5G SMART DIABETES: TOWARD PERSONALIZED DIABETES DIAGNOSIS WITH HEALTHCARE BIG DATA CLOUDS

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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.

1. 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.

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.

3. EXISTING SYSTEM

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.

4. 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.

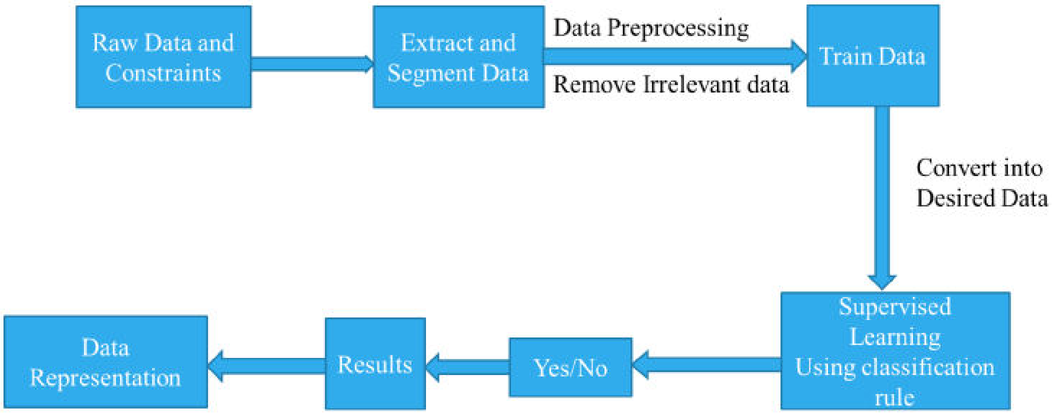


FIG 1 – SYSTEM ARCHITECTURE

5. METHODOLOGIES

MODULE

Admin Module:

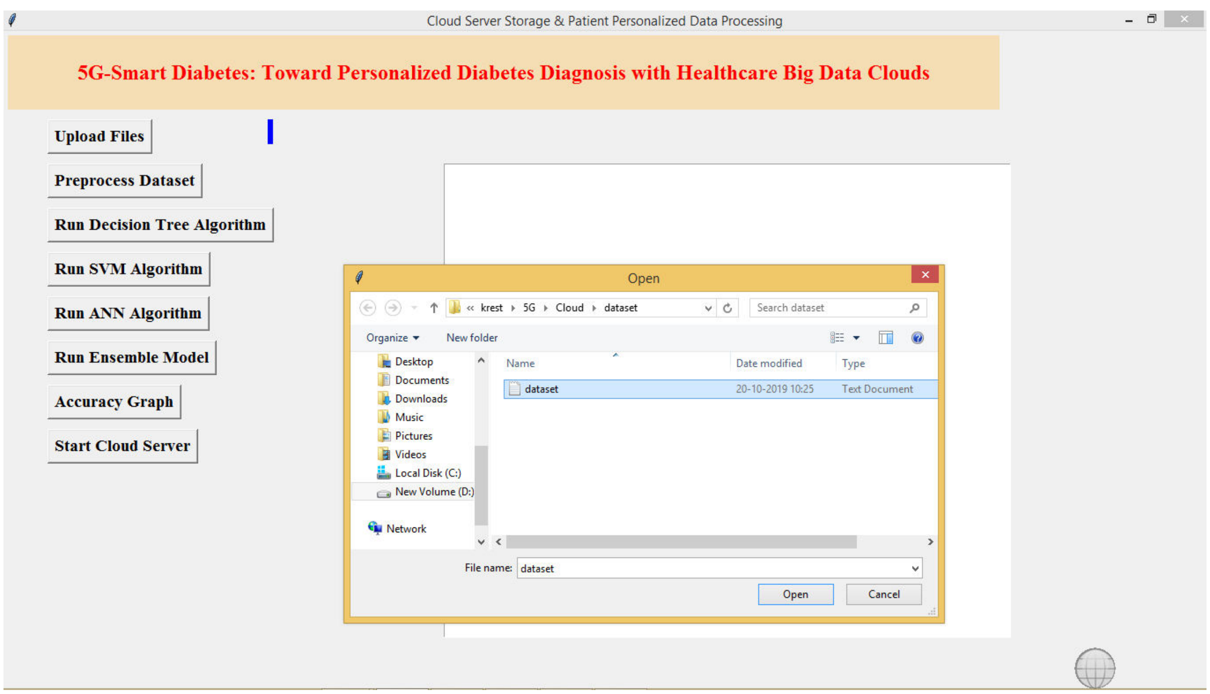
Here the admin input the pima dataset and then pre-process the data and then apply the classification algorithm like decision tree ,svm ,ann and ensemble classification method and then apply the accuracy graph and then start the cloud server

