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RESEARCH ARTICLE

Optimized Supervised Learning Framework for Gestational Diabetes Mellitus (GDM) Detection based on Recursive Feature Elimination (RFE)

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Abstract Supervised machine learning has been widely applied in healthcare, yet few studies emphasize feature selection's role in enhancing predictive accuracy. Identifying research that exclusively employs feature selection for GDM detection remains challenging. This study designs an optimized supervised learning framework using Recursive Feature Elimination (RFE) to improve early GDM detection and assist medical professionals in patient evaluation. RFE systematically ranks features by iteratively removing the least relevant ones until no further improvement through various estimators. The selected features are then used to build several frameworks based on five well established machine learning models. Results indicate that the integration of Recursive Feature Elimination (RFE) with a Random Forest as both estimator and classifier achieves the highest accuracy (97.31%) and F1-score (96.6%). These findings demonstrate RFE's effectiveness in optimizing feature selection, enhancing model accuracy, and reducing computational cost through utilizing 6 number of features. In conclusion, incorporating RFE within supervised learning frameworks significantly improves GDM detection. This research contributes to developing automated diagnostic tools that assist healthcare professionals in evaluating patient health and predicting diseases, ultimately enhancing early diagnosis and improving patient outcomes, especially for pregnant women at risk of GDM.

Keywords: Gestational Diabetes Mellitus, Recursive Feature Elimination, Feature Selection, Random Forest.

Introduction

Gestational diabetes mellitus (GDM) is defined as glucose intolerance that is first recognized during pregnancy. It is often considered a transient metabolic disorder primarily resulting from increased insulin resistance combined with insufficient β-cell compensation [1]. During pregnancy, the pancreatic β-cells fail to secrete enough insulin to meet the body's elevated metabolic needs. Although GDM is diagnosed based on elevated blood glucose levels detected during gestation, this condition does not necessarily indicate that the individual will develop diabetes after delivery. Nonetheless, it highlights the critical importance of consistent blood glucose monitoring throughout the pregnancy. Early detection and proactive management are key to minimizing both the occurrence of GDM and its associated adverse maternal and neonatal outcomes [2]. GDM is linked to a higher incidence of urinary tract infections and can alter vaginal pH and moisture levels, creating an environment conducive to microbial proliferation. In addition, hyperglycemia during pregnancy can impair foetal development and result in neonatal complications postpartum. In the long term, women who experience GDM have an increased risk of progressing to type 2 diabetes due to the body's impaired insulin sensitivity [2]. Offspring exposed to GDM in utero are also at greater risk of developing conditions such as childhood obesity, hypertension, and dyslipidemia. The diagnosis of GDM typically occurs between the 24th and 28th weeks of gestation, when insulin resistance tends to peak as a result of physiological changes driven by placental and foetal

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growth. This diagnosis is commonly made using the Oral Glucose Tolerance Test (OGTT). According to diagnostic criteria, GDM is confirmed if fasting plasma glucose (FPG) levels are ≥ 5.1 mmol/L or if 2-hour postprandial glucose levels (2-HPP) are ≥ 7.8 mmol/L [3]. However, earlier screening is advisable for individuals with known risk factors such as a personal or family history of GDM, obesity, or previous GDM diagnoses [4]. The question of whether universal screening should be adopted or limited to high-risk individuals remains under debate. Current studies suggest that universal screening strategies are more effective than selective screening in improving maternal and perinatal outcomes [5]. Although early OGTT screening is recommended, it poses financial and logistical challenges and may be of limited benefit since GDM often manifests later in pregnancy. To address this, predictive models based on early pregnancy clinical data should be developed to estimate the risk of GDM. Such models could help identify high-risk individuals who may benefit from early interventions, including lifestyle changes and pharmacological treatments. Leveraging machine learning methods, already applied in other disease screening contexts, offers a promising alternative approach for the early detection of GDM.

