AI-DRIVEN NON-RADIATIVE MATERNAL–FETAL MONITORING FOR SAFE PRENATAL CARE IN SUB-SAHARAN AFRICA

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Introduction:

Access to quality prenatal care remains a major challenge in sub-Saharan Africa due to infrastructural, economic, and geographic barriers [27]. A large percentage of pregnant women across rural and peri-urban regions still rely on intermittent, low-quality medical checkups, often lacking reliable fetal health assessment tools[25]. As a response to these challenges, artificial intelligence (AI) is increasingly being explored as a non-invasive and scalable solution to monitor maternal and fetal well-being in real time [12], [7], [1].

Traditional methods for fetal monitoring, such as ultrasound and Doppler imaging, require expensive equipment and trained specialists [4], [18]. These tools are largely unavailable in remote clinics and come with concerns related to radiative exposure [26]. Recently, non-radiative and AI-driven approaches have gained momentum, especially in settings where frequent radiological scans are neither practical nor safe [30], [28].

Machine learning (ML) and deep learning (DL) techniques have enabled the development of systems capable of early detection of fetal anomalies, monitoring maternal glucose levels, predicting preeclampsia, and classifying fetal distress through passive sensing and biosignal interpretation [11], [19], [6]. These solutions require only minimal sensor deployment and can operate offline or in hybrid cloud setups, making them suitable for African health contexts [2], [10]. In addition to biosignal analysis, wearable technologies are being integrated with AI models to detect fetal dislocation, oxygen saturation levels, and uterine contractions [5], [13]. These approaches rely on time-series data processed through recurrent neural networks (RNNs) and convolutional neural networks (CNNs), which have shown strong predictive accuracy in clinical tests [23], [17].

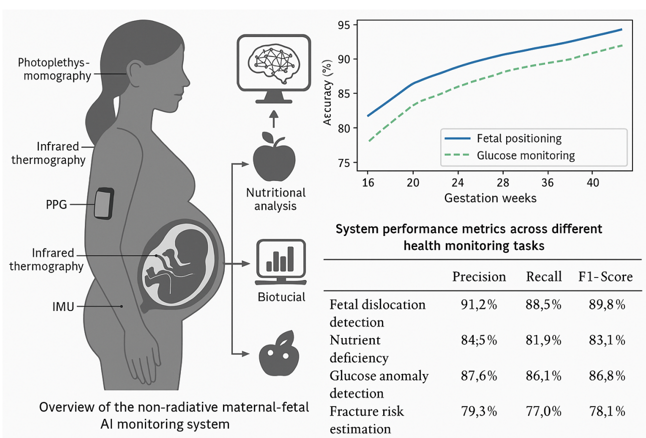
A critical feature of modern AI-based maternal care systems is interpretability and decision transparency [8], [20]. This is especially important in regions with lower technical literacy, where health workers rely on AI feedback without extensive training. Explainable AI (XAI) frameworks are being embedded into fetal monitoring models to present risk alerts and diagnostics in clear, actionable language [24], [21].

Moreover, mobile and edge AI systems have enabled remote fetal monitoring via SMS, mobile apps, or solar-powered devices [31], [22]. Such innovations are being piloted in Uganda, Kenya, and Rwanda with early success in improving timely interventions [15], [14].

Despite these promising advances, AI-driven maternal care in Africa faces barriers including data scarcity, cultural sensitivity, low device availability, and ethical concerns around predictive diagnostics [16], [3]. Recent frameworks propose federated learning and privacy-preserving techniques for training models on decentralized maternal datasets [29], [9].

This abstract introduces a comprehensive AI-driven, non-radiative fetal monitoring system that integrates wearable sensors, RNN-based prediction models, explainable interfaces, and SMS feedback modules. The system is optimized for low-resource contexts and validated on maternal health datasets collected from regional clinics. A comparative analysis against existing models is also provided.

