Actibetes: An Activity Recommender System for Patients with Diabetes

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***Abstract*—Diabetes remains a serious long-term complication where a sustained high blood sugar level is experienced. Prevention, as well as treatment, revolve around a healthy diet, physical exercise and maintaining a normal body weight. The following paper outlines the use of a mobile application to aid patients in making informed decisions in the maintenance of their condition. This report also introduces the background, the state-of-the-art, the initial system design and the evaluation plan.**

I. Introduction

Over 387 million people are affected by diabetes worldwide[1] which represents a striking 8.3% of the world's population. Considering its ability to more than double a person's fatality risk, we treat diabetes as a very serious condition. An important aspect in the proper treatment and management of diabetes is the correct maintenance of glucose levels throughout the day. Several factors play a key role in doing so, including a certain amount of physical activity. The correct amount of exercise depends both on current glucose levels as well as the individual's reaction and lag-effect to physical exercise. With an increased cost of diabetes in the coming decades, alongside alarming rising obesity rates[2], the usage of activity data will become more prevalent for the correct treatment of diabetes.

Smartphones provide a unique tool for integrating health monitoring in a patient's daily life. The concept behind Actibetes is to provide user tailored suggestions to help maintain adequate glucose levels through correlating the patient's blood sugar level fluctuations with corresponding levels of physical activity. As every individual has a very specific reaction to physical exertion, our system will be able to leverage the application's machine learning features to provide customised feedback. Actibetes uses the patient's location and the in-built iPhone accelerometer to gather and accumulate information regarding the levels of physical activity achieved by the user. User information is passed to the recommender engine, which selects and suggests an action that is believed to help the user achieve the healthcare target. We hope to confirm our hypothesis that a relation between the glucose concentration in blood and exercise does indeed exist and is significant enough to be modelled using machine learning. In addition, we predict that a multi-model structure will show better performance than single model structure when suggesting positive behavioral changes whilst managing diabetes.

II. Background and Context

A. Diabetes and its relation to exercise

Diabetes mellitus is defined as 'a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both'[3]. It increases the risk of heart disease and stroke[4], kidney failure[5], nervous system disease and other complications[6]. There are mainly two types of diabetes. Type I diabetes, also called Insulin-Dependent Diabetes Mellitus (IDDM), is caused by the body's inability to produce insulin, which must be therefore be treated with regular insulin doses. Other factors such as exercise can also have influence on patient condition. Type II diabetes is often referred as the non-insulin dependent diabetes mellitus (NIDDM), as it can be treated with or without regular insulin doses. The major cause of it is insufficient exercise and obesity, as well as genetics.

Lifestyle choices are believed to be significant factors in the development of diabetes. Smoking, stress, obesity and poor diet appear to increase the risk of diabetes[7], [8], [9]. Experiments have shown that doing exercise is likely to reduce the risk of diabetes complications by diminishing or preventing hyperinsulinemia and insulin resistance[10], [11]. This provides us with the motivation to deliver the Actibetes project, which encourages a healthy lifestyle through doing regular exercise and most importantly, assists patients with the management of diabetes.

B. M-Health

M-health is the abbreviation for mobile health and it is defined as 'the emerging mobile communications and network technologies for healthcare systems'[12]. Mobile applications have become increasingly popular for encouraging physical exercise and promoting the idea of a healthy lifestyle[13]. In 2012, one billion smartphones were in use worldwide and the cheap cost of mobile applications have made m-health a good choice to improve one's self-management and learn to live in a healthy fashion.

III. State-of-the-art

A. Current m-Health applications

M-Health is not a new concept and there are a wide range of commercialised m-health applications. Some common applications, such as 'Health', the pre-installed app for iOS devices, act as a personal data centre, which collects and stores information about a user's health and activity levels. However, the mobile app does not provide any suggestion or solution on how to effectively manage or improve the user's health. Other applications follow a proactive mechanism and deliver solutions to patients after analysing their data. The 'Pip' Project for example, which estimates the stress level through electrodermal activity, utilises gamification techniques to encourage users to control their stress level more effectively. Our Actibetes project uses the same idea and actively provides recommendations to patients. It is likely to encourage the engagement of patients and lead to satisfying results in chronic disease healthcare.

Research has shown that the adaptive mechanism is preferred in human-robot interaction[14] and user preferences is a good way for the system to learn about its new users. The 'HidrateSpark' smart water bottles track the amount of water consumed and remind users to drink more to meet the recommended daily water goal, which is customised for each individual. Many other applications also provide a customised service by requiring users to manually input their preferences (which is not adaptive in strict sense). Therefore, the user modelling in Actibetes is likely to be a good selling point since the forward models automatically adjust to the changes in users.

