IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 9, No. 4, December 2020, pp. 591~599
ISSN: 2252-8938, DOI: 10.11591/ijai.v9.i4.pp591-599

Design of meal intake prediction for gestational diabetes mellitus using genetic algorithm

Marshima Mohd Rosli, Nor Shahida Mohamad Yusop, Aini Sofea Fazuly
Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, 40450, Shah Alam, Malaysia

Article Info

Article history:

Received Dec 12, 2019
Revised Aug 28, 2020
Accepted Sep 10, 2020

Keywords:

Blood glucose
Gestational diabetes mellitus (GDM)
Recommender system
Systematic mapping

ABSTRACT

Gestational diabetes mellitus (GDM) is frequently described as glucose intolerance for pregnancy women. GDM patients currently practice the traditional method (record book) for recording blood glucose readings and keeping track of meal intake. This practice is not efficient and impractical for monitoring glucose level for GDM patients when we compared with mobile health monitoring technologies available today. Although, many applications have been developed for diabetes patients, but we do not found any application appropriate for GDM monitoring. In this study, we describe the design and development of mobile application for GDM monitoring using genetic algorithm that aims to predict recommended meal intake. We developed the mobile application for the GDM patients to maintain their blood glucose level through their meals. We tested the components of the mobile application and found that the prediction algorithm has successfully predicted the next meal intake according to the patient blood glucose levels. We hope this study will encourage research on development of self-monitoring applications to improve blood glucose control for GDM.

Corresponding Author:

Marshima Mohd Rosli
Department of Computer Science
Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA, Malaysia
Email: marshima@tmsk.uitm.edu.my

1. INTRODUCTION

Diabetes is one of the chronic diseases that is classified by a dramatic growth of blood glucose in human body [1-2]. If the patient fails to rule and overcome the disease, it will lead to many malfunctional organs which leads to many more chronic illnesses [3]. This acute illness can be composed to many types of diabetes. These types are found to be in adults and adolescents who comes from a different health backgrounds and genetics [4]. According to Aumiller and Dollahite [3], the types are type 1 (T1D), type 2 (T2D), gestational diabetes mellitus, impaired glucose tolerance and some rare form of diabetes.

Gestational diabetes mellitus (GDM) is one of the common pregnancy disorders specifically and highly prevalence among pregnant women [5]. Diabetes mellitus is an abnormal and a complicated malady that require the patients to take a good care of their selves by maintaining a persistent medical care of the glycaemic control [6]. GDM happens when the body meets a condition of developing carbohydrate or glucose intolerance during pregnancy. GDM is only found in pregnant women when they did their screening. It is only developed during pregnancy and it will emit after it. However, a GDM offspring will have an increasing risk of having type 2 diabetes in the future [7]. This epidemic disease will result to affect the mother and the newborn child. One of the vital affects is their nutrition development will be corrupted [8].

Pregnant women will need to undergo a health screening to test their glycaemic level in their body. Women who have previous GDM have the highest risk to have it again in their future pregnancy. Therefore, they are suggested to do earlier screening test than women with other risk factors and repeat it between 24 to 28 weeks if they are normal [5].

The glycaemic level is the indicator of the blood glucose level in human body. Basically, the sugar (called glucose) level in the bloodstreams comes from all the food that we eat. Human pancreas will produce a hormone called ‘insulin’ which transfer the blood to the body to use it as a day-to-day energy. Nevertheless, diabetes patients are facing a low insulin and cannot be functioning. Thus, the unneeded blood will stay in the bloodstream without dissolving in the tissues [9].

There is a specific level of glycaemic that the GDM patients need to maintain. However, every patient has their own specialized level based on many factors such as age, body mass index (BMI), health status and the after effect on controlling glycaemic level [10]. One of the ways to decrease the glucose level is by consuming low glycaemic index (GI) foods. These foods will decrease the response of glucose due to minor glucose arrival in it [11]. Low-GI diet helps the patient to reduce the need for insulin [12].

