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IID3 Classifier To Diagnosis Of High Blood Glucose Levels During Pregnancy

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Abstract

During period of women-pregnancy a rise some type of diabetes-disease as a result of high-blood-glucose level called the Gestational Diabetes Mellitus(GDM). As this type of diabetes harms the mother and her baby at the same time, and the chance of developing it is one in every 25 pregnancies. So, the risk of rising type2 diabetes afterward. The goal of this work is to design a model which can prognosticate the opportunity of diabetes during pregnancy with best accuracy. The blood-sugar concentration is the main characteristic that used to diagnose the infection, beside that the characteristic of smoky pregnant women in addition consider the weight and genetic factor of the pregnant woman. IID3–Decision tree as classifier used and evaluated by comparing the proposed with three other exist methods. Decision Tree, SVM and Naïve-Bayes are used in performance comparison on the same pregnant women dataset. To assessment the the functioning of proposed-model use Precision-measure, Accuracy, F-Measure, and Recall. Results obtained show the accuracy of proposed model is close level accuracy 88.36%. The results and findings are gotten by applied it on 986 GDM pregnant women during 2 years depend on some questionnaire about the conditions. As the results of this work is 56% of smoking pregnant women have overweight with high blood pressure(uncontrolled cases), while the rate of smoking pregnant women with moderate weight is 31% medium blood pressure (controlled cases), normal blood pressure is gotten with 9% of those non-smoking pregnant overweight-women with genetic factor , and 4% of those smoking pregnant women have normal-weight with normal blood pressure.

Keywords: GDM, Blood Sugar, Decision-Tree, pregnant smoking women, overweight.

Introduction:

Sometimes, a hormone prepared by the placenta ward off the body from using insulin to all intents and purposes , that is caused glucose accumulated in the blood instead of being retained without reflection by the cells this called Gestational diabetic.

GDM symptoms disappear following delivery. Usually 20 to 24 weeks into the pregnancy begin take place contra-insulin effect which some of these hormones(estrogen, cortisol, and human placental lactogen) which maintain the pregnancy in addition to nutrients and water that placenta supplies fetus. Although any woman have GDM during pregnancy, but the woman-age, overweight , gene factor of family and previously births to overweight infant [1]. Also there was another main effective factor that is the high-correlation of GDM with gestational-blood-pressure (B-P) and gentle-age[2]. Such that patients had GDM and The body blood of these persons fell within the pre hypertensive variety, so there an relative between GDM and BP[3].

Pattern recognition techniques are commonly used in healthcare field for classifying data into multiple various classes according to some rules or restrictions based a classifier strategy. Many investigators and there studies are carrying out some trials for detect the diseases using variants classification algorithms of pattern recognition approaches. First detected during pregnancy where Gestational-Diabetes (GD) is distinct as carbohydrate fanaticism that initiate. So high importance of detection for the prognosis of the women-pregnancy [4].

There are exist some related works and previous literatures that deals with recognizing the women infection of diabetes during period of pregnancy such that A.Chitra and S. Anto 2015[5] introduce a system which is used to diabetes diagnosis based on an ensemble system. Where, all steps of SVM-algorithm are applied to give the expected results and representation so these sets of steps can be consider as another attitude for conclusion and a means to check out the persons with non-identify imbalance of blood sugar level by amateur clients.

M.Durairj and G.kalaslvi 2015 [6] Depend on data mining techniques, they show that the ANN gives highest accuracy above 89% result than other C4.5, classifier, Suppourt vector Machine (SVM), K-Nearest Neighbour (KNN). G.Krishnaveni and Sudha 2017[7] present a classification techniques that able to diagnosis the infection of diabetic-disease depend on results for the applied these techniques like 76.3% for using discriminant-analysis, 71.1% applying KNN-technique, 76.1% for using NBayes-technique , 74.1% applying SVM together with Linear Kernel(KL) technique, and 74.1% as a result of SVM together RBF Kernel technique. I.Salman, and etal. in 2017[8] introduce a method of classification performed on diseases diagnoses of Pima-Indian-Diabetes. So taken fifty values of (K) in KNN vs. fifty values of hidden layers for ANN. Based on T-test to verify factors so ANN-classifier gets better results than KNN-classifier. American diabetes association (2018)[9] presents management of diabetes-pregnancy article which detects medical-care standard in diabetes. A.Shaik and M. Divya 2021[10] work on a one more than one classification model using multiple ensemble factor selection to enhancement the accuracy of classification some classes diabetes retinopathy databases. So B.Shamreen and M. Arya in 2021[11] find that the Light gradient Boosting Algorithm(LGBM) . Classifier gives the most accurate results of PIMA Indian Dataset where an accuracy of 95.20% was obtained. Ya.Liu, Z.Yu and H. Sun in 2021[12] used Regression predication model which used to identify the importance of the input-feature of the classification output. So get accuracy that is an increase of about 12% compared with when the feature is not used.

