Predicting Gestational Diabetes Mellitus Using Machine Learning Algorithms: A Comprehensive Review and Analysis

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Predicting pregnancy-related diabetes using machine learning (ML) provides a proactive healthcare strategy and permits identifying at-risk patients well in advance. This helps healthcare practitioners to consider early treatment options that can mitigate the risk of complications for mother and child. It examines large datasets for subtle patterns and underlying risk variables, providing better predictive accuracy. By managing gestational diabetes early, medical providers mitigate the risks of macrosomia, preterm birth, and maternal hypertension. Finally, the approach leads to more targeted and effective prenatal care, improving health outcomes and securing a better start for the baby and mother. Besides, predictions of diabetes in pregnancy are supposed to be carried out by using RF-a ML classification algorithm. Red Deer Algorithm (RDA), Jellyfish Search Optimizer (JSO), and Rhizotomy Optimization Algorithm (ROA) are utilized to increase the model's precision. This model has been selected to integrate with optimizers to enhance forecast accuracy. In diabetes circumstances, RFJS is observed to outperform other models, with a precision value of 0.9377, while the rank of the second best is from the RFRO model, having a precision of 0.932. The RFRD scheme has a precision of 0.9282, thus reflecting medium performance but higher than the RFC with its precision of 0.879. These results have provided significant insights into the current performance and potential of ML algorithm models in terms of prediction. The insight of such a result point out the direction of future research and further development in applying ML to predictive analytics in diverse fields.

Povzetek: Študija predlaga napovedovanje nosečniškega diabetesa z naključnim gozdom, okrepljenim z metahevrističnimi optimizatorji (RDA, JSO, ROA), za proaktivno in ciljno prenatalno oskrbo.

1 Introduction

Diabetes during pregnancy, also known as Gestational Diabetes Mellitus, is a disorder characterized by high blood sugar levels that appear or are diagnosed during pregnancy [1]. It is a significant health issue because of the possible negative impact on mother and fetal health [2]. Although the exact cause of GDM is unknown, it is considered a mixture of resistance to insulin, changes in hormone levels, and genetic predisposition [3]. Insulin resistance, one of the characteristics of GDM, occurs when the cells in the body become less responsive to insulin, a hormone that controls blood sugar levels [4]. This resistance requires increased insulin production to sustain normal blood sugar levels, a burden on the pancreas [5]. Pregnancy leads to physiological changes that physiologically increase insulin resistance due mainly to releasing hormones like lactogen from the human placenta and cortisol [6].

GDM is typically diagnosed between the 24th and 28th weeks of pregnancy with the use of glucose tolerance tests [7]. Although some women present with symptoms like polydipsia and polyuria, many cases of GDM are asymptomatic and are only diagnosed through screening testing [8]. Poorly managed or improperly treated GDM presents serious risks to both mother and child [9]. Maternal complications may involve preeclampsia, cesarean delivery, and the elevated risk of type 2 diabetes in later life [10]. The fetal complications include macrosomia (excess development of the fetus), trauma during delivery, hypoglycemia following birth, and elevated risk of obesity and diabetes later in life [11], [12], [13]. The management options for GDM primarily involve lifestyle changes in the form of dietary modifications and regular exercise to lower blood sugar levels [14]. When lifestyle modification alone is not practical, insulin therapy may be necessary to achieve appropriate glycemic levels [15]. In general, the management of GDM requires a multidisciplinary approach by obstetricians, endocrinologists, nutritionists, and other specialists to achieve optimum maternal and fetal outcomes [16]. Early recognition, prompt intervention, and suitable prenatal care can minimize the adverse effects of GDM and ensure the health and well-being of both mother and child [17].

The early detection of pregnancy-related diabetes, including GDM type 2, is clinically relevant as it can potentially reduce the serious complications associated with it for both the mother and child [18], [19].

Identification of a woman who may be at risk for GDM would facilitate early management and thus minimize complications from uncontrolled hyperglycemia during pregnancy [20]. Early prediction makes taking preventive interventions, including lifestyle changes and close blood glucose monitoring, more straightforward to improve maternal and fetal health outcomes [21]. Identifying high-risk people early in pregnancy allows healthcare practitioners to undertake therapies targeted at managing blood sugar levels and lowering the risk of GDM-related problems [22]. Furthermore, with early prediction, healthcare professionals can plan for prenatal GDM treatment through regular monitoring, special nutritional counseling, and possible pharmaceutical interventions if required [23]. Finally, early detection of pregnancy-related diabetes enables healthcare professionals to take initiative in controlling the disease to attain better outcomes regarding both mother and fetus and, consequently, diminish the overall burden of GDM on the healthcare system [24].

1.1. Objectives

Early diagnosis of pregnancy-related diabetes allows for early treatment and decreases the risk of adverse outcomes for mother and child. Earlier identification provides more personalized care programs, hence optimizing maternal glucose levels while reducing risks of complications such as macrosomia and birth trauma. A more sophisticated approach was decided upon to pursue the objective, utilizing the ML model of RFC, further enhanced through the incorporation of RDO, JSO, and ROA for predictive analytics. Predicting pregnancy-related diabetes using ML algorithms, such as the RFC, has several benefits. First, RFC is very good at handling complex, high-dimensional databases, which are very common in medical research; it can, therefore, effectively combine a wide range of predictors, such as demographic, clinical, and biochemical characteristics, to make reliable predictions. Besides, RFC resists overfitting, a common concern when sample sizes are small or the data is noisy. Its ensemble learning technique, which integrates many decision trees, reduces the likelihood of individual trees picking up noise in the data, leading to more trustworthy predictions.

1.2. Related works

Though there is an ongoing debate on the severity with which Gestational Diabetes Mellitus must be recognized and preserved, most doctors believe that diabetes found in early pregnancy has more serious effects and should be handled immediately after it is detected by Metzger et al. and Wyatt et al. [25], [26]. Ideally, this research should be conducted before pregnancy, as organogenesis is typically completed when pregnancy is detected. In this case, pregnancy wasn't determined till 9 weeks of pregnancy. A high blood sugar level during the first 8 weeks of pregnancy increases the chance of severe abnormalities by up to 15%, which is eight times greater than the risk reported in straightforward pregnancies (about 2%), according to Wyatt et al[27] Due to undetected underlying T2DM, the 2% risk estimate might continue to be an underestimate of the nondiabetic pregnant demographic. Luckily, 85 percent of hyperglycemic pregnancies don't result in significant abnormalities, which surprises many of us. Severe deformities are likely to cause early miscarriages; hence, they are not included in statistics. According to older studies, the prevalence of severe abnormalities might reach 25%. This higher historical prevalence is most likely the outcome of fewer biologically managed blood sugars owing to the lack of monitoring items and inadequate selection of insulin Jovanovic, Druzin, & Peterson et al. [28], [29].

The objective of therapy for women who get pregnant with weakly managed diabetes is to check for significant defects, focus on the 85 percent likelihood of a usual child, and optimize blood sugar management to that moment ahead. It is feasible to reduce Women with diabetes who have type 1 have an A1C of below six percent before and during pregnancy, and the outcomes of their pregnancies are comparable with that of the PG with no diabetes population [27]. Most doctors nowadays advocate these ladies can maintain their babies in the belly till the end of the ninth month with no scheduled premature sections(cesarean) or early childbirth. However, this training is still contentious in the field of perinatology.

Blood sugar (glucose) management afterward in PG affects embryonic development, and subsequent glucose levels can decrease the growth of macros to fewer than ten percent [30], [31], [32] The avoided development of macrosomia and its short- and long-term effects become the primary focus of glucose control. The frequency of type 2 diabetes among women of reproductive age worldwide is elevating at a rapid pace. Flegal et al.; Shaw, Sicree, and Zimmet [33], [34]. As an outcome, the count of unexpected births or PGs that happen with insufficient sugar level regulation throughout the crucial organogenesis phase is expected to rise, in addition to an upsurge in significant abnormalities. It is appropriate to examine a paradigm change for diabetes discovery/analysis in early PG and guidelines for prophylactic examination to determine people's impaired tolerance for glucose before pregnancy.

