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ENSEMBLE LEARNING BASED POSTPARTUM HEMORRHAGE DIAGNOSIS FOR 5G REMOTE HEALTH CARE

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Abstract: The fifth-generation (5G) communications enables various promising applications that were once impossible, e.g. remote healthcare with the help of fast and reliably delivery of medical data. Post-partum hemorrhage (PPH) refers to the massive blood loss after the birthing stage (within 24 hours), i.e.>500ml for the vaginal delivery, and >1000ml for the cesarean section. PPH is by far the most common cause of the mortality rate of pregnant women, as well as a primary cause of current pregnant mortality in China. Despite the great potential of prediction of PPH, there is currently no effective tool based on the limited raw data from the clinical trials. In the study, we retrospectively study the 3842 vaginal delivery cases in 2017 collected from Beijing Obstetrics and Gynecology Hospital, Capital Medical University. In particular, we obtain the prediction based diagnostic model relying on machine learning, and we adopt the ensemble learning to accomplish this task, by combining the results of various candidate methods. According to the experimental results, the accuracy of correct PPH diagnosis would approach 96.7%; the total disseminated intravascular coagulation (DIC) prediction accuracy approaches 90.3%. In this regard, we may conclude the proposed model based on machine learning would allow us to predict successfully the risk of PPH, and assess the critical level of PPH patient. We anticipate our study results would contribute to the reduction the mortality of pregnant women. According to the 2013 World Health Statistics, the maternal mortality rate in low-income countries were 410/100,000 live births. The majority of maternal deaths occurred mainly in Asian and African countries. Major causes of maternal deaths are similar across low-income countries, often obstetric in origin including hemorrhage, hypertensive diseases and maternal infections. 94% of births in Ethiopia are estimated to occur at home and 10% of maternal deaths are attributed to PPH. Uterine atony, or lack of effective contraction of the uterus, is the most common cause of PPH followed by infection, sub involution of the placental site, and inherited coagulation deficits. The majority of these fatal obstetric complications occur during labor and immediately after birth. In the low-income countries, more than three-quarters of maternal deaths due to the direct obstetric causes occur during and after birth. Organized diagnosis and management of PPH, including administration of uterotonic agents, controlled cord traction, and uterine massage after delivery of the placenta, are required to avoid maternal death.
Keywords: based learning ensemble postpartum hemorrhage

I. INTRODUCTION:

The fifth-generation (5G) communications allow for high speed and ultra-reliable data transmissions [1]–[3], which would boost various new demands and emerging applications [4],[5].

Recently, the Internet of Medical Things (IMT) has attached general interests in both academy and industry [6]. Combined with artificial intelligence (AI) and machine learning (ML), the remote healthcare thus provides the great promise to the remote medical decision in many critical situations, e.g. remote patient monitoring and remote medical learning [7]. Among them, the postpartum hemorrhage (PPH) diagnosis is one of such important scenarios. The American College of Obstetricians and Gynecologists (ACOG) defines PPH as a blood loss of >500 mL in the case of vaginal delivery, or >1000 mL in the cesarean section within 24 hours [8]. The World Health Organization (WHO) statistical analysis suggests that PPH remains the leading direct cause of maternal death worldwide, contributing to 27.1% of total maternal deaths [9]. Moreover, PPH causes several serious complications, such as shock, disseminated intravascular coagulation (DIC), and so on. Most of the PPH induced maternal deaths are relevant to the delay of clinical diagnosis. To this end, the early stage prediction of PPH and its complications is of great importance to reduce the maternal death ratio for obstetricians, which allows the obstetricians to provide the timeliest medical treatments for pregnant patients with a high risk of PPH. ACOG also suggested using the risk assessment tool to predict the occurrence of PPH [10].

