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Novel maternal risk factors for preeclampsia prediction using machine learning algorithms

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ABSTRACT

Preeclampsia and eclampsia are the most common obstetric disorders associated with poor maternal and neonatal outcome. The study's primary objective is to assess the accuracy of novel high-risk factors core using machine learning algorithms in predicting preeclampsia. The study included 400 pregnant women and used 27 novel high-risk factors to predict preeclampsia. The target variables for predicting preeclampsia are systolic and diastolic blood pressures. Various algorithms, including decision tree (DT), random forest (RF), gradient boosting, support vector machine (SVM), K-neighbors, light gradient boosting machine (LGBM), multi-layer perceptron (MLP), Adaboost classifier, and extra trees classifier are used in the analysis. The accuracy and precision of the LGBM classifier (0.85 and 0.9583 with F1 0.7188), support vector classifier (0.8417 and 0.92 with F1 0.7077), DT (0.825 and 0.913 with F1 0.6667), and extra trees (0.8167 and 0.9091 with F1 0.6452) are found to be better algorithms for prediction of preeclampsia. According to the novel high-risk factors score, 17.5% of pregnant women were identified as being at high risk for preeclampsia during the first trimester, which increased to 18.7% in 3rd trimester; in addition, 16% of pregnant women had a blood pressure of 140/90 mmHg and the above. Novel, high-risk scores and machine learning algorithms can effectively predict preeclampsia at an early period.

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1. INTRODUCTION

Preeclampsia is one of the most frequently occurring obstetrical conditions, accounting for a significant cause of maternal and neonatal morbidity and mortality globally [1]. It is usually discovered after 20 weeks of gestation and is closely involved in causing neonatal morbidity and mortality [2]. This condition affects 3-7% of pregnant women and can occur in first and subsequent pregnancies. Proteinuria, prenatal hypertension, and excessive weight gain, especially edema, are common diagnostic features for diagnosing preeclampsia [3]. This obstetrical condition substantially influences the mother's health and limits fetal growth, frequently leading to low birth weight babies, early deliveries, and intrauterine growth retardation [4]–[5]. The symptoms of preeclampsia include impaired vision, swelling throughout the body, frontal and occipital headaches, high blood pressure, and high levels of protein in the urine [2].

In India, 6.9% of pregnant women suffer from pregnancy induced hypertension (PIH). Its incidence in the nation ranges from 5% to 15%, with eclampsia prevalence at a rate of 1.5% [6]. Preeclampsia impacts the outcome of the pregnancy and delivery. The pathophysiology and underlying causes of preeclampsia are still unknown often; termination of pregnancy is the only effective therapeutic option in severe cases of preeclampsia and eclampsia. However, early detection, prediction, and management can reduce maternal and fetal complications, improving pregnancy outcomes [7]. Numerous high-risk factors in pregnant women have been linked to the onset of preeclampsia, advanced maternal age, increased parity, the presence of comorbidities, genetic vulnerability, and lab investigative indicators such as abnormal thyroid profiles, uterine artery doppler velocimetry, pregnancy-associated plasma protein-A (PAPP-A), placental insulin-like growth factor (IGF) valuses, and different general illnesses are the examples [8], [9].

The novel high-risk factors score, called Gestosis score, was invested by Dr. Gorakh Mandrupkar and refined by a team of distinguished medical professionals. This novel scoring approach was developed to improve the accuracy of predicting preeclampsia [10]. The Gestosis score incorporates many established and novel risk factors for pregnant women. This novel risk factors score assigned a range of scores 1, 2, or 3, indicating its potential influence on preeclampsia development. The sum of the score is determined after a comprehensive review of mother’s medical data and rigorous clinicalassessment. Suppose an antenat mother’s cumulative score is three or above; she is classified as "at risk for preeclampsia," her medical care must be adjusted appropriately early to prevent further complications [11].

There are two types of artificial intelligence: physical domain and virtual facet. Virtual tools encompass many scales comprising neural network-based medical conclusive supported systems and assimilated automated health recording platforms. Machine learning is a computer technology based on algorithmic mathematics that increases knowledge acquisition through experience learning. It is also used in the industry [12]. Machine learning approaches enable the model to learn and adapt to the data supplied to the system. The basic principle behind machine learning is to help algorithms understand and analyze data, recognize patterns, and ultimately provide forecasts and diagnoses. As a result, the algorithm can discover interconnected risk indicators and predict future sickness situations. As a result, medical professionals can make early patient referrals and treatment decisions, decreasing potential repercussions [13]. Deep learning (DL) has emerged as a transformative feature of artificial intelligence, capable of addressing subtle difficulties that standard artificial intelligence techniques might find difficult or unsolvable. Numerous recent research studies have shown the inherent potential of DL systems, demonstrating their ability to grasp complex data, achieve accurate picture identification, and systematically organize textual information [14].

The present study was a prospective investigation in which researchers gathered real-time data from pregnant women using the novel risk factors score in first and third trimesters of gestation. Subsequently, the collected data underwent comprehensive analysis employing robust machine learning techniques, both classification and regression models. The current study’s obejective is to assess the anticipative precision of the model’s technique in forecasting the probability of preeclampsia. To the researchers' knowledge, only one of our previous studies has utilized this score and algorithms to predict preeclampsia. However, the sample size in the last study was only 70. Consequently, the present investigators were interested in exploring the effectiveness of the novel risk factors score and machine learning algorithms in detecting the high risk antenatal for preeclampsia development with a large sample size. The study’s objectives were as follows;

- To analyze and categorize the factors of the novel high risk factors using machine learning techniques, which assists healthcare providers in making accurate prediction of preeclampsia
- To categorize the correlations between the novel factors likely to cause preeclampsia.
- To conduct a survey that detects the antenatal women at risk of preeclampsia.

