iGLU 4.2: A Non-invasive Intelligent System for Diabetes Likelihood Prediction using Glucose Values and Body Parameters

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***Abstract*—Diabetes is becoming a serious concern for human health. Therefore, people are possessive to maintain a balanced body glucose level for a healthy life. For this concern, people are following the early diagnosis processes, which can predict the stage of diabetes. However, glucose level prediction is not solely responsible for diabetes prediction. other body parameters and corresponding conditions are very important, which provide the precise likelihood of diabetes. So, the proposed system provides the quantitative analysis of diabetes probability. In this paper, a non invasive intelligent system has been proposed, which quantifies the likelihood of diabetes based on average diastolic blood pressure (DBP), body mass index (BMI), random average blood glucose value and skin thickness. The proposed system has been trained using multivariate PRM of degree 9. 532 subjects have been taken to train and validate the proposed PRM model with degree 9. In general, the accuracy 89.6% has been reported as a prediction of the true likelihood of diabetes. 0.0302 mean absolute error (MAE) has been confirmed in the predicted diabetes likelihood using an optimized PRM model. The proposed iGLU 4.2 diabetes likelihood prediction system helps the expert for early diagnosis and medication at different locations.**

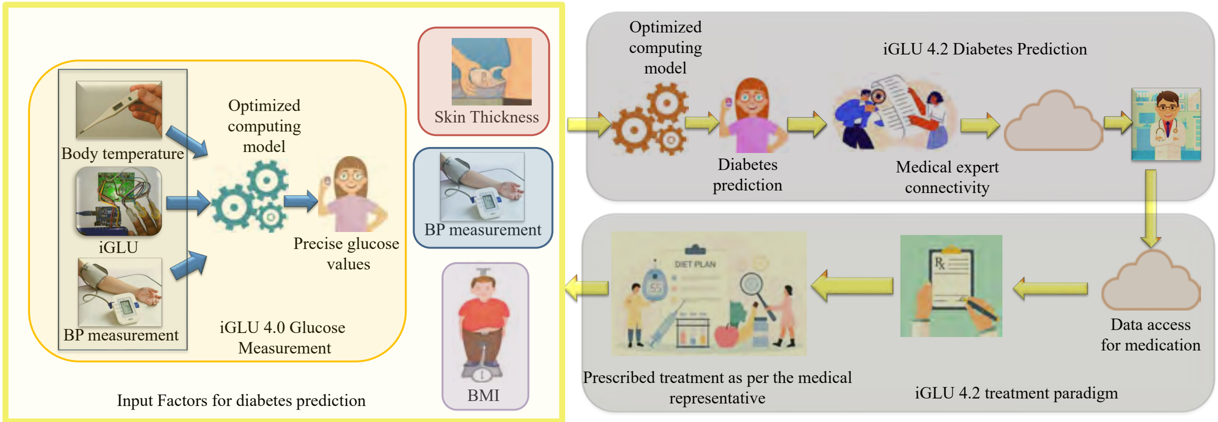
***Index Terms*—Diabetes Prediction, Non-invasive Glucose Monitoring, Smart Healthcare, Physiological Parameters**

I. Introduction

Nowadays, diabetes is a major and crucial health issue for human beings. Moreover, it is now the root cause of many diseases, such as heart disease, kidney failure, liver cirrhosis, etc. It is also a major issue in developed countries [1]. Nowadays, early diagnosis of diabetes and treatment are major parts of advanced healthcare. People follow the standard and prescribed diet plan to balance the glucose-insulin level for good health for a long time [2]. Blood glucose fluctuation represents the unbalancing of glucose levels due to a bad lifestyle or deficiency of insulin in the human body [3], [4]. An unbalanced diet plan with body mass index, blood pressure and random changes in glucose level are the main factors to increase the likelihood of diabetes. Sometimes, the high body temperature is responsible for the fluctuation of blood glucose levels. [5]. For observation of the factors, an analysis of the physiological and other body parameters is required to predict the early diabetes likelihood prediction. The variation in blood glucose levels out of normal range may not indicate the likelihood of diabetes. It may be possible because of sudden food intake. Therefore, it has been observed that only blood glucose measurement can't be the proper way of diagnosis. Some other physiological and body parameters are required to monitor for proper diagnosis. Hence, people are not only looking for disease diagnosis; they are focusing on early prediction of disease as well. Due to early prediction, people will have early prescribed treatment so that the disease could be cured as early as possible.

