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Machine Learning Algorithm and GESTOSIS Score Assisted High Risk Pregnancy Induced Hypertension Prediction

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ABSTRACT

This GESTOSIS scale is a validated tool which aids in predicting high risk women for Pregnancy-Induced Hypertension (PIH). This study aimed to use machine learning algorithms to determine the efficacy of the GESTOSIS score in predicting PIH. A prospective observational study was conducted on 70 pregnant women. The features in GESTOSIS scale classified as mild, moderate, or severe. The results showed that the Adaptive Boosting (AB) model precisely predicts the PIH with an accuracy range between 97% to 99% based on the results of regression and classification prediction models respectively with a true -positive rate (TPR) of 90%. The GESTOSIS score is concluded to be a simple scale that can be administered by all front-line health workers in the community without intrusive procedures.

1. INTRODUCTION

Hypertensive disorders in pregnancy are identified after the 20 weeks of gestation, impacting multi-systems within the body. The diagnostic criteria include raised blood pressure to the extent of 140/90 mmHg, high albumin levels, and pathological edema [1]. Pregnancy Induced Hypertension leads to many complications such as preeclampsia, eclampsia, HELLP syndrome, renal and liver failure, retinal detachment, cardiac disorders, and pulmonary edema [2]. If preeclampsia is not treated on time, it leads to the complication of eclampsia, which is the leading cause of maternal mortality and morbidity. Approximately 19 % of deaths are occurring due to PIH among all maternal deaths (WHO 2014) [1], irrespective of mothers espousing health-seeking behaviors to obtain relevant health care services from health care centers/healthcare professionals [3, 4].

According to the short-term statistics of the National Eclampsia Registry (NER 2013), FOGSI, ICOG, prevalence of pre-eclampsia, and eclampsia are 10.3% and 1.9%, respectively. Approximately 50% of these cases [5] are found during antepartum, while 13% of patients are reported in postpartum. About 4-6% of maternal deaths occur due to eclampsia. The causes of maternal mortality [6] in PIH are as follows; 1) Myths and misapprehensions of family members regarding pregnancy, 2) Poor socio-economic status that privations to proper medical care during pregnancy. 3) Lack of transportation facilities to commute the patient to the health care centers in case of any emergency. 4) Lack of medical professionals, i.e., multidisciplinary medical team at community centres and 5) Lack of PIH predictive tools [7].

The universal existing screening tests direct the prediction of PIH. However, most of them are invasive procedures and can be administered only by a physician/ medical officers, and they cannot be administered by all grass-root level health care professionals such as nursing officers/ ANMs, etc. In India, approximately 70% of the population [8] lives in rural communities. Thus, it is important to develop a simple scale to predict the PIH that all healthcare professionals can administer; therefore, early identification, referral, and proper care can be reached for indigent antenatal women. Preeclampsia prediction aids [1] in the prevention of perinatal and neonatal morbidity and mortality [9, 10]. Preterm birth is common in women with preeclampsia. Preterm newborns who were admitted to NICU significantly contribute to neonatal deaths at 95% confidence interval; however, aspirin administration beginning in the 11th week of pregnancy can reduce complications such as preterm deliveries, neonatal deaths, and maternal deaths [11].

Mandrupkar and team of FOGSI-GESTOSIS-ICOG developed the GESTOSIS score [12]. It helps to categorize the risk factors of pre-eclampsia and design predictive practices and preventive dealings. These methodologies allow the clinician to plan and provide systematic care in pregnancy to prevent eclampsia and other complications by adopting certain standardized clinical management protocols.

1.1 Machine learning algorithms' role in the prediction of preeclampsia

Because of the increasing development of artificial intelligence in various fields, machine-learning algorithms were developed and are now used in the medical profession. Machine learning or artificial intelligence mimics human function when processing the data [13]. Massive data and essential evidence-based information are mined using machine learning methods to create relevant models. According to Sonia Pereira et al., reports that pregnancy-related factors were used to predict accurate delivery techniques in order to determine how better services can be provided to antenatal

women in order to prevent the anticipated complications. In this study, five machine learning algorithms were used to diagnose the physical condition of the foetus [13].

Prospective studies can be conducted by recruiting women with PIH using the GESTOSIS score's criteria. Three machine-learning algorithms were used to detect preeclampsia early on: Deep Neural Networks (DNN), Logistic Regression (LR), and Support Vector Machine (SVM). The GESTOSIS parameters include maternal biodata, obstetrical characteristics, antenatal lab reports, and ultrasonography. Cross-validation was used to assess the calibration and discrimination under the receiver-operating curve (AUROC).

1.2 Novelty and contribution

According to the authors' review, currently, there hasn't been any research work done by using the GESTOSIS score and machine learning tools to predict pregnancy-induced hypertension. As a result, the current study encourages clinicians and grassroot health care professionals to use this tool to screen pregnant women high-risk for PIH. In addition, in this study, the problem-based learning techniques use machine learning algorithms to understand better prediction models, which are most fit to envisage the PIH accurately. This study will become the first to combine the literature of relevant studies on the GESTOSIS score. The current study guides new researchers to acquire basic skills in other engineering fields. The investigators from the field of Nursing conducted this study in collaboration with experts in engineering fields who had the skills to apply the machine learning predictive models. Machine learning tools are part of engineering, usually done either by coding or without coding.

To explain this study more specifically, tools-based simulation is considered an accurate method for visualizing and analyzing the data without having coding skills. The researchers in this study trained thoroughly with the tools and analysis done with engineering skills. These machine-learning tools are also simple to use for novice researchers and scientists to analyse their data.

In view of the above description, the following are the objectives of the current original study.

- To assess the antenatal women at high risk for prediction of pregnancy induced hypertension (PIH).
- To obtain in depth understanding and evaluate the risk elements by using machine learning models for prediction of pregnancy induced hypertension.
- To assess the efficacy of GESTOSIS score on prediction of pregnancy induced hypertension via machine learning algorithms.
- To comprehend the effect of dataset on the recital of predictive models for pregnancy induced hypertension.