User:

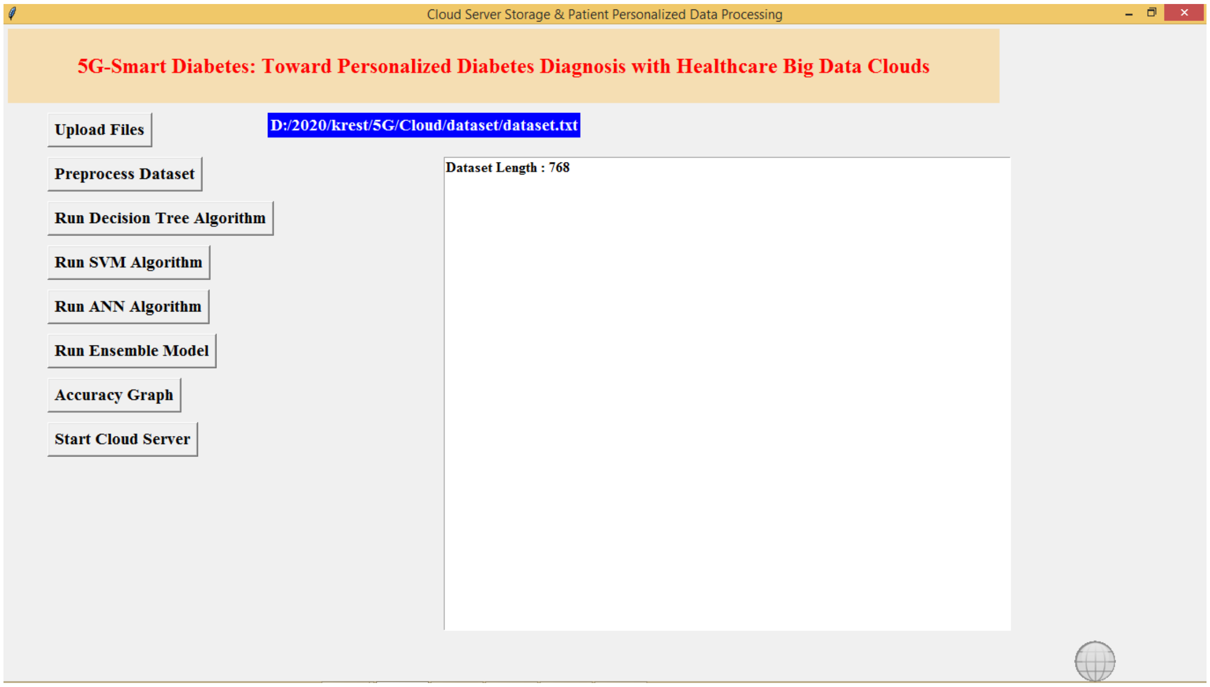
Here the use inputs the user symptom file and then out model gets connected to the cloud server and performs the prediction from the cloud server and then it returns back the results if the user data is diabetes or not with type of diabetes