The probability of DB in women increases with race, age, BMI, and history OF family[35], [36]. The goal of monitoring is to detect women with unfamiliar, already present T2DM whose blood glucose levels are high enough to endanger the baby's growth before they are typically examined. Although there are currently no studies that precisely answer this issue, historical statistics and scientific assessment imply that the women are more in danger: 1) Ladies with a GDM history or the delivery of a more significant than a nine-pound newborn; 2) women who weighed more than 9 pounds at birth or have an extended family history of T2DM; 3) Ladies who have had a diagnosis of a condition called acanthosis nigricans or pcos ovarian condition; 4) Ladies having a body mass index (BMI) higher than thirty kilograms per square meter; and 5) Ladies from social groups at high probability of T2DM, such as Native Southeast Asian, American, and Hispanic. 2% of enceinte ladies had undiscovered T2DM, 5% had GDM when diagnosed in the subsequent month of pregnancy, and another 1.5% will be discovered in the third trimester. It is recommended that women at high risk be tested when they are diagnosed with pregnancy. Formal testing is based on A1C levels over 5.3% and/or Postprandial blood sugar levels greater than 120 mg/dl, even if just once (after a heavy meal of carbohydrates). If the initial test is negative, repeating A1C and postprandial glucose testing every 4 weeks until 34 weeks gestation is advised, with at least one formal oral glucose tolerance test (OGTT) at 24-28 weeks. If blood sugar tolerance is expected after 34 weeks, discontinuing testing is appropriate.

2 Dataset and methodology

2.1.Data gathering

In Fig. 1, the wide-ranging effects of diabetes are discussed, ranging from blood pressure and pregnancy to its overall impacts on health and well-being. By examining these areas, a better understanding of the complicated interaction between diabetes and these critical determinants is sought to shed light on the intricate interplay affecting the course of this chronic illness.

- In diabetes, insulin malfunction causes metabolic abnormalities such as hyperglycemia and dyslipidemia. In academic terms, insulin's absence or poor activity impairs glucose absorption, glycogen synthesis, and lipid metabolism. This causes metabolic changes, including enhanced gluconeogenesis and lipolysis, which worsens hyperglycemia and lipotoxicity. Insulin insufficiency also influences cellular signaling pathways, including gene expression, protein synthesis, and cell proliferation. The delicate interplay between insulin and metabolic homeostasis is clarified via academic research using cellular and molecular approaches, influencing therapeutic options for improving insulin sensitivity and glycemic control in diabetes care [37].
- Diabetes causes skin thickness changes due to glycation, collagen cross-linking, and increased extracellular matrix deposition. These alterations impair skin flexibility and wound healing, leading to problems including diabetic ulcers and infections. Determining the effect of diabetes on skin thickness requires histological studies, biomechanical analysis, and research into molecular mechanisms that regulate collagen metabolism. Such study elucidates the pathophysiological mechanisms behind diabetic skin alterations, allowing for the development of tailored therapies to reduce complications and enhance patient outcomes [38].

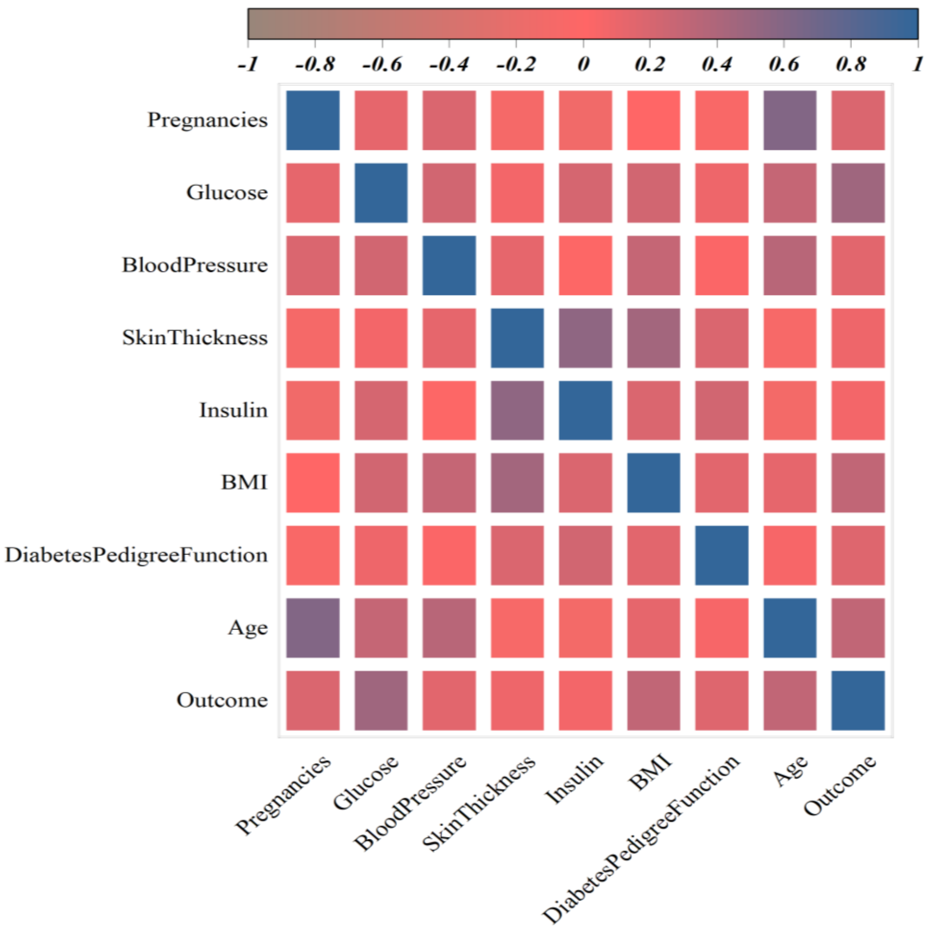


Figure 1: The correlation plot of the inputs and outputs variables

2.2.RFC

RFC entails many tree classifiers, all of which generate a classifier utilizing an unexpected vector collected separately from the input vector and offer a unit vote to the class that it believes is most likely to sort an input variable appropriatly [39]. RFC used in this investigation generates a tree by haphazardly choosing traits or mixtures of characteristics at each node. Bagging produces a training database that includes choosing every feature or characteristic mixture and haphazardly selecting N replacement samples, where N is the size of the original training set. Any occurrence pixels are sorted using the most frequently voted class among all tree predictors in the forest. Choosing characteristic measures and trimming strategies was critical for DT construction.

The attribute selection for DT initiation may be tackled in diverse ways, including direct quality measures. The two most popular attribute metrics used in decision tree induction are the skill gain ratio and the Gini index. The RFC picks attributes based on the Gini Index, which measures an attribute's impurity across classes. The Gini index for a specific training set T may be stated below: Select a single pixel haphazardly and indicate whether it belongs to a group.

$$the \sum\sum_{j\neq i}(f(c_i,T)/|T|)\big(f(c_j,T)/|T|\big) \tag{1}$$

$f\,(C_i\,,T)/\,|T|$ displays the likelihood that the chosen case falls within the group C_i.

