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EXISTENTIAL RISK PREDICTION MODELS FOR DIABETES MELLITUS

Moko Anasuodei[1] and Victor-Ikoh Maudlyn[2]

Department of Computer Science and Informatics, Federal University Otuoke, Nigeria

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ABSTRACT: *Diabetes mellitus is a disease of the human body that is caused by high blood sugar levels and inactivity, poor eating habits, being overweight etc. This paper reviewed, and analyzed diabetes mellitus Type 1, Type 2, and Gestational diabetes diverse risk prediction models and algorithms employed. In this study, the methodology adopted is the exploratory descriptive approach, which clearly describes the various deep learning and machine learning risk prediction model used for diabetes mellitus classification and forecasting problems. The Deep Neural Network Model algorithms given in this work have the highest score in terms of accuracy and outperformed machine learning models in terms of performance, there is also the issue of other various algorithms' precision. It is recommended that when conducting a classification and risk prediction survey on the different variants of diabetes mellitus, researchers consider using the algorithms explicitly described while paying close attention to their advantages and disadvantages, as well as their potential outcomes. It is also possible to combine deep learning techniques and machine learning algorithms to create ensemble models, which can improve prediction performance.*

KEYWORDS: Diabetes, Type 1, Type 2, Gestational, Deep Neural Network, Machine Learning

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INTRODUCTION

Diabetes is a multi-pronged locution for how your body transforms energy into food. It is regarded as a serious condition connected with an abdominal illness of the body whereby blood glucose levels have been incongruent because of a deficiency in the pancreas leading to low insulin or no insulin production at all, triggering insulin resistance to type 1 diabetes or cells, causing type 2 diabetes. The major source of diabetes is still unclear, nevertheless, scientists believe that diabetes is majorly ascribed to both genetic and environmental factors. It can be handled through treatment and medication, although it is incurable. Individuals with diabetes mellitus are vulnerable to some secondary health problems, for example, heart disease and nerve damage. (Larabi-Marie-Sainte *et al.* 2019)

There are three major diabetes forms: type 1, type 2 and gestational diabetes. Type 2 diabetes among these 3 is extremely common and accounts for 90% to 95% of all cases. Type 2 diabetes mellitus can be predicted, prevented, and reported based on lifestyle (for instance, low physical activity, obesity) and additional possibilities (for example, age, sex, race, and family history) usually develop later in life. Many models for predicting Type 2 diabetes have been developed, (Xie *et al*. 2019). However, Type 1 known as the aetiological type includes most cases, mainly due to pancreatic β - cell killing and ketoacidosis, its cases are attributed to an auto-immune process, or are ketoacidosis-prone and have no known anethogenesis or pathogenesis.

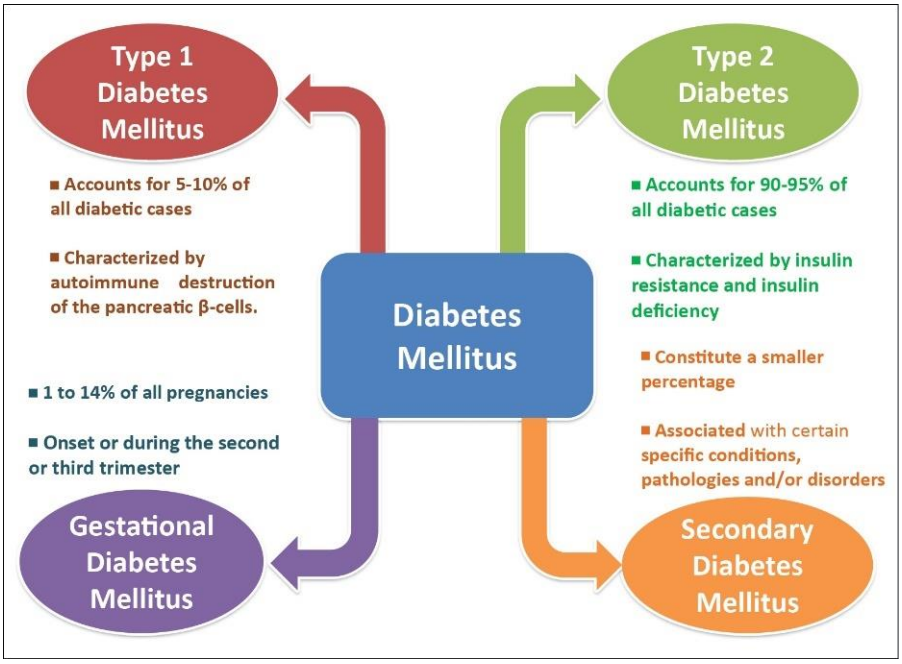

Figure 1. Classification of Diabetes Mellitus (Source: Banday et al 2020)

