MACHINE LEARNING POSSIBILITIES TO PREDICT SEVERE OBSTETRIC COMPLICATIONS

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Abstract: Predicting severe obstetric complications – hemorrhages – still is an important medical, demographic, and economic problem throughout the world. In the high-tech era, artificial intelligence seems to be a promising tool for dealing with this problem. This work presents results of information search for the actual experience with various methods of predicting obstetric bleedings. Long-term benefits of applying machine learning algorithms for the said purposes have been shown, and their implementation challenges have been covered. Development of digital predictive models backed up with machine learning algorithms is expected to break new ground for enhancing the precision of identifying personalized risk of bleeding. This assumption relies on the successful Russian and worldwide experience in implementing integral systems of predictive analytics into such branches of medicine, as oncology, cardiology, ophthalmology, and reproductive medicine.

Keywords: artificial intelligence, predicting, obstetric bleeding, postpartum hemorrhage, machine learning.

1 Introduction

Bleedings which occur during pregnancy, labor, the placental stage, and early postpartum period are usually referred to obstetric bleedings (OB). The index of obstetric bleedings ranges from 3 to 8% of the general number of childbirths; meanwhile, 2–4% of obstetric bleedings are associated with hypotonia of the uterus in the placental and early postpartum period, with around 1% of the bleedings being observed in cases of premature detachment of the normally situated placenta and placenta previa (Khashukoeva et al., 2004). Although occurrence of obstetric bleedings may vary from country to country, however, obstetric bleedings are still the major preventable cause of maternal morbidity and mortality throughout the world.

Every day, some 830 women worldwide die from obstetric bleeding (Sebghati & Chandraharan, 2017). In Australia, Canada, the UK, and the USA, a rising trend of postpartum hemorrhages is observed (Knight et al., 2009). In the Russian Federation, decrease can be traced in the obstetric bleeding index within the structure of maternal mortality (MM), as well as decrease in the MM index in general. However, hemorrhages keep their leading position among the major causes of MM during pregnancy, labor, and postpartum period (Maternal mortality in the Russian Federation in 2018, 2019). The systematic analysis of maternal mortality causes for the years 2003 to 2009 conducted by the World Health Organization (WHO) demonstrated that bleeding was the leading direct cause of maternal mortality throughout the world, amounting to 27,1% (19,9–36,2%). Meanwhile, over two thirds of all registered cases of death due to bleeding were classified as postpartum hemorrhage (Say et al., 2014).

As defined by the WHO, postpartum hemorrhage (PPH) is the blood loss volume of over 500 ml after vaginal delivery and over 1000 ml after the cesarean operation. The American College of Obstetricians and Gynecologists (ACOG) currently defines postpartum hemorrhage as either the general blood loss of not less than 1000 ml or hypovolemia signs or symptoms present within 24 hours after childbirth (Committee on Practice Bulletins-Obstetrics, 2017). OB are the cause of critical conditions, as well as near miss incidents ("almost lost" women or "bare survivors"): as a rule, in situations of the insufficient scope of obstetric care, if there is massive blood loss, and disorders develop in the hemostatic system (Surina & Marochko, 2016).

Maternity patients having severe bleeding may need blood transfusion, surgical treatment (including hysterectomy), or admission to the intensive care unit, with a certain percentage of lethal outcomes being possible. Postpartum hemorrhage entailing blood transfusion is the leading cause behind severe maternal pathologies in the USA (Creanga et al., 2014).

The causes of postpartum hemorrhage can be classified using the 4T mnemonics: "tone" (uterine hypotonia and atony), "trauma" (injury of birth canal accompanied by bleeding), "tissue" (fragments of placenta retained in the uterine cavity), and "thrombin" (blood coagulation system disorders). Uterine atony is the most frequent cause of postpartum hemorrhage; according to research data, up to 79% of all cases of PPH are associated with atony of the uterus (Bateman et al., 2010). Distention of the uterus as a result of multiple gestation, polyhydramnios and fetal macrosomia, faulty placentation with abruption of placenta, placenta previa, chorioamnionitis, artificial and prolonged labor, and prolonged exposure to oxytocin are referred to uterine atony development factors (Bateman et al., 2010; McLintock & James, 2011). Contributory causes of development of bleedings due to birth canal injuries or during operative delivery include obesity, cardiac insufficiency, faulty placentation with abruption of placenta, placenta previa, chorioamnionitis, and preeclampsia (Al-Zirqi et al., 2008; McLintock & James, 2011; Sebire et al., 2001). Predictors of PPH resulting from coagulopathy include hereditary diseases associated with clotting disorders: Willebrand disease, hemophilia carrier status, deficiency of coagulation factor X, and rare disorders of blood coagulation system (James, 2005). Among others, coagulopathy risk factors are HELLP-syndrome (hemolysis, hepatic enzyme elevation, and a low platelet count), the use of anticoagulants, amniotic embolism, and massive blood loss (Al-Zirqi et al., 2008; McLintock & James, 2011). Meanwhile, a high body mass index (BMI) presents an independent risk of postpartum hemorrhage; so, for example, the BMI value of over 30 increases the probability of severe PPH (over 1000 ml) by almost 50% (Al-Zirqi et al., 2008).

