An Integrated Cognitive System (ICS) For Diabetes Mellitus

Dr Vijay Franklin J, Kiruthikaa K V, Yuvaraj S, Ramya R

Abstract: In the recent times, as per the health records of most of the countries in the globe, the Diabetes Mellitus (DM) are the most dreaded disease which heavily impacts the health of its victims. A wide range of artificial intelligence and machine learning techniques are utilized in health care domain for identifying and diagnosing diabetes mellitus disorders. The proposed system deals with an intelligent cognitive system for prognosis, diagnosis, treatment and behavioral analysis for drug pattern selection. It is an integrated system, means that the system is composed of identification, classification, prognosis, diagnosis, therapeutic plan, drug recommendation and disease eradication modules.

Index Terms: artificial intelligence, case based reasoning, cognitive system, diabetes mellitus, decision trees, intelligent system, machine learning, support vector machine.

1. INTRODUCTION

Diabetes Mellitus (DM), commonly known as diabetes disease is a state of reduced insulin secretion. The Integrated Cognitive System (ICS) classifies the diabetic disorders into Micro-Vascular Diseases and Macro-Vascular Diseases. Neuropathy, Diabetic Retinopathy and Nephropathy are used for identifying the Micro-Vascular Diseases and Angina Pectoris and Myocardial Infarction are used for identifying the Macro-Vascular Diseases. ICS perceives the occurrence of diabetic disorder and act upon to diagnosis the effects and provide the suitable recommendations to eradicate the disorders. The logical system comprises the phases such as classification of diabetic disorders, prognostics of symptoms and complications, design of predictive identifiers (actors), development of diagnostic identifiers (actors), integrated cognitive system (actuators), interactions and recommendations.

2 RELATED WORK

N. Barakat et al. [1] represented an intelligible Support Vector Machine (SVM) algorithm for diagnosing diabetes related disorders and decisions were taken. The authors used a real-life diabetes dataset for performing their test. The proposed predictive algorithm generated results with accuracy 94%, sensitivity 93% and specificity 94%. Wheelock et al. [2] identified diabetes disorders that causes metabolic syndrome and classifies the visualization of short term risks, medium risks and long term risks of diabetes mellitus. Indexing factors for measurements include Body Ma-
-ss Index (BMI), blood pressure, serum cholesterol and plasma glucose level. From the study, it was clear that blood pressure and serum cholesterol has no significance in predicting and classifying the diabetic risks after BMI and glucose tolerance adjustments.

R.Priyadarshini et al. [3] proposed a method to predict diabetic disease in patients using extreme learning machine. The dataset was obtained from UCI repository. The authors initially carried out the experiment using back propagation neural network and then applied the extreme learning machine method as binary classifier on the same dataset. The prediction result showed that extreme learning machine method turned up with higher accuracy. A. Swain et al. [4] used Artificial Neural Network (ANN) and hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting and classifying diabetic disorders. Dataset comprising of 100 individuals with mean age of 42 years and with equal proportion of male and female records were used to conduct the experiment. Performance is measured based on prediction accuracy and their work revealed that the ANFIS method came up with high accuracy. Zou Quan et al. [5] stated that fasting glucose is the most important feature for prediction of diabetes mellitus. But, to achieve high accurate results, more features should be added. The authors performed their work using Luzhou and Pima Indians dataset obtained from hospitals in China. The classifiers used here are decision tree, random forest and neural networks with 5-fold cross validation. Principal Component Analysis (PCA) and minimum Redundancy Maximum Relevance (mRMR) were used in their model for reduction in dimensionality. The accuracy result obtained for Luzhou dataset 80% and for Pima Indians is 77%.Hsin-Yi Tsao et al. [6] demonstrated a prediction model for identifying diabetic retinopathy in high risk populations based on SVM with an accuracy of 79.5%.

