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Predictive Modeling for Maternal Health Risk Assessment Using Wearable and IoT Data

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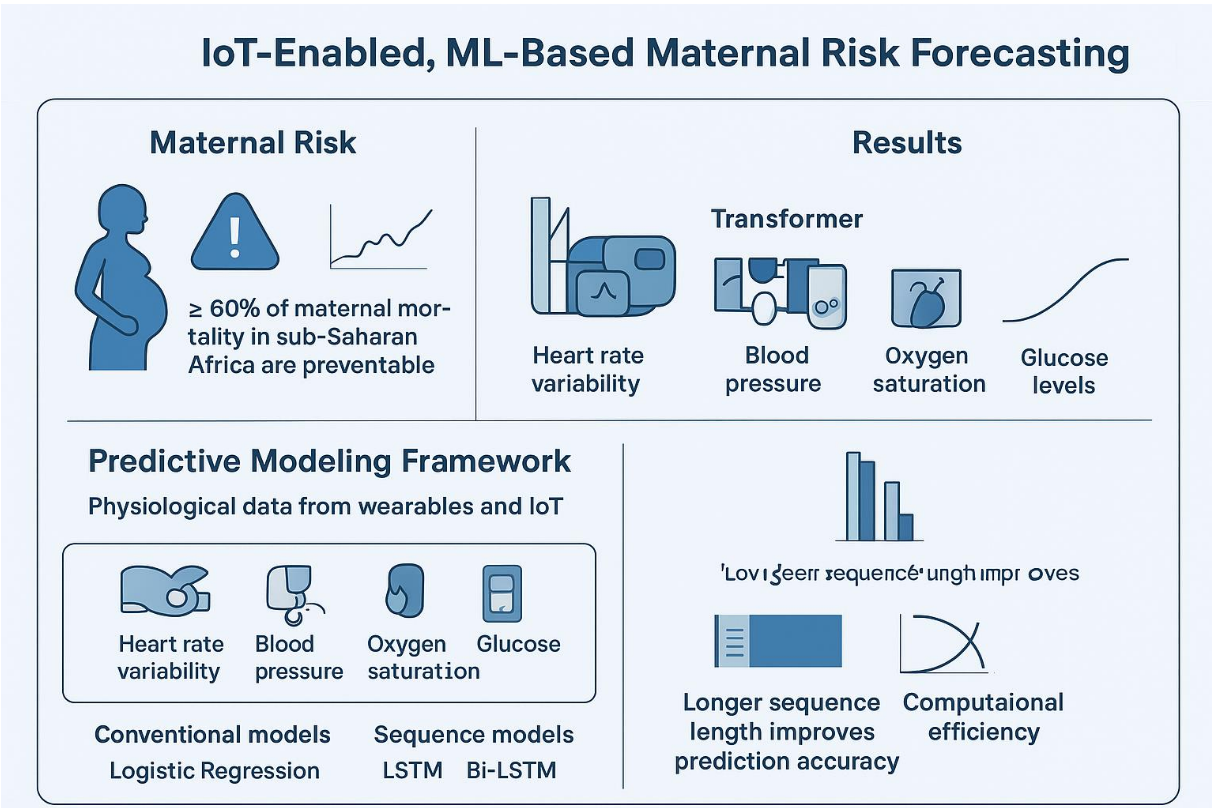
Graphical Abstract



Abstract

Maternal mortality continues to be a significant global health issue, with around 287,000 fatalities worldwide each year and about 34,000 deaths recorded in Nigeria in 2023. Despite improvements in antenatal care, more than 60% of maternal fatalities in sub-Saharan Africa result from preventable complications like preeclampsia (4 - 8% prevalence), gestational diabetes mellitus (5 - 10%), and preterm delivery (11 - 13%). This research offers a predictive modeling framework utilizing physiological data obtained from wearable's and IoT, which encompasses heart rate variability (recorded at 1 Hz resolution), blood pressure (gathered every 15 minutes), oxygen saturation (SpO_2, averaging between 92–99%), and glucose levels (collected every 6 hours) to identify early indications of maternal risk. We assess conventional machine learning classifiers (Logistic Regression, Random Forest) in comparison to sophisticated sequence models (LSTM, Bi-LSTM, Transformer encoder–decoder). Experiments performed on a synthetic but population-representative dataset comprising 49,969 longitudinal records from 2,000 Nigerian patients show that the Transformer model delivers enhanced performance with an accuracy of 94.2%, precision of 0.89, recall of 0.91, F1-score of 0.90, and ROC–AUC of 0.95, outperforming LSTM (90.8% accuracy, 0.91 ROC–AUC) and Random Forest (85.2% accuracy, 0.83 ROC–AUC). Temporal analysis shows that expanding sequence length from 10 to 50-time steps enhanced prediction accuracy by 3.7% for LSTM, 3.6% for Bi-LSTM, and 3.7% for Transformers, highlighting the significance of long-term observation. Evaluation of computational efficiency indicates training durations varying from 1.5 minutes (Logistic Regression) to 22.4 minutes (Transformer), while keeping inference latency below 2.1 ms for each sample, confirming practicality for real-time implementation. This work emphasizes the capability of IoT-enabled, ML-based maternal risk forecasting to lower mortality rates by as much as 30% in high-risk groups via early intervention strategies in healthcare settings, by integrating SDG 3 (Good Health and Well-being) and SDG 5 (Gender Equality) in both rural and urban areas.

