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Machine Learning Pipeline Integrating Real-time Multimodal Biosignal Sensor Data for Early Detection of Postpartum Hemorrhage

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Abstract

Postpartum hemorrhage (PPH) is one of the leading causes of maternal deaths worldwide, especially in low-resource regions where early detection and timely intervention are a challenge. Current methods detecting PPH include visual estimation of blood loss and are often inaccurate, leading to delays in diagnosis and treatment of PPH. This paper will propose an innovative machine learning pipeline that integrates real-time data from wearable biosignal sensors in conjunction with specific electronic medical records (EMRs) to predict the risk of PPH early on. Using non-invasive, real-time physiological monitoring, personal EMR data, and ML algorithms, this system will improve predictive accuracy, improving maternal health outcomes in areas where immediate access to medical care and necessary resources can be limited.

Keywords: Biosignal Sensors; Early Detection; Maternal Health; Postpartum Hemorrhage; Electronic Medical Records; Machine Learning.

1. Introduction

Postpartum hemorrhage is defined as heavy blood loss that exceeds 500mL after normal delivery, or 1000mL after cesarean section delivery within 24 hours after giving birth [1]. PPH accounts for approximately 25 percent of maternal deaths around the world, with most women being from low- and middle-income countries [2]. PPH is more likely to occur after cesarean section births and is associated with risk factors such as high BMI, hypertension, multiple pregnancies, and a few others. The associated complications of PPH are hypovolemia, shock, and death. These complications demonstrate the urgent need for early detection methods that are highly reliable and allow timely medical intervention to take place. Traditional methods for assessing blood loss involve visual estimation and can often be inaccurate due to factors like subjectivity and underestimation [3].

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These limitations emphasize the need for an objective approach that uses continuous monitoring of physiological parameters that indicate early signs and high risk of PPH.

Photoplethysmography (PPG) sensors measure blood volume changes in the smaller blood vessels of tissue found in the extremities of the body [4], [5]. Bioimpedance spectroscopy (BIS) provides insight on fluid shifts and body composition, which can be used as an indicator for hypovolemia [6]. Dual-near-infrared spectroscopy (NIR) measures hemoglobin concentration and oxygen saturation, which are both critical in detecting hemorrhage [7], [8]. The integration of all three sensors into a wearable device enables continuous monitoring of vital signs and other physiological features used in PPH risk assessment.

Machine learning algorithms have shown potential in early prediction of various diseases and clinical outcomes [18, 19]. By training on large datasets with real-world variability, machine learning models can identify patterns and understand correlations that might not be seen through traditional statistical methods [18]. Machine learning based approaches can outperform conventional methods of predicting PPH and offer far more accuracy [9]. However, some challenges with implementing machine learning based prediction systems for use in clinical settings are issues with quality of data, privacy and ethical issues, as well as integration with existing healthcare infrastructure.

In this paper, a comprehensive ML pipeline for early PPH detection will be introduced. The aim is to develop a system that is capable of non-invasive, real-time monitoring with the ability to predict hemorrhages prior to observable symptoms appearing. This paper is structured in the following manner: Section two presents a literature review of existing methods for PPH detection based on application of wearable sensors and ML in improving maternal health outcomes. Section three presents the methodology, which includes data preprocessing, system architecture and feature extraction. Section four discusses the analysis and results of the machine learning model. Finally, section five will conclude the paper with a concise summary of findings, limitations and opportunities for future research.

2. Literature Review

Traditional methods for predicting and managing PPH have limitations. The breakthrough of wearable biosensors and machine learning provides a more promising approach for earlier and more accurate PPH detection. Recent studies have explored these approaches with the aim to integrate continuous physiological monitoring and advanced analytics [20]. This section examines studies in this field, each contributing uniquely to the advancement of the early postpartum hemorrhage detection system.

2.1 Wearable Sensor Data for Maternal Health Monitoring

Allen et al. [5] performed a literature review on the clinical applications of photoplethysmography (PPG). PPG is an optical technique that measures blood volume changes in microvascular tissue. This paper discussed how PPG signals from peripheral parts of the body such as the fingers or ears, can provide parameters such as heart rate variability, blood pressure, and pulse. When these features are analyzed over a period, they can help detect early signs of hypovolemia, a major indicator of hemorrhages. Allen's work showed how simple, non-invasive signals can be used for monitoring vitals.

Groenendaal, Lee, and van Hoof [11] explored the potential of wearable bioimpedance spectroscopy (BIS) monitoring devices for various healthcare applications, including acute event detection such as hemorrhage. The paper noted that wearable BIS devices could detect subtle physiological changes in fluid loss, that precede hemorrhages. Overall, the research supports the idea that continuous bioimpedance monitoring can be integrated into an early prediction system for PPH.