2.3.Red deer algorithm (RDA)

Fig. 2 depicts the flowchart for the proposed RDA. Like other evolutionary algorithms, the proposed process begins with early Demographics (RD). A few of the most promising RDs in the general population were picked, such as male RDs; the remainder were known as hinds. Harems develop after fighting and roaring. A harem is a grouping of hinds. The population's female deer are shared among the aforementioned male RDs depending on their talents (fighting and screaming), power, and elegance. Male RD's elegance and strength are inversely related to their fitness score in GA. Roaring male RD is improving them and solutions in the area around them. When fighting, a male RD fights against another male RD. Two guys battling pick someone as the winner, corresponding to selecting the better value after fighting rather than the previous value for each solution in each stage. Soon after yelling and battling, the male RD divided the females between themselves [40]. The male leader of the harem is mating with a proportion of the hinds in his harem. And the male leader is constantly paired with a ratio of hinds in the same harem. Mating with the nearest hind, the hind closest to the male in RDA. This process serves as a counterpoint to developing new solutions, such as the offspring of RD throughout a generation. The RDA, like other meta-heuristic computations, consists of two phases: amplification and variation. During the intensification phase, two guys competing to be crowned champions means improving themselves. The male is coupling with the nearby hind legs in the surrounding communities. Screaming male RD haphazardly mated with a particular ratio of hinds in a harem in variety—intensity and diversity increase when the male RD in his herd mates with hinds.

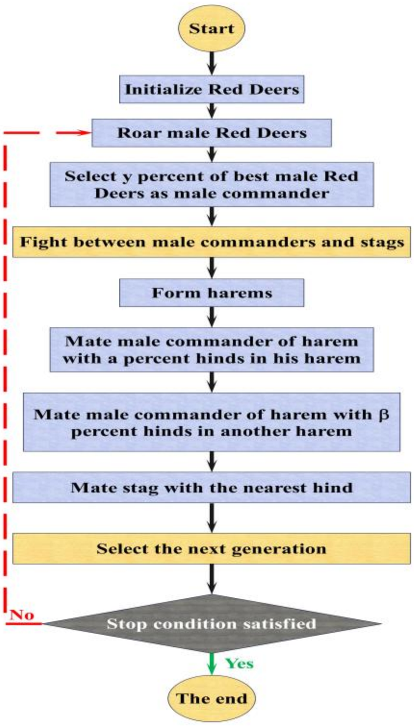


Figure 2: The flowchart of the RDA

2.3.1. Producing original red deer (RD)

Enhancing aims to determine the desired answer based on the problem's variables. An array of parameters to optimize is created. This array is known as a "chromosome" in GA nomenclature; however, it is referred to as "Red Deer" here. Thus, RD is the solution's equivalent. In an N_{var} –dimensional enhancement issue, an RD is a 1 N_{var} selection. The selection is structured as follows:

$$Red\ Deer = \left[X_1, X_2, X_3, \ldots, X_{N_{var}}\right] \tag{2}$$

Furthermore, each RD's function value may be determined in the following way:

$$Value - f(Red\ Deer) = f\left(X_1, X_2, X_3, \ldots, X_{N_{var}}\right) \tag{3}$$

To begin the optimization procedure, a starting group of size is formed to N_{pop} . The best RD is chosen for N_{male}, while the others are chosen for N_{hind}.

2.3.2. Roar male RDs

The male RD tries to boost their elegance at this time by yelling. RD males will replace older generations if they do better in objective functions (OF). The truth is that every male RD may change his position. Screaming male RD attracts ladies.

2.3.3. Select γ percent of best male RDs as male commanders

There is an enormous distinction among male RDs. Some achieve more tremendous success than others. In truth, men do not all have the same status in nature, with some seizing harems.

Male RD are classified into two categories: male leaders and stags. The count of leader males is associated with γ, which is:

$$N.male.com = round\{\gamma \cdot N_{male}\} \tag{4}$$

where $N.male.com$ is a large number of guys grabbing the harems. The male RDs are chosen as the best, while the rest are called "stags." The quantity of stags is calculated using the following method:

$$N \cdot stag = N_{male} - N.male.com \tag{5}$$

where $N \cdot stag$ is the stag number in male demographics.

2.3.4. Battle among male leaders and deer

Male commanders can combat stags at random. If the OF is better than the others, they are selected after a fight.

2.3.5. Formation of harems

A group of hinds taken by a male leader is called a harem. The strength of male leaders—whose abilities include fighting and roaring—determines how many hinds are kept in harems. To establish harems, hinds are proportionally shared among male leaders, and the normalized score of a male leader is determined as:

$$V_n = v_n - \max_i\{v_i\} \tag{6}$$

where the regularized value of the nth male leader is denoted by V_n, and v_n is its value. Every male leader's standardized power is defined as follows, taking into account the normalized value of all male commanders:

$$P_n = \left|\frac{V_n}{\sum_{i=1}^{N.male.com} V_i}\right| \tag{7}$$

From another perspective, a male leader's normalized authority is the proportion of hinds he would have. The total number of hind legs in a harem will be:

$$N \cdot harem_n = rand\{P_n \cdot N_{hind}\} \tag{8}$$

where $N \cdot harem_n$ displays the count of hinds of nth harem and N_{hind} displays the count of all hinds. To distribute the hinds throughout each male leader, a random pick is made Give $N \cdot harem_n$ hinds to it. These roe deer, together with the male, will form the nth female deer.

2.3.6. Mate male commander of harem with percent hinds in his harem

In stage E, the mating behavior begins. GA displays this fact as a "crossover" model. The male leader and the hinds in his harem is the parents. Their children represent the novel explanations. The correlation between the count of hinds in a female deer mating with their male leader ∝ is:

$$N \cdot harem_n{}^{mate} = round\ \{\propto \cdot\ N \cdot harem_n\} \tag{9}$$

With $N \cdot harem_n{}^{mate}$ representing the count of hinds from the nth harem ready to mate with these male RD. A random selection is made $N \cdot harem_n{}^{mate}$ of the $N\ .\ harem_n$.

2.3.7. Mate male commander of harem with β percent hinds in another harem

It is allowed for the male leader to mate with a portion of the hinds in a haphazardly selected harem. To increase his domain, the male RD assaults another harem. When there is only one male RD in a harem coupling with roe deer, the numbers are:

$$N \cdot harem_n{}^{mate} = round\{\beta. N. harem_n\} \tag{10}$$

With $N \cdot {harem_n}^{mate}$ representing the count of hinds from the nth harem ready to mate with these male RD. A random selection is made $N \cdot {harem_n}^{mate}$ of the $N.harem_n$, too.

2.3.8. Mate stag with the nearest hind

In this phase, each stag mates with the nearest hind. During the breeding cycle, male RD chooses to follow the convenient hind, which may be his favorite of all hinds. This roe deer might be within his harem or frequently different female deer. Every stag could come together with the closest roe deer. Thanks to this possibility, every male RD can mate with as few hinds as possible; in the worst situation, just one hind will mate. Distances between each stag and every hind must be calculated to determine the closest hind. Two dimensions are used to describe the method. The following formula is used to determine the separation in J-dimension space between a male RD and every hind:

$$d_i = \left(\sum_{j \in J} \left(stag_j - hind_j^i \right)^2 \right)^{1/2} \quad (11)$$

2.4.Jellyfish search optimization (JSO)

It is one of the most recent swarm-based metaheuristics, which Chou and Truong created in 2021 [41]. The JS method mimics the jellyfish's food-searching behavior in the water [42]. The JS method follows three simplified guidelines:

2.4.1. Ocean current

Jellyfish can sense the movement of the waves Eq. (12) and feed on tiny planktonic creatures.

$$\vec{O} = X' - \beta \times M \times r(0,1) \quad (12)$$

Here, $\vec{O}$ is ocean flow's direction, β (β > 0) specifies the length dispersal factor of $\vec{O}$, X' is the position of the present best jellyfish in the swarm, and M is the average location of all jellyfish. The new situation of each jellyfish is specified in the following order:

$$X_i(t+1) = X_i(t) + r(0,1) \times \vec{O} \quad (13)$$

Upon changing each jellyfish's status, a desired location, such as one with more food sources, is chosen as the jellyfish's present spot.

2.4.2. Jellyfish bloom

Inside a jellyfish bloom, jellyfish move passively and actively. The computational representations of these movements are shown here.