2. LITERATURE REVIEW

The authors evaluated relevant data for the current investigation from several types of databases using the certain criteria for their eligibilty. The present study's authors reviewed many electronic resources, including SCOPUS, PubMed, and Web of Science. The present study's review procedure adheres to the inclusion criteria. The investigations covered in this analysis were carried out between 2015 and July 2023 to understand their findings better. The majority of research used traditional statistical approaches for prediction of preeclampsia. Soongsatitanon and Phupong [15] surveyed to assess the prediction potential of uterine artery doppler, PI, and serum placental protein 13 (PP13) values for preeclampsia during the initial 12 weeks of gestation. A total of 353 samples were gathered, with fifteen predicting criteria considered. The study demonstrated that combining uterine artery, pulsatility index, and serum PP13 showed accurate predictive values for predicting preeclampsia. The negative predictive value was 94.4%, while its specificity, sensitivity, and positive predictive values were 62.9%, 58.6%, and 12.4%, individually. In addition, Serra *et al*. [16] presented a multivariate Gaussian model to investigate the efficacy of screening for predicting pregnancy-induced hypertension. There were thirteen predicting factors in the dataset. The researchers observed that integrating biophysical characteristics, maternal features, and placental growth factor (PlGF) resulted in better accuracy. This combined technique provided the prediction values of 94% for 10 percent of the false positive rate (FPR) and a detecting rate of 50% for five percent of the FPR with the area under curve (AUC) of 0.96 and a 95% confidence interval (CI) spanning from 0.94 to 0.98. Notably, adding PIGF to the list of biophysical markers increased the detection probability from 59% to 94%.

Furthermore, Gupta *et al.* [11] were among the first to investigate the hypertensive disorders of pregnancy (HDP) Gestosis score's potential for prediction of pregnancy-induced hypertension (PIH). The HDP Gestosis score divides the condition into 3 catetegories: mild, moderate and severe with measuring scores; 1, 2, 3 individually that provides a way to predict the chance of developing preeclampsia. According to their findings, the HDP Gestosis score predicted preeclampsia with an 83.1% of sensitivity, 97.51% of specificity, and 95.35% of diagnostic accuracy. Meshram *et al.* [17] have conducted a prospective study to assess the Gestosis score efficiency for prediction of PIH. The adaptive boosting (AB) model efficiently predicted pregnancy-induced hypertension, with accuracy rates ranging from 97% to 99% for both regression and classification predictive techniques, with a true positive rate of 0. 90.

Hiwale *et al*. [18] used supervised machine learning techniques to evaluate the risk levels of PIH. There were 19 predicting factors in the dataset. According to the outcomes of this study, the decision tree (DT) model displayed the better results than the support vector machine (SVM) and logistic regression (LR) method. Wanriko *et al*. [19] researched to examine the risk of hypertension disorders arising during pregnancy. They used seven machine learning models: LR, K-nearest neighbors (KNN), DT, random forest (RF), multi-layer perceptron (MLP), SVM, and naive bayes (NB). The results of their analysis revealed that, among these models, the RF model had the greatest accuracy in predicting HDP. Zhang *et al*. [20] conducted a study to identify blood variables related to severe preeclampsia in patients. They assessed eleven parameters in 248 pregnant women. They attempted to predict severe preeclampsia using three predictive models: RF, light gradient boosting machine (LGBM), and DT. Notably, the LGBM model, associated with markers of activated partial thromboplastin time percentage, levels of aspartate aminotransferase, and direct bilirubin values, showed significance. Another study was undertaken by Sufriyana *et al*. [21] who constructed an artificial intelligence model for predicting preeclampsia. They used a dataset that included 95 characteristics and 3318 cases of preeclampsia. The algorithms employed were SVM, ensemble, artificial neural network (ANN), machine learning-optimized LR, DT, and RF. With 17 predictors, RF produced the most advantageous results. The optimum AUC was obtained for external validation by deploying data from nine months to twelve months preceding its incidence and deploying a sequential or geographical fragment. The AUC of the temporal split was reported at 86 % and 88 % for the geographical division. The current study was a prospective examination in which data was collected from pregnant women using the novel risk factors score in the first and third trimesters. The algorithms' efficacy in predicting preeclampsia was evaluated using classification and regression models.

3. METHODS

3.1. Data collection, assessment of the novel risk factors scores and dataset

We gathered the data from pregnant women by assessing the novel factors risk score. Table 1 displays the novel factors score thats aids in providing a simple primary clinical evaluation for detecting and predicting preeclampsia. The risk rating procedure includes all existing and emergent risk factors for pregnant women. Each clinical risk factor is scored 1, 2, or 3 based on its importance in developing preeclampsia. A total score is determined regularly after a complete history and examination of the pregnant woman. If the total score equals or exceeds 3, the antenatl mother categorized as high risk for development of preeclampsia. Researchers obtained formal permission from the hospitals in Pune to assess pregnant mothers in the first trimester and third trimesters. The sample size was 400 pregnant women who were chosen employing a systematic random selection technique. Figure 1 explains that the trained data was entered into the computer to prepare the model. Following that, machine learning techniques were used. The model's input and original input data were introduced into the system to train the architecture efficiently. Finally, projections were produced based on the data collection.

The dataset includes 27 variables of the novel maternal high-risk factors score mentioned in Table 1. The dataset dataset attributes are the integer and float. The integer dataset type that is used to represent entire numbers, both positive and negative, with no fractional portion. The float (floating-point number) dataset type represents fractional parts of numbers. Floats can have a decimal point and are used to represent actual values. Bool (boolean) dataset represents a binary value that can be true or false.