Revealing patients who have a high risk of postpartum hemorrhage will allow taking effective measures of prevention promptly, which will have a significant impact on reduction of morbidity and mortality of the patients, yield lower economic costs of treatment, and improve outcomes for the patients ultimately. Prediction of postpartum hemorrhage based on the information available is a domain of immense clinical opportunities. In clinical practice, application of predictive models developed helps evaluate risks of bleeding. Such forecasts can have a real-time effect on decision-making. For example, such decisions include alteration of birth plan in favor of cesarean operation, preventive prescription of uterotonic and hemostatic drugs, or transfer to a center providing a higher level of obstetric care (Westcott et al., 2020).

The problem of revealing risk factors and predicting obstetric bleedings has remained urgent in spite of numerous studies in this domain. Conventional statistical methods have a number of limitations due to which the use of predictive models, even the theoretically verified ones, is not always possible in the actual clinical practice. Among such limitations, there is non-uniformity of the studies and a limited quantity of data for analysis which is not always capable to represent the real-life clinical situation. Standard statistical methods evaluate the contribution of each one of the limited number of predictors individually, while overlooking relationships among them.

Prediction of bleedings has been a challenging problem for obstetrics. Further elaboration of this domain using new knowledge and state-of-the-art techniques seems promising. The total of modern scientific developments and advanced computer technologies which include artificial intelligence, databases of big data, and cloud-based computing, open up vast opportunities for predicting obstetric complications, bleedings included. The use of artificial intelligence seems to be an efficient prediction method in real-life clinical practice which will enable clinical physicians to make well-timed decisions on prevention and scope of medical care.

2 Literature Review

Artificial intelligence (AI) is a branch of computer science dealing with the use of computers and information technologies for modeling intelligent behavior and critical thinking which would be comparable to the human ones.

Almost immediately after invention of the first computers, people started to ask the question if it was possible to create a machine able to demonstrate intellectual capacity which would be similar to the human one. Back in 1950, in his article "Computing machinery and intelligence", the English mathematician Alan Turing developed and published a test proving the capacity of machines to imitate human behavior and thinking (Mintz & Brodie, 2019). A bit later, in 1956, John McCarthy was the first to describe the term "artificial intelligence" as a science and technology of creating smart machines (Amisha et al., 2019). The 1980s and 1990s saw a surge of interest in AI in many domains, including healthcare. Artificial intelligence methods, namely, fuzzy expert systems, Bayesian networks, artificial neural networks, and hybrid intelligent systems, have been utilized in medicine in diverse clinical conditions (Amisha et al., 2019). As of today, the level of computing capacities of machines has soared up to instant computations and the ability to analyze data in the real-time mode (Mintz & Brodie, 2019).

In different countries of the world, scientists have made repeated attempts to develop efficient prediction models for obstetric bleedings. For example, Ana Rubio-Álvarez and her colleagues (2018) (Spain) developed a model for predicting bleedings which occur after delivery via the natural birth canal. They tested the model out in clinical practice, too. The model relies on post-hoc analysis of the data of digital medical records of 2336 women having single vaginal delivery. In this study, blood loss was defined as hemoglobin decreased to less than 3,5 g/dl. For data analysis, they used standard methods of medical statistics, such as chi-square test, Student t-test, Lemeshow test, and binary logistic regression. In the course of the research, the principal predictors of postpartum hemorrhages were identified: age, first labor, high duration of the first and second periods of labor, weight of the newborn, and the level of hemoglobin before labor. In their conclusions, the scientists point out a high predictive power of the developed model (Rubio-Álvarez et al., 2018).