2. RESEARCH DESIGN

We used the purposive sampling technique to enroll 70 antenatal women who had completed 20 weeks of gestational age. This study excluded antenatal women who had already been diagnosed with PIH. The final calculated sample size was 70, based on 10% of the estimated prevalence rate of PIH among all pregnancies at a 95% confidence level and 5% error at the margin.

2.1 Data correlation

Table 1. Significant input attributes with PIH target attribute

Sr. No.	Attribute	Correlation Coefficient	Association
1.	Risk_score_sum	+0.919	Very strong association
2.	History of PIH	+0.941	Very strong association
3.	Pre-eclampsia family history	+0.690	Moderate association
4.	GDM	+0.519	Moderate association
5.	Chronic Hypertension	+0.317	Weak Association

Table 2. Correlation between risk factor score of PIH and maternal demographics

Parameters	GESTOSIS Score		Total	Chi-square	p value
	At risk (≥3)	Not at risk (<3)			
Age in years					
18 – 25	12	26	38		
26 – 30	14	15	29	3.82	0.01
31 – 35	0	3	3		
Gestational age in weeks					
20 – 25	8	3	11		
26 – 30	5	12	17		
31 – 35	6	16	22	7.36	0.04
36 – 40	7	13	20		

Table 3. Association between target variable (PIH) and other input multi variables

Sr. No.	Input variables	P value	S value
1	Risk_Score_Sum	+0.919	+0.882
2	Pre-eclampsia family history	+0.690	+0.659
3	GDM	+0.519	+0.515
4	Women with CAD	+0.372	+0.398
5	Increased weight gain in pregnancy	+0.330	+0.334
6	Chronic Hypertension	+0.317	+0.302
7	Age interval	-0.263	-0.287
8	Below 19	+0.255	+0.272
9	Dylipidemia	+0.234	+0.203
10	Women with SGA	+0.234	+0.203
11	hypothyroidism	+0.234	+0.203
12	Pregnancy with IVF	+0.223	+0.247
13	Anemia	+0.183	+0.165
14	Primigravida	+0.169	+0.203
15	Pitting oedem	+0.141	+0.143
16	PCOD	+0.129	+0.129
17	Obesity	+0.119	+0.100
18	Above 35	+0.095	+0.109

Note: P value = Pearson correlation, S value= Spearman correlation

Identifying the correlation between the two variables is imperative to understand the significance between those variables. The values of correlation and chosen variables can affect the predicting tools. The linear relationship between two variables is determined by Pearson Correlations (PC) and Spearman correlations (SC). The correlation coefficient cascades between -1 and +1; -1 indicates a strong negative association among two variables, +1 indicates a robust positive association, while 0 indicates no linear association. A

correlation value of less than 0.3 designates a weak association, while values between 0.3 and 0.7 specify a moderate association. If the value is greater than 0.7, it specifies a sturdy association among two variables [14, 15].

Table 1 depicts the correlation between variables such as family history of Pre-eclampsia, Gestational Diabetes Mellitus (GDM), and Chronic Hypertension. In Table 1, all variables show positive values, which are generated using the Orange tool. Family history of preeclampsia, and GDM show moderate association (+0.690 and +0.519), whereas the previous history of PIH has very strong association.

Table 2 indicated that the age of the pregnant women and gestational age had a significant correlation with the PIH risk score.

Table 3 presented the 'P' and 'S' values of the target variables of pregnancy-induced hypertension in comparison to the other input multi variables.

2.2 GESTOSIS score scale

Table 4 indicated that GESTOSIS scale consists of 24 items, with scores ranging from 1 to 13 for mild symptoms, and each item has a score of 1. Items from 14–17 are classified as having moderate PIH symptoms, and each item has a score of 2. Items from 20 to 24 are classified as severe PIH symptoms, and each item receives a score of 3. The score is alloted based on the woman's responses and the clinician's assessment.

Table 4. GESTOSIS score for prediction of pregnancy induced hypertension

Sr. No.	Risk Factors	Score
1	Age above 35 years	1
2	Age below 19 years	1
3	Maternal Anemia	1
4	Obesity (BMI >30)	1
5	Pregnant for the first time	1
6	Short duration of sperm exposure	1
7	Woman born as small for gestational age	1
8	Family history of cardiovascular disease	1
9	Polycystic ovary syndrome	1
10	Inter pregnancy interval more than 7 years	1
11	Conceived with Assisted Reproductive (IVF/ ICSI) Treatment	1
12	Chronic vascular disease (Dyslipidemia)	1
13	Excessive weight gain during pregnancy	1
14	Maternal hypothyroidism	2
15	Family history of pre-eclampsia	2
16	Gestational diabetes mellitus	2
17	Obesity (BMI > 35 kg/M2)	2
18	Multifetal pregnancy	2
19	Hypertensive disease during previous pregnancy	2
20	Mental disorders	3
21	Inherited / Acquired Thrombophilia	3
22	Maternal chronic kidney disease	3
23	Autoimmune disease (SLE / APLAS / RA)	3
24	Pregnancy with Assisted Reproductive (OD or Surrogacy) Treatment	3

Pattern of risk scoring

- ✓ At Low risk for prediction of PIH- 1
- ✓ At Moderate risk for prediction of PIH– 2
- ✓ At High risk for prediction of PIH- 3
- ✓ With careful history and assessment of woman, a total score is obtained from time to time.

  When the total score is =/> 3; pregnant woman was marked as *'**At risk***

Professionals translated the GESTOSIS scale from English to Marathi. A native English speaker translated and checked its back. Throughout its conversion, it made subtle philosophical, social strata, theoretical, and dialectal sameness. This scale was pretested on ten antenatal women at Talera Pimpri Chinchwad Municipal Corporation (PCMC) hospital in Pune using interview and assessment methods. Cronbach's alpha was used to assess the reliability of the GESTOSIS score scale, and the value was 0.74, which falls within the acceptable range of reliability. The scale discovered was feasible to administer to pregnant women. Following were the steps involved in the design of the current study.