Again the aim of this research-paper is early detection for the prognosis of the women-pregnancy with a high rate of accuracy. The contributions of this work is suggested an idea used to raise the rate of accuracy and minimizing the diagnose classification problems by using the preprocessing method and IID3 classifier. One of the important things of this work concluded that data of electronic-medical record improves the accuracy of predicting gestational-diabetes. This paper presents a diagnosis and treatment of GDM through pregnancy-period in section2 with a short descriptor of IID3 as a classifier in section3, while section4 shows the diagnosis model with it's algorithms and section5 introduces the obtained results with some discussions to assess the performance of proposed work; section6 shows conclusions of this work according to obtained results.

2. GDM During Pregnancy Diagnosis and Treatment:

The early diagnosis and proper management may minimize the negative outcomes during the perinatal period [13][14]. According the existing literature reviews: the parameter of risk of GDM review during 1st embryonic period of pregnancy and include family history of GDM and/or diabetes. Most tests have poor +ve prognostic values and limited qualification[15]. Research-studies and statistics have shown that most women (and estimated in half) during the 6-9 years after pregnancy have GDM from type II. Table1 shows the parameters from datasets, which are using in test[16][17]. Table2 shows the Normal Glucose Level chart[18]. Necessary measure to diagnose and control GDM of pregnant, frequently at every visit to clinic , i.e. urine-glucose of pregnant-women is checked. When pregnant women reached the 24–32 weeks of gestational , they should do fasting-blood-glucose and 2-h OGTT where it was founded that +ve OGTTs and GDM are public in women aged more-than thirty years, the mass index of body(BMI) was more-than twenty five (kg/m^2), and parity was more-than four [19]. Although the important issues like watch the weight and work out-therapy, which are the first step of health care, but where glycemic-control is not good enough, insulin is given[20]. In order to obtain real data for the proposed model, the required data collected from 951 pregnant women of different age groups, from various social environments and with different disease records for a period of 30 months. The weight measured, age was determined, the genetic factor asked, the number of pregnancies was determined, and the pregnant woman was a smoker or not (History of smoking). GD susceptible women as pregnancy advances, will be suffering from disproportion between insulin making and insulin supplies which means there are pancreatic β-cell imbalance and a decrease in adaptive β-cell capacity. This result in not enough insulin emission and high blood sugar as a result [21].

Table1 The parameters effect of GDM from datasets

#	Parameters to be test	Abbreviate	Range
1	No of time pregnancy.	PRG	0-7
2	Plasma glucose concentration	PGC	>=0 and =<200
3	Diastoli-blood-pressure (mmHg)	DBP	0- 130

4	Tricps-skin-fold-thicknes (mm)	TSFT	>=0 and =<100
5	2-hour serum insulin (muU/ms)	INSl	>=0 and =<930
6	Mass-indexof body(wight in kg/ Sqr(hight in m))	MI	0-83
7	Class Parameter (infected 1 not 0)	CP	-
8	Diabetes pedigrees function.	DPI	>0 and ≤2.999
9	Age	Years	>=23 and =<80

Table2: Normal Glucose Level chart

#	**Factors**	**Level(** mg/dL)
1	Fasting: no glucose rise	95
2	1H after-glucose	180
3	2 H after-glucose	155
4	3 H after-glucose	140