3.2. Data pre-processing

Ensuring the quality and integrity of data is paramount, as data impurity, caused by noise, outliers, and missing or redundant data, can adversely impact the resulting outcome. In this study, we meticulously addressed these concerns by diligently eliminating missing values and outliers from our dataset. Subsequently, we employed sophisticated data transformation techniques to present the data in a suitable format for mining processes. Our research embraces a comprehensive approach, combining normalization, attribute selection, and random under-sampling to optimize data accuracy and facilitate robust analysis.

Table 1. Novel maternal high risk factors score for prediction of preeclampsia

Risk factor	Score
Women older than 35 years	1
Women younger than 19 years	1
Anemia in pregnancy	1
Body mass index more than 30	1
Woman pregnant for the first time	1
Cohabitation	1
Woman born as small for GA	1
History of heart diseases in family	1
Polycystic ovary syndrome (PCOS)	1
The gap between pregnancy >7 years	1
Pregnancy with ART	1
Mean Arterial pressure is more than >85 mm of Hg	1
Log term vascular conditions	1
Increased weight in pregnancy	1
Hypothyroidism in pregnancy	2
Preeclampsia history in family	2
Gestational diabetes mellitus (GDM)	2
BMI more than 35 kg/M2	2
Multifetal Gestation	2
History of HDPs in previous pregnancy	2
Pre-gestational DM	3
Long term history high blood pressure	3
Mental disorders	3
Inherited/acquired thrombophilia	3
Renal diseases in pregnancy	3
Autoimmune disease	3
Conception with assisted reproductive therapies	3

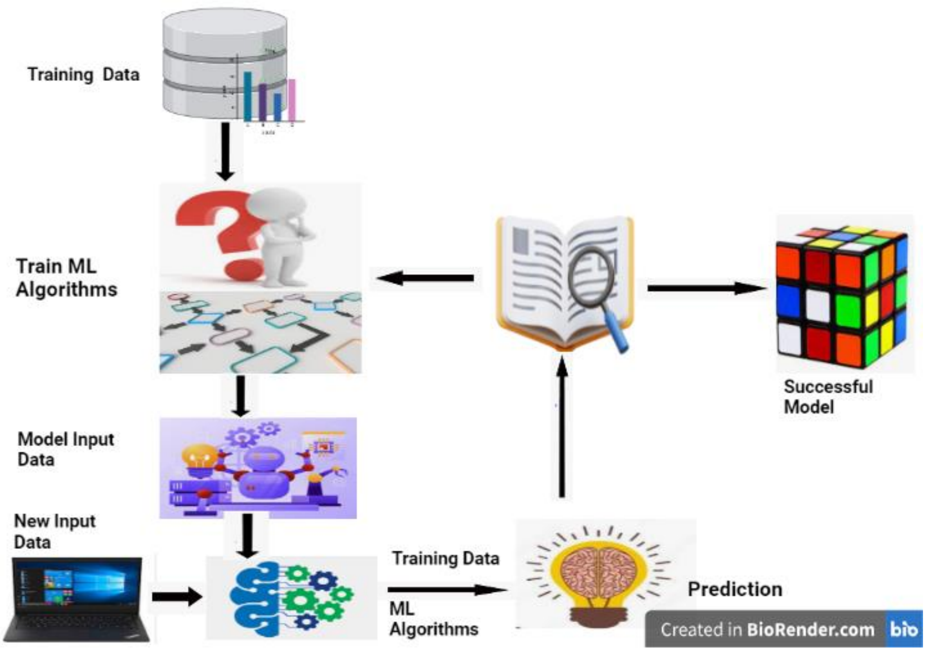

Figure 1. Proposed model for classifying novel maternal high risk factors for prediction of preeclampsia

3.3. Predictive model selection

The predictive model selection employs various machine learning classifiers, including DT, RF classifier, gradient boosting, support vector classifier (SVC), KNeighbors, XGB, and LGBM classifiers. For a classification task, various regression techniques, including linear regression, DT, RF, support vector regressor (SVR), MLP regression, and K-neighbors regressor, were used in classification techniques. It is accomplished using a binary classification strategy, which converts the problem into a classification problem by turning the target variable into binary classes. The transformation's threshold is three. All values above or equal to 3 are assigned to the positive class, while all values below three are assigned to the negative class. Thus, in the following subsections, we presented the theoretical meaning of these algorithms.

3.4. Ethics approval of research

The researchers received ethical approval from the symbiosis independent ethics committee, affiliated with Symbiosis International Deemed University (SIU), Pune. We obtained both written and verbal consent from study participants, indicating their willingness to participate in the study. The privacy and identity of participants' data were carefully maintained throughout the study.

4. RESULTS

The results are divided into three subsections: i) empirical consequence report (ECP), ii) descriptive statistics of HDP Gestosis score data analysis, and iii) survey data analysis (SDA). The ECP summarizes the study's findings, whereas the descriptive statistics give a deeper analysis of the HDP gestosis score data. Finally, the SDA delivers the survey results.

4.1. Empirical consequence report

Various metrics, including accuracy, precision, recall, and F1 scores, were tested in this study using regression and classification methods. These metrics rely on the given data to compute true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) [22]. Accuracy gauges how well the model predicts positive and negative instances. A higher accuracy indicates better overall prediction performance. Accuracy=(TP+TN)/(P+N), where TP and TN are total positive and negative classes. Precision signifies the proportion of instances the model accurately predicts as positive out of all instances it predicts as positive. A high precision indicates the model makes fewer false positive errors. Precision=TP/(TP+FP).