In recent years, many GDM patients practice the traditional method for recording blood glucose readings and keeping track of meal intake [13]. These practices are not efficient when we compared with mobile health monitoring technologies available today. In addition, health practitioners in hospitals are also using the traditional method on monitoring glucose level for GDM patients which can be very impractical. Although there is considerable variability in how mobile health applications are designed and used in healthcare, the use of self-managing health mobile for GDM has not been thoroughly investigated [13]. In particular, such system for controlling the glycaemic level and meal intake recommendations application is not yet to be found.

The ultimate goal of our research is to develop a GDM monitoring application for patients and medical practitioners. The application will store data in a centralised database and can be synchronised with others healthcare applications. As a first step, we need to construct a prediction algorithm for meal intake recommendation to maintain blood glucose level. We begin by developing a new self-monitoring mobile application for GDM patients to keep track of their glucose level by helping them acknowledging the calories in their daily meals in order to maintain the desired glucose level. The important component in maintaining the glucose level is to control the meal intake daily. Thus, the propose application will assist them predicting their glucose level through their daily meals. Therefore, the patients will be more aware of their health condition and can avoid for any further bad consequences earlier.

The contributions of this paper are:

– A prediction algorithm for meal intake recommendation using Genetic Algorithm.
– A mobile application for GDM self-monitoring.

The remainder of this paper is organized as follows: Section 2 describes the related work on GDM. Section 3 reports the methodology to construct the prediction algorithm and to develop the mobile application. Section 4 discusses the results and important findings of the proposed prediction algorithm and mobile application. Finally, we conclude and provide recommendation in Section 5.

2. MEAL INTAKE PREDICTION ALGORITHM

2.1. Prediction algorithms

There are many prediction algorithms available in the literature [14-23]. In this section we start with literatures on prediction algorithms which are peak glucose prediction using food intake, mobile personalized blood glucose prediction and blood glucose level prediction using intelligence-based modelling technique. Next, we present studies that discuss prediction model using machine learning techniques. Finally, we discuss how our previous work informed the development of the prediction algorithm presented in this paper.

A study conducted by Islam *et al.* [14] was to determine the level and peak of glucose level every time one type 1 diabetes patients took a meal. This idea had been taken account to avoid an overdosed insulin intake as the patient will not know their current level of glucose and they will take the suggested amount of insulin even if it is an unnecessary high. The application uses one input of insulin which is from the usual injections the type 1 diabetes patients are prescribed. Moreover, they use the patients’ specific parameters gathered from the professional doctor’s information which is denoted as ‘Sp’ and ‘Sh’. On the other hand, the system can use matching computer simulated glucose profiles with measured values to collect the data. To keep track of the post-meal activity, the system uses classic minimal model as a physiological model to both generalized liquid meal and normal meal such as soup and rice respectively.

Pustozerov *et al.* [17] conducted a study and developed an application for patients with GDM to monitor their blood glucose level and as a personalized recommender based on their BG level. They estimate the postprandial glucose level through the glycaemic load and index in their foods. As defined by [24], postprandial glucose is the concentration of plasma glucose level after eating.

The application collected several categories such as their background health history, biomedical signals and electronic diaries record which is the received daily input from the user's activities. Biomedical signal is their continuous blood glucose monitoring system information based on their postprandial response. User's background are their biometric characteristics, medical history, survey data and biochemical parameters. Example of concerned users' activities are their meals, sleep duration, physical activity, insulin injections and blood glucose measurements. These parameters reside in their continuous glucose monitor (CGM) system that use Medtronic iPro. Based on the parameters, the postprandial BG curved was obtained. Once the data were processed, it will be integrated to use in developing BG model prediction. They decided to use linear regression models with the use of lasso regularization as their prediction method.

Aibinu *et al.* [16] has taken an initiative in conducting a study on monitoring and predicting blood glucose level of type 1 patients. Parametric model identification which are autoregressive (AR) model and autoregressive moving average (ARMA) model, have been used to estimate the blood glucose level. Next, real-valued neural networks (RVNN) was used to estimate the model coefficients. To make it optimized, they use genetic algorithm (GA). Subsequently, the optimized coefficient model will be the input of the blood glucose level prediction.

