5G-Smart Diabetes: Toward Personalized Diabetes Diagnosis with Healthcare Big Data Clouds

[1]G.Prabhakar Raju, [2]Dharnasi Prasad
[1]Dept. of CSE, Jig Jiga University, Jig Jiga, Somalia Region, Ethiopia
[2]Dept. of CSE, Arba Minch University, Arba Minch, Gamo Gofa Region, Ethiopia

Abstract
Recent advances in wireless networking and big data technologies, such as 5G networks, med-ical big data analytics, and the Internet of Things, along with recent developments in wearable com-puting and artificial intelligence, are enabling the development and implementation of innovative diabetes monitoring systems and applications. Due to the life-long and systematic harm suffered by diabetes patients, it is critical to design effective methods for the diagnosis and treatment of diabe-tes. Based on our comprehensive investigation, this article classifies those methods into Diabetes 1.0 and Diabetes 2.0, which exhibit deficiencies in terms of networking and intelligence. Thus, our goal is to design a sustainable, cost-effective, and intelligent diabetes diagnosis solution with person-alized treatment. In this article, we first propose the 5G-Smart Diabetes system, which combines the state-of-the-art technologies such as wearable 2.0, machine learning, and big data to generate comprehensive sensing and analysis for patients suffering from diabetes. Then we present the data sharing mechanism and personalized data analysis model for 5G-Smart Diabetes. Finally, we build a 5G-Smart Diabetes testbed that includes smart clothing, smartphone, and big data clouds. The experimental results show that our system can effectively provide personalized diagnosis and treatment suggestions to patients.

The authors propose a 5G-Smart Diabetes sys-tem, which combines the state-of-the-art technolo-gies such as wearable 2.0, machine learning, and big data to generate compre-hensive sensing and anal-ysis for patients suffering from diabetes. They also present the data sharing mechanism and personal-ized data analysis model for 5G-Smart Diabetes.

Keywords
5G-Smart Diabetes, Diagnosis and Data sharing with Big data clouds.

I. Introduction
Diabetes is an extremely common chronic dis-ease from which nearly 8.5 percent of the world population suffer; 422 million people worldwide have to struggle with diabetes. It is crucial to note that type 2 diabetes mellitus makes up about 90 percent of the cases [1]. More critically, the situ-ation will be worse, as reported in [2], with more teenagers and youth becoming susceptible to dia-betes as well. Due to the fact that diabetes has a huge impact on global well being and economy, it is urgent to improve methods for the prevention and treatment of diabetes [3].

Furthermore, various factors can cause the dis-ease, such as improper and unhealthy lifestyle, vulnerable emotion status, along with the accu-mulated stress from society and work. However, the existing diabetes detection system faces the following problems:

- The system is uncomfortable, and real-time data collection is difficult. Furthermore, it lacks continuous monitoring of multi-dimen-sional physiological indicators of patients suf-fering from diabetes [4, 5].
- The diabetes detection model lacks a data sharing mechanism and personalized analy-sis of big data from different sources includ-ing lifestyle, sports, diet, and so on [6, 7].
- There are no continuous suggestions for the prevention and treatment of diabetes and corresponding supervision strategies [8, 9].

To solve the above problems, in this article, we first propose a next generation diabetes solu-tion called the 5G-Smart Diabetes system, which integrates novel technologies including fifth gen-eration (5G) mobile networks, machine learning, medical big data, social networking, smart cloth-ing [10], and so on. Then we present the data sharing mechanism and personalized data anal-ysis model for 5G-Smart Diabetes. Finally, based on the smart clothing, smartphone, and big data healthcare clouds, we build a 5G-Smart Diabetes testbed and give the experiment results.

Furthermore, the "5G" in 5G-Smart Dia-betes has a two-fold meaning. On one hand, it refers to the 5G technology that will be adopted as the communication infrastructure to realize high-quality and continuous monitoring of the physiological states of patients with diabetes and to provide treatment services for such patients without restraining their freedom. On the other hand, "5G" refers to the following "5 goals": cost effectiveness, comfortability, personalization, sus-tainability, and smartness.