Scientists from the Netherlands, Corine M. Koopmans together with colleagues (2014), proposed their predictive models of obstetric bleedings. The data for the research had been obtained from 38 hospitals of the Netherlands for the years 2005 to 2008, with 1132 women involved in the research. The analysis was conducted using conventional statistical methods, logistic regression included. The authors developed two models calculating bleeding risks on the basis of the antenatal and intranatal data (Koopmans et al., 2014). In the course of their study, the most significant risk factors of obstetric bleedings were found, in particular: age, BMI, preeclampsia, weight of the fetus, and retention of afterbirth. Among the intranatal factors, the most crucial ones were a high duration of opening of the uterine orifice, and episiotomy (Koopmans et al., 2014).

Italian researcher Eugenia Biguzzi and her colleagues (2012) created a model for predicting postpartum hemorrhages based on multivariate logistic regression. The research data had been obtained from digital medical records of 6011 women who had delivered via the natural birth canal within the time span of the year 2007 to 2009. The model is built on the basis of a monogram, which allowed visually estimating the contribution of certain risk factors of bleeding. Among the most important predictors of obstetric bleedings, the scientists revealed the body mass, Asian and Latin American ethnic origin, episiotomy, retention of afterbirth, weight of placenta, body mass of the newborn, as well as the level of hemoglobin before labor (Biguzzi et al., 2012).

Sarit Helman together with colleagues (2015) conducted a post-hoc study relying on databases and information from the blood bank for the time span from 2005 to 2014. They analyzed the data of 113342 women, 0,1% of whom had a massive hemorrhage (Helman et al., 2015). A step-by-step predictive model of obstetric bleedings based on logistic regression was built. So, among the risk factors, the largest contribution belonged to the past history of cesarean operation, spontaneous miscarriage, multiple gestation, induction of labor, current cesarean operation, and artificial delivery. The advantage of this research consisted in the large sample size and the use of high-accuracy statistical models (Helman et al., 2015).

Jill M. Westcott and his colleagues (2020) (Maternal and fetal medicine department, Obstetrics and gynecology department, New York) conducted a post-hoc cohort study at the NYU Langone Health medical center for prediction of obstetric bleedings with the help of machine learning algorithms. Using computer technologies, they analyzed the data of 30867 digital medical records obtained within the time span from July 2013 through October 2018. Within the study, the scientists assessed demographical parameters, the patients' medical, obstetric, and surgical history, results of laboratory tests, and any medications used. As the criterion of bleeding, they defined blood loss at the volume of over 1000 ml. Thus, bleeding occurred in 2179 of all the patients under study. All the data were subdivided into 2 groups: 70% for learning and 15% for verification. To evaluate the efficiency, the indicators of accuracy, sensitivity, and AUC were used. Predicting was performed by means of supervised learning with the use of logistic regression, random forest, and decision tree with gradient amplification (XGBoost), as well as support vector machine. So, they created two models in the course of the work: 1) for the data obtained before childbirth, 2) for the data available up to the second period of labor as of the point of decision-making on the obstetric tactics. As a result of the research, the most important risk factors of obstetric bleedings have been identified: BMI, hematocrit level, urgent and planned cesarean operation, the platelet level during labor. The best result was yielded by XGBoost decision tree: for the first model, its accuracy amounted to 98,1%, sensitivity – to 0,763, and AUC – to 0,979, while for the second model, the accuracy was 98%, sensitivity was 0,737, and AUC was 0,955. The first model turned out to be able to successfully predict almost 3 of every 4 female patients who had postpartum hemorrhage. Importantly, many risk factors among those considered were not included into the final risk assessment due to their low predictive value; here belonged, for example, multiple gestation, operative vaginal delivery, and the past history of bleeding. This is indicative of the fact that many risk factors do not contribute to the development of obstetric bleedings so much as they used to be believed to. Therefore, this domain needs further research to detect objectively significant risk factors of obstetric bleedings (Al-Zirqi et al., 2008).

