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Cloud of Things (CoT) based Diabetes Risk Prediction System using BiRNN

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Abstract

The introduction of Internet of Things (IoT) technology witnesses the continuous and distributed connectivity between different objects and people. Currently, with the emerging technological advances, IoT integrates with the cloud and evolves into a new term called "Cloud of Things" to further enhance human lives. Using predictive analytics and Artificial Intelligence (AI) approaches in the healthcare area allows for the development of more reactive and smart healthcare solutions. As a subfield of AI, the Deep Learning (DL) technique has the potential to analyse the given data accurately, provide valuable insights, and solve complex challenges with its ability to train the model continuously. This study intends to implement a deep learning model – Bidirectional Recurrent Neural Networks (Bi-RNN) to obtain a timely and accurate prediction of diabetes risk without requiring any clinical diagnosis. This method of processing the time series data will highly assist in ensuring preventive care and early disease intervention. The proposed model collects real-time data from IoT devices along with the medical data stored in Electronic Health Records (EHR) to perform predictive analytics. The proposed Bi-RNN based diabetes prediction model results in an accuracy of 97.75%, which is comparatively higher than other existing diabetes risk prediction models.

Keywords: Healthcare, Risk Prediction, Deep Learning, Neural Network, Cloud of Things

1. Introduction

Science and technology play a key role in human evolution. The recent advances in Information and Communication Technology (ICT) have leveraged innovative state-of-the-art solutions for various industries, including healthcare, communication, logistics, supply chain, agriculture, etc. These advancements are considered as the building blocks for the emerging

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potential distributed technology called “Internet of Things (IoT)”. The IoT emerges distinctively and has created a profound impact on our everyday lives, ranging from automating household appliances to robotic automation. IoT helps people and objects to connect with each other to perform a desired task in an autonomous way [1].

Along with the IoT advancements, another technology that has gained equal interest from researchers is cloud computing. This technology delivers on-demand services, which is popularly known as a pay-per-use model. It possesses unlimited virtual storage capability and the data stored in it can be retrieved from any place and at any time. Despite being unique in its own way, the technologies of cloud computing and IoT can be combined to offer more advantages in terms of enabling distributive intelligence, data storage and retrieval, computation, and so on [2]. Hence, the new hybrid technology “Cloud-IoT” has gained significant research interest in recent years.

The hybrid cloud-IoT technology is now applied in a wide range of real-time applications, and its application in healthcare has enabled various advantages. Incorporating cloud-IoT models in the healthcare industry has paved way for new innovations such as decision support, predictive risk analysis, remote patient monitoring, and big data analysis. This technology also helps to predict the risk of patients by evaluating their past medical history and data like their previous screening results, medical imaging data, and similar electronic health records that are stored in the cloud [3].

By incorporating AI technologies in Cloud-IoT model, further helps to identify the disease early, avoid the risk of complications, particularly in the elderly population, improve disease management, receive immediate medical assistance in emergencies, and reduce the healthcare expenses. The utilization of advanced AI techniques like Deep Learning (DL), the Cloud-IoT model can become more robust and reliable to autonomously process and learn complex healthcare datasets and offer solutions for complex problems [4]. The deployment of AI models in healthcare applications has outperformed the traditional healthcare models. In particular, the deep learning model, - Bidirectional Recurrent Neural Networks (Bi-RNN), delivers efficient performance in managing and processing the healthcare data by considering the real-time continuous values.

1.1 Motivation

Diabetes prediction has recently gained increasing research attention due to its advantages in enabling healthy living. When the glucose level of a patient goes high due to the lack of a hormone called insulin in human body, the person will suffer from a condition called diabetes [5]. This study particularly considers the area of diabetes prediction, as early-stage diabetes prediction can help the healthcare practitioners to prevent heart disease, nerve and blood vessels damage, and diabetic retinopathy. Timely disease prediction can save precious lives and enable healthcare advisors to take care of the conditions.

1.2 Contribution

The potential outcomes of this research study are as follows:

1. In the proposed Cloud-IoT model, the IoT sensors collect the data related to diabetes risk prediction and it is pre-processed in the cloud layer.
2. The processed data is then sent to the Fuzzy Inference System (FIS) to perform classification.
3. After classification, the proposed Bi-RNN model accurately predicts the risk of diabetes in patients.

The flow of this research study is as follows: Section 2 reviews the research literature and describes the recent research contributions made in the diabetes prediction domain. Section 3 presents the proposed methodology, architecture and flowchart. Section 4 depicts the result obtained and also a comparative analysis has been performed. Section 5 concludes the research study and provides few insights as a future research direction.

2. Literature Review

Machine Learning, a subsection of AI is recently used for enabling the computer to learn through past experiences. Recently, the Random Forest technique, which uses both regression and classification process is used to predict the presence of diabetes in a patient [6]. The type of diabetes and level of glucose has been found with the help of parameters like classification reports, accuracy, etc.