Passive motion: $$X_i(t+1) = X_i(t) + \lambda \times r(0,1) \times (w_b - L_b) \quad (14)$$

λ ($\lambda > 0$) displays a factor relating to the duration of inactive motion. $w_b and\ L_b$ are the bottom and higher limits of the search area, correspondingly.

Active motion: $$X_i(t+1) = X_i(t) + r(0,1) \times \vec{D} \quad (15)$$

where

$$\vec{D} = \begin{cases} X_i(t) - X_j(t) & if \quad g(X_i) < g(X_j) \\ X_j(t) - X_i(t) & if \quad g(X_i) \geq g(X_j) \end{cases} \quad (16)$$

Here, two functions $g(X_i)$ and $g(X_j)$ are the jellyfish i and j have different OF values.

2.4.3. Time control mechanism

A temporal control system governs the two sorts of jellyfish's movement within the bloom and their migrations toward ocean currents. The time control function is expressed as follows:

$$T(t) = \left| \left(1 - \frac{t}{MaxIter}\right) \times (2 \times r(0,1) - 1 \right| \quad (17)$$

t displays the time index provided as the cycle number, and $MaxIter$ indicates the repetition most significant number.

2.4.4. Population initialization

This optimizer employs the logistic map to construct the starting population.

$$X_{i+1} = \upsilon X_i (1 - X_i), \qquad 0 \leq X_0 \leq 1 \quad (18)$$

where X_i and X_0 are the chaotic values for the position of the $i - th$ Jellyfish and a haphazardly selected place, correspondingly. In every instance, υ is set to 4.

2.4.5. Boundary Handling Mechanism

When a jellyfish exceeds the confines of the specified search domain, it will be found inside them using Eq. (19).

$$\begin{cases} X'_{i,d} = (X_{i,d} - W_{b,d}) + L_{b,d} & if \quad X_{i,d} > W_{b,d} \\ X'_{i,d} = (X_{i,d} - L_{b,d}) + W_{b,d} & if \quad X_{i,d} < W_{b,d} \end{cases} \quad (19)$$

where $X_{i,d}$ and $X'_{i,d}$ are the present and updated position of the $d - th$ aspect of the $i - th$ jellyfish. $W_{b,d} and\ L_{b,d}$ are upper and Lower limits on the $d - th$ aspect of the search area, correspondingly. Fig. 3 displays the diaggram of JSO.

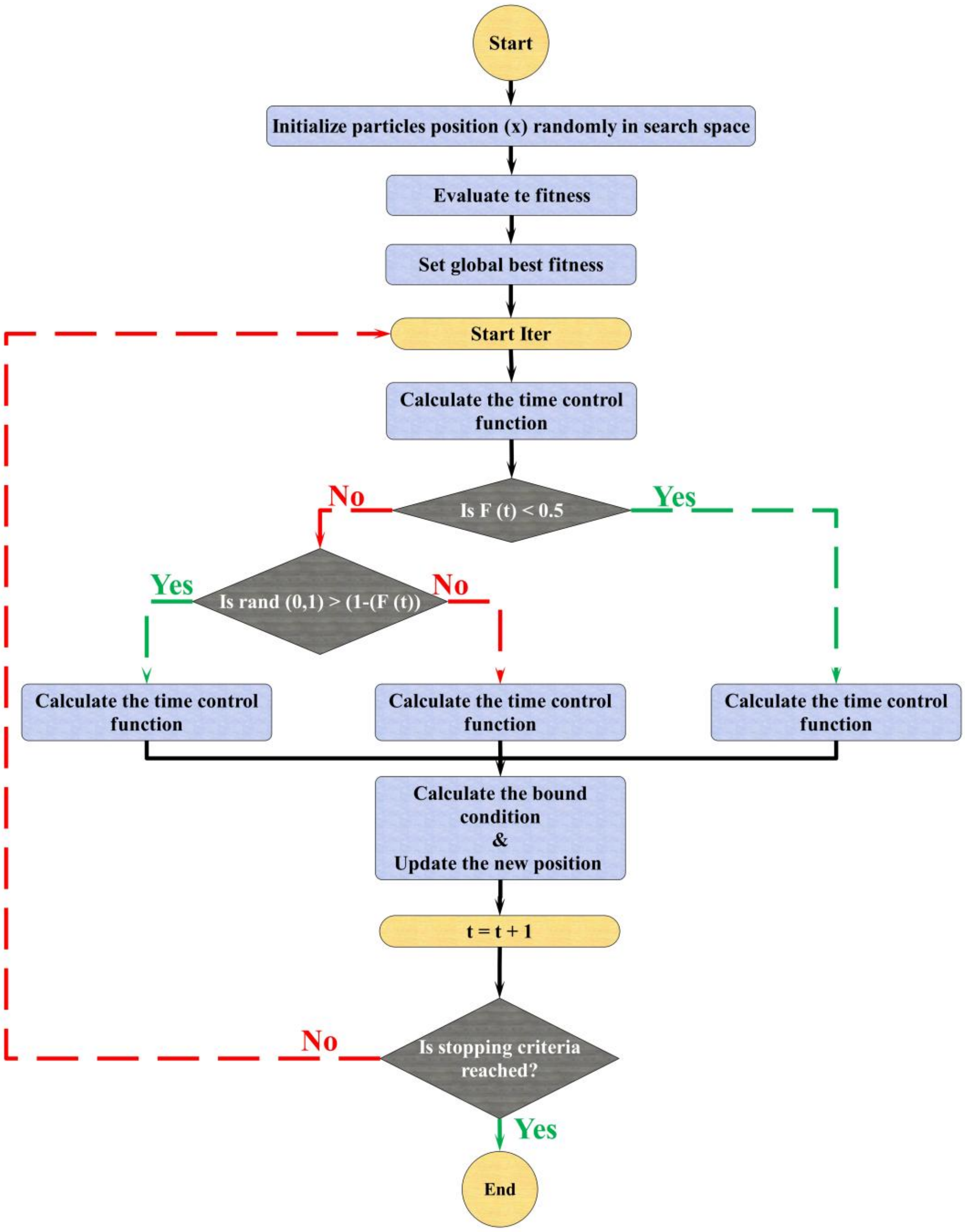


Figure 3: The diagram of JSO [41]

2.5. Rhizotomy optimization algorithm (ROA)

The suggested technique depends on three major rules. Bands of Exploration and Exploitation: A rhizotomy plume is a marine creature that employs multiple random search tactics to find the best areas to feed on large amounts of plankton [43]. When a swarm gathers, it begins to feed. The artificial ROA considers the two essential bands of a meta-heuristic approach. The swarm has two main motion types: exploitation and discovery; (ii) Rhizotomy goes or seeks for food, with a "motion control aspect" establishing when to switch between these actions; and (iii) the swarm's location and related function of objective identify the quality of food found at any given time [44].

2.5.1. Initialization of the population and setting boundary conditions

R, the octopus' gender is chosen at random.

$$x_i^* = \lambda x_i(1 - x_i), \qquad 0 \leq x_0 \leq 1 \tag{20}$$

The anticipated starting population of R. octopus, x_0 , goes to 0 and 1, $x_0 \notin \{0,0.25,0.75,1\}$, and feature λ is set to 4.0. The place value of the $i - th$ R. octopus is x_i. A R, when an octopus enters the search zone, it moves in the other direction. Eq. (21) shows this comeback tactic.

$$x_{i,d}^{*} = \begin{cases} (x_{i,d} - Ub_d) + Lb_d, if\, x_{i,d} > Ub_d \\ (x_{i,d} - Lb_d) + Ub_d\,, if\, x_{i,d} < Lb_d \end{cases} \quad (21)$$

R is situated in the $d-th$ metric. Octopus is designated by $x_{i,d}$; the new place, $x_{i,d}^{*}$, is Generated by validating the boundary restrictions. The top and lower boundaries of the field of exploration for the $d-th$ dimension is represented by Ub_d and Lb_d, correspondingly.

