5G SMART DIABETES

V.Sarala MCA(ph.d)[1], G Murali Krishna[2]

[1] Assistant Professor **MCA, DEPT, Dantuluri Narayana Raju College , Bhimavaram, Andharapradesh**
[2]PG Student of MCA, , Dantuluri Narayana Raju College , Bhimavaram, Andharapradesh

Abstract: Recent advances in wireless networking and big data technologies, such as 5G networks, medical big data analytics, and the Internet of Things, along with recent developments in wearable computing 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 diabetes. 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 personalized 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.

Index Term: - Medical big data analytics, 5G-Smart Diabetes testbed

I Introduction

Diabetes is an extremely common chronic disease 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 situation will be worse, as reported in [2], with more teenagers and youth becoming susceptible to diabetes 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 disease, such as improper and unhealthy lifestyle, vulnerable emotion status, along with the accumulated 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-dimensional physiological indicators of patients suffering from diabetes [4, 5].

• The diabetes detection model lacks a data sharing mechanism and personalized analysis of big data from different sources including 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 solution called the 5G-Smart Diabetes system, which integrates novel technologies including fifth generation (5G) mobile networks, machine learning, medical big data, social networking, smart clothing [10], and so on. Then we present the data sharing mechanism and personalized data analysis 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 Diabetes 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, sustainability, and smartness.

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

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 integrates smart clothing [3], mobile phones, and portable blood glucose monitoring devices to easily monitor patients' blood glucose and other physiological indicators.

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

Sustainability: By continuously collecting, storing, and analyzing information on personal diabetes, 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 information sharing among patients, relatives, friends, personal 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-motivated to perform a treatment plan in time. 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 architecture of 5G-Smart Diabetes. Then we explain the data sharing mechanism and propose the personalized data analysis model. Furthermore, we introduce the 5G-Smart Diabetes testbed.

2 Literature survey

1. S. Mendis, "Global Status Report on Noncommunicable Diseases 2014," WHO, tech. rep.; http://www.who.int/ nmh/publications/ncd-status-report-2014/en/, accessed Jan. 2015.

2. F. Florencia et al., IDF Diabetes Atlas, 6th ed., Int'l. Diabetes Federation, tech. rep.; http://www.diabetesatlas.org/, accessed Jan. 2016.

3. M. Chen et al., "Disease Prediction by Machine Learning over Big Healthcare Data," IEEE Access, vol. 5, June 2017, pp. 8869--79.

4. O. Geman, I. Chiuchisan, and R. Toderean, "Application of Adaptive Neuro-Fuzzy Inference System for Diabetes Classification and prediction},” Proc. 6th IEEE Int'l. Conf. E-Health and Bioengineering, Sinaia, Romania, July 2017, pp. 639--642.

5. S. Fong, et al. "Real-Time Decision Rules for Diabetes Therapy Management by Data Stream Mining," IT Professional, vol. 26, no. 99, June 2017, pp. 1--8.

6. B. Lee, J. Kim, "Identification of Type 2 Diabetes Risk Factors Using Phenotypes Consisting of Anthropometry and Triglycerides Based on Machine Learning," IEEE J. Biomed. Health Info., vol. 20, no. 1, Jan. 2016, pp. 39--46.

7. M. Hossain, et al., "Big Data-Driven Service Composition Using Parallel Clustered Particle Swarm Optimization in Mobile Environment," IEEE Trans. Serv. Comp., vol. 9, no. 5, Aug. 2016, pp. 806--17.

8. M. Hossain, "Cloud-Supported Cyber-Physical Localization Framework for Patients Monitoring," IEEE Sys. J., vol. 11, no. 1, Sept. 2017, pp. 118--27.

9. P. Pesl, et al., "An Advanced Bolus Calculator for Type 1 Diabetes: System Architecture and Usability Results," IEEE J. Biomed. Health Info., vol. 20, no. 1, Jan. 2016, pp. 11--17.

10. M. Chen et al., "Wearable 2.0: Enable Human-Cloud Integration in Next Generation Healthcare System," IEEE Commun. Mag., vol. 55, no. 1, Jan. 2017, pp. 54--61.

11. E. Marie et al., "Diabetes 2.0: Next-Generation Approach to Diagnosis and Treatment," Brigham Health Hub, tech. rep.; https://brighamhealthhub.org/diabetes-2-0-next-generation-approach- to-diagnosis-and-treatment, 2017, accessed Feb. 2017.

12. M. Chen et al., "Green and Mobility-Aware Caching in 5G Networks," IEEE Trans. Wireless Commun., vol. 16, no. 12, 2017, pp. 8347–61.