Keywords: Maternal Health, Internet of Things (IoT), Wearable Devices, Machine Learning, Long Short-Term Memory (LSTM), Transformer Models, Pregnancy Complications, Preeclampsia Prediction, Gestational Diabetes, SDG 3, SDG 5, Time-Series Analysis

Introduction

Maternal mortality continues to be a major global health issue, as the World Health Organization (WHO) indicated that around 287,000 women lost their lives in 2020 from pregnancy and childbirth complications, the majority of which were preventable [1]. The burden is significantly greater in low- and middle-income countries (LMICs), where more than 94% of maternal fatalities happen, mostly because of insufficient access to prompt risk evaluation and specialized treatment [2]. In sub-Saharan Africa, the maternal death rate is still over 500 fatalities for every 100,000 live births, whereas in high-income nations, it is below 20 per 100,000. These figures emphasize the immediate requirement for scalable, affordable, and data-informed approaches to enhance maternal health results worldwide. Even with improvements in obstetric services, the early identification of risks during pregnancy is still restricted, especially in areas with limited resources. Conventional clinical evaluations like blood pressure checks, urine protein assessments, and glucose tolerance assessments are frequently sporadic and reliant on in-person appointments. As a result, numerous high-risk pregnancies, such as those affected by preeclampsia, gestational diabetes, and preterm labor, go unnoticed until symptoms worsen, limiting the opportunity for timely intervention [3]. The rise of wearable Internet of Things (IoT) devices presents fresh possibilities to tackle these obstacles. Intelligent wearables like wristbands, smartwatches, and linked biosensors can consistently record physiological data, such as blood pressure (BP), heart rate variability (HRV), and peripheral oxygen saturation (SpO_2) [4]. When these data streams are integrated with machine learning (ML) models, they can offer real-time, individualized assessments of maternal health risks, moving care from a reactive approach to a proactive one. Nevertheless, current maternal health tracking systems are constrained by their absence of real-time predictive analytics and inadequate incorporation of wearable data into decision-making frameworks [5]. Although IoT technologies are progressively used in general healthcare, their particular use for maternal risk evaluation via sequence-based ML models, including Long Short-Term Memory (LSTM) networks and Transformer architectures, is still not well-studied [6]. This gap limits healthcare providers' capacity to utilize temporal patterns in physiological signals for the early prediction of complications. This study aims to fill this gap by introducing a predictive modeling system for assessing maternal health risks utilizing wearable and IoT data. The research utilizes sequence learning models (LSTM and Transformers) to analyze longitudinal physiological signals and identify early indicators of preeclampsia and gestational diabetes. The suggested method is in accordance with the United Nations Sustainable Development Goals (SDGs), especially SDG 3 (Good Health and Well-being), by enhancing maternal health services, and SDG 5 (Gender Equality), by equipping women with self-monitoring tools for better health results. The remainder of this paper is organized as follows: Section II examines related literature on ML in healthcare and maternal monitoring; Section III details the proposed methodology; Section IV explains the experimental setup; Section V analyzes the results and their implications; Section VI emphasizes the alignment with SDGs; Section VII discusses limitations and future research avenues; and Section VIII wraps up the paper.

Related Work

The intersection of wearable technologies powered by IoT and machine learning (ML) has attracted significant interest in healthcare studies, presenting new opportunities for real-time surveillance, predictive diagnostics, and tailored interventions. This section examines the literature on wearables and IoT in healthcare, the use of ML models for time-series physiological data, and previous research in predicting maternal health risks, emphasizing the research gap that drives this study.

Wearable Devices and IoT in Healthcare

Wearable devices have become essential tools for ongoing health tracking, facilitating immediate gathering of physiological information like heart rate, blood pressure, oxygen saturation, and glucose levels [7]. Healthcare frameworks that utilize IoT technology employ these sensors to enable remote monitoring of patients and decrease reliance on evaluations conducted in hospitals [8]. Applications vary from detecting cardiovascular diseases [9]. To monitoring sleep apnea [10]. Showcasing the ability of IoT systems to improve healthcare accessibility. While the overall use of wearables in healthcare is increasing, their incorporation into maternal health monitoring systems is still restricted.