Body temperature fluctuation and unbalanced blood pressure are pioneers for changes in internal physiological parameters. Unbalanced body mass index (BMI) and skin thickness are also supporting parameters for the likelihood diabetes prediction. Hence, these parameters with other factors are required to monitor along with glucose levels to predict the likelihood [6]. Hence, these parameters enhance the accuracy in prediction of likelihood of diabetes. Therefore, it is necessary to implement a real-time system for early likelihood diabetes prediction without pricking the blood. This system would be helpful to provide monitoring of the parameters to the experts at remote locations for continuous monitoring. The proposed system, iGLU 4.2 is an advanced version of likelihood diabetes prediction, which will not only scale the likelihood of diabetes through prediction of physiological parameters precisely, it can monitor the likelihood values continuously without pricking the blood. This proposed system will provide likelihood scores continuously, which will provide the required details to the experts and users for proper treatment on prior basis. This is presented with continuous data monitoring so that users and doctor can access the data at remote locations for early treatment. The patient may discuss to the medical expert regarding early prediction of diabetes so that it could be curable on time. The proposed system is represented in Fig. 1

The presented system, iGLU 4.2, is an advanced version of iGLU 4.1, which predicts the diabetes likelihood using body parameters along with glucose levels. iGLU 4.1 is a system for prediction along with insulin measurement, which categorizes it as semi-invasive. mode. This system can't be considered for continuous evaluation of diabates likelihood. To overcome this issue, iGLU 4.2 has been developed. The overall paper is organised in the following manner. Prior related work is reported in Section II. The proposed system is explored with



the mechanism in Section III. Sec
computing model for feasibilty a
analysis has been done in Section
the conclusion of current work wi

II. Prior Relat

Different methodologies and app
for glucose level measurement alo
In this way, various detection-ba
diabetes prediction frameworks ar
systems are under development fo
have observed various physiologic
diabetes prediction. Frequent gluc
developed, which are based on c
ing, and various parameters measu
invasive wearable sensors are test
for continuous glucose monitorin
configured with auxiliary circuits f
monitoring. These different appr
were precise and stable from a me
diabetic patients; they were neede
Such implantation of sensors bene
tation, pain, and other unavoidabl
such problems, non-invasive appr
higher demand, which actually redu
diseases and trauma. Additionally,
based systems offered the benefi
and medicine. However, blood glu
enough for early diagnosis and
predicts physiological parameters
for precise diabetes likelihood.
developed with a semi-invasive ap
The prior framework can not be co
diction. Hence, it is concluded that
based system is required for diabetes likelihood prediction. The current work demonstrates the advancement of iGLU 4.1, which provides the feature of diabetes likelihood prediction using body parameters along with glucose levels without pricking the blood. The evolution of iGLU for precise glucose detection and diabetes prediction with advanced features is represented in Fig. 2.

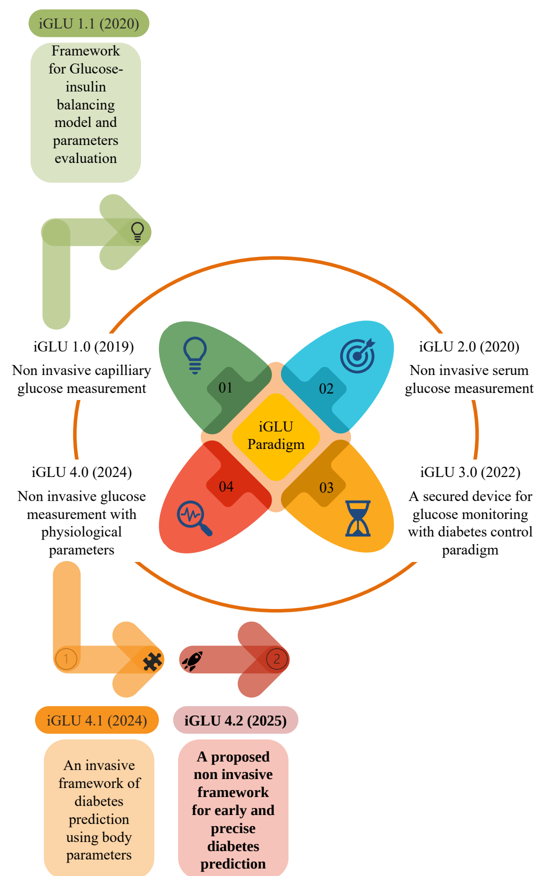


Fig. 2. Representation of iGLU evolution and prior related work

III. iGLU 4.2: Proposed Non-invasive Likelihood Prediction System for Early Diagnosis

The proposed iGLU 4.2 system is based on body parameters and glucose values received from iGLU 4.0 with a scheduled

