Remote Health Monitoring: Predicting Outcome Success based on Contextual Features for Cardiovascular Disease

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Abstract— **Current studies have produced a plethora of remote health monitoring (RHM) systems designed to enhance the care of patients with chronic diseases. Many RHM systems are designed to improve patient risk factors for cardiovascular disease, including physiological parameters such as body mass index (BMI) and waist circumference, and lipid profiles such as low density lipoprotein (LDL) and high density lipoprotein (HDL). There are several patient characteristics that could be determining factors for a patient's RHM outcome success, but these characteristics have been largely unidentified. In this paper, we analyze results from an RHM system deployed in a six month Women's Heart Health study of 90 patients, and apply advanced feature selection and machine learning algorithms to identify patients' key baseline contextual features and build effective prediction models that help determine RHM outcome success. We introduce Wanda-CVD, a smartphone-based RHM system designed to help participants with cardiovascular disease risk factors by motivating participants through wireless coaching using feedback and prompts as social support. We analyze key contextual features that secure positive patient outcomes in both physiological parameters and lipid profiles. Results from the Women's Heart Health study show that health threat of heart disease, quality of life, family history, stress factors, social support, and anxiety at baseline all help predict patient RHM outcome success.**

I. Introduction

Cardiovascular disease (CVD) remains the leading cause of death for both men and women [1]. But adopting lifestyle habits of healthy eating, exercise and self-management skills can greatly reduce the risk of CVD. Studies on the efficacy of remote health monitoring (RHM) systems continue to be mixed. RHM systems are increasingly proving to be effective in saving costs, reducing illness, and prolonging life [2]. However, providers remain skeptical about the benefits of RHM systems claiming limited evidence, where some studies have produced disappointing results [3]. Since we cannot claim RHM systems work for everyone, can we predict who will benefit from an RHM system? We attempt to investigate whether there are certain patient contextual features or characteristics that can aid in determining RHM outcome success. This type of information can guide us in improving our understanding of potential motivators that can enhance lifestyle changes and improve human behavior.

We designed a RHM system named Wanda-CVD that is smartphone-based and designed to provide wireless coaching and social support to participants. Wanda-CVD was deployed in a six-month study of 90 young black women with cardiovascular disease risk factors in an attempt to reduce risk factors as a preventive measure in accordance with the Institute of Medicine Report and the goals of Healthy People 2020 [4]. While the majority of the participants in the Women's Heart Health study resulted in positive outcomes, many also did not benefit. We analyze the outcome of the six-month study in comparison to baseline to find predictors of RHM outcome success.

This work will not only help better understand which people succeed using RHM systems, but also create a minimal subset of questions to screen patients prior to enrolling them in an ongoing RHM system. This could save time and resources, and help us learn how to mold our current health monitoring systems to suit different populations. Because dropout rates increase with questionnaire length, developing such a prediction model that does not require much patient contribution could also aid in identifying important questions that relate to the objectives and success criteria of a new study [5].

II. Related Work

Chronic conditions have been perceived as a unique market for the use of smartphone applications [6]. A recent review of over 60 studies found chronic conditions such as diabetes mellitus and cardiovascular disease have always been perceived as a special 'niche market' for smartphone apps [7]. Despite the increasing research on RHM systems, it remains to be seen whether the technical feasibility and effectiveness of such systems can generate optimal patient outcomes and prevent chronic disease in a cost effective manner [3]. Results from a RHM smartphone-based study on 134 patients with heart failure hospitalization matched with 134 control patients show high correlation between increases in body weight and hospitalization for heart failure beginning at least 1 week before admission [8].

Several RHM studies report patient characteristics of successful participants, however there is no research in the area of predicting outcome success based on a subset of patient contextual characteristics. In this paper we attempt to identify key contextual features that help predict participant outcome success based on BMI, waist circumference, LDL, and HDL.