The "Impaired Glucose Tolerance" class is now categorized as a phase of regulating impaired glucose because it can be seen in any hyperglycaemic disorder which is not diabetes. In a clinical stage of impaired fasting glycaemia, people with fasting glucose above the normal limits, but lower than those with a diabetes diagnosis, were classified. Gestational diabetes has

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been preserved, but now covers the groups previously classified as Gestational Impaired Glucose Tolerance (GIGT) and Gestational Diabetes Mellitus (GDM).

Diabetes in a broad sense and specific diabetes in genetic mutations or related genetic abnormalities needs proper, timely molecular diagnoses which can help analyze disease risk, predict the disease, and timely identify individuals who, family members, are at greater risk. In such cases, predictive molecular/genetic testing and preventive management can play a key role.

Diabetes mellitus has progressive effects including the advanced growth of specific retinopathic complications which can cause probable blindness, renal failure-related nephropathy and/or foot ulcer risk neuropathy, amputation, Charcot joints and autonomous dysfunction, including sexual dysfunction. The risk of cardiovascular, peripheral vascular and brain vascular disease is increasing for people with diabetes, and as such this study looks at the different existing risk prediction models and recommends a suitable model for the prediction of diabetes mellitus. This paper is aimed at reviewing the various existential risk prediction models for diabetes mellitus, reviewing and analysing the existing risk prediction models for the different variants and recommending the most efficient model for the different variants of diabetes mellitus risk prediction.

Diabetes Mellitus risk prediction models can be used for a range of things in medical practice, along with:

i. predicting the advancement of the distinct variants of diabetes mellitus.

ii. predicting therapeutic efficacy or patient prognosis of the disease.

iii. can commonly be used to predict the risk of adverse outcomes after the intervention when performing surgeries.

iv. models of risk prediction are now a significant part of clinical decision-making, which will offer a fast and easy way to evaluate the risk of the patient from diabetes or event that can then direct the treatment.

REVIEW OF RELATED WORKS

A variety of predictive models have been developed using various machine learning and deep learning algorithms to predict the various variants of diabetes mellitus. This section reviews the existing risk prediction models based on the different variants of diabetes mellitus.

Type 1 and Type 2

Xie *et al.,* (2019) study investigated 138,146 people, including 20,467 people with type 2 diabetes, who took part in a cross-sectional data experiment. Type 2 diabetes mellitus was predicted in the study using Support Vector Machine, Decision Tree, Neural Network, Logistic Regression, and Gaussian Naive Bayes classifier models. To further investigate the probable key risk factors of diabetes, univariable and multivariable weighted logistic regression were also applied. Area under the curve ranged from 0.7182 to 0.7949, with the neural network generating the highest accuracy score of 82.4%, as shown by the study's findings.

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Mahboob Alam *et al.*, (2019) projected that diabetes has important attributes, as is characterized by the relationship between different features. The range of tools is used for determining the range of significant attributes for clustering, prediction, and diabetes association rule mining. The main method of analysis of components was used to select significant attributes. Our results show a strong link between diabetes with BMI and glucose levels extracted via the Apriori procedure. A diabetes prevention method was developed using artificial neural networks (ANN), random forest (RF) and K-means clustering. The ANN technique produced 75.7 per cent more accurate and can help medical professionals make treatment decisions.

Deberneh and Kim (2021) developed a risk prediction model that will provide outstanding prediction information on the possibility of T2D emergent. The study exploited Logistic Regression, Random Forest, Support Vector Machine, XGBoost and ensemble machine learning algorithm with key features using ANOVA test, chi-squared tests, and recursive feature exclusion methods. The result from the study shows that the ensemble models performed superiorly to the single models used.

Larabi-Marie-Sainte *et al.* (2019) study reviewed and recommended the usage of Machine Learning and Deep Learning techniques to solve diabetes mellitus, by reviewing and comparing the performance of all the proposed Machine Learning and Deep Learning techniques-based (Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree, and Naive Bayes) diabetes numerous prognoses that have been made in the last six years. The research paper obtained classifiers accuracy of 68% - 74% and recommended the use of the studied techniques classifiers for diabetes prediction which can be enhanced by developing combined models.