Step 1: Collection of the data and explanation

The primary data was collected from antenatal women who had completed at least 20 weeks of gestation and visited Yashwantrao Chavan Memorial Hospital (YCM) antenatal OPD. To support the supplementary findings, the researchers revisited these women in the third trimester to validate the data collected in the second trimester. The investigators further re-evaluated the investigations, such as ultra-sonography to evaluate the fetal and placental weight about gestation age. Women who were found to be at high risk for predicting PIH were referred to an expert for further evaluation. This step consists of data processing, feature extraction, and variable correlation analysis.

Step 2: Descriptive statistics

One of the data mining methods involving mathematics and related data collection and elucidation is descriptive statistics for predicting a high PIH data set [16]. The Jeffreys's Amazing Statistics Program is a simple tool to use for researchers with limited computer skills [17].

Table 5 depicts the risk score for pregnancy-induced hypertension which is classified into Low Risk (1), moderate risk (2), and severe risk (3) for the prediction of hypertension in pregnancy based on the antenatal woman's highest score.

Table 5. Categorization of the risk score of the pregnancy induced hypertension

Risk_Score	Risk_ %	Risk _ Level	Risk_ Level	Participants
1	3			
2	5	1	Low Risk	43 (61.43)
3	8			
4	10	2	Moderate Risk	16 (22.86)
5	13			
6	16			
7	18	3	High Risk	11 (15.71)
8	21			
	Total			**70**

Table 6 shows the forty-three women fell under the low-risk criteria for pregnancy-induced hypertension, while the remaining women fell under the moderate and severe-risk criteria category.

The descriptive statistics in Table 7 show that the risk factor for pregnancy-induced hypertension had a higher mean value (PIH). Among the parameters chosen, there were no missing values. Table 7 findings indicate that the primary variables presented in this table are family history of pre-eclampsia,

eclampsia, history of GDM, chronic hypertension, and previous PIH history. The greatest mean (1.543), mode (1.000), and median (1.000) values can be seen in the parameter of previous history of PIH data. The family history of pre-eclampsia has a greater standard deviation (0.827), followed by the previous history of PIH. The values of the Standard Error of Skewness (0.287) for all chosen parameters are similar. However, the Skewness of PIH history is less apparent. The minimum (1.00) and maximum (3.000) values are higher in PIH.

Table 6. Distribution of the participants based on the different categories for the prediction of pregnancy induced hypertension

PIH category	Risk score sum	Frequency	Percentage	Cumulative percent
1 – Low risk category	1	8	18.605	18.605
	2	18	41.860	60.465
	3	17	39.535	100.000
	Missing	0	0.000	
	Total	**43**	**100.000**	
2 – Moderate Risk	4	9	56.250	56.250
	5	7	43.750	100.000
	Missing	0	0.000	
	Total	**16**	**100.000**	
3 – High risk	5	1	9.091	9.091
	6	4	36.364	45.455
	7	4	36.364	81.818
	8	2	18.182	100.000
	Missing	0	0.000	
	Total	**11**	**100.000**	

Table 7. Descriptive statistics of selected parameters in relation to the total risk score

Parameters	Risk score sum	Family History of Pre -eclampsia	GDM	Chronic Hypertension	History of PIH
Valid	70	70	70	70	70
Missing	0	0	0	0	0
Mean	3.414	0.429	0.257	0.086	1.543
Std. Error of Mean	0.218	0.099	0.081	0.049	0.090
Median	3.000	0.000	0.000	0.000	1.000
Mode	2.000	0.000	0.000	0.000	1.000
Std. Deviation	1.822	0.827	0.674	0.408	0.755
Skewness	0.778	1.423	2.268	4.614	0.993
Std. Error of Skewness	0.287	0.287	0.287	0.287	0.287
Kurtosis	-0.091	0.026	3.236	19.853	-0.512
Std. Error of Kurtosis	0.566	0.566	0.566	0.566	0.566
Minimum	1.000	0.000	0.000	0.000	1.000
Maximum	8.000	2.000	2.000	2.000	3.000
Sum	239.000	30.000	18.000	6.000	108.000
25th percentile	2.000	0.000	0.000	0.000	1.000
50th percentile	3.000	0.000	0.000	0.000	1.000
70th percentile	4.750	0.000	0.000	0.000	2.000

Figure 1 illustrates that the majority of the samples had a score between 1 and 5, with a mean value of 3. As a result, 61% of antenatal women are at low risk for PIH. Figure 2 to Figure 4 show that the majority of participants have no family history of preeclampsia, gestational diabetes, or chronic hypertension. Figure 5 depicts that majority (61.43%) of the participants fall under the risk level of 1 (Low Risk), and 16% of women with a history of preeclampsia are at high risk for PIH. Figure 6 reveals that 61%, 23%, and 16% of prenatal women fall into the low risk, moderate risk, and high risk groups for PIH, respectively.

Step 3: Development of the prediction models

The data was normalized for pre-processing, and correlation method was used to find the significant attributes in the data set. Total features are further classified into three types: independent attributes, dependent attributes, and meta attributes using Orange software, as shown in Figure 7.

Figure 8 and Figure 9 illustrated that a family history of PIH and a previous history of pre-eclampsia predicted susceptibility to pregnancy-induced hypertension.

Step 4: Evaluation of prediction model's performance

The Orange model was used to select nine algorithms, including Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Multi-layer Perceptron (MLP), k-Nearest Neighbors (kNN), Multiple Linear Regression (MLR), Decision Tree (DT), Gradient Boosting (GB), Random Forest (RF), and Adaptive Boosting (AB) as shown in Figure 10. The prediction models are created using the input data set and fine-tuning each algorithm's hyperparameter. After clicking on each algorithm, we can fine-tune the hyperparameters to maintain better prediction accuracy. To develop prediction models, 20-fold crop validation model is adopted.