This paper is organized as follows. Section III presents the Wanda-CVD system, and Section IV describes the details of the Women's Heart Health study. Section V describes the baseline questionnaires used in the study along with the definition of outcome success. Section VI discusses the machine learning framework used to predict RHM outcomes

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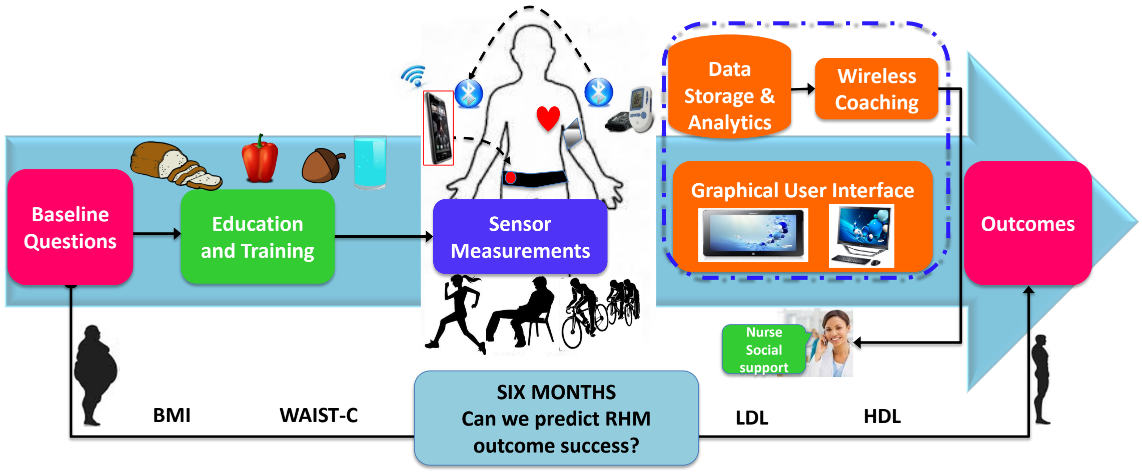

Fig. 1. Wanda-CVD System Architecture

success. Section VII provides results and discussion regarding the essential features selected and the accuracy with which these predictive models predict participant outcome success. Finally, we conclude in Section VIII.

III. Remote Health Monitoring System

There are several key components in the complete design of the Wanda-CVD system illustrated in Figure 1. The first component is the Android-based smartphone application designed as a means to collect data from the user, while displaying clinician feedback to the user. Using embedded sensors, Bluetooth, and Wi-Fi/cellular network technology, the smartphone application can be programmed to connect to many stand-alone patient monitoring systems. The application then transmits this information for storage to a backend server, and machine learning algorithms process the data to identify patterns and learn patient models. The system also provides wireless coaching in the form of automated messages prompting the user to take certain actions, such as measuring their blood pressure or reminding them to increase exercise intensity. The server provides a graphical user interface in the form of both a web- and tablet-based portal to supervising nurses to provide a visual cue and summary of what is happening with each patient, alerting them when a matter requires their attention.

IV. Women's Heart Health study

Our system has been deployed in the Women's Heart Health Study [9], [10], which is a UCLA IRB approved study of 90 young black women aged 25-45 years who have a minimum of two risk factors for CVD. In this study, 45 participants comprised the intervention group and received nutrition and lifestyle education and a smartphone-based remote monitoring system. The control group received usual care, including limited education and no technology and wireless coaching. After completion of baseline screening of cholesterol levels, blood pressure, and BMI; demographic and psychosocial questionnaires; and the educational classes, the participants were taught how to wear and manage the phones and blood pressure monitors. They were told that the primary purpose of the smartphone was to track their physical activity while providing a user interface and a mechanism for automated feedback.

V. Baseline Questionnaire and Outcomes

During the face-to-face baseline and 3- and 6-months visits, physiological as well as psychological outcomes were measured via anthropometric measures, questionnaires, and a software program. We focus on predicting success in the following four outcomes: waist circumference (WAIST-C), BMI, and LDL and HDL profiles. Table I lists the measurements taken, most in the form of questionnaires provided to the participants at baseline. The questionnaires are grouped into categories such as: participant family history (FAMHX), participant anxiety (BRIEFS) [11], participant depressive symptoms (PHQ), participant quality of life (SF), stress levels (STRESS), participant's perceived threat of heart disease (PMT) [12], and participant's available social support group (SOCSUP) [13]. Our goal is to identify a subset of the questions that aim to determine participant CVD study outcome success. Table II shows the rules that were used as the definition of success for each specific outcome.

VI. Predicting Outcome Success

The conventional feature selection algorithms usually focus on specific metrics to quantify relevance and/or redundancy to find the smallest subset of features that provides the maximum amount of useful information for prediction. Applying an effective feature selection algorithm not only decreases the computational complexity of the system by reducing dimensionality and eliminating redundancy, but also increases classifier performance by deleting irrelevant and confusing information.

