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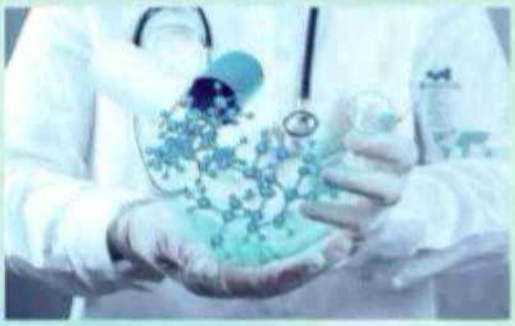

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www.bsmi.uz
https://newdaymedicine.com E:
ndmuz@mail.ru
Тел: +99890 8061882

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MODELING THE RISK OF PREECLAMPSIA BASED ON ARTIFICIAL INTELLIGENCE METHODS

Marzhona Zikrillaevna Nematova https://orcid.org/0009-0000-4105-1064

Bukhara State Medical Institute named after Abu Ali ibn Sina, Uzbekistan, Bukhara, A. Navoi Street, 1 Tel.: +998 (65) 223-00-50 Email**:** info@bsmi.uz

✓ ***Resume***

Preeclampsia is a multifactorial obstetric complication that occurs in the second half of pregnancy and is characterized by hypertension and dysfunction of various organs, significantly increasing the risk of maternal and perinatal morbidity and mortality. Despite considerable progress in understanding the pathophysiological mechanisms, effective methods for early detection and prediction of preeclampsia remain a pressing issue in clinical practice. This article presents an overview of modern approaches to predicting preeclampsia using artificial intelligence (AI) technologies. Machine learning algorithms, including random forests, gradient boosting, and deep neural networks, are discussed in the context of analyzing clinical, biochemical, and ultrasound data of pregnant women. Particular attention is given to the integration of multimodal data to improve prediction accuracy.

Keywords: preeclampsia, artificial intelligence, hypertension, pathophysiological mechanisms

МОДЕЛИРОВАНИЕ РИСКА РАЗВИТИЯ ПРЕЭКЛАМПСИИ НА ОСНОВЕ МЕТОДОВ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

Нематова Маржона Зикриллаевна https://orcid.org/0009-0000-4105-1064

Бухарский государственный медицинский институт имени Абу Али ибн Сины, Узбекистан, г. Бухара, ул. А. Навои. 1 Тел: +998 (65) 223-00-50 e-mail: info@bsmi.uz

✓ ***Резюме***

Преэклампсия — многофакторное акушерское осложнение, которое возникает во второй половине беременности и характеризуется гипертензией и нарушением функции различных органов, что существенно увеличивает риск материнской и перинатальной заболеваемости и смертности. Несмотря на значительный прогресс в понимании патофизиологических механизмов, эффективные методы раннего выявления и прогнозирования преэклампсии остаются актуальной проблемой в клинической практике. В данной статье представлен обзор современных методов прогнозирования преэклампсии с использованием технологий искусственного интеллекта (ИИ). Рассматриваются алгоритмы машинного обучения, включая случайные леса, градиентный бустинг и глубокие нейронные сети, применяемые для анализа клинических, биохимических и ультразвуковых данных беременных женщин. Особое внимание уделено интеграции многомодальных данных для повышения точности предсказаний.

Ключевые слова: преэклампсия, искуственный интеллект, гипертензия, патофизиологические механизмы

SUN'IY INTELEKT USULLARI ASOSIDA PREKLAMPSIYA XAVFINI MODELLASH

Marjona Zikrillaevna Nematova https://orcid.org/0009-0000-4105-1064

Abu Ali ibn Sino nomidagi Buxoro davlat tibbiyot instituti, O‘zbekiston, Buxoro, A.Navoiy ko‘chasi, 1-uy Tel.: +998 (65) 223-00-50 E-mail: info@bsmi.uz