In recent years, there has been an increasing amount of literature contributed to the prediction model using machine learning [22-23, 25-26]. Contreras *et al.* [22] presents the evidence of idea of a clinical decision support system joining a classifier of glycemic profiles and an indicator of blood glucose levels. The system was expected to distinguish information profiles as per a given situation and to produce prediction models based of these situations to estimate blood glucose levels. Besides, Rahman [23] proposed a novel hybrid rough set reasoning model (H2RM) that resolves issues of inaccurate prediction and management of type-1 diabetes mellitus (T1DM) and type-2 diabetes mellitus (T2DM). For verification of the proposed model, experimental data from fifty patients, acquired from a local hospital in semi-structured format, is utilized.

Kaliappan *et al.* [25] conducted a study on optimization algorithm to improve the processing of high dimensional data. The study proposed artificial bee colony (ABC) approach to minimize the execution time and to optimize the best cluster of datasets. Through few experiments, the study improved the time performance by reducing the execution time and classification error for selecting optimal clusters.

Ismail *et al.* [26] proposed a hybrid genetic algorithm neural network (GA-NN) model to replace the physical tests procedures of medium density fiberboard (MDF). The hybrid GA used a fixed probability rates for crossover and mutation for hybrid GA-NN model. The proposed model improved the existing genetic algorithm using adaptive mechanism to help identify the most suitable operator probability rates. Furthermore, the model able to reduce the testing time required as well as to reduce the cost.

In our previous work [27], we reported that many researchers developed techniques to deal with blood glucose prediction, especially for recommender system. However, there is a lack of research that focus on developing techniques to predict meal intake for monitoring blood glucose level. This indicate a need to develop application to predict meal intake for GDM patients. With respects to the reviewed literature, we found that GA algorithm contributes to giving the optimal outcome especially in biological evolution process. GA is mentioned as an effective and robust algorithm that helps find the best solution within many conditions. It is suitable for this study as the blood glucose prediction level must be accurate and optimal to help the user control their next meal intake.

2.2. Genetic algorithm

Genetic algorithm is an algorithm that have the concept of selecting the best individual or element from a pool of population [28]. The algorithm's concept is inspired by the science of genetic reproduction of humans. However, genetic algorithm is picking the best elements in a population, to mate and produce better offspring, iteratively until it achieves its best product as shown in Figure 1.

This algorithm consists three main steps which are selection, crossover and mutations. Selection is the step to select the best outcome out of the population. Each individual in the population will undergo fitness function to find out their fitness. Fitness function can be differ depending on the context of project.

Individuals with higher fitness have a higher chance of being picked out from the population to be the parents of new offspring. From the probability difference, they will choose the 'lucky' ones to conduct in next step. Crossover is the step when the two 'lucky' ones that have been picked will be mixed to product next generation as shown in Figure 2(a).

The genes in each individual will be separated and combined with the next individual. The point of crossover can be different for different output. Two common crossover point methods are single-point and double-point. Single point is to have only one section of the genes to be featured in the offspring. Meanwhile double-point crossover method is to have to points in the genes which contributes to two distinct parts of the individual to be combined with other individual and to add in the next generation.

The step of mutation describes the altering of the produced generation to increase diversity, at the same time helps in finding the best individual out of the population. It introduces the concept of randomness to the algorithm [28] as shown in Figure 2(b). Random genes from the offspring will be selected and changed to different character or element.

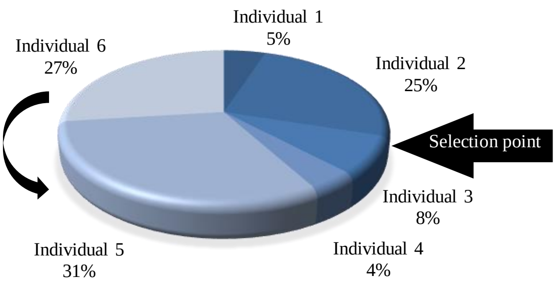
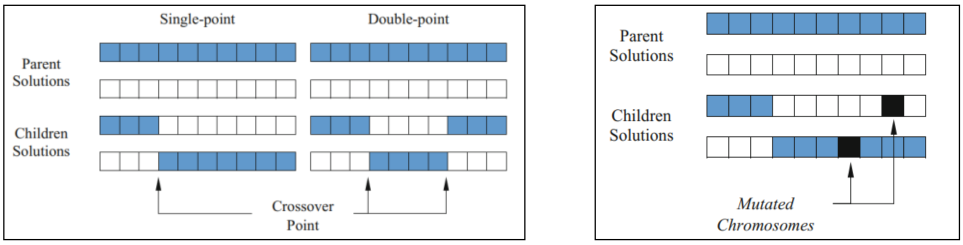