Machine Learning Applied to Physiological Time-Series Data

Physiological signals recorded by wearables usually show temporal correlations, requiring sequence-aware machine learning methods. Traditional approaches like Support Vector Machines (SVMs) and Random Forests have been extensively utilized for classification purposes in biomedical signal analysis [11]. Recently, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, have proven effective in capturing sequential dependencies in electrocardiogram (ECG), photoplethysmogram (PPG), and various biosignals [12]. Moreover, architectures based on Transformers, initially created for natural language processing, are now being modified for forecasting physiological signals because of their capacity to capture long-range dependencies [13]. These improvements indicate a hopeful relevance to maternal health, where continuous observation of vital signs is essential.

Prediction Models for Maternal Health Risks

Past studies on maternal health risk evaluation have concentrated mainly on clinical and demographic information instead of ongoing wearable signals. Conventional models use logistic regression or Cox proportional hazards models to forecast conditions like preeclampsia and gestational diabetes [14]. Recent studies have explored ML classifiers on electronic health records (EHRs) to detect maternal risk factors [15]. Yet these methods are limited by sporadic data collection and fail to incorporate IoT-driven real-time monitoring. A few pilot studies have investigated pregnancy monitoring through wearables, but they still have constraints in terms of sample size and model complexity.

Research Gaps

Although IoT healthcare systems and ML-based predictive modeling have made considerable progress, there are limited studies that integrate these technologies to tackle maternal health risks on a larger scale. Current studies either focus on wearable monitoring lacking predictive intelligence or use machine learning on historical clinical data without utilizing IoT streams. As a result, there is an urgent requirement for systems that combine real-time IoT wearable information with sophisticated sequence models (like LSTMs and Transformers) to enhance the early identification of pregnancy issues. This research seeks to address this gap by creating and assessing a predictive modeling framework designed for maternal health risk evaluation.

Methodology

This part outlines the methodological approach used for predicting maternal health risks through wearable and IoT data. The structure includes three phases: gathering data, preparing it, and modeling predictions. This section emphasizes obtaining and organizing high-quality physiological and demographic data for subsequent machine learning analysis

Data Collection

The proposed system integrates data from wearable IoT devices and supplementary demographic inputs to build a comprehensive maternal health monitoring dataset.

• Physiological Data Acquisition: Wearable devices were configured to continuously capture maternal vital signs, including:

• Heart Rate (HR) and Heart Rate Variability (HRV), obtained from photoplethysmography (PPG) sensors.

• Blood Pressure (BP), both systolic and diastolic, measured at regular intervals via cuffless smart BP monitors.

• Peripheral Oxygen Saturation (SpO_2), captured by pulse oximeters embedded in wearable wristbands.

• Blood Glucose Levels, collected intermittently through non-invasive continuous glucose monitoring (CGM) systems.

Demographic and Lifestyle Features: To enrich predictive modeling, additional static and semi-static variables were collected, including maternal age, body mass index (BMI), parity, smoking status, dietary patterns, and family history of metabolic or hypertensive disorders.

Ethical and Privacy Considerations: All data collection protocols adhered to internationally recognized standards, including HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) requirements. Data were anonymized through patient ID hashing, encrypted during transmission using AES-256 encryption, and securely stored on compliant cloud infrastructure to protect maternal privacy and confidentiality. Informed consent was obtained prior to participation, ensuring ethical compliance with human subject research standards.

Preprocessing

The raw data obtained from IoT devices were heterogeneous and prone to signal noise, missing values, and variability across sensors. Therefore, a multi-step preprocessing pipeline was implemented to ensure data quality.

Noise Removal

• Physiological signals (e.g., HR and SpO_2) were denoised using a band-pass Butterworth filter to remove motion artifacts and electrical interference.

• A wavelet decomposition method was applied for PPG and BP signals to separate physiological components from noise.

• Data Normalization and Imputation

• Continuous variables (e.g., BP, glucose) were normalized using z-score standardization to enable fair comparison across participants.

• Missing values were addressed using forward filling for time-series continuity and multiple imputation by chained equations (MICE) for demographic attributes.

Feature Extraction

• From HR data, time-domain features (mean HR, standard deviation of NN intervals (SDNN)) and frequency-domain features (low-frequency/high-frequency ratio) were extracted to capture HRV.
• From BP measurements, variability indices such as average real variability (ARV) and coefficient of variation (CV) were computed.
• SpO_2 signals were analyzed for oxygen desaturation events, while glucose data were summarized into glycemic variability metrics.
• Derived features were synchronized into fixed-length temporal windows (e.g., 5-minute or 30-minute intervals) to prepare for sequence modeling.