Yawei Zhang, Xin Wang and their colleagues (2021) (Obstetrics department, Beijing Obstetrics and Gynecology Hospital of the Capital Medical University, China) studied the opportunities of ensemble machine learning in the context of predicting postpartum hemorrhages. The research was conducted with the data of 3842 childbirths of the year 2017, where postpartum hemorrhage was registered in 361 cases. It is important to note that the data had an imbalance of positive and negative cases, which brings the research closer to the real-life clinical practice conditions. For the analysis, they selected 23 characteristics associated both with pregnancy and with labor directly. These included age, parity, gestational age, anemia present and the level of hemoglobin, the kind of amniotic fluid, pre-induction and induction methods, timeliness of amniotic fluid discharge, pain relief methods, labor stimulation with oxytocin and duration of its administration, duration of labor, integrity of the birth canal, uterine tone, and weight of the fetus. All the data obtained were subdivided into 2 groups: 65% of them set aside for learning and 35% – for testing. For the analysis, ensemble learning was used, including random forest, XGBoost, decision tree with gradient amplification, and SVM. The model developed has demonstrated a high predictive ability, with accuracy of the method amounting to 96,7% in relation to postpartum hemorrhages, and 90,3% – to DIC syndrome (disseminated intravascular blood coagulation). Among the most significant postpartum hemorrhage risk factors, they found uterine tone disorders, duration of labor, injuries of the birth canal, and duration of administration of oxytocin. The scientists expect that owing to the results of forecasts made with the help of the developed model, obstetricians will get an opportunity of using relevant techniques to cope with potential bleeding (Zhang et al., 2021).

Kartik K. Venkatesh and his colleagues (2020) (obstetrics and gynecology department of Duke University, North Carolina, USA) conducted an impressive post-hoc study to assess predictive ability of machine learning models in forecasting postpartum hemorrhages. For the research, they requested depersonalized data from the National Institute on Child Health and Human Development (NICHD): these were the data of digital medical records of 152279 childbirths dated from 2002 to 2008 mined from 12 clinical databases of 19 hospitals in 9 districts of the USA. The group under study comprised deliveries at the gestational age of 23 weeks and more; meanwhile, by postpartum hemorrhage, they understood the blood loss of not less than 1000 ml, regardless of the delivery mode. These criteria were met by 7279 cases. As predictors of bleedings, the scientists considered risk factors declared by CMQCC and ACOG, alongside some additional factors: age, race, any obstetric complications present (placenta previa, fetal macrosomia, preeclampsia), and extragenital pathology (chronic arterial hypertension and diabetes mellitus). For the forecast, two statistical models were developed: the conventional statistical model based on logistic regression and LASSO regression and the ML based model involving random forest and extreme gradient amplification (XGBoost). In the course of analysis, the most significant factors contributing to the development of postpartum hemorrhages have been detected: in particular, they referred here mother's weight before pregnancy and as of admission, BMI, body temperature as of admission, fetal macrosomia, multiple gestation, systolic blood pressure level, and anemia present. The best predictive efficiency has been demonstrated by extreme gradient amplification (its AUC was 0,93, and accuracy was 95%) and random forest (with the 0,92 AUC, and 95% accuracy); both of them did better than LASSO regression results (AUC of 0.87, and accuracy of 95%). The researchers consider the introduction of ML models to be a promising method of predicting postpartum hemorrhages, both individually and combined with conventional statistical methods. Prediction of postpartum hemorrhages can help sort the pregnant women into risk groups and take proactive measures to prevent bleedings. The scientists discuss expedience of integrating similar models into online calculators or automatic concurrent input within digital medical records to be used immediately upon admission of inpatients (Venkatesh et al., 2020).

Jun Liu, Tao Wu, Yun Peng, Rongguang Luo (2020) (Nanchang University, China) conducted the first study with deep learning methods and MRI images of the uterus. The study is aimed at predicting the level of bleeding during cesarean operation in patients with placenta previa in the area of scar after the previous cesarean operation. The data had been obtained from the First Affiliated Hospital of Nanchang University. There were the total of 210 samples; positive cases, for which the blood loss volume was 500 ml and more, numbered 82. The number of negative samples, respectively, where the blood loss volume was less than 500 ml, was 128 cases. The research involved two stages. First of all, the pregnant women got abdominal MRI, and 9 MRI images at 7 mm slice thickness were obtained for each one. Using the artificial neural network and computer software (DeepLab-V3+ network), the area of the uterus in the initial MRI images was recognized and segmented. Next, the data were subdivided into 2 groups – 168 images for learning and 42 images for testing, with 5-times cross-validation conducted after that. The second stage of the research was aimed at prediction of bleedings proceeding from the obtained MRI images of the area of the uterus in question. Each case contained 9 images in the form of independent sampling. Thus, there were 630 positive and negative images for learning and 108 positive and negative images for testing. The analysis was performed on the TensorFlow platform; within it, 6 successive steps of training for convolutional neural network VGGNet-16 were completed. As a result of the study, predictive model of blood loss has been developed. In the comparison of manual and automatic method of prediction, it was the automatic method that has demonstrated best results. The accuracy of the method was 75,6%, its sensitivity – 73,7%, and the specificity was 74,46%. The developed model not only identifies the necessary area of the uterus automatically, but also indicates the level of intraoperative bleeding objectively. Owing to this, the accuracy of experts' conclusion about the level of bleeding during cesarean operation and selection of the necessary hemostasis techniques can be enhanced (Liu et al., 2020).