The F1 score computes the mean of accuracy and recall to achieve a harmonious balance. When this number equals 1, the two are perfectly balanced, but a score of 0 indicates that one drastically exceeds the other. F1 score=2x((Precision*Recall)/(Precision+Recall)). The area under the receiver operating characteristic curve (AUC-ROC) assesses a techniques capacity to distinguish between positive and negative events at different threshold levels. A more excellent AUC-ROC value indicates that the model performs better in categorization.

Sensitivity is a recall, assesses the techniques capacity to forecast positive cases among all TP instances reliably. It helps to identify how well the model captures actual occurrences of the condition. Sensitivity=TP/(TP+FN). It evaluates the techniques' capacity to predict negative instances from all actual negative samples accurately. Specificity=TN/(TN+FP). TP represent the number of instances the model correctly predicts as positive. TN denote the number of instances the model accurately predicts as negative.

Table 2 presents the data of of hyperparameters that define the critical settings of each algorithm, influencing their behavior and performance during training and prediction. It shows the comprehensive overview of various machine learning classifiers and regression algorithms and their corresponding hyperparameters. Tables 3 and 4 depict the equivalent predictive performance results utilizing regression and classification prediction methodologies. When anticipating high risk for preeclampsia, the AB algorithm outperformed both prediction algorithms by obtaining accuracy from 97% to 99%. Notably, the multiple linear regression (MLR) prediction model is only relevant in the context of the regression prediction model.

Table 2. Fine-tuning the predictive regression model's hyperparameters

Algorithm	Hyper-parameters
Linear regression	-
DT repressor	Criterion: friedman_mse, Maximum Depth: 20, Minimum Samples Leaf: 1, Minimum partcipants Fragmented: 2
RF repressor	Criterion: friedman_mse, Maximum Penetration: 10, Mimimum participants Leaf: 1, minimum partcipants Split: 2, Number of Estimators: 50
SVR	C: 10, Gamma: auto, Kernel: rbf
MLP repressor	Activation: relu, Alpha: 0.0001, Hidden Layer Sizes: (50, 50), Learning Rating: invscaling Optimization Solver: adam
K neighbors repressor	N Neighbors: 7, Weights: distance

Table 3. Evaluation report of the classification model for prediction of preeclampsia

Classifier	Accuracy	Precision	F1 Score	AUC-ROC	Sensitivity	Specificity	TP	TN
DT	0.825	0.913	0.6667	0.75	0.525	0.975	21	78
RF	0.8083	0.84	0.6462	0.7375	0.5	0.975	20	78
Gradient Boosting	0.8417	0.8621	0.7246	0.7875	0.6	0.95	24	76
Support Vector	0.8417	0.92	0.7077	0.775	0.575	0.975	23	78
K-Neighbors	0.8	0.9	0.6	0.7125	0.45	0.975	18	78
LGBM	0.85	0.9583	0.7188	0.7813	0.575	0.9875	23	79
MLP	0.8417	0.8621	0.7246	0.7875	0.55	0.975	22	78
AdaBoost	0.725	1	0.2979	0.5875	0.175	1	7	80
ExtraTrees	0.8167	0.9091	0.6452	0.7375	0.5	0.975	20	78

Table 4. Regression report of the MLS for prediction of preeclampsia

Regressor	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Sensitivity	Specificity	TP	TN
Linear Regression	0.8167	0.95	0.475	0.6333	0.7313	0.475	0.9875	19	79
DT	0.7917	0.8571	0.45	0.5902	0.7062	0.45	0.9625	18	77
RF	0.7583	0.9231	0.3	0.4528	0.6438	0.3	0.9875	12	79
SVR	0.8083	0.9474	0.45	0.6102	0.7188	0.45	0.9875	18	79
MLP Regressor	0.7917	0.9412	0.4	0.5614	0.6938	0.4	0.9875	16	79
K-Neighbors Regressor	0.7417	0.8	0.3	0.4364	0.6313	0.3	0.9625	12	77

Figure 2 demonstrates the AUC and ROC values of gradient boosting, LGBM classifier, LGBM, LBBM, and MLP of 0.7875, 0.7813, 0.7813, and 0.7875, respectively. Figure 3 demonstrates that the linear repressor had 0.73 and the DT 0.70 AUC-ROC values. The Figures 4 and 5 represents a radar chart, which is used to compare multiple quantitative variables. Here we are comparing various machine learning classification algorithms on five performance metrics: accuracy, precision, recall, F1-score, and AUC-ROC. Each vertex of the chart represents a metric, and the further from the center a point is, the better the algorithm performs on that metric. The colored shapes represent each algorithm's performance profile across the metrics, allowing for a visual comparison of their strengths and weaknesses. The overlapping areas suggest that some algorithms perform similarly across different metrics. The heatmap in Figure 6 depicts the associations between various factors and blood pressure measurements. Systolic blood pressure is strongly associated with mean arterial pressure (0.95) and diastolic blood pressure (0.89). Weight correlates modestly with systolic blood pressure (0.29) and mean arterial pressure (0.23). Age at marriage is strongly correlated with age (0.83).