A. Cost Effectiveness
It is achieved from two aspects. First, 5G-Smart Diabetes keeps users in a healthy lifestyle so as to prevent users from get-ting the disease in the early stage. The reduction of disease risk would lead to decreasing the cost of diabetes treatment. Second, 5G-Smart Diabe-tes facilitates out-of-hospital treatment, thus reduc-ing the cost compared to on-the-spot treatment, especially long-term hospitalization of the patient.

B. Comfortability
To achieve comfort for patients, it is required that 5G-Smart Diabetes does not disturb the patients' daily activities as much as possible. Thus, 5G-Smart Diabetes inte-grates smart clothing [3], mobile phones, and por-table blood glucose monitoring devices to easily monitor patients' blood glucose and other physio-logical indicators.

C. Personalization
5G-Smart Diabetes utilizes various machine learning and cognitive comput-ing algorithms to establish personalized diabe-tes diagnosis for the prevention and treatment of diabetes. Based on the collected blood glucose data and individualized physiological indicators, 5G-Smart Diabetes produces personalized treat-ment solutions for patients.

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D. Sustainability

By continuously collecting, stor-ing, and analyzing information on personal dia-betes, 5G-Smart Diabetes adjusts the treatment strategy in time based on the changes of patients' status. Furthermore, in order to be sustainable for data-driven diabetes diagnosis and treatment, 5G-Smart Diabetes establishes effective informa-tion sharing among patients, relatives, friends, per-sonal health advisors, and doctors. With the help of social networking, the patient's mood can be better improved so that he or she is more self-mo-tivated to perform a treatment plan in time.

E. Smartness

With cognitive intelligence toward patients' status and network resources, 5G-Smart Diabetes achieves early detection and prevention of diabetes and provides personalized treatment to patients.

The remaining part of the article is organized as follows. We first present the system architec-ture of 5G-Smart Diabetes. Then we explain the data sharing mechanism and propose the per-sonalized data analysis model. Furthermore, we introduce the 5G-Smart Diabetes testbed. Finally, the conclusion of this article is given.

II. System Architecture of 5G-smart Diabetes

In this section, we briefly review the history of the development of diagnosis and treatment of dia-betes. The typical methods for diabetes treatment can be divided into two categories: Diabetes 1.0 [6] and Diabetes 2.0 [11]. We first introduce them, then propose our 5G-Smart Diabetes archi-tecture. The system architecture of 5G-Smart Dia-betes is elaborated, and an explicit comparison is provided in order to exhibit the advantage of 5G-Smart Diabetes.

III. History Of Diabetes Treatment

A. Diabetes 1.0

The acquisition of blood glucose is critical for diabetes diagnosis. Once serious, hospitalization of the patient is needed. With respect to the monitoring of blood glucose, doc-tors and nurses periodically collect indices of a patient each day, such as instantaneous blood glucose and two-hours-after-meal blood glucose. This manual method has high detection accuracy since medical equipment is utilized to measure blood glucose.

However, Diabetes 1.0 has three shortcom-ings:

- Since Diabetes 1.0 requires continuous hos-pitalization, the cost of Diabetes 1.0 is high.
- Intrusive collection of blood glucose indica-tors leads to low comfortability. In addition, there is a lack of personalized treatment. The patient treatment scheme is only based on analysis of blood glucose index, which is not eficient.
- Furthermore, once a patient is discharged, the conditions of the patient cannot be con-tinuously monitored in real time, and there are also no effective measures for the patient to supervise his or her own treatment. That is, Diabetes 1.0 consumes a large amount of medical resources while limiting the daily activities of patients.

B. Diabetes 2.0

This is a modern method that aims at automating most of the steps performed manually in Diabetes 1.0. Diabetes 2.0 has three advantages:

- It uses a wearable blood glucose monitoring device which can automatically monitor the blood glucose without the need for doctor's intervention.
- For the treatment of diabetes, Diabetes 2.0 conducts intelligent analysis based on the index of blood glucose and other physiologi-cal data of the patient in order to identify the therapeutic effects of drugs. Effects of differ-ent drugs are carefully studied to generate optimum personalized therapeutic sched-ules.
- Furthermore, Diabetes 2.0 methods are also looking at novel research initiatives using modern technology such as genetic engi-neering to finally cure diabetes. For example, the research on beta cells is to guarantee the regeneration of such cells, which are respon-sible for producing insulin in the human pan-creas.