13. C. Yao et al., "A Convolutional Neural Network Model for Online Medical Guidance," IEEE Access, vol. 4, Aug. 2016, pp. 4094--4103.

14. M. Anthimopoulos et al., "Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network," IEEE Trans. Med. Imaging, vol. 35, no. 5, May 2016, pp. 1207--16.

15. K. Hwang and M. Chen, "Big Data Analytics for Cloud/ IoT and Cognitive Computing," Wiley, 2017. ISBN: 9781119247029.

3. Implementation Study

As there is no staff available in unmanned restaurants, it is difficult for the restaurant management to estimate how the concept and the food is experienced by the customers. Existing rating systems, such as Google and TripAdvisor, only partially solve this problem, as they only cover a part of the customer's opinions. These rating systems are only used by a subset of the customers who rate the restaurant on independent rating platforms on their own initiative. This applies mainly to customers who experience their visit as very positive or negative.

3.1proposed methodology

PROPOSED SYSTEM

In order to solve the above problem, all customers must be motivated to give a rating. This paper

introduces an approach for a restaurant rating system that asks every customer for a rating after their visit to increase the number of ratings as much as possible. This system can be used unmanned restaurants; the scoring system is based on facial expression detection using pertained convolutional neural network (CNN) models. It allows the customer to rate the food by taking or capturing a picture of his face that reflects the corresponding feelings. Compared to

text-based rating system, there is much less information and no individual experience reports collected. However, this simple fast and playful rating system should give a wider range of opinions about the experiences of the customers with the restaurant concept.

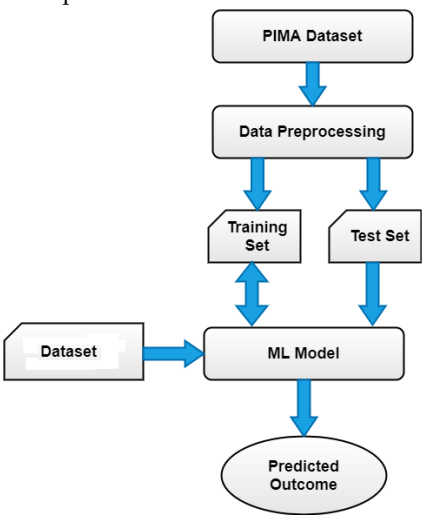


Fig 1: System Architecture

3.2 Methodology and Alogrithams

3.2.1 DATASET: -

The patient information was stored in diabetes dataset. The diabetes and non-diabetes patient differentiated here. It contains personal health data as well as results. The detailed dataset attributes shown below:

- Age
- Gender
- Diet
- Height
- Weight
- Systolic Blood Pressure (SBP)
- Diastolic Blood Pressure (DBP)
- Random Blood Sugar (RBS)
- Class variable (class)

3.2.2 .DATA PREPROCESSING

Preprocessing is the technique used to filter out or replace the mistaken data. Since we are collecting, the raw data there may be high chances for noisy, missing value or inappropriate values. In order to sort out the mistakes we are doing the process of pre-processing done to the raw data otherwise, data become unfeasible

1	GEN	Age	Diet	Height	Weight	SBP	DBP	RBS	CL_VAR
2	0	48	1	159	46	140	70	160	1
3	0	67	1	155	79	180	110	120	0
4	1	60	1	163	59	140	70	130	1
5	1	59	1	155	58	110	70	130	1
6	1	57	1	163	49	110	70	120	0
7	0	60	0	159	68	130	70	140	1
8	1	64	0	163	71	140	70	120	0
9	1	56	1	165	71	140	90	130	1
10	0	31	0	160	47	133	90	140	1
11	0	60	0	158	46	100	70	140	1
12	1	75	1	165	71	90	70	140	1
13	1	53	1	159	55	100	70	130	1
14	0	50	1	158	49	100	70	120	0
15	0	50	1	159	59	130	70	172	1
16	1	40	1	171	62	130	90	150	1
17	1	65	1	153	60	130	100	110	0
18	0	70	1	154	63	150	90	140	1
19	0	89	1	154	51	150	70	130	1
20	1	52	0	165	73	120	70	130	1