6.RESULTS AND SCREEN SHOTS

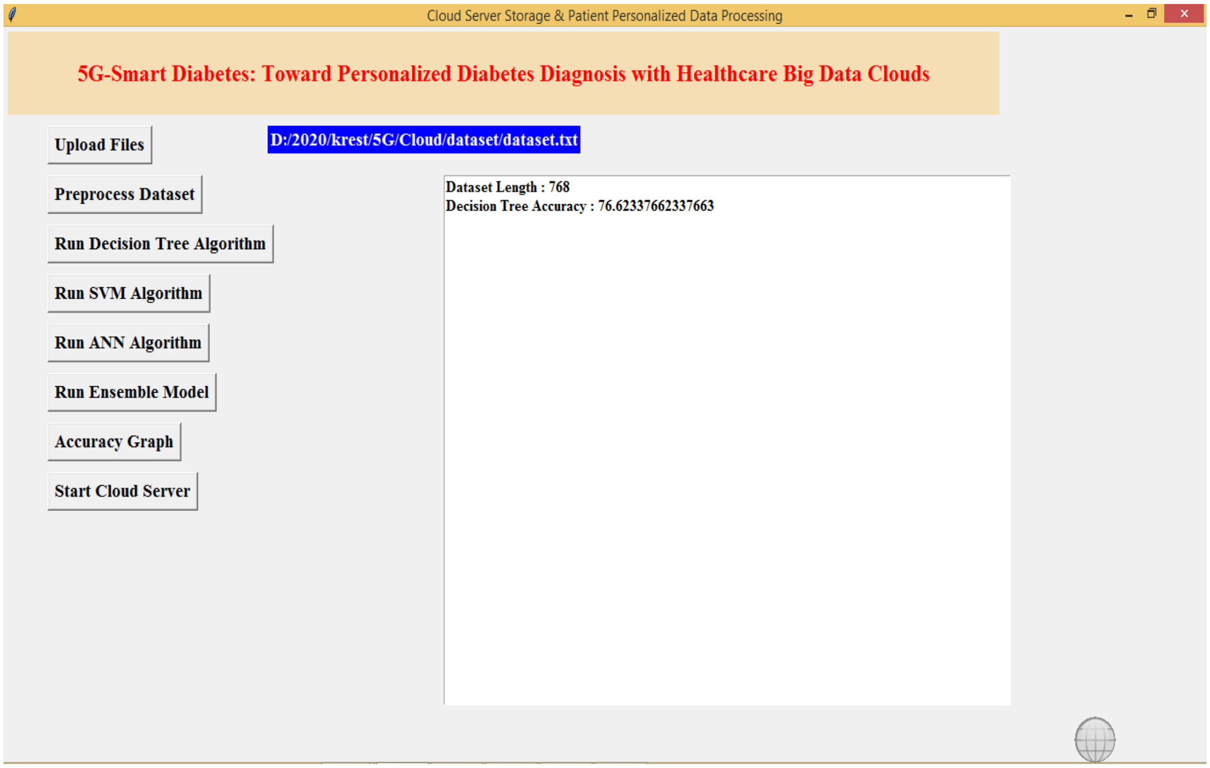
In above screen click on 'Upload Files' button to upload diabetes dataset



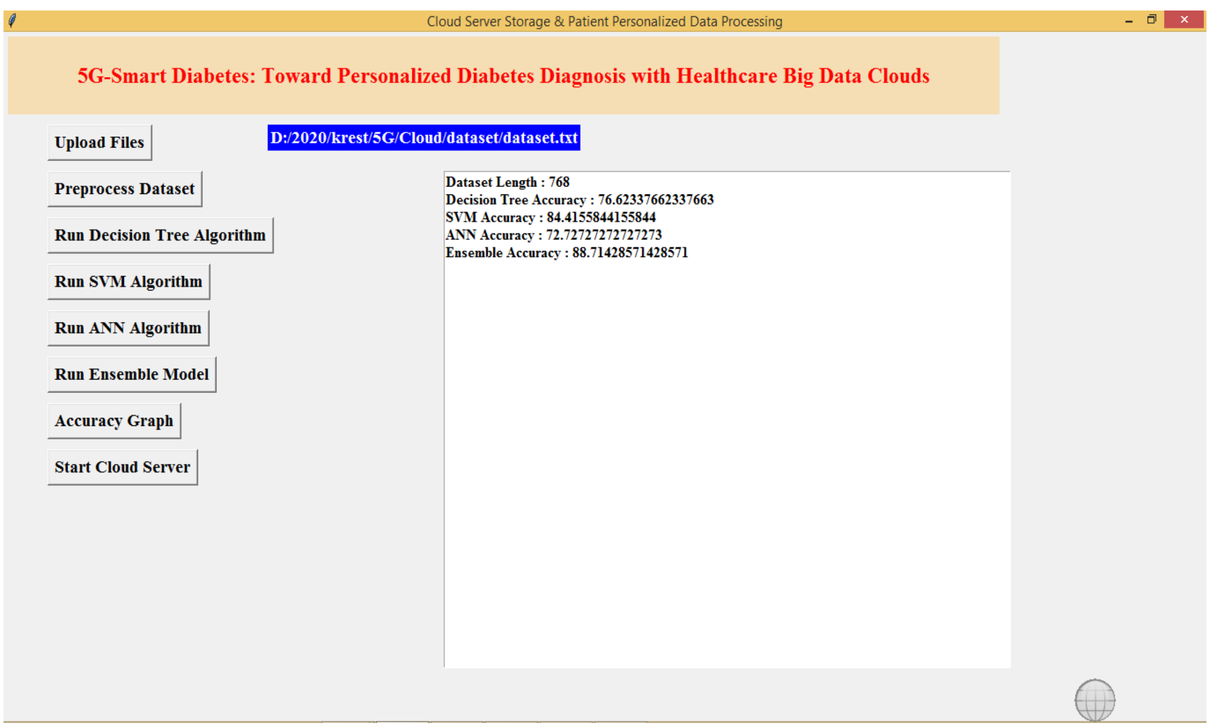
After uploading dataset click on 'Pre-process Dataset' button to clean dataset



