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EARLY PREDICTION OF GESTATIONAL DIABETES USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Gestational diabetes is a form of hyperglycemia that manifests itself in pregnant women. It's possible to experience complications during and after giving delivery if this happens to you at any point in your pregnancy. Particularly in locations where only occasional examinations of pregnant women are available, the hazards can be decreased if they are discovered early and handled. The healthcare industry is not immune to the widespread transformation brought about by intelligent systems developed using machine learning algorithms. This research suggests a combined prediction model for identifying pregnant women who may develop diabetes. The dataset was obtained from the Kaggle, Gestational Diabetes Mellitus (GDM DataSet), which includes records of 3526 pregnant women. Eight models including traditional (Support Vector Machine, Naive Bayes, Random Forest, Logistic Regression, XGBOOST, Decision Tree, SGD) and deep learning (Artificial neural nets) models were used, and the findings resulted in an accuracy ranging from 87%-97% across the models. The results show that deep learning models can significantly improve prediction accuracy.

Keywords: *Gestational diabetes, Machine learning, Medical technology , AI, Diabetes; pregnancy*

1. INTRODUCTION

Pregnancy-related gestational diabetes mellitus (GDM) is characterized by fluctu-ating blood glucose levels [1]. As insulin release gradually declines throughout the early stages of pregnancy, when the blood glucose levels fall. During the succeeding trimesters, this phenomenon is employed to gradually reduce insulin resistance while hardly raising insulin production or hyperinsulinemia. Insulin resistance can also be seen in placental hormones. The human body's metabolism during pregnancy is influenced by pre-established pathophysiologic mechanisms, which also permit the highest amounts of postprandial maternal glucose. A mother's later risk of acquiring diabetes and cardio-vascular disease [3,4], as well as the offspring's childhood obesity [5], are all associated with GDM in addition to perinatal morbidity [2]. Globally, the ratio of gestational pregnancy increased significantly over the past 20 years. Incidences of hyperglycemia varied significantly by area, with Southeast Asia having the highest prevalence at 27.0% and the Middle East and North Africa (MENA) having the lowest at 7.5%, according to the diabetes federation annual report [6]. In adults (20-79 years old), MENA was found to have the highest prevalence of diabetes and the lowest prevalence of hyperglycemia [6].

Gestational Diabetes Mellitus (GDM) can be prevented, and unfavorable pregnancy outcomes can be reduced by early detection and prediction of GDM [7]. However, a prior study found that the Oral Glucose Tolerance Test (OGTT) is often used to confirm GDM patients within a short amount of time. This presents a crucial chance for early fetal and placental development intervention. Although OGTT is frequently advised during the first trimester of pregnancy, it is expensive and frequently produces unreliable findings. The mid-to-late stages of pregnancy are when GDM commonly appears [8], making early detection essential for reducing further health risks. The development of a tool that aids in the early detection of Gestational Diabetes and helps save time and money may be greatly facilitated by the revolution in artificial intelligence and data science technology. Therefore, AI can assist in addressing two key GDM-related issues: (1) the cost of the oral glucose tolerance test; and (2) making it

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simple to check without the requirement for a lab test.