The risk associated factors attributed to PPH have been extensively researched based on conventional statistical methods [11]–[18]. Logistic regression model or lasso regression model was used for the PPH risk prediction [11], [12]. In particular, lasso/logistic regression models show low-but good discriminative ability [12]. Based on maternal clinical characteristics and medical history, a risk score was used for prediction of PPH [13],[14]. Although the conventional prediction methods are proved to be effective, the performance of prediction is unsatisfied: only 60% of women with high PPH risk are identified, whilst the other 40% of women who had PPH are not identified in advance [19]. With the recent advance of artificial intelligence (AI),various machine learning-based models have been developed in the medical fields. For instance, the performance of ensemble learning was assessed for automated diagnosis of breast cancer using an open access dataset in [20].Predictive models have been studied for cancer diagnosis using Support Vector Machines (SVMs) are developed in [21]. Prediction of heart disease risk using classification and regression tree (CART) was developed in [22]. A homogeneous ensemble is then created from the different CART models using accuracy based weighted aging classifier ensemble, which is a modification of the weighted aging classifier ensemble (WAE). In our concerned PPH prediction field, only a few machines learning based methods were studied [23]–[25]. A fuzzy expert system to predict the risk of developing PPH was developed in [23]. Besides, another Mamdani inference was used to simulate the experts reasoning and thereby enables the predictionary analysis. According to the previous study on this topic, we unfortunately find that the attained PPH prediction recall (sensitivity) would even approach 87.48%, which is far from reliable for automated analysis and practical deployment in the medical diagnosis. It is reported that XGBoost would perform better than logistic regression and Artificial Neural Network (ANN) for the repeat cesarean delivery in [24], [25]. However, their datasets were only for cesarean delivery and did not cover the vaginal delivery, and the ensemble learning method was not explored. Meanwhile, it should be noted that such machine learning models also incurs the stringent requirements on the amount of experimental data. Unlike the other fields whereby the observation of data is relatively less expensive, for the considered PPH problem the collection of clinical data is extremely time consuming. When the dataset is not large enough, then we can expect the deduced prediction model would be less reliable for practical applications.

In this paper, we study the ensemble learning in the context of PPH and thereby construct the complication prediction model, enabled by the recent advances on 5G communication and machine learning. The 5G communications would greatly facilitate the high-speed and highly reliable data collection via remote monitoring, which the new ML paradigm inspire us to develop new efficient methods on highly accurate automatic diagnosis. The main contribution of this work contains two folds. First, we collect a total of 3842 vaginal delivery cases in 2017 from Beijing Obstetrics and Gynecology Hospital, Capital Medical University. This large dataset potentially allows us to derive a reliable machine learning prediction model. Second, targeting at improving the PPH and its complication prediction performance of base learners, we carefully adapt an ensemble learning scheme to handle realistic challenges in the model accuracy, especially for the dataset with imbalanced samples as in our study (e.g., the positive samples are dramatically smaller than the negative ones). In particular, the selection of base learners in ensemble learning (e.g. ANN, SVM, regression, etc.), which is of great importance for the performance, has been rarely exploited in the literatures on PPH data analysis. To address this practical difficulty, we construct different EL schemes for both the PPH and DIC tasks, based on their features and limitations. We collected 23 PPH-relevant features of each patient as the input for our PPH prediction model. The importance of the input features is also studied and ranking of the features is obtained. For the base learners, after carefully evaluating the most popular ML methods, we use the Random Forest (RF), Extreme Gradient Boosting (XGB), Gradient Boosting Decision Tree (GBDT) and support vector machine (SVM) as the base learners,[1]based on the 3842 records dataset. On this basis, we explored the use of averaging and voting ensembles to improve predictive performance. In addition, the prediction performance of PPH complications, namely DIC, is evaluated. As demonstrated by our experimental results, the accuracy of correct PPH predictive diagnosis would surpass 90%; the total DIC prediction accuracy approaches 90.3%. Other performance metrics used for our imbalanced samples, e.g. the recall ratio, the F-measure as well as the Matthews correlation coefficient (MCC), are also investigated.

In this regard, we would conclude our proposed model based on well-designed ensemble learning allows us to predict successfully the risk of PPH, and assess the critical level of PPH patients. We anticipate our study results would contribute to the reduction the mortality of pregnant women.

II. DATASET FEATURE SELECTION

In the work, our study aims to construct a prediction model of PPH and its complications based on the method of ensemble learning. Our prediction results are expected to give the obstetricians necessary time to deal with the potential PPH, and therefore the proactive treatment can be carried out in advance, such as appropriate hemostasis, timely fluid resuscitation, massive transfusion protocol, and tranexamic acid. There are dozens of (or even more) associative features relevant to each patient. In practical clinic trails, collecting all the potential features for the prediction model would become rarely feasible for our large dataset involving 3842 records. Thus, the associative features shall be carefully selected, to balance the potential information loss and the complexity. The widely accepted rule in feature engineering is that more features do not necessarily leads to the improved prediction accuracy.