In healthcare, supervised machine learning is gaining prominence in various domains, including disease diagnosis [6-7]. The majority of studies concentrated on developing the supervised machine learning framework, neglecting the feature selection method. The study in [8] developed the Extreme Gradient Boosting (XGBoost) model for diagnosing and differentiating between Covid-19 and influenza A patients. The dataset has the following features: age, CT scan findings, temperature, lymphocyte count, fever, and cough. The research in [9] forecasts the occurrence of heart disease using a hard-voting ensemble, whereas the investigation in [10] anticipates atherosclerosis with ANN and KNN methodologies. Both investigations utilised the Cleveland dataset, which comprises the most significant 14 variables, including age, sex, resting blood pressure, among others. Additionally, the study in [11] introduced cervical cancer prediction via machine learning, utilising variables like as age, alcohol consumption, smoking, cancer history, HIV status, cervical surgery, and cytology through an ensemble technique derived from established supervised machine learning models. Furthermore, the study in [12] used a random forest model to diagnose chronic renal disease using 24 attributes, including age, blood pressure, albumin, blood urea, and haemoglobin, with an accuracy of 99.75%. Nevertheless, there are other research that have incorporated feature selection in the development of the supervised machine learning framework. The study in [13] employed GA and PSO-based feature selection for diagnosing coronary artery disease, enhancing accuracy to 93.08%. The study in [14] introduced the decision tree filter method for identifying the most significant features in diabetes detection, with an accuracy of up to 99.9%, surpassing conventional frameworks.

Recursive feature elimination is a method of supervised machine learning for feature selection, crucial for processing only relevant and significant input. The formulation of the RFE significantly enhances forecast output accuracy and simplifies the models considerably [15]. Recursive Feature Elimination (RFE) is a powerful technique because it acts as a wrapper method [16]. This means it uses a specific supervised learning algorithm, or 'estimator' (such as Random Forest or SVM, as used in this study), to guide the feature selection process. RFE's core mechanism is iterative and recursive: it repeatedly trains the chosen model on the current set of features and then identifies and removes the least important features, based on the model's feature importance metric (e.g., coefficient magnitude or Gini importance). This process continues until an optimal, predefined number of features is reached or until no further improvement in model performance (typically measured by cross-validation score) is observed. This systematic ranking and elimination enhances model accuracy and interpretability while simultaneously reducing computational cost.

A limited number of research incorporate Recursive Feature Elimination (RFE) inside a supervised machine learning framework for healthcare applications. The research in [17-18] demonstrated the integration of Recursive Feature Elimination (RFE) with the XGBoost model for the classification of breast cancer [17] and spinal diseases [18]. The study in [17] reduces the features utilised from the Wisconsin Breast Cancer Dataset (WBCD) for breast cancer classification, achieving an accuracy of 99.02%, while the research in [18] reports an accuracy of 97.56%. The study in [19] demonstrated that the use of RFE enhances hepatitis illness prediction accuracy from 85.87% to 94.78% using the SVM model. Overall, it can be interpreted that RFE can be regarded as a component in the development of an optimal supervised machine learning framework for healthcare. Numerous studies have concentrated on GDM [2][10][20] that presented a supervised machine learning framework for the detection of GDM. However, only a limited number of studies [21] have concentrated on developing an optimal framework utilising a feature selection technique known as forward selection. To our knowledge, no study has been conducted designing a supervised machine learning framework integrated with Recursive Feature Elimination (RFE) for gestational diabetes mellitus (GDM) detection. This research develops an optimal supervised machine learning framework that incorporates a Recursive Feature Elimination (RFE) mechanism for detecting Gestational Diabetes Mellitus (GDM). A comprehensive analysis employing various established supervised learning models has been conducted to determine the optimal framework for GDM identification.

Methods

Data Collection

Currently, the integration of medical research and machine learning has garnered significant attention. Consequently, countless datasets are accessible to the public via the internet. An abundance of datasets is readily accessible through many freely available repositories on the internet. The GDM dataset included in this study was sourced from the Kaggle repository, initially compiled by the research in [2]. The dataset was in .xlsx format. This dataset comprises 3,525 patient records, encompassing 15 features or attributes, with the objective of classifying patients as either GDM or non-GDM. The aforementioned 15 features constitute a comprehensive portrayal of numerous aspects pertaining to individuals' health and medical history. The dataset failed to indicate the trimester in which the data were collected. It is reasonable to presume that observations from each trimester are incorporated in the dataset, considering the significance of data from all trimesters in identifying GDM in pregnant women. In early pregnancy, particularly during the first trimester, essential risk factors and medical conditions such as a family history of gestational diabetes mellitus (GDM) or prediabetes which are commonly documented. The second trimester plays a central role in diagnosing GDM, typically involving tests such as the Oral Glucose Tolerance Test (OGTT) to evaluate maternal glucose regulation. As pregnancy progresses into the third trimester, clinical focus shifts toward monitoring the development of GDM and forecasting potential obstetric outcomes, often through metrics such as systolic and diastolic blood pressure. Although the dataset referenced in [2] does not explicitly categorize data by trimester, the inclusion of variables associated with specific pregnancy stages indicates a holistic framework for assessing and managing GDM throughout gestation.

