iGLU 4.1: An Intelligent Framework of Diabetes Prediction using Glucose-Insulin Values and Physiological Parameters

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***Abstract*—Nowadays, diabetes is a critical health issue for human beings. With the concern of being diabetic, people are more conscious of continuous glucose monitoring and medication. For this purpose, people are completely focused on smart monitoring devices, which can instantly measure glucose value without pain. However, the continuous glucose monitoring is not enough for diabetes prediction. Physiological parameters and other conditions are key factors that increase the likelihood of diabetes. Hence, it is required to propose a model, which predicts diabetes based upon the physiological parameters. In this paper, a machine learning-based diabetes prediction framework has been proposed, which evaluates the likelihood of diabetes based on diastolic blood pressure (DBP), body mass index (BMI), insulin intake, blood glucose value and skin thickness. The proposed framework has been calibrated using the DNN model. 543 subject observations have been taken to calibrate, validate and test the proposed DNN model. Overall 82% accuracy has been reported as a true prediction of diabetes. 0.0705 mean absolute error (MAE) has been observed in the predicted likelihood of diabetes using an optimized DNN model. The proposed iGLU 4.1 diabetes prediction paradigm helps the doctor diagnose and prescribe medication at remote locations.**

***Index Terms*—Diabetes Prediction, Non-invasive Glucose Monitoring, Smart Healthcare, Physiological Parameters, Real-time Systems**

I. Introduction

Diabetic patients have been increasing day by day and becoming a big issue for human health. 79%–82% deaths of diabetic patients have been declared by WHO in developing countries [1]. Nowadays, instant and precise diabetes prediction is a major part of smart healthcare. Generally, people prefer a balanced diet and medicine plan to keep blood glucose values in the normal range for a steady state [2]. Glycemic imbalance is the term used to describe when a person's body is unable to maintain a balanced amount of glucose [3], [4]. The main factor raising the likelihood of having diabetes is an imbalance of other physiological parameters. One of the primary causes of diabetes mellitus is an imbalanced diet and improper lifestyle [5]. Therefore, research on current healthcare trends focuses on early detection and improved treatment of diabetes. As a result, an analysis of the variables is necessary to determine the diabetes condition. The human body's unexpected fluctuations in glucose levels are caused by several factors. Changes in physiological factors may be linked to blood glucose fluctuations on several occasions.

High body temperature, or hypertension, is a responsible factor for changes in internal physiological parameters. Unbalanced body mass index (BMI) and skin thickness also indicate the likelihood of diabetes. Hence, such physiological parameters and other factors are required to predict the chance of diabetes. The blood glucose levels in an abnormal range with insulin intake also provide an important analysis of diabetes prediction [6]. Hence, these parameters are responsible for increasing the likelihood of diabetes. Therefore, it is required to implement a real-time framework for diabetes prediction that provides the necessary details of the patients to the experts at remote locations, where health centres are not available. The proposed framework, iGLU 4.1 is represented by the estimation of physiological parameters. This proposed framework will provide likelihood scores, which will help experts and users. This is being presented with data logging features in the cloud so that users and medical experts can access remote locations with prescribed diets and medicines. The patient could get a diagnosis immediately and get suggestions from other experts. The proposed paradigm is represented in Fig. 1 The presented framework iGLU 4.1, is an extension module of iGLU 4.0, which demonstrates the glucose prediction using physiological parameters. But, only glucose level prediction is not enough for justification of being diabetic. The likelihood of diabetes confirms the diabetes issues. Hence, iGLU 4.1 represents the glucose values as well as the likelihood of diabetes. So that, the patients can have the diagnosis as early as possible. The overall paper has been organised in the following arrangement. Prior research work is reported in Section II. The proposed framework is explained with the methodology in Section III. Section IV demonstrates proposed models for model training and validation. The experimental analysis has been done in Section V. Section VI represents the conclusion of current work with discussion of future direction.