This step helps in predicting the performance of predicting models with the available dataset. The parameters of the performance matrix are as follows; Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) [18].

Table 8 dipicts the tuned hyperparameter for both classification , and regression prediction model. AB algorithm performs better predictive results with the hyperparameter namely larning rate (0.50000), classifier algorithm (SAMME.R), and regression loss (Linear).

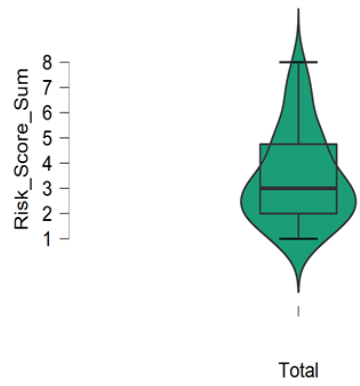


Figure 1. Boxplot for total risk score of PIH

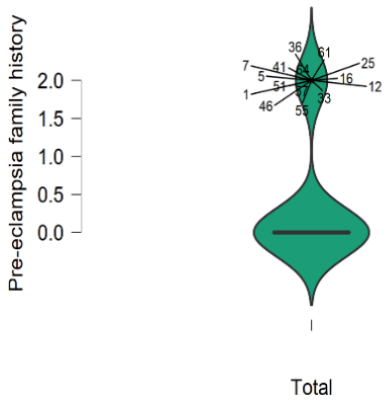


Figure 2. Boxplot for family history of preeclampsia

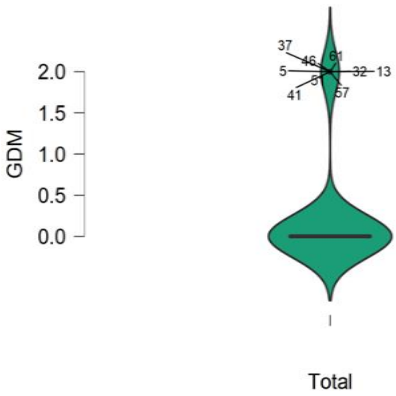


Figure 3. Boxplot for gestational diabetes

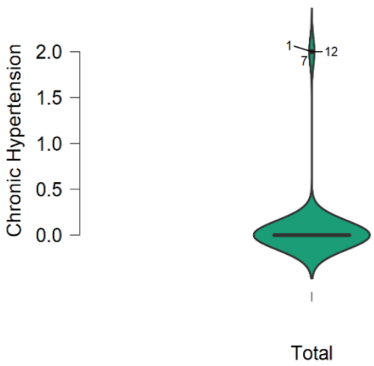


Figure 4. Boxplot for chronic hypertension

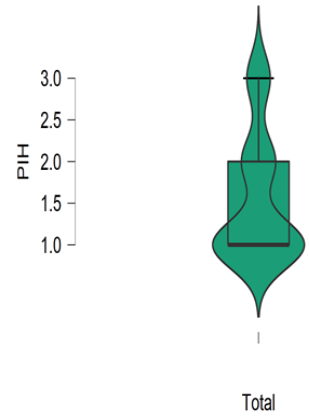


Figure 5. Boxplot for previous history of PIH

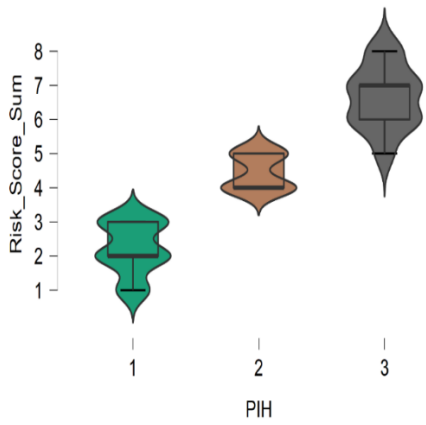


Figure 6. Boxplot between PIH and categories of risk

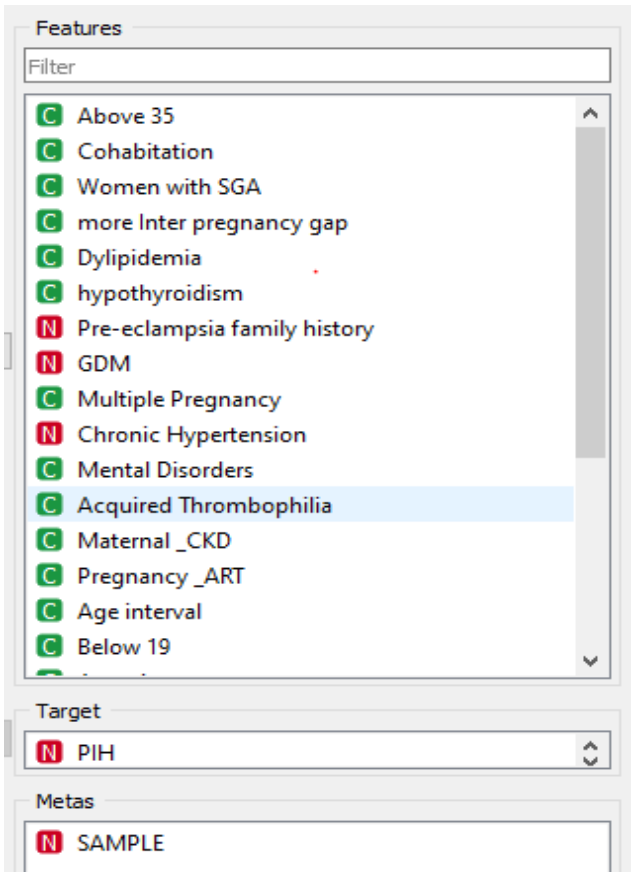


Figure 7. Feature separation using Orange software

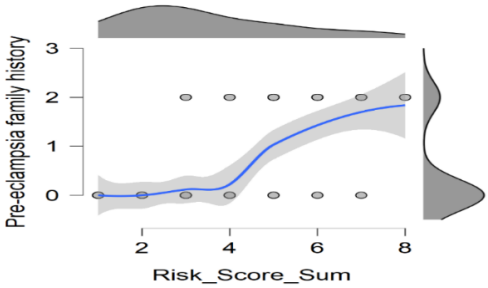


Figure 8. Scatter plot of preeclampsia and prediction of PIH

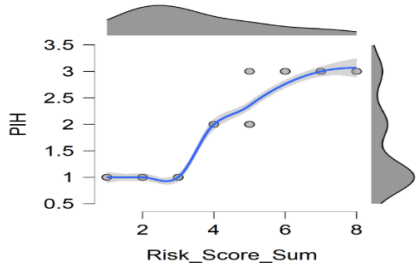


Figure 9. Scatter plot of history of PIH and prediction of PIH

Table 8. Hyper-parameter tuning of the classification and regression prediction model

Algorithm	Hyper-parameter	
SVM	Regression Cost (C)	0.10
	Complexity bound (v)	0.05
	Kernel function	Polynomial
	Numerical tolerance	1.0
	Iteration limit	20
SGD	Classification: Squared ε insensitive	0.01
	Regression: Squared ε insensitive	0.00
	Regularization	Ridge (L2)
	Strength (α)	0.01000
	Learning rate	Constant
	Initial learning rate (η_0)	0.0032
	Number of iterations	10
MLP	Neurons in hidden layers	128,64,32,8
	Activation	Identity
	Solver	Adam
	Regularization	α=15
	Maximum number of iterations	28
KNN	Number of neighbors	5
	Metric	Euclidean
	Weight	Uniform
MLR	Regularization	Ridge (L2)
	Regularization strength (α)	19
DT	Minimum number of iterations in leaves	10
	Do not split subsets smaller than	2
	Limit the maximal tree depth to	10
	Stop when majority reaches (%)	99