Overall, the goal of Diabetes 2.0 is to boost the smartness of real-time monitoring and treat-ment, which also expands the autonomy of patient. In combination with intelligent analysis of drug effects, the cost of treatment can also be controlled, and continuous and personalized treatment can be realized. The use of non-intru-sive measurement technologies can also alleviate the pains caused by the intrusive blood glucose monitoring of Diabetes 1.0.

However, Diabetes 2.0 may not be affordable for normal users because the wearable device is typically expensive. For example, the selling price for a single set of a dynamic blood glucose mon-itoring meter produced by Medtronic (a famous American medical instrument company) is more than $10,000. Thus, it is critical to design a sus-tainable, cost-effective, and intelligent diabetes diagnosis solution.

IV. 5G-Smart Diabetes Architecure

Compared to the intrinsic hospital-oriented features of Diabetes 1.0 and Diabetes 2.0, 5G-Smart Diabetes realizes effective prevention and post-hospitalization treatment of diabetes. Physiological monitoring is no longer limited to blood glucose detection but includes other critical physiological indicators. Effective measures are taken to monitor the real life and exercise of a user. Comprehensive conditions of the user are monitored in a long-term and sustainable fashion. The system architecture of 5G-Smart Diabetes is shown in Fig. 1, which includes three layers: the sensing layer, personalized diagnosis layer, and data sharing layer.

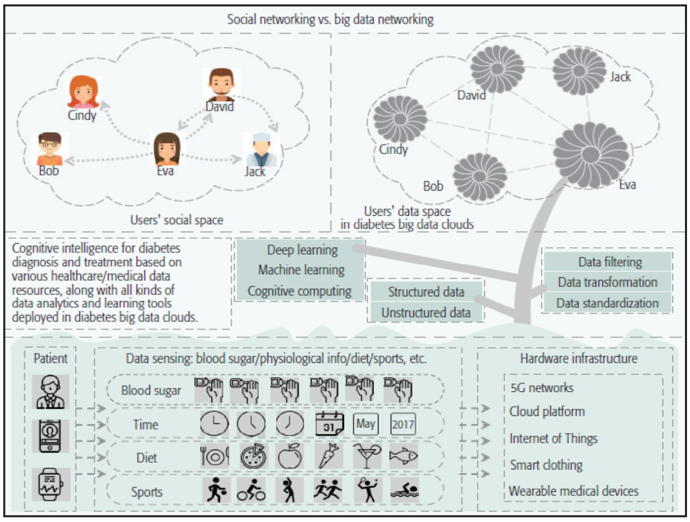

Fig. 1: System Architecture of 5G-Smart Diabetes

As we know, data sharing among patients, friends, and personal health advisors enables more valuable data provisioning for a more accurate disease analytics and diagnosis, facilitating the better care and treatment for patients. However, howto share data in a highly cost-efficient fashion in social space and data space is a challenge issue.

A. Sensing Layer

This layer collects blood sugar, physiological information, diet information, and sport information through a blood glucose monitoring device, a wearable 2.0 device (i.e., smart clothing), and a smartphone. The blood glucose monitoring device can be equipped to conduct individual home-based blood glucose monitoring. For the monitoring of the physiological indicators of users, smart clothing is employed to collect a user's real-time body signals, such as temperature, elec-trocardiograph, and blood oxygen. With respect to exercise and diet monitoring, a smartphone can collect the activity data from a patient and record the statistics of his or her diet. Furthermore, we also collect data from users when they are in the hospi-tal. All the collected data are offloaded to the health-care big data cloud through the 5G network.

B. Personalized Diagnosis Layer

In this layer, healthcare big data of the patients are jointly processed by utilizing modern machine learning methods to build efficient personalized models for analyzing and predicting the disease. This layer includes data fusion of blood sugar, physiologi-cal information, diet and sport information, data preprocessing, and the proposition of a cognitive intelligence model based on machine learning, deep learning, and cognitive computing.