Utilizing Deep Learning (DL) approaches for various disease prediction tasks have become highly successful, and this technology eventually outperforms human expertise. However, its real-time application is highly limited due to a lack of interpretability and medical knowledge. To overcome this, researchers have built a disease prediction model by using a combination of deep learning and knowledge representation learning approaches by considering the range of physical examination values, which is further divided based on the medical practitioner's expertise. This hybrid approach highly assists in early diabetes detection and performing related diagnosis [7].

While implementing a classifier model in diabetes prediction, the input data used may contain noise. This may affect the performance of the classifier. To overcome this challenge, ensemble learning method is highly preferred and with multiple base learners, it has the ability to train multiple classifiers to solve any particular challenge or problem [8]. This helps to solve the class imbalance problem that occurs in the process of diabetes prediction and classification.

Particularly for detecting Type-2 diabetes, researchers have recently considered the health parameters like insulin level, cholesterol level, age, weight of people from various age groups. The data will then be used to perform the classification task. Recently the JRip technique is used to formulate the rules and Multi-Layer Perceptron (MLP) is used to develop class labels and improve the prediction accuracy [9].

Despite the hype, in the process of Type-2 diabetes prediction, researchers have encountered various uncertainties. To overcome this, a multi-modal self-attention framework has been developed to extract the features from the dataset, which comprises of routinely checked EHR data. This helps to perform prediction irrespective of the absence of the dropout layer and even when the model is uncertain [10].

A new Internet of Medical Things (IoMT) framework has been built to anlayze the data obtained from the Wireless Body Area Network (WBAN) using a Fog computing framework. Further, the diabetes prediction will be performed on the Fog architecture, and the decision-making process will be completed by integrating the fog-cloud architecture with the ANN model [11].

A model for predicting gestation diabetes [12] is presented by developing a prediction framework that includes an IoT layer and Fog-Cloud layer, which additionally includes a data searching methodology and an explainable algorithm for prediction. By including the explainability feature, a medically intuitive framework has been developed.

The above-mentioned recent research works related to the diabetes diagnosis and risk prediction has mostly preferred to use a machine learning algorithm. The classification and prediction accuracy achieved by the existing methods can be further enhanced by employing deep learning algorithms [13]. Furthermore, by combining the fuzzy model with Recurrent

Neural network (RNN) algorithm can produce efficient outcomes and can outperform the existing models. The next section will describe the proposed methodology to perform accurate diabetes disease classification and risk prediction.

3. Methodology

The Internet of Things (IoT) supports the interaction between objects or things and people; this feature enables the utilization of IoT in various real-time applications. Despite the hype, in the healthcare applications, IoT is now widely used to connect a large number of devices. As a result, processing and storing the big data generated from all the connected devices has become a significant challenge [14]. To overcome this, the proposed study has designed and developed a cloud-IoT to process the big data resources effectively.

The proposed model intends to predict the risk of diabetes by using the following models:

- Data Collection
- Data Pre-Processing
- Feature Optimization
- Decision-Making using FIS
- Bi-RNN based Diabetes Risk Prediction

The overall architecture of the proposed model is depicted in the Figure.1 below:

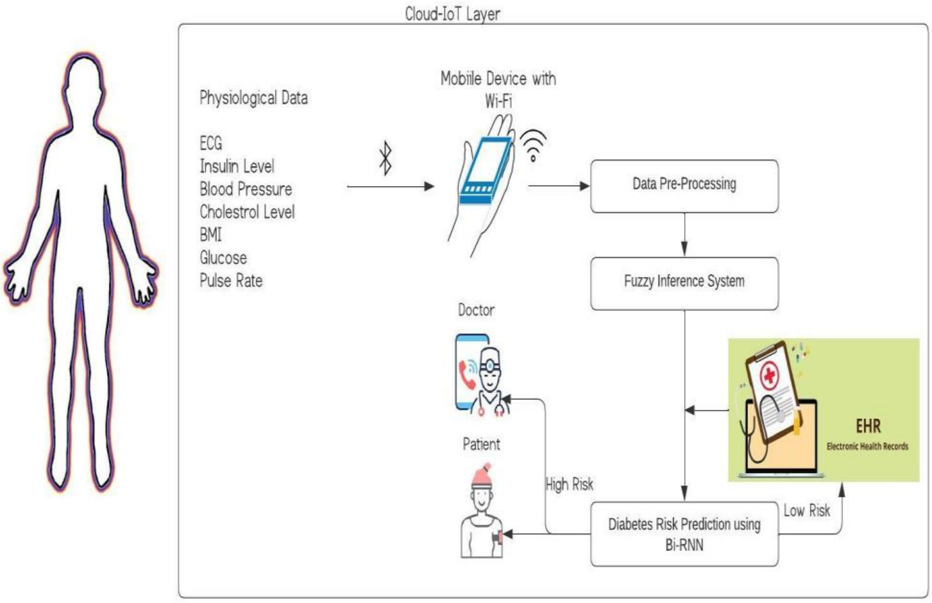

Figure 1. Proposed CoT and Bi RNN based Diabetes Risk Prediction Model

3.1 Data Collection

The proposed diabetes prediction model has obtained data from two different sources: 1) By directly getting the data from patients by checking their physiological data such as electrocardiogram (ECG) level, insulin level, cholesterol level, body mass index, visual blurriness, and blood glucose level. These data are collected from their routine health monitoring using wearable devices. The collected data from the smart wearables will be transferred through Bluetooth to the gateway device [15], which will be mostly the mobile phone of the user. The gateway device will then forward the data to the cloud layer to perform further processes. 2) The data will be collected from the Electronic Health Records (EHR) available in the hospitals. The second data source will be mainly used to perform the risk prediction analysis.

3.1.1 Dataset

To perform the experimental analysis and predict the diabetes risk from the given data, the Pima-Indians-Diabetes-Dataset from the OpenML repository [16] is considered. The proposed algorithm/pseudocode is implemented on the aforementioned diabetes dataset, which includes 8 attributes as mentioned in Table 1

Table 1. Dataset Description

Attributes	Description
Age	Age of a person in years
Sex	1 = Female; 0 = Male
Pregnancies	No. of times the person is pregnant
Glucose	Measurement of glucose level in blood. This value should be normaly in the range of 72 to 108 mg/dL.
BloodPressure	Measurement of the force on the artery walls when heart pumpos blood to the entire body. The ideal range is 120/80 mmHg (This value varies based on age)
Skin Thickness	Thickness of human skin. The ideal thickness range is 2-2.5mm
Insulin	Measurement of insulin levels in blood. Normal insulin level in fasting is <25 mIU/L
BMI	Measuremt of body fat based on height and weight. For adults, ideal BMI ranges from 18.5 to 24.9.

Diabetes Pedigree Function	Calculation of diabetes risk based on the individual's age and family history of diabetes.

3.2 Data Pre-Processing

The most effective data processing requires a novel method for handling missing data. To achieve this, the noise should be eliminated and feature selection and optimization should be done. Initially, while obtaining data from the first category mentioned in primary data source, the data may include inconsistencies and noise. Here, the proposed model employs a Dynamic Data Reconciliation (DDR) filter [16] to eliminate noise, duplicate data, and data discrepancies. DDR can be used to correct inaccurately measured data and calculate data from the process for unknown parameters close to real time. After this filtering, this study has used two other data filtering methods, such as useless value removal and missing valuee replacement.

3.3 Feature Optimization

Feature optimization is the method of reducing the number of features in order to reduce computation complexity and increase the performance of the proposed DL model. The three main processes involved in this process are feature importance, feature selection, and feature reduction. This study mainly performs the feature importance process by assigning a score to each attribute in a dataset to show its significance and relevance. Hence, the most significant features can be selected based on the feature relevance score. Thus, by removing attributes with lower scores, the feature set can be optimized. Here, the feature importance is done by using

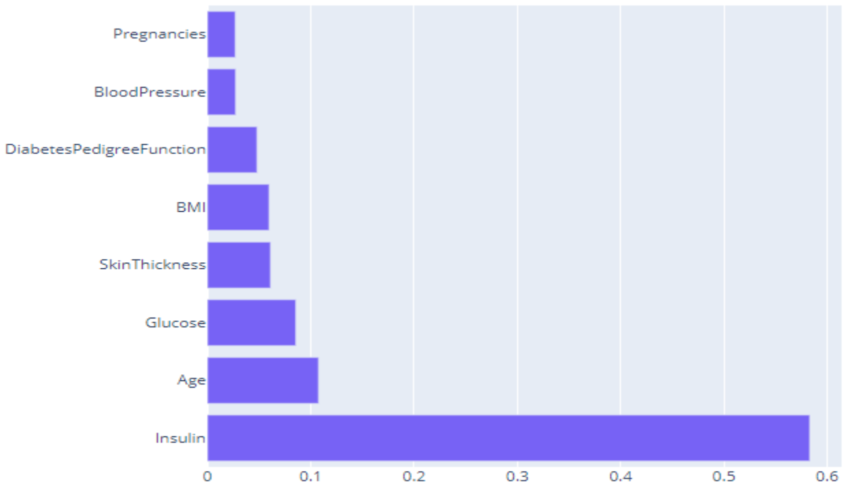

Figure 2. Feature Importance of the Proposed Model

Random Forest Algorithm [18]. This helps to further structure the dataset. The Figure.2 above shows the feature importance of the proposed model

3.4 Decision-Making using Fuzzy Inference System (FIS)

Fuzzy systems are related to analysing imprecise data and model the intrinsically complex events in everyday life. A typical Fuzzy Inference System (FIS) [19] is composed of four components: a fuzzifier, inference tool, base knowledge, and defuzzifier. The inputs can be either numeric or alphabetical variables. Fuzzifier assigns input to the suitable fuzzy sets. Next, the inference tool maps the input to output by using a reasoning method, which utilizes the knowledge gained from the set of fuzzy rules given as a base knowledge. The base knowledge includes the control rules and an expert knowledge to map the input to output. If the output linguistic variable needs to converted to a numeric output, a defuzzifier will be used.

