Using Machine Learning on Wearable Smart Watch Devices to Track Nutritional Intake

A. Leah Zulas
Washington State University
Department of Electrical Engineering and Computer Science
alzulas@wsu.edu

Edward Kuo
Washington State University
Department of Electrical Engineering and Computer Science
edward.kuo@wsu.edu

Seyed Ali Rokni
Washington State University
Department of Electrical Engineering and Computer Science
alirokni@eecs.wsu.edu

ABSTRACT

Obesity rates in the United States, Mexico and Europe are at an all time high bringing with it diseases like cardiovascular disease and diabetes. Health care providers are attempting to keep up with this issue by recommending nutrition management behavioral plans that include multiple techniques, but these techniques often fail to keep users motivated to continue the program. A wearable device that could recognize when a user is eating and then notify them via a smart phone to track their current meal may greatly increase compliance. This research uses a smart watch to track accelerometer and gyroscope data of users and then uses supervised machine learning algorithms to classify eating behaviors from not eat behaviors. Random Forest with sampling had the greatest accuracy of all algorithms tested, but more research is needed.

Author Keywords

Pervasive Computing; Nutrition Monitoring; Smart Watch; Internet of Things; Heath Care

INTRODUCTION

An estimated 17% of children ages 2-19 are obese and an estimated 34.9% of adults are obese in the USA. Obesity is linked to other diseases such as cancer, cardiovascular disease, and diabetes. Obesity costs about $78.5 Billion dollars to treat annually. About 1 in 4 deaths in the USA are related to cardiovascular disease[4]. Nutrition monitoring is important in the prevention and treatment of diseases such as obesity, cancer, cardiovascular disease, and diabetes. Current technology on the market for nutrition tracking include diaries, phone applications, and wearables; however these forms of tracking have a variety of compliance issues. Participants and patients frequently forget to log what they have eaten and when. This can have detrimental issues for health care providers and researchers who are attempting to find solutions to diet problems. If eating and drinking can be sensed by a smart watch worn on the users dominant hand, this could aid patients and participants in remembering to log what foods they are eating through properly timed notifications.

There are many varieties of technology used to track nutrition currently. Paper journal food diaries require large amounts of dedication and must be used properly to be effective. Many people forget to write down exactly what food items they consumed and the nutrients that is absorbed into their body. This results in inaccurate monitoring which could negatively affect their health.

Phone applications to monitor nutrition are flexible as various methods can be used with this device but without being worn on the body, it cannot detect nutritional intake. One advantage of phone applications is that the phone is able to use its internal GPS to show location which may help in determining eating detection if the user often eats at a restaurant of cafeteria [6]. When compared to the paper journal diary, phone applications may help users gain satisfaction and motivation to track nutrition. However, improper use of prompting the user to eat will not result in weight changes for those attempting to monitor nutrition [7]. The ability to provide a greater amount of modifiability in an application can also help users sustain self-monitoring behaviors as the application can cater to a great amount of needs for a greater amount of users [2]. One application used a necklace with a piezoelectric sensor which could distinguish solids and liquids eaten using a voltage reading from the sensor with high accuracy[1].

Finding ways to make nutrition monitoring easier for people to use may reduce the number of deaths related to poor nutrition and may also reduce the amount of money used to treat patients every year. This experiment utilized the Samsung Gear 2. This research collected accelerometer and gyroscope data from participants to use advanced machine learning algorithms on that data in an attempt to predict when a user is eating throughout the day. A smart watch of this type could assist users by sensing when eating has begun and then prompting the user to record the foods that they are eating in a smart phone application.

This is different from some other wearable applications such as an upper armband or a body sensor, as the arm-band sensor is not able to detect minute arm movements. A smart watch is more closely matched to the activity of eating, creating better

Figure 1. Samsung Gear Watch 2 in Neon Yellow.

sensing and prediction. The smart watch also has an interface with additional benefits including desirability. Having an interface to look at is useful so the user can have feedback for actions used on the device, for example, notifications to enter in data into their smart phone.

This research aims to create a clear argument for why a smart watch might be a good wearable to detect eating, and therefore may be a useful tool for further research into diet and nutrition monitoring.

METHODS

Participants

Participants consisted of four Washington State university students, one graduate student and three undergraduate students. These participants were all associated with the pervasive computing laboratory at WSU, and were intended only as assistants for a pilot study proof of concept.

