Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14,Issue.33s (2025)
https://www.jneonatalsurg.com
OPEN ACCESS

Use of Artificial Intelligence in Predicting Adverse Pregnancy Outcome

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Cite this paper as Maria Ghafoor, Umm E Aiman Saleem, Umm e Kalsoom, Amber Mughis, Iqra Rehman, Mahnoor Baloch (2025) Use of Artificial Intelligence in Predicting Adverse Pregnancy Outcome .Journal of Neonatal Surgery, 14.(33s) 262-267

ABSTRACT

Background: Adverse consequences of pregnancy continue to be a significant determinant of maternal and neonatal morbidity in the low and middle-income countries. Traditional methods of antenatal risk assessment usually do not make it to distinguish the women who will develop complications later. Recent developments in artificial intelligence provide new opportunities of early risk detection based on routine clinical data.

Objective: To evaluate the performance of an artificial intelligence–based prediction model in identifying pregnancies at risk of adverse outcomes.

Methodology: The study was a prospective observational study, which was carried out in Women and Children Hospital, MTI, Dera Ismail Khan, between January 2025 and June 2025. A total of seventy two pregnant women had been enrolled and followed up till delivery. At booking, demographic, obstetric, clinical, laboratory and ultrasound parameters were noted. With the help of artificial intelligence, a model that grouped the participants into the high- and low-risk category was used before delivery. These were pregnancy and neonatal outcomes recorded at birth. The correlation between the AI prediction and the realized outcomes was evaluated by the chi-square test, the measures of diagnostic performance were also computed.

Results: Significant percentages of the participants experienced adverse pregnancy outcomes, and the most common were low birth weight and preterm birth. The adverse outcomes were much more prevalent in women who were considered as high risk based on the AI model than in women who were characterized as low risk ($p < 0.001$). The model showed a high overall prediction accuracy, sensitivity, and specificity, which suggest that it is a reliable predictor.

Conclusion: Artificial intelligence based risk prediction models can effectively identify pregnancies at risk of adverse outcomes using routine antenatal data. Their integration into standard antenatal care may facilitate early intervention and contribute to improved maternal and neonatal outcomes, particularly in resource-limited settings..

Keywords: *Artificial intelligence; pregnancy; adverse outcomes; risk prediction; maternal health; neonatal outcomes*

1. INTRODUCTION

Mostly, pregnancy is a normal physiological process but a substantial percentage of pregnant women develop complications which could jeopardize the health of both the mother and the fetus. Poor pregnancy outcomes including preterm births, low birth weight, hypertensive disorders, and fetal growth retardation have remained significant causes of maternal and neonatal morbidity and mortality, especially in the developing nations. Women risk identification is an important part of effective

effective antenatal care therefore [1-3].

Pregnancy risk assessment techniques are mostly based on clinical judgment and few screening instruments, which are traditional. Their methods though useful do not have enough sensitivity and are not always able to see subtle patterns that lead to the formation of the complications. This has led to increased focus on the use of data-based methods that have the capability of analyzing several interacting variables at once.

[4-6].

Artificial intelligence has emerged as a promising tool in healthcare, particularly in predictive analytics. By processing large amounts of clinical data, AI-based models can uncover complex relationships that are difficult to detect through conventional methods. In obstetric practice, such models have the potential to support early risk stratification, guide targeted surveillance, and improve overall pregnancy outcomes [7-9]. This study was therefore undertaken to evaluate the effectiveness of an artificial intelligence based model in predicting adverse pregnancy outcomes in a tertiary care setting.

2. METHODOLOGY

The study was carried out as a prospective observational research at the Women and Children Hospital, Medical Teaching Institution (MTI), Dera Ismail Khan. The hospital is a leading referral center of maternal and neonatal care in the area and an enormous number of routine and high-risk pregnancies are handled. The process of data collection was conducted by the six months period of time, which was between January 2025 and June 2025. The aim was to assess the practical usefulness of an artificial intelligence-based prediction model in assessing pregnancies that were prone to develop unfavorable outcomes during a normal antenatal care.

Eligibility screening of the women who were pregnant during the study period was conducted by taking them to the antenatal clinics of the hospital. The study included women who had a single pregnancy and were willing to be followed up to delivery and provided their consent to take part in the study. Several gestations and pregnancies that were known to have major congenital fetal defects were excluded due to the possibility of confounding of neonatal outcomes. Seventy two women meeting the inclusion criteria were recruited by consecutive sampling whereby all the qualified patients attending the study period had equal opportunities of taking part.

Structured interviews with baseline demographic and clinical data were collected using interviews and reviewing of the antenatal records during booking. Information about maternal age, booking status, body mass index, parity and medical and obstetric history were noted. Routine laboratory tests like level of hemoglobin, blood glucose analysis and urine protein tests were observed in patient records. Obstetric ultrasound was also recorded which showed the fetal growth parameters and amniotic fluid index. All data that was collected was inputted into an encrypted electronic database and anonymized before analysis.