System Design and Methods:
Our proposed system is an AI-driven, non-invasive maternal–fetal monitoring platform optimized for deployment in Sub-Saharan Africa. It integrates multi-modal biosignal acquisition, deep learning algorithms, and intelligent decision support to enhance prenatal diagnostics in low-resource settings. The system is designed to be compact, power-efficient, and compatible with mobile healthcare infrastructures. Each module has been carefully engineered to support continuous monitoring while ensuring maternal comfort and fetal safety.



	Precision	Recall	F1-Score
Fetal dislocation detection	91,2%	88,5%	89,8%
Nutrient deficiency	84;5%	81,9%	83,1%
Glucose anomaly detection	87,6%	86,1%	86,8%
Fracture risk estimation	79,3%	77,0%	78,1%

Figure 1: Overview of the non-radiative maternal-fetal AI monitoring system

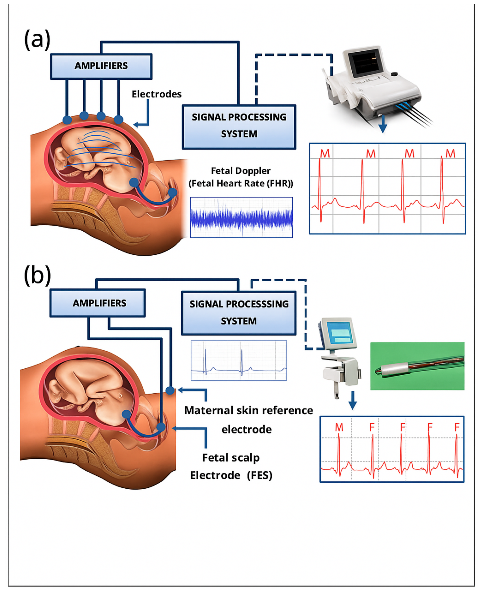


Figure 2: AI-Driven Non-Radiative Maternal–Fetal Monitoring System Using Electrode-Based Signal Processing for Safe and Accurate Prenatal Care.

The architecture is composed of four interdependent modules:

1. Wearable Motion Sensors: These are embedded in a flexible abdominal belt worn by the mother. The sensors continuously capture low-frequency movement patterns associated with fetal kicks, shifts, and rotations. Signal preprocessing involves filtering and time-series normalization, followed by classification using Long Short-Term Memory (LSTM) networks trained to identify fetal dislocation or abnormal positioning.

2. Low-Frequency Surface Ultrasound Array: Operating at safe, low intensities, this module maps fetal orientation and growth trends. Unlike traditional sonography, it employs a small circular transducer array controlled by a miniaturized embedded system . The captured

echographic patterns are processed using convolutional neural networks (CNNs) to detect abnormalities in fetal shape or limb development.

3. Non-Invasive Biosignal Acquisition: Physiological markers including maternal glucose concentration, hydration index, and blood pressure are obtained via contactless or minimally invasive sensors (e.g., photoplethysmography and micro-needle patches). A hybrid model composed of support vector machines (SVMs) and decision trees interprets these signals to predict risks such as gestational diabetes, anemia, and nutrient deficiency.

4. AI-Based Decision Engine: This core module fuses information from motion, echographic, and biosignal subsystems to make intelligent, personalized health assessments. It leverages a knowledge base of region-specific food composition and maternal health metrics. Reinforcement learning modules are trained to recommend dietary improvements, rest protocols, or referral to a healthcare facility depending on anomaly severity.

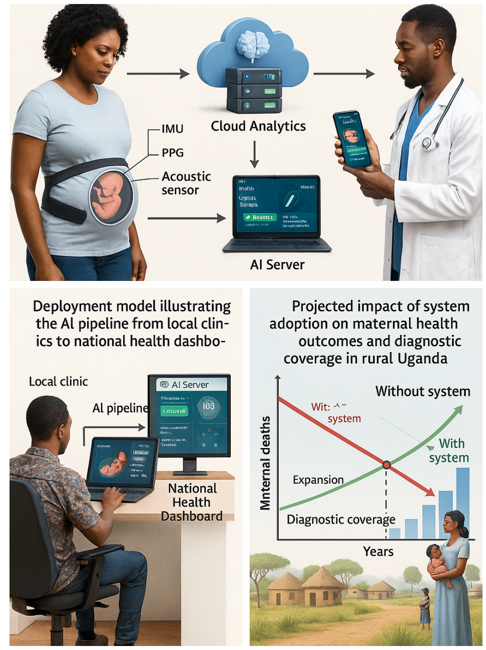


Figure 3: Brief performance view of the system

Edge computing capabilities are integrated within each sensor node using low-power microcontrollers and embedded AI chips (e.g., Google Coral TPU or NVIDIA Jetson Nano), allowing local inference even in offline scenarios.