II. Prior Related Research Work

Various diabetes prediction mechanisms have been proposed for instant and proper diagnosis with medication. In this way, invasive and minimally invasive measurement technology-

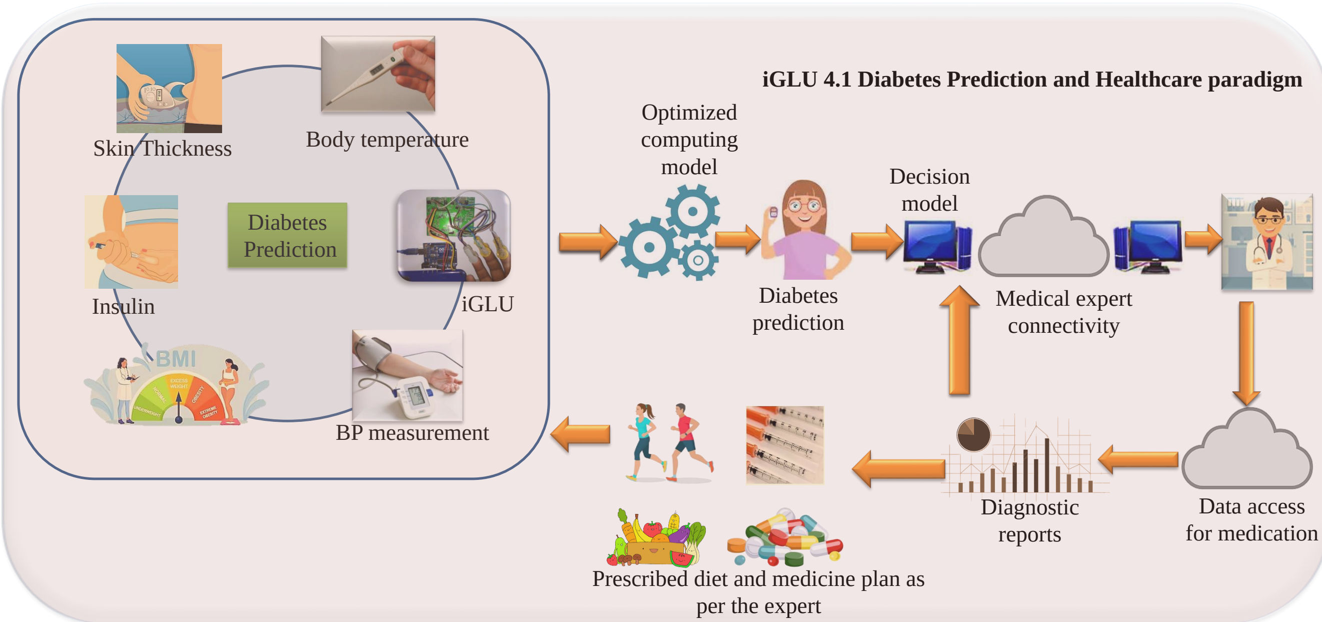

Fig. 1. Representation of iGLU 4.1 paradigm using IoMT framework

based handheld devices have been available for a long time [2]. Frequent glucose monitoring sensors were developed using minimally invasive techniques [7]. The wearable chips are inserted to analyse the membrane's immobilised glucose oxidase findings for continuous glucose monitoring. Using an implantation technique, glucose monitoring biosensors are set up with auxiliary frameworks to create a continuous glucose monitoring environment. These semi invasive invasive techniques have been tested on diabetic patients who need critical care. Such techniques cause skin irritation, pain, and trauma [8]. To reduce irritation and trauma, non-invasive measurement techniques came into existence, which reduced the chances of blood-related diseases. Moreover, the devices based on non-invasive techniques represented the advantages of instant diagnosis and medication. However, the measurement of blood glucose is not enough to confirm the likelihood of diabetes. The work presented earlier, predicts physiological parameters along with glucose values for precise prediction of true blood glucose levels. Hence, it is concluded that the estimation of physiological parameters along with glucose values increases the likelihood of diabetes, which directly represents true glucose levels. The proposed work represents the advancement of iGLU 4.0, which provides the feature of diabetes prediction using physiological parameters with a diabetes control framework. The evolution of iGLU for precise measurement and control with advanced features is represented in Fig. 2.