- *Dr Vijay Franklin J, Professor, Bannari Amman Institute of Technology, India.*
- *Kiruthikaa K V, Assistant Professor, Bannari Amman Institute of Technology, India.*
- *Yuvaraj S, Assistant Professor, Bannari Amman Institute of Technology, India.*
- *Ramya R, Assistant Professor, Bannari Amman Institute of Technology, India.*

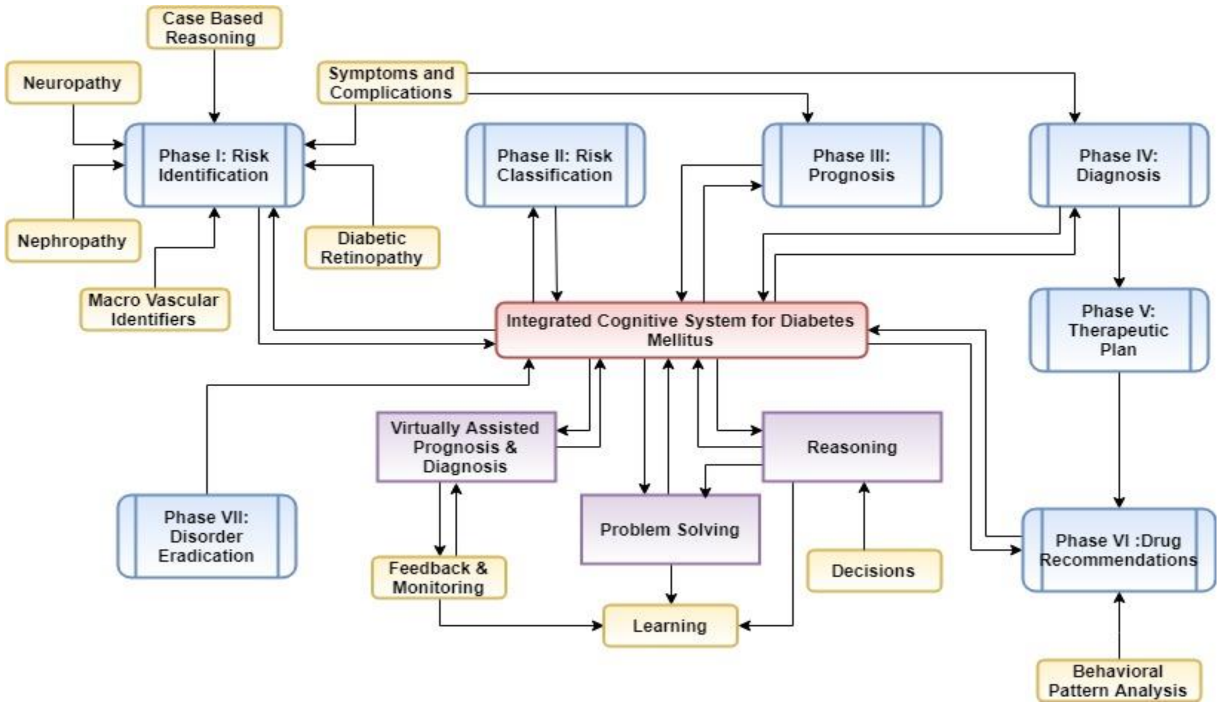

***Fig.1**. Architectural Design of ICS*

3 PROPOSED SYSTEM

The proposed system deals with an in telligent cognitive system for prognosis, diagnosis, treatment and behavioral analysis for drug pattern selection. Insulin Dependent Diabetes Mellitus (IDDM) patients requires insulin injections to normalize blood glucose metabolism, in order to prevent ketoacidosis and coma, and to decrease the risk of later life overturning impediments.Intensive Insulin Therapy (IIT), entailing in 3 to 4 doses for every day, or in the use of hypodermic insulin pumps, is the most effective way to alleviate blood glucose, and therefore to decrease or stay IDDM impediments. Every 2 to 4 months' duration, the patients are monitored for the metabolic control. The test procedures and the data are analyzed to generate the shortcomings that lead to the diabetic disorders. Several methods [7], [8], [9], [10], [11], [12], [13], [14], [15] have been developed to predict and analyze diabetic retinopathy, neuropathy nephropathy, angina pectoris and myocardial infarction. The DM disorders and complications are identified by several stages of the prognosis and diagnosis. Each stage is acting independently and also it fails to produce the accurate results and recommendations. The integration of stages with proper dependency and classification improves the effectiveness and the efficiency of the prognosis and diagnosis mechanism. The use of suitable Artificial Intelligence (AI) procedures, such as knowledge based classifications, Intelligent Data Analysis and Case Based Reasoning, might augment the strategy of the complete service. It should be possible to allow the users take advantage of an intelligent entity for episodic rehabilitation assessment and amendment. Based on the findings from the formal methods, there are certain drawbacks in AI systems for DM diagnostics and prognostics. To overcome those drawbacks, there is a need for developing an intelligent diagnostics supporting system to predict, analyze, monitor and support the diabetic patients to provide the treatment. This proposed system ICS leads to the scheming of an intelligent diabetes diagnostics system as well as to the formation of a knowledge base for the problem. The work designates the structure of the decision tree for diabetes diagnostics and establishes the decision rules in each phase of the system. In current era, the cognitive tools, like neural networks, genetic algorithms, fuzzy logic and others AI techniques are very familiar to solve the applications with complicated issues pertaining to the area of medical diagnostics. The cognitive system is capable to act effectively on the prognosis and diagnosis of various diseases like neoplastic diseases, heart and cerebro-vascular diseases and many others. Also these systems are self-healing systems which plays the actions based up on the rational reasoning and decision rules. The ICS also consist of the classifiers which are cognitive entities that categorize the