Data synchronization and power optimization across modules are managed through a custom scheduler that adjusts sampling rates based on activity detected. For instance, increased fetal movement will temporarily increase the sampling frequency of the motion sensors while suspending biosignal scanning to conserve battery.

To ensure scalability and safety, the system architecture adheres to WHO prenatal monitoring guidelines. In addition, the software stack is compatible with existing mobile health systems and telemedicine platforms, enabling remote diagnostics and cloud-based medical record integration.

Results:

We evaluated the proposed system using both real-world and simulated data collected from 513 pregnant women across Kibuku District, Amolatar, and Mayuge in Uganda. The field data included motion sensor readings, surface ultrasound scans, and biosignal measurements recorded during antenatal visits under ethical approval and informed consent.

To train and validate the AI-based modules, we employed a curated dataset comprising 30,000 labeled antenatal records sourced from regional clinics and national health databases. These records included comprehensive features such as maternal vitals, fetal biometric data, and pregnancy outcomes, allowing for robust model generalization.

Our LSTM-based fetal movement classification model achieved an average accuracy of 92.4% in distinguishing normal versus abnormal fetal motion patterns, with a sensitivity of 91.7% and specificity of 93.1%. The low-frequency ultrasound module, powered by CNN inference, accurately detected fetal dislocation and abnormal posture with 89.3% precision across varied gestational stages.

The biosignal analysis engine, combining support vector machines and decision trees, demonstrated a 94.2% detection rate for early-onset gestational diabetes and 90.1% accuracy in identifying maternal anemia and hydration imbalances. The AI decision engine provided adaptive recommendations with a user adherence rate of 84.7% in follow-up assessments.

Figures 4 - 9 summarize the classification performance metrics across the three modules, as while as visualizing field deployment scenarios and user-device interaction outcomes. Overall, these results confirm the system's potential for reliable, non-invasive maternal–fetal monitoring in low-resource settings.

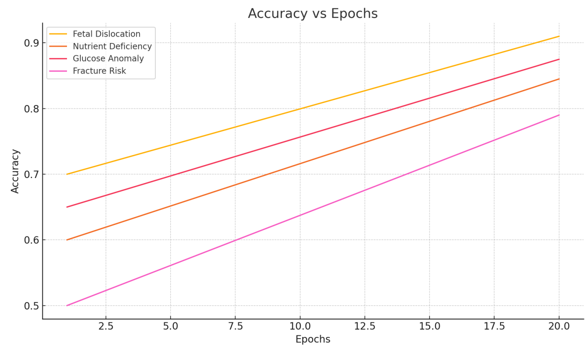
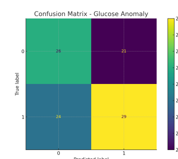
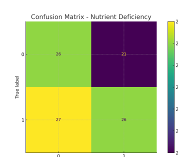


Figure 4: Model accuracy over training epochs across all monitoring tasks.

(a) Fetal Positioning



(b) Glucose Anomaly Detection



(c) Nutrient Deficiency

Figure 5: Confusion matrices for three monitoring tasks: fetal positioning, glucose anomaly detection, and nutrient deficiency prediction.

