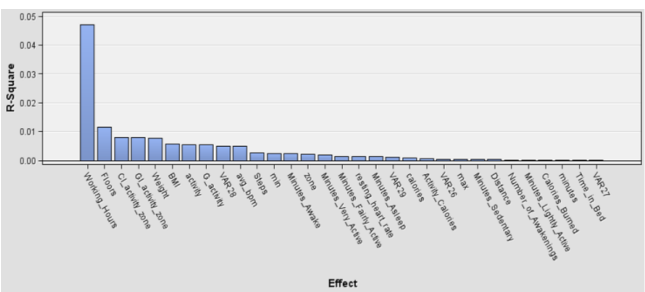


Fig. 4. The variable importance plot.

## IV. MODELING PROCESS

This paper aims to detect the stress levels of an individual. Normally, ordinal logistic regression models are used when the dependent variable has more than two categories and can have nominal and/or continuous independent variables. In the data set, the response variable *stress_level* is categorical and ordered (Low < Medium < High) in nature, so we attempted to fit the cumulative probabilities of the response variable with the cumulative logit model, probit model, and complementary log-log model in our study.

### A. *Hypothesis Building*

To assess the impact of physical activity, sleep patterns, working hours, and heart rate on an individual's stress levels, the following hypotheses were formulated. H: Hypothesis, H0: Null Hypothesis

H1: Physical activity is considered as a strategy for managing stress.

H0: Physical activity is not considered as a stress management strategy.

H2: Sleep deprivation is an indicator of human stress.

H0: Sleep deprivation doesn't lead to human stress.

H3: Long working hours have a negative impact on human stress.

H0: Long working hours doesn't have any impact on human stress.

H4: Change in heart rate is an indicator of human stress.

H0: Change in heart rate has no role in defining human stress.

### B. *Logistic Model to Support Hypothesis 1*

Physical activity works as a de-stress agent for an individuals. Regular indulgence in physical activity such as walking, climbing stairs, and minutes active will help to reduce stress levels. To test this hypothesis, a logistic model was built using various the physical activity related attributes including calories burned, steps, floors, distance, minutes sedentary, minutes lightly active, minutes very active, and minutes fairly active. The final model based on an ANOVA test shows the number of floors climbed, minutes sedentary, minutes fairly active, and minutes very active are influential factors in determining the stress level of an individual. In addition, the multiplicative term minutes sedentary : minutes very active reflects the conditional relationships and can influence the stress levels of an individual.

### C. *Logistic Model to Support Hypothesis 2*

Sleep patterns are also indicators of an individual's health and stress levels. Usually people who have low stress will be able to get good sleep. To test this hypothesis with the data set, a logistic model was applied to the sleep data set and the coefficients were computed. In the data set, various attributes including minutes asleep, minutes awake, time in bed and number of awakenings were related to sleep and chosen for model building to check their influence on the stress levels. The final model based on an ANOVA test shows the minutes awake was the only influential factor in determining the stress levels in an individual.

### D. *Logistic Model to Support Hypothesis 3*

A competitive work environment contributes to maximum stress. Jobs that demand high working hours are those that cause more stress in an individual. Long working hours are considered as a good indicator for determining an individual's stress levels. In the data set, the working hours of the participants have been recorded. The final model shows an individual's working hours are a significant influential factor (based on p-value) in determining their stress levels.

### *E. Logistic Model to Support Hypothesis 4*

To measure the variability of the heart rate, no medical equipment was used to capture the ECG. Instead it was modeled using the following formula:

Maximum heart rate = 217 - (0.85 * valid$Age)

The maximum heart rate showcases the fluctuation in the heart rate on an individual. The closest the individual achieves during physical activity, the better it helps in reducing their stress levels. To test this hypothesis, a logistic model was built using various heart rate related attributes including the average bpm, maximum, minimum, and resting heart rate, activity (WALK, SPORTS, RUN) and heart rate zones (Fatburn, Cardio, Peak).

The final model shows the average bpm, maximum and minimum heart rate are positive indicators of stress and calories, resting heart rate and heart rate zone are a negative indicator (de-stress agents) of stress. In addition, the activity type (RUN, SPORT, WALK) doesn't contribute to stress.

### *F. Combined Model*

The basic form of the multiple regression model is shown below:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \ldots\ldots + \varepsilon$$

Table III shows the list of attributes used for stress detection.