Fig 2: Before Preprocessing

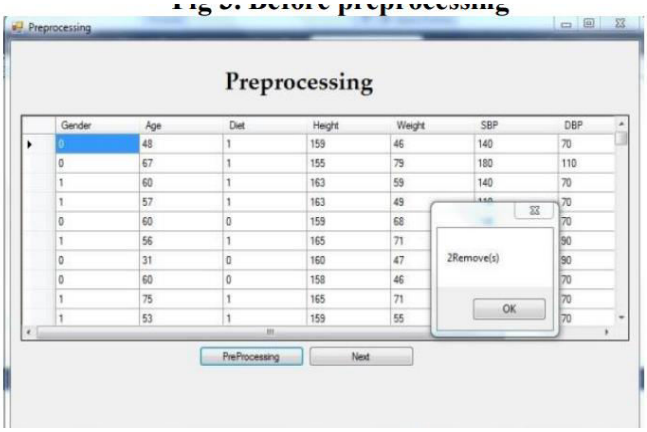


Fig 3: After Preprocessing

3.2.3. FEATURE SELECTION

Admin Module:

Here the admin input the pima dataset and then pre-process the data and then apply the classification algorithm like decision tree ,svm ,ann and ensemble classification method and then apply the accuracy graph and then start the cloud server

User:

Here the use inputs the user symptom file and then out model gets connected to the cloud server and performs the prediction from the cloud server and then it returns back the results if the user data is diabetes or not with type of diabetes

3.2.4. TRAINING MODELS

3.2.4.1 Decision Tree:

Decision trees can be learned from training data. Training data will typically comprise many instances of the following kind:

attributeK class

attributeK class

The decision tree learning algorithm recursively learns the tree as follows: Assign all training instances to the root of the tree. Set current node to root node.

1. For each attribute

a. Partition all data instances at the node by the value of the attribute.

b. Compute the information gain ratio from the partitioning.

2. Identify feature that results in the greatest information gain ratio. Set this feature to be the splitting criterion at the current node.

a. If the best information gain ratio is 0, tag the current node as a leaf and return.

3. Partition all instances according to attribute value of the best feature.

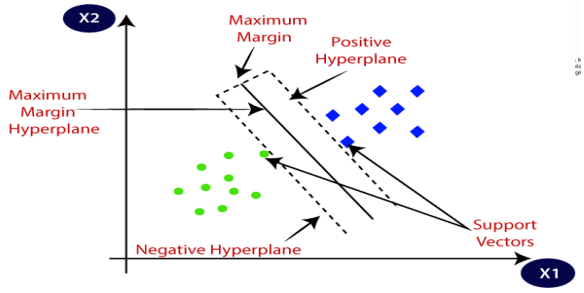
4. Denote each partition as a child node of the current node.

5. For each child node:

a. If the child node is "pure" (has instances from only one class) tag it as a leaf and return.

b. If not set the child node as the current node and recourse to step 2.

Svm :-support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



4 Results and Evolution Metrics

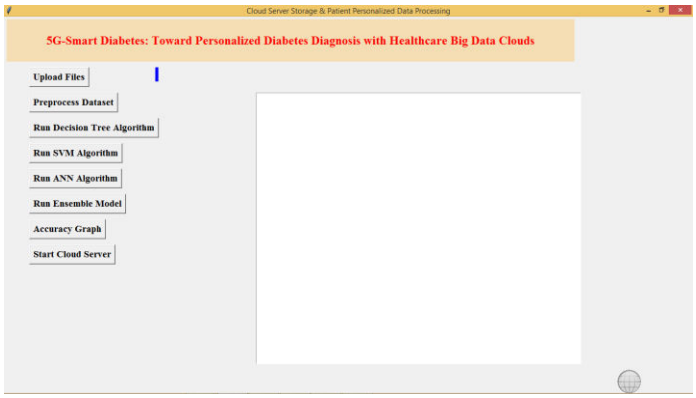


Fig: In above screen click on 'Upload Files' button to upload diabetes dataset

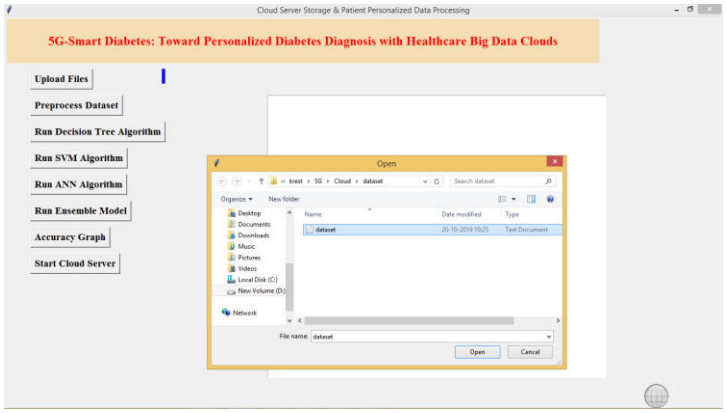


Fig: After uploading dataset click on 'Pre-process Dataset' button to clean dataset