✓ ***Rezyume***

Preeklampsiya — homiladorlikning ikkinchi yarmida yuzaga keladigan va arterial bosimning oshishi hamda turli organlar funksiyasining buzilishi bilan kechuvchi ko‘p omilli akusherlik asoratidir. Bu holat onaning va tug‘ilayotgan bolaning sog‘lig‘i uchun jiddiy xavf tug‘diradi, perinatal va onalik kasallanishi hamda o‘lim holatlarining ortishiga olib keladi. Patofiziologik mexanizmlarning chuqur o‘rganilganiga qaramay, preeklampsiyani erta aniqlash va bashorat qilishning samarali usullari hozirgi kungacha dolzarb muammo bo‘lib qolmoqda. Ushbu maqolada sun’iy intellekt (SI) texnologiyalaridan foydalangan holda preeklampsiyani prognoz qilishning zamonaviy usullari ko‘rib chiqiladi. Klinik, biokimyoviy va ultratovush ma’lumotlarini tahlil qilishda qo‘llanilayotgan mashinali o‘rganish algoritmlari, jumladan, tasodifiy o‘rmonlar, gradient busting va chuqur neyron tarmoqlari yoritib beriladi. Bashoratlarning aniqligini oshirish uchun ko‘p formatli ma’lumotlarni integratsiyalash masalasiga alohida e’tibor qaratilgan.

Kalit so‘zlar: preeklampsiya, sun’iy intellekt, gipertenziya, patofiziologik mexanizmlar

Relevance

Currently, there are three most commonly used preeclampsia risk assessment systems (RAS):

1. the NICE risk assessment system (National Institute for Health and Clinical Excellence, UK);
2. the ACOG risk assessment system (American College of Obstetricians and Gynecologists, USA);
3. the FMF risk assessment system (Fetal Medicine Foundation, UK).

The NICE RAS identifies moderate- and high-risk groups based on the following factors: age ≥ 40 years; BMI ≥ 35 kg/m²; nulliparity; family history of preeclampsia; interpregnancy interval > 10 years; hypertensive disorders in previous pregnancies; chronic hypertension; chronic kidney disease; diabetes mellitus; and autoimmune diseases. [1].

The ACOG RAS identifies moderate- and high-risk groups based on the following factors: age ≥ 35 years; BMI > 30 kg/m²; first pregnancy; family history of preeclampsia; chronic hypertension; kidney disease; autoimmune diseases; and type 1 or type 2 diabetes mellitus. [2].

According to FIGO recommendations, the prediction of preeclampsia risk should be based on the patient’s medical history and risk factors identified through first-trimester prenatal screening. [3].

In a study by N. O’Gorman et al., the predictive accuracy of the NICE and ACOG[4]. risk assessment systems was evaluated. The detection rates of preterm and term preeclampsia using the NICE scale were 39% and 34%, respectively. Corresponding detection rates using the ACOG scale were 90% and 89%, with a false-positive rate of 64.3%.

Predicting preeclampsia using artificial intelligence algorithms

Due to the insufficient effectiveness of current preeclampsia prediction methods proposed by major international obstetrics and gynecology organizations—NICE and ACOG[4]. —research laboratories worldwide are continuing to search for reliable methods of assessing preeclampsia risk based on biophysical factors, biochemical markers, and AI algorithms. [5]. This approach aims not only to improve predictive accuracy but also to provide an individualized risk estimate.

Currently, the list of FIGO-recommended parameters for first-trimester screening in singleton pregnancies includes:

- maternal characteristics, medical history, and comorbidities;
- placental growth factor (PlGF), secreted by trophoblast cells;
- pregnancy-associated plasma protein-A (PAPP-A), secreted by the syncytiotrophoblast;
- uterine artery pulsatility index (PI);
- mean arterial pressure (MAP).

One of the first attempts to combine the analysis of biochemical markers with machine learning algorithms to develop a predictive model for preeclampsia (PE) was made by L.C. Kenny et al. [6]. The researchers used genetic programming to identify patterns in the changes of plasma metabolite levels in patients with PE. The analysis included 87 plasma samples from pregnant women with PE and 87 control samples from healthy pregnant women. Gas chromatography was performed, and the resulting data were processed using genetic programming algorithms. As a result, a model was developed with sensitivity and specificity of 100% and 98%, respectively.

Various combinations of maternal history data, instrumental studies, or laboratory markers can be used to generate predictions. Each research team independently determines which features to include in the model. In their study, S.M. van Kuijk et al. limited the number of variables used to predict recurrent early-onset PE to five: [7]. body mass index (BMI), gestational age at previous delivery, fasting blood glucose level, presence of hypertension, and birth weight of the previous baby being small for gestational age. According to the authors, this limited set of features helps prevent model overfitting due to the small dataset. Their database included 407 pregnant women with a history of early-onset PE leading to preterm delivery. After statistical processing, a predictive model was developed that can identify women at low risk of recurrent PE using the five features listed above. The model achieved an AUC of 0.65. Given the small sample size, the authors emphasized the need for external validation on a larger dataset.