B. Current diabetes management applications

There are currently a vast range of diabetes applications which help diabetics manage their condition and improve their average blood glucose concentration variation throughout the day. The applications differ by functionality, where basic applications provide a simple logbook for diabetic patients to log their blood glucose, carbs, and insulin units. More advanced applications are able to automatically transfer blood glucose readings from a modest range of blood glucose meters, and upload this to a centralised system that can be accessed by clinicians. A detailed comparison of a few of these applications are shown in Appendix A.

IV. System Design

A. Overview

Actibetes is designed to enable users to log diabetes-related parameters such as blood glucose concentration, insulin units taken, and also activity data such as the duration of exercise, and type of exercise. As well as providing functionality for users to manually enter the previously mentioned parameters, Actibetes will leverage the power of location services to track users' movements and automatically record this activity data. This data will be utilised by a recommender system to provide personalised, tailored feedback to the user of the application, to help them better manage their condition. The Actibetes system will consist of a mobile application (iOS), a database server for storing user activity data, and an adaptive recommender system which analyses the activity data to provide useful feedback. Further compatibility advancements include syncing data from fitness devices such as Fitbit, to reduce the burden of excessive data entry into the application. Figure 1 shows a high-level description of the system.

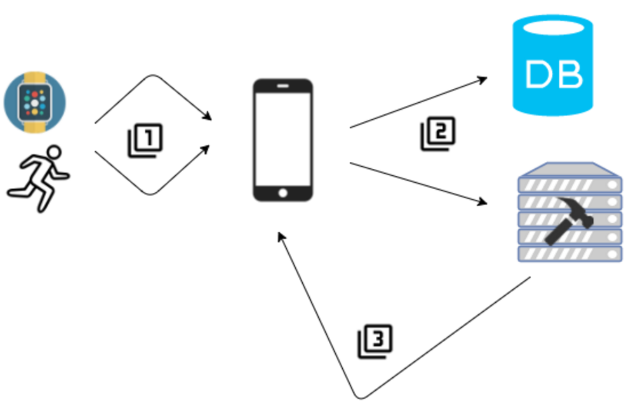

Fig. 1. High-level architectural design of the Actibetes Application

1) Activity data is recorded by the mobile application either by manual entry or from fitness devices such as Fitbit and to a lesser extent, the Apple Watch
2) This recorded data is sent to a database for secure data storage, and to the adaptive recommender system for analysis
3) When the analysis is complete, the recommender communicates results back to the mobile application.

B. Front-end mobile application

The front-end mobile application is the main entry point for users of the application. Users will be able to log activity data through a mobile application built on an iOS device. Front-end development will be carried out using Swift 2, Apple's novel programming language. The development environment is Xcode, which have been installed on the Macs in the computer labs on Level 3. Figure 2 shows a wireframe of the potential application. The user interface should be clean, clutter-free and easy to use to enable users to quickly have a view of their activity and blood glucose, and easily allow them to add new entries. The front-end mobile application will consists of the following features:

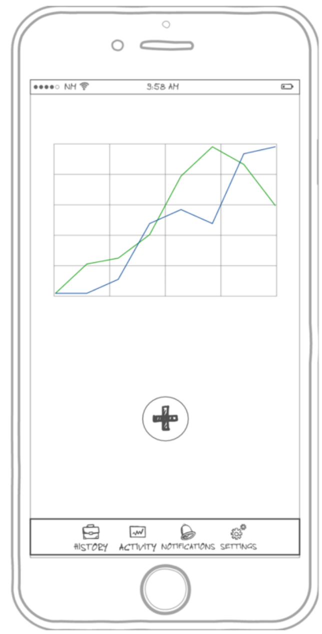

Fig. 2. Wireframe of the Actibetes Application

- Entry of Activity Data: The application will allow users to log parameters relating to activity data such as the amount of time spent exercising, and the type of exercise. This kind of data is difficult to capture using the sensors available in a smartphone, so will require the user to manually enter this data. However, if the user uses a fitness device such as a Fitbit, the activity data from this device, as well as potentially the heart rate (if available), will be able to be accessed using Fitbit's public API.
- Use of Location Data and Accelerometer Data to Track User Activity: The application will utilise the iOS Core Location framework to track distance run by a user, their average pace, and also allow users to view the route that has been run. The accelerometer data will also be used to track the number of steps taken by a user over a specific period of time.
- Viewing of Historical Data: Users will be able to view historical entries entered into the application. This will enable them to see how different kind of activities affected blood glucose levels, enabling them to alter their exercise regime as they see fit in the future.
- Display of Recommender System Data: The front-end mobile application will asynchronously communicate user activity data to the back-end server, which will analyse this data and respond with valid, user-tailored recommendations on how to improve average blood glucose concentration.

