iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** V **Month of publication:** May 2022

DOI: https://doi.org/10.22214/ijraset.2022.42578

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue V May 2022- Available at www.ijraset.com

Predictive Model for Type II Diabetes: Deep Learning with Probability Density Function

Mrs. K. Gandhimathi[1], Dr. N. Umadevi[2]
[1]Ph.D Research Scholar, Department of Computer Science Sri JayendraSaraswathyMahaVidyalaya CAS, Coimbatore, India
[1]Assistant Professor, PG & Research Department of Computer Science, Hindusthan College of Arts and Science, Coimbatore, India
[2]Associate Professor & Head, Department of Computer Science & Information Technology Sri JayendraSaraswathyMahaVidyalaya CAS, Coimbatore, India.

Abstract:* Diabetes mellitus is a scientific ailment defined by hyperglycemia caused by a lack of absolute or relative insulin efficiency in the human body. Diabetes prediction is one of the newest and fastest-growing technologies in medical data analysis. The clustering method for grouping diabetes data based on cluster head properties is the focus of this study. This study proposes a new BG prediction method called RNN, which is based on recurrent neural networks (RNN). The probability of values of the variable is calculated using the probability density function (PDF). For pre-processing and missing value analysis, we used an enhanced Decision Tree and a weighted K-means method. The proposed method uses the weighted Binary Bat Optimization algorithm for feature selection. In terms of diabetic categorization, numerical findings reveal that when compared to other existing methods, the DP-RNN approach with PDF produces the way PDF-DPRNN produces the more accurate classification result.
Keywords: PDF, RNN, Decision Tree, Bat Optimization, Diabetes mellitus.

I. INTRODUCTION

Diabetes mellitus, or high blood sugar, is a progressive and permanent illness in which the body is unable to generate or use enough insulin. The blood glucose level is generally very high [1]. According to the Globe Health Organization (WHO), the number of diabetics in the world will rise to 333 million by 2025, up from 135 million in 1995 [3]. Uncontrolled and unmonitored diabetes can cause issues in different parts of the human body, including the skin, kidneys, heart, nerves, blood vessels, and healing of the feet [2].

Diabetes mellitus (DM) can cause coronary autonomic neuropathy as well as a slew of other problems [1]. If the condition progresses, specific blood vessels that supply the retina become blocked, preventing blood flow to select retinal regions [4].

In recent years, machine learning and deep learning have exploded in popularity. In a variety of domains, machine learning technologies such as medical prognostics and optical character recognition are being used [5]. Using modern computational approaches, such as a deep neural learning network [14] with probability density function, this research provides a high-precision model for diabetes prediction (PDF).

In this suggested framework, the PD-RNN classification result is compared to existing techniques. Type 2 diabetes develops when blood glucose levels are too high [7]. The most common type of diabetes is blood sugar, which is obtained from the food we eat. Insulin helps glucose travel from the bloodstream to the cells of our bodies, where it is converted into electricity. As a result, glucose does not reach type 2 diabetes cells and remains in the bloodstream.

The following sections make up this paper: Section II lists significant publications in this field, and Section III details the proposed technique, which involves dataset selection, pre-processing, and classification using PDF-RNN. Section IV provides the findings and evaluations of the results, which are reinforced by Section V, which contains the research's general conclusion.

II. BACKGROUND STUDY

The blood glucose level diagnosis is a standard study field, and various studies are being conducted in this area. The goal of automatic screening detection is to diagnose the need for greater human life care.

The multimodal approach, developed by Bouallal, D. et al. [2], outperforms the thermal image-based process model, especially in complicated circumstances**.**A cross-sectional clinical investigation on 122 diabetes type 2 patients was done as part of this approach. A diagnostic examination was used to identify the three risk groups: low-risk (R0), medium-risk (R1), and high-risk (R2) (R2).