Materials

Samsung Gear 2 was the device chosen to monitor eating detection. This watch can collect gyroscope and accelerometer data. Due to the data required from any given device, this watch was the best choice from available consumer options. Some downsides of this watch include that it is not fashionable and participants have noted that it was uncomfortable. There was also a learning curve when using this device. For example, when charging the watch, the participant has to make sure that the pins are aligned with the watch on the charger in order to charge. There were multiple instances of improperly connecting the charger to the watch. There were also issues with recording data with the watch. Some participants could not find the application at first, some found the application but could not figure out how to use it.

The application inside the watch consisted of a button at the top right corner of the screen with the rest of the screen blank. When the button was pressed, a drop-down menu was displayed where a user could press the buttons to start and stop data collection. Whenever "Start Collection" was pressed, a box would appear that read "Start Collection." During this time there became available a button on the watch face, when the application was in use, that read "Begin Eating." When this button was pressed the following data would be labeled as a positive instance of eating. Clicking this button made the button change to "Stop eating." When stop eating was pressed, then the following data would be labeled as negative instances, or "not eating." At this time, the button would return to "Begin eating." If "Stop Collection" was pressed afterwards, all buttons and boxes would be removed from the screen. Data was sampled at 10 samples per second during peak use. If the watch hibernated for any reason (e.g., the user wasn't very active), the application pushed the data collected to a file and waited for the watch to return from hibernation before continuing collection.

Android Debugger (ADB) is a device management tool that allows a device to communicate with a computer. It provides various device management capabilities similar to UNIX shell. ADB was used to extract the data from the Samsung Gear 2 watch to the computers used in data anlysis.

Procedures

Participants were invited to the pervasive computing lab on Washington Stat University campus and received a fully charged Samsung Gear 2 watch and charger to use for this experiment. The participant equipped the watch on their dominant eating hand. Throughout the day during the course of any meal or snack, the participant selected "Start eating" on the smart watch application to record when eating begins. After the participant completes their meal, they then selected "Stop eating" on the application. Data was then uploaded to a computer from the watch using ADB. While the watch was not in use, the participant was instructed on how to make sure the watch charged properly.

Feature Extraction

Features directly from the watch included a time stamp in milliseconds since January 1st, 1970, accelerometer x,y,z, gyroscope x,y,z, and a classification. To better analyze these features, windows of time were created to track the patterns of actions over time. This allows sparse or noisy data to be reduced to a more stable set of points. The window was chosen using window sizes derived from past research and was set to n = 60 data points [3, 5]. The final features created for the data set were date and time of the beginning of the window, day of the week, hour of the day, length of window in milliseconds, average accelerometer x, y, z, average gyroscope x, y, z and an average classification broken down at .5 (i.e., <.5 = 0, >.5 = 1). In the final analysis date and time of the beginning of the window and day of week were removed as they did not add precision. This is mostly likely due to the lack of hours spent using the watch. If weeks were gathered over a longer time, day of the week and dates would hold more routine and patterns that could be more useful to the final analysis.

Machine Learning Algorithms

A subset of the data was utilized to run the first analysis of the data for efficiency. One data set from a single user was tested including 184,224 data points after feature extraction, 58 of which were labeled as eating. The algorithm with the highest accuracy rate on this set was then run on the larger data set of 9,138,385 data points with 74,462 of which were eating points. This data was gathered from 4 users, utilizing the watch over several days for approximately 30 hours of final data.

A review of the literature revealed that accelerometer and gyroscope data is often analyzed best using either K nearest

	Correctly Classified	Misclassified as not eating	Misclassified as eating
Perceptron	99.9685	58 (all points eating)	0
Support Vector Machines	99.9685	58 (all points eating)	0
Naïve-Bayes	99.8187	0	334

Figure 2. Worst algorithm outcomes.

	Correctly Classified	Misclassified as not eating	Misclassified as eating
K1NN	99.9967	4	2
K2NN	99.978	4	0
J48	99.9951	3	6
Random Forest	99.9973	3	2
Random Forest with Sampling	99.9995	1	0

Figure 3. Best algorithm outcomes.

neighbors (KNN), J48 trees, or random forest algorithms [3, 5]. A variety of other popular machine learning algorithms were also attempted including, voted perceptron, support vector machines, and Naïve-Bayes. K nearest neighbor was run with K=1 and K=2, however K=3 began a decline in accuracy. The random forest algorithm was also run with sampling to improve its accuracy before moving onto the larger dataset. Every algorithm was run with 10-fold-cross-validation. Future work may wish to use a leave-one-day-out cross-validation technique to better approximate actual use, as 10-fold may produce artificially high results [3].

RESULTS

Tests with basic perceptron, support vector machines (SVM), and Naïve-Bayes all returned incredibly flawed results (see Figure 2). Perceptron and SVM fail due to the non-linearity of the data. There is no linear equation that can draw a line to correctly divide the data. Naïve-Bayes fails due to the lack of ability to use probabilities to find the correct outcome of the window.