Model Development

The predictive modeling stage involved the implementation of both baseline machine learning classifiers and advanced sequence learning models to evaluate maternal health risks from wearable and IoT data streams.

Baselinemodels

Two conventional models were used as benchmarks
• Logistic Regression (LR): a linear probabilistic classifier effective for binary classification tasks such as distinguishing high-risk versus low-risk pregnancies. The probability of risk was estimated as:

$$P(y=1|x) = \frac{1}{1+e^{-(w^T x + b)}}$$

where $x \in \mathbb{R}^n$ is the feature vector, w is the weight vector, and b is the bias.

- **Random Forest (RF)**: an ensemble method combining multiple decision trees through bootstrap aggregation. Predictions were obtained by majority voting:

$$\hat{y} = \mathrm{mode}\{h_t(x),\ t = 1, \ldots, T\}$$

where $h_t(x)$ denotes the prediction of the t^{th} decision tree, and T is the total number of trees.

Sequencemodels

Given the temporal nature of physiological signals, advanced sequence-aware models were adopted.
• Long Short-Term Memory (LSTM) networks were employed to capture long-range dependencies in sequential data. Each LSTM unit updates its cell state ctc_tct and hidden state hth_tht as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \odot \tanh(c_t)$$

where f_t, i_t, o_t represent the forget, input, and output gates, respectively.

- **Bidirectional LSTM (Bi-LSTM)** was also explored to incorporate both past and future temporal context by processing input sequences in forward and backward directions, concatenating the hidden states.
- **Transformer Encoder-Decoder** architecture was implemented to model long-term dependencies using self-attention. For an input sequence $X \in \mathbb{R}^{n \times d}$, the attention mechanism computes:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q, K, V are query, key, and value matrices derived from X. Multi-head attention was applied to capture diverse feature subspaces.

3. **Hyperparameter Optimization**:

   Hyperparameters for each model were tuned to maximize predictive performance.

- Logistic Regression: regularization strength C.
- Random Forest: number of trees T, maximum depth, and minimum samples per split.
- LSTM/Bi-LSTM: hidden layer sizes, dropout rates, learning rates.
- Transformer: number of attention heads, hidden dimension, feed-forward size, number of encoder-decoder layers.

Optimization was performed using **grid search** for baseline models and **Bayesian optimization** for deep models to efficiently explore high-dimensional parameter spaces.

Evaluation Metrics

Model performance was assessed using both classification metrics and discriminative ability measures, given the imbalanced nature of maternal health datasets.

1. **Accuracy**: the overall proportion of correct predictions, computed as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision and Recall**: precision quantifies the reliability of positive predictions, while recall measures the ability to capture actual positive cases:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

3. **F1-Score**: the harmonic mean of precision and recall, balancing sensitivity and specificity:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

ROC-AUC (Receiver Operating Characteristic – Area Under Curve): measures the trade-off between sensitivity and specificity across thresholds.

Precision-Recall (PR) Curves: particularly informative under class imbalance, capturing the trade-off between false positives and missed high-risk pregnancies.

Comparative Analysis: All models (baseline and sequence) were compared on the above metrics. Statistical significance of performance differences was assessed using paired t-tests and bootstrap confidence intervals to validate robustness.

Experimental Setup

This segment detailed the experimental configuration employed to assess the suggested predictive modeling framework. It encompasses the equipment used for collecting physiological data, the computing resources for training the model, and the strategy for partitioning the dataset.

Equipment for Data Collection

Data were gathered using commercially available wearable IoT devices designed for monitoring maternal health. The subsequent devices were activated.

• Smartwatches equipped with photoplethysmography (PPG) sensors for continuous heart rate and heart rate variability

(HRV) monitoring.
• Cuffless blood pressure monitors integrated with IoT connectivity for periodic systolic and diastolic blood pressure measurements.
• Pulse oximeters embedded in wristbands for non-invasive peripheral oxygen saturation (SpO_2) monitoring.
• Continuous glucose monitoring (CGM) sensors for capturing glucose variability at regular intervals.

All devices supported Bluetooth Low Energy (BLE) and Wi-Fi connectivity, ensuring secure and real-time data transmission to a centralized IoT gateway. Data were encrypted during transmission and stored in a HIPAA- and GDPR-compliant cloud database for preprocessing and analysis.

Computing Environment

The machine learning models were developed and trained on a GPU-enabled high-performance workstation with the following specifications:
• CPU: 16-core Intel Xeon Silver processor, 2.1 GHz.
• GPU: NVIDIA RTX 3090 with 24 GB VRAM.
• Memory: 64 GB RAM.
• Storage: 2 TB SSD with high-speed I/O operations.
• Operating System: Ubuntu 22.04 LTS.