In the past ten years, some researchers have attempted to use machine learning to make early predictions of GDM. According to a recent meta-analysis study published in December 2021 [9], relevant parameters for the models have been identified, and published prognostic models for predicting the risk of GDM have been analyzed, compared, and meta-analyzed. 25 trials with women over 18 without a history of major disease were included. Area under receiver operating characteristic curve (AUROC) for ML models predicting GDM was 0.8492. The pooled sensitivity was 0.69 (95% CI 0.68-0.69; P.001; I2=99.6%), the pooled specificity was 0.75 (95% CI 0.75-0.75; P.001; I2=100%). One of the most often used ML approaches, logistic regression, has a pooled overall AUROC of 0.8151, but non-logistic regression models exceeded it with an AUROC of 0.8891. Additionally, maternal age, family history of diabetes, BMI, and fasting blood glucose were the four factors that were most frequently used in models developed utilizing the various feature selection strategies. Comparing machine learning approaches to traditional screening techniques, the study found that ML approaches are promising for predicting GDM. To promote their adoption, it is important to emphasize the need of quality assessments and consistent diagnostic criteria. Recent research centered on creating an early GDM prediction machine learning model (ML) [10,11], which was developed using Python 3.6.5 and assessed using a dataset gathered by the researchers themselves. The outcomes of a number of trials were examined from a number of angles. The results of the experiment demonstrated that the OD-DSAE model performed better than the other approaches that were being evaluated, reaching high precision of 96.17%, recall of 98.69%, specificity of 89.50%, accuracy of 96.18%, and F-score of 97.41%. Developing machine learning models for early detection of gestational diabetes can have several important benefits [12-16]: (i) it can facilitate early intervention by healthcare professionals who can help control blood sugar levels, minimize complications, and improve outcomes for both the mother and the baby; (ii) healthcare providers can closely monitor and manage the mother's health, reducing the risk of complications, such as preeclampsia, preterm birth, and macrosomia (large birth weight); (iii) enables healthcare professionals to provide personalized care based on each individual's unique risk profile characterized by a wide range of variables, including ma-ternal health history, lifestyle factors, and biomarkers, to identify patterns and risk factors; (iv) early detection and management can help prevent or minimize the need for expensive medical interventions, hospitalizations, and neonatal intensive care for both the mother and the baby; and (v) this data-driven approach can assist healthcare professionals in making more informed decisions regarding screening, diagnosis, and treatment strategies. Therefore, this paper aims to develop a new machine learning model to make early prediction of gestational diabetes and provide a reliable and an accurate model in consequence to previous authors. Hence, the authors developed new models and used eight models including traditional (SVM, Naive Bayes, Random Forest, Logistic Regression, XGBOOST, Decision Tree, SGD) and deep learning (ANN) models were used, and the findings resulted in an accuracy ranging from 87%-97% across the models. The results show that deep learning models can significantly improve prediction accuracy.

The rest of this paper is organized as (1) introduction that gives an overview about the problem and the spread of gestational diabetes globally followed by (2) the related works that discussed and present some of the recent published works in this issue. Next by (3) the material and research methodology that show how the work implemented followed by (4) the results and discussion and end by (5) the study conclusion.

2. RELATED WORKS

As a result of the huge technological advances made over the past 20 years, several research have concentrated on how artificial intelligence, telemedicine, and mobile health might be used to improve healthcare. For managing and treating chronic diseases, providing remote patient specialist care, and aiding therapeutic outcomes offered to patients by healthcare experts, AI, data science, and information technologies provide an automatic or semiautomatic assistance tool. The most recent studies have focused on the use of mobile health technologies and robots to treat chronic diseases like diabetes and hypertension.

Xiong et al. [17] built a first-19 weeks' risk identification strategy with a large number of possible GDM detectors using support vector machines (SVM) and light gradient boosting machines (lightGBM). Zheng et al. [18] developed a simple method to predict GDM in Chinese women during their earlier pregnancies using biochemical indicators and an ML model. In a scenario where

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only a few clinicians and a few pieces of clinical equipment are required, Shen et al. [19] investigated the potentials of the best AI technique for GDM evaluation. Additionally, the study produced an app with an AI architecture.

Furthermore, the implementation of GDM detection on the PIMA dataset using several ML algorithms has been published in the literature [20]. Several ML approaches' accuracy was verified through measurements. The management of the diabetic PIMA dataset used the confusion matrix, Receiver Operating Characteristic (ROC), and AUC values as a visual depiction of the importance of ML techniques. Srivastava et al. [21] proposed a statistical approach for assessing gestational diabetes mellitus using Microsoft Azure AI services. It is an ML Studio with a drag-and-drop-perceived algorithm that performs exceptionally well. The classifier used in this method to determine the existence of GDM was based on the traits that appear in the early stages of pregnancy. The Cost- Sensitive Hybrid Model (CSHM) and five traditional ML models were employed in the development of prediction algorithms to identify the imminent threats of GDM in temporally collected EHRs [22]. The data cleaning process was completed, and a tiny amount of data was recorded and collected for a data set.

In the earlier study [23], a Radial Basis Function Network (RBFNetwork) was constructed, estimated for performance, and compared with an ANN model to identify possible GDM scenarios that could negatively affect pregnant women and the fetus. Parameters were trained in Ye et al. [24] using a variety of ML and traditional LR approaches. Du et al. [25] used three different classifiers to determine the target in the case of a subsequent infection. The precision of the prediction enables the clinician to make a better decision and engage in routine preventive. Finally, it is found that the DenseNet approach identifies gestational diabetes as the target with the least level of flexibility.