In the proposed FIS system, the inputs considered are glucose (blood glucose level), blood pressure, and ECG. Then, the member function is initiated. Later, they are fuzzified into a fuzzy value range.

The working of the proposed FIS for diabetes risk prediction is depicted in Figure 3.

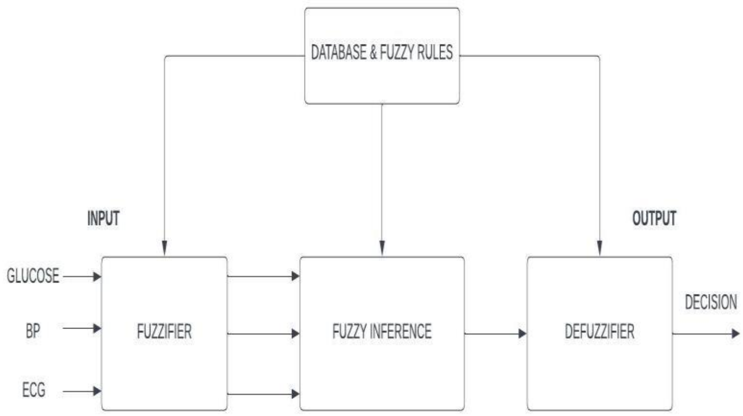

Figure 3. Proposed FIS for Diabetes Risk Prediction

Table 2. Shows the Initialized Variables and Fuzzy Sets

Variable	Fuzzy Set
Blood Glucose	{Low, Normal High Risk}
Blood Pressure	{Low, Normal High Risk}
ECG	{Low, Normal High Risk}

Table 3. Shows the Sample Blood Glucose Range

Defined Member Function (β)	Range
Low	69 or below
Normal	70 - 140
High	140 and above

The fuzzy rules and corresponding member functions are used to given the decision. Here, the notification about high-risk conditions and overall risk status will be sent and also the data will get stored in the cloud.

The below illustrated Algorithm 1 shows the classification of diabetes risk prediction using FIS based on the given input health data.

Algorithm

Step 1: The given inputs and member function β_1 determines the fuzzy system

Step 2: Determine diabetes risk using β_1 (Glucose), β_1 (BloodPressure), β_1 (ECG) as β_1 (Normal) or β_1 (Low) or β_1 (High).

Step 3: If risk state β_1 (Low) or β_1 (High)

Send alert using Apache Spark RealTime Analyzer and store the information in cloud storage

Step 4: Else send the information to cloud storage

Step 5: End

3.5 Data Prediction using Bi-Directional Recurrent Neural Network (Bi-RNN)

The supervised algorithms are more likely to face challenges while making predictions with sequences. These problems may also differ for both input and output sequences.

The proposed model identifies the risk as low or high by learning the parameters in terms of backward and forward direction to enhance the existing BiLSTM model and the learning ability. The existing BiLSTM model has a constraint that the cell can only consider the past content but not the future content [20]. To overcome this challenge and keep the information in the memory for an extended period of time, the Bidirectional RNN model is implemented. BiRNN includes two different hidden LSTM layers, which can compare the output in opposite directions are used. This helps us to learn about the future. BiRNN reduces the occurrence of gradient diminishing problems.

In existing Bi-LSTM, the sequences used are

$$Input\ Sequence\ A = (A_1, A_2 \ldots\ A_n)$$
$$Computation\ in\ Forward\ Direction\ \uparrow C_f = (\uparrow C_1, \uparrow C_2 \ldots \uparrow C_n)$$
$$Computation\ in\ Backward\ Direction\ \downarrow C_b = (\downarrow C_1, \downarrow C_2 \ldots \downarrow C_n)$$
$$Final\ Output\ B = (B_1, B_2, \ldots\ B_b \ldots\ B_n)$$

In the proposed Bi-RNN model, an activation function has been selected to influence the training process and the performance of the given task.

Here, in the proposed prediction model this research study has used the new activation function proposed by Diganta Mishra [21], Mish, stated as

$$f(x) = x. \tanh[Softplus(x)]$$

Further, to address the divergence issue in LSTM cell, a new activation function called logmoid function [22] is used. This setup helps to reduce the prediction errors and eliminated the negative values. Further, exponential linear unit (ELU) is included after output gating. Figure 4 shows the proposed Bi-RNN Architecture