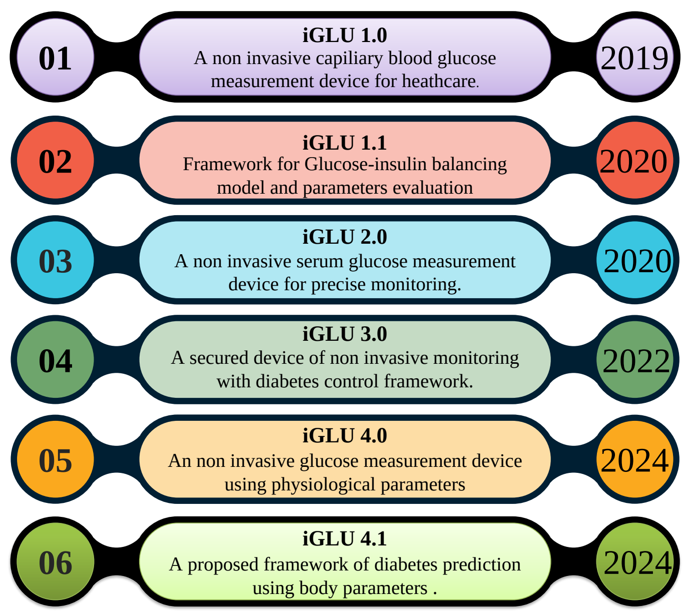

Fig. 2. The evolution of iGLU for precise measurement and control with advanced features

III. iGLU 4.1: Proposed Non-invasive Diabetes Prediction with Physiological Parameters

The proposed iGLU 4.1 device is based on glucose values received from iGLU 4.0 and other physiological parameters. The likelihood of diabetes is predicted through BMI, DBP, insulin intake, and skin thickness. The non-invasive glucose value, along with other physiological parameters, are used as predictors to train the mathematical model as per the prior available likelihood score of diabetes. The model has been trained and validated with enough observations, which have been collected and arranged for diabetes prediction [17]. The proposed design framework for diabetes prediction collects

TABLE I
PRIOR NON-INVASIVE WORKS WITH TECHNOLOGY ADVANCEMENT

Related Works	Method	Module	Cost	Reliability	Functional Specification
Praful,et al. [9]	Photo -acoustic	Sensing+ Measurement	High	High	BGM
Jain,et al. [10]	mNIRS	Sensing	Low	Mod.	BGM
Jain,et al. [11]	optical	Sensing+ Trained Model	Low	High	BGM
Joshi,et al. [12]	optical	Sensing+ Trained Model	Low	High	Serum Glucose Measurement
Joshi, et al. [13]	optical+ Data Security	Sensing+ Trained Model	Low	High	BG,Insulin Measurement
Jain, et al.[14]	Computing Model	Trained Model	Mod.	Mod.	Glucose Insulin Model
Murad, et al.[15]	optical	Online	-	-	Glucose Detection
(iGLU 4.0) [16]	optical+ Model	Sensing+ Measurement	Mod.	High	Glucose Balancing Paradigm
iGLU 4.1	**Prediction Model**	**Sensing+ Measurement**	**Mod.**	**High**	**Diabetes Prediction**

different attribute values from distinct available devices. The collected output has been compared to the reference likelihood scores from an accuracy point of view. The flow of the proposed framework for diabetes prediction is represented in Fig. 3.

A. Novel Contribution of Current Paper

The proposed diabetes prediction framework measures the likelihood of diabetes using various physiological parameters. It also decreases the chance of the misconception that someone has type 2 diabetes or not. The proposed framework is based on a multi-sensing approach from glucose measurement to other physiological parameters. The collected inputs are processed to the optimised prediction model for prediction [10]. The collected parameters have supported to have a precise and instant diagnosis. The proposed framework requires a prior setup for measurement. The model can predict the occurrence of diabetes at any time [18]. The system will be handheld after configure to be used everywhere. The proposed iGLU 4.1 is used to identify and segregate diabetic people. The proposed system stores all parametric values in the cloud to consult with the individual. The **novel contribution in current paper** are as follows:

1) A precise, non-invasive framework with diabetes prediction is proposed to estimate the likelihood of diabetes without an HbA1c test.
2) The overall framework has been trained, validated and tested for optimized prediction using collected and arranged datasets for precise estimation for diagnosis and treatment.
3) All parameters are stored and accessible by medical consultants and users using the IoMT framework.