Alim and Imtiaz [12] conducted a systemic review on wearable sensors for monitoring maternal health during pregnancy. This study highlighted the potential of various wearable sensors to detect complications of pregnancy such as PPH at an early stage by continuously tracking physiological parameters such as blood pressure, oxygen saturation levels, heart rate and fetal movements. To ensure patient comfort and compliance, the wearable biosensors were often integrated into accessories or maternity garments.

Zhao et al. [13] introduced a 3D e-textile system that leverages microfiber-based electrodes to capture electrophysiological signals during exercise. Electronic textiles, also known as e-textiles, integrate biosensors into garments for continuous health monitoring. The microfiber-based electrodes cover a greater amount of surface area, are soft and securely adhere to the skin. Using this system, a multichannel e-textile was developed and tested among expecting mothers to monitor maternal ECG, and uterine EMG signals. This is a recent advancement in wearable technology design that ensures durability and comfort, making it suitable for the next generation of long-term maternal health monitoring devices.

Lord et al. [13] evaluated the AccuFlow sensor in a pilot study. Sensors were applied to the wrist, forearm, bicep and chest of 25 patients while undergoing cesarean delivery. The AccuFlow sensor is non-invasive and performs rapid measurement of perfusion to detect intrapartum blood loss. Results from the study showed that wrist perfusion showed a stronger correlation with calculated blood loss as compared with traditional estimation methods. Therefore, demonstrating the capability of wireless, cellular-capable sensors in real-time assessment of changes in perfusion.

2.2 Machine Learning for PPH Detection

Baeta et al. [9] performed a systematic review comparing the predictive power of ML models with traditional statistical approaches in the context of predicting PPH risk. The analysis of 35 studies showed that ML models had a 95% higher chance of accurately predicting PPH compared to the conventional statistical methods used. The authors also noted that ML models often require many predictors. This could limit their applicability in rural and low resource settings. However, the authors also suggested that with appropriate feature selection and model optimization, these challenges could be tackled, and revolutionary early warning solutions for obstetric emergencies could be developed.

Mehrnoush et al. [14] developed both traditional statistical and ML models to predict PPH from clinical data. Findings from the study indicated that ML models, particularly random forest algorithms, outperformed traditional logistic regression models in terms of accuracy and sensitivity. Key predictors included maternal age, mode of delivery, and pre-existing hypertension. The researchers also discussed the importance of feature selection in maximizing model performance and advocated for combining biosignal data with EMR-based risk factors.

Liu et al. [15] proposed an approach that incorporated uterine contraction metrics into the dataset used in the ML framework for predicting PPH post-delivery. By integrating features such as contraction frequency, intensities, and recovery time, the LightGBM and logistic regression hybrid model was able to achieve an AUROC score of 0.803. This research demonstrated that the combination of classical risk factors with temporal features from uterine activity can significantly improve predictive performance. This study highlights the value of including physiological parameters such as real-time uterine monitoring in predictive models to allow a more dynamic risk assessment.

A study conducted by Shah et al. [16] applied ML algorithms to data collected from wearable devices in a Kenyan population. The naïve Bayes model was able to achieve an accuracy of 95% and specificity of 97% in predicting PPH. This shows the feasibility of combining wearable sensor data with ML techniques for use in low-resource settings.

These studies collectively support the feasibility and applicability of integrating wearable biosignal sensors data into an ML pipeline for early detection of PPH, an opportunity for transforming maternal healthcare.

3. Methodology

3.1. Multi-modal Biosensors and Data Preprocessing

ML algorithms can identify complex patterns from cleaned datasets. This capability can be applied to problems in obstetrics such as analyzing subtle physiological changes in a patient that precede a postpartum hemorrhage [17]. Wearable biosignal sensors such as PPG, BIS and NIR allow continuous health monitoring without disrupting the standard clinical workflows. The use of all three sensors together creates a holistic view of physiological features and can be used by a trained ML model to provide an immediate risk assessment for each patient. The selected sensors include:

a) Photoplethysmography (PPG) - Captures volumetric changes of blood in peripherals and provides insight into heart rate and blood pressure. PPG waveform analysis allows extraction of information such as systolic and diastolic blood pressure trends [4].
b) Bioimpedance spectroscopy (BIS) - Measures the electrical impedance of tissues to estimate fluid volume shifts and the body composition of a person. Can measure BMI and changes in hydration that correlate with hemorrhages [6].
c) Dual near-infrared spectroscopy (NIR) - Provides insight into oxygenated tissues and allows for calibration-based estimation of hemoglobin levels [7].