data in which the system has to be trained with collected data set using various classifiers like decision tree and SVMs. In order to minimize the execution time and improve the efficiency of a system, the dimension of data set must be analyzed and the same can be used for classification to get better results. DM disorders are mapped with the classification patterns and classification decisions are made by the prognostic and diagnostic data sets. Sensors are another set of cognitive entities which are foreground modules for perceiving the information from the environment. The Intelligent agents are deployed to find appropriate perceiving entities to acquire the information for the knowledge base establishment through actors and percepts. The symptoms and the complications of the DM disorders are analyzed and the Classified Knowledge Base for Type 1 (CKB T1) and Type 2 (CKB T2) are established. Fig 1.depicts the architectural design of ICS, comprised of the following modules:

- Phase I : Risk Identifier
- Phase II : Risk Classification
- Phase III : Prognosis
- Phase IV : Diagnosis
- Phase V : Therapeutic Plan
- Phase V : Drug Recommendation
- Phase VI : Disorder Eradication

3.1 Phase I: Risk Identifier
The diabetic disorders are produced due to the insufficient functionality of the pancreas to produce the required insulin for the metabolism. This phase of risk identifier is used to find the insulin deficiency and predict the disorders arisen in the human body. Risk identification consist of two parts, in the first part generates a computational model that identifies the diabetic disorder efficiently and in the next part, a cognitive forecasting system is developed that is able to debrief the patient's information and details to originate the strategies rendering to risk level, in order to effective management of health conditions. The following algorithm is proposed to identify the risks.

Risk Identification Method

- Establish the Micro vascular and Macro Vascular Identifiers.
- Perform Case based reasoning based on the inference rules.
- Perceive the information from the samples collected from the Micro vascular and Micro vascular identifiers.
- Initialize the parameters for Bacterial foraging optimization.
- Perform Chemotaxis, Swarming, Reproduction, Elimination and dispersal operations.
- Compare with the inference rules and training sets.
- Calculate of error rate and accuracy percentage.

3.2 Phase II: Risk Classification
The identified risks are classified by construction of decision tree and SVM. In the decision tree the highest perceived information from the Bacterial Foraging Optimization (BFO) is considered as a root node. Based upon the perception ratio the branches and leaves are determined. BFO tree is constructed by passing the parameters I (Inference Rules), T (Training dataset), F (Features for prediction) and O (output attribute).The following processes construct the decision tree:
Step 1: Construction of Empty Tree (T→Ø)
Step 2: Select the training feature present in the perceived information from the BFO.
Step 3: Compute the Perceived Information ratio.
Assume the P is the population size, and R is the risk categories pi is the population collection category of Risk Ri the perseverance ratio is calculated by,

$$PR(p) = (p1, p2, p3, \dots \dots pn) = -\sum_{i=1}^{m} pr\ log2\ pri \qquad (1)$$