2.5.2. Food searching strategies

Scientists speculated that R, the octopus, migrated utilizing LW like honeybees and sharks [45]. The writer observed that the octopus' mobility pattern changed with time. This type of pattern is best reproduced with fast simulated annealing (FSA). The generating function is embedded within all these food-searching patterns, governing the parameter-updating mechanism throughout the search process. This approach incorporates ROA and relies on three distinct random search strategies: LW, fast simulation of annealing (or food-seeking strategies), and SA. Data comparisons identify the optimal motion plan for the system. The first sortie, termed "Levy flight" after French mathematician Paul Levy [46], displays a random walk with variable step lengths. Moving in a multifaceted environment necessitates taking random steps in various directions.

where x_i is the R, the octopus's present perfect place, x_i is the new R, place of octopus. A step toward the objective, x_i will be shown by R. octopus at x_i if $f(x_i) > f(x_i)$ this phase concludes a heavy-tailed Levy journey, which may be expressed as a simple power law, as illustrated in Eq. (22).

$$L(s) \approx |s|^{1-\beta}, where\ 0 < \beta \leq 2 \quad (22)$$

s is the accidental parameter. The Levy step scale, where u and v originate from typical patterns of shipping, may be calculated as $s = {u}/{|v|^{1/\beta}}$. It is feasible to modify the position with the highest concern for food in Eq. (23):

$$x_{next} = x_i \times rand(0,1) \quad (23)$$

Unplanned motions or flights from the Levy distribution are depicted as $\mu \times \mathrm{rand}(0,1)$, w is the ith random statistic is a widely spread random integer between 0 and 1. The extra motion component has been referred to as the FSA [47]. It is associated with LW through a cost function that integrates prey density f(x), or prey abundance. Similarly, the length of every step, $s = |y - x|$, Eq. (24) is picked haphazardly from a Cauchy likelihood.

$$p(s) = {1}/{\pi} \times {T}/{(s^2 + T^2)} \quad (24)$$

The temperature (T) affects the magnitude of step-length changes. Eq. (24) calculates the acceptable probability value for accepting the new placement.

$$P = min\left\{1, exp({\Delta f}/{T}\right\} \quad (25)$$

$\Delta f = f(y) - f(x)$ is the cost difference between the present location and prior places. The new post must be more severe than the current one to be accepted; that is, if $\Delta f > 0$ it will be recognized, at which point R. Octopus will return to its native location. With the early temperature being T_0 and the step counter being k, the heating approach is planned in terms of $T(k) = {T_0}/{k}$, and FSA [48] converges to the global ideal (maximum). The length of each stage in the third R, octopus motion approach is haphazardly generated from a Gaussian distribution, making it a special kind of LW search strategy.

$$g(s) = (2\pi T)^{-D/2} e^{({\Delta x^2}/{2T})} \quad (26)$$

While Δx denotes the rate of shift X (variables vector), D denotes the size of the search region (count of elements in the cost function). Therefore, $x_{next} = x_i + \Delta x$ means the present state and x_{next} displays the following set of settings.

2.6. Performance evaluator

Classifier performance is assessed using a range of parameters. The term "$accuracy$" refers to the proportion of correctly predicted observations. Three popular measures are $precision$, $accuracy$, and $recall$. Overall $accuracy$, which includes both real negatives and positives, is referred to as $accuracy$. Reduced accuracy might be the outcome of unbalanced datasets. $Recall$ assumes minimal mistakes and searches for positives. The $F1\ score$ works well in schools with a variety of student demographics because it strikes a balance between $recall$ and $accuracy$. Both true positives and false negatives can be handled by it. These metrics aid in determining how effective ML models is.

$$\mathrm{Accuracy} = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}} \quad (27)$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP + FP}} \quad (28)$$

$$\mathrm{Recall} = \mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{P}} = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \quad (29)$$

$$\mathrm{F1\ score} = \frac{2 \times \mathrm{Recall} \times \mathrm{Precision}}{\mathrm{Recall + Precision}} \quad (30)$$

In the computations below, the letter TP displays an optimistic projection regarding the lucky event. When a situation has a bad ending, the acronym FP signifies a good perspective. A pessimistic prediction based on TN yields the same result as a real negative. When the genuine conclusion is positive, the FN symbolizes a dismal future.

3 Result and discussion

The findings of the hybrid models are painstakingly presented, with various charts and tables for thorough comparison. These visual and tabular representations provide a complete review to determine which model contributes the most effectively to the prediction process. The research effort tries to bring out nuances in the prediction skills by carefully examining performance data and graphical depictions that are of considerable significance in providing insights into each model's relative strengths and limitations. Such in-depth study enhances knowledge and aids informed decision-making in selecting the most effective model for predictive tasks.

3.1. Convergence curve

Convergence curves from the prediction procedure measure performance increase as a function of training cycles for an ML model. They show how a model starts to have lower error or loss with each cycle of learning from the training data. Analyzing a convergence curve provides important information regarding the model's learning dynamics, including convergence rate, stability, and possible overfitting. A steep drop in mistakes followed by a plateau indicates good learning, but unpredictable behavior may suggest difficulties that require attention. Understanding convergence curves helps to optimize model parameters, improve forecast accuracy, and ensure resilience in real-world applications.

The convergence curve of the three hybrid models, namely, RFRD, RFJS, and RFRO, are shown in Fig. 4. Herein, in the result section, it is observed that the RFJS model starts cycle with the lowest accuracy among the presented models. Beginning with an accuracy of about 0.525, this model achieves 0.825 accuracy by the 50th cycle. Its optimal performance, however, touches the peak at 0.95 at around the 130th cycle and, as such, outperforms many models like RFRD. RFRD, beginning at a higher accuracy greater than 0.525, has already started cycle and increases performance up to 0.800 at the 50th cycle. Subsequently, it concludes the process with an accuracy of nearly 0.900 by the 100th cycle. Conversely, the RFRO model demonstrates an accuracy of approximately 0.950 by the 120th cycle, indicating superiority over RFRD but inferiority to RFJS models.