1) **Logit model:** The formula used for the ordinal logistic regression is shown below:

$$g(p) = \log(p / (1 - p))$$

The initial model was built with the following attributes and then an odds ratio was computed for the model.

$$\text{Stress level } (Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \beta_{11} X_{11} + \varepsilon$$

| | OR | 2.5 % | 97.5 % |
|---|---|---|---|
| Working.Hours | 0.9151556 | 0.8066488 | 1.0379488 |
| Minutes.Sedentary | 0.9986635 | 0.9976175 | 0.9996984 |
| Floors | 0.9755698 | 0.9558073 | 0.9949764 |
| Number.of.Awakenings | 0.9063143 | 0.7722217 | 1.0637282 |
| BMI | 1.0231230 | 0.8980216 | 1.1656420 |
| Time.in.Bed | 1.0073708 | 1.0032756 | 1.0118025 |
| avg_bpm | 1.0223681 | 1.0052635 | 1.0405454 |
| Fatburn | 0.9978115 | 0.9856530 | 1.0100731 |
| Cardio | 0.9237168 | 0.8490367 | 1.0037720 |
| maxrate | 0.9710788 | 0.9226583 | 1.0215089 |
| Minutes.Asleep | 0.9913219 | 0.9867950 | 0.9955012 |

Fig. 5. The odds ratio with confidence intervals used for the logit model.

TABLE III: THE LIST OF ATTRIBUTES USED FOR STRESS DETECTION

| | |
|---|---|
| X1 | Working hours |
| X2 | Minutes sedentary |
| X3 | Floors |
| X4 | Number of awakenings |
| X5 | BMI |
| X6 | Time in bed |
| X7 | Minutes asleep |
| X8 | Average bpm |
| X9 | Fatburn |
| X10 | Cardio |
| X11 | Maximum heart rate |

The following interpretations were made from the logit model, as shown in Fig. 5.

a) For each unit increase in the BMI, the odds of moving from low stress to medium stress or from medium stress to high stress are 1.023.
b) In the same way, if the person increases one floor more to his daily activity, the odds of moving from low stress to medium stress or from medium stress to high stress decreases, and was in fact reduced by a factor of 0.975 [Physical activity is a de-stress agent].
c) For each one hour increase in working hours, the odds of moving from low stress to medium stress or from medium stress to high stress decreases, and was in fact reduced by a factor of 0.915. This depends on how an individual handles his/her workload.

2) **Probit Model:** The formula used for the probit model is shown below:

$$g(p) = \phi^{-1}(p)$$

The odds ratio was computed for the probit model and was combined with the confidence intervals.

| | OR | 2.5 % | 97.5 % |
|---|---|---|---|
| Working.Hours | 0.9403941 | 0.8746588 | 1.0102563 |
| Minutes.Sedentary | 0.9992406 | 0.9986329 | 0.9998459 |
| Floors | 0.9859484 | 0.9740105 | 0.9976180 |
| Number.of.Awakenings | 0.9440706 | 0.8593246 | 1.0368712 |
| BMI | 1.0156434 | 0.9389548 | 1.0985240 |
| Time.in.Bed | 1.0042381 | 1.0018287 | 1.0067393 |
| avg_bpm | 1.0139245 | 1.0036421 | 1.0244963 |
| Fatburn | 0.9986371 | 0.9913289 | 1.0060197 |
| Cardio | 0.9514818 | 0.9029119 | 1.0025233 |
| maxrate | 0.9809319 | 0.9514832 | 1.0111376 |
| Minutes.Asleep | 0.9949762 | 0.9924265 | 0.9974413 |

Fig. 6. The combined odds ratio and confidence intervals used in the probit model.

The following interpretations were made from the probit model shown in Fig. 6.

a) For each fluctuation in the average_bpm, the odds of moving from low stress to medium stress or from medium stress to high stress are 1.01.
b) In the same way, if the person increases the amount of cardio in their daily activity, the odds of moving from low stress to medium stress or from medium stress to high stress decreases, and is in fact reduced by factor 0.951.