Popular classification systems' fundamental flaw is that they depend on exact labels for typical class labels, which are impossible to use in real-time scenarios. In the case of closest neighbor-related outlier prediction systems, some of the considerations are 'points' that correspond to dense regions, whilst the outliers fall under sparse regions. The Local Outlier Factor (LOF) mechanism is one of the most well-known models to date. The local estimation of score point density underlies the main concept of LOF. Based on the comparison of the local densities of the data points to their k-nearest neighbors' (k-NN) mean local densities, a score is assigned to each data point. Thus, one of the key limitations of this model is its O(n2) complexity. Clustering technology is used to collect the data into clusters for outlier prediction algorithms. These areas, however, are not a part of the clusters of "outliers."

Because the primary objective of clustering is to identify the clusters, outliers are often considered to be the result of a clustering process that was not adequately tuned. The major motivation for this strategy is the complexity of O(n2) clustering algorithms. When predicting statistical outliers, these approaches rely on normal data points in areas of stochastic technique with high probability, while the anomaly is present in areas with low probability. The Gaussian distribution, which combines a statistical inference test with a parametric statistical distribution to supply data and estimate an unknown sample in this manner, typically lends itself to statistical models. However, the fundamental flaw in this approach is the discontinuity of the data points. Therefore, the hypothesis is false if the largest dimension of the data is present. When a point contains fewer minimum sufficient points than a given threshold value, it has been deemed an outlier for the purposes of distance-based outlier prediction [26].

In this context of deploying ML techniques in prediction of various conditions, this contributes to the research domain by developing a new model using effective and efficient algorithms and techniques.

3. MATERIALS AND METHODS

3.1. Materials

In this study dataset from Kaggle, Gestational Diabetes Mellitus (GDM Data Set), Of the 3526 pregnant women is used [36]. The summarized characterization for the dataset as follows. The dataset has 3525 rows (2153 for 0, 1372 for 1) with two classes (GDM/Non GDM) and 15 columns for the features and 3525 instances as shown in Figure 1. In The Table 1. the dataset has 15 features (Age, No of Pregnancy, Gestation in previous Pregnancy, BMI, HDL, Family History, unexplained prenatal loss, Large Child or Birth Default, PCOS, Sys BP, Dia BP, OGTT, Hemoglobin, Sedentary Lifestyle, Prediabetes) four of them have missing attribute values (BMI, HDL, Sys BP, OGTT) which can reduce a model accuracy significantly. Therefore, preprocessing missing

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attribute values by calculating the mean value to predict the missing values.

Figure 1 Distribution of dataset

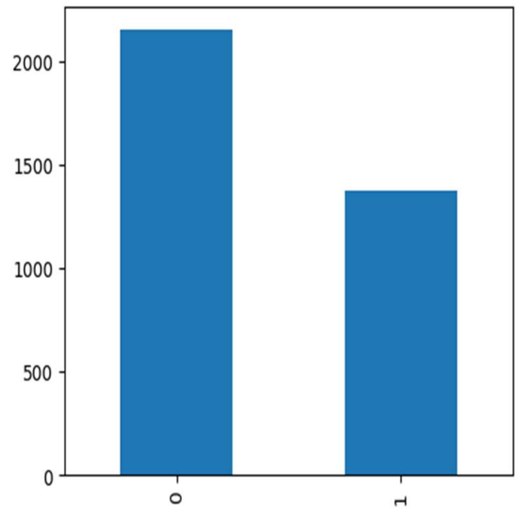

Table 1. The feature of Dataset.

feature	Type
Case Number	int64
Age	int64
No of Pregnanc	int64
Gestation in previous Pregnancy	int64
BMI	float64
HDL	float64
Family History	int64
unexplained prenetal loss	int64
Large Child or Birth Default	int64
PCOS	int64
Sys BP	float64
Dia BP	int64
OGTT	float64
Hemoglobin	float64
Sedentary Lifestyle	int64
Prediabetes	int64

3.2. Methods

The main objective of this study is to develop a model that can effectively determine GDM diagnosis at early pregnancy. A model with both machine learning (ML) and deep learning (DL) techniques is designed to understand the impact of two models in the dataset. To investigate the benefits and strengths, both traditional machine learning models and a deep learning model have been used. Performance of a diverse range machine learning methods including Logistic Regression, Decision Tree, Naive Bayes, XGBoost, Support Vector Machine, SGD Classifier, and Random Forest classifier was investigated. These models show different algorithms and methods which allow to utilize their effectiveness in classifying dataset. As shown in Figure 2, we obtain 20% of the data for testing, and the remaining 80% of the data for training samples.