C. Data Sharing Layer

This layer includes users' social space and data space. Specifically, in the social space, as illustrated in Fig. 1, both Eva and David are diabetes patients. Through online social networks, they share their information on diabetes with each other, then motivate each other to fight against diabetes. As Cindy and Bob are Eva's family members, Eva shares her disease information with them in order to handle a possible emergen-cy situation. Meanwhile, the disease information is also shared with Jack, who has a long history of suffering from diabetes with successful expe-rience in curing the disease. Jack can trace Eva's and David's status in time to help them as their personal healthcare advisor if needed. In the data space, different patients live in different regions and store their personalized data in different clouds. As illustrated in Fig. 1, Eva and Cindy have strong social relationships; however, they store data onto different clouds, which are far away. Thus, when Eva and Cindy share data, the com-munication cost needs to be considered.

Table 1 shows a comparison of the advantag-es and disadvantages of Diabetes 1.0, Diabetes 2.0, and 5G-Smart Diabetes. Seven features are compared, including cost, comfort, network sup-port, personalization, sustainability, scalability, and treatment pattern. From Table 1, we can see that 5G-Smart Diabetes is better than Diabetes 2.0 in the following four aspects:

- 5G-Smart Diabetes adopts social networking services to realize treatment supervision of the patient by relatives and friends.
- Since the blood glucose index is associated with physiological indices, 5G-Smart Dia-betes utilizes physiological data, food con-sumption data, and exercise data to increase the eficiency and performance of the diag-nosis and treatment of diabetes.

Table 1: Comparisons of Diabetes 1.0, Diabetes 2.0, and 5G-Smart Diabetes

Solution	Cost	Comfortability	Network support	Personalization	Sustainability	Scalability	Treatment pattern
Diabetes 1.0	High	Low	N/A	Low	Low	Low	Hospitalization, manual measurement, manual injection
Diabetes 2.0	Medium	Medium	Social network	High	Low	Low	Automatic and smart blood glucose sensing devices, contrasting analysis of drug effects, beta cell restoration, beta cell preservation
5G-Smart Diabetes	Low	High	5G networks, social networks, big data networks	High	High	High	User-oriented data fusion, treatment intelligence via data analytics

V. Data Sharing And Personalized Analysis Model For 5G-smart Diabetes

In this section, we introduce the data sharing and personalized diabetes treatment of 5G-Smart Dia-betes. As shown in Fig. 2, the 5G-Smart Diabe-tes system first integrates the 5G network, social network, and big data network to discover the interconnection between social relationship and physical data location at clouds, facilitating data sharing with joint social space and data space. Then, based on machine learning and cognitive computing, the 5G-Smart Diabetes system can get an intelligent diagnosis by analyzing multidi-mensional big data related to diabetes to pro-vide personalized diabetes diagnostic services to patients. In the following section, we introduce the mechanisms of data sharing and the personal-ized analysis model in detail.

VI. Data Sharing Mechanism For 5G-smart Diabetes

As shown in Fig. 1, patients can be simultane-ously located in two different spaces (i.e, social space and data space). Social space is derived from the massive and complicated social links among patients, friends, personal health advi-sors, and doctors. Data space is constructed on the basis of those patients' data stored in dif-ferent clouds. That is, patients living in different areas intend to store their personal data profiles in different clouds, such as a hospital cloud, a third-party healthcare cloud, and various edge clouds [12]. Typically, closely located patients may put their data in the same cloud or two dif-ferent clouds that are geographically close to each other.

As we know, data sharing among patients, friends, and personal health advisors enables more valuable data provisioning for more accu-rate disease analytics and diagnostics, facilitating better care and treatment of patients. However, how to share data in a highly cost-efficient fash-ion in social space and data space is a challenge issue. This is because when a user's mobility is considered in data space, the communication cost for data sharing can vary tremendously among dif-ferent patients living in different areas.

Thus, we consider the following two cases of data sharing:

- Eva and David are good friends in a social network, as shown in Fig. 1. Fortunately, they also select the same data center to store their data. For this case, data sharing hap-pens within the same data center cloud with low communication cost.