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue V May 2022- Available at www.ijraset.com

The diabetes prediction results show that the medium-risk (MR1) group had a higher average foot surface temperature than the low-risk (R0) group, with a p0, 1 difference. With p0.01, the temperature difference measured during a cold stress test differs dramatically from R0 to R1 on one side and R1 to R2 on the other. Finally, R1 to R2 (p0.1) was the mean absolute deviation from the left to the right foot.

The hybridized patch approach was suggested by A. Chandran et al. [4] to identify proliferative diabetic retinopathy. Specialists can save time and effort by using electronic ophthalmology equipment, which can treat severe cases right away.

The author of this study, Kumar, S., and Kumar, B. [9], proposed a new method for detecting diabetic retinopathy by correctly estimating the number and size of micro aneurysms. The sensitivity and accuracy results show that the suggested diagnostic technique is more effective at detecting non-proliferative diabetes.

Vahidi, O. et al. [15] established a methodology for diagnosing cardiovascular deficits in a diabetic community of patients with type 2 diabetes. Using a particle filtering technique, the circumstances and glucose metabolic rates in several organs, as well as a pancreatic insulin secretion rate, were assessed. Hepatic abnormalities, pancreas, and peripheral diabetes type 2 patients can be diagnosed using nonlinear filtering system and mathematical model methods.

III. SYSTEM MODEL

This section introduces the recommended RNN DP-RNN approach, which is often used in natural language processing, speech recognition, and other time series-related tasks due to its natural benefits for rapid capture. RNN can be used to process the BG data series.

A. Dataset

The Diabetes Dataset is available on the KagglePlat platforms used in this proposed work. The major goal is to diagnose the patient and determine whether or not the patient has diabetes. This medical record has a total of 17 features that can be used to predict disease.

B. System Architecture

The proposed framework is the architecture for predicting type 2 diabetes. The standard dataset received from Kaggle is used in this system. This dataset is further pre-processed such that it may be utilized to forecast disease outcomes effectively. The data is separated after the pre-processing is performed. The PDF-RNN is used to train this segregated data. We can get the procedure results after we've made the prediction. Many measures can be used to evaluate the model. We focused on accuracy, precision, and F-measure because these measures have a significant impact on the model's improvement.

C. Methods

Traditional computer approaches do not require the extraction, sorting, and classification of functions to be expressed explicitly in deep learning networks. In exchange, individuals become part of a larger learning network. The main mechanism is self-learning based on the data. RNN makes use of the probability density approach (PDF).

IV. DISCUSSION

This section presents numerical results on the efficacy and benefits of the suggested PDF-RNN model for BG prediction. The ROC, where the X-axis represents the False Positive Rate and the Y-axis represents the True Positive Rate.ROC=TPR=TP/(TP+FN)

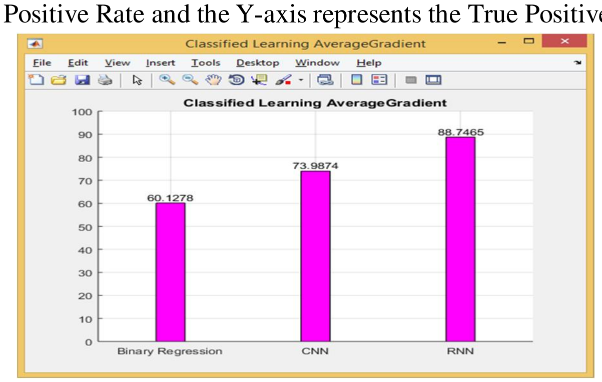


Figure 6: Learning Average Gradient Classification Result

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue V May 2022- Available at www.ijraset.com

The Average Gradient of Binary Regression is 60.1278, CNN is 73.9874, and PDF-RNN is 88.7465, as shown in Figure 6.

Initial coefficient values, also known as feature coefficients, are the first step in the technique. This could be 0.0 or some other number. 0.0 is the coefficient. The cost of the coefficients is calculated by putting them in and measuring the cost. The expense derivative is calculated as cost = f (coefficient). The derivative is a calculus word that corresponds to the pitch of the equation at a specific step.