Moreover, a deep learning technique was integrated into the analysis by using a common model which is Dense layer. The model used the ANN pre-trained model as the base model and added a few dense layers with ReLU activation functions in the two layers and a sigmoid function was used in the last layer. The model was compiled and trained for 20 epochs. Optimizer that implements in our model is Adam algorithm.

4.RESULTS AND DISCUSSION

Machine learning algorithms have been used to develop different models to determine GDM diagnosis at early pregnancy. To determine the performance of diabetes for pregnancy women population, performance of all the five several models are evaluated such as precision, recall, Accuracy and F1 score. Accuracy indicates our classifier is how often correct in diagnosis of whether pregnancy women is diabetic or not. To determine the ability provides by classifier, correct positive predictions of pregnancy women diabetes, Precision has been used. Recall or sensitivity is used in our models to find out the proportion of actual positive cases of pregnancy women diabetes correctly identified by the classifier used. Recall is used to set classifier’s strength of determining negative cases of pregnancy women diabetes. Moreover, the calculation of weighted average for precision and recall provides F1 score [27].

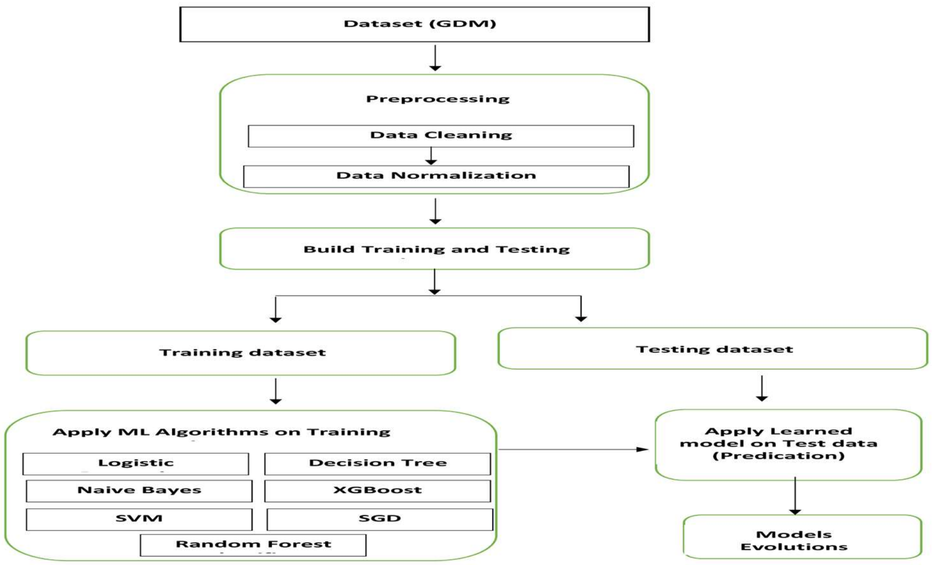

Figure 2 Model Architecture

4.1. Naive Bayes Classifier

The Naive Bayes model results indicate that an accuracy of 95 % was achieved for both the training and validation data. The classification report shows that the negative class had a precision of 0.96 and a recall of 0.96, while the positive class had a precision of 0.93 and a recall of 0.93. The model's overall accuracy was 95%, indicating reasonable performance for pregnancy women diabetes detection. The confusion matrix (Figure 3) demonstrates that 240 data was accurately classified as negative for diabetes, and 430 data was classified as positive for diabetes. However, 18 negative data was misclassified as positive, and 17 positive data was misclassified as negative.