IV. PROPOSED DNN MODEL FOR DIABETES PREDICTION WITH VALIDATION AND TESTING

The deep neural network-based computing model is utilised to predict diabetes. The output response of the current framework is quantitative for accuracy and performance analysis [19]. It is necessary to validate and test the trained model for precise prediction [20]. The basic characteristics of the collected and arranged parametric data are shown in Table II. The data has been collected from persons in the age range of 21–81 years. According to Table II, the male subjects were taken from ages 22–81, and the female subjects were taken from ages 21–65 [21]. The data has been collected as per the random checked people for experimental analysis. The high range of data has been considered to train and validate the computing model from an accuracy point of view [3]. Insulin intake patient data has been collected, which was found to be more than 50% of the total sample size. A DNN model is implemented for precise diabetes prediction. Statistical analysis has been done to obtain the accuracy and performance parameters [22]. The proposed DNN model representation is shown in Fig. 4. It develops the complex relationship between input values and the output response. In this represented model, measured parameters of five channels (all input values) are combined [23].

TABLE II
CHARACTERISTICS OF COLLECTED AND ARRANGED DATA

Basic terms	**Subjects with Insulin intake**	**Samples with Parameters**
Gender Male:- **300** Female:- **243**	**Gender wise** Male:- **200** Female:- **153**	**BP and Skin Thickness** All samples with different BP, Skin Thickness
Age (Years) Male:- **22-81** Female:- **21-65**	**Age wise** 21-34 Yrs:- **50** 35-81 Yrs:- **303**	**Body Temperature, BMI** All samples with different body temperature, BMI

V. EXPERIMENTAL ANALYSIS AND RESULTS

The presented DNN model integrates five inputs with digital representation for diabetes prediction [24]. 10 hidden layers have been used to predict the response. Fig. 5 explores the methodology of diabetes prediction using the proposed model. The complete algorithmic flow is presented for estimation. The given flow chart is demonstrated for prediction purposes. The DNN model has been implemented with the LM algorithm [23]. The data size is 543, from which 70% subjects are randomly selected for training the specified model. The trained model is then validated and tested by 30% subjects as per the default ratio of the model. After implementing the proposed model, 0.0705 MAE, and 82% average accuracy have been confirmed in the predicted likelihood of diabetes. The predicted responses have been represented as per the segregated data by age. The diabetes predictions are represented in Fig. 6. The persons have been taken from ages 21-81. The data has been taken from people at random without any specific protocol of gender and age [7]. The same data set has been