The two most well-known feature selection categories are the filter and wrapper methods. Filter methods use a specific metric to score each individual feature (or a subset of features together), and are usually fast and much less computationally intensive. Wrapper methods usually utilize a classifier to

TABLE I
BASELINE MEASUREMENTS AND QUESTIONNAIRES

Acronym	Measurements	Purpose
	Clinical Measures	Waist, BMI, BP, Lipids
FAMHX	Demographics-Health History	Family & Medical
BRIEFS	Brief Symptom Inventory	Anxiety
PHQ	Patient Health Questionnaire	Depressive Symptoms
MOSSAS	Medical Outcomes Study-SAS	Adherence
SF	MOS-SF-12	Quality of Life
PMT	Protection Motivation Theory	Health threat of heart disease self efficacy
STRESS	INTERHEART STRESS	Stress
SOCSUP	Perceived Social Support Scale	Social Support

TABLE II
DEFINING OUTCOME SUCCESS AND FAILURE

Outcome	Success
Body mass index (BMI)	If BMI Loss $> 1\ Ib/inch^2$
Waist Circumference (WC)	If WC Loss $>= 1\ inch$
High density lipoprotein (HDL)	If HDL increases
Low density lipoprotein (LDL)	If LDL decreases

evaluate feature subsets in an iterative manner according to their predictive power [14], and then the optimal feature subset and classifier combination is selected. We applied the wrapper method, testing using 10-fold cross validation on multiple combinations of feature subsets and classifiers, including: k-Nearest Neighbors (kNN, with k=1 and k=3), Bayesian Networks (BayesNet), Support Vector Machines (SVM), Random Forest (with n= 10, 50, and 100 trees), C4.5 Decision Trees (C4.5DT). Figure 2 provides an illustration of the system architecture, where an optimal feature subset and classifier is trained based on baseline questionnaires to distinguish between participants that succeed and fail in the study.

VII. RESULTS AND DISCUSSION

The results of the six month trial show the following benefits in outcomes: 49% of the participants lost waist circumference, 30% decreased their BMI, 60% increased their HDL levels, and 55% decreased their LDL levels.

After performing feature selection for each of the measured outcomes, we found that the Random Forest classifier with 100 trees provided the fastest and most accurate prediction results for our dataset. Random Forest is an ensemble learning classification method comprising a collection of decision tree predictors operating based on independent and identically distributed random vectors. In this process, each tree casts a unit vote for the most popular class [15], [16] .

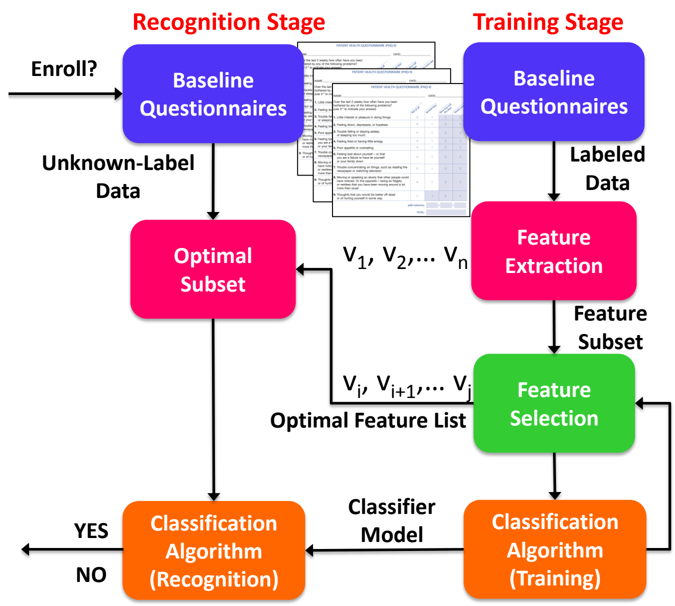

Fig. 2. Wanda-CVD Prediction Methodology

The classifier then assigns a probability to each data sample. We adjusted cut-off thresholds on the probability to generate labels for each sample, and false positive and true positive rates for each cut-off point.

