How well can we predict perinatal mortality and its associated risk factors using machine learning models -a case study on Malawi

The study investigates factors associated with perinatal mortality in a low-income southeastern African nation by applying machine-learning techniques to data from 489 pregnant women who were being monitored for iron-deficiency treatment. The goal was to identify early predictors of stillbirths and neonatal deaths and to evaluate how effectively machine-learning models can classify high-risk pregnancies.

The dataset contained 56 medical, socioeconomic, and demographic variables, with a strong imbalance between normal and adverse outcomes. After data cleaning and use of a specialized oversampling method to correct class imbalance, several models were trained. Ensemble algorithms—particularly Gradient Boosting and Random Forest—achieved the strongest predictive performance, reaching accuracy levels around 0.76–0.78 and the highest ROC-AUC scores after hyperparameter tuning. Logistic regression was the fastest and still performed reasonably well.

Feature-ranking methods (filter-based metrics, model-based importance, permutation importance) and SHAP analysis highlighted several major predictors. Medical factors such as elevated respiratory rate, abnormal blood pressure, anemia, and low maternal weight were highly associated with adverse outcomes. Economic conditions were also influential: lower hospital expenditure, lack of land or assets, reliance on daily-wage income, and lack of access to safe water markedly increased risk. Social factors—including minimal maternal education, teenage pregnancy, and belonging to certain marginalized communities—also contributed. Among the iron-deficiency treatment groups, oral iron supplementation produced better outcomes than intravenous alternatives.

The study notes several limitations. The sample is small and not nationally representative, since it includes only iron-deficient pregnant women under clinical observation. Some important predictors—such as newborn sex, labor-room conditions, and early postnatal data—were unavailable. Additionally, the dominance of certain demographic groups in the dataset may introduce bias.

Despite these constraints, the study demonstrates that machine-learning models can effectively identify pregnancies at high risk for perinatal loss in resource-limited settings. It suggests that policymakers should prioritize early detection of medical complications, expand maternal support programs for low-income households, strengthen community-level prenatal monitoring, and favor oral iron supplementation for iron-deficient mothers. It also calls for larger, more representative datasets that incorporate health-system quality and immediate newborn-care variables to improve prediction accuracy and guide targeted interventions.