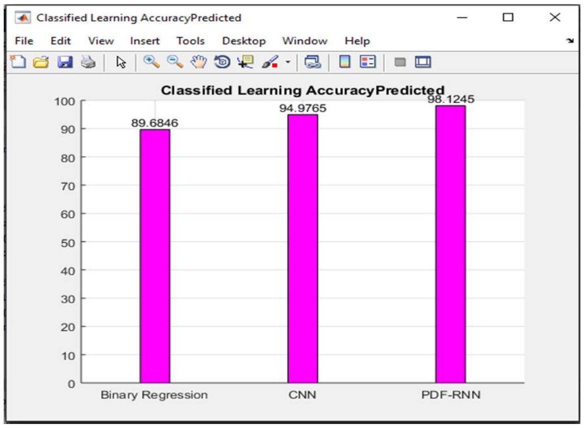


Figure 7: Learning Accuracy Predicted

100 percent accuracy = (properly predicted class/total tested class) with successful classifications, TPR and TNR can be as high as 100%. This is also true for precision and precision parameters. On the other hand, FPR and FNR might be as close to 0% as possible.

The Accuracy Predicted Binary Regression value for categorized learning is 89.6846, CNN is 94.9765, and PDF-RNN is 98.1245.

Table 1: Result Comparison Table

Method/ Measurement	BR	CNN	Proposed Method (PDF-RNN)
Accuracy	89.6846	94.9765	98.1245
Average Learning	60.1278	73.9874	88.2465
Classification with True data	85.3214	90.5213	94.5267
Sensitivity	86.2479	92.1236	97.8546
Specificity	40.3215	27.5645	12.5478
Precision	86.8566	94.3321	97.5499
Recall	12.6547	5.9874	2.8974
F Measure	8.6654	7.8846	3.5128

The overall comparison result table for Binary Regression, Convolution Nerural Network, and PDF-Recurrent Neural Network is shown in Table 1.

V CONCLUSION

We investigate machine learning methods for diabetes BG prediction in this proposed strategy. Many patients' data can be used in existing methods such as Logistic Regression, CNN, and PDF-RNN to improve prediction precision. When compared to the CNN and Logistic Regression approaches, the numerical results reveal that the suggested PDF-RNN solution has enhanced all diabetes types. The results for categorized accuracy are 98.1245. PDF-RNN can detect BG fluctuations, and the most significant effects are seen in terms of BG prediction precision. Instead of BG fluctuation, classification of additional factors or consequences will be done in the future.

REFERENCES

[1] Alkhoori, T. M., Alsafar, H. S., &Khandoker, A. H. (2014). Analysis between ECG and respiration signals in type II diabetic patients in the UAE. 2nd Middle East Conference on Biomedical Engineering. doi:10.1109/mecbme.2014.6783274

[2] Bouallal, D., Bougrine, A., Douzi, H., Harba, R., Canals, R., Vilcahuaman, L., &Arbanil, H. (2020). Segmentation of plantar foot thermal images: application to diabetic foot diagnosis. 2020 International Conference on Systems, Signals and Image Processing (IWSSIP). doi:10.1109/iwssip48289.2020.9145167

[3] Choden, P., Seesaard, T., Eamsa-ard, T., Sriphrapradang, C., &Kerdcharoen, T. (2017). Volatile urine biomarkers detection in type II diabetes towards use as smart healthcare application. 2017 9th International Conference on Knowledge and Smart Technology (KST). doi:10.1109/kst.2017.7886086

[4] Chandran, A., Nisha, K. K., &Vineetha, S. (2016). Computer aided approach for proliferative diabetic retinopathy detection in color retinal images. 2016 International Conference on Next Generation Intelligent Systems (ICNGIS). doi:10.1109/icngis.2016.7854014

