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Original Research Article

A Comprehensive Survey for Enhancing Maternal Health Care Services in Rural Regions Through Machine Learning

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Abstract: Maternal health in rural regions remains critically challenged by geographic isolation, inadequate infrastructure, and shortage of skilled providers, resulting in persistently poor outcomes and complex barriers to care. This study explores the potential of machine learning to transform maternal healthcare delivery in these underserved areas through predictive analytics, remote monitoring, and intelligent decision support offering scalable solution, personalized care, proactive solutions and optimize resource allocation. Study proposes a framework that integrates machine learning algorithms with mobile health platforms and community health worker support tools. These technologies enable real-time analysis of maternal health indicators such as blood pressure, glucose levels, and fetal heart rate facilitating timely interventions and reducing the need for travel. To guide future, a review on clinical context, intervention type, and impact was conducted. Findings were mapped to an implementation framework to identify key challenges, facilitators, and determinants of successful deployment of maternal health innovations in rural.

Keywords: Predictive Analytics, Decision Support Systems, Random Forest, Logistic Regression, Neural Networks.

INTRODUCTION

Maternal health services in rural areas continue to be constrained by critical challenges such as poor infrastructure, limited availability of qualified healthcare professionals, restricted service access, and transportation hurdles. These issues often result in unfavourable health outcomes for both mothers and infants. However, leveraging Artificial Intelligence and Machine Learning through mobile health applications presents a promising strategy to mitigate these barriers and improve the delivery and quality of maternal care in marginalized regions [1]. Maternal health is a foundational aspect of global public health, yet disparities in access, service quality, and outcomes remain widespread especially in rural and low-resource environments. Despite progress in medical care, preventable conditions such as haemorrhage, high blood pressure, and infections continue to be major contributors to maternal mortality. The World Health Organization (WHO) estimates that over 800 women lose their lives each day due to pregnancy-related causes that are largely avoidable. In this viewpoint, Machine Learning a subset of Artificial Intelligence is emerging as a transformative approach to improving maternal healthcare [2]. By processing extensive and complex health data, ML algorithms can reveal subtle patterns, anticipate risks, and support timely, targeted interventions that traditional methods may fail to detect. Machine Learning can be leveraged to improve Maternal Health Care Services in Rural Regions. It outlines a data-driven approach to enhance access to and quality of care for pregnant women in underserved areas. Block diagram in Fig 1. shows the basic Enhancing Maternal Health Care Services in Rural Regions Through Machine Learning.

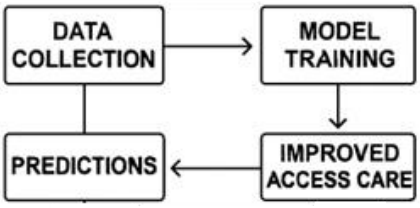

Fig 1: Predictive Health System for Rural Maternal Care

Initial step involves gathering relevant health data from pregnant women in rural regions. This could include vital signs, medical history, test results, and even social determinants of health, potentially collected via sources like health facility records or mobile health applications and wearable devices. The collected data is then used to train Machine Learning models [3]. These algorithms learn patterns and relationships within the data to understand and predict maternal health outcomes or risks, such as the likelihood of complications like preeclampsia or gestational diabetes. Once trained, the machine learning models can make predictions about individual patients' health risks or needs. For example, they can identify high-risk pregnancies or predict potential complications, enabling proactive intervention. By identifying at-risk individuals, resources can be prioritized and directed to those most in need. Telemedicine and AI-powered virtual assistants can also bridge geographical gaps, providing remote consultations and support. Predictions enable timely and personalized interventions, potentially reducing maternal and neonatal complications and improving overall health outcomes [4,5]. This entire process is aimed at creating a more efficient, proactive, and accessible maternal healthcare system in rural regions, ultimately leading to better health and safety for mothers and their new-borns, especially where traditional healthcare infrastructure and resources are limited [4,6]. The Fig 2 illustrates a Machine Learning based system for pregnancy and post-natal risk prediction.