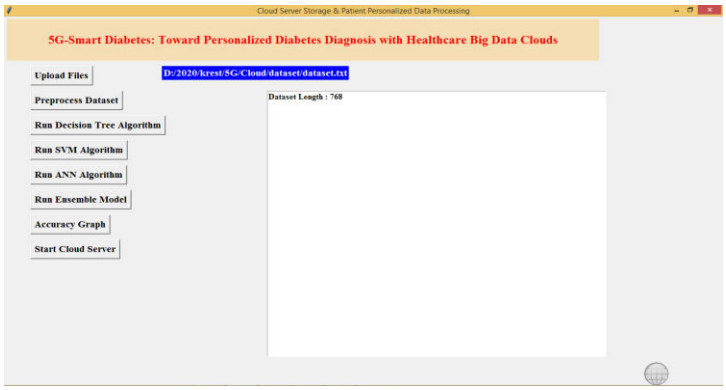


Fig : In above screen after pre-process total dataset records are 768. Now click on 'Run Decision Tree Algorithm' to build decision tree model and below is its accuracy

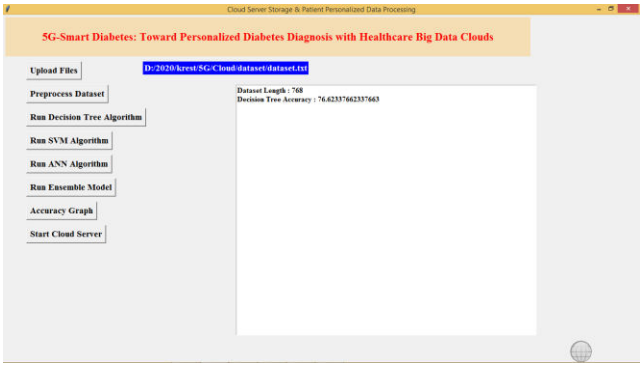


Fig : Similarly run other buttons to build models with algorithms

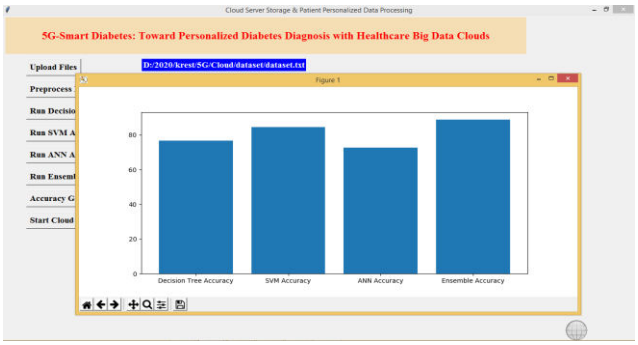


Fig: In above screen graph x-axis represents algorithm name and y-axis represents accuracy values.

Now click on 'Start Cloud Server' button to start server and this server will receive data from user and predict disease details.

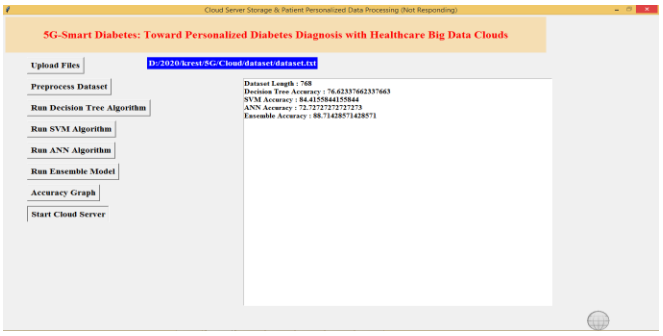


Fig : In above screen cloud server started and now double clicks on 'run.bat' file from User folder to start User sensing application and to get below screen