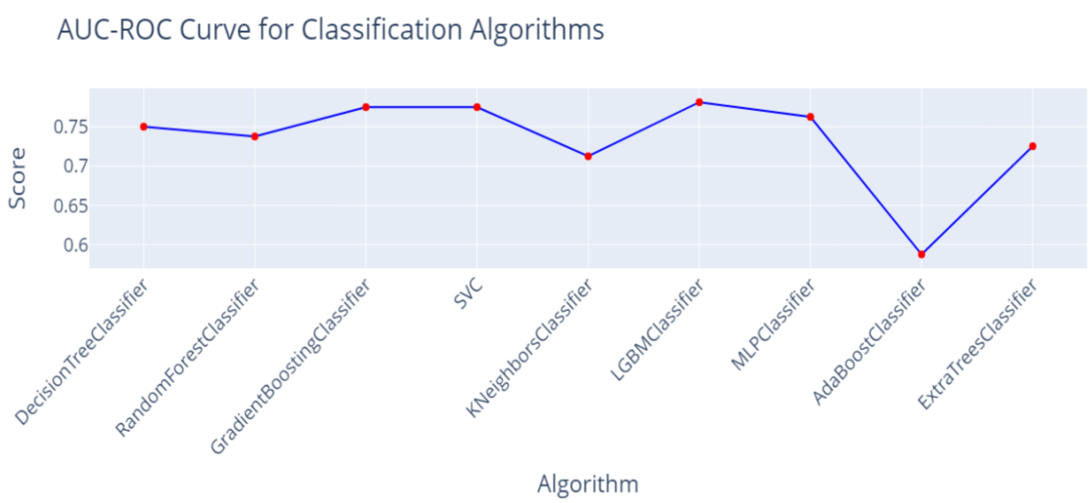

Figure 2. AUC- ROC curve classification algorithms

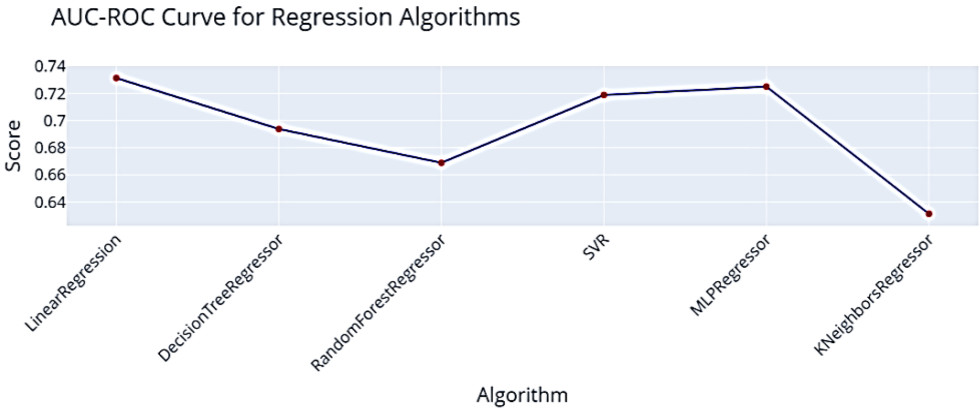

Figure 3. AUC-ROC curve regression algorithms

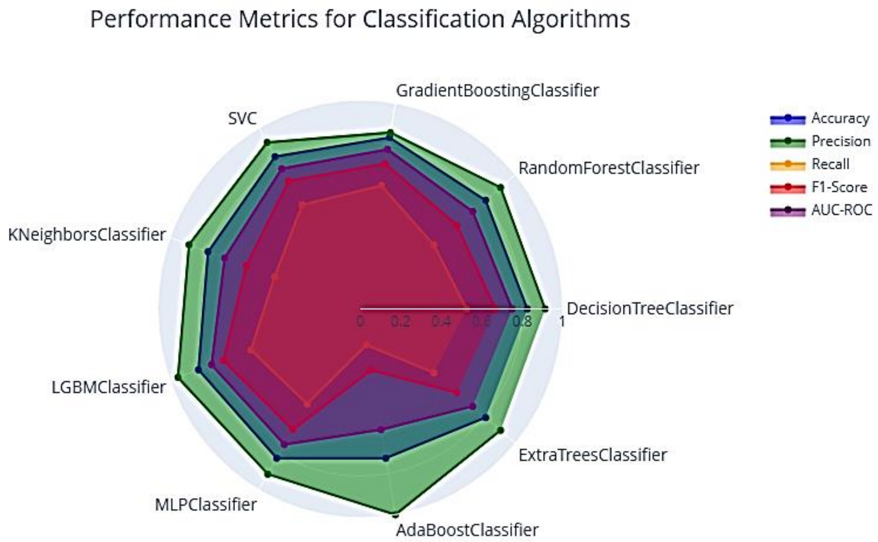

Figure 4. Performance metrics for classification algorithms

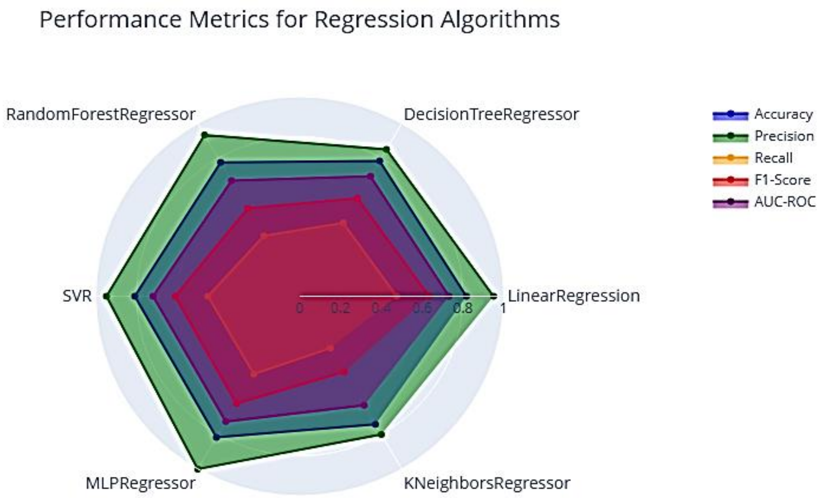

Figure 5. Performance metrics for regression algorithms

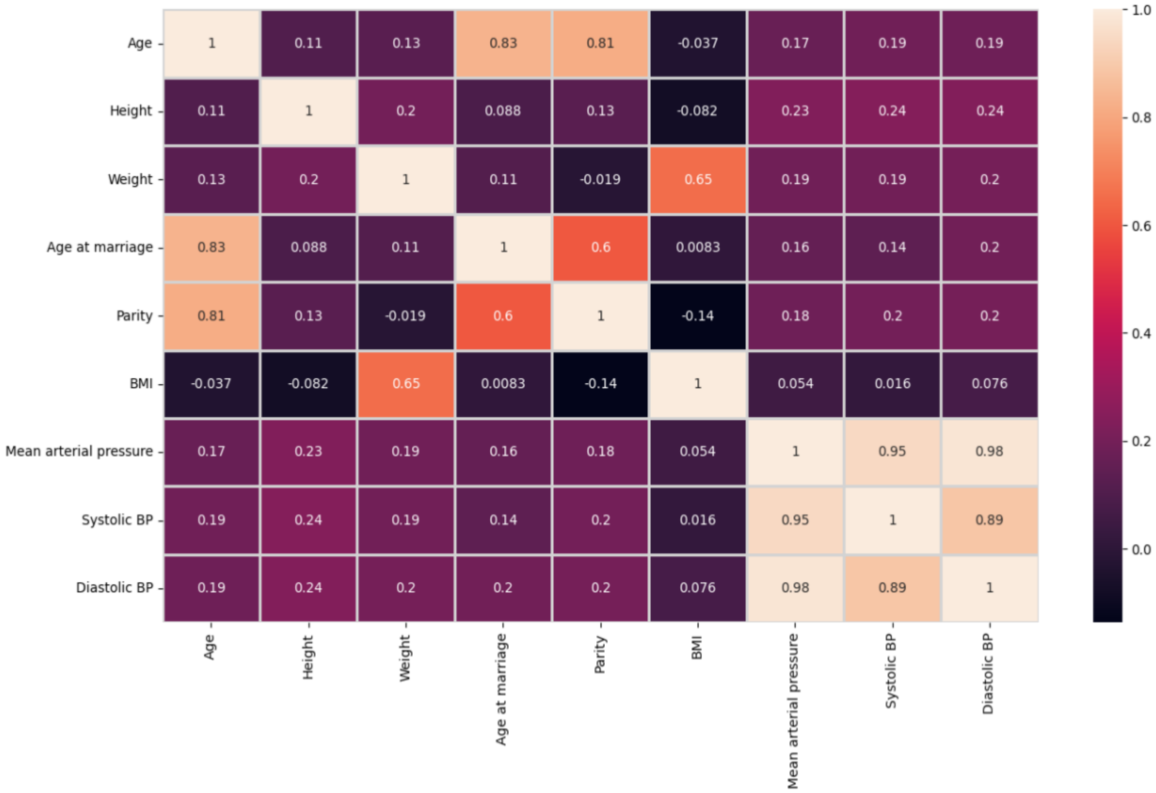

Figure 6. Correlation between different parameters in respect to blood pressure values

Figure 4 represents various classification algorithms namaely SVC, K-neighbors' classifier, LGBM classifier, MLP classifier, gradient boosting classifier, RF classifier, DT classifier, extra trees classifier, and adaboost classifier. The gradient boosting classifier has the outermost boundary in the majority of the metrics, suggesting that it has the highest scores in most of the metrics shown. Thus, we can infer that the gradient boosting classifier is the best performing algorithm among those listed in this specific evaluation. Figure 5 shows various regression models namely RF regressor, DT regressor, linear regression, K-neighbors regressor, MLP regressor, and SVR. The best performing algorithm according to this chart would be the one with the largest area enclosed, representing high values across all the mentioned metrics. In this case, the RF regressor seems to have the largest area covered in the chart, indicating that it performs best overall on the given metrics. Figure 6 shows a positive relationship between BMI and age, BMI and height, and parity and weight growth in the setting of increasing blood pressure throughout pregnancy.