The dataset used in this proposed approach was comprised of physiological signals that were collected from the multimodal biosensors mentioned above and EMR data. The dataset was cleaned by removing features such as platelet count that would require a laboratory blood test and would not be measured through a wearable device. If real-world clinical data is used, the biosignal data would have to be cleaned using bandpass filtering to reduce motion artifacts and baseline drift. Continuous variables such as hemoglobin and BMI were normalized using standard scaling. EMR-based features such as delivery mode, parity, and hypertension that are in the form of yes or no inputs and the target which is the PPH outcome are set as 0 or 1 based on absence or presence. The final dataset consisted of 1000 synthetic samples generated using AI having 16 features.

3.2. System Architecture

The proposed architecture, shown in Figure 1, is a three-layer framework for keeping an eye on and predicting the risk of postpartum hemorrhage (PPH) early on.

Data acquisition layer combines several biosensors to pick up physiological signals in real time. A ring worn on the finger has a photoplethysmography (PPG) sensor built into it that constantly checks pulse-related parameters. A silicone pocket holds bioimpedance spectroscopy (BIS) electrodes around the abdomen. These electrodes measure fluid impedance and look for changes in how body fluids are spread out. Two near-infrared (NIR) sensors are also put near dense muscle tissue to measure hemoglobin saturation. To establish a reliable baseline, the NIR sensors are worn approximately one month prior to delivery for prenatal data collection. After giving birth, all three sensing modalities work together to allow for full monitoring.

Processing layer does preprocessing on the raw signals from the biosensors. This includes removing noise, normalizing the signals, and getting rid of artifacts. After the signals have been cleaned, they are turned into features in both the time and frequency domains to find important physiological patterns. These features are combined with electronic medical record (EMR) data to make a multimodal dataset that shows both real-time and clinical information.

In prediction Layer, a trained binary classification model takes the processed features and uses them to guess the risk of PPH. The model makes risk assessments in real time, which lets doctors and other health professionals make decisions and take action quickly. This layered architecture makes sure that data flows smoothly from acquisition to actionable insights, which leads to better maternal healthcare outcomes.

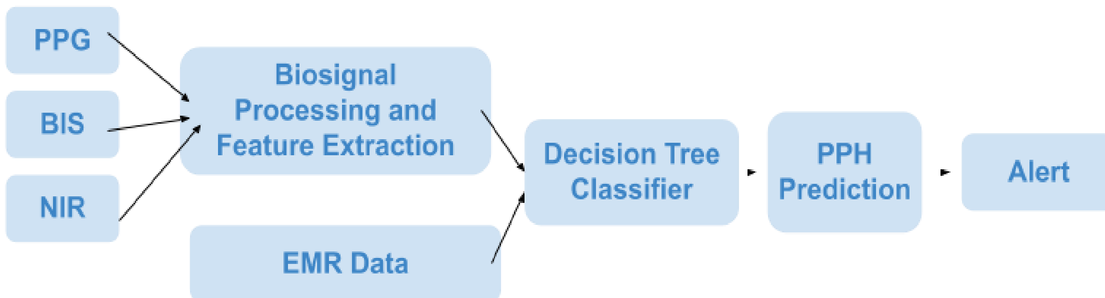

Figure 1. System architecture diagram showing data from sensor to alert

3.3. Sensor to Feature Mapping and Feature Selection

Table 1 below shows features that are used in the model that are mapped to sensor outputs and additional clinically relevant EMR inputs. Additional features from EMR data include maternal age, gestational age, parity, delivery mode, use of oxytocin, previous PPH, multiple gestation, placenta conditions, prolonged labor and hypertension.

Table 1. Sensor to Feature Mappings.

Feature	Sensor Source	Mapping Procedure
Systolic BP	PPG	Pulse interval and waveform shape
Diastolic BP	PPG	Pulse interval and waveform shape
Prenatal Hemoglobin	Dual NIR	Calibration for accurate estimation
Maternal BMI	BIS	Impedance and body composition
Estimated Blood Loss	BIS	Estimate fluid volume shifts

4. Results Analysis and Discussions

The dataset used was split into 80:20 parts for training and testing. Four different models were trained and evaluated. Among all classifiers as highlighted in Table 2 above, XGBoost had the highest accuracy at 92.0%. This means the XGBoost model was able to classify 92% of all patient's PPH outcomes correctly as yes or no and is the most reliable in terms of providing accurate predictions. The model with the second highest accuracy was Logistic Regression at a close 91.5%. The models with the lowest accuracies were Random Forest at 90.5%, followed by Decision Tree at 89.0%.