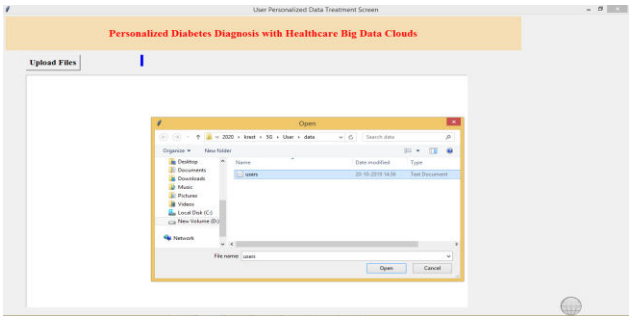


Fig : After uploading user's data will get below prediction results

Fig 5:- predicated as fraudulent

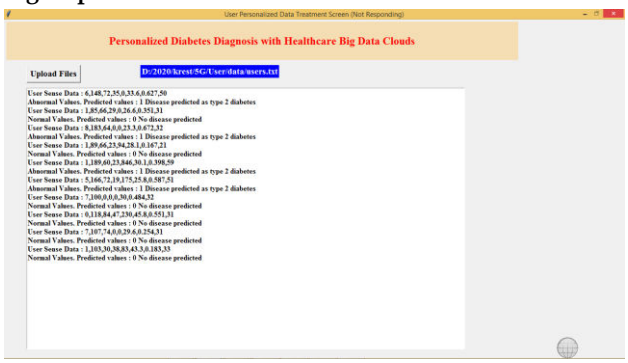


Fig: In above screen for each user's data we predicted 0 and 1 values and also indicates patient values as normal or abnormal

All algorithms code you can see inside Cloud/Cloud.py file, in below screen we can all algorithms from python

5 Conclusion

In this article, we first propose a 5G-Smart Diabetes 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-effective, 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 personalized diagnosis and treatment suggestions to patients

6 References

1. S. Mendis, "Global Status Report on Noncommunicable Diseases 2014," WHO, tech. rep.; http://www.who.int/nmh/publications/ncd-status-report-2014/en/, accessed Jan. 2015.

2. F. Florencia et al.,IDF Diabetes Atlas, 6th ed., Int'l. Diabetes Federation, tech. rep.; http://www.diabetesatlas.org/, accessed Jan. 2016.

3. M. Chen et al., "Disease Prediction by Machine Learning over Big Healthcare Data," IEEE Access, vol. 5, June 2017, pp. 8869--79.

4. O. Geman, I. Chiuchisan, and R. Toderean, "Application of Adaptive Neuro-Fuzzy Inference System for Diabetes Classification and prediction},'' Proc. 6th IEEE Int'l. Conf. E-Health and Bioengineering, Sinaia, Romania, July 2017, pp. 639--642.

5. S. Fong, et al. "Real-Time Decision Rules for Diabetes Therapy Management by Data Stream Mining," IT Professional, vol. 26, no. 99, June 2017, pp. 1--8.

6. B. Lee, J. Kim, "Identification of Type 2 Diabetes Risk Factors Using Phenotypes Consisting of Anthropometry and Triglycerides Based on Machine Learning," IEEE J. Biomed. Health Info., vol. 20, no. 1, Jan. 2016, pp. 39--46.

7. M. Hossain, et al., "Big Data-Driven Service Composition Using Parallel Clustered Particle Swarm Optimization in Mobile Environment," IEEE Trans. Serv. Comp., vol. 9, no. 5, Aug. 2016, pp. 806--17.
8. M. Hossain, "Cloud-Supported Cyber-Physical Localization Framework for Patients Monitoring," IEEE Sys. J., vol. 11, no. 1, Sept. 2017, pp. 118--27.
9. P. Pesl, et al., "An Advanced Bolus Calculator for Type 1 Diabetes: System Architecture and Usability Results," IEEE J. Biomed. Health Info., vol. 20, no. 1, Jan. 2016, pp. 11--17.
10. M. Chen et al., "Wearable 2.0: Enable Human-Cloud Integration in Next Generation Healthcare System," IEEE Commun. Mag., vol. 55, no. 1, Jan. 2017, pp. 54--61.
11. E. Marie et al., "Diabetes 2.0: Next-Generation Approach to Diagnosis and Treatment," Brigham Health Hub, tech. rep.; https://brighamhealthhub.org/diabetes-2-0-next-generation-approach- to-diagnosis-and-treatment, 2017, accessed Feb. 2017.
12. M. Chen et al., "Green and Mobility-Aware Caching in 5G Networks," IEEE Trans. Wireless Commun., vol. 16, no. 12, 2017, pp. 8347–61.
13. C. Yao et al., "A Convolutional Neural Network Model for Online Medical Guidance," IEEE Access, vol. 4, Aug. 2016, pp. 4094--4103.
14. M. Anthimopoulos et al., "Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network," IEEE Trans. Med. Imaging, vol. 35, no. 5, May 2016, pp. 1207--16.
15. K. Hwang and M. Chen, "Big Data Analytics for Cloud/ IoT and Cognitive Computing," Wiley, 2017. ISBN: 9781119247029.