In this PR is the Probability of occurrence of risk. And the attributes are calculated by,

$$\Pr(p, A) = \sum_{j=1}^{v} (p1j + p2j + p3j \dots \dots + pnj)/P \qquad (2)$$

$$Gain\ Ratio\ (GR) = (PR) - \Pr(p, A)/ - \sum_{j=1}^{v} \left(\frac{pr}{p}\right) log2\ (\frac{pr}{P}) \qquad (3)$$

Step 4: Choose the feature with highest gain ratio
Step 5: Revise the decision tree T with all the obtained information
Step 6: Remove the redundant relationships in the tree
Step 7: Stop the process.

The obtained results are refined by the SVM classifier. It is a combinational approach for Support Vector Machine and Fuzzy Logic:
Step 1: Receive the Inputs from the Decision Tree (GR)
Step 2: The Classification of Diabetics Disorders based on the Glycemic ranges.
Step 3: For each input and output
Step 4: Create Fuzzy sets () {Create fuzzy sets for all Parent and Child nodes of the Decision tree}

3.3 Phase III & Phase IV: Prognosis & Diagnosis
The next phases of the proposed system are prognosis and diagnosis. In this phase, prognosis is carried out based on neural networks to prefigure the presence of risk in patients. Training and testing were conducted on the patients' dataset and the weight from the training result will be used for prediction. Diagnosis is done using expert system with fuzzy logic techniques. Expert system makes use of decision rules to identify patient's risk with respect to symptoms. Further, whenever fuzzy data are encountered, fuzzy logic technique is used to improve the cognitive sense of the system.

3.4 Phase V & VI: Therapeutic Plan and Drug and Recommendations
Based on the outputs of the previous phases, the accurate Therapeutic Plan and drug recommendations are provided using behavioral pattern analysis.

3.5 Phase VII: Disorder Eradication
This phase is closely associated with the domain called virtually assisted prognosis and diagnosis. The main objective of this phase is to provide patients with an effective action prominent to good glycemic control, and to attain a cautious stability between insulin treatment, nutrition and physical activity, thus postponing the start and/or slowing the development of enduring disorders. It provides a suitable level of constant and concentrated care through web monitoring and cognitive consultation services. It allows for a cost effective intensive care of a large number of patients, automated data collection and the administration of a large set of therapeutic conventions.

3.6 Advantages of ICS
- The ICS performs accurate identification of diabetic disorders and to provide effective recommendations for Diabetic management.
- The diabetic disorders and its risks are identified by the case based reasoning and clinical results.
- Risk classification is performed based on the inference rules through the decision tree and Support Vector Machine (SVM).
- The therapeutic plan is developed by the phases of prognosis and diagnosis procedures with respect to the disorder classification.
- The cognitive reasoning and supervised learning enable the system to make the decisions on drug recommendations.
- The virtually assisted diagnosis enables the experts and the patient to monitor, eradicate the disorders remotely and lively.

4 CONCLUSION

An Integrated Cognitive System (ICS) includes vital processes such as disease identification, prognosis, diagnosis, drug recommendation and decision making using artificial intelligence and machine learning techniques which further enhances the system as expert system that intelligently solves the problem of diabetes mellitus disorders. The expert system includes new methods for risk identification, classification, prognosis and diagnosis, incorporated with knowledge base and accommodates the integration of decision making for drug recommendation based on the inference rules and process modeling. The integrated system performs the stated functionalities using the essential constituents such as intelligent agents, knowledge base, inference engine, inference strategy, dialog control, reasoning, learning, interfaces, and decision trees.

REFERENCES

[1] N. Barakat, A. P. Bradley and M. N. H. Barakat, "Intelligible Support Vector Machines for Diagnosis of Diabetes Mellitus," in IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 4, pp. 1114-1120, July 2010.

[2] Wheelock, K. M., Sinha, M., Knowler, W. C., Nelson, R. G., Fufaa, G. D., & Hanson, R. L., “Metabolic risk factors and type 2 diabetes incidence in American Indian children”, in the Journal of Clinical Endocrinology & Metabolism, 101(4), 1437- 1444, 2016.