Data Processing

The dataset had missing values for the features BMI, HDL, Systolic Blood Pressure, and OGTT. During this phase, various events transpire, including the imputation of missing data prior to its subsequent processing into appropriate formats. The missing values were imputed using median values rather than eliminating samples with missing data to maintain the sample size. Furthermore, employing the median to impute missing values allows for the preservation of vital information, enabling the model to continue learning from the existing data. Moreover, imputing missing values with the median proved to be a superior method compared to substituting with the mean or omitting the samples, as the median serves as a more dependable and representative measure of central tendency, especially in the presence of skewed distributions, as evidenced by the results depicted in Figure 1. This is because the median is less affected by outliers and remains closer to the centre of the data than the mean. The data exhibited a predominantly positive skewness, as illustrated in the picture. Consequently, employing median values for imputing missing data was a pragmatic decision. In addition to imputing missing values, feature scaling or standardisation was conducted throughout the data preprocessing step. Feature scaling was employed to standardise all numerical characteristics, ensuring that the mean and standard deviation of the numerical values are precisely '0' and '1'. Standardisation was employed for feature scaling rather than normalisation, as it is less influenced by outliers due to its reliance on the mean and standard deviation.

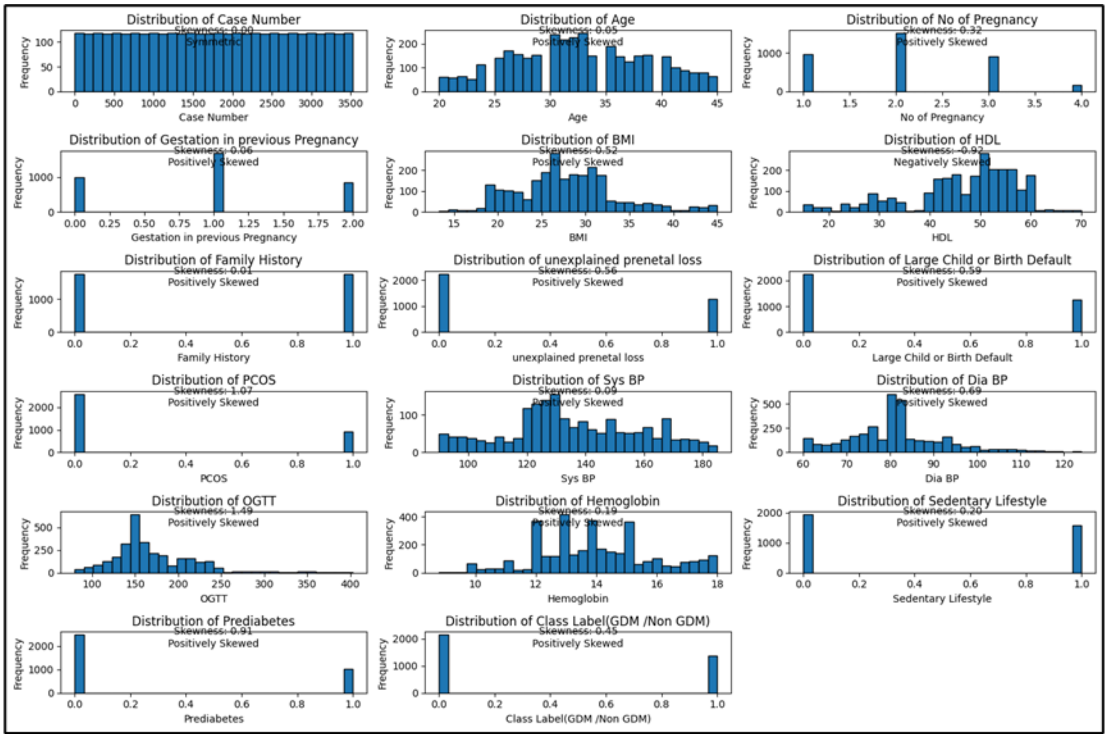

Figure 1. Data distribution

Feature Selection

RFE was a method that identified the most significant features from the GDM training dataset for predicting the target variable. This method employed a feature selection wrapper approach, utilising a distinct machine learning algorithm at its core, encapsulated by Recursive Feature Elimination (RFE) to select the desired features. RFE analysed the training dataset to identify a subset of features, starting with all available features and systematically removing them until the target number of features was achieved or until accuracy improvements ceased, aiming to enhance prediction accuracy and reduce classifier execution time [22]. The binary feature selection process involves the analysis of the GDM dataset, defined as a sample space $X = \{x_1, x_2, \dots, x_n\}$, a target label set $\Upsilon = \{y_0, y_1\}$ and a feature set $H = \{f_1, f_2, \dots, f_r\}$. This dataset can be formalized in Equation (1) as:

$$F(X,Y) = \{(X_i, Y_i) \mid X_i \in R^n, Y_i \in \{y_{0,}\, y_{1,}\}\}_{i=1}^{k} \tag{1}$$

Here, each instance $X_i = \{x_1, x_2, \dots, x_n\} \in R^n$ corresponds to a data point in the dataset, and $\Upsilon_i \in \{y_0 = 0, y_1 = 1\}^t$ epresents the binary class labels. If a data point x_i is associated with the label y_j then $y_{ij} = 1$ otherwise $y_{ij} = 0$. Furthermore, the matrix $X = \{x_1, x_2, \dots, x_n\}^T \in R^n$ encapsulates all instances, while $\Upsilon = \{y_0, y_1\}^T \in \{0,1\}^{n*1}$ represents the matrix of corresponding output labels [14].

This study developed many RFE feature selection models by integrating various estimators, including Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine. The k-fold cross-validation was configured at 3. The primary mechanism of the RFE is illustrated in Figure 2. The chosen features from the developed model were subsequently incorporated with the supervised learning frameworks for GDM identification in the following step.