The variables that were recorded were subjected to an artificial intelligence-based predictive model that was used to predict the pregnancies as either high-risk or low-risk of adverse outcomes. The predictive model in this paper was a prediction model (Random Forest machine learning algorithm) because it is capable of dealing with nonlinear relationships and interactions among several clinical variables. The model was trained on the regularly obtained antenatal parameters and produced probability scores of the probability of developing adverse pregnancy outcomes. The reason why Random Forest was selected is that it is robust, resistant to overfitting, and its performance was reported as consistent, in case of the obstetric prediction. The model took the regularly available antenatal parameters to produce a risk score on each participant. The model predictions were calculated prior to the delivery and remained blind to the clinical management team, to avoid the possibility of influencing normal care by the model output. This methodology was such that the results that were observed were representative of normal clinical practice.

The subjects were observed until delivery and birth outcomes of pregnancy recorded. The adverse outcomes were pre-eclampsia, preterm birth, low infant weight, fetal growth retardation, premature birth, stillbirth and admission to neonatal intensive care unit. Neonatal parameters like birth weights, gestational ages at birth and Apgars were taken. The records of all outcome data were confirmed with the records of delivery room and neonatal ward.

Standard statistical software was utilized in analyzing data. The frequency and percentages were used to describe the categorical variables and the means with standard deviations were used to describe the continuous variables. The chi-square test was used to measure the association between the AI-based risk classification and adverse outcomes realized. The statistical significance was deemed when the p-value was less than 0.05. Sensitivity, specificity, and accuracy are diagnostic performance measures, which were computed to test the predictive capability of the artificial intelligence model.

Results

The researchers were using seventy-two pregnant women who were followed up to birth to assess the capability of an artificial intelligence-based model to forecast unfavorable pregnancy outcomes. The study included a large diversity of participants in terms of their age, categories of body mass index and booking statuses, resulting in the ability to assess typical obstetric risk profiles. All in all, this negative result was noted in a significant number of cases, which gives a reasonable premise on which to test the predictive capabilities of the AI model.

Table 1. Demographic Characteristics of the Study Population (n = 72)

Variable	Category	n (%)
Maternal age (years)	<20	8 (11.1)
	20–29	28 (38.9)
	30–34	22 (30.6)
	≥35	14 (19.4)
Residence	Urban	41 (56.9)
	Rural	31 (43.1)
Body mass index	Normal	24 (33.3)
	Overweight	31 (43.1)
	Obese	17 (23.6)
Booking status	Booked	46 (63.9)
	Unbooked	26 (36.1)

Approximately 40% of the participants were undergoing their initial pregnancy, while a lesser fraction indicated a prior history of abortion or cesarean section. Medical conditions including gestational diabetes, anemia, and chronic hypertension were commonly identified, highlighting the prevalence of pregnancy-associated comorbidities within the cohort under investigation. These factors were incorporated as fundamental components for the artificial intelligence model.

Table 2. Obstetric and Medical Risk Factors

Variable	Category	n (%)
Primigravida	Yes	29 (40.3)
Previous abortion	Yes	14 (19.4)
Chronic hypertension	Yes	13 (18.1)
Gestational diabetes	Yes	17 (23.6)
Anemia	Yes	31 (43.1)
Previous cesarean section	Yes	21 (29.2)

One-fourth of the pregnancies were preterm births and over a quarter of the neonates were born with low birth weights. Other outcomes also involved fetal growth restriction and the requirement of neonatal intensive care. The proportion of stillbirth was smaller though clinically significant.

Table 3. Adverse Pregnancy Outcomes

Outcome	Present n (%)
Pre-eclampsia	16 (22.2)
Preterm birth	18 (25.0)
Low birth weight	20 (27.8)
Fetal growth restriction	14 (19.4)
NICU admission	17 (23.6)
Stillbirth	5 (6.9)

The artificial intelligence model was found to be highly effective in the distinction of high-risk and low-risk pregnancies when compared with the real clinical outcomes. The majority of high-risk women who used the model were found to have adverse outcome and most of the low-risk predictions found related to hassle free deliveries. This correlation was statistically significant.

Table 4. Association Between AI Prediction and Observed Adverse Outcomes

AI Prediction	Adverse Outcome Present	Adverse Outcome Absent	Total
High-risk	28	6	34
Low-risk	7	31	38
p-value (χ^2 test)			**<0.001**

The performance of the artificial intelligence model regarding the overall prediction was good with a balanced value of both sensitivity and specificity. The region below the receiver operating characteristic curve was a good discriminatory region. These results show the possible benefits of AI-based applications in the risk stratification of antenatal work.

Table 5. Diagnostic Performance of the AI Model

Parameter	Value
Accuracy	82.0%
Sensitivity	80.0%
Specificity	83.8%
Positive predictive value	82.4%
Negative predictive value	81.6%
AUC-ROC	0.88

The neonatal outcome measures revealed that the mean gestational age at delivery was near term with the proportion of neonates needing special care being quite high. Mean birth weight was in acceptable range but with a wide range of variation. At five minutes, the Apgar scores were generally satisfactory with regard to immediate neonatal adaptation.