[5] Chammas, N., Juric, R., Koay, N., Gurupur, V., & Suh, S. C. (2013). Towards a Software Tool for Raising Awareness of Diabetic Foot in Diabetic Patients. 2013 46th Hawaii International Conference on System Sciences. doi:10.1109/hicss.2013.563

[6] Caravaggi, P., Berti, L., Leardini, A., Lullini, G., Marchesini, G., Baccolini, L., &Giacomozzi, C. (2017). Biomechanical and functional alterations in the diabetic foot: Differences between type I and type II Diabetes. Gait & Posture, 57, 12–13. doi:10.1016/j.gaitpost.2017.07.063

[7] Choi, S. M., Lee, K.-M., Kim, H. J., Park, I. K., Kang, H. J., Shin, H.-C., … Lee, J. W. (2018). Effects of structurally stabilized EGF and bFGF on wound healing in type I and type II diabetic mice. ActaBiomaterialia, 66, 325–334. doi:10.1016/j.actbio.2017.11.045

[8] Innocenti, F., Bartalucci, F., Boni, V., Vicidomini, S., Mannucci, E., Monami, M., &Pini, R. (2014). Coronary artery disease screening in type II diabetic patients: Prognostic value of rest and stress echocardiography. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 8(1), 18–23. doi:10.1016/j.dsx.2013.10.010

[9] Kumar, S., & Kumar, B. (2018). Diabetic Retinopathy Detection by Extracting Area and Number of Microaneurysm from Colour Fundus Image. 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN). doi:10.1109/spin.2018.8474264

[10] Peng, Y., Ren, D., Song, Y., Hu, Y., Wu, L., Wang, Q., … Cong, H. (2019). Effects of a combined fucoidan and traditional Chinese medicine formula on hyperglycaemia and diabetic nephropathy in a type II diabetes mellitus rat model. International Journal of Biological Macromolecules. doi:10.1016/j.ijbiomac.2019.12.201

[11] Paranjape, R., & Gill, S. (2010). Agent-Based Simulation of Healthcare for Type II Diabetes. 2010 Second International Conference on Advances in System Simulation. doi:10.1109/simul.2010.13

[12] Rodrı́guez-Morán, M., & Guerrero-Romero, F. (1999). Increased Levels of C-Reactive Protein in Noncontrolled Type II Diabetic Subjects. Journal of Diabetes and Its Complications, 13(4), 211–215. doi:10.1016/s1056-8727(99)00047-1