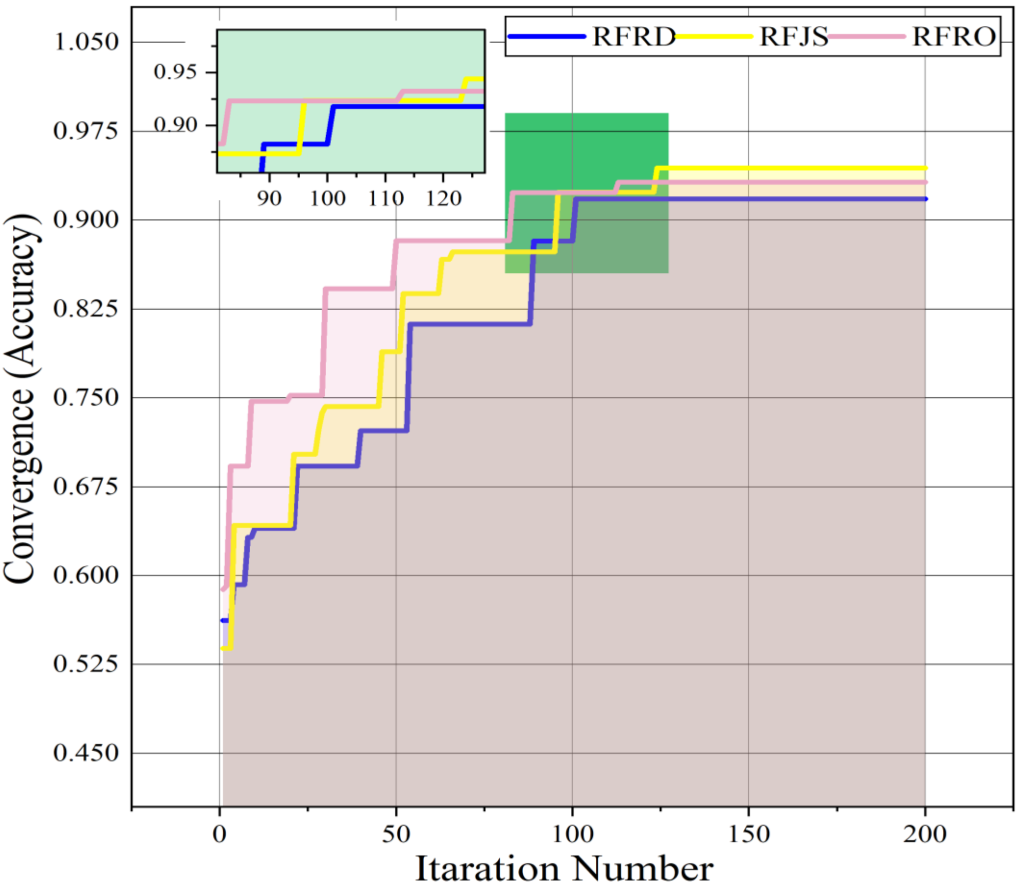


Figure 4: The convergence curve of the three presented hybrid models

3.2. Models' comparison

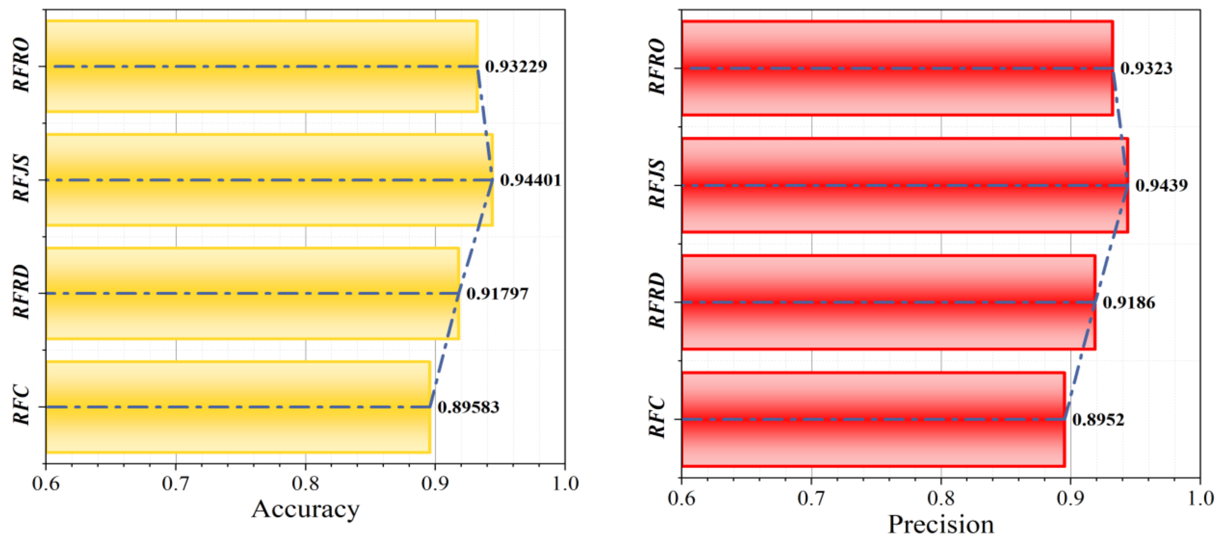
In Table 1, a comparison is made between RFC and its mixed forms in terms of outcomes during the training and testing phases. For instance, in the training phase, it is observed that the RFC model achieves an accuracy of 0.9033, which is the lowest among the base models. However, as demonstrated by the RFDR's $accuracy$ of 0.9275 and the RFRO's $accuracy$ of 0.9442, the $accuracy$ of the model is much enhanced when paired with optimizers. With an accuracy of 0.9517, the RFJR achieves the best $accuracy$.

In the testing phase, the precision values of these models indicate that RFJS, with a precision value of 0.9253, is favored over the other models. The RFRRO model, with a precision value of 0.9027, can be considered the second-best model. Other models, such as RFRD and RFC, demonstrate their lower performance in this comparison, with precision values of 0.894 and 0.875, accordingly.

Table 1: RFC-based models achieved results through the performance evaluators

Section	Model	Metrics			
		Accuracy	Precision	Recall	F1 _Score
Training	RFC	0.9033	0.9033	0.9033	0.9027
	RFRD	0.9275	0.9299	0.9275	0.9265
	RFJS	0.9517	0.9517	0.9517	0.9515
	RFRO	0.9442	0.9444	0.9442	0.944
Testing	RFC	0.8783	0.8756	0.8783	0.8762
	RFRD	0.8957	0.894	0.8957	0.8945
	RFJS	0.9261	0.9253	0.9261	0.9255
	RFRO	0.9043	0.9027	0.9043	0.9021

The performance of the presented model is demonstrated through a bar plot in Fig. 5 in all phases. It is observed that the RFJS model, with a recall value of 0.944, can be considered the best model in this comparison. Following this, the RFRO model, with a recall value of 0.9323, is proven to have the highest recall value among the other models. However, the RFRD model, with a recall value of 0.918, is identified as the hybrid model with medium performance, albeit with a recall value higher than that of the RFC model, which stands at 0.8958. Furthermore, it is demonstrated that the RFC model does not aid much in the prediction process, with an F1 score value of 0.8948. Moreover, the RFDR performs worse than the RFRO model, which has an $F1\ score$ of 0.9317, and the RFJS model, which has an $F1\ score$ of 0.9437.



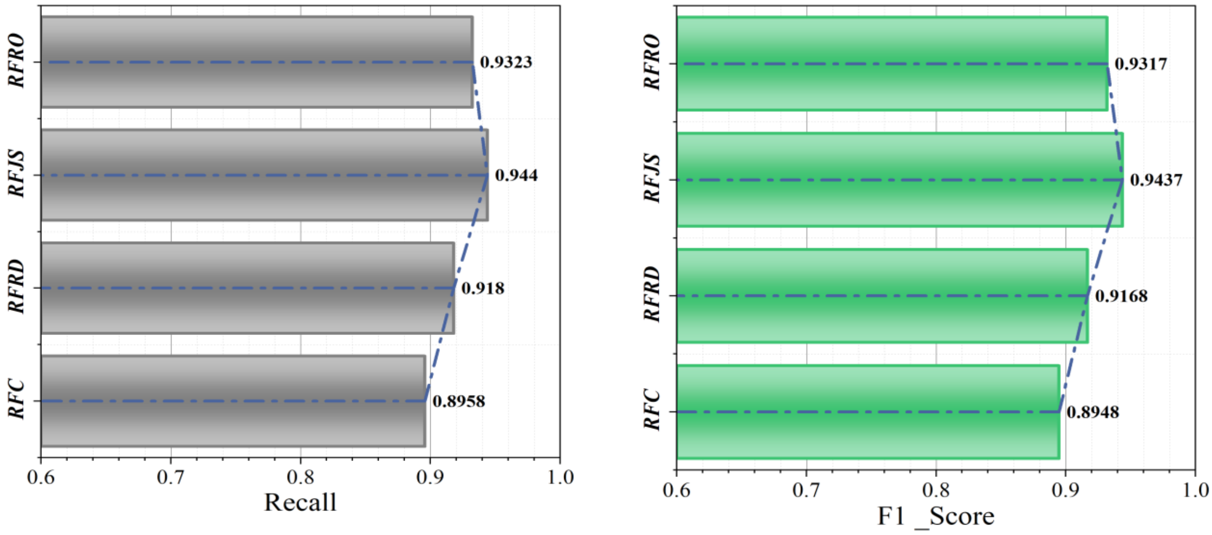


Figure 5: Bar graph showing the models' performance over all phases

In Table 2, the performance of the models is presented and contrasted across both Healthy and Diabetes conditions. For example, the RFC model displays a *precision* value of 0.9038 when they are in a healthy state and 0.879 when they are in a diabetic state. When compared to the best scheme, RFJS, which has a *precision* of 0.9472 under healthy conditions and 0.9377 under diabetic conditions shows the worst performance. The RFRO outperforms the RFDR, which records a *precision* value of 0.913 under the same situation, with a *precision* value of 0.9324 in a healthy state. Furthermore, the RFDR's *accuracy* value under the diabetic condition is 0.9282, which indicates that it functions less well than the RFRO, which has a *precision* value of 0.932 under the same scenario.