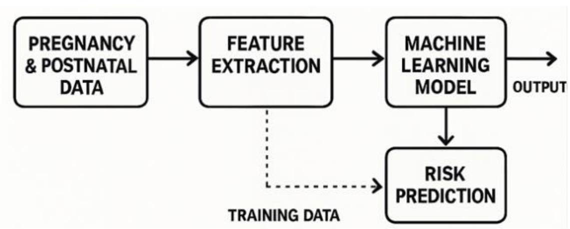

Fig 2: Machine Learning based system for Maternal health prediction

This outlines a common workflow in healthcare analytics, where data is leveraged to build predictive models for identifying potential risks in maternal and infant health. The raw input data collected during a woman's pregnancy and after childbirth. It can include a wide range of information such as demographic details, medical history, vital signs (e.g., blood pressure, heart rate), lab results (e.g., blood sugar, haemoglobin), ultrasound measurements, details about previous pregnancies, and postnatal health indicators [7,11]. Feature extraction often involves data cleaning, handling missing values, and transforming raw data into a format suitable for machine learning, such as converting categorical variables into numerical ones [8, 9]. The "Training Data" label indicates that a portion of this extracted data is used to train the machine learning model. A machine learning algorithm (e.g., Random Forest, Gradient Boosting, Support Vector Machine, Neural Networks) is trained using the "Training Data" to learn patterns and relationships between the extracted features and known outcomes [9]. The goal is for the model to generalize these patterns so it can accurately predict outcomes for new, unseen data. After the machine learning model is trained, it can then be used to predict the risk level for new individuals based on their "Pregnancy & Postnatal Data" after undergoing feature extraction. This step involves applying the trained model to new data to generate a prediction, such as classifying a pregnancy as high-risk or low-risk, or predicting the likelihood of certain complications [7,10]. This represents the final result or output of the system, which is the predicted risk level or outcome [11]. This output can then be used by healthcare professionals for early intervention, targeted care, and resource allocation to improve maternal and infant health outcomes.

STATE OF ART RELATED WORK

Academicians and researchers are increasingly exploring and developing machine learning models and artificial intelligence systems to enhance maternal health in rural areas, according to various reports. These technologies hold immense promise in addressing the unique challenges faced by rural communities, such as geographical isolation, limited infrastructure, and a shortage of healthcare professionals. Researchers, ambitious by an inherent desire to explore and innovate, have contributed a vital role in shaping the progress within Enhancing maternal health care services in rural regions academic disciplines. A few of their key contributions are outlined below. In Paper [12, 13] suggests that routinely collected health data have the potential to play an important role in helping determine women's risk of common postpartum complications leading to hospital admission. This information can be presented to clinical staff after delivery to help guide immediate postpartum care, delayed discharge, and post-discharge patient follow up. For such a system to be effective and valued, it must produce accurate predictions, and findings suggest areas through Gradient boosted trees were used with five-fold cross-validation to compare model performance. where routine data collection could be strengthened to this end. In paper [14] suggests machine learning based models incorporating electronic health record (EHR) derived predictors, could augment symptom-based screening practice by identifying the high-risk population at greatest need for preventive intervention, before development of postpartum depression (PPD). In paper [15, 16] suggested a novel approach Using only routinely collected obstetrical data, this study aimed to develop a predictive model suitable for real-time use with an electronic medical record for predicting postpartum haemorrhage (PPH) and identified clinical feature thresholds that can guide intrapartum monitoring for PPH risk. These results suggest that our model is an excellent candidate for prospective evaluation and could ultimately reduce PPH morbidity and mortality through early detection and prevention. Machine learning methods, assessing model performance using the area under the receiver operator characteristic curve and number needed to evaluate. In paper [17, 18] suggests the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) aims to improve the health of low-income pregnant and postpartum women, infants, and children up to age five. It provides participants with supplemental foods, nutrition education, breastfeeding support, and referrals to healthcare and social services. Research consistently demonstrates the positive impact of WIC on infant health outcomes, notably reducing the incidence of preterm birth, low birthweight, small size for gestational age, and infant mortality. To address this, a recent study utilized high-dimensional data to predict individual risk of poor infant health outcomes and employed a novel approach called double machine learning to analyse WIC's effects across different risk levels. In paper [19] The integration of machine learning into the study of pregnancy-related disorders and complications is a relatively recent development, marked by rapid expansion in recent years. Its applications are multifaceted, contributing not only to diagnostic support but also to improved clinical management, therapeutic decision-making, and enhanced pathophysiological insight into perinatal conditions. As the field grapples with diverse data types, rising data complexity, emerging technologies, and a growing demand for translational research, ML is poised to become an increasingly vital tool in advancing the landscape of obstetrics and gynaecology. In paper [20] author introduces a machine learning framework to enhance fetal health prediction, emphasizing early detection of complications like fetal distress. Traditional tools such as cardiotocography and ultrasound often suffer from subjective interpretation, leading to diagnostic delays. To address this, advanced ML models XGBoost, Blending, and Stacking—are applied and outperform Random Forest and KNN, achieving accuracy. These models effectively process complex indicators, improve classification, and support clinical decision-making. The approach also tackles small datasets and generalization challenges, offering faster, more precise assessments and advancing AI-driven prenatal care. In paper [21] This study presents a novel ML-based approach for maternal risk prediction, leveraging class-wise performance analysis to distinguish risk levels. The models showed high accuracy, with the high-risk class achieving 90% prediction success. GBT with ensemble stacking performed best, reaching a score across all metrics. The framework's strength lies in its class-specific evaluation, enabling precise risk stratification. In paper [22, 23] Author presents a deep hybrid model for classifying maternal health risks during pregnancy by integrating artificial neural networks and random forest algorithms. By leveraging the complementary strengths of both models, the framework aims to enhance accuracy and efficiency in risk prediction. The dataset includes clinical indicators such as age, blood pressure (systolic and diastolic), blood sugar, body temperature, and heart rate—split into training and testing sets. Final predictions are selected through a maximum probability voting mechanism, where the most confident output from either ANN or RF is chosen as the optimal classification. In paper [24] This study develops an IoT-enabled system to monitor and predict pregnancy risk levels, particularly in remote settings. Real-time data from vital signs HR, BP, FM, and temperature are collected non-invasively to detect abnormalities early. Machine learning models were evaluated, with Exploratory Data Analysis highlighting key risk indicators. A fine-tuned Random Forest Classifier achieved accuracy, and the model was deployed via an Android app for practical, on-the-go risk assessment. Recent collaborative studies show that machine learning is moving beyond experimental use and becoming a practical tool in maternal and fetal healthcare.