C. Recommender system

An adaptive recommender system based on the HAMMER architecture will be used for action selection and recommendation[15]. Multiple models will be used to imitate the behaviour of the demonstrator and to learn the reactions of patients. The imitation learning process of models leads to the adaptive nature of the system and makes it suitable for the long-term chronic disease healthcare.

The basic unit in the HAMMER architecture is an inverse-forward model pair, which is commonly used in motor control theory. The inverse model takes user state and, ideally, the goal state, to generate the action which is most likely to lead to the goal state. The forward model reads the command from the inverse model and predicts the next user state assuming the user executes this command. Error signals from comparing the actual and the predicted states are used to adjust the confidence levels of the inverse models.

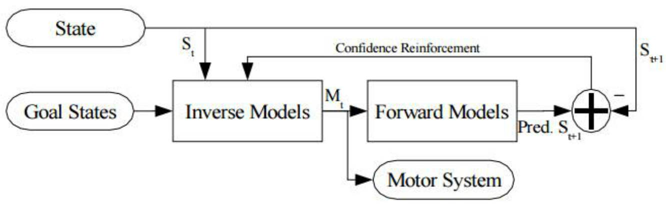

Fig. 3. The basic unit of the HAMMER architecture[16]

In this project, multiple models using different machine learning algorithms will be implemented in parallel. In the learning phase, inverse models learn the behaviour of the demonstrator, in this case, healthcare professionals. Forward models learn the response of patients, i.e changes in glucose levels after various actions. Forward models are for user modelling and it adjusts to the possible changes that might happen in long-term healthcare, for example, the physical health of the patient. Models compete with each other in action suggestion and the action suggested by the model with the highest confidence level will be selected and delivered to user through the mobile application.

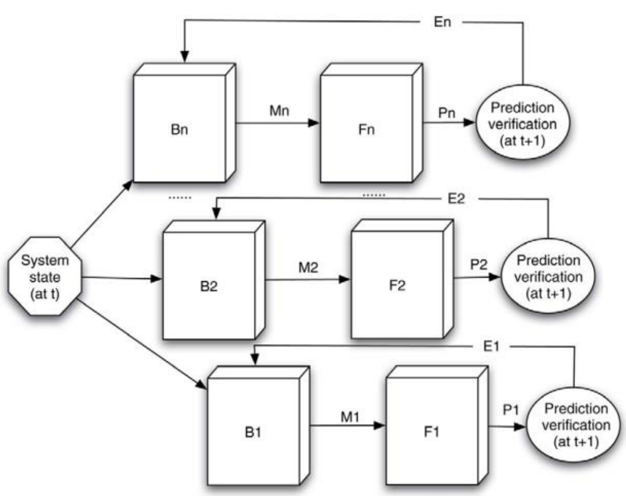

Fig. 4. The parallel operation of multi-model structure in HAMMER[15]

Currently, the skeleton of the HAMMER architecture has been constructed and demonstrations are available to show the parallel operation of models. HAMMER has been wrapped with RESTful API so that it is able to communicate with external devices after uploading it onto Google App Engine. The inverse and forward models are awaiting implementation. Regarding the machine learning techniques, several algorithms have been considered. The relation between exercise and glucose level is likely to be linear and the linear regression model will be implemented first. Decision tree and Support Vector Machine might be used in early-stage development[17]. The Java library for general-purpose machine learning is available on Github.