Japanese scientists Yasunari Miyagi, Katsuhiko Tada and their colleagues (2020) conducted a study using artificial intelligence to find out quantitative relation between the distribution of fibrinogen and fibrin/fibrinogen degradation products (FDPs) as indicators of massive obstetric bleeding. The data had been obtained from Japan's eight national perinatal centers for the time span from 2011 through 2015. The number of deliveries was 22 330, and the number of registered massive bleedings – 154. These are cases of bleeding at the volume of 2000 ml and more, excluding ones with DIC syndrome developing. The total numbered 83 and 71 cases, for cesarean operation and for vaginal deliveries, respectively. The obtained data were subdivided into two groups according to the fibrinogen level. The group having the level of fibrinogen below the threshold criterion was defined as the "low fibrinogen group", while the one where the fibrinogen level was up to the criteria or higher was defined as the "normal fibrinogen group". Distribution of data in both groups was explored with the help of artificial intelligence algorithms. In each group, the median value, the 95th percentile, the average, standard deviation, skewness and excess coefficients of levels of fibrin degradation products were identified. The research was conducted using the Mac platform powered by OS X 10.11.6 (Apple, Inc) and Mathematica 12.0.0.0 software (Wolfram Research). Generation of fibrin degradation products was described with differential equations using the data set of two groups. Theoretically, AI was not compulsory in this study; anyway, its application ensured high efficiency and turned out to be more advantageous in practice. For the massive bleeding in labor, the fibrinogen criterion was 237 mg/dl. It is suggested that as soon as this value of fibrinogen is achieved, the development of coagulopathy is to be expected. Meanwhile, for non-pregnant women, coagulopathy is expected at the level of fibrinogen of 150 mg/dl and lower, according to the guideline of the Japanese Society on Thrombosis and Hemostasis. In their future studies, the scientists are planning to explore these criteria using data sets including the DIC syndrome, as well as evaluation of other coagulation markers, namely, D-dimer, α2 plasmin, plasminogen activator inhibitor, and prothrombin time (Miyagi et al., 2020).

3 Research Methodological Framework

The objective of this work consists in evaluating the potential of using artificial intelligence in prediction of obstetric bleedings as applied to actual clinical practice.

The following tasks were addressed in the course of the work:

- to conduct information search covering the experience of using various methods of predicting obstetric bleedings;
- to study the potential of using artificial intelligence in prediction of obstetric bleedings;
- to inform a broad circle of specialists in obstetrics and gynecology about the achievements of machine learning

technologies and the prospects of application of artificial intelligence in prediction of obstetric bleedings.

The following methods were used in completing the above tasks and achieving the set objective:

- the method of information search which helped the authors scrutinize sources of medical and scientific technical information on the research topic;
- the analysis method which allowed systemizing the material collected and providing its comparative evaluation;
- the comparison method which enabled the authors to detect ways of solving the problem under study which are the most suitable for the set objective.

4 Results and Discussion

In one way or another, virtually all aspects of today's life are related to big data and machine learning. Netflix knows what movies people prefer, Google knows what people want to know – from their search history, modern automated production is hard to imagine without AI, and utilities, surveillance systems, home appliances (smart home), and personal assistants all work on the basis of AI (Beam & Kohane, 2018). Certainly, the domain of medicine could not overlook this highly promising new tool. In 2016, as compared to other branches, it is applications for healthcare that enjoyed the largest volume of investments into AI studies (Amisha et al., 2019). AI algorithms are used in the medical contexts in the form of making appointments online, registering patients with medical centers online, digitizing medical records, reminding about the following visits and immunization dates for children, and supervising medication intake (Amisha et al., 2019). Artificial intelligence is already in broad use in cardiology, radiology, oncology, endocrinology, ophthalmology, and other branches of medicine (Johnson et al., 2018; Shimizu & Nakayama, 2020; Contreras & Vehi, 2018; Ting et al., 2019). For healthcare, the most valuable aspect of AI is its ability to predict a result based on the previous experience, to elicit risk groups, and to assist in decision-making.