Table 2. The percentage of Naive Bayes model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	96	96	96	448
Class 1	93	93	93	257
Accuracy			95	705

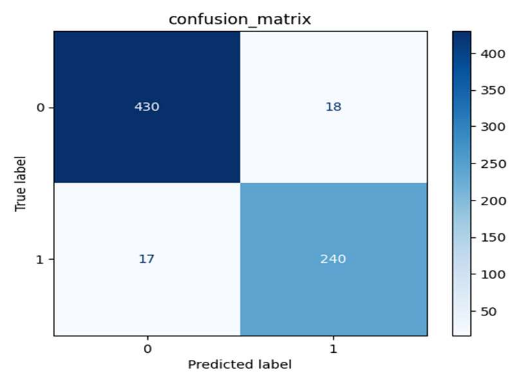

Figure 3 Confusion Matrix for Naive Bayes model results.

4.2. SVM Classifier

The Support Vector Machine Classifier (SVM) model results indicate that an accuracy of 97 % was achieved for both the training and validation data. The classification report shows that the negative class had a precision of 0.98 and a recall of 0.98, while the positive class had a precision of 0.96 and a recall of 0.97. The model's overall accuracy was 97%, indicating reasonable performance for pregnancy women diabetes detection. The confusion matrix (Figure 4) demonstrates that 437 data was classified as negative for diabetes, and 250 data was accurately classified as positive for diabetes. However, 11 negative data was misclassified as positive, and 8 positive data was misclassified as negative.

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Table 3. The percentage of SVM model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	98	98	98	448
Class 1	96	97	97	257
Accuracy			97	705

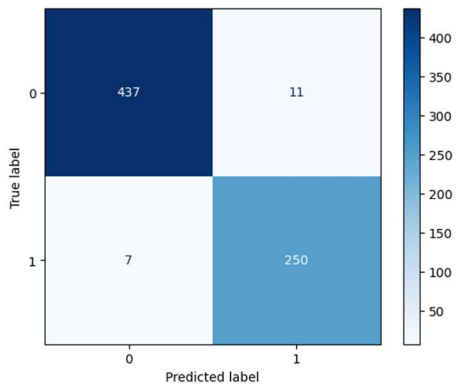

Figure 4 Confusion Matrix for SVM model results

4.3. Random Forest Classifier

The Random Forest Classifier model results indicate that an accuracy of 96 % was achieved for both the training and validation data. The classification report shows that the negative class had a precision of 0.98 and a recall of 0.96, while the positive class had a precision of 0.94 and a recall of 0.97. The model's overall accuracy was 96%, indicating reasonable performance for pregnancy women diabetes detection. The confusion matrix (Figure 5) demonstrates that 432 data was classified as negative for diabetes, and 249 data was accurately classified as positive for diabetes. However, 16 negative data was misclassified as positive, and 8 positive data was misclassified as negative.

Table 4. The percentage of Random Forest model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	98	96	97	448
Class 1	94	97	95	257
Accuracy			97	705

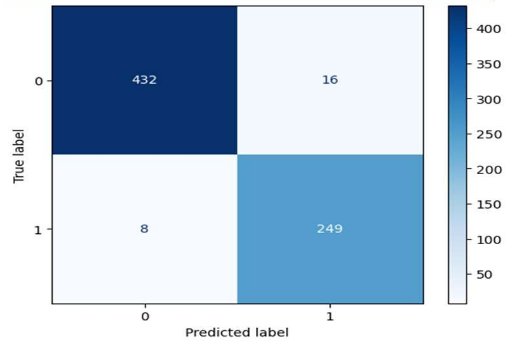

Figure 5 Confusion Matrix for Random Forest model results.

4.4. Logistic Regression Classifier

The Logistic Regression model results indicate that an accuracy of 95 % was achieved for both the train-ing and validation data. The classification report shows that the negative class had a precision of 94% and a recall of 98%, while the positive class had a precision of 0.96 and a recall of 0.90. The model's overall accuracy was 95%, indicating reasonable performance for GDM detection. The confusion matrix (Figure 6) obtains those 439 data was classified as negative for diabetes, and 231 data was accurately classified as positive for diabetes. However, 9 negative data was misclassified as positive, and 26 positive data was misclassified as negative.

Table 5. The percentage of Logistic Regression model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	94	98	96	448
Class 1	96	90	93	257
Accuracy			95	705

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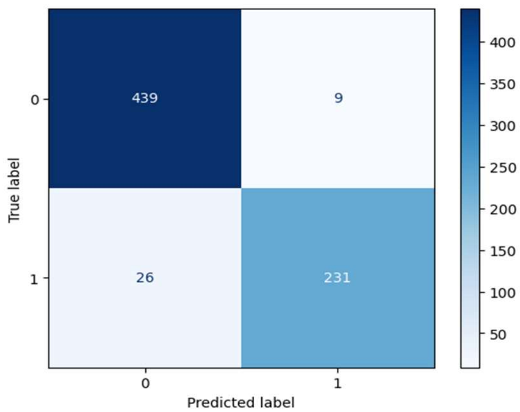


Figure 6 Confusion Matrix for Logistic Regression model results.