A. PPH FEATURES

For the primary goal of PPH prediction, our clinical team maintains a large dataset consisting of 3842 patient records, with 361 PPH records which were collected during 2017 at the Beijing Obstetrics and Gynecology Hospital. The dataset, as common cases, is also characterized by the significant imbalance positive/negative samples. I.e., the true PPH occurrence ratio accounts for 9.4%, which is a moderate value for the patient class of vaginal delivery. To achieve better prediction performance, the assessment indicators of PPH and its complication DIC have been systematically reviewed, by comprehensively exploring their relationship with the blood loss [27], [28]. On this basis, we have further studied and selected 23 features with high relation to the occurrence of PPH. These features are categorized into ''Present Gestation'' and ''Factors related to delivery'', as shown in Table 1. The data formats and categories of such selected features are described by Table 1. We use f0 to f22 to denote the 23 features in Table 1 sequentially. It should be noted that, according to the ranking analysis of such features, we believe such features constitute a relatively complete description or representation of PPH, which are expected to produce the good prediction diagnosis model.

B. DIC FEATURES

DIC is a typical complication developed following PPH. Based on the 361 patients who have PPH, a total number of 212 PPH patients were included in the DIC dataset, among which only 7 PPH patients presented the DIC complication. For the DIC dataset, we have also carefully selected 19 features, as shown in Table 2. We use f0 to f18 to denote the 19 features shown in Table 2 sequentially.

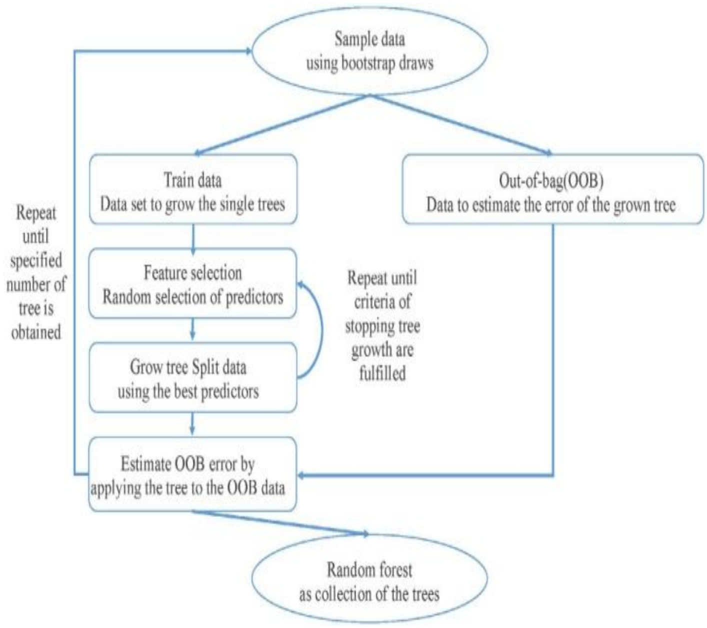


FIGURE 1. Random forest algorithm

III. BASE LEARNERS FOR ENSEMBLE LEARNING

As discussed, the machine learning algorithms are utilized to perform automated diagnosis for PPH and DIC. To be specific, we adopt the ensemble learning in this paper, with four base learners of random forest (RF), gradient boosting decision tree (GBDT), XGBoost (XGB) and SVM. As such, our ensemble learning collects different merits of four methods, and enable the more reliable prediction model. The well-known ANN and logistical regression (LR) are not included in this section, but we have tested their performances in Section V.