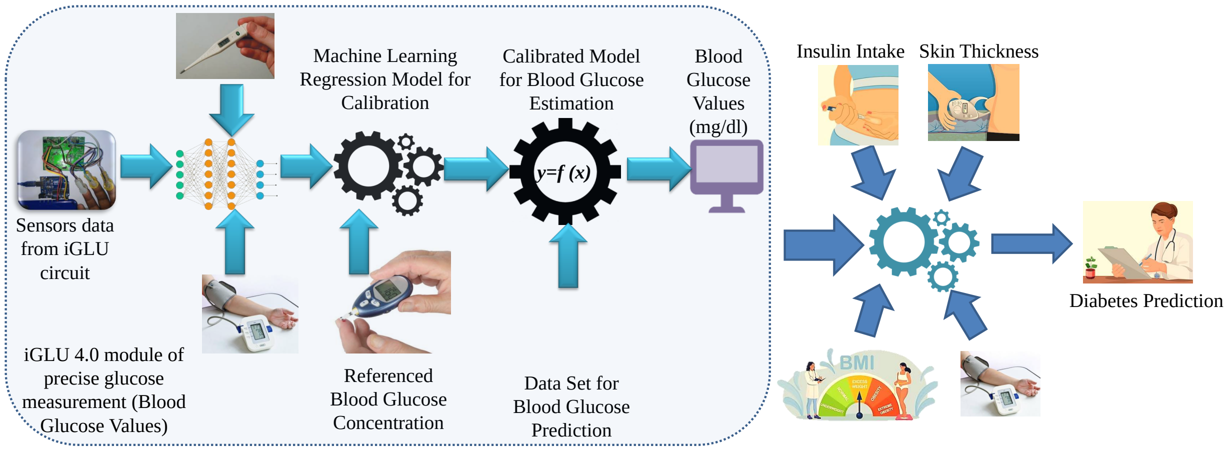

Fig. 3. The process flow of iGLU 4.1 proposed framework for diabetes prediction.

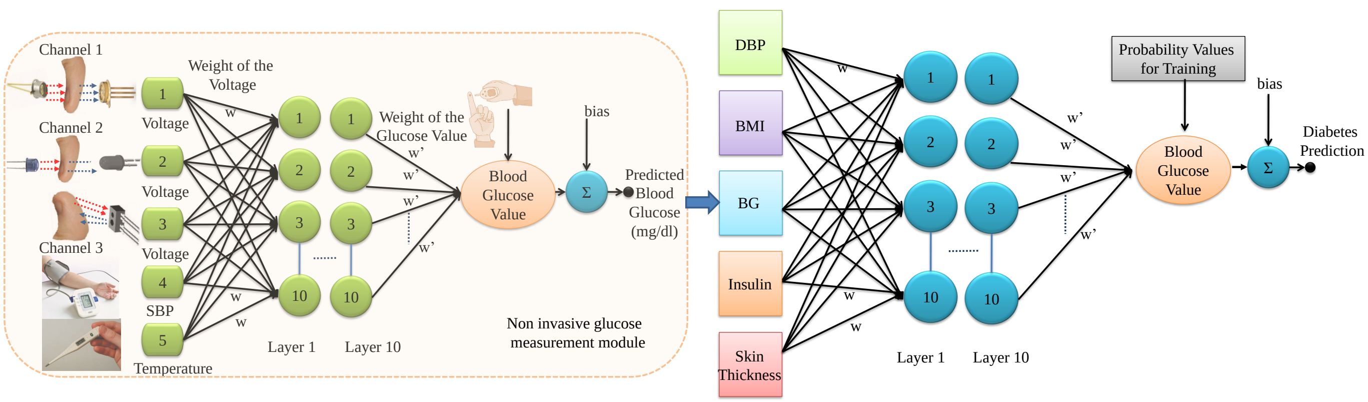

Fig. 4. Proposed DNN model representation of diabetes prediction

used to train the polynomial model. 70% samples have been taken for training purposes. The trained model is further validated and tested using 15% samples for each. After the analysis, it has been observed that maximum accuracy has been achieved using the proposed DNN model. The presented box plot and histogram demonstrate the range of error prediction of diabetes. It is represented in Fig. 7 and 8.

The tabular representation demonstrates further advancement compared to prior related work in Table III.

TABLE III
COMPARISON WITH PRIOR WORKS

Works	R^2	MAE	Sample	Range	Application
Kirubakaran, et al. [25]	0.91	-	Pancreas	Specific	Glucose Prediction
Singh, et al. [26]	0.8	-	Saliva	Specific	Glucose Prediction
Mohammadi, et al. [27]	-	-	Body	-	Glucose Detection
Erick, et al. [28]	0.9	-	Capillary Blood	High	Glucose Detection
Jain, et al. [13]	0.96	12.6	Blood	High	BG-Insulin Model
Jain, et al. iGLU [11]	0.95	6.35	Capillary Blood	High	BG Prediction
Joshi, et al. iGLU 2.0 [12]	0.97	4.92	Serum	High	Serum Glucose Prediction
Joshi, et al. iGLU 3.0 [13]	0.90	9.96	Serum	High	BG Prediction & Security
iGLU 4.0 [16]	0.97	9.2	Blood+ Body(SBP)+ Temperature	High	BG Balancing Paradigm
iGLU 4.1	**0.9**	**0.0705**	**Whole Body**	**Moderate**	**Diabetes Prediction**