TABLE I
NON-INVASIVE PRIOR RELATED WORKS

Related Works	Detection	Approach	Cost	Type	Application
Oladosu et al. [8]	- -	Data Analysis	-	-	Likelihood prediction
Jain,et al. [9]	mNIRS	Non-invasive	Low	Device	BGM
Jain,et al. [10]	optical	Non-invasive	Low	Device	BGM
Joshi,et al. [11]	optical	Non-invasive	Low	Device	Serum Glucose Measurement
Joshi, et al. [12]	optical+ Data Security	Non-invasive	Low	Framework	BG,Insulin Measurement
Jain, et al.[13]	Computing Model	Trained Model	Mod.	Framework	Glucose Insulin Model
Kaliappan, et al.[14]	-	Data Analysis	-	-	Likelihood prediction
(iGLU 4.0) [15]	optical+ Model	Non-invasive	Mod.	Framework	Glucose Balancing Paradigm
iGLU 4.1	Prediction Model	Invasive	Mod.	Framework	Likelihood prediction
iGLU 4.2	**Prediction Model**	**Non-Invasive**	**Mod.**	**Framework**	**Likelihood prediction**

time. The parameters have been collected without pricking blood. The likelihood diabetes prediction has been done through BMI, average value of BP, and skin thickness along with randomly collected glucose values. The non-invasive glucose level and body parameters have been considered as independent variables to train the computing model with the dependent variable likelihood score of diabetes. The model has been trained, validated, and tested with 532 subjects. The data has been collected and arranged for likelihood prediction [16]. The proposed system for likelihood prediction collects different parametric values from some other wearable and non-invasive systems. The collected response has been monitored and compared with reference likelihood values for accuracy monitoring. The flow of the proposed system of likelihood prediction is represented in Fig. 3.

A. *Novel Contribution of Current Paper*

The proposed diabetes likelihood prediction system scales the level of likelihood for early prediction using random glucose levels with body parameters. The proposed system can segregate the patients into type 1 and type 2 diabetic people. The proposed system is using multiple handheld devices along with the iGLU 4.0 system for glucose level measurement and body parameter monitoring. The input values of the parameters are processed for prediction [9]. After the data processing, the proposed system would be able to predict the likelihood values. The system required combined handheld devices for data collection so that likelihood values could be examined. The computing model would be able to predict and segregate without any environmental constraint. The overall proposed system would be a single unit after configuration that would be used everywhere. The proposed iGLU 4.2 is used to analyze the diabetic people on a prior basis. The **novel contribution of the current paper** are as follows:

1) An accurate, non-invasive system for likelihood prediction with glucose values is proposed, which has reduced the risk of trauma and blood-related disease.
2) The overall configured system has been calibrated, validated and tested for accurate and optimised prediction using handheld device data with iGLU 4.0.
3) The values of the parameters would be stored for future correspondence so that the treatment could be provided accordingly.

IV. PROPOSED POLYNOMIAL REGRESSION MODEL (PRM) FOR DIABETES LIKELIHOOD PREDICTION

The polynomial regression-based computing model has been examined to predict diabetes likelihood. The output response of the proposed system is quantitative for real-time prediction during analysis [17]. The system has been analyzed at different levels of polynomial degree along with calibration, validation, and testing of the optimized model [18]. The basic characteristics of the collected data from the handheld device, along with iGLU 4.0, are shown in Table II. The data has been collected

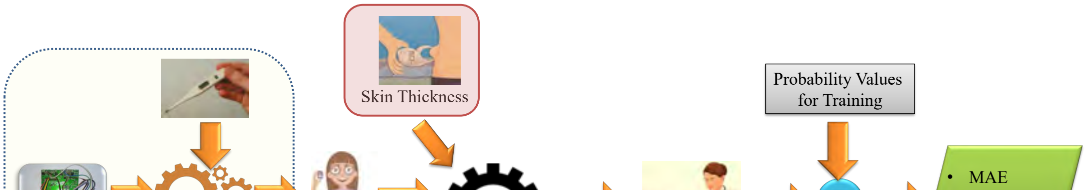
TABLE II
DATA CHARACTERISTICS FOR IGLU 4.2 DEVICE