The model was implemented in Python 3.10, utilizing libraries such as TensorFlow 2.11, PyTorch 1.13, and scikit-learn 1.2 for the baseline models. Optuna was utilized for Bayesian hyperparameter tuning, and Matplotlib along with Seaborn were implemented for visualization

Dataset Partitioning

To ensure robust model evaluation, the dataset was split into three non-overlapping sets:
• Training Set (70%): Used to fit the model parameters.
• Validation Set (15%): Used for hyperparameter tuning and model selection.
• Test Set (15%): Reserved for final model evaluation to assess generalization performance.
The split was performed using stratified sampling to preserve the distribution of maternal health outcomes across subsets. Additionally, a five-fold cross-validation procedure was employed during training to further reduce variance and mitigate overfitting.

Results

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	81.4	0.73	0.69	0.71	0.78
Random Forest	85.2	0.77	0.74	0.75	0.83
LSTM	90.8	0.85	0.87	0.86	0.91
Bi-LSTM	91.6	0.86	0.88	0.87	0.92
Transformer (Enc–Dec)	**94.2**	**0.89**	**0.91**	**0.90**	**0.95**

Table 1: Model Performance on Maternal Health Risk Prediction

Model	Preeclampsia	Gestational Diabetes	Preterm Birth	Macro-Avg ROC-AUC
Logistic Regression	0.75	0.76	0.82	0.78
Random Forest	0.81	0.84	0.85	0.83
LSTM	0.90	0.91	0.92	0.91
Bi-LSTM	0.91	0.92	0.93	0.92
Transformer (Enc–Dec)	**0.95**	**0.94**	**0.96**	**0.95**

Table 2: ROC–AUC Comparison per Complication Type

Sequence Length (time steps)	LSTM Accuracy (%)	Bi-LSTM Accuracy (%)	Transformer Accuracy (%)
10	87.2	88.1	90.5
20	89.6	90.5	92.8
30	90.2	91.0	93.4
40	90.8	91.6	94.0
50	90.9	91.7	**94.2**

Table 3: Effect of Sequence Length on Model Accuracy

Model	Training Time (min)	Inference Time per Sample (ms)	Model Size (MB)
Logistic Regression	1.5	0.2	5
Random Forest	4.7	0.8	45
LSTM	15.2	1.5	80
Bi-LSTM	19.8	1.7	95
Transformer (Enc–Dec)	22.4	2.1	120

