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# Temporal Ensemble Learning for Robust Maternal Health Risk Prediction in Dynamic Clinical Environments

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## Abstract

Maternal mortality and morbidity continue to pose serious public health concerns worldwide, especially in resource-constrained regions where delayed identification of complications limits timely medical intervention. Conventional risk assessment approaches often depend on manual evaluation and fixed clinical thresholds, which are insufficient for capturing the complex and dynamic physiological changes that occur during pregnancy. To address these limitations, this study introduces a real-time Maternal Health Risk Stratification System (MHRSSS) based on a stacked Long Short-Term Memory (LSTM) ensemble framework. The proposed system leverages a comprehensive dataset of maternal health indicators, including age, blood pressure, blood glucose levels, and heart rate, to enable accurate risk prediction. To mitigate the impact of class imbalance commonly observed in medical datasets, the Synthetic Minority Over-sampling Technique (SMOTE) is applied, enhancing the model's ability to detect high-risk cases effectively. The architecture integrates a hybrid ensemble strategy, combining traditional machine learning models such as Random Forest and Gradient Boosting with an LSTM network to capture both static and temporal patterns in the data. A soft-voting mechanism is employed to aggregate model predictions and produce the final risk classification. Experimental evaluation demonstrates that the proposed framework significantly outperforms individual baseline models, achieving an accuracy, precision, recall, and F1-score of 99.03%. In comparison, the Extra Trees Classifier (ETC) and Random Forest Classifier (RFC) achieved notably lower performance levels. The system is implemented through a user-friendly Tkinter-based interface, enabling healthcare professionals to perform real-time, data-driven risk assessment and support early clinical decision-making, ultimately contributing to improved maternal health outcomes.

**Keywords:** Maternal health, risk stratification, Long Short-Term Memory (LSTM), ensemble learning, healthcare analytics, maternal mortality,

## 1. Introduction

Maternal health risk refers to a range of conditions and clinical indicators that can adversely affect women during pregnancy, childbirth, and the postnatal period. These risks are strongly associated with maternal mortality and require timely identification and appropriate management to prevent life-threatening complications. Traditional perspectives often focus on pregnancy and delivery; however, maternal health challenges extend beyond childbirth, making continuous monitoring essential even during the postpartum phase. Addressing these risks proactively is crucial for safeguarding both maternal and neonatal well-being. Despite advances in healthcare, maternal health remains a critical global concern. Each day, hundreds of women lose their lives due to preventable pregnancy- and childbirth-related complications, highlighting significant gaps in healthcare accessibility and quality, as shown in figure 1. In addition, millions of newborns fail to survive their first month of life, underscoring the need for comprehensive maternal and child healthcare strategies. Interventions such as access to family planning services and appropriate birth spacing have been shown to substantially

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lower both maternal and infant mortality rates, emphasizing the importance of preventive healthcare measures.

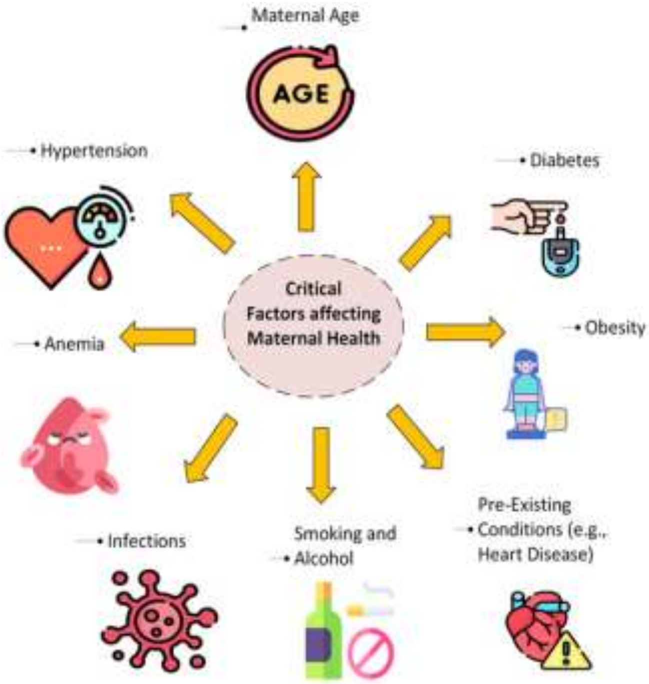



Figure. 1: Remote health monitoring system using IoT sensor data.