4.2. Exploratory cervical data analysis

ECDA explains the relationships between two or more variables. These variables indicate the properties of the input data utilized for predicting the target variable. Correlation is a computational approach that evaluates how one variable changes another, revealing information about the strength of their link. It is used as a bivariate analytic measure to define the relationships between variables [23]. Identifying correlations is critical with novel maternal high-risk factors score analysis since it aids in identifying essential elements by highlighting the relation between each variable. Furthermore, the two variables had a positive association with one another.

4.3. Survey data analysis

Another part of our research study was analyzing the data using descriptive statistics. It helped us understand how many pregnant women were at high risk for preeclampsia. The significant findings of Tables 5 and 6 provide a comprehensive overview of the descriptive statistics for the selected parameters. The mean pragnncy in weeks and body mass index (BMI) of tatal pregnant women 25.61 ± 6.7 years and 25.82 ± 3.7 kg/m2, respectively. 78.5 % of the women were primigravida, while 86.25 % had a family history of preeclampsia. Figures 7 and 8 depict the novel maternal high-risk factors score: 17.5% of pregnant women were identified as being at high risk for preeclampsia in the first trimester, and this number rose to

18.7% in 3rd trimester; furthermore, 16% of pregnant women had a 140/90 mmHg blood pressure value. As a result, the novel maternal high-risk factors score can effectively predict the occurrence of preeclampsia at an early stage.