3. Improved-Iterative Dichotomiser3(IID3) Classification Algorithm[22]:

A Greedy algorithm is an approach of implementing a tree of decision, so an Iterative Dichotomiser3(ID3) is an classification algorithm that follows it by picking a top quality attribute utmost Information Gain (IG) or bare-lowest Entropy (H), where (H) is a calculate of the un certainty in the set of data S as shown in eq(1) [23]

$$\mathbf{H(S)} = -\sum_{\mathbf{c}\in\mathbf{C}}(\mathbf{p}(\mathbf{c})\log_2\mathbf{p}(\mathbf{c})) \quad (1)$$

Where S is the current set of data for H is being computed d, C is the classes-set in S, p(c) is the proportion of the elements-number in c to the elements-number in set S.

In ID3, H is computed for each residual attribute. The attribute with the least H is used to divide S on that special iteration. i.e. H = 0 implies all are of same category. IG(A) decide the value of improbability in S was condensed later than dividing S on attribute A as shown in eq(2)

$$\mathrm{I\,G(S|A)} = \mathrm{H(S)} - \sum_{t\in T}(p(t)H(t) \quad (2)$$

H(S) is the Entropy of S, T is the sub-sets created from splitting set S by attribute A such that Entropy of subset t.

IID3 algorithm gets a tree of decision with fewer numbers of leaves and elevated prognostic-accuracy. Algorithm1 shows the main steps of IID3 which is an improved on traditional-ID3[24].

4. Steps of the proposed Diagnosis During Pregnancy

The methodology applied explains the steps of this work on the dataset and the important features affecting the diagnosis based on the IID3 algorithm to solve the research problem and achieve the goal, which is to classify and determine the category of risk. Fig1 shows the main steps of the proposal methodology.

Algorithm1: The main steps of IID3

Input: Values from data set i.e

Attribute set : A = {A_1, A_2, ..., A_X } for X-conditions attributes with values-range {R_1, R_2, ..., R_X} , R_D= {D_1, D_2, ...,D_Z} where D is a decision attribute with Z values.

Sample set : S = {(x_i , y_i)‖x_i∈ D_1* D_2*... *D_n, yi ∈ R_D } //* y_i is an output of which correlated with it

Stop condition :A is empty or y as single-value has elements in training-set

Output: DT //* decision Tree

Begin

Step1:Generate the DT

Step2:Compare with stop condition if match

Step2.1: If not match then

Begin

2.1.1 Calculate the IG using $\mathrm{Gain}(\mathrm{CA}_{(\mathrm{D},,\mathrm{S})})[\mathrm{i}] = \mathrm{E}_{\mathrm{DA}}(\mathrm{D}) - \mathrm{E}_{\mathrm{CA}}(\mathrm{A_i}, \mathrm{S})$

2.1.2 Calculate the frequency using $\mathrm{FA_K} = \frac{\mathrm{N_K}}{\mathrm{N}}$

2.1.3 Calculate the attributes-weight of attributes by means of the training-set $\mathrm{WA_K} = \frac{\mathrm{FA_K}}{\sum_{\mathrm{K=1}}^{\mathrm{N}} \mathrm{FA_K}}$