Figure 1. The probability difference between individuals [28]



(a) (b)

Figure 2. (a) The crossover step for genes in the individuals [28], (b) The mutations of the offspring [28]

3. PROJECT DESIGN

3.1. GDM mobile application architecture

In this study, we propose a mobile application to recommend sufficient next meal intake in line with the ideal glucose level for GDM patients. This mobile application specifically built for patients to help them in maintaining their glucose level through their meals. Collection of meals were collected by web scraping from a specific nutrition website. Then, the current glucose level will be inserted by the patient or user and processed with GA algorithm. The algorithm helps in finding the optimal and create diversity in the solution. The outcome of this project will assist the patients with GDM to control their glucose level first-hand, without the need to approach the doctors for diet prescriptions.

Figure 3 shows the application architecture that starts by the input of the current glucose level from the user. The input will then be processed by the recommender component that apply GA to give out the optimal next meals for the user. The algorithm reads the collection of meals from a file. The collection of meals in the file were scraped using Web Scraper tool on the internet.

3.2. GDM mobile application flowchart

Figure 4 presents the flowchart of the mobile application for GDM. First, the patients need to input their current glucose level with a correct format. Otherwise, the patients will need to re-enter their glucose level. The inserted glucose level then will be processed by applying GA to recommend meals. The system will display the information of the recommended meals and the range of their current glucose level.

In the input component, the system will prompt the user to enter their current glucose level. The glucose level will be in the unit of mg/dL. The inserted glucose level will be passed in the system and continue processing the glucose level with GA to recommend the user with suitable meals for the patients to maintain an ideal glucose level. The application will acknowledge the user on what is the current status of their glucose level. The status of glucose level are low, ideal and high. Then, the system will alter the next glucose level to ideal glucose level and recommend their next meal intake.

In the prediction process, the system will recommend the next suitable meals that corresponds to an ideal glucose level using GA. Next, the system will propose the next recommended meals to the user for them to maintain an ideal glucose level. The algorithm reads the meals from a file that are scraped from the internet using web scrapper tool.

3.3. GDM mobile application modules

Figure 5 shows the use case diagram for the GDM mobile application. In the diagram, we use user as the actor who are going to use the application. The user has three functions including view glucose range, view targeted glucose level and recommended meals. The system is responsible to display the range and identify the glucose level and recommend suitable meals to the user.