K=1 KNN and K=2 KNN did very well, but took 45-60 minutes to run on the smaller data set. There was inadequate time on any given machine to run KNN on the full dataset, therefore reducing its usability as an algorithm for this pilot test (see Figure 3).

J48 had a low amount of errors, but was overshadowed by the low errors in Random Trees (see Figure 3).

DISCUSSION

The results of this study suggest that a Random Forest machine learning algorithm can correctly identify eating from not eating on our limited data set. However, there are many limitations to this study. First, the smart watches battery does not allow for longer data collection periods. If a watch with a longer battery life was purchased for future work, a participant could wear the watch from the moment they woke up to the moment they went to bed at night. This would result in approximately 16 hours of data collection instead of only 6 hours a collection cycle.

The time and computational capacity for machine learning for this study were limited. This meant that only test runs could be done on the smaller data sets, and larger data sets could not be reviewed more extensively. With access to a server or an available bank of computers, K2NN could have been tested more extensively.

The data set available was limited. This study was only a proof of concept for a larger study in the future, therefore there were limited resources available for collecting data. Only 4 participants were utilized from the lab to gather data, leading to low power and not nearly enough individual differences obtained. A greater amount of data from more participants will lead to more unique outcomes and a more robust model. With a greater amount of data, it may become possible to create test cases for proper separation between model learning and model testing.

This research did not utilize leave-one-day-out cross-validation. Other research suggests that this type of cross-validation leads to the best results on accelerometer and gyroscope data in wearable devices [3]. Future research will need to test using this cross-validation method for more certainty in the results of the model.

Future research should attempt to cover other areas such as, the addition of GPS, attempting to detect routines in behavior eating, wearing the watch on the non-dominant hand, and the differences between eating and drinking.

Attempting to detect eating behavior from wearable devices has many complexities involved, as humans are complicated to study. There may be differences between handedness, cohort, routines, and culture. Eating a burger may be different from eating a gyro. This may cause further complexity as the number of testers grows. It will be important in the future to gather as many different kinds of people as possible.

If the results of this study follow after further investigation, applications of the model given can greatly increase the ability of professionals to assist clients and patients in attaining their health care goals. This application, in combination with a smart phone application, would allow users to be properly reminded to track their nutritional intake and physicians could be notified as to the length of any given eating session. While more research is required, this initial step suggests that this concept is a plausible solution to the nutrition tracking problem.

ACKNOWLEDGMENTS

We thank all the volunteers who wore the watch and tracked their eating habits. We would also like to thank the support of the pervasive computing laboratory on campus.

REFERENCES

1. Nabil Alshurafa, Haik Kalantarian, Mohammad Pourhomayoun, Jason J Liu, Shruti Sarin, Behnam Shahbazi, and Majid Sarrafzadeh. 2015. Recognition of Nutrition Intake Using Time-Frequency Decomposition in a Wearable Necklace Using a Piezoelectric Sensor. *Sensors Journal, IEEE* 15, 7 (2015), 3909–3916.

2. Adrienne H Andrew, Gaetano Borriello, and James Fogarty. 2013. Simplifying mobile phone food diaries: design and evaluation of a food index-based nutrition diary. In *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare*. ICST (Institute for Computer Sciences,

Social-Informatics and Telecommunications Engineering), 260–263.

3. Katherine Ellis, Suneeta Godbole, Simon Marshall, Gert Lanckriet, John Staudenmayer, and Jacqueline Kerr. 2014. Identifying active travel behaviors in challenging environments using GPS, accelerometers, and machine learning algorithms. *Frontiers in public health* 2 (2014), 39–46.
4. Cynthia L Ogden, Margaret D Carroll, Brian K Kit, and Katherine M Flegal. 2014. Prevalence of childhood and adult obesity in the United States, 2011-2012. *Jama* 311, 8 (2014), 806–814.
5. John Staudenmayer, Shai He, Amanda Hickey, Jeffer Sasaki, and Patty Freedson. 2015. Methods to estimate aspects of physical activity and sedentary behavior from high-frequency wrist accelerometer measurements. *Journal of Applied Physiology* 119, 4 (2015), 396–403.
6. Edison Thomaz, Irfan Essa, and Gregory D Abowd. 2015. A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 1029–1040.
7. Christopher C Tsai, Gunny Lee, Fred Raab, Gregory J Norman, Timothy Sohn, William G Griswold, and Kevin Patrick. 2007. Usability and feasibility of PmEB: a mobile phone application for monitoring real time caloric balance. *Mobile networks and applications* 12, 2-3 (2007), 173–184.