End

Step3:Find the best splitting attribute with maximum weighted

Step4:Attach into DT

Step5:Generate branches for nodes

Step6:Self recursion of generate the DT

End

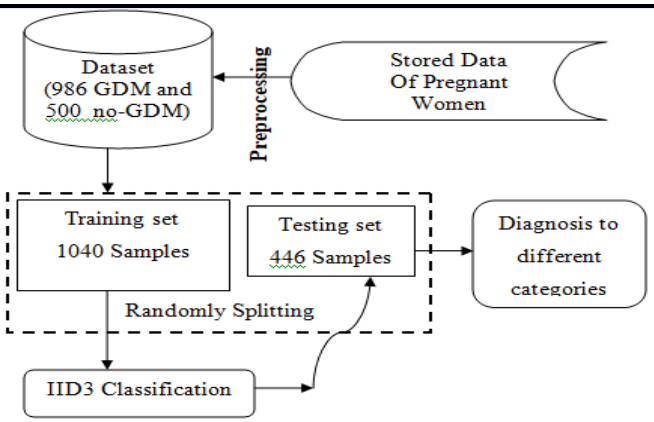

Figure (1): General schema plan of the proposed method

As a first to start this work, a dataset was adopted that enables to reach an accurate decision based on real data and follow-up time for changing cases. The contents of this dataset are information's records of 986 GDM pregnant women and 500 non-GDM pregnant, collected during 2 years depend on some questionnaire about the conditions. Some analyzing and preprocessing on the dataset was done to remove the redundant and to complete a missing values, so some encoding of attributes of each record of information using correlation matrix, features selection algorithm, and data scaling with normalization techniques to transform data into suitable forms for dealing as an aid factor to recognize the patterns. Using Z-score algorithm to data scaling, eq(3) shows the mathematical model of scaling operation.

$$z = \frac{z - \bar{x}}{\sigma_x} \qquad (3)$$

Where ,. $\bar{x}$*is mean*, and , is standard deviation of variable values.

This technique is useful when we don't know the exact minimum and maximum values of the input data, or when there are outliers that have a significant impact on the data range. So algorithm2 describes the dataset analysis and preprocessing procedures. Then as next step do randomly crack this dataset to 70% as the training-dataset with 30% present the test data.

Algorithm (2) Dataset analysis

Input : Features of GDM , n
Output: Statistical values for each GDM-features

Begin

Step1: n = Count number of scores in sample.

Step2: For Each f_i.Feature in GDM dataset Do //* i=0,….,n

Begin

Compute $\bar{f}$. and SD //* $\bar{f}$ is a mean = $\sum_{i=1}^{n} \frac{x_i}{n}$,*i*=1-*n*-, and SD=$\sum_{i=1}^{n}((f_i - \bar{f})^2/n-1)^{0.5}$

Mn(f_i) and Mx(f_i.) //* Mn is Minimum values of the Feature (f_i.) , Mx is Maximum values of the Feature (f_i)

25% (f_i)= 25% quartile //* using $K(n+1)/100$,k =25,n =number of data .

50% (f_i) = 50% quartile //* using $K(n+1)/100$,k =50,n =number of data .

75%, (f_i.)= 75% quartile //* using $K(n+1)/100$,k =75,n =number of data .

End

End

The features affecting the decision-making process filtered from among all the features obtained through the process of collecting information from pregnant women. This import ant step is to reduce the time spent applying the rules for decision-making. The process of selecting the

influential features based on higher entropy value. The nominees features to predicate the GDM as shown in table3 After feature extraction step some features have low or no effect of the GDM detection during period of pregnancy so other features as have high effect as shown in table4. All information records divided into such class as shown in table5 to be use at the next step to make accurate decision. Next step apply classification procedure shown as algorithm3, the decision tree implemented based on IID3 classifier as shown in fig2. Each feature in the data set is represented as a vector of data, for each sub-tree was assigned the appropriate feature according the rules of this sub-tree then calculated the IG, frequency, and weight of attributes for each. The aim of this routine aimed to generate the final decision-tree after compare with stop condition if match or not. IID3 algorithm based on weighted-IG that is a main factor of splitting process i,e. the correlation and link of current- situation-parameters with linger

situations-parameters and the relationship among all situation(conditions)-parameters and the choice in the steps forward of this process. The output of the classification procedure based on collect many decision trees to obtain the final decision.

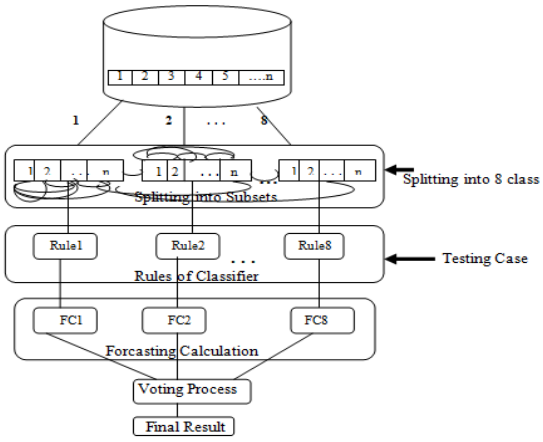

Figure2: classification procedure

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Algorithm3: Classifier-routine
Input: Values from data set //* which prepared as each feature in dataset as a vector of data **Output:** DT //* Final Decision Tree
Begin Step1: Load input values from dataset Step2: Split the input values into 8 class Step3: for each class from 1 to 8 do Step3.1: call IID3 decision tree Step4: Put together all results of Decision tree from step3 Step5: Do the voting according the frequent results Step6: Return the final DT **End**