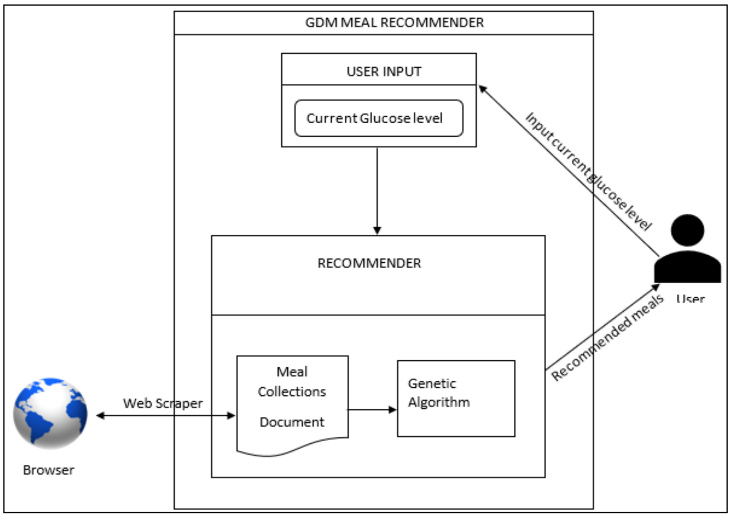


Figure 3. Architectural design of the system

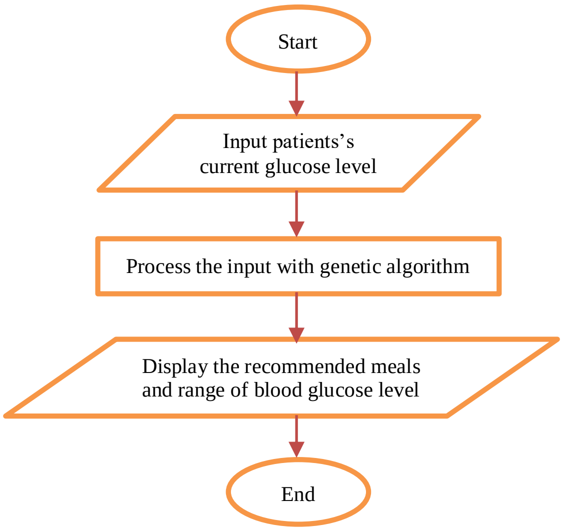


Figure 4. Flowchart of the system

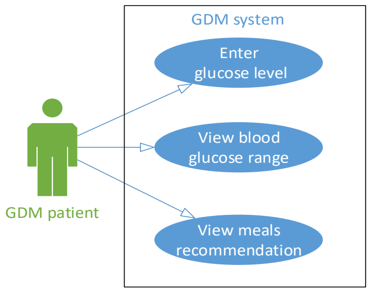


Figure 5. Use case diagram of the application

4. METHODOLOGY AND DEVELOPMENT

This section describes the steps for collecting data from the nutrition websites, adding library to Java and developing pseudo code using genetic algorithm for next meal prediction.

4.1. Collecting data from the web

Step 1: Creating new SiteMap for new WebScraping
New SiteMap is required to start on a new project of scrapping. New name of the sitemap which was “food-data” added with the link of the website chosen.
Step 2: Creating the selectors
The selectors indicate the different types of data that wants to be extracted from the website. In this case, the selectors were made by the categories, sub-categories, the name of the food and the nutrition of the food which are fat, protein, and carbohydrates. The selectors were put in graph to give a clearer view.
Step 3: Scraping the data and export it to CSV file
The data were extracted simply by pressing the “Scrape” button. After the data were completely scraped, it is exported as CSV files. The data has unnecessary attributes that are needed to be reduced. Out of the 12 attributes collected, only 4 of the attributes were found significant in the context of this project as shown in Figure 6. The attributes left to be processed in this project were Food-links which is the food name, protein, fat and carbohydrates. This collection of data was stored in XLS-type file named “food-data-xls” and were added in “assets” folder in Android Studio and be read from it.

1	food-links	protein	fat	carbohydrates
2	Asian Noodle Stir-fry, Vegan	7g	7g	50g
3	Caesar Salad	29.9g	29.9g	19.7g
4	Balance Bar, Honey Peanut	7g	7g	21g
5	Meatless Deli Slices, Peppered, Vegan	3g	3g	6g
6	Baby Corn Blend, Frozen Veggies	1g	1g	9g
7	Balance Bar+, Chocolate Banana Plus Antioxidants	6g	6g	22g
8	Balance Bar Gomix, Mixed Berry Crisp	6g	6g	21g
9	Artichoke Hearts, Quartered	0g	0g	6g
10	BBQ Cheddar Steak	19.5g	19.5g	70g

Figure 6. Sample of reduced attributes

4.2. Developing pseudo code for meal intake prediction using genetic algorithm

Figure 7 shows the code segment for genetic algorithm implementation for meal intake recommendation. In calculate fitness function, we first execute the selection and crossover the blood glucose populations. Then, we get the blood glucose population data and merge it in the mutation to find the fitness population. Finally, we recommend the predicted meals that consume appropriate calories based on the most fitness blood glucose.

```
Begin
Input Blood Glucose level
If blood glucose <120
BG=120
Else if blood glucose > 140
BG=140

Generate population set for blood glucose
If nutrition from meals available
Count number of calories
Calculate nutrition classes
If nutrition classes available
Set possible chromosomes from nutrition values
The initial set of chromosomes generated
Calculate the fitness function
Fitness function = possible chromosomes
While the possible chromosomes are not equal to best chromosomes
Mutate, cross over and create new set of chromosomes
End Loop
If best chromosomes found
Display best chromosomes and fitness function
Generate list of recommendation meals
End
```