Table 2: Model performance in the four different conditions

Model	Condition	Metric		
		Precision	Recall	F1-Score
RFC	Healthy	0.9038	0.94	0.9216
	Diabetes	0.879	0.8134	0.845
RFRD	Healthy	0.913	0.966	0.9388
	Diabetes	0.9289	0.8284	0.8757
RFJS	Healthy	0.9472	0.968	0.9575
	Diabetes	0.9377	0.8993	0.9181
RFRO	Healthy	0.9324	0.966	0.9489
	Diabetes	0.932	0.8694	0.8996

The line symbol plot in Fig. 6 compares the models' predicted values with the measured values. It is observed that the RFC model's predicted value exhibits a significant difference from the measured value, with 215 out of 500 under healthy conditions. Similarly, under diabetic conditions, it shows minimal variation, with 220 out of 499 measured values. Next, in healthy conditions, the RFRD model shows consistency with 239 out of 500 measured values, nearly matching the performance of the RFRO model, which likewise records 239 out of 500 observed values. Conversely, under diabetic conditions, the RFDR's performance weakens, as evidenced by 225 out of 499 measured values, contrasting with the RFRO model's 232 out of 499 measured values under the same conditions. However, as previously noted, the RFJS model emerges as the most effective, achieving 240 out of 499 measured values under diabetic conditions and 240 out of 500 measured values under healthy conditions.

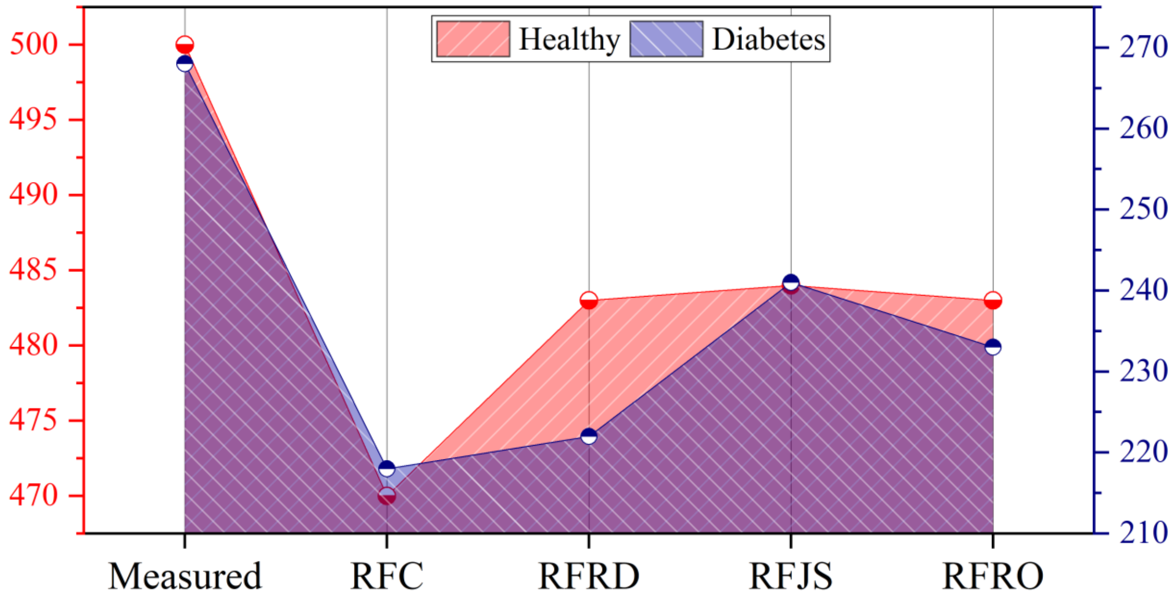
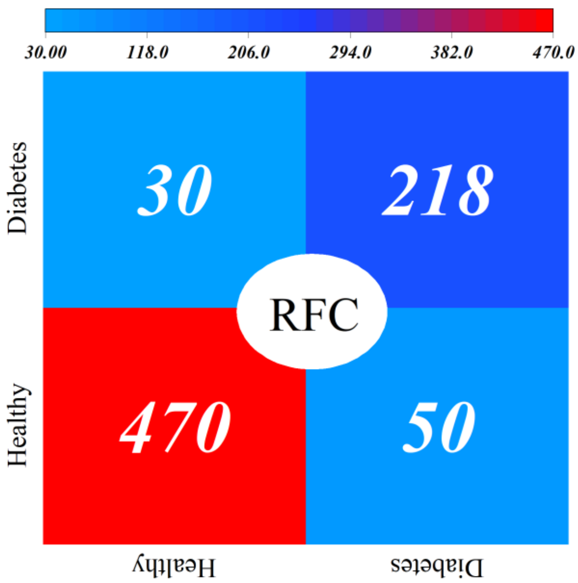
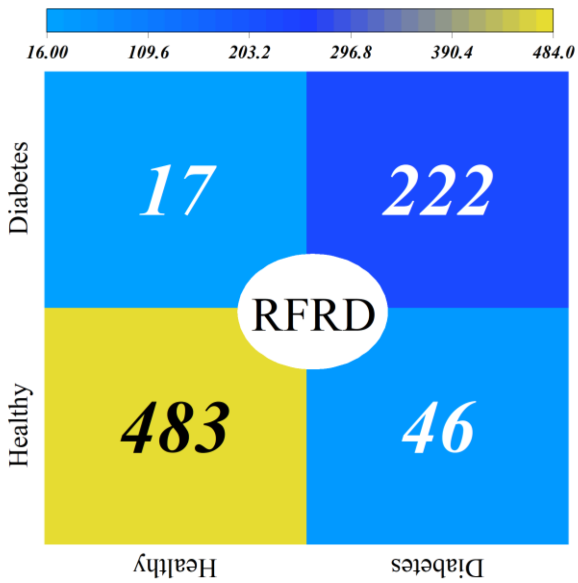


Figure 6: A line-symbol plot showing the models' percentage difference

The confusion matrix displayed in Fig. 7 comprehensively compares the models' measured values and misclassifications across healthy and diabetic conditions. Notably, the RFC model showcases a commendable 94% accuracy under healthy conditions, albeit with 30 patients misclassified under diabetic conditions. Conversely, its performance diminishes under diabetic conditions, registering an 81.34% accuracy, accompanied by 50 patients being misclassified under healthy conditions.

In stark contrast, the RFJS model emerges as the epitome of effectiveness, boasting a remarkable 96.8% accuracy under healthy conditions, with a mere 16 patients misclassified under diabetic conditions. Similarly, even under challenging diabetic conditions, this model maintains its superiority, achieving an impressive 89.92% accuracy, with only 27 patients misclassified under healthy conditions. Such data emphasize the significant increase in performance observed between the weakest model, RFC, and the most robust model, RFJS, stressing the importance of model selection in adequately diagnosing patients under varied health situations.