D. Database

Incorporating a database into the system design enables us to decouple the business logic (recommender system code) of the system from the persistence of data. It introduces an element of redundancy into the system as having a database running on a separate server than that of the recommender system provides data protection in the unfortunate event that the server running the business logic goes down. A centralised database also enables the user to access his/her data across multiple devices, instead of being restricted to one device. The database will be mainly be used to store historical data entered by the user. This will enable the user to keep track of past entries into the Actibetes application. The application will communicate with a database server, which will be running a web service allowing us to remotely perform CRUD (Create, Read, Update and Delete) operations on data. There are several ways to implement the database server, and we are currently considering two implementations, although this is liable to change:

- Node.js and MongoDB Application Stack: Node.js is a JavaScript Runtime built on Google Chrome's V8 engine, used for building fast, and easily scalable web applications. MongoDB is a database that enables developers to store JSON objects. To be more specific, MongoDB stores JSON (JavaScript Object Notation) as BSON (Binary JSON) which is a more efficient for data storage, and also querying data. The combination of these two technologies enable us to easily build RESTful services that produce JSON to be persisted into the database. Because MongoDB is compatible with JSON, there is no need for any data transformation. The mobile application will be able to make HTTP calls to the RESTful service to perform CRUD operations on the database.
- PHP and MySQL Application Stack: PHP is an open-source scripting language commonly used for web development. It can be used to construct a web service which sits on top of a MySQL database. MySQL is a simple Relational Database Management System which can be used to create databases that store data in the form of tables. Once again, the mobile application will be able to make HTTP calls to the web service to perform CRUD operations on the database.

V. Experiments and Evaluation

Based on our hypothesis mentioned previously, our system design will be evaluated through three criteria:

- Overall system performance. The three components which form the complete system are expected to cooperate smoothly and to communicate with each other through passing a range of data types.
- Performance of Inverse models. For example, the averaged prediction accuracy of individual inverse models across a number of patients.
- Performance of Forward models. For example, the accuracy of user modelling for a number of patients.
- Performance of the parallel multi-model structure. The recommendation accuracy is expected to be improved compared to the single model structure.

The data set for model training and evaluation will come from the Diabetes Data Set from UCI Machine Learning Repository[18]. Health data of 70 patients with Insulin Dependent Diabetes Mellitus is available, with the data consisting of the date, time, activities and glucose concentration of the patients. The activities recorded include typical exercise, more-than-usual exercise, less-than-usual exercise and many other daily activities that might affect blood glucose concentration. It is considered as a good starting point to use this data set and if the data set for Type II Diabetes Mellitus is also available, we will extend the scope of our research.

VI. Conclusion

Diabetes has been the source of growing concern over the past few years due to lifestyle shifts including changing eating habits high in refined carbohydrates and sugar. To counteract this uprising in diagnostics, patients have to remain physically active to prevent or manage their condition, which is even more critical for Type II diabetes. The NHS recommends a minimum of 150 minutes of moderate intensity aerobic activity per week and bi-weekly muscle-strengthening activities. The physical activity allows the cells to be more sensitive to insulin whilst also removing the excess glucose from the bloodstream, in addition to contributing to overall wellbeing. Our mobile application will harness the capabilities of recent smartphones with their increasing amount of sensors and locations services to proactively learn about its respective users and suggest daily lifestyle modifications in line with the recommended response to dealing with diabetes. These suggestions can range from increase daily cardio and aerobic exercising to a more balanced daily routine. In the future, we see this application being integrated with the next generation continuous glucose monitors to allow regular suggestions leading to a more healthy lifestyle and better management of diabetes[19].

References

[1] Y. Shi and F. B. Hu, "The global implications of diabetes and cancer," *The lancet*, vol. 383, no. 9933, pp. 1947–1948, 2014.

[2] E. S. Huang, A. Basu, M. O'Grady, and J. C. Capretta, "Projecting the future diabetes population size and related costs for the us," *Diabetes care*, vol. 32, no. 12, pp. 2225–2229, 2009.

[3] D. Mellitus, "Diagnosis and classification of diabetes mellitus," *Diabetes care*, vol. 28, p. S37, 2005.

[4] N. Morrish, S.-L. Wang, L. Stevens, J. Fuller, H. Keen, W. M. S. Group, *et al.*, "Mortality and causes of death in the who multinational study of vascular disease in diabetes," *Diabetologia*, vol. 44, no. 2, pp. S14–S21, 2001.

[5] A. Alwan *et al.*, *Global status report on noncommunicable diseases 2010.* World Health Organization, 2011.

[6] C. for Disease Control, P. (CDC), C. for Disease Control, P. (CDC), *et al.*, "National diabetes fact sheet: national estimates and general information on diabetes and prediabetes in the united states, 2011," *Atlanta, GA: US Department of Health and Human Services, Centers for Disease Control and Prevention*, vol. 201, 2011.

[7] A. Abdullah, A. Peeters, M. De Courten, and J. Stoelwinder, "The magnitude of association between overweight and obesity and the risk of diabetes: a meta-analysis of prospective cohort studies," *Diabetes research and clinical practice*, vol. 89, no. 3, pp. 309–319, 2010.