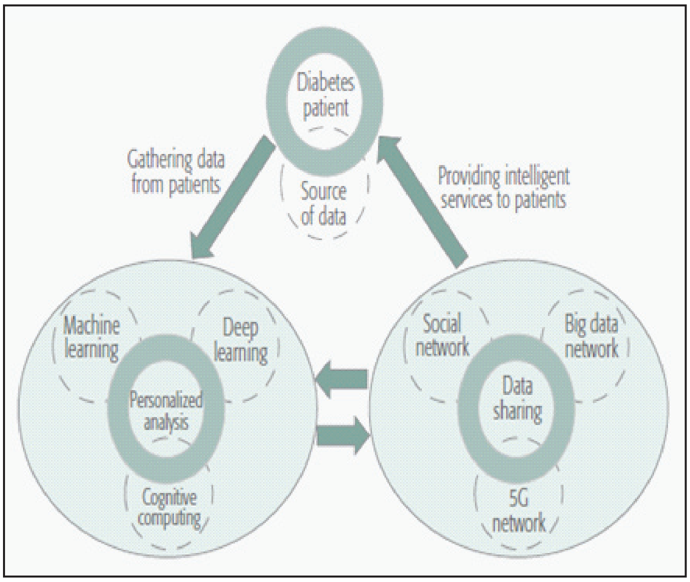

Fig. 2: Data Sharing and Personalized Analysis Model for 5G-smart Diabetes.

- Eva and Cindy are good friends in a social network. However, they live in different cities. For this case, they are close to each other in social space, while far away in data space. However, Eva has a close friend, Bob, and Bob's data is located in the same data center with Cindy. Thus, Bob trusts Cindy and shares data with Cindy at a lower com-munication cost.

As we know, there are lots of works addressing the issue of data sharing over social networks. However, to the best of our knowledge, there is no work yet studying how to share data in big data networking. In this article, we propose an innovative data sharing mechanism by jointly con-sidering the data distance and social relationship of two users. Let us assume there are n diabetes patients in a particular area.

The data distance $D = (d_{i,j})$ n×n elaborates the data distance of various pairs of users. D is an important factor to evaluate the communication cost for data sharing. $d_{i,j}$ represents the data dis-tance between patient i's data and patient j's data in clouds. If patient i and patient j select different clouds at a far distance to store their data, $d_{i,j}$ is large. When $d_{i,j} = 0$, it means patient i selects the same cloud to store his/her data as patient j. The social relationship $W = (w_{i,j})_{n\times n}$ represents the social relationship of patient i and patient j. If large. Thus, in the design of a data sharing mech-anism, it is necessary to maximize the sharing of data (i.e., W), while ensuring the minimum com-munication cost (i.e., D).

Table 2: Statistics on Data Changes in each Stage of Data Preprocessing.

Processing step	Change of dataset
(0) Original records	12,366 persons who have taken health examinations, 757,732 items of health examinations for persons produced
(1) Removal of health examination data irrelevant to diabetes	9594 persons qualified, 716,173 items qualified
(2.1) Data integration	9594 records produced; each record consists of 234 features
(2.2) Invalid features elimination	9594 records qualified, 43 features qualified in one record
(2.3) Duplicate data elimination	9550 records qualified, 43 features qualified in one record
(3) Data labeling	469 records for diabetes, 9081 records for normal
(4) Data filling	Missing value filling, no change in data size
(5) Data conversion	9550 records qualified, 50 features qualified in one record
(6) Data standardization	No change in data size

VI. Personalized Data Analysis Model For 5G-smart Diabetes

The establishment of the personalized data analy-sis model for 5G-Smart Diabetes is based on the data, which includes public data and personal-ized data. Typically, the public data come from hospital diabetes big datasets with the removal of users' privacy and sensitive information. The personalized data make up a user's personal data-set. In this article, we first use public data to train a public diabetes diagnosis model. Then we can obtain a personalized data analysis model based on the public diabetes diagnosis model and per-sonalized data. The specific process is as follows.

We first obtain the dataset of in-hospital diabe-tes patients (i.e., users' electronic medical records, EMRs). The EMR data include structured data and unstructured data. For the structured data, according to the doctor's advice, we select fea-tures associated with diabetes . For the unstruc-tured data, which include text and image data, we use a convolutional neural network (CNN) [13, 14] to select a feature. Then we use feature fusion and a deep learning algorithm for data analytics in order to obtain a public diabetes diagnosis model. Through this model, we can get the users' risk assessment of diabetes.