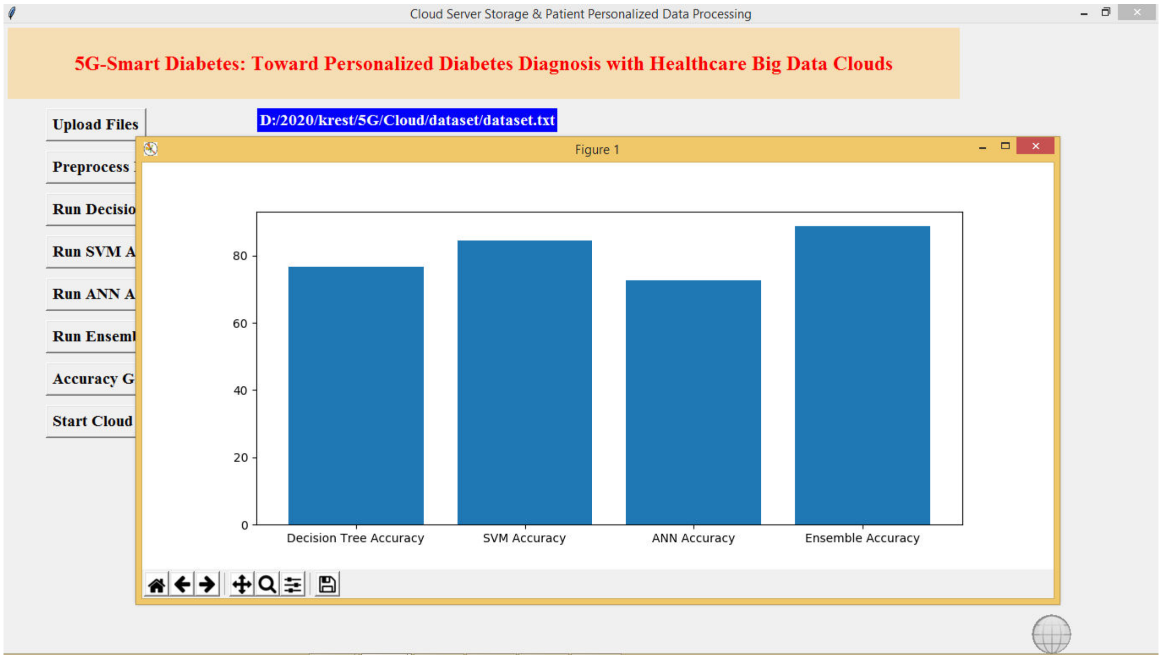
In above screen after pre-process total dataset records are 768. Now click on 'Run Decision Tree Algorithm' to build decision tree model and below is its accuracy