VI. Conclusion and Future Direction

The proposed paradigm of diabetes prediction consists of precise non-invasive glucose values and estimated physiological parameters. The proposed framework delivers the feature to provide supporting data related to diabetes, which would provide support to medical experts to examine diabetic people. The combination of five different parameters processing and diabetes evaluation system is highlighted. The proposed framework is an analytical model to provide a better diagnosis with less effort from the consultant without any significant delay. Hence, the proposed work will be a comparatively optimized solution. It is concluded that the iGLU 4.1 will be supporting

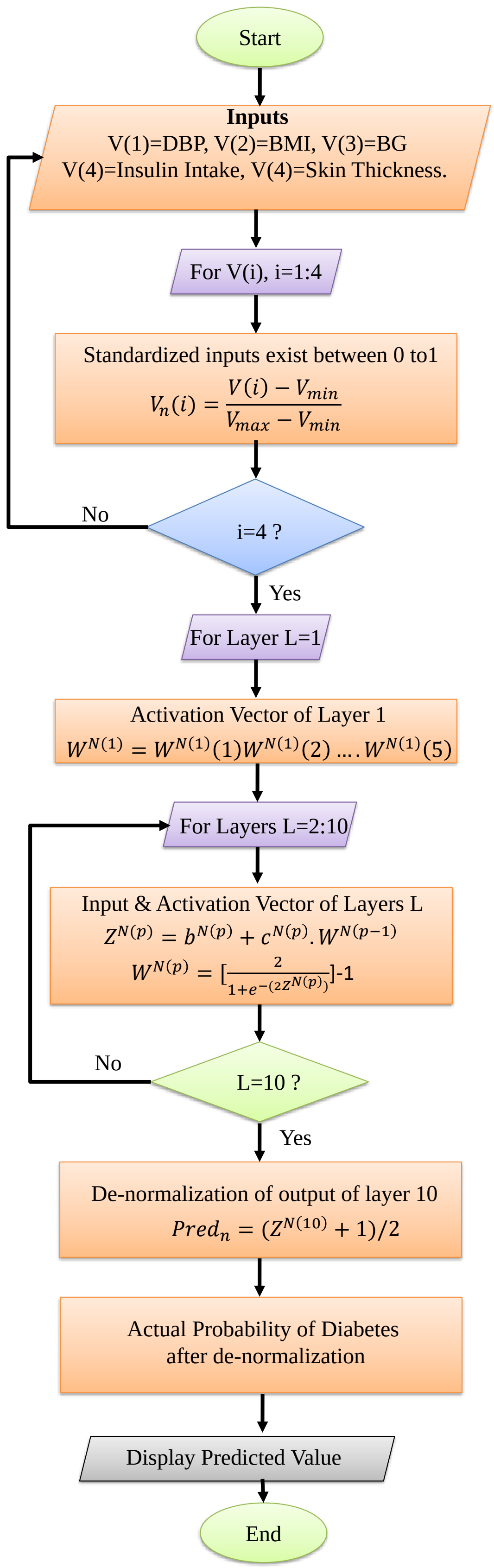

Fig. 5. Algorithmic flow of the diabetes prediction with specified expressions.