Figure 7. Pseudo code for meal intake predictions using genetic algorithm

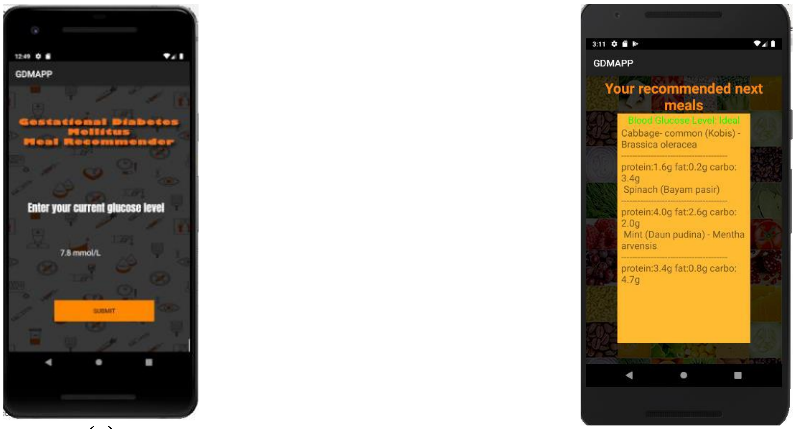
5. PROPOSED APPLICATION

5.1. GDM application design

This section shows the user interfaces for the GDM mobile application. The application consists of two pages:

– Main page: to insert the current glucose level.
– Output page: to display the next recommended meals.

A user can start using the application by entering the blood glucose level and click on Submit button. The user then gets a list of recommended next meal intake. The list of recommended meal intake is generated by the mobile application using genetic algorithm. As shown in Figure 8, the main page is purposely built as the first page to serve the patient every time they open the mobile application. The user needs to enter their current glucose level and click on Submit button to process the information.



(a) (b)

Figure 8. (a) User interface for blood glucose input, (b) User interface for meal recommendation

After submitting the blood glucose level, the user will be prompted an output page that display the recommended meals as shown in Figure 8. The mobile application will generate a list of recommended next meals that processed by genetic algorithm to find the optimal and create diversity in the solution.

5.2. Testing results

We performed a functional testing to uncover the logic errors in the application. We tested two types of components in the mobile application: (1) input (2) recommender. We designed three test cases for testing the input component and two test cases for the recommender component. We used 10 samples of blood glucose level to test the functionality of the application. We conducted the functional testing with five users. Table 1 shows the results of the functional testing for five test cases.

The components are tested with various test cases to uncover any errors. According to Table 1, both of the components that undergoing the functional testing have passed and met the expected results. This indicates that the application can be used to predict the next recommended meals based on current blood glucose levels.

Table 1. Testing results for GDM application

Components	Test cases	Expected outcome	Results	Pass/Fail
Input	Enter ‘0’	Application will display “Please enter a number”,	Application display ‘Please enter a number’	Pass
	Enter ‘50ml’	Application will display an error message	Application display ‘Please enter a correct format of input’	Pass
	Enter ‘-5’	Application will display an error message	Application display ‘Please enter a positive number’	Pass
Recommender	Enter ‘6.1’	Application will display a list of recommended next meals.	Application display recommended meals.	Pass
	Enter ‘7.5’	Application will display a list of recommended next meals.	Application display recommended meals.	Pass

6. DISCUSSIONS

This study set out with the aim of developing a mobile application that recommend sufficient next meal intake in line with the ideal glucose level for GDM patients. This mobile application specifically built to help GDM patients in maintaining their glucose level through their meals. Collection of meals were collected by scraping data from a specific nutrition website. We applied the Genetic Algorithm to predict the optimum results of meals intake and to determine the diversity of the results.

The GDM mobile application provides a platform for GDM patients to conduct self-monitoring of blood glucose levels based on meal intake. The application able to recommend the patient the next meal that they need to take in order to maintain, lower or higher their blood glucose level, without the need to approach the doctors for diet prescriptions. The doctors can suggest to their patients to use this application as a self-monitoring tool to monitor their blood glucose level.