GB	Method: Gradient Boosting (scikit-learn)	True
	Number of trees	100
	Learning rate	0.100
	Limit depth of individual trees	3
	Do not split subsets smaller than	2
	Fraction of training instances	1.00
RF	Number of trees	32
	Replicable training	True
	Limit depth of individual trees	5
	Do not split subsets smaller than	5
AB	Weak learner	DT
	Number of estimators	15
	Learning rate	0.50000
	Classification algorithms	SAMME.R
	Regression loss function	Linear

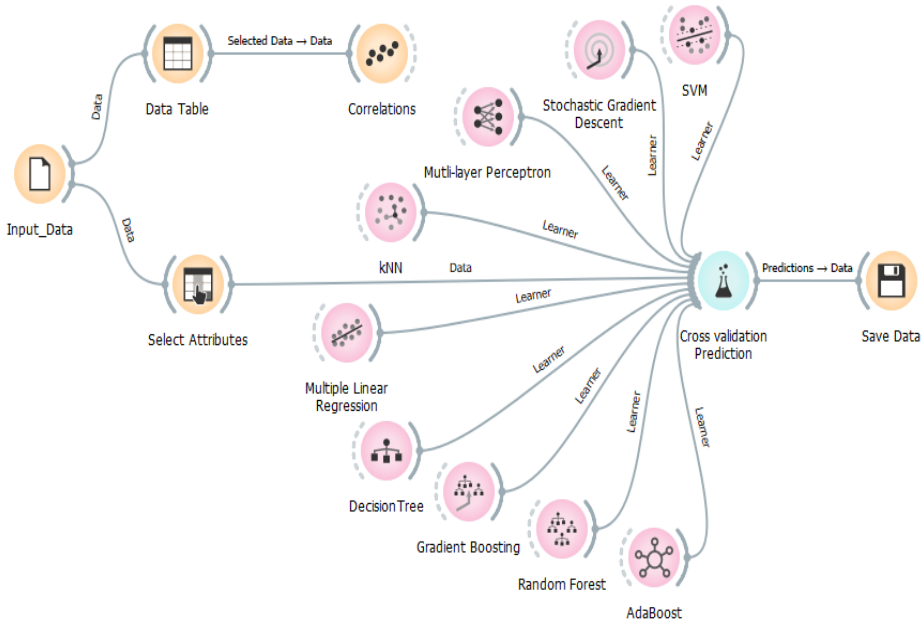


Figure 10. Workflow of prediction model using Orange software

3. RESULTS AND DISCUSSION

The previous section on research design covered the general development of prediction models using machine-learning algorithms. This section discusses the results of data processing and scale validation. The validation results assisted the researchers to understand the GESTOSIS score's accuracy in predicting antenatal women at high risk for pregnancy-induced hypertension.

According to the GESTOSIS score, approximately 38% of the women were at risk of predicting pregnancy-induced hypertension.

Table 9. Distribution of the samples based on the obstetrical characteristics

Parameters	Obstetrical variables	f	%
Gestational age in weeks.	20 – 25	11	15.7
	26 – 30	17	24.3
	31 – 35	22	31.4
	36 – 40	20	28.6
Antenatal check-ups	Regular	70	100
	Irregular	0	0
	Nil	0	0

Table 10. Antenatal women at high risk for PIH based on the GESTOSIS score n=70

Risk factor score	f	%
High risk (≥3)	27	38.38
Mild risk (<3)	43	61.42
Total	70	100

Table 9 indicates The average gestational age of the participants is 28 weeks, and they all had regular antenatal check-ups. Table 10 and Table 11 showed, following the administration of the GESTOSIS score, 27 (38.38 %) women scored greater than 3. As a result, these women are considered at high risk of Pregnancy Induced Hypertension (PIH). These women were followed up and evaluated using the criteria listed above. 88.88% of women had blood pressure greater than 140/90 mmHg and 62.96 % of participants had > 2+ urine albumin. According to the Table 12, approximately 55.55% of antenatal women out of 27 had a positive at risk (≥3) as per the GESTOSIS score.