4.5. XGBOOST Classifier

The XGBOOST Classifier model results indicate that an accuracy of 97 % was achieved for both the training and validation data. The classification report shows that the negative class had a precision of 0.98 and a recall of 0.97, while the positive class had a precision of 0.95 and a recall of 0.96. The model's overall accuracy was 97%, indicating reasonable performance GDM detection. The confusion matrix (Figure 7) obtains those 436 data was classified as negative for diabetes, and 248 data was accurately classified as positive for diabetes. However, 12 negative data was misclassified as positive, and 9 positive data was misclassified as negative.

Table 6. The percentage of XGBOOST model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	98	97	98	448
Class 1	95	96	96	257
Accuracy			97	705

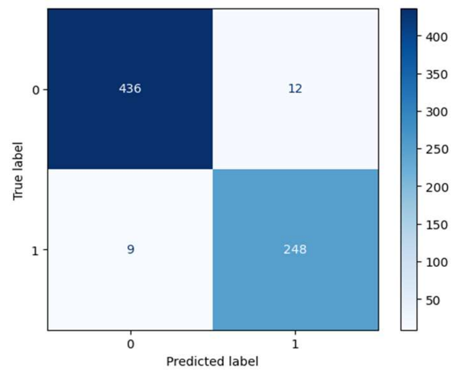


Figure 7 Confusion Matrix for XGBOOST model results.

4.6. Decision Tree Classifier

The Decision Tree Classifier model results indicate that an accuracy of 97 % was achieved for both the training and validation data. The classification report shows that the negative class had a precision of 0.98 and a recall of 0.97, while the positive class had a precision of 0.95 and a recall of 0.96. The model's overall accuracy was 97%, indicating reasonable performance for GDM detection. The confusion matrix (Figure 8) obtains those 436 data was accurately classified as negative for diabetes, and 248 data was classified as positive for diabetes. However, 12 negative data was misclassified as positive, and 9 positive data was misclassified as negative.

Table 7. The percentage of Decision Tree model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	98	97	98	448
Class 1	95	96	96	257
Accuracy			97	705

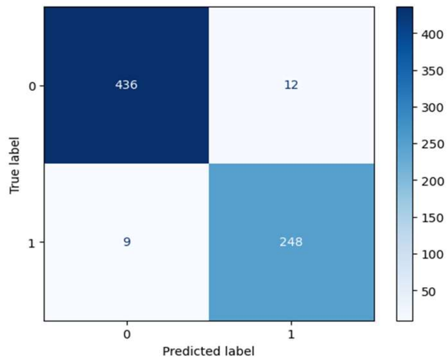


Figure 8 Confusion Matrix for Decision Tree model results

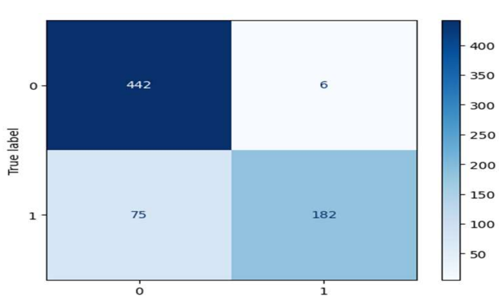
4.7. SGD Classifier

The SGD model results indicate that an accuracy of 88 % was achieved for both the training and validation data. The classification report shows that class 0 had a precision of 0.85 and a recall of 0.99, while class 1 had a precision of 0.97 and a recall of 0.71. The model's overall accuracy was 88%, indicating reasonable performance for pregnancy women diabetes detection. The confusion matrix (Figure 9) demonstrates that 442 in-stances was accurately classified as negative for diabetes, and 182 instances was classified positive for diabetes. However, 75 negative instances were misclassified as positive, and 6 positive instances was misclassified as negative.

Table 8. The percentage of SGD model results in the testing dataset.