Advanced models like XGBoost, GBT, and ANN–RF hybrids outperform traditional methods in predicting antenatal care uptake, assessing preterm birth risk, and enabling real-time monitoring via the Internet of Things. ML solutions have progressed from theoretical concepts to real-world applications implemented through mobile apps and MCPS systems, specifically designed for underserved communities. According to Indeed, taxonomy-based frameworks combine sensor data with personal, social, and environmental factors to improve patient-centred care. A comparative analysis of six classifiers (SVM, RF, LR, MLP, GBM, and XGBoost) revealed XGBoost as the most accurate for predicting preterm birth, though its interpretability regarding individual variable influence is limited. Table 1: shows the summary of the State of Art related work and the identification of the gap for the research is shown in Table 2. Machine learning holds significant promise for enhancing maternal and fetal healthcare, but several critical research gaps need to be addressed before its full potential can be realized.

Focus Area	ML Techniques Used	Key Findings / Outcomes
Postpartum complications risk prediction	Gradient Boosted Trees + 5-fold CV	Routine health data can guide postpartum care; model performance highlights data gaps
Early screening for postpartum depression (PPD)	EHR-based ML models	ML augments symptom-based screening by identifying high-risk individuals pre-PPD onset
Predicting postpartum haemorrhage (PPH)	ROC analysis, NNE metrics	Real-time EMR-based model using obstetrical data; identifies clinical thresholds for PPH
Evaluating WIC program impact on infant health	Double Machine Learning	WIC reduces adverse outcomes; ML stratifies risk and quantifies program effectiveness
ML in pregnancy-related disorders and complications	General ML integration	ML supports diagnostics, management, and pathophysiological insights; field rapidly evolving
Fetal distress prediction	XGBoost, Blending, Stacking vs RF, KNN	Advanced models outperform traditional tools; improve accuracy and generalization
Maternal risk stratification	GBT + Ensemble Stacking	High-risk class achieved 90% accuracy; class-wise evaluation enhances precision
Maternal health risk classification	Deep Hybrid (ANN + RF)	Combines strengths of ANN and RF; uses clinical indicators with max-probability voting
IoT-based pregnancy risk monitoring in remote areas	Random Forest + EDA	Real-time vitals used for early detection; deployed via Android app.

Table 1: Key findings

Identified Gap	Description / Opportunity
Limited interpretability of ML models	Many models (e.g., XGBoost, ensemble methods) offer high accuracy but lack transparency on variable influence.
Sparse integration of socio-environmental determinants	Few studies incorporate broader social, behavioral, or environmental factors beyond clinical indicators.
Underrepresentation of rural and low-resource settings	While some work targets underserved areas (e.g., IoT-based monitoring), most models are trained on urban datasets.
Lack of longitudinal and multi-phase maternal tracking	Most models focus on isolated events (e.g., PPH, PPD); few track maternal health across prenatal to postpartum phases.
Limited real-time deployment and scalability	Few models are integrated into scalable platforms (e.g., EMRs, mobile apps) with real-time feedback loops.
Absence of federated or privacy-preserving learning approaches	No mention of techniques that enable secure, decentralized model training across institutions or regions.
Minimal focus on equity-aware model evaluation	Class-wise performance is explored, but fairness across demographic subgroups (e.g., caste, income, geography) is rarely assessed.
Few studies address comorbidity or multi-risk prediction	Most models target single outcomes (e.g., PPH, PPD); integrated risk prediction across multiple conditions is lacking.
Limited use of explainable AI (XAI) frameworks	Interpretability tools like SHAP, LIME, or counterfactual reasoning are not widely applied to maternal health models.
Scarcity of prospective clinical validation	Many models are retrospective; few have been tested in live clinical workflows or evaluated for real-world impact