Table 11. Efficacy GESTOSIS score on prediction of PIH

Parameter	f	%
Blood pressure		
≤140 / 90 mmHg	3	11.11
≥140 / 90 mmHg	24	88.88
Mean Arterial Pressure		
<100 mmHg	17	62.96
>100 mmHg	10	37.03
Urine Albumin Test		
< 2+	17	62.96
> 2+	10	37.03
Platelet count:		
<100,000/mm3 .	21	77.77
> 100,000/mm3 .	6	27.22
Fetal weight – report of ultra-sonography		
Correlating to the gestational age	22	81.48
Not correlated to the gestational age	5	18.51
Placental weight - ultra sonography		
Correlating to the gestational age	19	70.37
Not correlated to the gestational age	8	29.62

Table 12. Efficacy of GESTOSIS score on prediction of PIH

GESTOSIS score	f	%
Positive (At risk (≥3)	15	55.55
Negative (No at risk (<3)	12	44.44
Total	27	100

Furthermore, in this study, the Orange tool is utilized for data pre-processing, significant feature identification using correlation methods and predictions using different prediction algorithms with its comparative evaluation. The Orange tool is open source data mining software which perform data visualization, data analysis, and model developement. For the regression problem, the Orange software generates four performance metrics, namely, MSE, RMSE, MAE, and R^2. All these performance metrics were applied to compare prediction model performance. The limiation is that, users do not have a choice to choose the performance metrices. For the classification problem the software generated evaluation

metrices are namely Precision, Recall, F-Measure, Accuracy, and RMSE [18].

Table 13 and Table 14 show similar prediction performance results based on regression and classification prediction models, respectively. In both prediction models, the AB algorithm performed better, with an accuracy of 97% to 99% in predicting PIH. The MLR prediction model, on the other hand, is only relevant in the regresion prediction model.

Table 13. Performance of individual algorithms based regression prediction

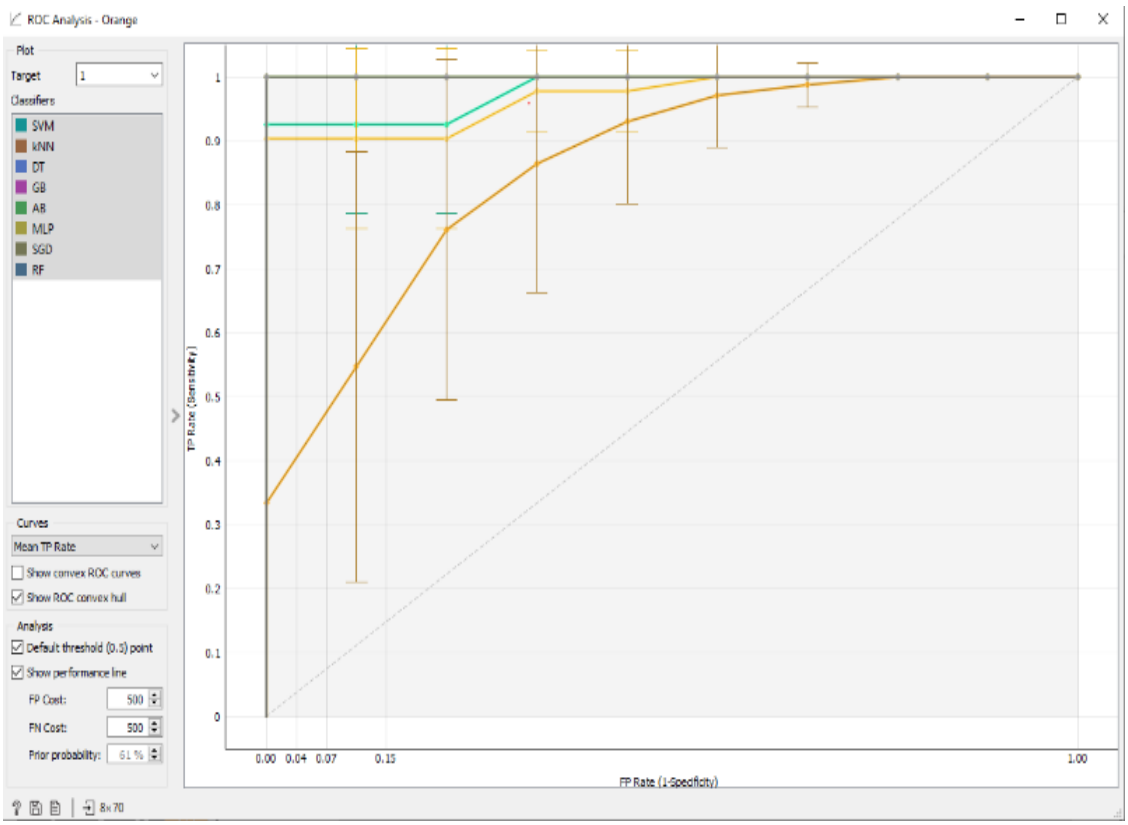
Sr. No.	Algorithm	MSE	RMSE	MAE	R^2
1	SVM	0.165	0.407	0.334	0.706
2	SGD	0.147	0.383	0.308	0.739
3	MLP	0.130	0.360	0.271	0.769
4	KNN	0.121	0.347	0.191	0.786
5	MLR	0.095	0.309	0.247	0.830
6	DT	0.063	0.251	0.126	0.888
7	GB	0.031	0.175	0.046	0.945
8	RF	0.017	0.132	0.032	0.969
9	**AB**	**0.014**	**0.120**	**0.014**	**0.975**

Note: *SVM- Support Vector Machine, SGD- Stochastic Gradient Descent , MLP- Multi-layer Perceptron , KNN- k-Nearest Neighbors, MLR- Multiple Linear Regression, DT- Decision Tree, GB- Gradient Boosting, RF- Random Forest, AB- Adaptive Boosting*