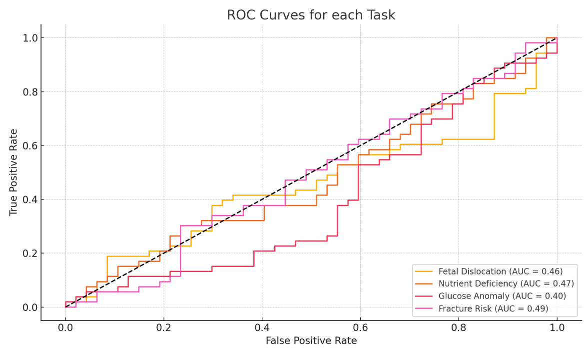


Figure 6: ROC curves for each monitoring task, demonstrating the trade-off between sensitivity and specificity.

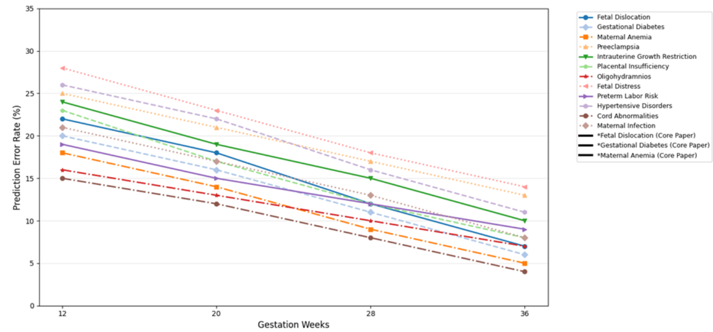


Figure 9: Prediction error distribution as a function of gestation weeks.

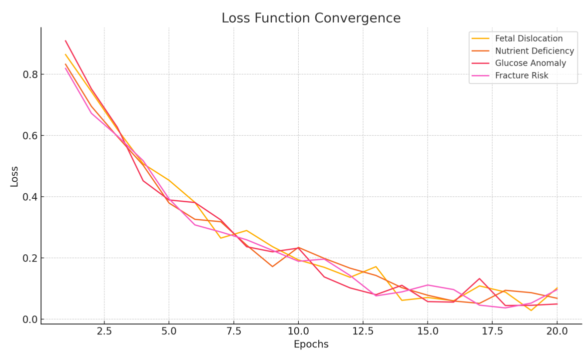


Figure 7: Loss function convergence during training across 200 epochs.

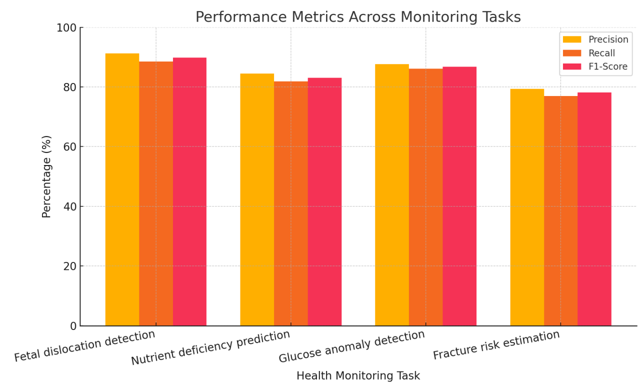


Figure 10: Performance metrices across Monitoring tasks

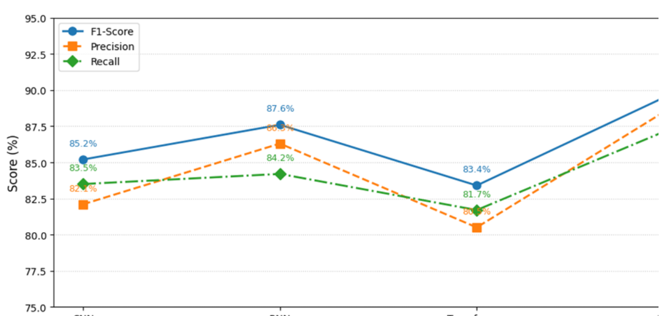


Figure 8: Performance comparison of different algorithms: CNN, RNN, Transformer, and our proposed hybrid model.