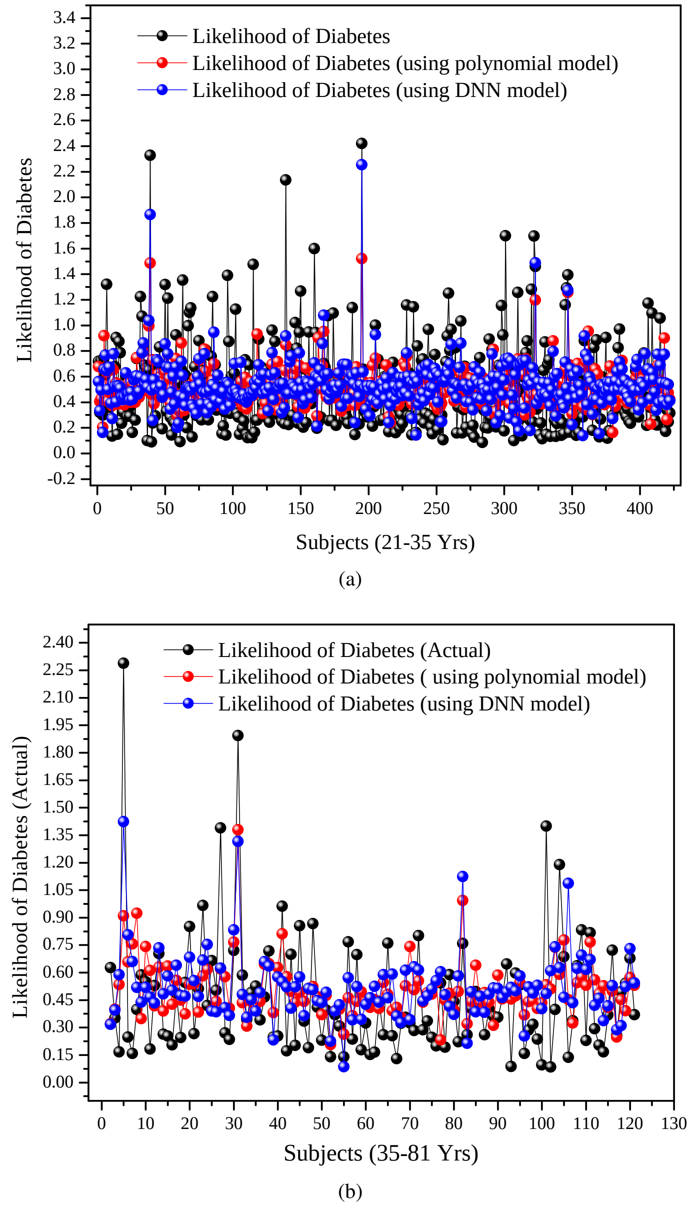

Fig. 6. Estimated responses of likelihood of diabetes

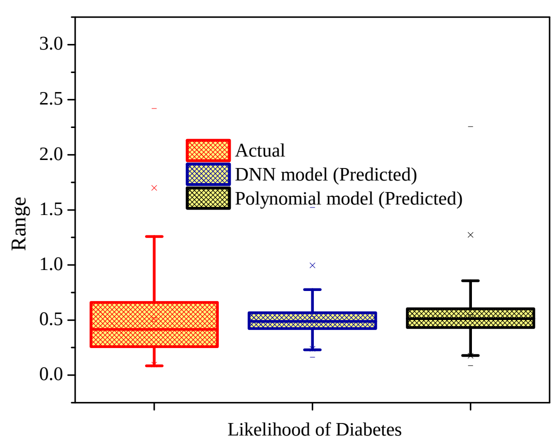

Fig. 7. Error Analysis during prediction of diabetes using computing models

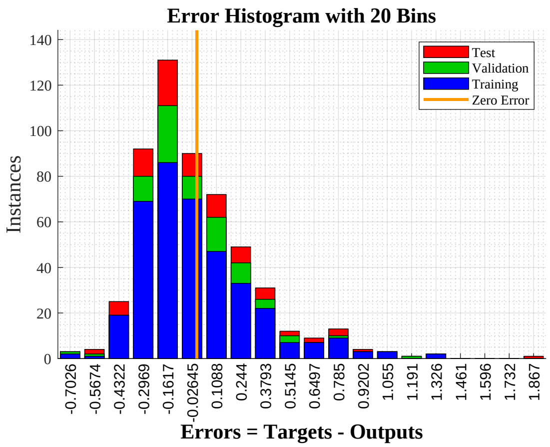

Fig. 8. Error Analysis using histogram during prediction of diabetes using computing models

to segregate the diabetic people. A significant accuracy of 82% has been achieved using an optimized model of the likelihood of diabetes.

In future plan, it is required to design a non-invasive glycosylated haemoglobin (HbA1c) test framework along with diabetes prediction. This will facilitate diabetes prediction and average blood glucose values of the previous 2-3 months. HbA1c test is always found an introductory test.

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