Table 2: Gap identification

CHALLENGES AND INFLUENCING FACTORS IN HEALTHCARE SERVICES

3.1 Performance Metrics for Comparative Analysis

Machine learning is increasingly being integrated into diverse fields, notably healthcare, where it shows considerable promise in the detection and diagnosis of complex medical conditions. This research utilizes ML approaches to estimate the risk of pregnancy-related complications by analyzing patients' historical clinical records and physiological metrics, with the goal of supporting early identification and timely intervention. The prediction framework employs a range of machine learning algorithms—including Logistic Regression, Decision Tree, Linear Discriminant Analysis, Support Vector Machine, and K-Nearest Neighbours each trained on historical patient data to enable risk prediction for new cases. To assess different approaches, apply performance metrics such as precision, Sensitivity, recall, F1 score, and accuracy. Accuracy represents the proportion of accurately predicted instances (which includes both true positives and true negatives) compared to the overall number of instances. It offers a broad indication of overall correctness.

3.2 Machine Learning in Maternal Health: Applications and Impact

Machine learning is transforming maternal health, based on recent global research and real-world deployments are shown in Table 1 [24,25]

Application Area	ML-Driven Innovation	Impact on Maternal Health
Risk Prediction	ML models analyze EHRs, vitals, and history to forecast complications	Enables early intervention and targeted monitoring for high-risk pregnancies.
Real-Time Monitoring	IoT-enabled wearables track maternal and fetal vitals; ML detects anomalies.	82% reduction in stillbirths and neonatal deaths in Malawi pilot deployment.
Imaging & Diagnostics	Deep learning interprets ultrasound scans; smartphone AI detects anaemia, infections.	Improves diagnostic accuracy and expands access in low-resource settings.
Mental Health Screening	NLP and sentiment analysis detect postpartum depression and anxiety.	Facilitates timely mental health support and reduces long-term complications.
Clinical Decision Support	AI systems assist clinicians in diagnosing complications and recommending treatments.	Improves decision-making and reduces preventable maternal deaths.
Personalized Care	ML tailors care plans based on individual risk profiles and real-time data.	Enhances treatment precision and resource efficiency.
Data Security & Access	Block chain-integrated ML systems ensure secure, decentralized medical records.	Builds trust, improves continuity of care, and protects patient privacy.

Table 3: Applications and Impact

3.3 Challenges in Applying ML to Maternal Health services

Challenge	Description
Data Quality & Diversity	Inconsistent, incomplete, or biased datasets—especially in low-resource settings—limit model accuracy.
Privacy & Ethical Concerns	Sensitive maternal data requires robust privacy safeguards and ethical oversight.
Integration with Clinical Workflows	ML tools often lack seamless integration with existing healthcare systems and protocols.
Limited Interpretability	Black-box models hinder clinician trust and adoption, explainability is crucial.
Infrastructure Gaps	Many regions lack the digital infrastructure needed to deploy ML solutions effectively.
Regulatory & Legal Barriers	Unclear guidelines around AI use in healthcare slow down deployment and scaling.

Table 4: Challenges to Maternal Health services.

3.4 Future Scope of ML in Maternal Health

Opportunity Area	Future Direction
Multimodal Data Fusion	Combining EHRs, imaging, wearables, and genomics for holistic risk prediction.

Personalized Preventive Care	Dynamic ML models that adapt to individual profiles and evolving health conditions.
Federated Learning	Privacy-preserving ML across decentralized datasets to improve global model robustness.
Explainable AI (XAI)	Enhancing transparency to support clinical decision-making and regulatory compliance.
AI-Driven Policy Design	Using ML insights to inform maternal health policies and resource allocation.

Table 5: Future Scope.

CONCLUSIONS

ML presents an opportunity to revolutionize maternal healthcare in rural areas. It can enhance access to care, improve diagnostic accuracy, and enable personalized treatment plans. To ensure that this technology serves all women equitably and effectively, proactive measures are needed to address challenges related to data, infrastructure, ethics, and workforce readiness. A future where every woman, regardless of location, has access to the highest quality of maternal healthcare can be achieved by focusing on responsible implementation and fostering collaboration.

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