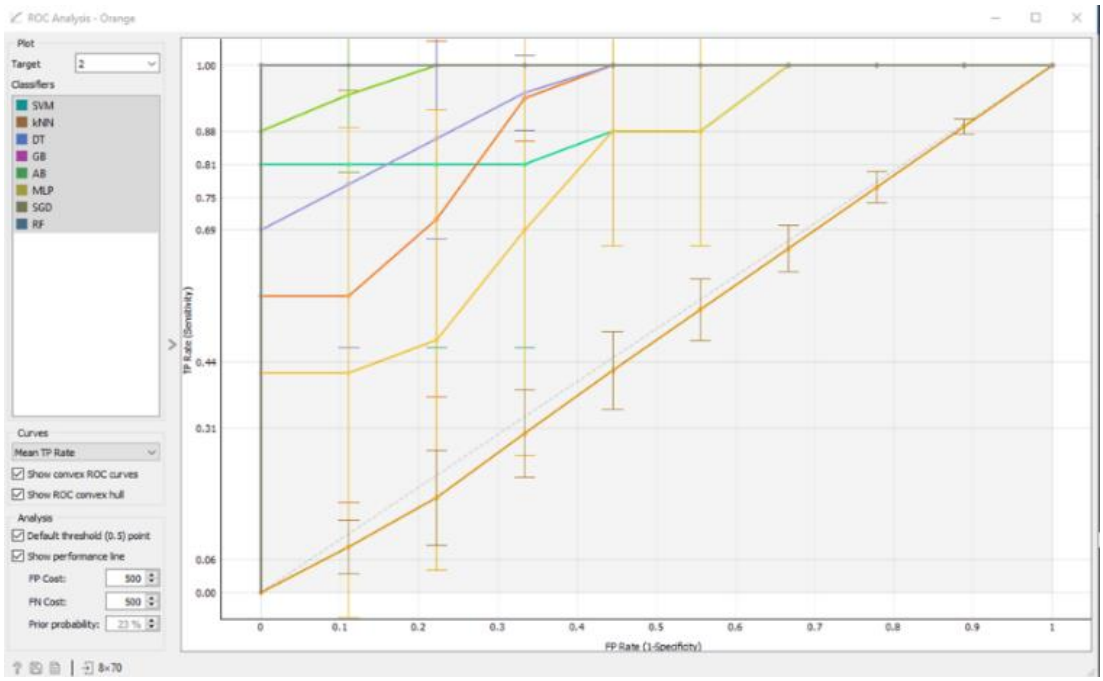
Table 14. Classification prediction using machine learning algorithms

Model	AUC	CA	F1	Precision	Sensitivity	Accuracy
SGD	67%	69%	64%	61%	69%	69%
MLP	89%	76%	73%	76%	76%	78%
kNN	96%	79%	76%	78%	79%	79%
SVM	92%	84%	84%	84%	84%	84%
DT	97%	91%	91%	91%	91%	91%
RF	98%	93%	92%	95%	93%	93%
GB	99%	97%	97%	97%	97%	97%
AB	99%	99%	99%	99%	99%	99%

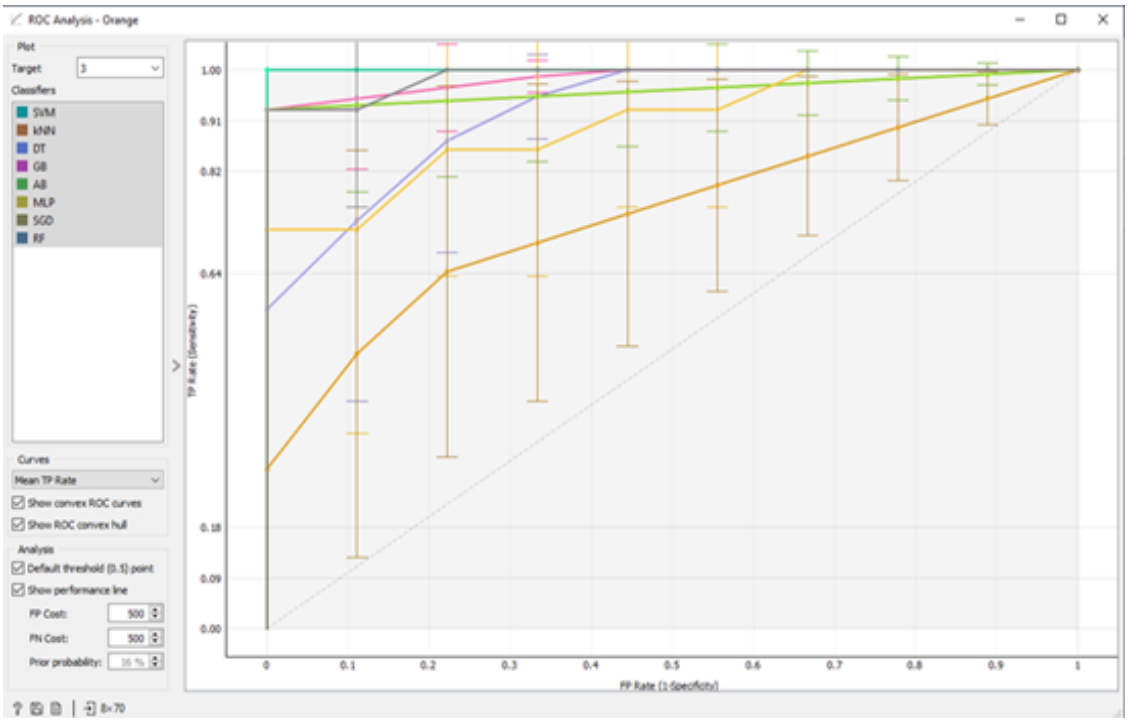
Note: *SVM- Supoort Vector Machine, SGD- Stochastic Gradient Descent, MLP- Multi-layer Perceptron, KNN- k-Nearest Neighbors, MLR- Multiple Linear Regression, DT- Decision Tree, GB- Gradient Boosting, RF- Random Forest, AB- Adaptive Boosting,* ***AUC****- Area under curve, CA- Classification accuracy*



(a) Target 1 classifier for Low Risk of PIH



(b) Target 2 classifier for Moderate risk of PIH



(c) Target 3 classifier for High Risk of PIH

Figure 11. Different models ROC curve-based classification prediction evaluation

Evaluating the ROC curve (Figure 11) and the area under the ROC curve (Table 13 and Table 14) for the algorithms run in the second stage of modelling revealed that the AB algorithm shows better prediction resuts in all PIH targets.