3) **Complementary Log-Log model:** The formula for the complementary log-log model is shown below:

$$g(p) = \log(-\log(1-p))$$

The odds ratio was computed for the complementary log-log model and it was combined with the confidence intervals.

| | OR | 2.5 % | 97.5 % |
|---|---|---|---|
| Working.Hours | 1.0613836 | 0.8746588 | 1.0102563 |
| Minutes.Sedentary | 0.9991091 | 0.9986329 | 0.9998459 |
| Floors | 0.9842776 | 0.9740105 | 0.9976180 |
| Number.of.Awakenings | 0.9368932 | 0.8593246 | 1.0368712 |
| BMI | 1.0250054 | 0.9389548 | 1.0985240 |
| Time.in.Bed | 1.0054705 | 1.0018287 | 1.0067393 |
| avg_bpm | 1.0136068 | 1.0036421 | 1.0244963 |
| Fatburn | 0.9980655 | 0.9913289 | 1.0060197 |
| Cardio | 0.9438432 | 0.9029119 | 1.0025233 |
| maxrate | 0.9770001 | 0.9514832 | 1.0111376 |
| Minutes.Asleep | 0.9937149 | 0.9924265 | 0.9974413 |

Fig. 7. The combined odds ratio and confidence intervals used for the clog-log model.

The following interpretations were made from the Clog-log model shown in Fig. 7.

a) For each unit increase in working_hours, the odds of moving from low stress to medium stress or from medium stress to high stress are 1.061.
b) In the same way, if the person increases their BMI, the odds of moving from low stress to medium stress or from medium stress to high stress increases by a factor 1.025.

## V. Results

The Akaike information criterion (AIC) is used to quantify the relative quality of logistic models for a given data set. Given a set of models for the data, the AIC estimates the quality of each model, relative to each of the other models. The lower the AIC value, the better the model. Table IV shows the AIC values of the different models used in our study.

TABLE IV: A Comparison of the Models Based on AIC.

| Model comparison parameter | Logit | Probit | Clog-log |
|---|---|---|---|
| AIC | 782.8842 | 781.6256 | 786.8999 |

Our study clearly indicates that Probit was the most suitable model for the data set and our final model based on an ANOVA test. Fig. 8 shows the efficiency of the models based on the AIC value.
Final Model:

$$Stress.Level \sim X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 + X_{10} + X_{11} + X_2{:}X_9 + X_1{:}X_5 + X_9{:}X_{11} + X_3{:}X_5 + X_1{:}X_2 + X_1{:}X_{11} + X_1{:}X_7 + X_4{:}X_5 + X_3{:}X_{10} + X_4{:}X_9$$

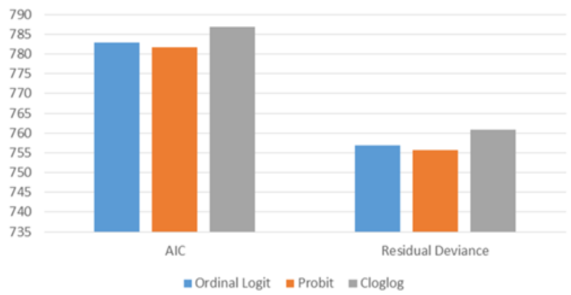


Fig. 8. The efficiency of the models based on AIC.

### A. Hypothesis testing

Table V shows the hypothesis results:

TABLE V: The Hypothesis Testing Results.

| H No | Hypothesis granularity | Hypothesis | Result: Significant | Direction |
|---|---|---|---|---|
| H1 | Overall period | Physical activity is considered as a strategy for managing stress. | Yes | Negative |
| H2 | Overall period | Sleep deprivation is an indicator of human stress. | Yes | Positive |
| H3 | Overall period | Long working hours have negative impact on human stress. | Yes | Negative |
| H4 | Overall period | Change in heart rate is an indicator of human stress. | Yes | Negative |

## VI. Conclusions

In this work, a study has been carried out on the behavioral symptoms of stress using a wireless physical activity tracker developed by FITBIT. Physical activity acts as a de-stress agent on human stress. Floors and sedentary minutes from the physical activity data set are significant and negative in nature. Therefore, by increasing the amount of physical activity in daily life, one can reduce his/her stress levels. Sleep shortage and insomnia are common signs of stress. Our study shows the time in bed is a significant and positive indicator of stress. The stress level is determined by the amount of sleep a person is getting in a day, but not on the number of awakenings. Similarly, working hours are a significant and negative indicator of stress. This means stress generated due to working hours depends on how a person handles his/her workload. Next, the average bpm indicates any fluctuations in heart rate, which is a significant and positive indicator of stress. Finally, the body mass index (BMI) is a significant and positive indicator of stress. Therefore, changes in heart rate and an increase in BMI increase the stress levels of individuals.

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