We then generated Receiver Operating Characteristic (ROC) curves to evaluate the performance of each classifier. The area under the curve (AUC) is then used to measure the discrimination, or the ability of the classifier to correctly classify RHM participant outcome success for each outcome category. Figure 3 provides ROC curves for WAIST-C, BMI, and the HDL and LDL lipid profiles. We see the AUC for WAIST-C is excellent at 92.4%, as are those for the HDL and LDL predictors (91% and 83%, respectively), while the AUC for BMI is at 73%. The worse predictor for BMI could potentially be attributed to greater challenge in predicting weight loss; it also further bolsters prior research concluding that waist circumference is more closely linked to cardiovascular disease risk factors than is BMI [17]. The remainder of this section discusses the features selected for each predictor.

A. *Waist Circumference*

Approximately 48% of the participants lost at-least one inch from their waist circumference after the six-month intervention. The most prominent features were associated with the following categories: PMT, insurance coverage, Medical Outcomes Study (SF-12), and family history of medical disease. When generating the predictor, the following features were selected using the Pearson correlation coefficient, resulting in a 92.4% AUC predictor for waist circumference:

1) PMT14: (Thoughts about your health) I only know how to cook with salt and fat. Response ranged from ”Strongly Agree” to ”Strongly Disagree.”

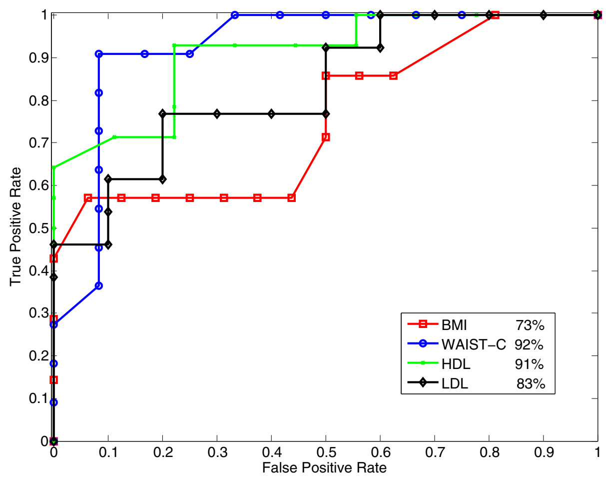

Fig. 3. ROC curves with corresponding AUC to measure performance of each predictor corresponding to each of the following outcomes: WAIST-C, BMI, and lipid profile (HDL, LDL).

2) INSURA: (General Information) Are you currently covered by any of the following health insurances? Government insurance (Medicare, Medicaid, Veteran's Administration health plan, military medical plan, or other government-reimbursed care). The binary response is either "Yes" or "No."
3) SF-3A: During the past 4 weeks, how much of the time have you had a problem with your work or other regular daily activities as a result of your physical health, and accomplished less than you would like? Response ranged from "All of the time" to "None of the time."
4) FAMHX: Grandparents having Stroke/TIA or a Mother with Heart Disease.

All participants who answered closer to disagree for a question regarding only knowing how to cook with salt and fat did well in the study, while those who agreed with this statement were unsuccessful at a reduction in waist circumference. Of those participants who had functional problems at work or while performing daily activities, 40% benefitted from the study and succeeded in the WAIST-C outcome. In addition, participants with first degree relatives having a stroke or heart disease (FAMHX) also were successful at reducing their waist circumference, as were those with government insurance and low income.

Motivation is defined as the force that initiates, guides and maintains goal-directed behavior, and a protection motivation theory postulates the three crucial components of a fear appeal to be (a) the magnitude of noxiousness of a depicted event, (b) the probability of that event's occurrence, and (c) the efficacy of a protective response [12]. Family history, especially in the form of a first-degree relative with a stroke or some other sequel to heart disease, such as heart failure, seems to have been successful motivation for some of the participants regarding WAIST-C outcome, and may have caused them to take action.

B. Body mass index (BMI)

Approximately 30% of the participants lost at least 1 $Lb/inch^2$ after the six month intervention, 57% of whom also lost waist circumference. The most prominent features were associated with the categories STRESS and SOCSUP. When generating the predictor the following features were selected using the Pearson correlation coefficient, resulting in a 73% AUC predictor for BMI:

1) STRESS4: Have you experienced a major life event in the past year such as marital separation, divorce, loss of job, retirement, business failure, violence, death or major injury or illness of a close family member, death of a spouse or other major stress? Response is binary, either "Yes" or "No."
2) STRESS1: Do you experience stress at home? Response ranged from "Never experienced stress at home," to "Have permanent stress at home."
3) SOCSUP7: I can count on my friends when things go wrong. Response ranged from "Strongly Agree" to "Strongly Disagree."