The GDM mobile application is unique and tailored for all Malaysian because it will recommend meals that use our local ingredients. It seems that the potential of this application will highly be used by users from Malaysia and would significantly helping them acknowledging the calories in their daily meals in order to maintain the desired glucose level. In the future, the GDM application will able to store data in a centralised database and to synchronise with other health management applications.

7. CONCLUSION

The purpose of this study is to propose a new self-monitoring mobile application for GDM patients to monitor their blood glucose levels based on the meal intake recommendation. Currently, GDM patients practice the traditional method for recording blood glucose readings and keeping track of meal intake. Although there is many self-managing applications are designed in healthcare, but we do not found any application appropriate for GDM monitoring. Besides, most of the studies discussed about self-managing applications for diabetes. This study discussed the design and development of mobile application for GDM monitoring using genetic algorithm that aims to predict recommended meal intake. The mobile application engine consists of genetic algorithm to predict the most optimum results of recommended meals and to determine the diversity of the results. The mobile application help GDM patients by acknowledging the calories in their daily meals in order to maintain the desired glucose level. Thus, the application will assist them predicting their glucose level through their daily meals. We are currently working on developing GDM monitoring system for patients and medical practitioners. The application will store data in a centralised database and can be synchronised with others healthcare applications. We hope that this will encourage the research community to consider self-monitoring mobile application to improve blood glucose control in patients with GDM.

ACKNOWLEDGMENTS

The authors would like to thank the Universiti Teknologi Mara for their financial support to this project under FRGS Grant No. 600-IRMI/FRGS 5/3 (212/2019).

REFERENCES

[1] M. R. Malim *et al.*, "A Markov Chain Model for Diabetes Mellitus Patients," in *Proceedings of the Third International Conference on Computing, Mathematics and Statistics (iCMS2017)*, Singapore: Springer Singapore, 2019, pp. 483-488.

[2] S. Mutalib, S. Abdul-Rahman, and A. Mohamed, "Mining frequent patterns for genetic variants associated to diabetes," in *Proceedings - International Workshop on Database and Expert Systems Applications, DEXA*, 2014.

[3] W. D. Aumiller and H. A. Dollahite, "Pathogenesis and management of diabetic foot ulcers," *J. Am. Acad. Physician Assist.*, vol. 28, no. 5, pp. 28-34, May 2015.

[4] X. M. Zhen, X. Li, and C. Chen, "Longer-term outcomes in offspring of GDM mothers treated with metformin versus insulin," *Diabetes Res. Clin. Pract.*, vol. 144, pp. 82-92, Oct. 2018.

[5] K. KC, S. Shakya, and H. Zhang, "Gestational Diabetes Mellitus and Macrosomia: A Literature Review," *Ann. Nutr. Metab.*, vol. 66, no. 2, pp. 14-20, 2015.

[6] "Standards of Medical Care in Diabetes--2014," *Diabetes Care*, vol. 37, no. Supplement_1, pp. S14-S80, Jan. 2014.

[7] P. Damm, A. Houshmand-Oeregaard, L. Kelstrup, J. Lauenborg, E. R. Mathiesen, and T. D. Clausen, "Gestational diabetes mellitus and long-term consequences for mother and offspring: a view from Denmark," *Diabetologia*, vol. 59, no. 7, pp. 1396-1399, Jul. 2016.

[8] S. Anazawa, "Gestational diabetes mellitus," *Nihon Rinsho.*, vol. 73, no. 12, 2015.

[9] H. C. *et al.*, "Investigating the perceived benefits, barriers and beliefs towards physical activity in pregnancy among women with gestational diabetes mellitus," *Ir. Med. J.*, 2017.