A survey by Goutham *et al*. (2020) presented a classification methodology for the use of deep learning architectures for diabetic and normal heart rate variability (HRV) signals, the study used short-term long storage (LSTM) and a convolutionary neural network (CNN) to extract the complicated time dynamic characteristics of the input HRV. These features are then transferred to the classification support vector machine (SVM). In CNN and CNN architecture performance improvements are 0.03%, and 0.06%. The proposed classification system can assist clinicians in diagnosing diabetes with ECG signals of 95%.

Lai *et al.* (2019) proposed two machine-learning models, Gradient Boosting Machine and Logistic Regression to aid in the diagnosis of individuals at slightly elevated risk of developing diabetes. The problem of unbalanced data was solved using classical statistical and modern learning machine techniques, such as the adjusted threshold and class weight method.

Zhou *et al.* (2020) built a risk prediction model for Type 1 and Type 2 diabetes mellitus with deep neural network hidden layers to prevent overfitting, using the drop-out regularization model. The study adjusted several constraints and adopted the binary cross-entropy loss function, which gained a highly precise neural network prediction model. The outcome of the experiments demonstrates the efficiency and effectiveness of the intended DLPD model. The best exercise accuracy in the data series for diabetes type is 94.02.174%, and in Pima Indians, the exercise accuracy is 99,4112%.

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Recommending a new model for predicting type 2 diabetes mellitus based on data mining techniques for (T2DM). Wu *et al.* (2018) identified that the main problems associated with risk prediction are improving the precision of the prediction model and expanding the model's application by incorporating data from additional sources. The model is comprised of two components: an improved K-means algorithm and a logistic regression algorithm depending on a variety of preprocessing procedures. The suggested model was then tested on two additional diabetes datasets as part of the research.

Ayon and Islam (2019) investigated the distinctiveness of diabetes centred on numerous medical factors using engaged deep neural network techniques. The precision for five-fold cross-validation was found to be 98.35 per cent which is relatively high compared to other methods used to predict diabetes mellitus.

Kopitar *et al.* (2020) study equates machine learning-based prediction models for the prediction of diagnosed T2DM (i.e. Glmnet, RF, XGBoost, Light (GBM) with regularly used regression models. The prediction efficacy was evaluated with 100 bootstrapping iterations in various data subsets simulating new input data in six months. A simple regression model with the smallest average RMSE of 0.838, preceded by RF (0.842), Light GBM (0.846), Glmnet (0.859) and XGBoost with six months of data available (0.881).

Abbas *et al.* (2020) created a non-linear SVM-based prediction model for identifying individuals at relatively high risk of developing type 2 diabetes. To build the model, the prediction power of features deriving from the OGTT information was first evaluated and personal data such as age, ethnicity and BMI were considered. The study showed that the properties derived from plasma glucose concentrations provide an excellent subset of properties and the toughest predictive power for the potential progress of T2DM with a feature selection algorithm.

Using qualitative and quantitative methods, Moko and Onuodu (2021) study projected a risk prediction model for Type 2 diabetes in Nigeria, developed employing machine learning models based on logistic regression, SVM, and Gradient Boosting as the highest predictive accuracy score of 98%, Decision Tree and Random Forest. The study opined that further studies should be pitched towards attaining a higher Type 2 diabetes mellitus risk prediction model, applying more features.

Gestational Diabetes

A new clinical and biomarker risk prediction model proposed by Sweeting *et al.* (2019) for the first quarter accurate stratification of risk for gestational diabetes mellitus (GDM) diagnosis in an Australian multiethnic population for early pregnancies. This approach to GDM risk management addresses the resource limits linked to increasing GDM prevalence by focusing on prevention and early intervention for women most at risk, with the help of multivariate regression, GDM was examined. ROC curves were used to evaluate the model's ability to forecast the diagnosis of GDM in the early stages of pregnancy (before 24 weeks of gestation) as well as the overall diagnosis of GDM. Only those women whose risk is identified in the new prediction model may need to go to OGTT and initial diagnostic tests can be prioritized more correctly to better risk subcohorts, such as early risk at GDM.