XGBoost emerged as the best-performing model in recall where it got 99.3 percent, which indicates that this model was able to identify 99.3% of positive PPH cases out of all the patient cases. This is a very important metric particularly in clinical settings where missed PPH cases could lead to medical emergencies and life-threatening delays in care. Random Forest had a recall score of 97.2%, followed by Logistic Regression at 96.5%. Decision Tree had the lowest recall of 94.4%, suggesting that it could potentially miss true cases of PPH and delay timely detection.

Table 2. Model Performance Comparison.

Model	Accuracy	ROC AUC	Precision	Recall	F1 Score
Logistic Regression	0.915	0.879	0.919	0.965	0.942
Decision Tree	0.890	0.851	0.905	0.944	0.924
Random Forest	0.905	0.857	0.902	0.972	0.936
XGBoost	0.920	0.867	0.904	0.993	0.946

In terms of precision, Logistic Regression had the best score of 91.9%. Meaning that 91.9% of actual positive PPH cases were identified as positive. The other three models had nearly identical precision, with Decision Tree, XGBoost, and Random Forest achieving 90.5%, 90.4%, and 90.2% respectively. When dealing with medical cases and PPH, it is important to prioritize recall over precision, to ensure all positive cases of PPH are identified even if it means having to identify cases that are not PPH as PPH positive. False positives are not a major concern in terms of healthcare monitoring for hemorrhages.

The F1 score considers both the recall and precision in its metric. XGBoost has an F1 score of 94.6%, indicating that it is the best performing model in terms of both precision and recall. The Logistic Regression has the second highest F1 score at 94.2%, which is very close to the XGBoost's performance, even though it had a higher precision score in comparison. The Random Forest classifier was in third, scoring 93.6%, followed by Decision Tree in last place, at 92.4%.

In terms of ROC-AUC, Logistic Regression was at 87.9%, confirming that it has the best overall performance with classifying PPH and no PPH patient groups (see figure 2). XGBoost attained an ROC-AUC score of 86.7%, which also proves it as a strong PPH classifier for this dataset. Random Forest and Decision Tree had lower scores of 85.7% and 85.1% respectively and were slightly weaker discriminators for assessing PPH.

Overall, XGBoost had the highest accuracy, F1 score and recall. It is the best classifier among the group since it has demonstrated a strong lead in most model performance metrics, especially recall. Logistic Regression was the second-best classifier since it had the highest ROC-AUC and precision along with the second highest F1 score and accuracy.

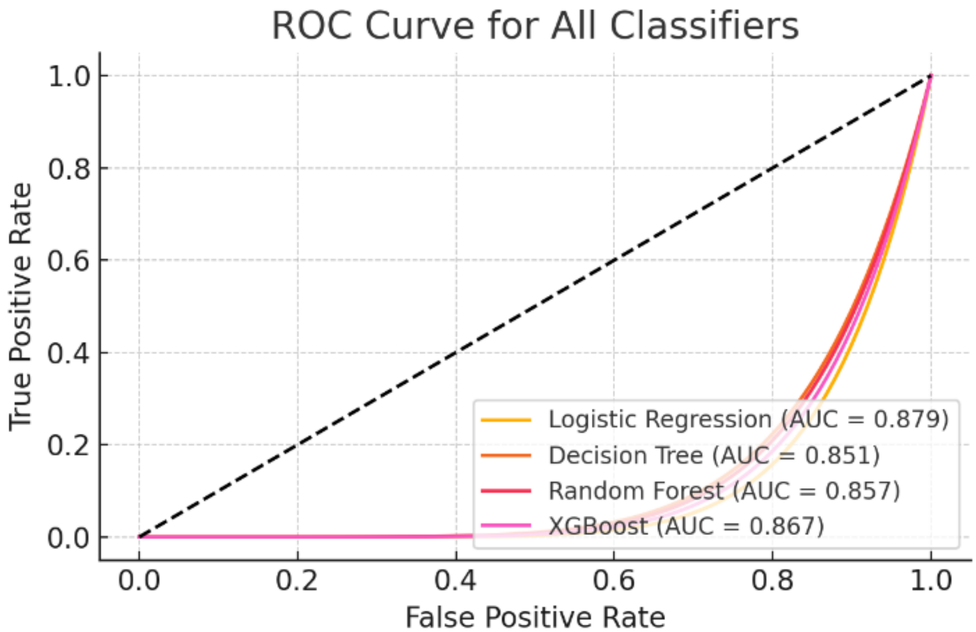

Figure 2. ROC Curve for All Classifiers

Feature importance analysis as shown in Figure 3 below showed that the model heavily relied on estimated blood loss, hemoglobin levels, and maternal BMI. This was consistent with the obstetric literature mentioned in the literature review section [4], [5], [7].