Basic terms	**Subjects with Insulin intake**	**Samples with Parameters**
Gender	**Gender wise**	**BP and Skin Thickness**
Male:- **290**	Male:- **-**	All samples with
Female:- **242**	Female:- **-**	different BP, Skin Thickness
Age (Years)	**Age wise**	**Body Temperature, BMI**
Male:- **22-65**	22-65 Yrs:- **-**	All samples
Female:- **18-75**	18-75 Yrs:- **-**	

from people of ages 18–75 years. According to Table II, the male subjects have been considered from ages 22–65, and the female subjects have been considered from ages 18–75. The data has been collected and arranged using medical protocols for experimental analysis. The larger data has been considered for system calibration and validation of the computing model from an accuracy point of view [3]. The balanced data of type 1, type 2 and healthy people have been considered for system training for true prediction. A PRM model has been observed and implemented for precise likelihood prediction. Performance analysis has been done to obtain and confirm the accuracy along with other statistical parameters [19]. The proposed PRM model with mechanism is represented in Fig. 4. It configures the input values for output prediction. In this represented model, the parameters of four channels (all input values) are arranged [20].

V. EXPERIMENTAL ANALYSIS AND RESULTS

The presented PRM model configures four inputs numeric values for diabetes prediction [21]. Polynomial degree 9 of interaction has been observed for precise likelihood prediction. Fig. 5 represents the work flow of likelihood prediction using the proposed analyzed computing model. The given



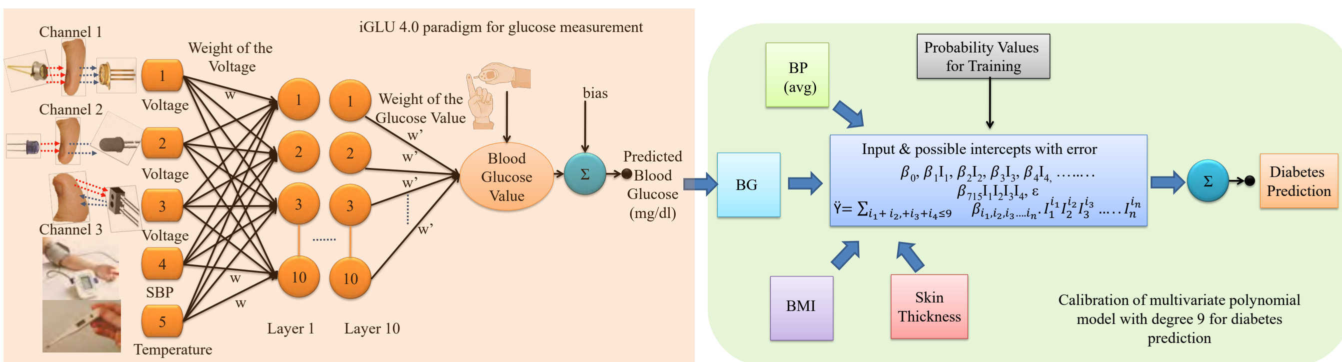


Fig. 4. Proposed PRM model of degree 9 for diabetes likelihood prediction

pseudocode is presented for prediction purposes. The PRM model has been examined and implemented using interaction model of polynomial degree 9. 532 subjects have been taken for examining the feasibility. 70% subjects have been taken for system training purposes, and the remaining 30% have been considered from a validation and testing point of view. After examing the proposed model, 0.0302 MAE, and 89.6% average accuracy have been observed from the prediction. The likelihood predictions are represented in Fig. 6. The data has been taken from people with gender and age-wise for precise model prediction [7]. The data has been used to calibrate the PRM model. 70% of people's data has been segregated for training purposes. The calibrated model is analyzed for validation and testing using 15% for each. After the observation, it has been analyzed that maximum accuracy has been achieved using the proposed PRM model of interaction degree 9. The box plot and histogram represented the level of error prediction in likelihood. It is demonstrated in Fig. 7 and 8. Comparative analysis to prior related work is represented in Table III.