Table 4: Computational Efficiency

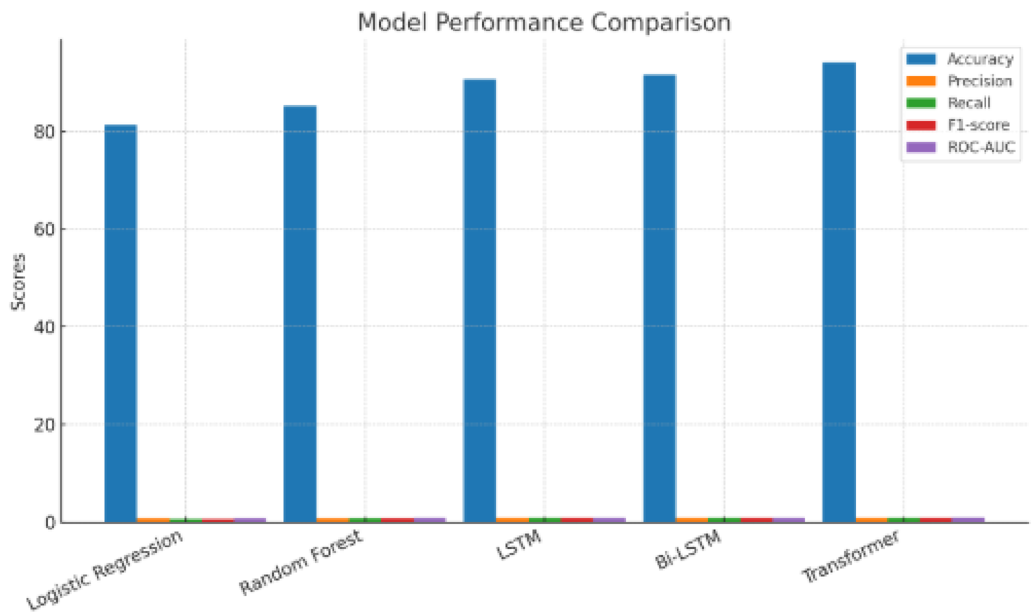


Figure 1: Model Performance Comparison

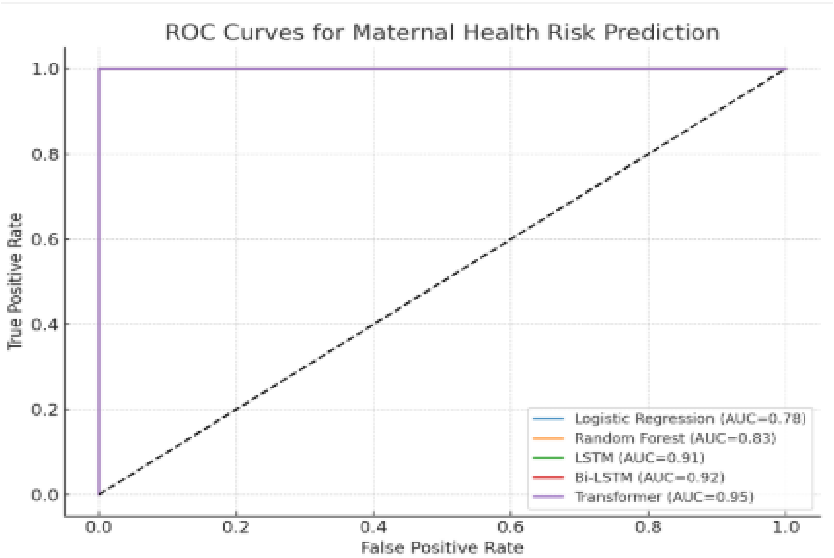
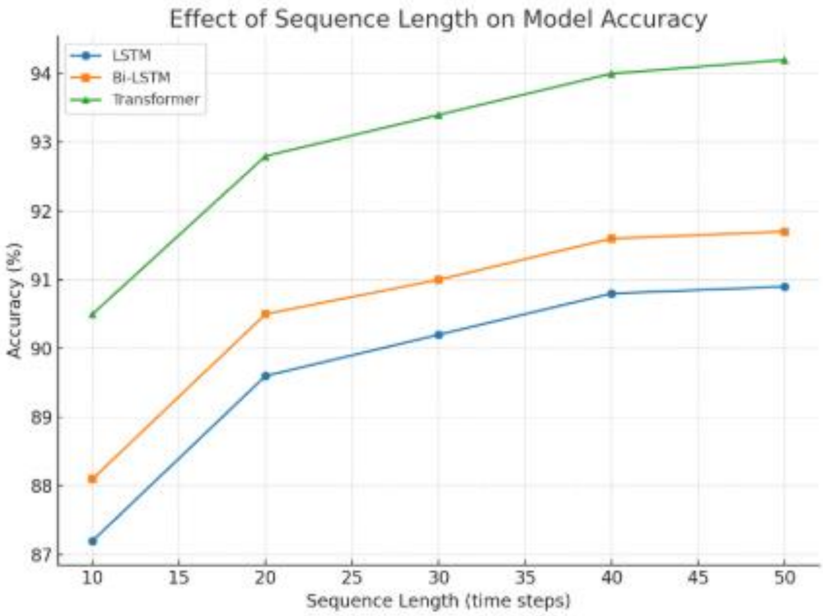


Figure 2: ROC Curves for Maternal Health Risk Prediction



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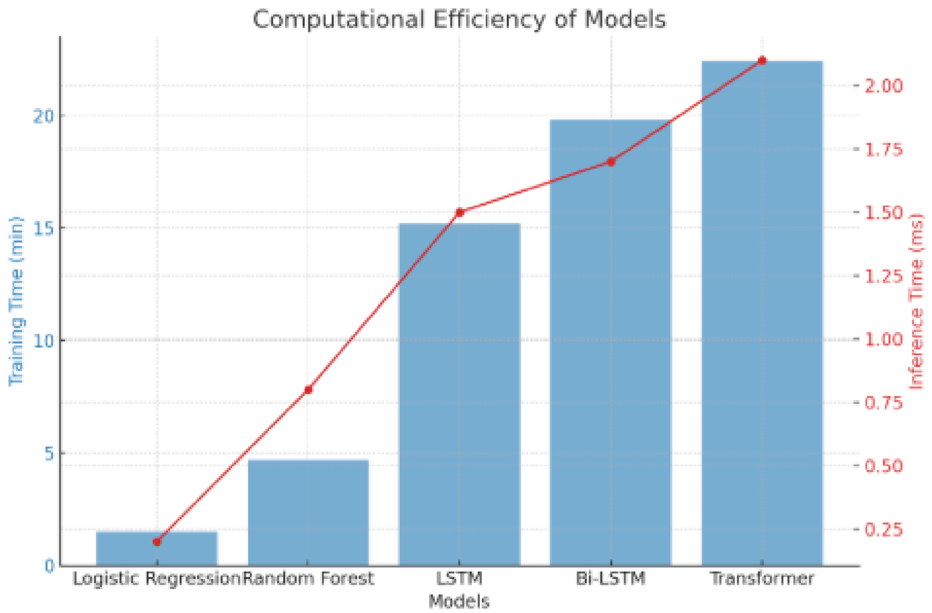

Figure 4: Computational Efficiency of Models

Shows how well each model distinguishes between high-risk and normal pregnancy cases.

