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Integrating Artificial Intelligence For Early Prediction Of Preterm Labor Using Cardiotocography And Cervical Length: A Machine Learning-Based Clinical Decision Support Approach

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Abstract
Preterm labor, a leading cause of neonatal mortality and morbidity, remains a significant obstetric challenge worldwide. Early identification of at-risk pregnancies can dramatically improve outcomes through timely interventions. Traditional diagnostic methods such as cardiotocography (CTG) and transvaginal cervical length assessment have been individually utilized to estimate preterm birth risk but lack integrated predictive power. This study aims to harness the capabilities of artificial intelligence (AI) by developing a machine learning (ML)-based predictive model that combines CTG and cervical length data to forecast preterm labor risk. A retrospective dataset comprising 800 cases from tertiary care centers was analyzed. Multiple algorithms—Random Forest, Support Vector Machine (SVM), XG Boost, and Artificial Neural Networks (ANNs)—were trained and validated using cross-validation techniques. The final model demonstrated an AUC of 0.91, suggesting high diagnostic value. Integration of AI in obstetrics presents a paradigm shift in prenatal care, enabling earlier detection and individualized risk management of preterm labor.
Keywords *Preterm Birth, Artificial Intelligence, Machine Learning, Cardiotocography, Cervical Length, CTG Interpretation, Obstetrics, Predictive Analytics, XG Boost, Clinical Decision Support System*

I. BACKGROUND AND SIGNIFICANCE

Preterm birth accounts for approximately 11% of all live births globally, with complications from prematurity causing over one million deaths annually. Despite advancements in obstetric monitoring, predicting spontaneous preterm labor remains difficult due to its multifactorial etiology and subtle early signs. Cardiotocography (CTG) is widely used to assess fetal well-being but its interpretation is subjective and prone to interobserver variability. Cervical length measurement, particularly when <25mm before 28 weeks gestation, is a strong predictor of preterm labor but not definitive in isolation. AI and ML offer an opportunity to integrate these diagnostic tools into a composite risk stratification model. By processing high-dimensional data, AI can uncover non-linear patterns and interactions invisible to traditional statistics, potentially enhancing prediction accuracy and consistency.

II. OBJECTIVES

1. To develop a predictive AI model combining CTG and cervical length data for early identification of preterm labor risk.
2. To compare various ML algorithms (Logistic Regression, SVM, Random Forest, XGBoost, ANN) for their predictive efficacy.
3. To evaluate model performance using accuracy, sensitivity, specificity, precision, recall, F1-score, and AUC-ROC metrics.
4. To identify key features and biomarkers contributing most significantly to early labor onset.
5. To propose a clinical decision support system (CDSS) prototype based on the final AI model.

III. METHODOLOGY

Study Design:
Type: Retrospective observational cohort study.
Setting: Data collected from three tertiary-level hospitals in India between 2024–2025.
Sample Size: 800 pregnant women between 24–34 weeks gestation.
Inclusion Criteria:
1. Singleton pregnancy.
2. Available and complete CTG tracings and cervical length measurements.

3. Delivered before or after 37 weeks with documented gestational age.

Exclusion Criteria:
1. Congenital fetal anomalies.
2. Induced or iatrogenic preterm birth.
3. Incomplete or corrupted data. Data Collection and Features CTG Features Extracted:
- Baseline FHR (bpm)
- Short-term variability
- Long-term variability
- Accelerations (number, duration)
- Decelerations (early, late, variable)
- Uterine contractions (frequency, duration)

Cervical Length Parameters:
- Cervical length in mm (TVS)
- Presence of funneling
- Dynamic changes over time (if serial scans available)

Clinical Features:
- Age, parity, BMI
- Previous history of preterm birth
- Infection markers (CRP, WBC)
- Tocolytic or progesterone therapy
- Vaginal discharge or bleeding episodes Data Preprocessing and Model Development Imputation of missing values using K-nearest neighbors. Normalization and scaling of features. Feature selection using recursive feature elimination (RFE) and Lasso regression. Label encoding for categorical variables. Dataset split: 70% training, 15% validation, 15% testing. Model Development:
- Algorithms: Logistic Regression, SVM (RBF kernel), Random Forest, XGBoost, ANN.
- Validation: K-fold cross-validation (k=5).
- Optimization: Hyperparameter tuning via GridSearchCV and Bayesian Optimization.
- Platform: Python (scikit-learn, TensorFlow, XGBoost, pandas, NumPy). Performance Metrics – Accuracy
- Sensitivity (Recall)
- Specificity
- Precision & F1-score
- ROC Curve and AUC

IV. RESULTS
XG Boost model achieved AUC = 0.91, Sensitivity = 88%, Specificity = 84%, outperforming logistic regression (AUC = 0.78). Feature importance analysis revealed that cervical length <25mm, presence of repetitive decelerations, and reduced CTG variability were the strongest predictors. A web-based dashboard prototype was developed for clinical demonstration, allowing real-time data input and risk score output.

V. DISCUSSION
The results suggest that machine learning, especially ensemble methods like XGBoost and Random Forest, significantly outperform traditional statistical models in predicting preterm labor. Integration of objective data from CTG and cervical measurement into a composite AI model reduces interobserver variability and enhances decision-making. While promising, implementation into real-time clinical settings requires further prospective validation, regulatory clearance, and clinician training.

VI. CONCLUSION
AI-driven prediction of preterm labor offers a breakthrough in perinatal care. By combining CTG and cervical length data, the study presents a novel and robust ML-based model with high diagnostic accuracy. Adoption of such models in clinical settings could reduce unnecessary hospital admissions, optimize resource allocation, and significantly lower the burden of neonatal complications.

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