89% of the participants that experienced a major life event in the past year (STRESS4) did not succeed in decreasing their BMI. All the participants that responded confirming permanent or several periods of stress at home did not succeed in decreasing their BMI, and the 86% that did succeed in decreasing BMI experienced less stress at home. With the exception of one, all participants who succeeded in decreasing BMI had a friend they could count on (SOCSUP7).

C. Lipid Profile: HDL

Approximately 58% of the participants succeeded in increasing their HDL levels. The features that were most important in predicting success in HDL outcomes included: PMT29, PMT23, MOSSAS9, SF3B, and PHQ9. When generating the predictor, the following features were selected, resulting in a 91% AUC predictor for HDL:

1) PMT29: My family won't eat healthy foods even if I cook them. Response ranged from "Strongly Agree" to "Strongly Disagree."
2) PMT23: If I want to, I can eat foods with less salt and fat. Response ranged from "Strongly Agree" to "Strongly Disagree."
3) MOSSAS9: Limit sodium in diet (ate less than 2500mg per day). Response ranged from "All the time" to "None of the time."
4) SF3B: During the past 4 weeks, how much of the time have you had this problem with your work or other regular daily activities as a result of your physical health? Were limited in the kind of work or other activities. Response ranged from "All of the time" to "None of the time."
5) PHQ9: Thoughts that you would be better off dead or of hurting yourself in some way. Response ranged from "Not at all" to "Nearly every day."

We see here that PMT is also an important feature in predicting HDL levels. Another important predictor was adherence to diet. Participants who limited their sodium intake were successful in increasing their HDL levels, whereas those who had functional problems at work or while performing daily activities did not succeed in predicting HDL outcome, and neither did those who had thoughts of being dead or hurting themselves (PHQ9).

D. Lipid Profile: LDL

Approximately 57% of the participants reduced their LDL levels. The features that were most important in predicting success in LDL outcomes included: BRIEFS2, BRIEFS5, PHQ4, PHQ7, PMT25, and PMT20. When generating the predictor, the following features were selected, and resulted in a 83% AUC predictor for LDL:

1) BRIEFS2: How much were you distressed by being: Suddenly scared for no reason. Response ranged from "Not at all" to "Extremely."
2) BRIEFS5: How much were you distressed by spells or terror or panic. Response ranged from "Not at all" to "Extremely."
3) PHQ4: Over the last 2 weeks, how often have you been bothered by: Feeling tired or having little energy. Response ranged from "Not at all" to "Nearly every day."
4) PHQ7: Over the last 2 weeks, how often have you been bothered by having: Trouble concentrating on things, such as reading the newspaper or watching television. Response ranged from "Not at all" to "Nearly every day."
5) PMT20: My chances of having a heart disease are very small. Response ranged from "Strongly Agree" to "Strongly Disagree."
6) PMT25: Compared to other people my age, my chances of getting heart disease in the future are not very high. Response ranged from "Strongly Agree" to "Strongly Disagree."

The participants who often reported high anxiety as a result of distress from sudden fear (BRIEFS2) failed to decrease their LDL levels. Participants distressed by spells of terror or panic (BRIEFS5), 83%, failed to decrease their LDL levels. 75% of the participants that had responded closer to "Often" regarding feeling tired or having little energy (PHQ4) failed in the LDL outcome. Also, all the participants who had trouble concentrating on things such as reading the newspaper or watching television also failed in decreasing their LDL levels.

VIII. Conclusion

Results of this study show the potential benefit gained from a remote health monitoring system in reducing CVD risk factors. We provide results for a six month Women's Heart Health study showing the potential of an RHM system to reduce certain CVD risk factors in young black women ages 25 to 45. We deployed feature extraction and classification algorithms to design a predictor of RHM outcome success. The predictors for BMI, WAIST-C, HDL, and LDL resulted in AUC values of 92.4%, 73%, 91%, and 83%, respectively. The features were selected from the following baseline contextual measurements: health threat of heart disease, quality of life, family history of disease, stress, social support, study adherence, and anxiety, and show promise in the potential of a subset of features to predict RHM outcome success.