Table 5. Descriptive statistics of selected parameters

	Age	Height	Weight	Age at marriage	Parity	BMI
MEAN	25.61	5.37	64.63	22.03	1.085	25.82
STD	4.33	0.20	7.38	2.324	0.82	3.14
MIN	18	4.8	39	18	0	18.2
25%	23	5.2	62	20	1	24.9
50%	25	5.5	65	22	1	25.3
75%	28	5.5	67	24	1	27.1
MAX	39	5.8	87	28	3	33.6

Table 6. Difference in the distribution of the factors in I and II trimester of pregnancy

Variables	I Trimester				III Trimester				P value
	Negative	%		%	Negative	%	Positive	%	5.96E-08
Age > 35yr	384	96	5.96E-08	4	384	96	16	4	2.19E-15
Maternal anemia	293	73.25	2.19E-15	26.75	291	72.75	109	27.25	9.31E-19
BMI more than 30 to less than 35	359	89.75	9.31E-19	10.25	353	88.25	47	11.75	1.51E-12
Primigravida	314	78.5	1.51E-12	21.5	310	77.5	90	22.5	0.0001332
Mother born with SGA	394	98.5	0.0001332	1.5	394	98.5	6	1.5	2.93E-11
Family history of CAD	345	86.25	2.93E-11	13.75	345	86.25	55	13.75	0.1289
PCOD	392	98	0.1289	2	393	98.25	7	1.75	0.8195
Gap between the pregnancy is >7 years	399	99.75	0.8195	0.25	399	99.75	1	0.25	0.2865
Pregnancy with ART	395	98.75	0.2865	1.25	395	98.75	5	1.25	1.61E-13
Mean arterial pressure >85	205	51.25	1.61E-13	48.75	200	50	200	50	1
Long term vascular conditions	400	100	1	0	400	100	0	0	4.54E-18
Obesity in pregnancy	385	96.25	4.54E-18	3.75	385	96.25	15	3.75	2.85E-11
Hypothyroidism	390	97.5	2.85E-11	2.5	390	97.5	10	2.5	1
Preeclampsia history in family	400	100	1	0	400	100	0	0	0.0594
GDM	397	99.25	0.0594	0.75	397	99.25	3	0.75	7.86E-42
Essential hypetention	398	99.5	7.86E-42	0.5	398	99.5	2	0.5	1
Maternal chronic kidney disease	400	100	1	0	400	100	0	0	5.96E-08

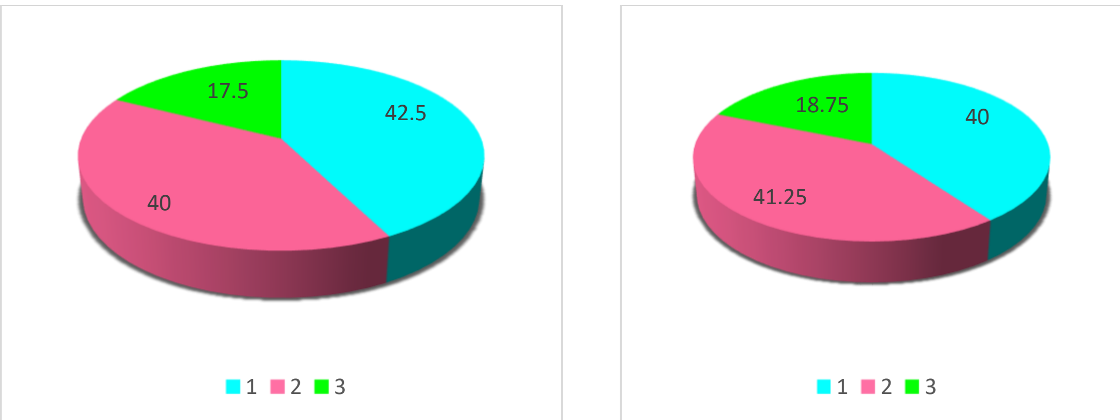

Figure 7. Total score distribution in 1st and 3rd trimester in percentages

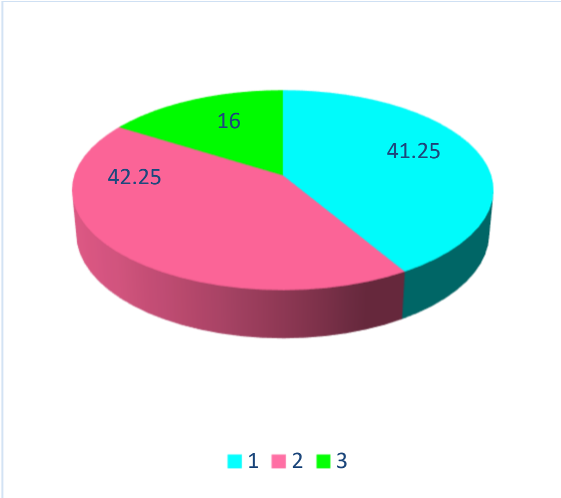

Figure 8. Distribution of the blood pressure in 3rd trimester more than/equal to 140/90mmHg

5. DISCUSSION

Multiple guidelines recommend particular indicators to detect high risk antenatal women for preeclampsia. As a result of these guidelines, obstetricians frequently prescribe aspirin as a preventive strategy in the early stages of pregnancy. However, current research has found that these guidelines have poor predictive performance [24]. In 2017, European authors stated that the NICE guidelines had a 40% predictive rate with a 10% FPR [25]. Another study published in 2019 by Asian authors revealed a detecting rate of 26% and a FPR of 5.5%. Furthermore, the detection rate of American College of Obstetricians and Gynecologists (ACOG) recommendations was 54.6%, with a FPR of 20.4% [26].