Table3: The nominees features

#	**Pregnant features**
1	Family history
2	Age
3	Kidney problems
4	Smoking+ overweight
5	Parity (age≥40)
6	Routine diet
7	No. of cases
8	High blood pressure
9	BMI
10	Overweight
11	smoking
12	2H Mean Glucose value
13	Sport exercises

Table 4:The features affecting pregnancy.

#	Pregnancy features	GDM	None GDM
1	No. of cases	986	500
2	Age	25±8.5years	22±5years
3	BMI	20±6 Kg/m^2	15±5 Kg/m^2
4	Smoking with overweight	28±10 Years, 20±6 Kg/m^2	23±5 Years, 15±5 Kg/m^2
5	Parity (age≥40)and smoking	≥4	≤3
6	2-H Mean Glucose value	154.5±8	99±15

Table5: Descreption of classes used in proposal

#	Descreption
1	Smoking pregnant +overweight+D -Medical history
2	Smoking pregnant +without overweight+ D -Medical history
3	nonSmoking pregnant + overweight+ D -Medical history
4	nonSmoking pregnant +without overweight+ D -Medical history
5	Smoking pregnant +overweight+without D -Medical history
6	Smoking pregnant +without overweight+ without D -Medical history
7	nonSmoking pregnant + overweight+ without D -Medical history
8	nonSmoking pregnant +without overweight+ without D -Medical history

5. Discussion of the Results:

Result of this work is shown in table6, the percentage of correctly classified as GDM was 61%, 33% and 81% respectively while the percentage of correctly classified as non-GDM was 18%, 42%, and 13% respectively, then the total rate of correctly classified was 79%, 75% and 94% in a very short time.

Table 6:Result of propose method

#	Dataset size	#Correctly classified as GDM		#Correctly classified as nonGDM		Rate of Total correctly classified	Time (in Msec.)
1	386	234	0.61	68	0.18	0.79	12.3
2	119	47	0.33	50	0.42	0.75	9.2
3	883	713	0.81	106	0.13	0.94	15.7

Table7: p-value of chi-square test

			GDM %	Non-GDM%	P-value
Features	**BMI**	under weight	2.5	97.5	
		normal	10.0	90.0	
		overweight	50.0	50.0	0.234
		puffy	75.0	25.0	-
	MH	Diabetes-Midecal History	35.0	65.0	
		No Diabetes-Midecal History	12.0	88.0	0.222 -
	AGE	Age (23-28)Year	2.5	97.5	
		Age(29-34) Year	12.5	87.5	0.345
		Age(34-39)Year	75.0	25.0	-
	Smo kg	No Smoking	100.0	0.0	0.002
		Smoking	5.5	94.5	-

This work decided to depend on some effective features in diagnosis process so use some classes based on these features see table5. The p-value measure define as it is the possibility of gaining a chi-square as big that in the present test and so far the data will still hold up the assumption. From table7 notice that a P value is too smaller than 0.05 which is mean these features are effective in GDM diagnosis while other features have a p-value is bigger than 0.05 indicates a note that no upshot was sensible.

The discussion of the results is to evaluate the proposal which based on using IID3 as classifier, assume working on the same dataset of pregnant women as table8 introduces the clear image of IID3-performance vs ID3-performance where sensitivity, confidence, F-score which is a measure[20][21] of a model's accuracy on a dataset, and kappa measure which used to assess the performance of a classification model of IID3 is more than these values one in ID3,