	Precision	Recall	F1-score	Support
Class 0	85	99	92	448
Class 1	97	71	82	257
Accuracy			89	705

Figure 9 Confusion Matrix for SGD model results.



4.8. Applying Neural network (Deep Learning)

There are three layers in ANN model (using Dense layer) and the size of each layer and its activation function is shown in the Table 3. The Neural network (ANN) model results indicate that an accuracy of 97%, precision of 95% , recall of 96% and F1_score 95% were achieved.

Table 9. SIZE OF ANN LAYERS.

Layer (type)	Output Shape	Param #	Activation Function
dense_24 (Dense)	(None, 16)	558	Relu
dense_25 (Dense)	(None, 8)	480	Relu
dense_25 (Dense)	(None,1)	38	Sigmoid

Table.10. Shows the different performance for each individual classifier. SVM, XGBOOST, Decision-Tree and ANN have the highest accuracy value with 97%. However, SGD has the least accuracy value with 89% to determine pregnancy women diabetes. Moreover, Logistic Regression and SGD demonstrate the slightly higher Precision value with 96% comparing with other models. Furthermore, SGD has the least Recall and F1_score performances among all the machine learning algorithms with 73% and 83%. Figure 10 represents the performance for each individual classifier. The figure describes that the SGD model is the worst performer since it gained the least accuracy of 89% and Recall of 73%. However, the SVM model yielded a slightly high accuracy and prediction i.e., accuracy of 97% and prediction 95%.

Table 10. Comparison the performance for different models classifier.

Model	accuracy	Precision	Recall	F1_score
Naive Bayes	0.95	0.93	0.93	0.93
SVM	0.97	0.95	0.97	0.96
Random Forest	0.96	0.94	0.96	0.95
Logistic Regression	0.95	0.96	0.89	0.92
XGBOOST	0.97	0.95	0.96	0.95
Decision Tree	0.97	0.95	0.96	0.95
SGD	0.89	0.96	0.73	0.83
ANN	0.97	0.95	0.96	0.95

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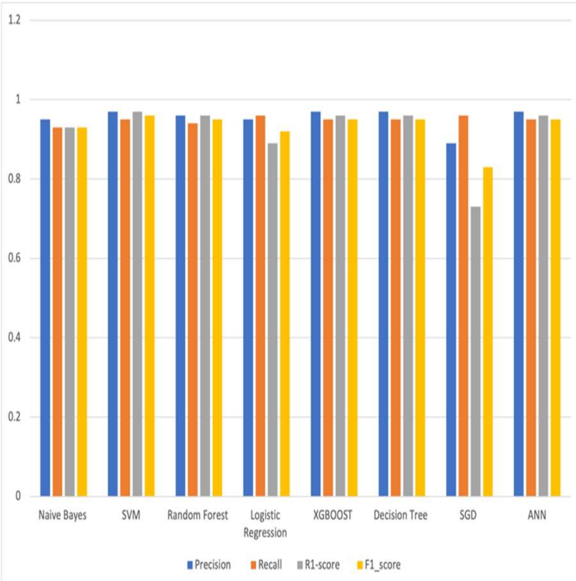

Figure 10 The Performance For Each Individual Classifier.

The proposed model in the table showcases promising results compared to the other studies. It employs a combination of multiple machine learning algorithms such as Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), XGBoost, Stochastic Gradient Descent (SGD), and Artificial Neural Network (ANN) for predicting gestational diabetes. The proposed model achieves high accuracy rates ranging from 95% to 97%, indicating its ability to correctly classify the instances. Moreover, the precision scores range from 0.92 to 0.97, reflecting the model's ability to provide accurate positive predictions. The sensitivity scores range from 0.83 to 0.96, demonstrating its ability to correctly identify positive cases, while the specificity scores range from 0.95 to 0.97, indicating its proficiency in correctly identifying negative cases. Overall, the pro-posed model outperforms most of the other models (two studies used the same dataset [10 and] by the same authors too, and others using different dataset [28-34]) in terms of accuracy, precision, sensitivity, and specificity, making it a promising approach for gestational diabetes prediction. The proposed model also displayed effective results com-pared to a recent meta-analysis of 25 studies [37], which identified accuracies of various models ranging from 80%-90%.

Table 11. Comparison Of Proposed Model With Models Used In Other Studies.