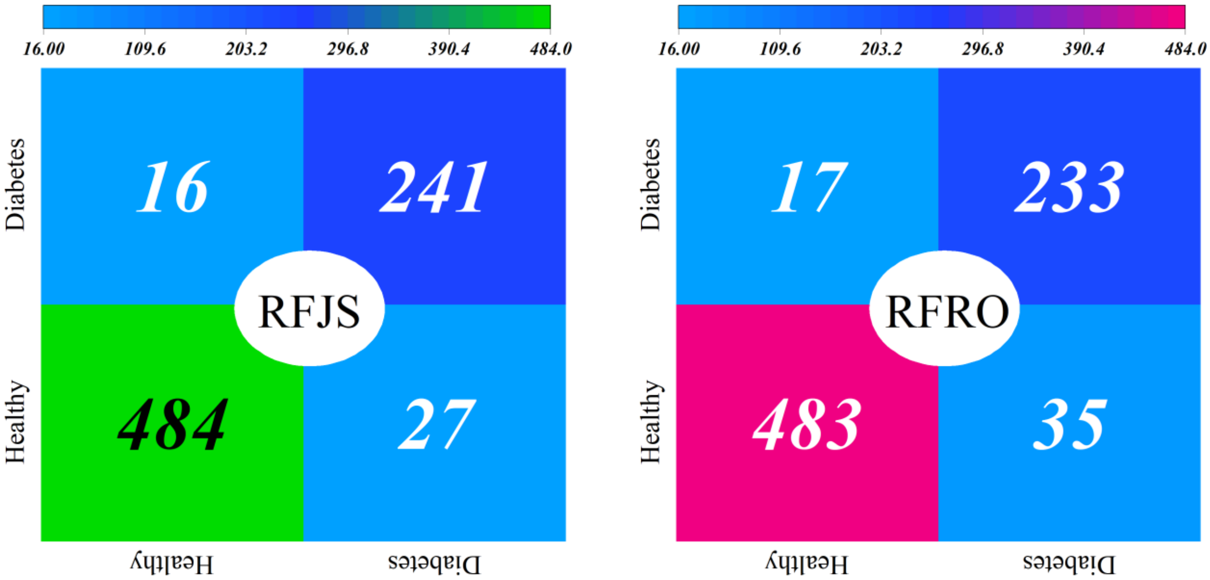


Figure 7: Confusion matrix for the accuracy of the models in four presented conditions

The Shapely Additive explanations (SHAP) in Fig. 8 show how numerous circumstances, such as pregnancy or blood pressure, affect the chance of acquiring diabetes. The following explanation gives a concise definition of how these factors influence the development of diabetes.

- Pregnancy causes complicated metabolic changes, which can have a substantial influence on diabetes. In gestational diabetes, pregnancy hormones can interfere with insulin activity, resulting in high blood sugar levels. Pre-existing diabetes, either type 1 or type 2, may require much tighter control during pregnancy to minimize risks of complications both for the mother and the child. Poorly managed diabetes during pregnancy carries risks such as macrosomia (considerable birth weight), congenital anomalies at birth, and maternal issues like hypertension. Successful management through food and exercise and, if necessary, medication under medical supervision to ensure optimum health for mother and fetus during this critical period.
- Hypertension, or high blood pressure, often accompanies diabetes and forms a lethal combination that exacerbates cardiovascular disease. High blood pressure accelerates the progression of diabetic nephropathy, retinopathy, and neuropathy, leading to an increased risk of heart disease, stroke, and kidney failure. The interaction between hypertension and diabetes is a delicate one, with complex processes such as endothelial dysfunction, inflammation, and oxidative stress, which encourage a vicious cycle of organ damage. Appropriate treatment measures aimed at both illnesses include lifestyle changes, medication adherence, and regular monitoring, which are crucial in reducing the cumulative risk and improving the long-term outcome in patients with concurrent diabetes and hypertension.

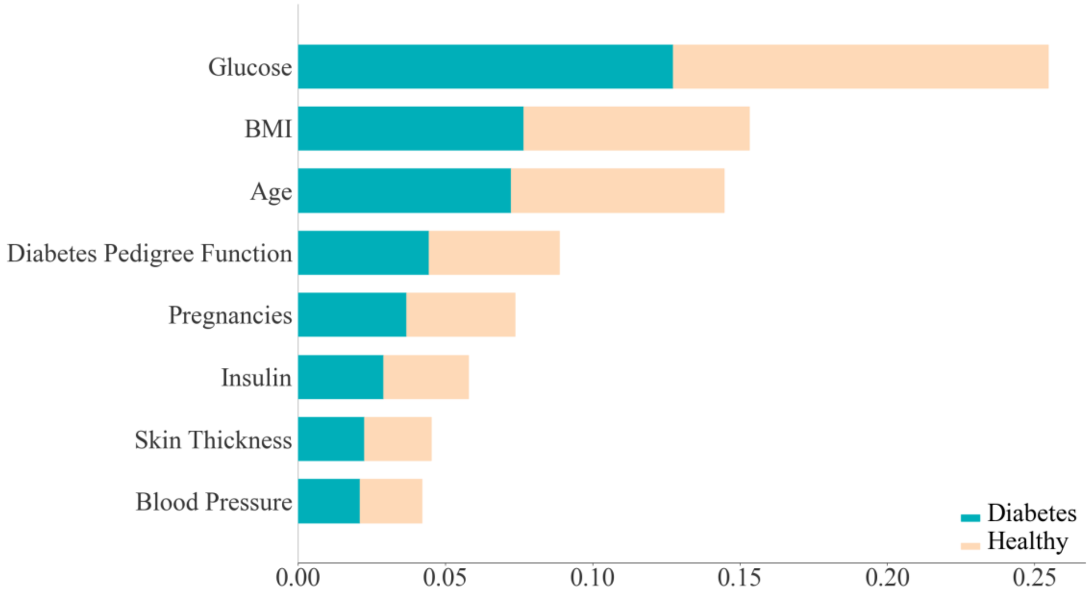


Figure 8: The SHAP sensitivity analysis of the most accurate developed model

4 Conclusion

Pregnancy-induced diabetes, medically termed gestational diabetes mellitus, can often stay well after childbirth. Research has shown that women diagnosed with GDM are at a higher risk of developing type 2 diabetes later in life. Children born from moms with GDM may also be at a higher risk for obesity and type 2 diabetes. This intergenerational transfer of metabolic risks underlines the importance of postoperative follow-up and lifestyle changes for both mother and child. Addressing GDM through early identification, adequate therapy during pregnancy, and health measures afterward is critical to reduce its long-term impact on mother and child health. Moreover, diabetes prediction during pregnancy is proposed with the RF, an ML classification model. It uses RDA, JSO, and ROA to increase the model's precision. Here, it has been determined to propose optimizers integrated with a model for enhanced prediction performance. These results indicated that RFJS, with the best performance of all compared models, resulted in a value of 0.9377 regarding diabetic conditions. The RFRO model, therefore, with a value of 0.932, stands out as the second-best scheme. The RFRD model, with a precision of 0.9282, shows middle performance and a higher value than RFC, recording a precision of 0.879. Even though ML could be of help in predicting pregnancy-induced diabetes, there are limits. In case biases within the dataset are not handled well, they may have an impact on predictions. Imbalances in demographic representation or missing data might limit model generalizability. Furthermore, interpretability issues occur when sophisticated models hide the reasons behind forecasts, limiting clinician trust and decision-making. Scalability difficulties arise as models are deployed across a variety of healthcare settings. Integrating existing electronic health record systems presents technological challenges, possibly affecting workflow efficiency. Besides, model performance can degrade over time due to changes in patient demographics or healthcare practices, and the models will require re-calibration, ethical considerations regarding privacy and permission when working with sensitive data of patients, and developing and implementing a model keeping in view all regulatory requirements, such as GDPR or HIPAA. The clinical utility will thus depend on the availability of real-time data streams and their seamless integration into clinical workflows. Implementation issues may hamper uptake and reduce the influence of predictive models on patient care. Despite these limits, continuing research seeks to overcome these issues through better data-gathering methods, model interpretability methodologies, and collaboration between healthcare experts and data scientists.

Authorship contribution statement

Shuai Zhao: Writing-Original initial drafting, Conceptualization, Supervision, Project administration.

Huiqin Ren: Methodology, Software

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author statement

The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.

Ethical approval

All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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