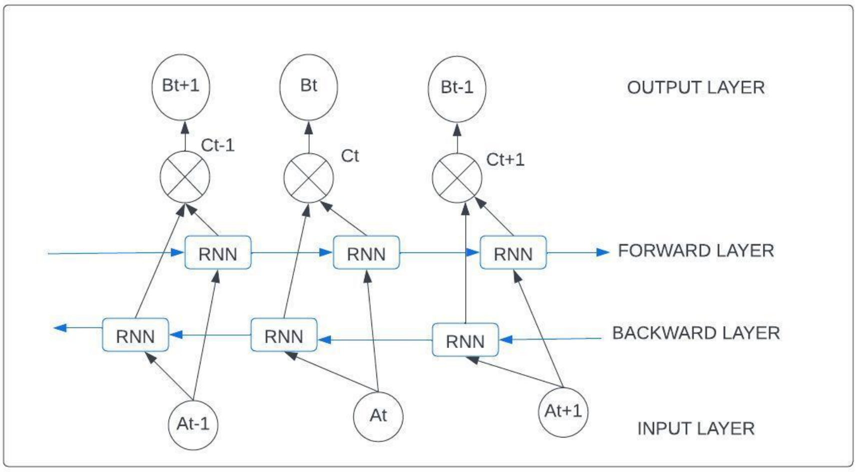

Figure 4.1. Proposed Bi-RNN Model

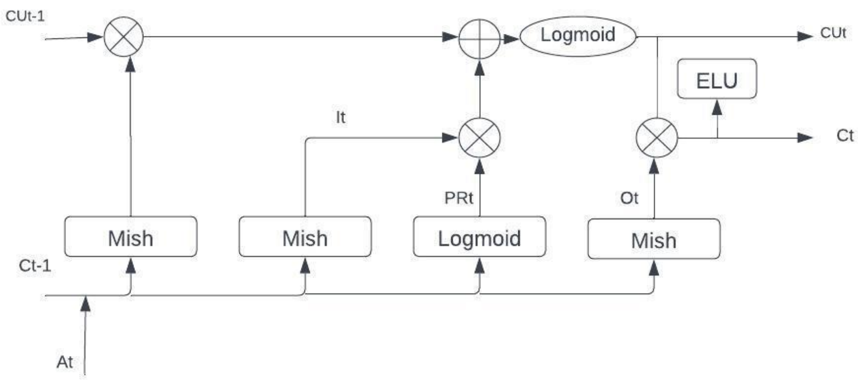

Figure 4.2. Single RNN Structure of the Proposed Bi-RNN Model

$$f_t = Mish\ (W_f A_t + W_{cf} C_{t-1} + h_f)$$
$$I_t = Mish\ (W_i A_t + W_{ci} C_{t-1} + h_i)$$
$$O_t = Mish\ (W_o A_t + W_{co} C_{t-1} + h_o)$$
$$PR_t = logmoid\ (W_c A_t + W_{cc} C_{t-1}) + h_c$$
$$CU_t = f_t \times C_t + I_t \times \hat{C}_t + logmoid$$
$$C_t = O_t \times C_t$$
$$B_t = O_t \times C_t \times ELU$$

Wherein, f_t denotes forget gate; I_t denoted input gate; O_t denotes output gate, C_t denotes the activation factor used in cell; $h\ (f, i, o, c)$ denotes bias vectors; $W\ (f, i, o, c)$ denotes the weight matrix; C denotes the hidden value; A_t denotes the memory cell input; PR_t denotes the previous memory cell; CU_t denotes the current memory cell; B_t denotes the final output.

4. Experimental Setup

This study evaluates the proposed FIS integrated deep learning model (BiRNN) on the Pima-Indians-Diabetes-Dataset. The original dataset contains only 8 attributes with 5303 records. Hence, the data records were increased by using a data generator tool called "DATPROF" [23] to analyse the effectiveness of the proposed model. The data records are increased to a size of 50,000, which is further split for training and testing in 80:20 ratio. The proposed model has two hidden layers and a dense layer. Here, the nodes will be selected automatically based on the obtained accuracy value. The obtained IoT data is sent to a cloud server to perform classification and feature extraction. This experiment is carried out in TensorFlow.

5. Performance Analysis

Followed by the initial data pre-processing in the first model, the disease prediction is carried out using FIS model in the second model, and finally, the last proposed diabetes risk prediction model uses a combination of FIS and BiRNN. The proposed model is assessed using four performance metrics namely: precision, accuracy, recall and F1Score. These metrics are calculated as follows

$$Precision = \frac{TP}{FP + TP}$$

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN}$$

$$Recall = \frac{TP}{FN + TP}$$

$$F_1Score = \frac{2TP}{2TP + FP + FN}$$

6. Results and Discussion

This study finally evaluated and compared the implementation with traditional RNN, Fuzzy based RNN and the proposed BiRNN.