A. RANDOM FOREST

Random forest model is widely used for classification. In principle, such a random forest model is one bagging-type ensemble (collection) of decision trees, which trains several trees in parallel and thereby uses the majority decision of the trees as the final decision of whole forest model. Usually, individual decision tree model is easy to interpret, but the whole model is nonunique and exhibits high variance. Random Forest combines the two concepts of Bagging and Random Selection of Features by generating a set of T regression trees. The algorithm flow of RF algorithm is illustrated in Fig. 1, whereby the sample data is obtained using bootstrap and the splitting predictor is selected from a randomly selected subset of predictors [29]. Each tree thus constitutes a standard classification or regression tree (CART) which uses the so-called decrease of Gini impurity (GI) as a splitting criterion. In practice, the GI is computed by:

$$I_G(p) = \sum_{i=1}^{J} p_i \sum_{k \neq i} p_k = \sum_{i=1}^{J} p_i(1-p_i) = 1 - \sum_{i=1}^{J} p_i^2, \quad (1)$$

Where J is the total number of classes, p_i is the fraction of items labeled with class i in the set T ,i∈ {1,2,...,J}. Meanwhile, the out-of-bag (OOB) error serves as an important feature of RF, which is simply the average error frequency obtained when the observations from the data set are predicted using the trees for which they are OOB – they are not used to construct the trees.

B. GRADIENT BOOSTING

Gradient enhancement is a kind of machine learning techniques used for regression and classification problems, its weak prediction model (usually the decision tree) generated forecast model in the form of collection. It likes other strengthening methods, building the model in the form of stage, and by allowing the optimization of the loss function of arbitrary separable variables to a generalized model. Thus, the generic gradient boosting model is specifically described in **Algorithm 1** [30].

The negative gradient $g_t(x)$ along the observed data is denoted as:

$$g_t(x) = E_y\left[\frac{\partial \psi(y, f(x))}{\partial f(x)}\right]_{f(x)=\hat{f}_{t-1}(x)} \quad (2)$$

Where ft(x) is the estimated function at the t-th iteration. Because it is rarely feasible to identify one general solution for a boost increment in the functional space, one may alternatively choose another new base-learner function h(x,θ) increment which is expected to be mostly correlated with $g_t(x)$. According to eq. (2), we find the best gradient descent step-size ρ_t, and then the function estimate is updated by eq. (3).

Algorithm 1 Gradient Boosting **Input**:

input data $(x,y)_{i=1}^{N}$ number of iterations M choices of the loss-function ψ(y,f) choice of the base-learner model h(x,θ) **Algorithm:**

1. initialize $\hat{f}_0$ with a constant
2. **for** t=1 to M **do**
3. compute the negative gradient $g_t(x)$
4. fit a new base-learner function $h(x, \theta_t)$
5. find the best gradient descent step-size ρ_t:

$$\rho_t = \arg\min_{\rho} \sum_{i=1}^{N} \psi[y_i, \hat{f}_{t-1}(x_i) + \rho h(x_i,\theta_i)] \quad (3)$$

6. Update the function estimate:

$$\hat{f}_t \leftarrow \hat{f}_{t-1} + \rho h(x_i,\theta_t) \quad (4)$$

7. **end for**

IV. ENSEMBLE LEARNING:

In order to attain the highest accurate mode which outputs the highest probability of the positive class prediction, we combine the results based on a well-known voting principle [32]. That means, based on the common voting rule, the final output corresponds to the dominant output results of the RF, GBDT, XGB and SVM base learners. In this way, we can avoid the less convincing result and attain the highest probability of the positive class prediction. That means, if the proposed automated diagnosis model gives a ''1'' prediction for a patient, then the probability that PPH occurs on this patient with the probability approximating 1. For each base learner (RF, GBDT, XGB or SVM), we used a grid-search method to obtain the optimal value for the main hyper parameters. For PPH prediction, since the prediction target is the blood loss volume of each patient, each base learner (RF, GBDT or XGB) outputs a blood loss volume prediction result.

If these blood loss volume prediction results are combined softly first and then compared with the PPH threshold (500 mL), we call it Softly Combined Ensemble Leaning (EL-SC); otherwise, if the blood loss volume prediction results of the base learners are decided to be true or false hardly using the PPH threshold (500 mL) and then the resultant binary prediction results are combined, we call it Hardly Combined Ensemble Leaning (EL-HC). We compare the performances of two kinds of EL combination scheme in Section V. For SVM, only binary PPH results are used as the training data and test data, which means the blood loss volume data, are compared with the threshold (500 mL) first. For the DIC prediction, since the prediction target is that whether DIC occurs or not, the binary prediction results of all base learners are combined directly.

V. EXPERIMENTAL RESULTS:

The effectiveness of our designed ensemble learning method for both the PPH and DIC prediction is verified by our collected clinical datasets in Beijing Obstetrics and Gynecology Hospital. The numerical evaluation is based on the Python 3.8 platform.