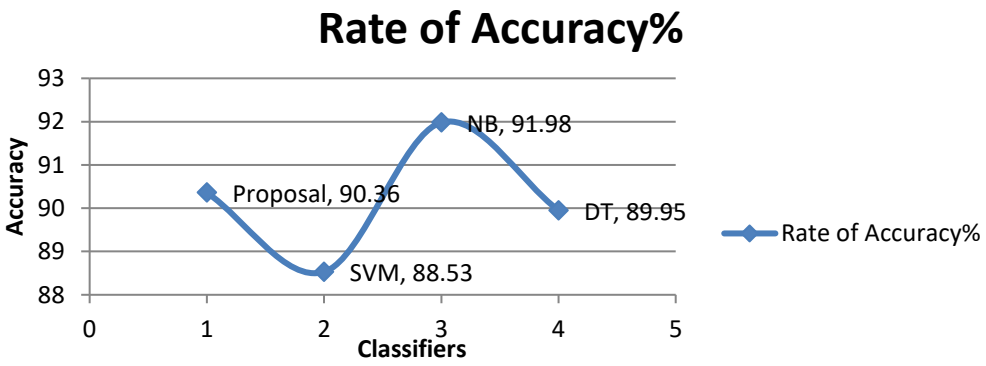
Table 8: performance of ID3 vs.IID3

	Recall	Precision	F-Score	Kappa-Statistic
ID3	75.56	91.46	81.88	0.3816
IID3	95.39	96.53	95.89	0.5099

The target of Recall is to recognize all Real-Positive cases in a Medical field. So Recall submits to as True-Positive-Rate (tpr). Eq (4) is express of Recall measure.

Table 9: Perform the proposal vs. SVM, NB,and DT

Classifier	#data records	Correctly classified	Missed classified	Precision	Rate of Accuracy %	Recall	F-score
Proposal	986	891	95	0.9653	90.36	0.9539	0.9589
SVM		873	113	0.9530	88.53	0.9356	0.9442
NB		907	79	0.9784	91.98	0.9537	0.9658
DT		888	88	0.9758	89.95	0.9456	0.9604



Figure(3):Rate of accuracy of different classifiers

$$\text{Recall} = \text{Senstivity} = \text{tpr} = \frac{\text{TP}}{\text{RP}} = \frac{\text{A}}{\text{A} + \text{C}} \quad \ldots\ldots\ldots (4)$$

Where TP is true positive cases, and RP is real positive cases.

Precision is called True Positive Accuracy (tpa), being a measure of accuracy of Predicted Positives in contrast with the rate of discovery of Real Positives (tpr). Eq(5) is represent the Precision measure as follows:

$$\text{Precision} = \text{Confidence} = \text{tpa} = \frac{\text{TP}}{\text{PP}} = \frac{\text{A}}{\text{A+B}} \dots\dots\dots(5)$$

Where PP is predicate positive cases.

To evaluate the performance of this work against other exist methods, as shown in table8 based on various measures. Increase precision due to decrease recall and vice versa then try to maximize F-score where it is define as eq(6):

$$\text{F} - \text{score} = 2 \times \frac{\text{Senstivity} \times \text{Confidence}}{\text{Senstivity} + \text{Confidence}} \dots\dots\dots(6)$$

So, the accuracy, sensitivity, confidence and F-score of the proposal is acceptable according other exist classifiers as shown in fig(3) and thus good pointer of the performance of this work.

As clear from table9, note that this work results are acceptable and reliable when compare the performances of proposed algorithm with the other algorithms are evaluated on different measures i.e. Precision, Accuracy, F-Score, and Recall where Accuracy is measured over correctly classified instances .

6. Conclusions:

The result of this work agrees with many other works that GDM is more common in pregnant diabetic patients, especially in those who are overweight and smokers and whom are hysterical diabtes. Important findings of this work that the verdict and early involvement in the routine life, help and reduce risks of the mother and the offspring. The classifier algorithm called IID3 which deals with all relation-links between the condition factors and the remain-conditions factors that make the decision high accurate so the tree of IID3 algorithm has not-many leaves. Results show that the data of medical-record (especially electronic) for pregnant women can effectively enhance the accuracy of expecting GDM. As a limitation of this work was the data collected from participants where the body mass index of the pregnant in the first months of her pregnant period different from its on the last months and level of Level of culture and education were important factor to get the data.

7. ACKNOWLEDGMENT

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