Globally, maternal deaths continue to be disproportionately concentrated in low- and middle-income countries, where healthcare resources and timely interventions are often limited. Regions such as Sub-Saharan Africa and South Asia account for most of these fatalities. In response to these challenges, there is an increasing interest in leveraging advanced computational techniques to enhance maternal risk assessment. This study focuses on developing an intelligent maternal health risk prediction system using Transfer Learning (TL), which enables efficient knowledge adaptation from existing models to improve predictive accuracy and support clinical decision-making.

## 2. Related Work

### 1. Wearable Technology for Maternal Monitoring

Wearable technology has emerged as a key enabler for continuous maternal health monitoring. Lopez et al. [1] developed a wearable-based system to monitor hypertension during pregnancy using wristband devices that capture physiological signals such as heart rate, activity levels, and sleep patterns. Their findings demonstrated the feasibility of non-invasive and long-term monitoring solutions. Similarly, Grym et al. [16] validated the practicality of wearable devices in clinical environments, confirming their effectiveness in continuous data collection and early detection of potential complications. Furthermore, Azimi et al. [15] proposed an IoT-based framework to assess sleep quality among pregnant women, emphasizing the role of smart devices in identifying health anomalies through personalized analytics.

### 2. Deep Learning in Fetal and Maternal Health Prediction

Deep learning techniques have shown significant promise in analyzing complex biomedical data. Zhao et al. [2] introduced a convolutional neural network (CNN)-based model for predicting fetal acidemia using fetal heart rate signals. Their approach demonstrated superior performance by capturing intricate temporal and non-linear patterns. This highlights the capability of deep learning models to extract meaningful insights from high-dimensional physiological data, outperforming traditional statistical approaches.

### 3. Adaptive and Intelligent Healthcare Systems

From a system design perspective, Kumar et al. [3] proposed a flexible and adaptive maternal health monitoring architecture capable of dynamically updating predictions based on real-time data. Such adaptability ensures personalized healthcare support throughout pregnancy. Complementing this, Kopanitsa et al. [11] emphasized the importance of Clinical Decision Support Systems (CDSS), which integrate structured and semi-structured healthcare data to assist clinicians in making accurate and timely decisions.

### 4. Machine Learning Models for Risk Prediction

Several studies have explored machine learning algorithms for predicting pregnancy-related complications. Bertini et al. [4] conducted a comprehensive review highlighting the effectiveness of models such as Support Vector Machines (SVM), Random Forest, and XGBoost. Their findings demonstrated that ML models can achieve high predictive accuracy when trained on diverse datasets. Similarly, Wang et al. [13] showed that integrating demographic and medical history data improves prediction performance, particularly in assisted reproductive scenarios.

### 5. Ensemble Learning and Data Preprocessing Techniques

Enhancing prediction accuracy through advanced techniques has been widely studied. Raza et al. [5] proposed an ensemble learning-based framework incorporating key physiological indicators such as blood pressure while addressing dataset imbalance issues. In addition, Rahman et al. [8] emphasized the importance of preprocessing techniques, demonstrating that normalization, cleaning, and transformation significantly improve classification performance, especially for SVM-based models.

### 6. Mobile Health (mHealth) Applications

Mobile health technologies have extended the accessibility of maternal healthcare systems. Moreira et al. [6] developed a smartphone-based maternal monitoring system using a Naive Bayes classifier for real-time decision-making. Additionally, Moreira et al. [10] proposed an SVM-based preterm birth prediction model designed for mobile platforms. These approaches highlight the importance of lightweight, scalable solutions that can operate effectively in resource-constrained environments.

### 7. Prediction of Specific Pregnancy Complications

Targeted prediction of pregnancy-related complications has been a major research focus. Jhee et al. [7] developed a stochastic gradient boosting model for early detection of pre-eclampsia, incorporating biological markers for improved accuracy. Similarly, Bruno et al. [14] applied logistic regression models to identify severe maternal complications, achieving strong discriminative performance as indicated by high AUC values.