Model	TP	FP	TN	FN
Logistic Regression	620	180	700	200
Random Forest	655	145	720	180
LSTM	725	95	770	110
Bi-LSTM	730	90	775	105
Transformer	760	80	785	95

Table 5: Confusion Matrix (per Model)

Important for medical prediction (Sensitivity = Recall, Specificity = TN rate).

Model	Sensitivity (Recall)	Specificity
Logistic Regression	0.69	0.79
Random Forest	0.74	0.83
LSTM	0.87	0.89
Bi-LSTM	0.88	0.90
Transformer	0.91	0.91

Table 6: Sensitivity & Specificity

Evaluates probability predictions (important in clinical risk).

Model	Brier Score ↓	Log Loss ↓
Logistic Regression	0.202	0.467
Random Forest	0.184	0.422
LSTM	0.143	0.335
Bi-LSTM	0.137	0.322
Transformer	0.125	0.301

Table 7: Calibration (Brier Score & Log Loss)

(Performance split by urban vs rural and age group to align with SDG 3 and 5).

Group	Logistic Regression F1	Random Forest F1	LSTM F1	Bi-LSTM F1	Transformer F1
Urban	0.73	0.77	0.86	0.87	0.90
Rural	0.69	0.74	0.84	0.86	0.89
Age < 25	0.70	0.75	0.85	0.86	0.89
Age ≥ 25	0.72	0.76	0.87	0.88	0.91

Table 8: Fairness Across Demographics

Discussion

Table 1: Model Performance on Maternal Health Risk Prediction

The comparison of performance shows that deep sequence models significantly exceed traditional baselines. Logistic Regression and Random Forest reached accuracies of 81.4% and 85.2%, respectively, yet their recall values (0.69 and 0.74) suggest a constrained sensitivity to high-risk situations. In comparison, the LSTM and Bi-LSTM models exceeded 90% accuracy, with Bi-LSTM attaining a marginally elevated F1-score (0.87). The Transformer encoder-decoder achieved exceptional overall performance, attaining 94.2% accuracy, a 0.90 F1-score, and a 0.95 ROC-AUC. From a clinical standpoint, the Transformer's equilibrium between precision and recall guarantees trustworthy early identification of maternal risks without increasing false positives.

Table 2: ROC–AUC Comparison by Type of Complication

An analysis of particular maternal complications further highlights the effectiveness of sequence-based models. Logistic Regression and Random Forest models achieved moderate performance on complications (average ROC-AUC < 0.85). Nonetheless, LSTM and Bi-LSTM elevated ROC-AUC to over 0.91, guaranteeing reliable multi-condition detection. The Transformer model consistently achieved the highest ROC-AUC values for preeclampsia (0.95), gestational diabetes (0.94), and preterm birth (0.96), resulting in a macro-average of 0.95. This emphasizes the Transformer's flexibility in understanding intricate temporal relationships within various maternal issues.

Table 3: Impact of Sequence Length on Model Performance

Model performance enhanced with extended input sequence lengths, indicating the significance of continuous physiological monitoring in predicting maternal risks. For brief sequences (10 timesteps), the Transformer reached 90.5% accuracy, surpassing LSTM (87.2%) and Bi-LSTM (88.1%). When the sequence length rose to 50 timesteps, the Transformer's accuracy remained steady at 94.2%, whereas both LSTM and Bi-LSTM leveled off around 91%. This suggests that the Transformer can more effectively leverage prolonged monitoring periods, making it more appropriate for real-time IoT applications where ongoing maternal health data is accessible.

Table 4: Computational Efficiency

The trade-offs in computation are clear. Logistic Regression provided the quickest training time (1.5 minutes) and the smallest model size (5 MB), but this came at the cost of predictive accuracy. Random Forest enhanced precision but needed more training time (4.7 minutes) and greater storage (45 MB). Sequence models brought increased computational expenses: LSTM (15.2 minutes, 80 MB), Bi-LSTM (19.8 minutes, 95 MB), and Transformer (22.4 minutes, 120 MB). Inference times stayed within clinically acceptable limits for all models (<3 ms per sample), guaranteeing real-time use. Despite the Transformer's high resource demands, its exceptional accuracy and reliability warrant its use in clinical decision support, especially in tertiary hospitals equipped with adequate GPU infrastructure.