Because of these limitations, the foetal medicine foundation has recommended other measures such as mean arterial pressure (MAP), serum PlGF, and the uterine artery pulsatility index. This alternative strategy performed better, with prediction rates ranging from 70% to 80% and a FPR of 10% to 20% [26]. Nonetheless, these attributes are associated with invasive procedures that are impossible for all healthcare personnel to perform, particularly in rural areas. The authors recently devised a simple grading system called the HDP Gestosis score. All healthcare professionals, including grassroots-level healthcare providers, can easily use this score to predict the likelihood of preeclampsia in women in the first three months of gestation. This novel maternal high-risk factor score was used in the current study to identify pregnant mothers at high risk for preeclampsia. The dataset was then analyzed using machine learning methods to determine its ability to predict high-risk women for preeclampsia. Researchers followed up with the antennal women from the first to third trimesters and evaluated how well a simple scoring instrument could predict preeclampsia. It helps healthcare practitioners make precise judgments, extend timely care to pregnant women, and aid in preventing the complications of preeclampsia at an early stage.

Machine learning and computational methods have recently established a notable association with numerous datasets that would otherwise be difficult to prove by manual correlation. Manual computation and interpretation using typical statistical analysis techniques becomes time-consuming when dealing with large amounts of complex data. Numerous predictive models in obstetrics have been developed utilizing machine learning techniques [27]. However, only a handful of studies have utilized machine learning predictive models to detect HDP [28]. Sufriyana *et al*. [21] established a robust model that uses uterine artery Doppler measures and particular biomarkers to predict HDP [21]. In contrast, Jee *et al*. [29] constructed a technique that integrated prenatal and prenatal variables in initial days of 2nd trimester. Sufriyana used upgraded models in another investigation, covering demographic characteristics and health data from early to late gestation. To predict the development of HDP, a cohort study gathered variable data during the first parental visit [30]. Maric and colleagues recently proposed using 64 common clinical markers to predict HDP in its early stages. The AUROC suggested a reasonable performance, with sensitivities of 0.79 and 45.2%, respectively [31].

In our study, researchers used 27 navel maternal high-risk factors; data was gathered in the first trimester and 3rd trimester and used to predict the women's high risk for preeclampsia using classification and regression models. Various machine learning methods were used to analyze the dataset, including DT, RF, gradient boosting, support vector classifier, K-Neighbors classifier, LGBM classifier, MLP classifier, adaboost classifier, and extratrees classifier. Notably, the DT, gradient boosting, support vector classifier, LGBM classifier, and MLP classifier outperformed the others regarding HDP predicting. These models have accuracy and precision metrics of 0.825 and 0.913, 0.8417 and 0.8621, 0.8417 and 0.92, 0.85 and 0.9583, and 0.8417 and 0.8621, respectively. In comparative research, Jhee *et al* [29]. used the DT model, the RF, stochastic gradient boosting (SGB), SVM, and the NB classification technique to predict late-onset preeclampsia. These models' performance statistics were as follows: The RF method scored 0.894, the LR model scored 0.806, the DT model scored 0.857, the SVM scored 0.573, and the NB classification scored 0.776. Importantly, the SGB model produced the best results, with an FPR of 0.009 and an accuracy of 0.973.

Furthermore, a better-performing classifier models in the current study, including DT, RF, SVC, K-neighbors classifier, LGBM classifier, MLP classifier, and extratrees classifier, had sensitivity and specificity values of 0.525 and 0.975, 0.5 and 0.975, 0.45 and 0.975, 0.575 and 0.9875, 0.55 and 0.975, and 0.5 and 0.975. Marin *et al*. [32] used machine learning algorithms to predict preeclampsia based on age, blood pressure, BMI, and weight data. In this study, pregnant women were asked to wear a bracelet equipped with a sensor linked to the user's mobile device and to transmit patient information to healthcare experts through Bluetooth. The overall accuracy, specificity, and sensitivity were reported to be 80%, 72%, and 92.5%. Furthermore, Li *et al*. [33] enrolled 3759 pregnant mothers who received regular hospital treatment. XGBoost emerged as the clear winner among five distinct machine learning algorithms, including gradient boosting (XGBoost), LR, and SVM. It outperformed the other models, with a remarkable AUC of 0.955, F1 scores of 0.571, recall of 0.789, precision of 0.447, and accuracy of 0.920.

In the present study, 17.5% of pregnant women in their first and 18.7% in their third trimesters were classified as having a high risk for preeclampsia. Furthermore, in the third trimester, 16% of pregnant women had a blood pressure value of 140/90 mmHg. As a result, the current novel score effectively predicts the prevalence of preeclampsia. A lower prevalence rate of 15.01% was observed in recent research [10]. Similarly, Mishra *et al*. [34] found a 15.4% prevalence of HDP in Indian women.

6. IMPLICATIONS OF THE STUDY

Our findings show that using novel maternal factors score in conjunction with machine learning algorithms for early prediction of preeclampsia is effective. This score is simply applied by frontline healthcare practitioners. Early detection and intervention may help to reduce healthcare expenses associated with treating severe instances of preeclampsia. Future researchers might use an interdisciplinary approach. Long-term studies will improve the research by increasing the validity and application of their findings.

7. CONCLUSION

According to our review, the present research will be the second to use the novel maternal factors score to collect data during both the first and third trimesters to evaluate the novel maternal high-risk factors scores and machine learning algorithms predictive ability for detecting high-risk antenatal mothers for preeclampsia. In conclusion, a novel maternal high-risk factors score effectively identified women for preeclampsia. This study's use of machine learning techniques produced significant results in predicting the likelihood of preeclampsia. Overall, the score appears as a unique marker with diagnostic accuracy for anticipating the development of preeclampsia, which allows healthcare practitioners to manage high-risk mothers for preeclampsia at an early stage to prevent ensuing complications.

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