[8] S. Melmed, K. S. Polonsky, P. R. Larsen, and H. M. Kronenberg, *Williams textbook of endocrinology*. Elsevier Health Sciences, 2015.

[9] A. Pan, Y. Wang, M. Talaei, F. B. Hu, and T. Wu, "Relation of active, passive, and quitting smoking with incident type 2 diabetes: a systematic review and meta-analysis," *The Lancet Diabetes & Endocrinology*, vol. 3, no. 12, pp. 958–967, 2015.

[10] N. G. Boulé, E. Haddad, G. P. Kenny, G. A. Wells, and R. J. Sigal, "Effects of exercise on glycemic control and body mass in type 2 diabetes mellitus: a meta-analysis of controlled clinical trials," *Jama*, vol. 286, no. 10, pp. 1218–1227, 2001.

[11] N. B. Ruderman and S. H. Schneider, "Diabetes, exercise, and atherosclerosis," *Diabetes Care*, vol. 15, no. 11, pp. 1787–1793, 1992.

[12] C. Doukas, T. Pliakas, and I. Maglogiannis, "Mobile healthcare information management utilizing cloud computing and android os," in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pp. 1037–1040, IEEE, 2010.

[13] P. Klasnja and W. Pratt, "Healthcare in the pocket: mapping the space of mobile-phone health interventions," *Journal of biomedical informatics*, vol. 45, no. 1, pp. 184–198, 2012.

[14] A. Sekmen and P. Challa, "Assessment of adaptive human–robot interactions," *Knowledge-Based Systems*, vol. 42, pp. 49–59, 2013.

[15] Y. Demiris and B. Khadhouri, "Hierarchical attentive multiple models for execution and recognition of actions," *Robotics and autonomous systems*, vol. 54, no. 5, pp. 361–369, 2006.

[16] M. Johnson and Y. Demiris, "Abstraction in recognition to solve the correspondence problem for robot imitation," *Proceedings of TAROS*, pp. 63–70, 2004.

[17] A. Al-Hmouz, J. Shen, J. Yan, and R. Al-Hmouz, "Enhanced learner model for adaptive mobile learning," in *Proceedings of the 12th international conference on information integration and web-based applications & services*, pp. 783–786, ACM, 2010.

[18] M. Lichman, "UCI machine learning repository," 2013.

[19] M. Senior, "Novartis signs up for google smart lens," *Nature biotechnology*, vol. 32, no. 9, pp. 856–856, 2014.

Appendix A
Comparison of current diabetes management apps

Criteria	mySugr	Diabetes Pilot Pro	Glooko	Diabetes in Check
User Interface Design	Cluttered, but well designed	Poorly designed	Clean and well designed	Moderate design
Ease of Use	Easy to use	Moderately easy to use	Easy to use	Slightly difficult to use
Compatibility with glucose monitors	Only compatible with iHealth gluco, iBGStar(Germany only) and GL50evo BG monitors	None	Reasonably extensive, compatible with over 50 BG meters and popular insulin pumps	None
Ability to view historical data	Yes	Yes	Yes	Yes, but just previous 7 days
Recommendation System	No, but there is a 'challenges' system, which sets small challenges for user to keep them motivated	No	No	No, but app offers helpful advice on how to manage BG levels
Price	Free version has limited functionality, paid version has subscription scheme of £2.29/month, £20.99/per year, and £104.99 for lifetime	Free for a week, requires £2.29/month afterwards	Basic logging app is free, subscription service of $59.99 required to enable app communicate with BG meters	Free
Activity tracking	No	Possible integration with fitness trackers and other health apps by using Apple's HealthKit	Can track activity by obtaining data from fitness trackers	Offers manual logging of duration of exercise
Reminder system	Easy to use, however doesn't support location-based reminders	Clunky, also doesn't support location-based reminders	Easy to use, however doesn't support location-based reminders	Easy to use, however doesn't support location-based reminders
Ability to add written notes to blood glucose entries	Easy to use	Easy to use	Easy to use	Easy to use
Food database	Present	Present	Present	Present
Compatibility with fitness devices such as Fitbit, Withings, etc	No compatibility	No compatibility	Compatible with: Fitbit, Strava, Moves, Withings, iHealth, Jawbone, RunKeeper	No compatibility

TABLE 1

Fig. 5. Table comparing the feature set of current diabetes management apps