Then we establish a personalized data analysis model based on the multi-source and multi-di-mension data. The personalized data includes user daily life data (i.e., working, sleeping, physi-cal exercise and food intake) collected by smart-phone and wearable 2.0, and the blood glucose index collected by medical devices. All this infor-mation is sent to the healthcare big data cloud. In the cloud, we first use the public diabetes model and transfer learning [15] to label the risk assess-ment of diabetes. Then, based on the blood glu-cose index collected by the medical devices, the label will be verified for its correction. When we obtain the ground-truth diabetes risk assessment label, we re-train the personalized data to get a stronger personalized data analysis model.

Based on the personalized data analysis patient i and patient j are close friends, wi,j should be large. When $w_{i,j} = 0$, the two patients do not know each other. In this article, we assume that data sharing is more likely to happen when $w_{i,j}$ is model, the 5G-Smart Diabetes system can get a more concrete and targeted personalized risk assessment and therapeutic schedule, which can provide detailed daily advice to guide a patient to improve the self-treatment of diabetes.

VII. 5G-smart Diabetes System Testbed and Evaluation

A. 5G-smart Diabetes System Testbed

A testbed has been designed to verify the fea-sibility of the 5G-Smart Diabetes system. In our testbed, we use a blood glucose device to collect individual home-based blood glucose. The user's health related data is collected by a wearable 2.0 device (i.e., smart clothing). The statistics of user diet data and the stream of activity data when the user is doing exercise indoors or outdoors can also be collected using the user's smartphone if he or she wants it to be. We also design an intel-ligent app to cooperate with all kinds of sensing devices in order to provide convenient services for patients. Furthermore, we develop a cloud platform using our data center in the EPIC lab. All the collected data offload to the cloud platform via the interface of the smart app. In addition, the results of the analysis and treatments are fed back to the app.

B. Data Collection from a Hospital

We collect a health examination dataset from a hospital in Hubei Province, China. As shown in Table 2, the health examination dataset involves 12,366 people and consists of 757,732 data items. Since there are different types of health examination, the data and features (items in health examination) that are not related to diabe-tes should be eliminated. Subsequently, the data is annotated with the health examination results. The persons monitored are divided into two groups: normal people and diabetes patients. At last, the health examination data is formatted and preprocessed in the following ways.

First, we exclude irrelevant health examina-tion data from the dataset; there remain 716,173 data records, which correlate to 9594 different people after the elimination step. Then we delete irrelevant features and label the data. After this labelling, we obtain 469 diabetes patients and 9081 normal persons. Third, we fill those nullable features and convert the inconsistent data. For data filling, we adopt mean value filling to the real values and highest frequency value filling to the discrete values. For data conversion, we perform binary feature conversion for the discrete values. Finally, we standardize data.

VIII. The Testbed of Machine Learning Algorithms

To validate the performance of our proposed 5G-Smart Diabetes testbed, three representative machine learning algorithms — decision tree, sup-port vector machine (SVM), and artificial neural networks (ANN) — are adopted to establish dif-ferent models for the public diagnosis of diabetes. We also use the ensemble method to conduct integration of the models. Finally, optimal predic-tion is obtained through synthesizing the advan-tages of each model.

Decision Tree: For the decision tree, we set the depth of the decision tree algorithm from 2