[10] W.-J. Kim, M.-S. Shim, and J.-Y. Kim, "Management of Hyperglycemia in Type 2 Diabetes: A Patient-Centered

Approach Developed by the American Diabetes Association and the European Association for the Study of Diabetes," *J. Korean Diabetes*, 2012.
[11] B. Kaur, R. Quek Yu Chin, S. Camps, and C. J. Henry, "The impact of a low glycaemic index (GI) diet on simultaneous measurements of blood glucose and fat oxidation: A whole body calorimetric study," *J. Clin. Transl. Endocrinol.*, 2016.
[12] T. P. Markovic *et al.*, "Randomized Controlled Trial Investigating the Effects of a Low-Glycemic Index Diet on Pregnancy Outcomes in Women at High Risk of Gestational Diabetes Mellitus: The GI Baby 3 Study," *Diabetes Care*, 2016.
[13] S. Pais, D. Parry, K. Petrova, and J. Rowan, "Acceptance of using an ecosystem of mobile apps for use in diabetes clinic for self-management of gestational diabetes mellitus," in *Studies in Health Technology and Informatics*, 2017.
[14] S. Islam, J. Leech, C. C. Y. Lin, and L. Chrostowski, "Peak Blood Glucose Prediction Algorithm Following a Meal Intake," in *2007 Canadian Conference on Electrical and Computer Engineering*, 2007, pp. 579-582.
[15] A. Purwar and S. K. Singh, "Hybrid prediction model with missing value imputation for medical data," *Expert Syst. Appl.*, vol. 42, no. 13, pp. 5621-5631, Aug. 2015.
[16] K. A. Eskaf, "Blood glucose level prediction for diabetic patients using intelligent techniques," 2011.
[17] E. Pustozerov, P. Popova, A. Tkachuk, Y. Bolotko, Z. Yuldashev, and E. Grineva, "Development and Evaluation of a Mobile Personalized Blood Glucose Prediction System for Patients With Gestational Diabetes Mellitus," *JMIR mHealth uHealth*, vol. 6, no. 1, p. e6, Jan. 2018.
[18] D. Zeevi *et al.*, "Personalized Nutrition by Prediction of Glycemic Responses," *Cell*, vol. 163, no. 5, pp. 1079-1094, Nov. 2015.
[19] N. Nai-arun and R. Moungmai, "Comparison of Classifiers for the Risk of Diabetes Prediction," *Procedia Comput. Sci.*, vol. 69, pp. 132-142, 2015.
[20] L. Grandinetti and O. Pisacane, "Web based prediction for diabetes treatment," *Futur. Gener. Comput. Syst.*, vol. 27, no. 2, pp. 139-147, Feb. 2011.
[21] M. P. Sapna, S; Tamilarasi, A; Kumar, "Implementation of Genetic Algorithm in Predicting Diabetes," *Int. J. Comput. Sci. Issues*, vol. 9, no. 1, pp. 234-240, 2012.
[22] I. Contreras, J. Vehi, R. Visentin, and M. Vettoretti, "A Hybrid Clustering Prediction for Type 1 Diabetes Aid: Towards Decision Support Systems Based upon Scenario Profile Analysis," in *Proceedings - 2017 IEEE 2nd International Conference on Connected Health: Applications, Systems and Engineering Technologies, CHASE 2017*, 2017.
[23] R. Ali, J. Hussain, M. H. Siddiqi, M. Hussain, and S. Lee, "H2RM: A hybrid rough set reasoning model for prediction and management of diabetes mellitus," *Sensors (Switzerland)*, 2015.
[24] American Diabetes Association, "National Diabetes Statistics Report, 2014," *Natl. Diabetes Stat. Rep.*, 2014.
[25] S. S. Ilango, S. Vimal, M. Kaliappan, and P. Subbulakshmi, "Optimization using Artificial Bee Colony based clustering approach for big data," *Cluster Comput.*, 2019.
[26] F. S. Ismail and N. A. Bakar, "Adaptive mechanism for GA-NN to enhance prediction model," in *Proceedings of the 9th International Conference on Ubiquitous Information Management and Communication - IMCOM '15*, 2015, pp. 1-5.
[27] S. M. Rosli, M. M. Rosli, and R. Nordin, "A mapping study on blood glucose recommender system for patients with gestational diabetes mellitus," *Bull. Electr. Eng. Informatics*, 2019.
[28] S. Mirjalili, "Genetic Algorithm," in *Evolutionary Algorithms and Neural Networks: Theory and Applications*, Cham: Springer International Publishing, 2019, pp. 43-55.