Studies	Dataset	Method	Accuracy	Precision	Sensitivity	Specificity	F-measure
Chan et al. [28]	Collected personally by authors	SVM	71%	-	65%	-	60%
Hu et al. [29]	Collected personally by authors	Stepwise LR, XG Boost ML	84.2%, 83.7%	60%, 69%	50%, 25%	92%,97%	-
Kurt et al. [30]	Collected personally by authors	SVM, RF	85%,88%	-	62%,45%	91%,100%	64%,62%
Ullah et al. [14]	BRFSS	KNN	98.3%	98%	98%	98%	98%
Khanam et at. [31]	PIDD	LR,SVM	78.8%,77.7%	78%,77%	79%,78%	-	78%,77%
Jingyuan et al. [32]	cohort of pregnant women established in Qingdao	LR, RF, SVM, ANN, New-Stacking	85.6%, 86.9%, 80.1%, 86.2%, 85.2%	-	66%, 63%, 81%, 64%, 75%	94%, 97%, 79%,96%, 89%	-
Lu et al. [33]	Collected personally by authors	LR, XGBoost, LightGBM, LSTM	86.9%, 89.2%, 88.4%, 91%	53%, 59%, 57%, 71%			58%, 65%, 63%, 66%
Jader & Aminifar [34]	Public and private laboratories in the Iraqi	DT, RF, SVM, KNN, LR, NB	81%, 83%, 86%, 89%, 85%, 85%	-	-	-	-

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	Kurdistan Region						
Rani [35]	Kaggle, GDM	KNN, LR, DT, RF, SVM	78%, 78%, 99%, 97%, 77%	-	-	-	-
A. Sumathi.. et al [10]	The same dataset	OD-DSAE, DSAE , Neural networks, Logistic regression, Voted perceptron, Logit boost, Decision tree	96.10%, 89.15, 75.39%, 77.21%, 65.10%, 74.08%, 73.82%	96.17%, 88.62%, 83.20%, 88.00%, 86.90%, 84.60% 81.40%			
A. Sumathi et al [11]	The same dataset	Ensemble Method, Random Forest Logistic Regression, KNN, SVM	94.24%, 92.39%, 91.60%, 84.96%, 82.49%	94.00%, 93.00%, 92.00%, 85.005 82.00%			
Proposed Method	Kaggle, GDM	NB, SVM, RF, LR, XGBOOST, SGD, ANN	95%, 97%, 96%, 95%, 97%, 97%, 89%, 97%	0.93% 0.95% 0.94% 0.96% 0.95% 0.95% 0.96% 0.95%	-	-	93%, 96%, 95%, 92%, 95%, 95%, 83%, 95%

From a theoretical perspective, the findings contribute to the field of machine learning in healthcare by demonstrating the effectiveness of various algorithms for predicting gestational diabetes. The comparison of different models provides insights into their performance and helps identify the most suitable approaches for this specific task. These findings enhance our understanding of the strengths and weaknesses of different machine learning techniques in the context of gestational diabetes prediction.

From a practical standpoint, the results have significant implications for healthcare professionals and researchers working in the area of gestational diabetes. The high accuracy, precision, sensitivity, and specificity achieved by the proposed model suggest its potential for clinical applications. Healthcare practitioners can utilize these models as decision support tools to aid in early detection and intervention for gestational diabetes, leading to improved patient outcomes. Moreover, the comparison of multiple models allows practitioners to choose the most appropriate algorithm based on their specific requirements and available resources.

Additionally, these findings highlight the importance of leveraging machine learning techniques in healthcare settings to address complex medical conditions like gestational diabetes. The ability to accurately predict and identify high-risk individuals can enable targeted interventions and personalized healthcare approaches. Furthermore, the comparative analysis of different studies encourages further research and development in this field, fostering advancements in predictive modelling techniques and ultimately improving the overall quality of care for pregnant women at risk of gestational diabetes.

5. CONCLUSION

This research article presented a ML-based GDM prediction, classification models and deep learning models. The input medical data was initially pre-processed in four levels such as format conversion, class labelling, normalization, and missing value replacement. Then, the pre-processed

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data was fed into ML model to determine the appropriate class label. Eight models were developed and used to make the early prediction. We used SVM, Naive Bayes, Random Forest, Logistic Regression, XGBOOST, Decision Tree, SGD and ANN. In comparison to the latest and updated findings in the research studies, the proposed model achieved a better model accuracy.

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