3.1 Discussion

Leelavathi et al. studied the efficacy of Uterine Artery Doppler Ultrasonography and the roll-over test in predicting pregnancy-induced hypertension. The antenatal women were screened with Doppler artery ultrasonography at the gestational age of eleven to thirteen weeks. The women were followed up at twenty-one to twenty-four weeks, and the roll-over test was performed at twenty-eight to thirty-two weeks to see if they were at high risk for pre-eclampsia and eclampsia [19]. In the current study, 37.1% of women were at high risk for pregnancy-induced hypertension. Blood pressure, mean arterial pressure (MAP), platelet count, and urine albumin tests were performed on these 26 women. About 53.8% (14) of women were significantly at high risk for hypertension prediction. In detail, approximately 92.31% of women had blood pressure levels higher than 140/90 mmHg.

Antenatal women with a positive roll-over test possess a significantly higher risk of having a small gestational age baby. It was confirmed during their antenatal check-ups by

ultrasonography and examination of pre-pregnancy and pregnancy weight gain. Women who weigh fifty kilograms or less and gain less than ten kilograms during pregnancy or who have a weight gain disparity of 20% or less, pose a significant risk for developing Small for Gestational Age (SGA) fetus [20]. Women with a positive GESTOSIS score had a significantly high SGA fetus in the current study, a mean arterial pressure greater than 100 mmHg, and elevated urine albumin levels. About 30% of women's placental and fetal weights were not correlated with gestational age; they were observed to be lower than expected values.

However, previous research conducted by Kaypour et al. [21], they concluded that the roll-over test alone cannot predict pregnancy-induced hypertension but if this test is combined it with other predictive tools such as Doppler artery ultrasonography and the GESTOSIS score can provide more accurate results in predicting hypertensive diseases in pregnancy. According to Andersen [22], single tools, such as the roll-over test, are insufficiently sensitive and specific as a screening test. Finally, Marshall and Newman [23] suggested that roll-over tests be combined with other predictive tools to achieve more positive results.

Sufriyana et al. looked into validating an artificial intelligence (AI) tool for predicting pregnancy-induced hypertension. The data set includes 95 personal characteristics and the medical history of pregnant women. Six algorithms for comparison were created by automating the receiver operating characteristics curve (AUROC). This economic model was primarily used to predict PIH [24]. The predictive analytics software acts as an artificial intelligence in obstetrics, assisting in diagnosing preeclampsia. Machine learning algorithms will aid in improving the accuracy of preeclampsia risk calculation in pregnant women [25].

The Expert System for Preeclampsia Prevention Program (ESPPP) is used to detect pregnancy-induced hypertension. This program uses pragmatic criteria to diagnose and recommend treatment for PIH [26]. Marin I et al. used a non-invasive technique to detect the presence of preeclampsia.

The blood pressure is measured using an i-bracelet Eurostars smart bracelet, an "Intelligent bracelet for blood pressure monitoring and detection of preeclampsia." Every pregnant woman's age, weight, and blood pressure measurements are used as input data. A series of hidden states comprised the prediction model [27]. Zhang X et al. studied the relationship between blood data characteristics of antenatal women in severe PIH [28].

According to a retrospective study, uric acid, erythrocyte haemoglobin concentration, globulin, platelet distribution width, potassium ion, age, family history of hypertension, systolic blood pressure, diastolic blood pressure, pulse, and gestational age greater than 34 weeks were independent risk factors for prediction of preeclampsia. The optimal Light 5 GBM algorithm parameters were discovered using a 5-fold cross-validation algorithm after screening these independent risk factors using univariate analysis and logistic regression analysis. The preeclampsia prediction model based on the Light GBM machine learning algorithm has a higher prediction effect for prediction of PIH [29].

4. CONCLUSIONS

Today, there are numerous diagnostic methods available to detect hypertensive pregnancy disorders. However, they are not always available to pregnant women, especially in sub-centers and primary health care centers. The GESTOSIS score is a simple predictive tool that all front-line health care workers can use. Preeclampsia can be predicted early on, and pregnant women can receive definitive treatment at the appropriate time to reduce the negative outcome of the pregnancy. The GESTOSIS score scale can be used in primi and multipara mothers with a history of PIH. The GESTOSIS score is endorsed by the Federation of Obstetrics and Gynecological Society in India (FOGSI). This tool is considered a low-cost alternative to other tests and simultaneously ensures the efficacy of the test. It is a simple, cost-effective, and economic scale that can be employed during the initial assessment of all antenatal women to predict the risk of pregnancy-induced hypertension. Based on the parameters of the GESTOSIS score scale, various machine learning algorithms can be employed to predict pre-eclampsia.

This study provides information regarding the associating factors responsible for predicting pregnancy-induced hypertension. Early prediction helps to provide accurate treatment to pregnant women at the right time. In this study, it is attested that the adoption of data mining techniques on the medical data has a large scope for diagnosis and prediction of diseases that indicates the medical professionals to provide the preliminary care for life-threatening disease conditions. Data mining techniques help in enhancing care and maximizing salvage rates. In this article, various prediction machine-learning algorithms are deployed on medical data sets to understand the risk factors responsible for causing PIH. This study recommends that future researchers apply a sequential model to this data set, including a recursive deep neural network that increases the accuracy levels in predicting PIH. This study concludes to state that provided factors comprised in the GESTOSIS score optimally can be used on the optimal dataset for the prediction of PIH.

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