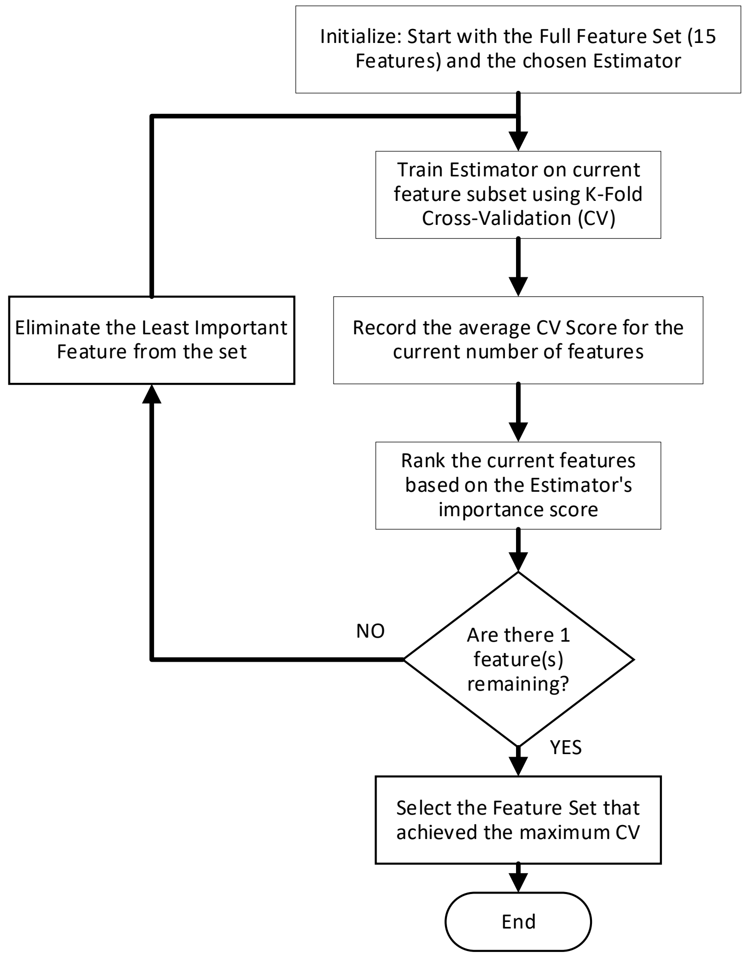

Figure 2. RFE Mechanism Block Diagram

Supervised learning frameworks development and performance evaluation

At this stage, after acquiring the selected features, these fetures were input into several constructed supervised learning frameworks for GDM detection. These frameworks differ from one another based on the classifiers employed, which include Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Naïve Bayes (NB). The GDM dataset was divided into 80% training data and 20% testing data, with the selected features evaluated using the previously described five classifiers.

To thoroughly evaluate the performance of the proposed model, a confusion matrix was utilized. Classifier performance was assessed using several metrics, including accuracy and the F1-score. Accuracy represents the proportion of correctly classified instances relative to the total number of cases. Precision quantifies the correctness of positive predictions, whereas recall reflects the model’s capability to detect all actual positive cases. The F1-score, which is the harmonic mean of precision and recall, offers a balanced measure of the model’s effectiveness in identifying GDM cases while minimizing false positives. The evaluation process was guided by the formulations presented in Equations (2) through (5).

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + False\ Negative + True\ Negative} \tag{2}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{3}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (4)$$

$$F1 - Score = 2 \times \frac{(Recall\ \times Precision)}{(Recall + Precision)} \quad (5)$$

Results and Discussion

Table 1 presents a comparative analysis of the results obtained from various estimators, namely LR, DT, RF, and SVM, in relation to the quantity of optimally selected features following the implementation of Recursive Feature Elimination (RFE). The results indicate that RF and DT yield the optimal minimum number of features, which is six. Tables 2-5 illustrate the performance of selected features from the estimators utilised by various classifiers to achieve an optimised supervised machine learning framework for GDM detection. In summary, it can be stated that specific estimators, such as LR and SVM (refer to Table 3 and Table 5), exhibited enhancements in accuracy and F1-score when utilising