Table 4. Comparative Analysis in Terms of Accuracy

	Accuracy		
Data Used	**RNN**	**FRNN**	**Proposed BiRNN**
10	93.04	94.1	95.1
30	95.22	95.78	97.2
50	95.55	96.01	97.79
70	95.69	97.61	98.51
90	96	97.73	98.79
100	96.32	98.5	98.86

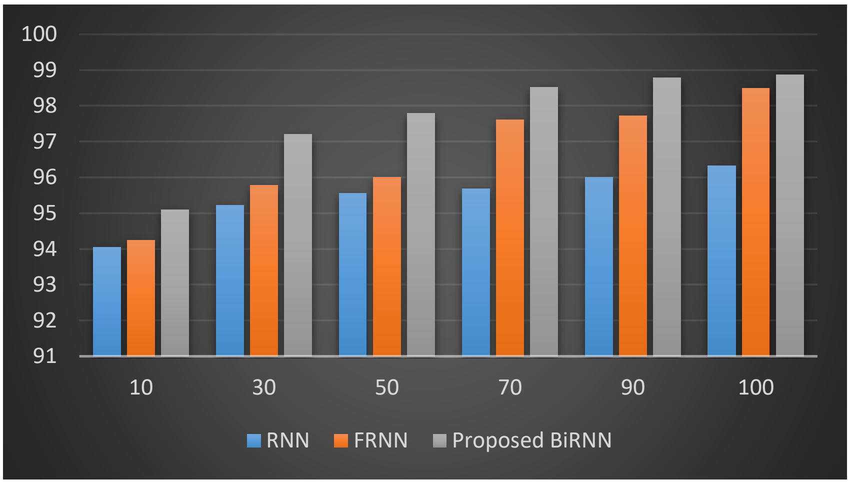

Figure 5. Graphical Comparative Analysis in terms of Accuracy

Table 5. Comparative Analysis in terms of Precision

	Precision		
Data Used	**RNN**	**FRNN**	**Proposed BiRNN**
10	94.25	94.8	95.2
30	94.75	96.91	96.94
50	94.92	97.52	97.92
70	94.85	97.9	98.43
90	95.32	98.55	98.72
100	95.66	98.73	98.79

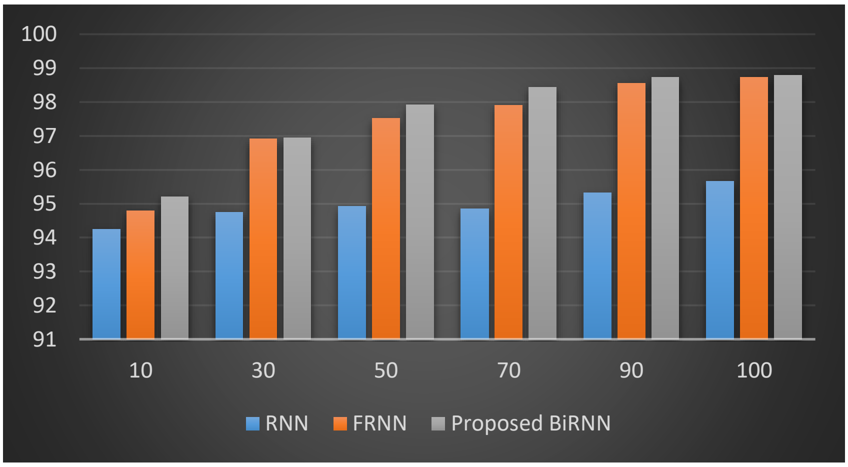

Figure 6. Graphical Comparative Analysis in terms of Precision

Table 6. Comparative Analysis in terms of Recall

	Recall		
Data Used	RNN	FRNN	Proposed BiRNN
10	94.53	94.72	95.11
30	94.52	96.84	96.89
50	94.92	97.52	97.81
70	95.25	97.93	98.66
90	95.93	98.1	98.82
100	95.96	98.2	98.99

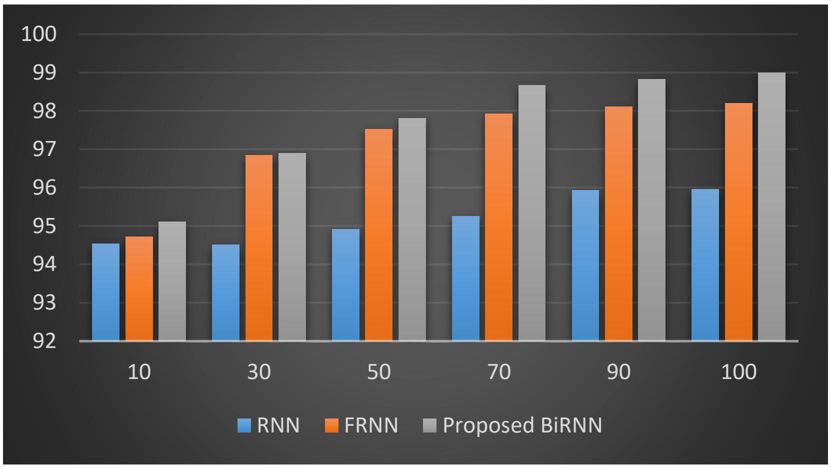

Figure 7. Graphical Comparative Analysis in terms of Recall

Table 7. Comparative Analysis in terms of F1-Score

	F1-Score		
Data Used	RNN	FRNN	Proposed BiRNN
10	94.54	94.76	94.85
30	94.82	96.51	96.98
50	94.95	97.29	97.72
70	95.21	97.69	98.46