VI. Conclusion and Future Direction

The proposed system of likelihood prediction is represented for precise non-invasive glucose values along with diabetes likelihood prediction. The proposed system provides

TABLE III
Quantitative Analysis with Prior Works

Works	R^2	MAE	Object	Technology	Application
Kirubakaran, et al. [22]	0.91	-	Pancreas	Image Sensing	Glucose Prediction
Singh, et al. [23]	0.8	-	Saliva	Electrical sensing	Glucose Prediction
Mohammadi, et al. [24]	-	-	Body	dual wave sensing	Glucose Detection
Erick, et al. [25]	0.9	-	Capillary Blood	- -	Glucose Detection
Jain, et al. [12]	0.96	12.6	Blood	Multi wave sensing	BG-Insulin Model
Jain, et al. iGLU [10]	0.95	6.35	Capillary Blood	Multi wave sensing	BG Prediction
Joshi, et al. iGLU 2.0 [11]	0.97	4.92	Serum	Multiple sensing	Serum Glucose Prediction
Joshi, et al. iGLU 3.0 [12]	0.90	9.96	Serum framework	Hybrid	BG Prediction & Security
iGLU 4.0 [15]	0.97	9.2	Blood+ Body(SBP)+ Temperature	Hybrid Framework	BG Balancing Paradigm
iGLU 4.1	0.90	0.0705	Whole Body	Moderate	Likelihood Prediction
iGLU 4.2	**0.92**	**0.0703**	**Whole Body**	**Multiple sensing**	**Likelihood Prediction**

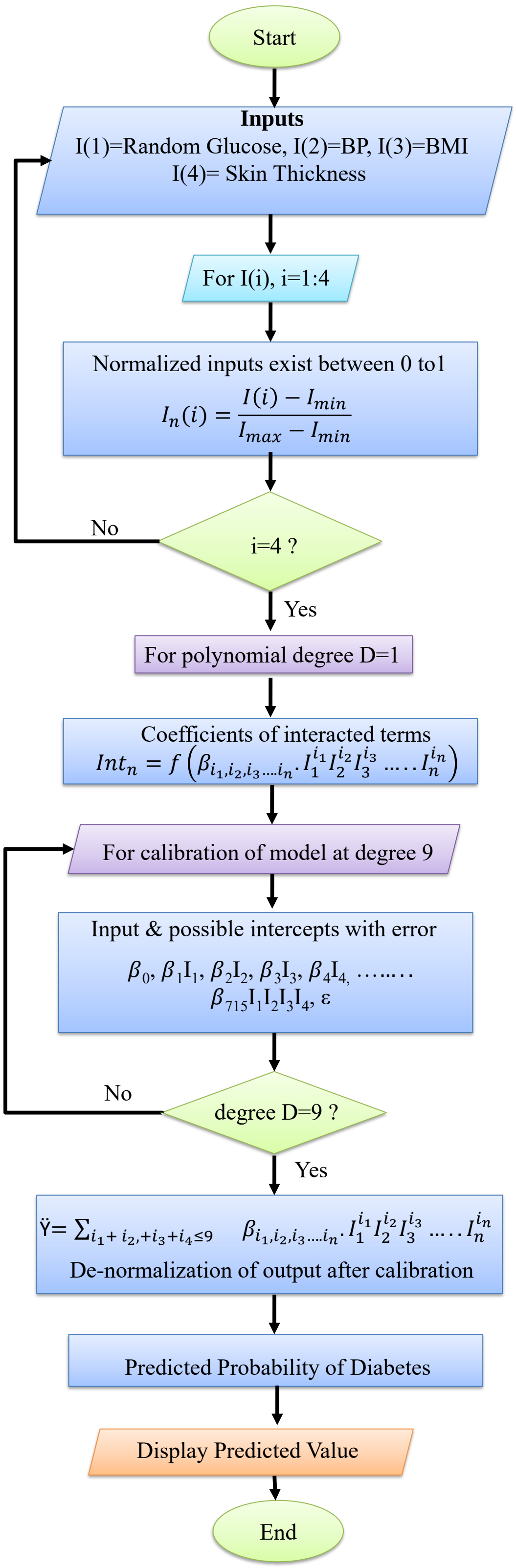
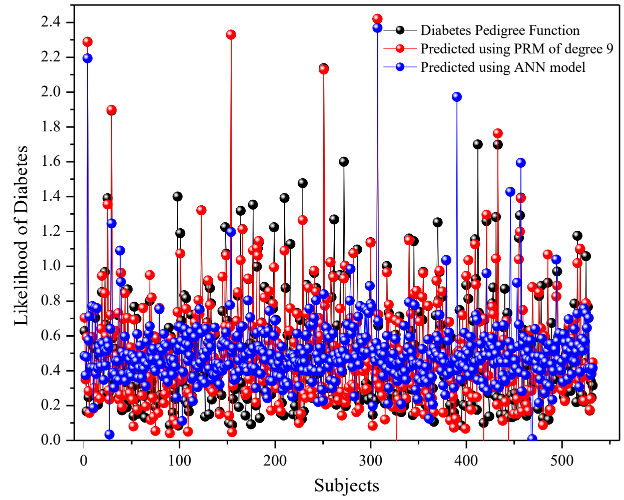
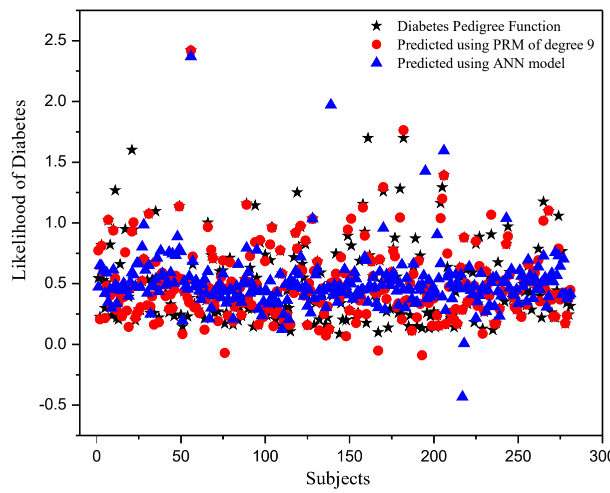