selected features with various classifiers. This may be attributed to these estimators selecting a substantial number of features while effectively eliminating those that can be deemed as noise. Simultaneously, the frameworks utilising estimators such as random forest and decision tree (see Table 2 and Table 4) exhibited a reduction in performance when the chosen features were specified. The limited selection of characteristics, specifically 6 from the original 15, is the cause. The integration of RF as both estimator and classifier (see Table 2) outperforms other combinations, attaining an accuracy of 97.3% and an F1-score of 96.6%. Thus, it can be concluded that the most effective supervised machine learning framework for predicting gestational diabetes mellitus (GDM) is the use of random forest as both estimator and classifier, as this approach achieved the highest accuracy and F1-score with only six features.

This might due to the Random Forest's strength lies in its Gini importance metric, which is highly robust for non-linear, complex datasets like medical data. As a tree-based model, RF effectively handles the non-linear interactions between features and provides a reliable, data-driven ranking score, making the RFE elimination process more accurate. Futhermore, RF is an ensemble method that reduces overfitting and variance by aggregating the predictions of multiple decision trees. This robustness allows it to generalize well to the test set, leading to the high reported accuracy and F1-score.

Table 1. Features-selected by estimator

Estimator	Number of Features-selected	Features-Selected
LR	14	'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', and 'Prediabetes'
DT	6	'BMI', 'HDL', 'Sys BP', 'Dia BP', 'OGTT' and 'Prediabetes'
RF	6	'Gestation in Previous Pregnancy', 'BMI', 'HDL', 'PCOS', 'Dia BP', 'OGTT' and 'Prediabetes'
SVM	12	'Age', 'No. of Pregnancy', 'Gestation in Previous Pregnancy', 'HDL', 'Family History', 'Unexplained Prenatal Loss', 'Large Child or Birth Default', 'PCOS', 'OGTT', 'Hemoglobin', 'Sedentary Lifestyle' and 'Prediabetes'

Table 2. Result of RF as an Estimator with RFE

Classifiers Model	Accuracy		F1-score	
	All features	Selected features	All features	Selected features
LR	0.940	0.952	0.921	0.938
DT	0.960	0.959	0.949	0.946
RF	0.966	0.973	0.957	0.966
SVM	0.962	0.962	0.951	0.951
NB	0.939	0.936	0.921	0.917