90	95.33	97.96	98.96
100	95.47	98.53	98.98

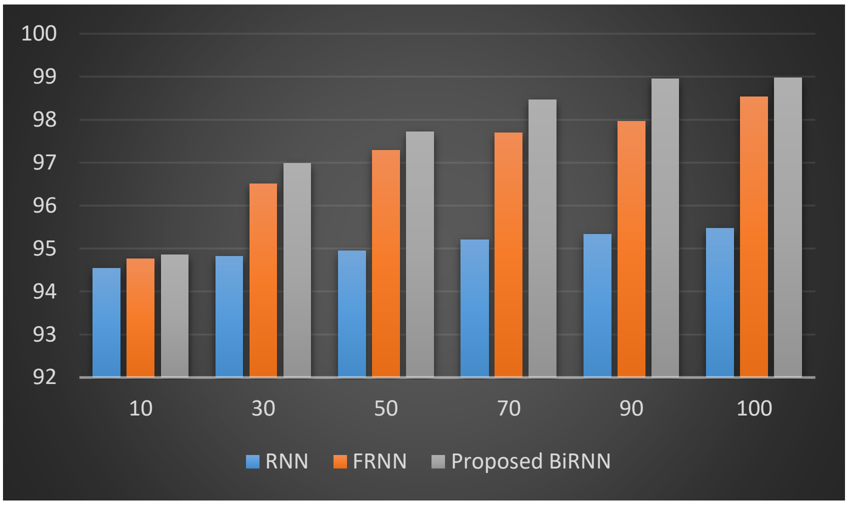

Figure 8. Graphical Comparative Analysis in terms of Recall

The aforementioned comparative analysis results on accuracy, precision, recall, and F1Score of the proposed BiRNN model, RNN, and FRNN models clearly shows that the proposed BiRNN model outperforms the other existing RNN and only Fuzzy Inference System (FIS) incorporated RNN (FRNN) model.

Figure 9 shows the overall comparison of RNN, FRNN and the proposed BiRNN Model

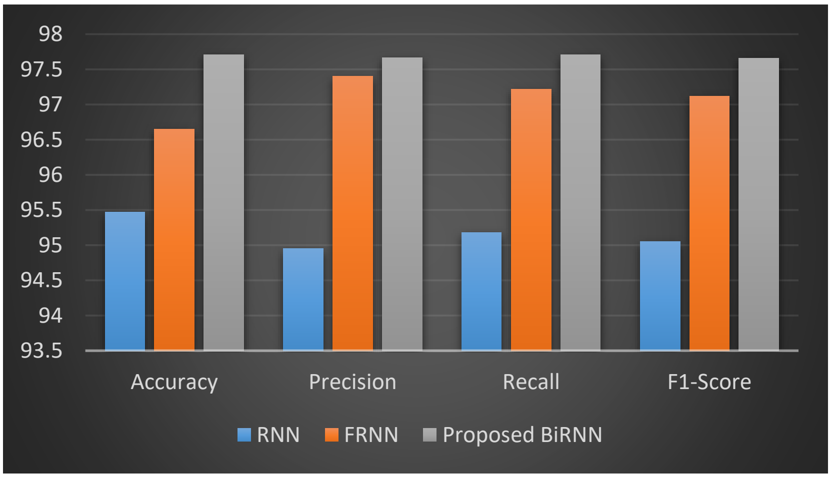

Figure 9. Overall Comparison of RNN, FRNN and the Proposed BiRNN Model

7. Conclusion

From the obtained results, it is clearly evident that the proposed model outperforms the other disease prediction models. As the existing disease prediction systems have more delay and is time- sensitive, when the number of devices connected to IoT and the data generation increases, the existing models face significant challenges in terms of resource utilization. Despite the hype, the Cloud of Things model is also inadequate in handing and big data and assisting the decision-making process. The proposed model performs diabetes prediction and reports or alerts the user with high-risk information. The model can be deployed in edge computing framework in the near future to reduce the communication latency.

References

[1] Hou, Kun Mean, Xunxing Diao, Hongling Shi, Hao Ding, Haiying Zhou, and Christophe de Vaulx. "Trends and Challenges in AIoT/IIoT/IoT Implementation." *Sensors* 23, no. 11 (2023): 5074.

[2] Volpert, Simon, Philipp Eichhammer, Florian Held, Thomas Huffert, Hans P. Reiser, and Jörg Domaschka. "The view on systems monitoring and its requirements from future Cloud-to-Thing applications and infrastructures." *Future Generation Computer Systems* 141 (2023): 243-257.

[3] Mishra Ph. D, Kamta Nath, and Subhash Chandra Pandey Ph. D. "Enhancing the Concert of M-health Technologies in Smart Societies Using Cloud-IoT-Based Distributive Networks." In *Cloud-IoT Technologies in Society 5.0*, pp. 133-161. Cham: Springer Nature Switzerland, 2023.