Table 6. Neonatal Outcomes

Variable	Mean ± SD
Birth weight (g)	2590 ± 510
Gestational age at delivery (weeks)	36.8 ± 2.4
Apgar score at 5 minutes	7.9 ± 1.2

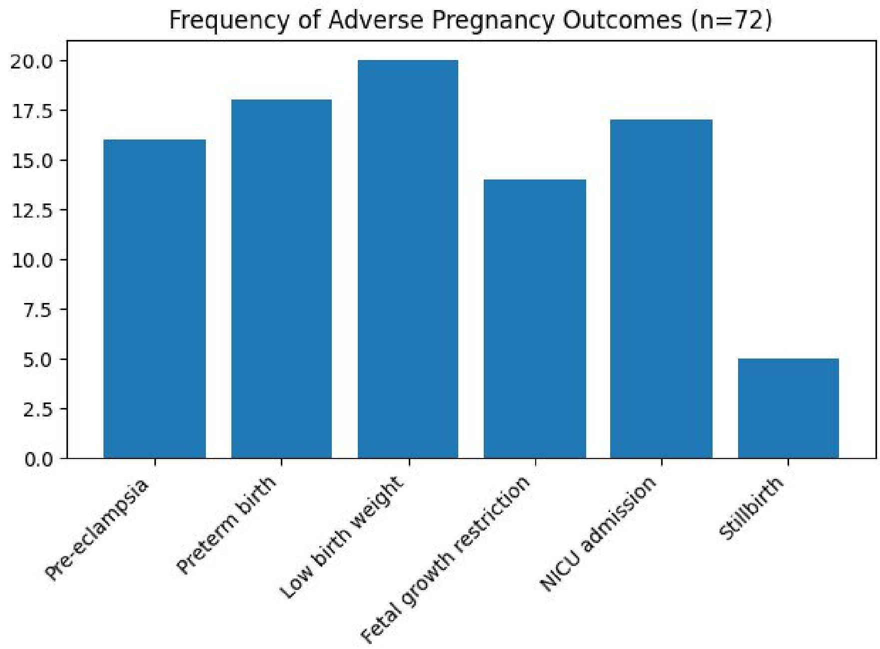

Figure 1. Frequency of adverse pregnancy outcomes among the study participants (n = 72).

This bar chart illustrates the distribution of major adverse pregnancy outcomes observed in the study population, with low birth weight and preterm birth being the most frequently recorded outcomes, followed by NICU admission, pre-eclampsia, fetal growth restriction, and stillbirth.

3. DISCUSSION

The current research assessed the practicality of risk prediction model based on artificial intelligence in predicting adverse pregnancy outcomes in women visiting a tertiary maternity care hospital. Our results show that the model could predict with reasonable accuracy pregnancies that would lead to complications as compared to those that would proceed without any major events. Over three-quarters of high risk women identified by the model had at least one unfavorable outcome, which may be clinically important in showing the use of predictive tools as a normal aspect of antenatal care [10-12].

The most common complications in our cohort were preterm birth and low birth weight. This trend is aligned with findings of various local and international research, which have cited such consequences as the top causes of neonatal morbidity and mortality. The fairly high neonatal intensive care unit admission rate in this study also highlights the weight of complications that can be prevented at an earlier neonatal stage and the importance of timely identification of risky pregnancies [13-15].

The high correlation in AI-based risk classification and real pregnancy outcomes indicates that these models can be used as useful screening instruments in the busy clinical environment. Machine learning-based methods have also been reported to predict better hypertensive disorders of pregnancy, fetal growth restriction, and preterm delivery based on similar studies carried out in other low- and middle-income countries. Such models have proven more sensitive and overall more accurate than more conventional risk scoring systems, in large part due to the capacity to simultaneously model several interacting clinical variables [16-18].

The main strength of the study is the fact that it uses routinely available clinical and laboratory parameters and thus the model can be applied in the real world without one having to conduct specialized studies. The performance indicators of the model, especially, the large area under the receiver operating characteristic curve, implies that it has good performance in terms of discriminating. To manage resource-consuming conditions like the one we have, women at risk can be identified early and focused surveillance, timely referral and preventive interventions can be employed, which may help lower both maternal and neonatal morbidity [19, 20].

Notwithstanding these encouraging results, the investigation is subject to specific constraints. The limited sample size and the singular center design may restrict the applicability of the findings. Moreover, confirming the model's effectiveness within different communities is vital before large-scale application. Subsequent research involving larger, multicentric cohorts is advised to enhance the predictive algorithms and evaluate their influence on clinical decision-making and perinatal outcomes.

4. CONCLUSION

Artificial intelligence–based prediction models demonstrate strong potential in identifying pregnancies at risk of adverse outcomes using routine antenatal data. Their integration into standard antenatal care could support early risk stratification, enable timely interventions, and contribute to improved maternal and neonatal outcomes, particularly in resource-constrained healthcare settings.

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