Table 3. Result of LR as an Estimator with RFE

Classifiers Model	Accuracy		F1-score	
	All features	Selected features	All features	Selected features
LR	0.940	0.946	0.921	0.929
DT	0.960	0.956	0.948	0.944
RF	0.966	0.962	0.957	0.951
SVM	0.962	0.963	0.951	0.953
NB	0.939	0.936	0.921	0.917

Table 4. Result of DT as an Estimator with RFE

Classifiers Model	Accuracy		F1-score	
	All features	Selected features	All features	Selected features
LR	0.940	0.952	0.921	0.938
DT	0.960	0.957	0.949	0.945
RF	0.966	0.962	0.957	0.950
SVM	0.962	0.960	0.951	0.949
NB	0.939	0.889	0.921	0.848

Table 5. Result of SVM as an Estimator with RFE

Classifiers Model	Accuracy		F1-score	
	All features	Selected features	All features	Selected features
LR	0.940	0.950	0.921	0.936
DT	0.960	0.963	0.949	0.952
RF	0.966	0.967	0.957	0.958
SVM	0.962	0.962	0.951	0.951
NB	0.939	0.939	0.921	0.920

Figure 3 illustrates the results of the RFE utilising RF as the estimator, indicating that the ideal number of features is six, which yields the best model performance as demonstrated by the cross-validation score. The study indicates that the most significant features when employing Random Forest as an estimator are 'Gestation in Previous Pregnancy', 'BMI', 'PCOS', 'Dia BP', 'OGTT', and 'Prediabetes'. Figure 4 illustrates the confusion matrix for the integration of Random Forest as both the estimator and classifier. A total of 420 patients without GDM were accurately identified as not having the condition, while 8 patients with GDM were erroneously classified as not having it. Additionally, 11 patients without GDM were mistakenly predicted to have the condition, and 266 patients with GDM were correctly identified as having it.

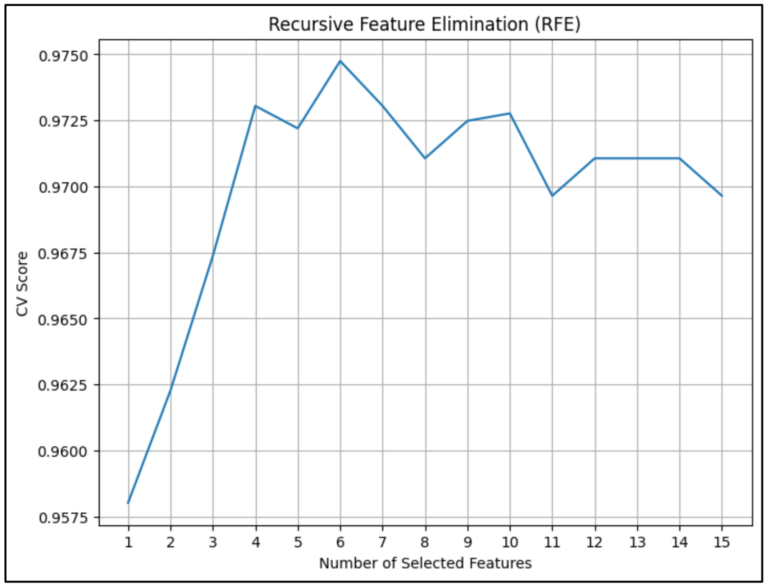

Figure 3. Graph of Number of Selected Features and the Cross-validation Score For RF as Estimator