[4] Ahmad, Shahnawaz, Iman Shakeel, Shabana Mehfuz, and Javed Ahmad. "Deep learning models for cloud, edge, fog, and IoT computing paradigms: Survey, recent advances, and future directions." *Computer Science Review* 49 (2023): 100568.

[5] Rastogi, Rashi, and Mamta Bansal. "Diabetes prediction model using data mining techniques." *Measurement: Sensors* 25 (2023): 100605.

[6] Devi, K., Kumar, J. S., Poovizhi, S., & Krishnan, M. (2022). Analytical study on diabetes prediction-using random forest classifier. International Journal of Health Sciences, 6(S4), 6404–6413

[7] Xu, He, Qunli Zheng, Jingshu Zhu, Zuoling Xie, Haitao Cheng, Peng Li, and Yimu Ji. "A deep learning model incorporating knowledge representation vectors and its application in diabetes prediction." *Disease Markers* 2022 (2022).

[8] Tripathi, Deeksha, S. Reshmi, Arpita Nath Boruah, and Biswajit Purkayastha. "Diabetes Prediction Using Machine Learning Analytics: Ensemble Learning Techniques." In 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), pp. 1-7. IEEE, 2022.

[9] Sreedevi, B., Durga Karthik, J. Glory Thephoral, M. Jeya Pandian, and G. Revathy. "A Novel Neural Network Based Model for Diabetes Prediction Using Multilayer Perceptron and Jrip Classifier." In *Pervasive Computing and Social Networking: Proceedings of ICPCSN 2022*, pp. 345-351. Singapore: Springer Nature Singapore, 2022.

[10] Nasir, Tayyab, and Muhammad Kamran Malik. "SACDNet: Towards Early Type 2 Diabetes Prediction with Uncertainty for Electronic Health Records." *arXiv preprint arXiv:2301.04844* (2023).

[11] Yıldırım, E., Cicioğlu, M. & Çalhan, A. Fog-cloud architecture-driven Internet of Medical Things framework for healthcare monitoring. Med Biol Eng Comput 61, 1133–1147 (2023).

[12] El-Rashidy, N., ElSayed, N.E., El-Ghamry, A. et al. Utilizing fog computing and explainable deep learning techniques for gestational diabetes prediction. Neural Comput & Applic 35, 7423–7442 (2023).

[13] Batool, Rubab Zahra, Ali Hassan, Rizwan Ahmad, Waqas Ahmed, Joel JPC Rodrigues, and Ayman Radwan. "Fuzzy-Layered Recurrent Neural Network based Hybrid SWIPT Protocol for Cooperative Networks." *IEEE Communications Letters* (2023).

[14] Kumar, Mohit, Ashwani Kumar, Sahil Verma, Pronaya Bhattacharya, Deepak Ghimire, Seong-heum Kim, and ASM Sanwar Hosen. "Healthcare Internet of Things (H-IoT): Current Trends, Future Prospects, Applications, Challenges, and Security Issues." *Electronics* 12, no. 9 (2023): 2050.

[15] Qaq, Hasan, Omkar Kulkarni, and Yuming Jiang. "Reliable Sensor Data Gathering with Bluetooth Mesh: An Experimental Study." In *2023 Joint European Conference on*

Networks and Communications & 6G Summit (EuCNC/6G Summit), pp. 687-692. IEEE, 2023.

[16] https://www.openml.org/search?type=data&status=active&id=43483&sort=runs

[17] Hu, Guiting, Luping Xu, and Zhengjiang Zhang. "Gaussian process regression combined with dynamic data reconciliation for improving the performance of nonlinear dynamic systems." *Nonlinear Dynamics* (2023): 1-19.

[18] Scornet, Erwan. "Trees, forests, and impurity-based variable importance in regression." In *Annales de l'Institut Henri Poincare (B) Probabilites et statistiques*, vol. 59, no. 1, pp. 21-52. Institut Henri Poincaré, 2023.

[19] Saraf, Pranay, and Prasad Lokulwar. "Intelligence Furnished by Fog Intelligent Clinical Decision Support System for Healthcare Applications (FICDSS)." *International Journal of Intelligent Systems and Applications in Engineering* 11, no. 9s (2023): 08-24.

[20] Lin, Haijun, Sirao Zhang, Qinghao Li, Ya Li, Jianmin Li, and Yuxiang Yang. "A new method for heart rate prediction based on LSTM-BiLSTM-Att." *Measurement* 207 (2023): 112384.

[21] Misra, Diganta. "Mish: A self regularized non-monotonic activation function." *arXiv preprint arXiv:1908.08681* (2019).

[22] https://www.linkedin.com/pulse/activation-functions-neural-networks-leonardo-calderon-j-/

[23] https://www.datprof.com/solutions/synthetic-test-data-generation/