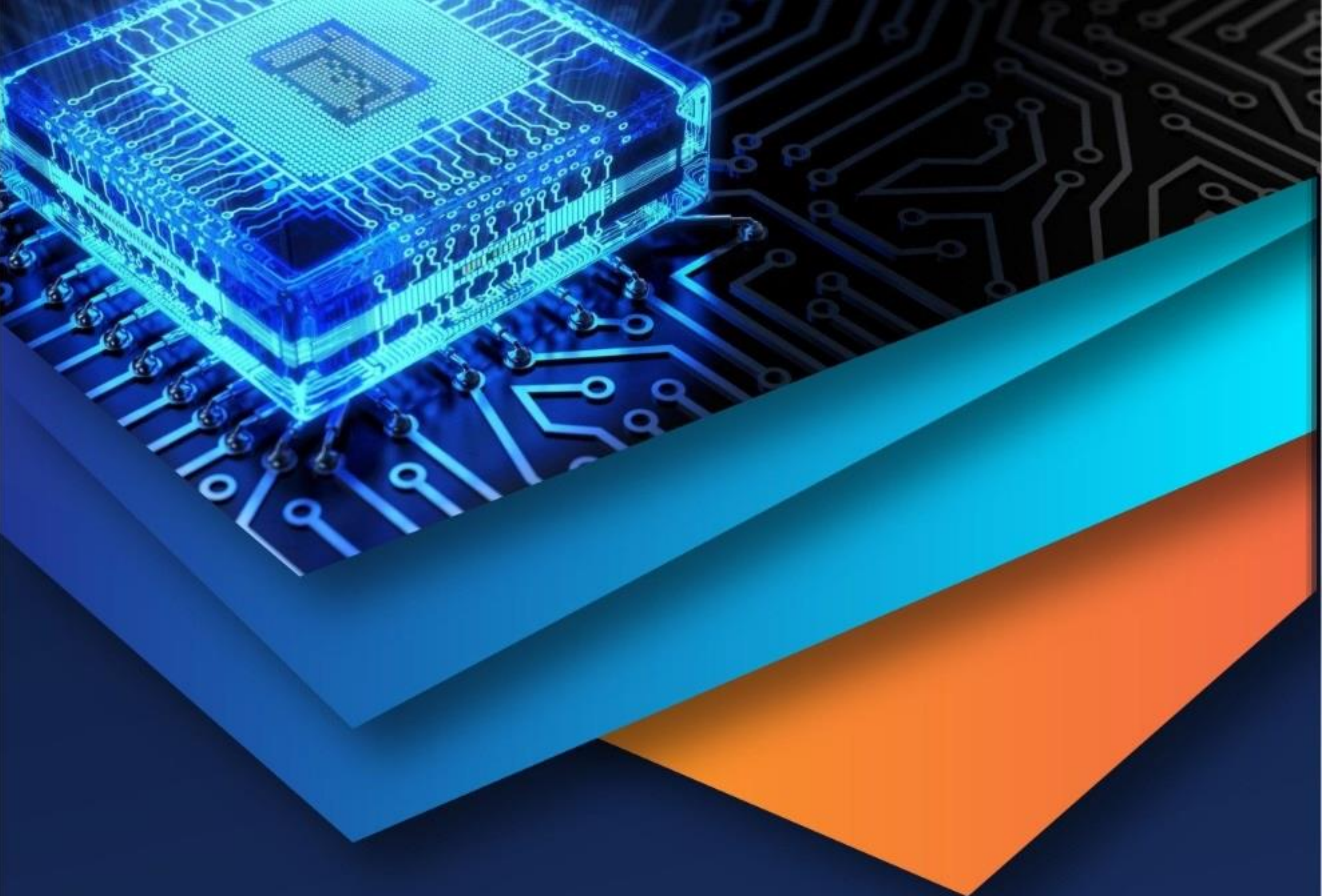
[13] shahbazian, H., Aleali, A. M., Rashidi, H., Latifi, S. M., Rashidi, M., Yazdanpanah, L., … Moradi, M. (2019). Frequency of type I and II diabetes in newly diagnosed diabetic patients: Measuring C-Peptide level. Diabetes & Metabolic Syndrome: Clinical Research & Reviews. doi:10.1016/j.dsx.2019.04.018

[14] Shirzaiy, M., Heidari, F., Dalirsani, Z., &Dehghan, J. (2015). Estimation of salivary sodium, potassium, calcium, phosphorus and urea in type II diabetic patients. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 9(4), 332–336. doi:10.1016/j.dsx.2013.02.025

[15] Vahidi, O., Gopaluni, R. B., & Kwok, K. E. (2011). Detection of organ dysfunction in type II diabetic patients. Proceedings of the 2011 American Control Conference. doi:10.1109/acc.2011.5991034

[16] Vahidi, O., Kwok, K. E., Gopaluni, R. B., & Sun, L. (2010). Development of a physiological model forpatients with type 2 diabetes mellitus. Proceedings of the 2010 American Control Conference. doi:10.1109/acc.2010.5531636

[17] Yang, J., Chen, H., Nie, Q., Huang, X., &Nie, S. (2020). Dendrobium officinale polysaccharide ameliorates the liver metabolism disorders of type II diabetic rats. International Journal of Biological Macromolecules. doi:10.1016/j.ijbiomac.2020.08.007



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

ISI

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)