R.M. Villa et al. conducted a study to identify factors that influence both the risk and severity of PE [8]. Their database consisted of 903 cases of pregnant women with known PE risk factors. The researchers used a Bayesian algorithm for cluster analysis, classifying patients into groups based on observed combinations of risk factors. A total of 25 risk factor combinations were identified. For each group, the risk of different PE subtypes was calculated, and a heatmap was created for visualization. The study found that the risk of developing PE increases exponentially with the number of risk factors. It was also noted that the risk profiles of women with severe PE and preterm delivery differ from those with term pregnancies.

Two subsequent studies on PE prediction were based on neural network technology. E. Tejera et al. proposed using heart rate variability (HRV) indices to classify patients into groups with normal blood pressure, hypertension, and PE [9]. A total of 568 short ECG recordings were collected from 217 pregnant women, with varying gestational ages. Maternal history and blood pressure data were also included. The best performance was achieved by a predictive model based on an artificial neural network, with an AUC of 0.95.

S.K. Neocleous et al. employed a multi-slab neural network structure [10]. Their database included 6,838 birth records. The model used 15 input features, including mean arterial pressure (MAP), uterine artery pulsatility index (PI), racial and ethnic background, and more. The resulting model showed high predictive accuracy: 83.6% on the training set and 93.8% on the test set.

A large-scale study on PE risk assessment was conducted by I. Marić and colleagues [11]. Their dataset consisted of 16,370 birth records, and 67 risk factors were considered (maternal characteristics, laboratory test results, medication use, etc.). The predictive model was built using elastic net regression and gradient boosting algorithms to estimate the risk of early- and late-onset PE. The AUC values were 0.89 and 0.79, respectively.

P.C. de Souza et al. proposed including ophthalmic artery Doppler parameters in PE risk assessment [12]. Maternal central nervous system hyperperfusion, diagnosed using this method, is closely linked with the pathophysiological mechanisms of PE. The study included 415 singleton pregnancies between 18 and 23 weeks of gestation. All participants underwent Doppler ultrasound of the uterine and ophthalmic arteries. The model used maternal history, MAP, uterine artery PI, and ophthalmic artery Doppler data. Several multivariate predictive models were developed. The first model used only maternal history; the second added MAP and uterine artery PI. However, the best results were achieved with the third model, which included maternal history, MAP, uterine artery PI, and ophthalmic artery Doppler data, achieving an AUC of 0.71.

M. Fouad et al. studied the role of plasma biomarkers and uterine artery Doppler parameters in PE prediction [12]. Specifically, tumor necrosis factor-alpha (TNF-α) levels were measured in the plasma of 500 patients between 11 and 13 weeks of gestation. Doppler ultrasound was also performed to determine the mean uterine artery PI. At a TNF-α threshold of ≥14 pg/mL, sensitivity and specificity for PE prediction were 67.8% and 98.0%, respectively. A mean PI ≥1.7 yielded 100.0% sensitivity and 84.4% specificity. The combination of both parameters increased the accuracy of prediction, with sensitivity and specificity reaching 88.6% and 100.0%, respectively. Thus, simultaneous use of both markers improves PE prediction accuracy.

A team led by J. Zhou evaluated the impact of certain biochemical plasma indicators—triacylglycerols (TAG), high-density lipoproteins (HDL), and uric acid—on the accuracy of PE prediction [13]. Biochemical blood tests were performed at 20 weeks of gestation for 1,000 women with singleton pregnancies to measure lipid and uric acid levels. The patients were followed through delivery,

and outcome data were statistically analyzed. Three significant biomarkers were identified, along with their respective sensitivity and specificity values: TAG (75% sensitivity, 53% specificity), HDL (82% sensitivity, 34% specificity), and uric acid (54% sensitivity, 65% specificity). The combination of all three biomarkers yielded a sensitivity of 92% and specificity of 50%. Since only the combined biomarker model had an AUC above 0.7, statistical theory suggests that only combinations of biomarkers can provide effective PE prediction.

A recent study by J.H. Jhee et al. focused on developing a predictive model for late-onset PE, using a dataset of 11,006 medical records [14]. Of the initially selected risk factors, 14 were used to build the model (including systolic blood pressure, blood urea nitrogen, creatinine levels, etc.). An ensemble approach was applied using several AI algorithms: decision tree, logistic regression, naive Bayes classifier, support vector machine, random forest, and stochastic gradient boosting. The best performance was demonstrated by the stochastic gradient boosting model, achieving an AUC of 0.973.