[3] R. Priyadarshini, N. Dash and R. Mishra, "A Novel approach to predict diabetes mellitus using modified Extreme learning machine," 2014 International Conference on Electronics and Communication Systems (ICECS), Coimbatore, 2014, pp. 1-5.

[4] A. Swain, S. N. Mohanty and A. C. Das, "Comparative risk analysis on prediction of Diabetes Mellitus using machine learning approach," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, 2016, pp. 3312-3317.

[5] Zou Quan, Qu Kaiyang, Luo Yamei, Yin Dehui, Ju Ying, Tang Hua, “Predicting Diabetes Mellitus With Machine Learning Techniques”, in the journal of Frontiers in Genetics, Vol.no:9, 2018, pp.515.

[6] Hsin-Yi Tsao, Pei-Ying Chan and Emily Chia-Yu Su, “Predicting diabetic retinopathy and identifying interpretable biomedical features using machine learning algorithms”, in 13th International Symposium on Bioinformatics Research and Applications (ISBRA 2017), pp.111-121.

[7] Hosseini SM, Maracy MR, Amini M, Baradaran HR. A risk score development for diabetic retinopathy screening in Isfahan-Iran. J Res Med Sci. 2009;14(2):105–10.

[8] Semeraro F, Parrinello G, Cancarini A, Pasquini L, Zarra E, Cimino A, Cancarini G, Valentini U, Costagliola C “Predicting the risk of diabetic retinopathy in type 2 diabetic patients”, J Diabetes Complicat. 2011;25(5):292–7.

[9] Ogunyemi O, Kermah D. Machine learning approaches for detecting diabetic retinopathy from clinical and public health records. In: AMIA 2015 Annual Symposium Proceedings, American Medical Informatics Association; 2015, p.983–90.

[10] D. Nathani, M. H. Barnett, J. Spies, J. Pollard, and M. C. Kiernan, “Predicting a diagnosis of pathologically confirmed vasculitic neuropathy,” Journal of Neurology, Neurosurgery & Psychiatry, vol. 89, no. 6, pp. A7.2–A7, May 2018.

[11] G. Jerums and R. J. MacIsaac, “Predicting renal function decline in patients with T2DM,” Nature Reviews Endocrinology, vol. 10, no. 7, pp. 381–382, May 2014.

[12] I. Blech, M. Katzenellenbogen, A. Katzenellenbogen, J. Wainstein, A. Rubinstein, I. Harman-Boehm, J. Cohen, T. I. Pollin, and B. Glaser, “Predicting Diabetic Nephropathy Using a Multifactorial Genetic Model,” PLoS ONE, vol. 6, no. 4, p. e18743, Apr. 2011.

[13] M. Krochmal, G. Kontostathi, P. Magalhães, M. Makridakis, J. Klein, H. Husi, J. Leierer, G. Mayer, J.-L. Bascands, C. Denis, J. Zoidakis, P. Zürbig, C. Delles, J. P. Schanstra, H. Mischak, and A. Vlahou, “Urinary peptidomics analysis reveals proteases involved in diabetic nephropathy,” Scientific Reports, vol. 7, no. 1, Nov. 2017.

[14] W.-C. Lee, C.-Y. Fang, H.-C. Chen, S.-K. Hsueh, C.-J. Chen, C.-H. Yang, H.-K. Yip, C.-L. Hang, C.-J. Wu, and H.-Y. Fang, “Aspiration Thrombectomy and Drug-Eluting Stent Implantation Decrease the Occurrence of Angina Pectoris One Year After Acute Myocardial Infarction,” Medicine, vol. 95, no. 17, p. e3426, Apr. 2016.

[15] S. V. Arnold, J. A. Spertus, P. G. Jones, D. K. McGuire, K. J. Lipska, Y. Xu, J. M. Stolker, A. Goyal, and M. Kosiborod, “Predicting Adverse Outcomes After Myocardial Infarction Among Patients With Diabetes Mellitus,” Circulation: Cardiovascular Quality and Outcomes, vol. 9, no. 4, pp. 372–379, Jul. 2016.