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Zhang *et al.* (2020) research is aimed at developing a new model that incorporates ultrasound data on the dispersion of maternal fat and inflammatory factors in the blood. 1.158 pregnant women treated at Tangshan Gongren Hospital and Tangshan's other flagship hospitals were divided into GDM and non-GDM groups, and their diagnostic results at 24-28 weeks of pregnancy were used to compile clinical data on the women in each group. The meaning of maternal clinical parameters for GDM diagnosis was analyzed using univariate analysis, and a GDM prediction model was developed using stepwise regression analysis. Using the Homer-Lemeshow goodness of fit test and a ROC curve, the model's accuracy was evaluated. According to the model, factors like age, pre-pregnancy BMI, family history of diabetes mellitus, polycystein ovary syndrome, GDM history, high systolic pressure, glycosylated haemoglobin levels, triglyceride concentrations, and overall cholesterol levels all contributed to low levels of lipoprotein Cholesterol.

Benhalima *et al.* (2020) prediction model were developed with easily available early pregnancy clinical variables using multivariable logistic regression analysis. Based on the WHO criteria for 2013, the prediction model had a moderately precise GDM. The proposed model for the prediction can recognize women at the peril of having GDM before or during early pregnancy so that pregnancy outcomes can be improved promptly.

Diabetes Mellitus Risk Prediction Models

The speed of each machine learning and deep learning model was assessed based on the studies carried out on risk prediction for the different types of diabetes mellitus as shown in table 1 from 2017 till date. The commonest classifiers for risk prediction of diabetes shown in table 1 were deep neural network (ANN) for Deep Learning and Machine Learning: support vector machine (SVM), Logistic Regression and Random Forest.

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Table 1. Risk Prediction Model

S/N	Diabetes Type	Risk Prediction Model	Pros	Cons	Prospects
1.	Type 2	An improved K-means and Logistic Regression. *Wu et al. (2018)*	i. It avoids erasing too much original data. ii. The model can adapt to various datasets	and spends additional time during the part of preprocessing.	To continuously train and optimize the proposed model with real and latest patient data to be provided by a hospital. The data set should be sufficiently large to train and predict to achieve an optimal result.
2.	Type 1 and Type 2	Deep learning predicting diabetes (DLPD) model, with the best training accuracy score of 94.02174% *Zhou et al (2020)*	i. The model can project the future existence of diabetes in patients and the diabetes type experienced by a patient, type 1 or type 2. ii. The model can handle the volume of data.	The presented model's precision has not been compared to those of any other models.	There is a need to improve the model by determining all possible complications, including an appropriate sequence in terms of the perceived percentage of compilation that can occur, which is critical. Other deep learning algorithms and techniques can be incorporated into the model to boost and enhance it for automated diabetes analysis.
3.	Diabetes Mellitus	CNN 5-LSTM with SVM- 95.7% *Goutham et al (2018)*	the non-intrusive, adaptable, and reproducible system can serve as a dependable tool for clinicians to detect diabetes.	Involves a substantial amount of input data.	The deep learning approach must be improved by including omics data to predict the onset of diabetes.
4.	Type 2	Logistic Regression, Random Forest, XGBoost, Support Vector Machine, and	i. it can be used to aid healthcare practices by enabling its practitioners and diabetes educators to make	i. Normal, prediabetes and diabetes were all defined solely by	The use of a variety of datasets reduces the complexity of classifying prediabetes, which is caused by an intersection with

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		ensemble classifiers (Classifier Integration Model (CIM), Soft Voting (SV) Algorithm) and Stacking Classifier (ST) *Deberneh and Kim (2021)*	better clinical decisions and extend the lives of their patients. ii. can help to minimize T2D risks, progression, and related complications both for clinical professionals and patients in advance.	FPG level; HbA1c and the oral glucose tolerance test (OGTT) were not included. ii. Supplementary data sources must be used to validate the models developed in this study.	normal and diabetes classes. The second step would be to make the prediction models more straightforward and to develop the user experience for web and mobile applications are recommended.
5.	Diabetes Mellitus	Deep Neural Network with a prediction accuracy score of 98.35%. *Ayon and Islam (2019)*	Produced a more state-of-the-art result, when compared to other models.	The precision of the output is determined by the strength of the link between units.	Shows the need to conduct anomaly detection and prediction that can be done from input data.
6.	Type 2	Glmnet (0.859%), RF, XGBoost, LightGBM *Kopitar et al (2020*)	The accessibility of more data correlates positively with improved predictive effectiveness and a more balanced weighting of variables is based on priority.	i. The population studied did not include older people in whom T2DM is more predominant. ii. Since only one database with a relatively small sample size was used, a significant amount of data was left out.	The use of various ensemble construction techniques should be examined, as well as the stacking and blending of distinct prediction models.