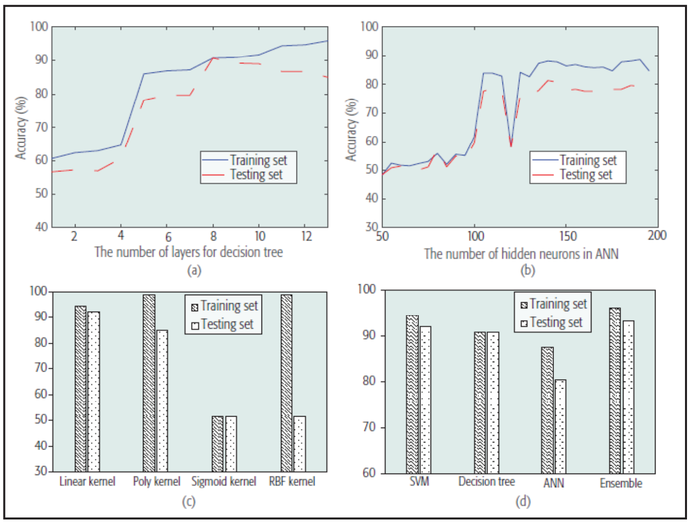

Fig. 3: The testbed of machine learning algorithms: a) decision trees with different layers; b) ANN with different hidden neurons; c) SVM with different kernels; d) accuracy comparison of SVM, decision tree, ANN, and ensemble.

layers to 13 layers. Fig. 3a shows the accuracy of the algorithm for the training set and the test-ing set for different depths of the decision tree. From the figure, we can see that the highest test-ing set accuracy is achieved by the decision tree algorithm when the depth is 8. Thus, we adopt a tree structure with the depth value of 8 as the prediction model.

A. ANN

Fig. 3b shows the changes in accu-racy in the training and testing sets for different numbers of neurons in the hidden layer. Accord-ing to Fig. 3b, the highest accuracy for the ANN is obtained when the number of neurons is 110. Therefore, the model with 110 neurons in the hid-den layer is used as the prediction model.

B. SVM

For SVM, we use four different kernel functions: linear kernel, poly kernel, sigmoid ker-nel, and RBF kernel. Figure 3c shows the compar-ison of the accuracy of the SVM algorithm for the training and testing sets with different kernel func-tions. As seen from Fig. 3c, the optimal testing set accuracy is obtained with linear kernel. Therefore, linear kernel is adopted as the prediction model for SVM.

C. Ensemble

As shown in Fig. 3d, the combined model generated by the integration produces bet-ter prediction performance compared to each single model.

IX. Suggestions on Prevention and Treatment of Diabetes

As shown in Fig. 4 for patients with diabetes, the corresponding suggestions are given based on the following aspects: diet, sport, and data sharing in a social network. Furthermore, these suggestions also take into account the patient's physiological status and daily diet/exercise. The suggestions are as follows in detail.

A. Diet

Based on the patient's blood glucose index and physiological status, suggestions for breakfast, lunch, and dinner are given, as shown in Fig. 4a. In addition, we can see that the diet should be mixed coarse-grained food, wheat flour, and rice together in a meal with a suficient amount of protein. This is because high cellulose, high protein, low fat, and no sugar can reduce blood glucose. Furthermore, according to the patient's blood glucose index, the app reminds the patient to take oral hypoglycemic drugs or receive insulin treatment.

B. Sport

As shown in Figs. 4b and 4c, the app tracks the motion of patients and the statistics of motion data. This is because reasonable participa-tion in physical exercise can increase the patient's physique.

C. Data Sharing in a Social Network

Fig. 4d shows data sharing for patients in social networks. Sharing diabetes data can effectively supervise diabetes patients and promote positivity about them, enabling continuous treatment.

X. Conclusion

In this article, we first propose a 5G-Smart Dia-betes system that includes a sensing layer, a personalized diagnosis layer, and a data sharing layer. Compared to Diabetes 1.0 and Diabetes 2.0, this system can achieve sustainable, cost-ef-fective, and intelligence diabetes diagnosis. Then we propose a highly cost-efficient data sharing mechanism in social space and data space. In addition, using machine learning methods, we present a personalized data analysis model for 5G-Smart Diabetes. Finally, based on the smart clothing, smartphone and data center, we build a 5G-Smart Diabetes testbed. The experimental results show that our system can provide per-sonalized diagnosis and treatment suggestions to patients.