### 8. Sensor-Based Monitoring Systems

Sensor-based frameworks provide real-time insights into maternal health conditions. Allahem et al. [12] introduced a system that monitors uterine activity using wearable sensors to detect premature labor risks. By integrating sensor networks with mobile applications, the system generates real-time alerts based on personalized thresholds, enabling proactive intervention.

### 9. Role of Artificial Intelligence in Maternal Healthcare

Artificial intelligence plays a transformative role in modern maternal healthcare systems. Mapari et al. [9] highlighted how AI-driven approaches enable early detection of complications, personalized treatment planning, and remote monitoring. These advancements significantly improve healthcare accessibility and efficiency, particularly in underserved regions.

## 3. Proposed System

This research focuses on building a decision-support tool for healthcare providers to identify pregnancy-related risks early as shown Figure 2. By processing clinical vitals through a multi-layered computational framework, it classifies patients into "Low," "Mid," or "High" risk categories.

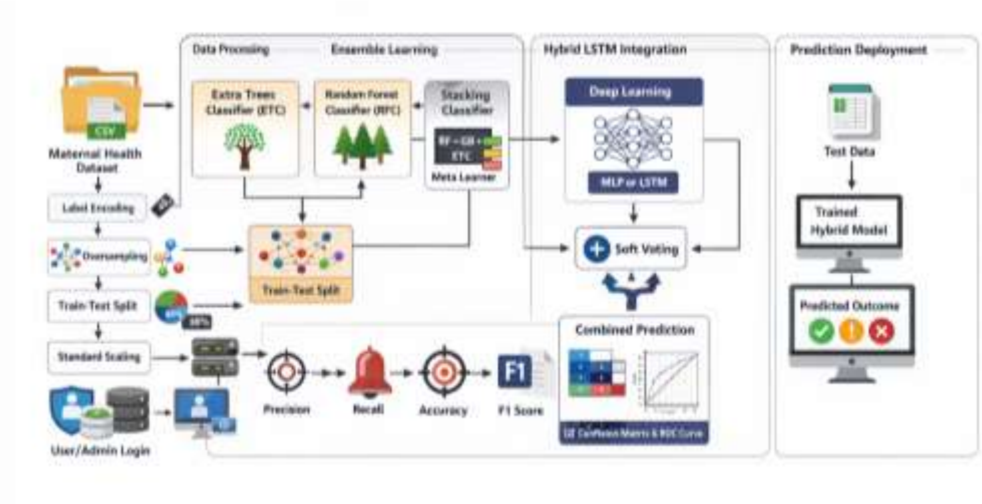



Figure. 2: Proposed MHRSSS architecture.

### 1. Data Processing Pipeline

The system begins by loading a dataset containing patient vitals (Age, Systolic/Diastolic Blood Pressure, Blood Sugar, Body Temperature, and Heart Rate). It employs SMOTE to balance the dataset. In maternal health, "High Risk" cases are often the minority; without SMOTE, the model might fail to learn the specific patterns of these critical cases.

### 2. The Hybrid Modeling Strategy

The "Stacked LSTM-Ensemble" framework is the core innovation. Instead of relying on a single algorithm, it combines three distinct approaches:

- **Ensemble Learning:** It uses RFC and GBC as base learners. These are "bagging" and "boosting" methods that look at the data from different statistical angles.
- **Long Short-Term Memory (LSTM):** This is a type of Recurrent Neural Network (RNN) designed to capture complex, non-linear dependencies. While LSTMs are famous for time-series data, here they act as a deep-feature extractor for clinical vitals.
- **Stacking (Meta-Learning):** An ETC acts as the "final judge" (meta-learner). It takes the predictions from the RFC, GBC, and LSTM and learns which model to trust more for specific types of patient data.

### 3. User Experience & Application Roles

The project is wrapped in a Graphical User Interface (GUI) built with Tkinter, featuring two distinct access levels:

1. **Admin:** Responsible for system maintenance. They handle data uploading, trigger the SMOTE analysis, and train the models.
2. **User:** Focuses on clinical application. They use the "Prediction" module to upload new, unseen patient records and receive immediate risk assessments.