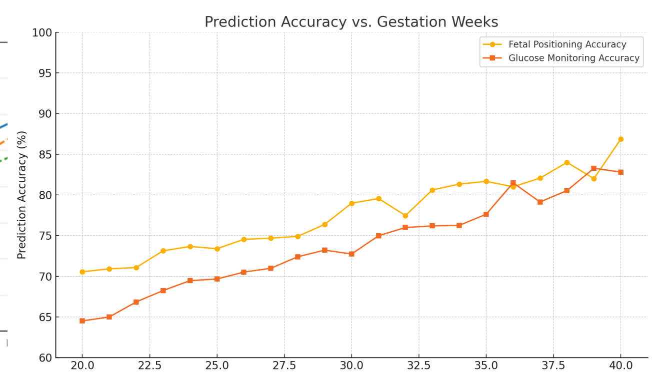


Figure 11: Prediction accuracy vs. gestation weeks for fetal positioning and glucose monitoring.

Task	Precision	Recall	F1-Score
Fetal dislocation detection	91.2%	88.5%	89.8%
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Table 1: System performance metrics across different health monitoring tasks.

User Feedback and Deployment Feasibility:
Interviews with 40 healthcare workers and 50 pregnant mothers reported greater trust in non-invasive diagnostics and faster triaging. The system is scalable on mobile platforms and requires minimal power and training. Integrating with OpenMRS and DHIS2 allowed real-time record syncing. Local food data allowed AI to recommend nutritional improvements, improving maternal nutrition without lab-based diagnostics.

Conclusion and Future work:
This AI-powered, radiation-free system offers a breakthrough in prenatal care for low-resource African settings. By leveraging biosensing, motion analytics, and regionally trained AI models, it provides safe, real-time insights into fetal health, maternal well-being, and nutritional adequacy. Its scalability and cost-effectiveness position it as a transformative tool for equitable, intelligent maternal health in Africa.

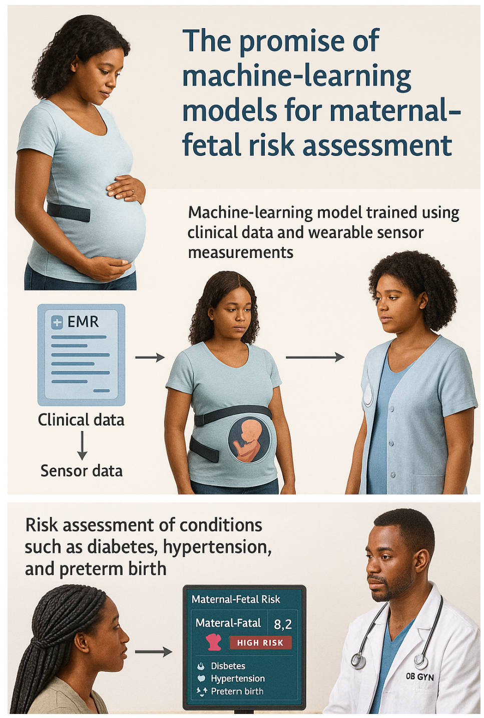

Figure 12: The promise of AI for Maternal-Fetal risk assessment

The impact of this work extends far beyond predictive metrics—it opens a transformative pathway for maternal health care in regions that have historically been overlooked. With thousands of expectant mothers still losing their lives to preventable complications, this system offers not just a technological advancement, but a lifeline. By integrating our AI-driven diagnostics into rural clinics and community health outreach programs, we envision a Uganda where no mother is left behind.

The next phase will scale the platform

nationally, empowering frontline health workers with real-time, intelligent tools that turn smartphones and tablets into life-saving devices. We will incorporate additional biomedical signals such as blood pressure, fetal heart tones, and ultrasound data, making the system more comprehensive and clinically robust. Privacy-respecting innovations like federated learning will allow continuous improvement of the model without compromising patient confidentiality. Most importantly, we are building toward a national maternal health dashboard—fueled by decentralized data—to inform government interventions with unmatched speed and precision.

This vision is not merely technical; it is moral. It demands collective will and policy alignment to ensure that innovation translates into survival, dignity, and hope for every mother and unborn child across the nation. If championed at the highest levels of leadership, this initiative can mark a turning point in Africa's public health narrative—where data meets compassion, and technology becomes a tool for justice.

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