References

[1] (2011) Centers for disease control and prevention. heart disease and stroke prevention-addressing the nation's leading killers. chronic.pdf. [Online]. Available: http://www.cdc.gov/chronicdisease/resources/publications/aag/dhdsp.htm

[2] J. Sarasohn-Khan. (2011) California healthcare foundation. the connected patient: Charting the vital signs of remote health monitoring. CIM.pdf. [Online]. Available: http://www.chcf.org/publications/2011/02/the-connected-patient

[3] S. Mattke. (2010) Rand corp. health and well-being in the home. a global analysis of needs, expectations, and priorities for home health care technology. RANDOP323.pdf. [Online]. Available: http://www.rand.org/pubs/occasionalpapers/OP323.html

[4] C. D. Gillespie, C. Wigington, and Y. Hong, "Coronary heart disease and stroke deaths - United States, 2009," *MMWR Surveill Summ*, vol. 62 Suppl 3, pp. 157–160, Nov 2013.

[5] J. McCambridge, E. Kalaitzaki, I. R. White, Z. Khadjesari, E. Murray, S. Linke, S. G. Thompson, C. Godfrey, and P. Wallace, "Impact of length or relevance of questionnaires on attrition in online trials: randomized controlled trial," *J. Med. Internet Res.*, vol. 13, no. 4, p. e96, 2011.

[6] M. Terry, "Medical Apps for Smartphones," *Telemed J E Health*, vol. 16, no. 1, pp. 17–22, 2010.

[7] J. J. Oresko, H. Duschl, and A. C. Cheng, "A wearable smartphone-based platform for real-time cardiovascular disease detection via electrocardiogram processing," *IEEE Trans Inf Technol Biomed*, vol. 14, no. 3, pp. 734–740, May 2010.

[8] S. I. Chaudhry, Y. Wang, J. Concato, T. M. Gill, and H. M. Krumholz, "Patterns of weight change preceding hospitalization for heart failure," *Circulation*, vol. 116, no. 14, pp. 1549–1554, Oct 2007.

[9] N. Alshurafa, J.-A. Eastwood, S. Nyamathi, W. Xu, J. J. Liu, M. Pourhomayoun, H. Ghasemzadeh, and M. Sarrafzadeh, "Battery optimization in smartphones for remote health monitoring systems to enhance user adherence," in *Proceedings of the 7th International Conference on PErvasive Technologies Related to Assistive Environments*, ser. PETRA '14, 2014.

[10] N. Alshurafa, J.-A. Eastwood, M. Pourhomayoun, S. Nyamathi, L. Bao, B. Mortazavi, and M. Sarrafzadeh, "Anti-cheating: Detecting self-inflicted and impersonator cheaters for remote health monitoring systems with wearable sensors," in *BSN'14*, 2014, pp. 1–6.

[11] L. R. Derogatis and N. Melisaratos, "The Brief Symptom Inventory: an introductory report," *Psychol Med*, vol. 13, no. 3, pp. 595–605, Aug 1983.

[12] S. K. Wurtele and J. E. Maddux, "Relative contributions of protection motivation theory components in predicting exercise intentions and behavior," *Health Psychol*, vol. 6, no. 5, pp. 453–466, 1987.

[13] G. D. Zimet, S. S. Powell, G. K. Farley, S. Werkman, and K. A. Berkoff, "Psychometric characteristics of the Multidimensional Scale of Perceived Social Support," *J Pers Assess*, vol. 55, no. 3-4, pp. 610–617, 1990.

[14] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *J. Mach. Learn. Res.*, vol. 3, pp. 1157–1182, Mar. 2003. [Online]. Available: http://dl.acm.org/citation.cfm?id=944919.944968

[15] L. B. Statistics and L. Breiman, "Random forests," in *Machine Learning*, 2001, pp. 5–32.

[16] G. Guidi, M. C. Pettenati, R. Miniati, and E. Iadanza, "Random forest for automatic assessment of heart failure severity in a telemonitoring scenario," *Conf Proc IEEE Eng Med Biol Soc*, vol. 2013, pp. 3230–3233, 2013.

[17] S. Zhu, Z. Wang, S. Heshka, M. Heo, M. S. Faith, and S. B. Heymsfield, "Waist circumference and obesity-associated risk factors among whites in the third National Health and Nutrition Examination Survey: clinical action thresholds," *Am. J. Clin. Nutr.*, vol. 76, no. 4, pp. 743–749, Oct 2002.