**4. Performance Evaluation**

To ensure the system is medically safe, it generates a confusion matrix and performance graphs. It evaluates the framework using four key metrics: accuracy, precision, recall, and F1-score. High recall is particularly prioritized here, as missing a "High Risk" case (a false negative) is the most dangerous outcome in maternal healthcare.

**4. Dataset description**

The dataset used for this project was collected from maternal health records and IoT-enabled devices, focusing on key medical attributes that influence maternal well-being. It includes medical, demographic, and physiological parameters that help in assessing the risk of maternal complications during pregnancy. The dataset was cleaned, normalized, and divided into training and testing sets for model development.

The dataset typically contained the following attributes:

- **Age (years):** Represents the age of the mother, as maternal risks increase with higher or lower age ranges.
- **Systolic Blood Pressure (mmHg):** Indicates the pressure in arteries during heartbeats. High or low values are linked to complications.
- **Diastolic Blood Pressure (mmHg):** Measures arterial pressure between heartbeats. Abnormal values affect maternal health.
- **Blood Sugar Level (mg/dL):** Helps detect gestational diabetes, a common pregnancy risk factor.
- **Body Temperature (°C):** Monitored for early detection of infections and abnormalities.
- **Heart Rate (bpm):** Provides insights into maternal and fetal health conditions.
- **Risk Level (Target Variable):** Categorized as Low, Mid, or High Risk, which is the outcome predicted by the model.

**4.1 Result analysis**

Result analysis is a crucial stage in any study or experiment, as it involves interpreting the collected data to draw meaningful conclusions. It helps in identifying patterns, relationships, and trends within the results. Through analysis, raw data is transformed into useful information that supports or refutes the research objectives. This process also allows researchers to evaluate the accuracy and reliability of their findings. By comparing expected outcomes with actual results, one can determine the success or limitations of the study. Additionally, result analysis aids in making informed decisions and recommendations for future research or practical applications.

The figure 3 depicts that the first count plot (before SMOTE) shows an imbalanced distribution of maternal risk categories where one class contains significantly more samples than the others, indicating that the dataset is biased toward a particular risk level. Such imbalance can negatively affect model learning because the classifier may favor the majority class and ignore minority risk cases. After applying SMOTE, the second plot demonstrates that all three categories (high, mid, and low risk) become approximately equal in count, meaning synthetic samples were generated for minority classes to balance the dataset. This balancing improves model fairness and enables the machine learning and hybrid LSTM models to learn patterns from all risk levels effectively, resulting in more reliable prediction performance.

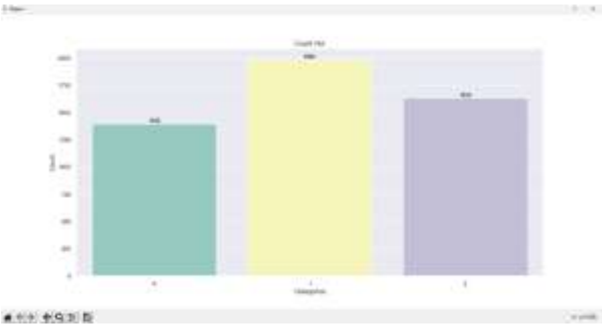
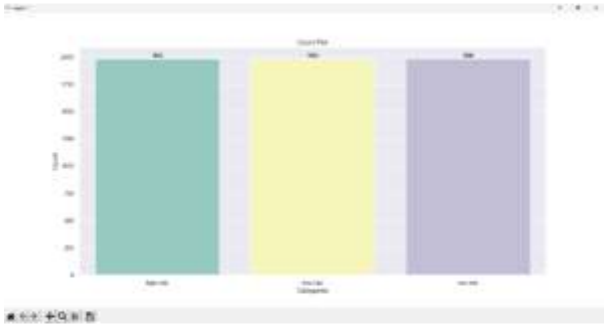


Figure. 3:



Count plots obtained before and after smote

The figure 4 shows confusion matrix of the proposed Hybrid stacked LSTM-ensemble model demonstrates very high classification performance across all maternal risk categories. Almost all high-risk, mid-risk, and low-risk samples are correctly predicted, with only a very small number of misclassifications occurring between neighboring classes. The diagonal values are extremely dominant compared to the off-diagonal elements, indicating that the hybrid fusion of stacking ensemble and LSTM effectively captures complex relationships in the dataset. Unlike the individual machine learning models, the hybrid model significantly reduces confusion between risk levels and produces highly reliable predictions. This matrix confirms that the proposed approach provides superior accuracy and consistent maternal risk stratification.