D. Wright and colleagues proposed a novel approach to assessing the risk of developing preeclampsia (PE) based on the competing risks model [15]. To implement this concept, the researchers compiled a database of records from 58,884 pregnant women at 11–13 weeks of gestation. Detailed information was collected on each respondent (medical history, weight, height, ethnicity, etc.). The obtained values of mean arterial pressure (MAP) and uterine artery pulsatility index (PI) were converted to multiples of the median (MoM)—a statistical measure that reflects the degree of deviation of a particular parameter from the median value for a given gestational age.

In the competing risks model, gestational age is treated as a continuous variable. The underlying assumption is that if pregnancy were to continue indefinitely, every woman would eventually develop PE. Whether or not PE manifests at a specific gestational age depends on the relative timing of delivery and the potential onset of PE. A Gaussian distribution model was built for the gestational age at delivery with PE. In this approach, risk factors act by shifting the distribution curve: for low-risk patients, the curve shifts to the right—indicating that delivery is likely to occur before the onset of PE. For high-risk patients, the curve shifts to the left—indicating a higher likelihood of PE developing before delivery.

This model detected 90% of preterm PE cases and 57% of all PE cases, at a 10% false-positive rate.

In a subsequent study, the same research team again applied the competing risks model for PE prediction [16], this time including placental growth factor (PlGF) and pregnancy-associated plasma protein-A (PAPP-A) among the evaluated risk factors. The updated model identified 96% of preterm PE cases and 54% of all PE cases, still at a fixed false-positive rate of 10%.

Research by D. Wright et al. continued with various combinations of risk factors [17, 18]. One study sharing similarities with the above was conducted by S. Andrietti et al. [19], who also used the competing risks model for prediction. Variables included maternal characteristics as well as biophysical and biochemical markers obtained during screening at 35–37 weeks of gestation. The analysis showed that combining maternal characteristics with biomarker data significantly improved prediction accuracy compared to maternal characteristics alone (84% vs. 35%).

As a result of the above-mentioned studies, the Fetal Medicine Foundation (FMF) developed a risk calculation algorithm for PE. After entering input data (maternal characteristics, instrumental and laboratory findings, medical history, etc.), clinicians receive an individualized risk estimate for developing PE.

M.Y. Tan and colleagues hypothesized that screening based on the competing risks model would be more accurate than the approach recommended by NICE. This hypothesis was confirmed: in all three comparison scenarios, the competing risks model outperformed the NICE system. In the first case, using maternal characteristics, MAP, and PAPP-A yielded a 12.1% improvement in detection. Replacing PAPP-A with PlGF increased the difference to 28.2%. In the third and final configuration, adding uterine artery PI further improved performance, resulting in a 41.6% gain in detection accuracy [20].

To compare the effectiveness of the FMF calculator with two other widely accepted PE risk assessment systems (NICE and ACOG), a research team led by L.C. Poon analyzed data from 34,573 women. The results led to several important conclusions: among women who tested positive by the NICE and ACOG criteria but negative by the FMF algorithm, the risk of preterm PE dropped to background levels or below. The authors concluded that this demonstrates the superior effectiveness of the competing risks model-based approach [21].

It is also worth noting that studies aimed at implementing the competing risks model in clinical practice have shown promising results [22]. Continued work in this direction appears highly promising and necessary.

Conclusion

Every year, approximately half a million women around the world die from causes related to hypertensive disorders of pregnancy (HDP), and about 12% of maternal deaths result from severe complications associated with these conditions. Despite the availability of effective preventive measures, preeclampsia (PE) and eclampsia remain among the leading causes of maternal morbidity and mortality, primarily due to the lack of accurate risk assessment and prediction methods.

The statistics from Rosstat regarding birth outcomes are also concerning—recent reductions in perinatal mortality associated with HDP have been achieved mainly through decreased early neonatal mortality, largely due to significant advances in neonatal intensive care and resuscitation. However, obstetrics and gynecology have not seen comparable breakthroughs, particularly in reducing stillbirth rates, which is largely due to the lack of effective treatment for HDP. This is explained by the inability to influence the pathogenesis of HDP after placentation has been completed.

Therefore, the implementation of predictive analytics and clinical decision support systems in obstetrics and gynecology—based on artificial intelligence algorithms and the development of highly accurate, iterative predictive models that continuously refine risk assessments as new diagnostic data become available—has the potential to build a consistent chain of effective preventive measures, starting from the preconception stage through the second trimester. This approach could significantly reduce the incidence of PE and other pregnancy complications related to HDP, positively impacting both reproductive health and the demographic situation in the Republic of Uzbekistan.

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