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7.	Diabetes Mellitus	Logistic Regression and Gradient Boosting Machine (GBM) techniques with AROC for the proposed GBM model are 84.7% with a sensitivity of 71.6%. *Lai et al (2019)*	i. Utilizes the adjusted threshold and class weight methods to deal with the problem of imbalanced data. ii. The sensitivity and specificity for detecting people with diabetes mellitus in clinical settings are both substantial.	The proposed model by the study was compared to only 2 (Decision Tree and Random Forest) models	
8.	Diabetes Mellitus	RF (0.8857) J48, Neural Network, *Zou et al (2018)*	The study gives room to achieve maximum accuracy if all attributes are used.	The model cannot predict the type of diabetes, due to the data used. There is data unbalance.	There is a need to predict diabetes based on types and to examine the proportion that may improve the accuracy of diabetes predictions.
9.	Diabetes Mellitus	Naive Bayes (NB), Artificial Neural Network (ANN), Decision Tree (DT) and Deep Learning (DL) 98.07% *Naz and Ahuja (2020)*	Provides health officials and specialists with structured diabetes knowledge.		Incorporating omics data for disease onset prediction will enhance the precision of the Deep Learning approach. To create a reliable application or website that uses the stated DL algorithm to assist healthcare professionals in the timely detection of diabetes.
10.	Gestational Diabetes	Combined multivariate prediction model with an overall score of 0.93% *Sweeting et al (2019)*	i. Preeclampsia and a huge multi-ethnic cohort with forward-looking information attained at first quarter screening.	i. Possible bias in measuring the risk factors in maternal self-reporting of GDM.	Future validation in other cohorts should be explored; the position of these markers in the pathogenesis and treatment of GDM should be explored, and the

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			ii. The non-fasting measurement of biomarkers improves the viability of the model during pregnancy.	ii. There is a need for external validation between the biomarkers and ethnicity. iii. The early GDM sub-cohort optimized model is derived from smaller samples, additional validation in larger sub-cohorts is required.	effectiveness and cost-benefit of the shared intervention and or preventative techniques should be evaluated following a favourable early risk forecast of GDM.
11.	Type 2	Ensemble learning method (RF-WFS and XGBoost 93.75% Accuracy) *Xu and Wang (2019)*	Considering the model's classification accuracy and performance, it's flexible enough to work with a variety of data.	Dataset used is not recent.	To verify the efficiency and performance of the proposed model, it is essential to analyze the most recent patient hospital data to be a model training and prediction dataset.
12.	Gestational Diabetes	Multivariable Logistic Regression Analysis *Benhalima et al (2020)*	The study used a large pregnant cohort with prospective data collection on obstetrical history, clinical risk factors, biochemical indicators, and comprehensive data on socioeconomic status, diet, and physical activity during early pregnancy.	Pregnancy weight was self-reported, and no information on biochemical risk factors was gathered before the study's participants became pregnant.	More research is needed to diagnose and classify women at risk of GDM outlined in this model earlier than usual to minimize pregnancy outcomes.

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13.	Diabetes Mellitus	Machine Learning (SVM, RF – 83.64%) and Deep Learning (CNN) Techniques. *Yahyoui et al (2019)*	It demonstrates the efficacy of DNNs in assisting doctors in disease prediction.	No feature selection or calculation was done to ascertain feature importance.	Boost prediction accuracy by introducing an automatic deep feature method to the feature extraction step and by creating a better fitting model.
14.	Gestational Diabetes	Univariate analysis. The area under the curve value was 0.911 (95% CI, 0.893-0.930) *Zhang et al (2020)*	Women with GDM were found to be older, have higher BMIs, and had higher Hba1c levels than women without GDM.	The model's prediction begins in the second trimester but might not be generalizable.	Before the results may be applied to the broader public, large-scale multi-centre clinical trials are essential. Pregnant rats on a high-fat diet may be utilized to research the link between liver function and adipose tissue.
15.	Type 2	Stepwise Logistic Regression, Penalized Regression and Support Vector Machine (SVM), *Bae and Park (2018)*	The model's performance was at its peak when both common and rare inputs were employed.	It's demographic and genetic-based	Analysis including other constant traits, such as BMI and metabolic syndrome-related variables, necessitate the inclusion of other data.
16.	Type 2	support vector machine (SVM) 96.80% *Abbas et al (2019)*	Provides doctors with a cost-effective and efficient method for screening those who are more likely to develop T2DM in the future.	a prediction model based on the features derived only from the plasma glucose concentrations measured during an OGTT	When compared to other T2DM prediction models, the one used in this study performs much better in terms of accuracy and sensitivity combined.