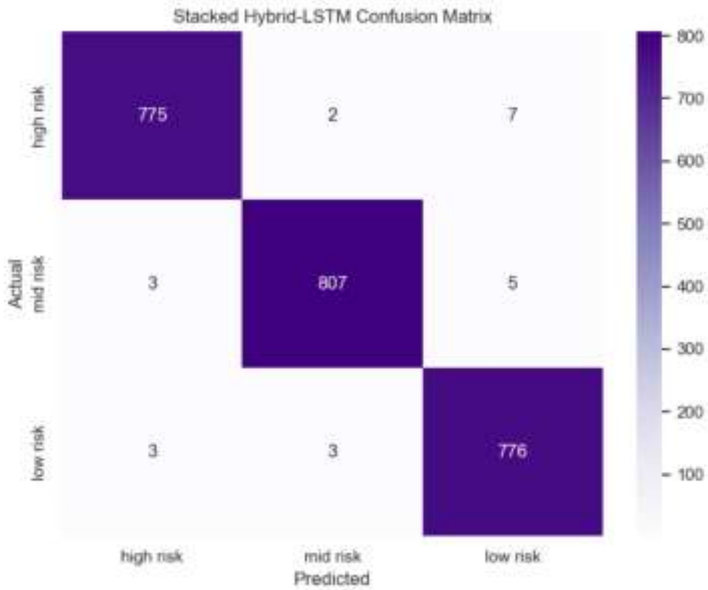



Figure. 4: Confusion matrix obtained using proposed hybrid stacked LSTM-ensemble model.

The performance comparison table 1 demonstrates a clear improvement in prediction capability when moving from traditional machine learning models to the proposed hybrid deep learning approach. The Random Forest Classifier shows the lowest performance, achieving around 70% accuracy with relatively lower precision and recall, indicating that it struggles to correctly distinguish maternal risk categories and produces more misclassifications. The Extra Trees Classifier performs significantly better, reaching approximately 88% across all evaluation metrics, which suggests stronger pattern learning and more balanced predictions across high, mid, and low risk levels. However, the proposed Hybrid stacked LSTM-ensemble model dramatically outperforms both conventional models by achieving about 99% accuracy, precision, recall, and F1-score. This near-perfect performance indicates that combining the stacking ensemble with the LSTM network effectively captures complex relationships in maternal health parameters and minimizes classification errors, making it the most reliable model for maternal risk stratification.

Table 1: Obtained quality metrics using existing and proposed models.

| **Algorithms Name** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **ETC** | 88.23% | 88.08% | 88.11% | 88.11% |
| **RFC** | 70.36% | 69.72% | 67.72% | 70.01% |
| **Hybrid Stacked LSTM-Ensemble** | 99.03% | 99.03% | 99.03% | 99.03% |

## 5. Conclusion

The development of the MHRSS marks a significant advancement in the application of artificial intelligence within the healthcare domain. By shifting from traditional, static rule-based assessments to a dynamic, data-driven approach, this project successfully addresses the complexities of pregnancy-related clinical monitoring. The core innovation, the Proposed Hybrid Stacked LSTM-Ensemble Framework, demonstrates the power of combining classical machine learning with deep learning architectures. The experimental results validate this approach, as the proposed framework achieved an exceptional Accuracy of 99.03%, significantly outperforming standalone models like Extra Trees Classifier (88.23%) and Random Forest Classifier (70.36%). The consistent Precision, Recall, and F1-Score of 99.03% indicate that the model is highly reliable and balanced, successfully minimizing dangerous false negatives through the integration of SMOTE for class balancing. Ultimately, this system provides a robust, scalable, and objective "second opinion" for healthcare practitioners. By facilitating real-time, high-precision risk detection, the project contributes to earlier clinical interventions, effectively reducing potential complications and moving a step closer to the global goal of improving maternal survival rates and neonatal outcomes.

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