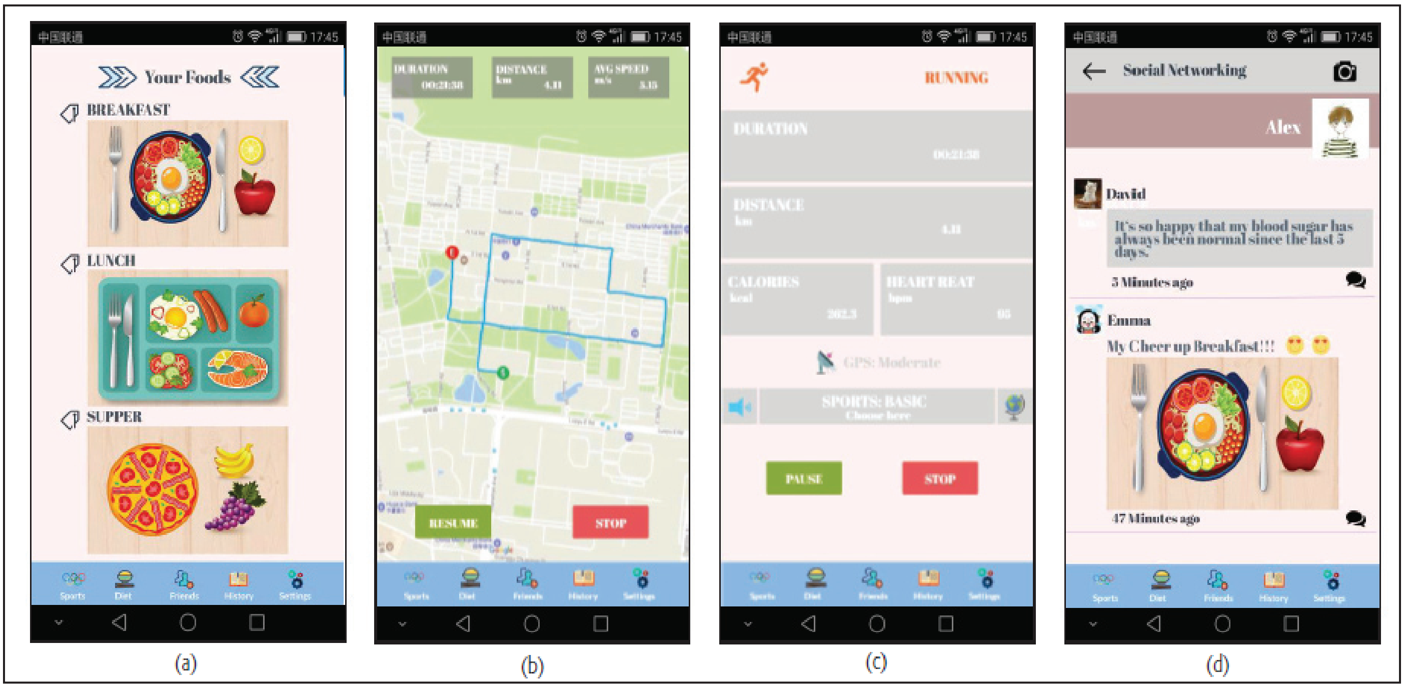

Fig. 4: Suggestions on prevention and treatment of diabetes: a) diet; b) sports; c) statistics; d) social networking.

XI. Acknowledgements

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Mr. G.Prabhakar Raju received M.Tech degree in Computer Science and Engineering from JNTU University. Pursuing Ph.D. in Computer Science and Engineering from Shri Venkateshwara University. He is working as a Lecturer in Department of Computer Science and Software Engineering, Jigjiga University, Jigjiga, Ethiopia. He is an active member of ISTE and having 17 years of work experience in Software Industry and Teaching. To his credit he is having publications in National and International Journals. His research interestsinclude Big Data, Hadoop, Data Mining and Data Warehousing, Software Engineering, Computer Networks and Artificial Intelligence

Mr. Dharnasi Prasad, well known Author and excellent teacher Received B.Tech(CSIT) and M.Tech (Software Engineering) from Jawaharlal Nehru Technological University and as well as pursuing my Ph.D in Software Engineering from Shri Venkateswara University is working as Lecturer in Computer Scienace and Engineering and Department BAIS (Business Adminstration and Information System) from Arba Minch University, He is an active member of ISTE.he has 17 years of teaching experience in various engineering colleges. To his credit no of publications both national and international conferences /journals. His area of Interest includes Data Base Management, Compiler Design, mobile computing, computer organization, Software Engineering, Computer Network, Windows Programming and other advances in computer Applications.