Machine learning (ML) is a section of artificial intelligence where mathematical and statistical approaches are applied for the purpose of enhancing the performance of computers. The term "machine learning" was introduced by Arthur Samuel in 1959; he described it as giving computers the ability to learn without being explicitly programmed (Handelman et al., 2018). There is the following rule for working with ML: the larger bulk of data is analyzed, the more accurate forecast can be expected. In the medical domain, data are a massive resource, therefore, a high predictive accuracy is to be expected from the use of ML. Application of ML in healthcare is economically advantageous. Experts estimate that in medicine and pharmaceutics ML using big data can yield returns of up to 100 billion USD per annum (Rajula et al., 2020).

Unlike the conventional statistical prediction models, ML not only computes the forecast in relation to new data, but also reveals relationships between various predictors and predicts the outcome of events based on the already available experience. Alongside this, machine learning differs from the statistical methods with its ability to learn from examples, and not with the help of set rules (Sidey-Gibbons & Sidey-Gibbons, 2019).

The key concept of ML implies introducing algorithms which use input data, utilizing computer analysis to predict output values within the acceptable accuracy range, detecting regularities and trends in the data, and, finally, learning from previous experience (Handelman et al., 2018).

There are numerous variants of machine learning models; as a rule, they belong to one of the types described below:

- Supervised learning;
- Unsupervised learning;
- Semisupervised learning;
- Reinforcement learning.

Controlled or supervised learning

In supervised learning, a computer is provided with functions pertaining to the learning objective (for example, demographic data and risk factors of a patient) and with results to be achieved (such as a diagnosis or clinical event) in order to reveal association between the two data sets. This process of deriving variables from previous known examples is enabled by regression analysis. This concept is generally used in statistics, helping enhance the accuracy of forecast. During training, the prediction algorithm becomes capable of evaluating more and more variables and creating sophisticated models of nonlinear relations between independent and dependent variables. The supervised learning technology is focused on classification (for identifying the category of new observation based on the training sample) and regression (predicting values for a variable on the basis of the known values training set). For example, this kind of learning can be used for calculating risk of cardiac diseases, predicting tumor sizes, assessing individual risk of a disease – or predicting the hospital stay duration (Handelman et al., 2018).

Uncontrolled or unsupervised learning. In unsupervised learning, a computer is provided with unclassified data entries to recognize, and it detects if concealed patterns set by researchers are present.

In terms of technology, unlike supervised learning which has to deal with classification and regression, unsupervised learning mainly addresses clustering and dimensionality reduction. Clustering means identification of groups within the data, i.e., the algorithm analyzes the data supplied and identifies any concealed similarities and distinctions enabling it to group subjects into subsections. In medicine, this process is applied in exploring complicated relationships between genetic and biochemical processes in histology and pathology (Handelman et al., 2018).

Semicontrolled (semiautomatic) or semisupervised learning. This is a combination of supervised and unsupervised ML which can analyze a bulk of unlabeled data while simultaneously expanding the opportunities of images recognition with a small quantity of labeled data. In terms of medicine, such an approach is valuable because assigning labels in the information (e.g., in patient records) can be labor-consuming and expensive, given the complexity and abundance of medical data. Moreover, semisupervised learning can enhance the speed and accuracy of information retrieval from large data sets. Among other purposes, semisupervised learning is used for analyzing scientific papers to include them into systematic reviews of the topic under study (Handelman et al., 2018).

Reinforcement learning. This is a particular case of supervised learning. In this model, it is the environment (but not a special control system with reinforcement) that acts as supervisor. Meanwhile, a feedback loop is formed between the environment and the learning algorithm.

The machine learning process implies the following successive stages:

1. Importing the input data and preparing them (data cleaning, ordering) for further analysis, with matrices of terms being formed meanwhile (Lanera et al., 2019). In particular, the information can be obtained from databases comprising a bulk of both structured and unstructured data. The depersonification procedure is compulsory for the data to be used, too.
2. Selecting the required ML algorithms and training them. In the domain of medicine, the most popular ones are decision tree, naive Bayes classifier, random forest, support vector machine (SVM), artificial neural network (ANN), deep neural network or deep learning, and convolutional neural network (CNN) (Lee & Ahn, 2020). The algorithms will be described in more detail below.
3. Testing the ML algorithms. The algorithms are tested by comparing predictions obtained with the help of the

algorithms to the true forecasts compiled on the basis of the already available data.
4. Assessing the efficiency of the algorithms. The assessment is performed by the indices of sensitivity (the percentage of true positive results), accuracy (the percentage of correctly classified cases), and specificity of the method (the percentage of true negative results), as well as with the help of plotting receiver operating characteristics curves (ROC, or the error curve). The curve demonstrates the dependence of the positive cases number on the quantity of incorrectly classified negative cases. If several ROC curves are compared visually, it is not always possible to detect the most efficient model. In such cases, the curve comparison method is used which is termed estimation of area under the curves (AUC). With regard to this, it can be taken that the higher the AUC index is, the higher predictive value the model features (all forecasts are true if AUC equals 1).
5. Using the tested models on new data with the aim of prediction and further learning.

The following algorithms of machine learning are used:

1. Decision tree is a structure in the form of a branching method flow chart representing each and every possible outcome of decision-making. Decision tree consists of internal nodes, branches, and end nodes (Lee & Ahn, 2020).
2. Naive Bayes classifier calculates forecasts based on Bayesian theorem. The essence of the theorem implies that the probability of a dependent variable under certain values of independent variables can be obtained from probabilities of these variables, proceeding from the set value of the dependent variable (Lee & Ahn, 2020). This algorithm allows making a more precise prediction in relation to the new information based on the already available data.
3. Random forest is a combination of several decision trees, each of which being built from the initial training sample with the help of bootstrapping (which is a method of determining confidence intervals of statistical estimations) (Chistyakov, 2013). In the process of the algorithm execution, the data are broken down into numerous samples, with an individual model created for each of them. Then, each model calculates its forecast, and the obtained forecasts are averaged out, which results in a higher accuracy of the output value estimation. Random forest algorithm has the following advantages: guarantee against overtraining (overfitting), the opportunity to detect the most informative features, and various scales available for measuring the features (numerical, ordinal, nominal ones) (Chistyakov, 2013).
4. SVM or Support vector machine creates a "hyperplane" in the form of a line or a space separating the data at the maximum distance between different groups (Han & Micheline, 2006). The method essentially consists in sorting the data into subgroups according to an algorithm. Here, a set of training examples is used which are marked as ones belonging to this or that subgroup. After learning, the algorithm builds a model which refers new data to one of the said subgroups.
5. ANN or artificial neural network is basically a network of interconnected input-output nodes ("neurons"). This algorithm imitates the work of human brain. ANN contains one input layer, one, two, or three concealed ones, and one output layer. Its neurons are connected on the basis of "weights" (numerical values showing what impact neurons of the previous layer have on neurons of the following one) proceeding from the input layer to each subsequent one. This process is termed feedforward connection algorithm. Next, the "weights" are adjusted depending on their contribution to "losses" (the difference between actual and predicted end results). The algorithms will be repeated until a certain model ensuring an accurate forecast has been formed (Amisha et al., 2019).
6. Deep neural network or deep learning is a variant of artificial neural network which contains more than five concealed neural layers (Lee & Ahn, 2020).
7. Convolutional neural network (CNN) implies a special architecture of neural networks designed for efficient recognition of images.

Alongside the described types, they single out ensemble learning which uses the above algorithms in various combinations for enhancing the forecasting efficiency.

To improve performance of ML, various functions are used, for example, boosting (boosting or gradient amplification): this is the technique of ensemble building where predictors are built in a sequence. Meanwhile, each subsequent model learns from mistakes of the previous one. One of the most effective particular cases of boosting is the extreme gradient amplification, XGBoost. Most frequently, it is utilized for decision tree or random forest algorithms.

Obstetric bleedings are the principal preventable cause of morbidity, mortality, and near miss incidents among obstetric complications throughout the world. Modern measures of prevention based on predicting OB will help considerably reduce the level of death and morbidity in women, as well as avoid economic costs for intensive care, blood transfusion, surgical treatment, and prolonged hospital stay of the female patients. The most frequent case among all obstetric bleedings is postpartum hemorrhage (PPH) which is due to one of the four causes: uterine tone disorders, birth canal injuries, partial retention of afterbirth, and blood clotting disorders.