Fig. 5. Algorithmic flow of the likelihood prediction of iGLU 4.2.



(a) All Subjects



(b) Validation

Fig. 6. Analysis of likelihood diabetes prediction

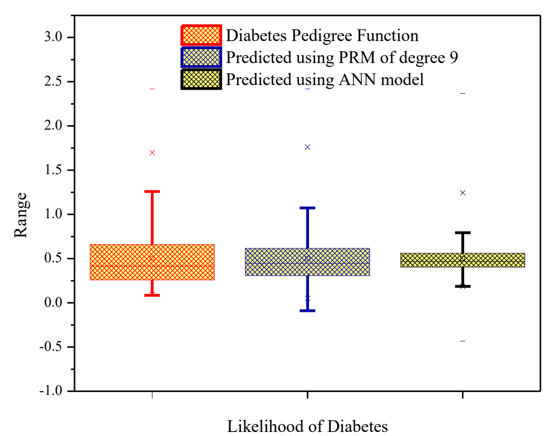


Fig. 7. Box plot analysis of diabetes likelihood prediction using prediction models

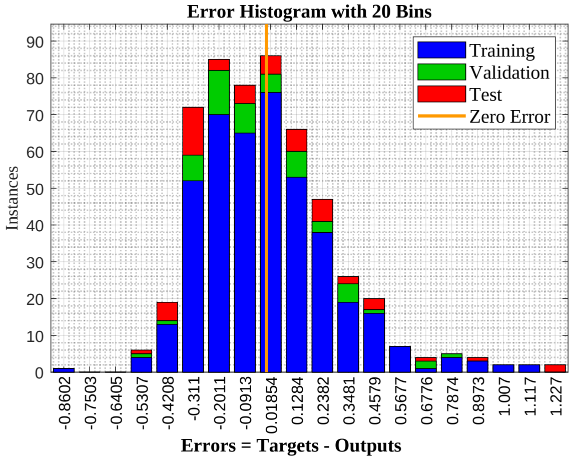


Fig. 8. Histogram Analysis of error for likelihood prediction using prediction models

the relevant data for precise confirmation, which would help the medical representative to observe the data for diabetes confirmation. The configuration of four different parameters and likelihood system is highlighted. The proposed system is an advanced form of likelihood prediction, which provide maximum confirmation chance of diabetes or not, which helps to experts to provide the medical treatment on an earlier basis. It is observed that the iGLU 4.2 will be supportive in segregating the diabetic people accurately. A significant average accuracy of 89.6% has been achieved using the PRM model of the likelihood of diabetes. In the future plan, it is required to design a non-invasive diabetes confirmation system. This will facilitate the confirmation of being diabetic at patient level for uniform and prior treatment.

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