Similarly run other buttons to build models with algorithms

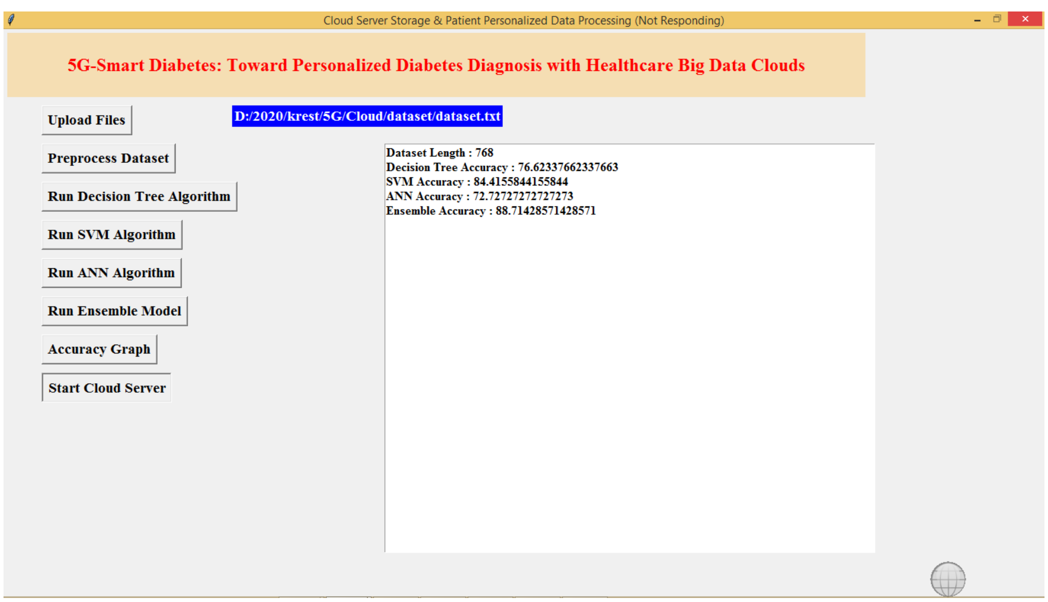


In above screen we got accuracy for all algorithms, now click on 'Accuracy Graph' button to get accuracy of all algorithms

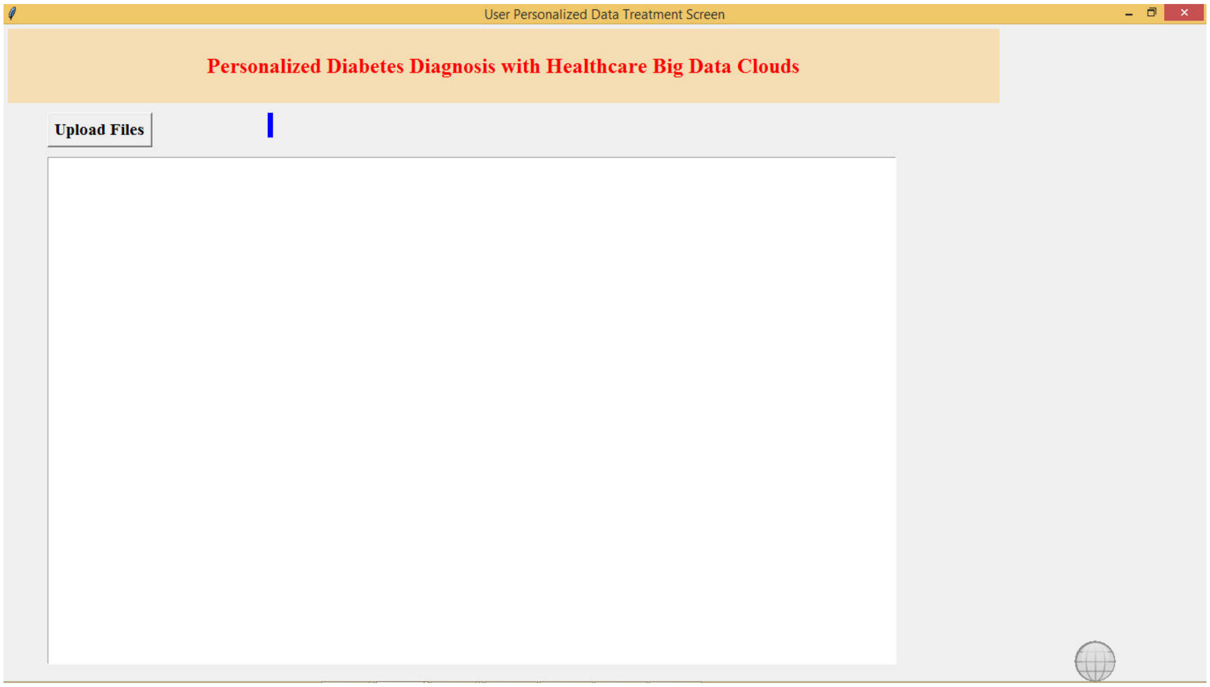


In above screen graph x-axis represents algorithm name and y-axis represents accuracy values.

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



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



In above screen click on 'Upload Files' button to upload test file and to predict patient condition

7. CONCLUSION AND FUTUTRE SCOPE

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.

8. 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.

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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.

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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.

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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.

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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.