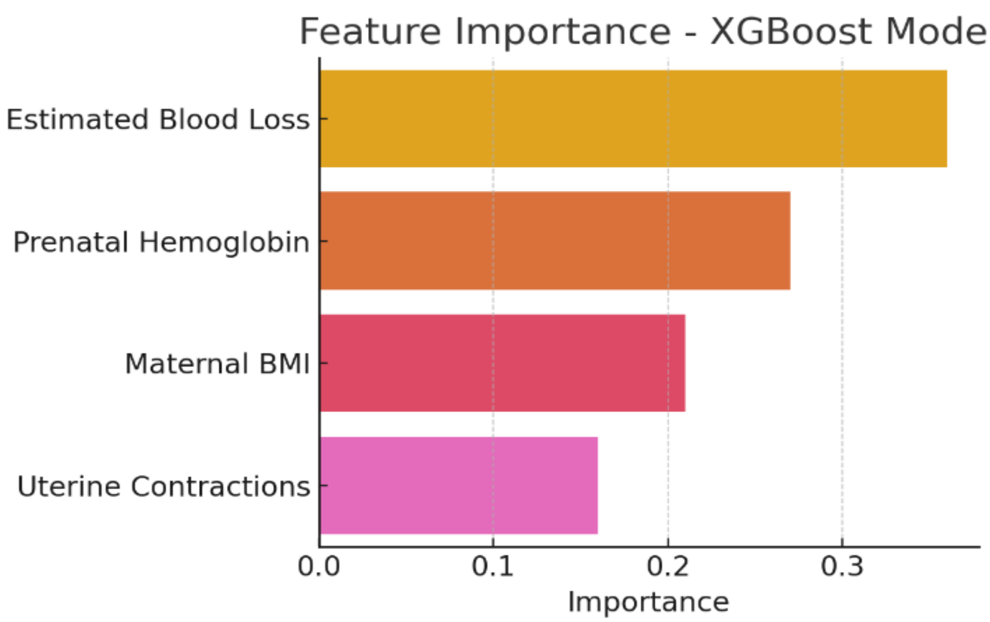

Figure 3. Feature Importance for XGBoost Model

Among the models evaluated, XGBoost demonstrated the best overall performance, achieving a high recall rate of 99.3%. In clinical applications it is crucial to minimize false negatives as much as possible. Additionally, the feature importance analysis confirmed the relevance of established clinical indicators, such as estimated blood loss and prenatal hemoglobin levels.

These results suggest that binary classification models such as XGBoost trained on PPG, BIS, Dual-NIR data and EMR derived features will help streamline risk assessment of PPH, especially in rural clinics where trained obstetricians may not always be available and delays in diagnosis can be fatal.

5. Conclusions and Future Works

This paper presented an ML pipeline that integrates data from multimodal biosensors such as PPG, BIS and NIR with EMRs and leverages binary classification models for early PPH detection. Among the classifiers tested, XGBoost achieved the highest accuracy and recall. The feature importance analysis confirmed the relevance of established clinical indicators. Overall, the findings support the feasibility of deploying an ML-enhanced wearable in maternity care to fulfill a significant gap in low-resource regions. The proposed system offers clinical value by providing early detection alerts, continuously monitoring risk, reducing maternal fatalities and optimizing triage in the current healthcare system. This ML pipeline provides a solution highly customizable to each patient's health profile, this solution reduces subjectivity in clinical decision-making in current obstetric healthcare, it predicts PPH prior to the onset of observable symptoms, helps triage patients for management protocols, and most importantly, alerts clinicians early on during the postpartum monitoring phase.

However, some challenges in the system include the process of sensor calibration and data fusion that require standardization. Another limitation is integrating real hospital EMR data because it poses privacy and ethical issues. Future work involves gaining authorized access to real-world clinical data such as EMRs or utilizing estimated blood loss data from simulation PPH models. Additionally, an unsupervised ML model can be used to predict platelet count and other features that serve as important indicators of PPH but were omitted from the dataset at this time. These can later be re-incorporated and used to train and validate the XGBoost model.

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Data Availability Statement
Not applicable.

Conflicts of Interest
The author declares no conflicts of interest.

Ethical Approval and Consent to Participate
Not applicable.

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