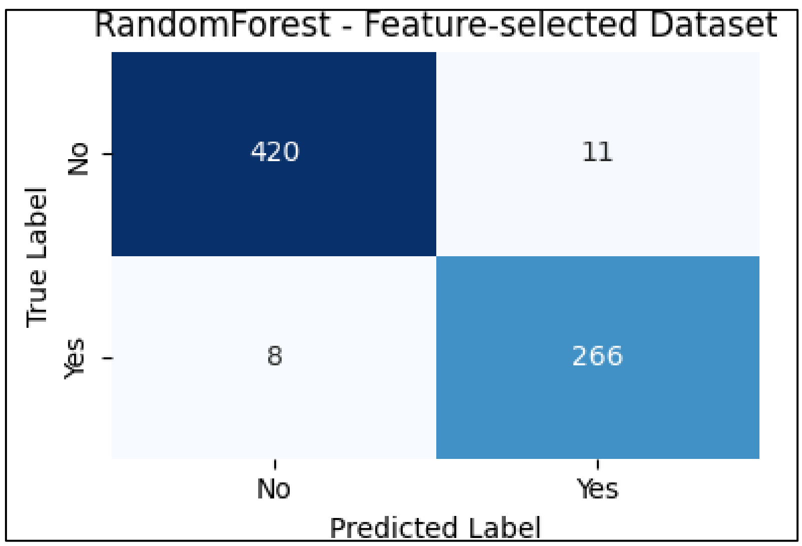

Figure 4. Confusion Matrix for Combination of RF as Both Estimator and Classifier

Furthermore, Table 6 depicts the proposed framework utilising RF as estimators, integrated with several classifiers, in comparison to the study in [2], which employed the same dataset without a feature selection mechanism. Overall, the suggested system, especially in the absence of RFE for feature selection, surpasses nearly all frameworks presented in [2]. The introduction of RFE within the framework demonstrates superiority over both the framework lacking RFE and the framework presented in [2], indicating that the RFE-based framework is more effective than the ensemble-based framework. It is posited that identifying the noisy characteristics initially is more critical than enhancing the classifier's discriminative power in the development of GDM detection frameworks.

Table 6. Comparison of Accuracy Results between Proposed and Previous Work

Classifiers Model		Overall Performance			
Existing Work [3]	Proposed Work	Accuracy Without RFE		Accuracy with RFE	
		Existing Work [3]	Proposed Work	Existing Work [3]	Proposed Work
LR	LR	0.916	0.940	-	0.951
RF	RF	0.924	0.966	-	0.973
SVM	SVM	0.825	0.962	-	0.962
kNN	-	0.850	-	-	-
Ensemble	-	0.942	-	-	-
-	DT	-	0.960	-	0.959
-	NB	-	0.939	-	0.936

Conclusion and Future Recommendations

This study shows that Recursive Feature Elimination (RFE) significantly improves the performance of machine learning models. The implementation of RFE enhances critical performance indicators, including as accuracy and F1-score, while simultaneously decreasing processing time. RFE serves as a crucial tool in feature selection methods, as it specifically identifies the most pertinent features to enhance machine learning algorithms. The analysis indicates that the Random Forest algorithm, employing six essential features (Gestation in Previous Pregnancy, BMI, PCOS, Diastolic Blood Pressure, OGTT, and Prediabetes) selected through Recursive Feature Elimination, is the most effective machine learning approach for detecting the presence or absence of Gestational Diabetes Mellitus. This study showed that combining Recursive Feature Elimination (RFE) with a Random Forest as both estimator and classifier produced the best results, outperforming other classifiers used in this research, including Logistic Regression, Decision Tree, Support Vector Machine, and Naïve Bayes, and also demonstrating improvements over models that did not incorporate RFE.

The development of an algorithm for the early detection of gestational diabetes mellitus (GDM) has achieved its objectives, demonstrating the framework's effectiveness in identifying both the presence and absence of GDM. This study's findings are expected to enhance the development of automated GDM detection. RFE has shown effectiveness in improving model performance; however, the choice of features and their impact on performance may depend on the particular context. In addition to Recursive Feature Elimination (RFE), other feature selection methods may yield different results, which are not considered or analysed in this study. Future research is expected to explore alternative feature selection methods, including forward selection, backward selection, and exhaustive feature selection, to determine the most effective approach. Future research should examine larger datasets to validate the findings and potentially produce more accurate results. Future research may explore the development of Artificial Intelligence applications for the identification of gestational diabetes mellitus (GDM). This application may present the findings of the study and offer an intuitive interface for physicians, professionals, and patients. This application may employ machine learning models, such as RFE, and potentially deep learning techniques in future research, to provide real-time, accessible, and accurate diagnostic tools for enhanced GDM management.

Conflicts of Interest

The authors affirm that there are no conflicts of interest related to the publication of this manuscript.

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