A. PERFORMANCE EVALUATION FOR PPH PREDICTION

Our collected PPH dataset consists of 3842 records. In the analysis, 3500 records that are 65% of all records are used as training dataset; while the remaining 1342 records are used as the test dataset. Among the 3842 records, there are 361 positive PPH patients. The training dataset contains 2500 records with 242 positive PPH instances, whilst the testing dataset contains 1342records with total 119 positive PPH instances. The ratios of the positive instances for the training dataset (8.87%) and the testing dataset (9.68%) are approximately equal. In order to evaluate the performance of the compared base learning methods and ensemble learning, two well-known performance measures in classification were used, especially for the imbalance data set as in our cases. These are the commonly used classification accuracy, F-measure and MCC. Classification accuracy (A) is the ratio of true positives and true negatives obtained by the designed classifier over the total number of records in the test dataset, as given by (9)

$$A = \frac{TN + TP}{TP + FP + FN + TN}$$

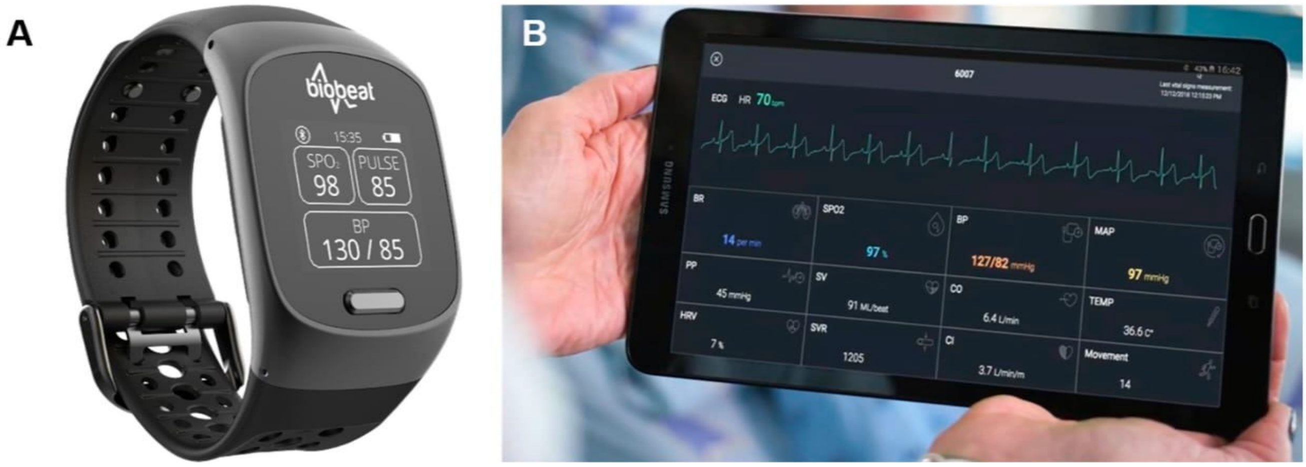
VI. CONCLUSION:

In this paper, we study the PPH predictive diagnosis problem by resorting the machine learning techniques. Two main contributions are (1) the collection of large clinical dataset, and (2) the well-designed ensemble learning method. Our PPH and DIC dataset involves 3842 and 212 records, respectively. The ensemble learning is designed to integrate four basis methods, i.e. random forest, extreme gradient boosting, gradient boosting decision tree and SVM for PPH prediction. With the trained prediction diagnostic model, the accurate results have been obtained. As shown, the accuracy of correct PPH diagnosis would achieves 96.7%; the total disseminated intravascular coagulation (DIC) prediction accuracy would surpass 90%. As a result, the proposed model based on machine learning enables to predict successfully the risk of PPH, and assess the critical level of PPH patient. We anticipate our study results have the great potential to the reduction the future mortality of pregnant women. In the future, we may further extend the dataset to further adapt our proposed method to improve the generalizability

APPENDIX:

In this analysis, we have used the grid-search method to obtain the proper configuration of various ML methods and the designed EL method. To be specific, we have adopted the sk learn. ensemble software tool for RF and GBDT, whilst we used the xgboost software tool for XGB

OUTPUT IMAGE:



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