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METHODOLOGY AND DISCUSSION

The method adopted in this study is an exploratory descriptive approach. The study explores the existential predictive models and subsequently describes them analytically.

From this research, it was gathered that different risk prediction models exist for diabetes mellitus in Type 1, Type 2, and Gestational diabetes. Such that Deep Learning models specifically the Neutral Network Model in this study presented a higher performance compared with the Machine learning models, but machine learning is a commonly adopted method from the more than 15 reviewed articles for risk prediction for Diabetes Mellitus because they can predict precisely without being programmed, while the deep learning models are enormously costly to train due to the multifaceted data models.

As shown in Figure 2. Below, are the reviewed risk prediction models for the different variants of diabetes mellitus.

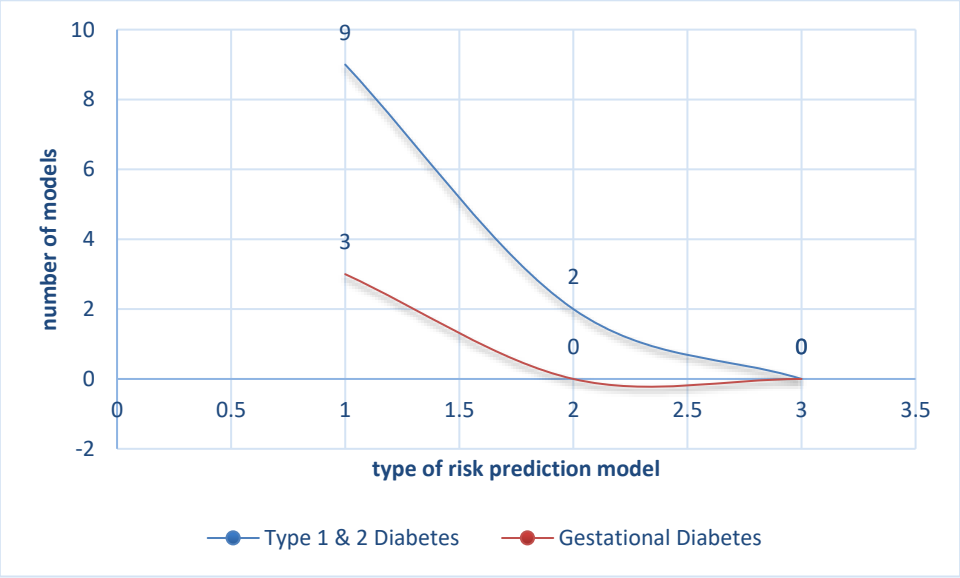

Figure 2. Reviewed Risk Prediction Models

In summary, the algorithms for the Deep Neural Network Model have achieved the highest precision and accuracy score and should be used in the classification and forecasting problems of Diabetes Mellitus. There is also the competitive precision in other algorithms. Therefore, in the classification and risk prediction survey this study proposes considering using the algorithms explicitly explained in table 1 above, paying key attention to their advantages, disadvantages, and the prospects they proffer. These methods can also be used in conjunction with other deep learning or machine learning techniques to create ensemble models that improve prediction accuracy even further.

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CONCLUSION AND RECOMMENDATIONS

Diabetes mellitus (DM) is a debilitating illness that is incredibly prevalent, with the body being unable to metabolize glucose. Early diagnosis of the disease saves patients money and lowers their risk of developing serious health complications in future. The risk predictive models for Diabetes Mellitus reflect the risk patterns being developed and validated. Using either a Deep Learning or Machine Learning model, these models can be incorporated in an automated form to assist doctors in assessing the risk of Diabetes Mellitus in their patients. The prediction model can also be used in medical studies on primary treatment for Diabetes Mellitus as a positive effect of recurrence preventive measures. The work studied different existing risk prediction models for Type 1, Type 2 and gestational diabetes by reviewing more than 10 articles and suggested the use of Deep learning models such as the Deep Neural Network model to be used for any variant of Diabetes Mellitus risk prediction, and it can also be combined with a high-performance machine learning model such as Support Vector Machine.

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