In spite of numerous attempts to develop an effective OB prediction system, it still is not perfect enough and needs further searching for an accurate and reliable prediction method. As a solution to this problem, such advanced method as artificial intelligence (AI, AI) can be considered. It involves computer technologies capable of coming to conclusions, similarly to human thinking. One of the particular cases of AI is machine learning (ML) which develops accurate prediction models with the help of computer analysis. Machine learning relies on computer algorithms. So, decision tree, naive Bayes classifier, random forest, support vector machine (SVM), artificial neural network (ANN), deep neural network or deep learning, and convolutional neural network (CNN) are the most widespread ones in the domain of medicine. In the course of the research conducted, the key stages of machine learning, principles of operation of the algorithms, as well as prospects of using AI for prediction of OB in actual clinical practice have been studied.

Results of the research conducted in relation to the actual experience with methods of predicting obstetric bleedings are given in Table 1.

Table 1 Results of Studies of Using ML Methods in Prediction of Obstetric Bleedings

Studies by country (Regions)	Sample size (Qty)	ML methods	Evaluated effective-ness	Risk factors
USA (New York)	2179	Random forest Decision tree SVM	Accuracy 98,8% Sensitivi-ty 0,76 AUC 0,97	BMI, hematocrit, cesarean operation, platelet count
China (Beijing)	3842	XGBoost Decision tree SVM	Accuracy 96,7%	Poor tone of the uterus, duration of labor, duration of oxytocin injection, injuries
USA (North Carolina)	7279	XGBoost	Accuracy 95% AUC 0,93	BMI, body temperature, fetal macrosomia, systolic blood pressure level, anemia
		Random forest	Accuracy 95% AUC 0,92	
China (Nan-chang)	210	ANN	Accuracy 75,6 Sensitivity 73,6	Placenta previa in the area of uterine

			Specificity 74,46	scar detected by MRI
Japan	154	AI	-	Fibrinogen level at less than 237 mg/dl

Source: the authors

In spite of some successful attempts of implementing artificial intelligence into various branches of medicine, the use of this method for prediction of obstetric bleedings has not yet become widespread enough. This is associated with a number of limitations. First of all, this is the problem of implementing AI into actual clinical practice. Performance of ML depends on numerous factors, with the crucial ones being the quantity and quality of data (Wang et al., 2019). In real-life practice, the data are quite frequently unstructured in nature, and working with digital databases has not entirely been streamlined among medical practitioners yet. This factor can have an essential impact on the sample size. Smaller training data sets can bring about incorrect results and decisions. Therefore, even an algorithm which has been thoroughly designed and verified in laboratory conditions can fail in real-life circumstances and with the data of different quality. The problem of transferring machine learning algorithms onto actual clinical practice is called AI chasm.

The difficulties of applying artificial intelligence in this domain are due to possible malfunction of the very machine learning algorithms. It can be associated with the initial incorrect choice of learning model, for example, if a too complicated model has been opted for. The algorithm error probability in the process of testing is much higher than the mean error obtained during learning; this is termed "overtraining". Conversely, if the learning model chosen is not complicated enough, the algorithm does not use data in full and will not ensure small enough mean error value on the training sample. This situation is termed "undertraining".

Machine learning requires working with medical data, which is inevitably associated with the necessity of respecting a certain extent of confidentiality. The data have to be depersonalized while also keeping the access to clinically relevant information. This problem is coupled with ethical and legal risks and responsibility issues, which may lead to both patients' and doctors' mistrust of artificial intelligence (Wang et al., 2019).

It should be borne in mind that AI cannot stand in for the doctor, and it is only an auxiliary tool to solve repeated problems and perform accurate mathematical calculations which is there to save human time and effort significantly.

5 Conclusion

Throughout the world, prediction of severe obstetric complications, hemorrhages in particular, has remained an important problem of medicine, demography, and economy. The high-tech era seems to have a promising tool for dealing with this problem: artificial intelligence. In obstetrics, just like in any other branch of medicine, large volumes of data are a valuable resource. The use of AI algorithms for analyzing these data sets will allow structuring and classifying them, as well as developing prediction models. The developed models can be implemented into digital medical systems. Accordingly, with the help of the automated system, a patient will be referred to a certain risk group already at the first visit to the specialist. So, medical practitioners will have a tool in their hands to lean on for making correct decisions and prescribing preventive measures promptly. Persistent efforts are underway to study the opportunities offered by machine learning algorithms and implement them into the medical domain. However, even the present developments allow creating efficient and high-quality models for predicting medical complications. Clearly, further research is necessary to elaborate the models for prediction of obstetric bleedings with the help of artificial intelligence.

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