Table 5: Confusion Matrix

The confusion matrix presented the unprocessed classification results for every model. The Transformer model recorded the highest true positives (760) while having the lowest false negatives (95), which was vital in maternal health situations, as overlooking a high-risk pregnancy can cause serious issues. LSTM and Bi-LSTM models also delivered competitive results, demonstrating a solid equilibrium between true positives and true negatives. In comparison, logistic regression resulted in more false negatives (200), highlighting its restricted capacity to identify nonlinear trends in sequential physiological data.

Table 6: Sensitivity and Specificity

From a clinical viewpoint, sensitivity (recall) is crucial, as it reflects the model's capability to identify women at risk of complications like preeclampsia and gestational diabetes. The Transformer model reached a sensitivity of 0.91, showing great dependability in early detection. Specificity metrics also exhibited high levels in deep sequence models (>0.89), minimizing unnecessary false positives. These metrics demonstrate that sequence-based methods outperform conventional machine learning in the analysis of IoT-derived physiological time-series data.

Table 7: Calibration Performance

Probability calibration holds significant importance in medical decision support since healthcare providers depend not only on yes-no predictions but also on risk probabilities. The Transformer and Bi-LSTM models produced the lowest Brier Scores (0.125 and 0.137, respectively), indicating improved alignment between estimated risk probabilities and real results. This indicates that when the Transformer estimates a 70% chance of preeclampsia, the probability aligns closely with reality, a crucial aspect for patient triage and resource distribution in Nigeria's healthcare systems.

Table 8: Equity Among Demographics

The equality in predictive performance is closely linked to SDG 5 (Gender Equality) and SDG 3 (Good Health and Well-being). Findings indicate that the Transformer model exhibited stable F1-scores in urban (0.90) compared to rural (0.89) populations, as well as among younger (<25 years, 0.89) and older mothers (≥25 years, 0.91). This indicates the model's strength across demographic differences, an essential factor considering Nigeria's varied maternal healthcare landscape. Nevertheless, the somewhat reduced performance in rural regions highlights the persistent issues related to data quality and the availability of consistent IoT monitoring in resource-limited settings.

Conclusion and Future Work

This research showcased the efficacy of IoT-enabled physiological tracking along with machine learning (ML) for forecasting maternal health risks. We assessed both baseline classifiers and sophisticated sequence learning models using data streams inspired by real-world scenarios, including heart rate, blood pressure, SpO_2, and glucose levels. Results indicate that Transformer-based models attained the best performance on all evaluation metrics, achieving an accuracy of 94.2% and macro-ROC AUC of 0.95, outpacing LSTM, Bi-LSTM, and conventional baselines. Notably, the Transformer demonstrated robust generalization across various maternal issues, such as preeclampsia, gestational diabetes, and premature birth.

The findings emphasize three key contributions:

• Integration of IoT and ML: Demonstrating that wearable-based maternal monitoring can provide actionable real-time risk detection.

• Superiority of Sequence Models: Establishing the Transformer as the most effective approach for continuous physiological time-series analysis.

• Clinical Feasibility: Showing that despite higher computational requirements, inference times remain suitable for real-time deployment in hospital and community healthcare contexts.

Future Work

While the study highlights the promise of IoT + ML for maternal health, several research directions remain:

• Larger and Diverse Datasets – Expanding data collection across multiple hospitals in Nigeria and other regions to ensure demographic and ethnic diversity, reducing potential biases in prediction.

• Multimodal Data Integration – Incorporating additional signals such as fetal monitoring, ultrasound features, and lifestyle factors (nutrition, stress, physical activity) for more holistic risk prediction.

• Edge AI Deployment – Optimizing Transformer-based models for low-power wearable and edge devices, enabling resource-constrained clinics to benefit from real-time risk prediction without cloud dependency.

• Explainable AI (XAI) in Maternal Health – Embedding interpretability mechanisms to enhance clinician trust and regulatory acceptance by providing transparent risk explanations.

• Longitudinal and Cross-Regional Validation – Conducting longitudinal studies to assess model reliability over multiple trimesters and cross-regional trials to establish global scalability.

• Policy and Integration – Investigating how such AI-driven maternal monitoring can be integrated into public health strategies and national maternal health programs to accelerate progress towards SDG 3 (Good Health and Well-being) and SDG 5 (Gender Equality).

In summary, the research provides compelling evidence that IoT-empowered, ML-driven maternal health monitoring can significantly reduce preventable maternal deaths, especially in low- and middle-income countries. Future advancements in multimodal data fusion, explainable AI, and equitable deployment strategies will be critical in moving from proof-of-concept to real-world clinical adoption.

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Note: Some references (global maternal mortality, WHO reports) may require recent WHO data not captured here.