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A Stacked LSTM-Ensemble Framework for Real-Time Maternal Health Risk Stratification System

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ABSTRACT

Maternal mortality and morbidity remain significant global public health challenges, particularly in low-resource settings where timely clinical intervention is often hindered by delayed risk detection. Traditional risk assessment methods rely heavily on manual triage and static clinical thresholds, which frequently fail to capture the complex, non-linear physiological patterns associated with pregnancy-related complications. The research proposes a stacked LSTM-ensemble framework for a real-time Maternal Health Risk Stratification System (MHRSSS). The system utilizes a dataset of maternal vitals, including age, blood pressure, blood glucose, and heart rate. To address inherent data imbalances, the Synthetic Minority Over-sampling Technique (SMOTE) was employed, ensuring robust sensitivity toward high-risk cases. The core architecture implements a hybrid approach, combining a stacking ensemble (utilizing random forest and gradient boosting) with a Long Short-Term Memory (LSTM) neural network. The final classification is determined through a soft-voting probability fusion mechanism. Experimental results demonstrate that the proposed hybrid framework significantly outperforms standalone models, achieving an accuracy, precision, recall, and F1 score of 99.03%, compared to 88.23% for the Extra Trees Classifier (ETC) and 70.36% for the Random Forest Classifier (RFC). The system is deployed via a user-friendly Tkinter GUI, providing healthcare practitioners with a reliable, real-time tool for objective risk stratification, thereby facilitating early medical intervention and improving maternal health outcomes.

Key words: Risk stratification, maternal health, long-short-term memory, clinical thresholds, physiological patterns.

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1. INTRODUCTION

Maternal health risk (MHR) includes factors that can lead to unfavorable outcomes before and after childbirth and is closely linked to maternal mortality. It is critical to identify and handle this risk to prevent complications that may result in maternal death. Premature mortality emphasizes taking proactive steps to reduce risks during pregnancy. In contrast, postpartum concerns recognize that risks to a mother's health continue after childbirth and work to maintain her well-being. Reducing maternal death rates and improving overall maternal health requires effective risk management along the spectrum. Maternal health is a global crisis, and every day, 830 women die from pregnancy- or childbirth-related complications. Shockingly, 2.7 million newborns die within their first 4 weeks out of 130 million annual births. Accessible contraception and improved birth spacing can reduce maternal mortality by 30% and child mortality by 20% (World Health Organization, 2021). Approximately 287,000 women died

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due to complications related to pregnancy and childbirth in 2020, with 95% of these deaths occurring in low- and lower-middle-income countries. The majority of maternal deaths occur in Sub-Saharan Africa and Southern Asia, accounting for around 87% of the global total. A growing focus has recently been on investigating automated and computerized methods for determining MHR.

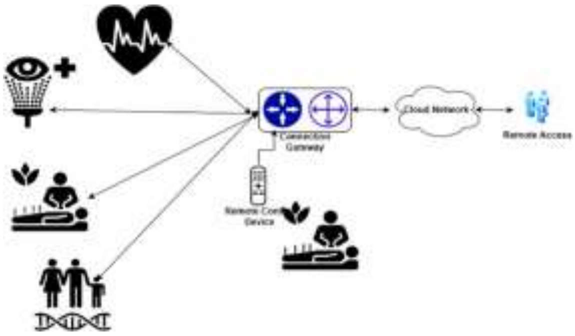

Figure 1. Remote health monitoring system using IoT sensor data.

Thus, this research aims to build an automated system for MHR prediction by utilizing transfer learning (TL). TL is well known for providing accurate and easily understandable diagnostic information, making it a favored tool in medical research.

2. LITERATURE SURVEY

Recent development of AI and ML has brought paradigmatic changes in maternal healthcare. Technology has huge potential in improving diagnostic accuracy, personalized care, and unequal access to health. For instance, Mapari et al. [1] identified that AI made the key contribution to complications being detected early, treatment being performed in an individualized manner, and patient monitoring being performed from a distance. Further, Bertini et al. [2], through a review of 31 studies on the application of ML models for prediction of perinatal complications, reported performances of up to 95.7% and 99.7%, respectively, with SVM and XGBoost for neonatal mortality. This evidence the capability of ML in exploiting electronic medical records, medical imaging, and biological markers for predictive modeling. Bruno et al. [3] developed logistic regression models to predict severe maternal morbidity with an AUC of 0.937. Equally, Jhee et al. [4] developed a stochastic gradient boosting method for the early onset of pre-eclampsia with biological markers at a highly cited AUC value of 0.924 and an accuracy of 97.30%. Also, stretching further into fetal health, deep learning-based convolutional neural networks proposed by Zhao et al. [5] were used for the prediction of fetal acidemia. An excellent AUC of 0.978 and accuracy of 98.4% were observed in explaining the complex physiologic analytes. Other applications involve the usage of ML for risk management rather than simple prediction.

Kopanitsa et al. [6] described CDSSs for early risk identification in pregnancy, emphasizing the role high-value and interpretable models play within this process of decision-making support. These systems leverage structured and semistructured datasets; therefore, they provide complete support not only to the care of patients but also to health organization management. Examples of more specific applications of ML to obstetric care include preterm birth prediction. Moreira et al. [7] developed an SVM-based system suitable for mobile health applications, featuring high predictive accuracy. Another good example is presented by Wang et al. [8], who proposed the use of ML for predicting complications in pregnancies achieved with the help of assisted reproduction techniques. They mentioned that demographic and medical history data need to be integrated in order to improve model results. In this regard, Raza et al. [9] came up with another proposal of an ensemble learning-based feature engineering approach in the area of maternal health risk analysis, considering major risk factors such as systolic

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and diastolic blood pressure. Their paper underlined the importance of handling class imbalances of the dataset for dependable predictions. Complementing these findings,

Rahman et al. (2024) [10] illustrated, with specific tasks, how preprocessing could enhance the performance of the SVM in the classification of health risks and ensure significant improvement in accuracy. Allahem et al. [11] proposed a framework to monitor pregnant women with high risks of premature birth. They aimed to reduce preterm birth by collecting uterine contractions through a body sensor and informing women via a mobile application if the collected information was above some personalized thresholds. In [12], the authors used a smartphone-based system enabled by a Naive Bayes Classifier, performing real-time decision-making.

Wearable devices have also been utilized to collect maternal health parameters continuously. In [13], a model is proposed for hypertension monitoring during pregnancy. In this study, a commercial wristband was leveraged to monitor heart rate, step count, and sleep. The proposed model was evaluated in a healthcare center for three months. Pregnant women were satisfied with this model, as they could monitor their own health in a non-invasive way. In [14], the authors presented an IoT-based monitoring system for objective sleep quality assessment. They used a smart wristband to collect sleep information from mothers continuously and provide a personalized model indicating the degradation of sleep quality according to each person's data. Kumar et al. [15] proposed an architecture for health monitoring during pregnancy, considering the needs for adaptation of the system based on collected health data. Grym et al. [16] also evaluated the feasibility of using a smart wristband by conducting a case study on maternal health to monitor 20 pregnant women for seven months.

3. PROPOSED SYSTEM

The research focuses on building a decision-support tool for healthcare providers to identify pregnancy-related risks early, as shown in Fig. 2. By processing clinical vitals through a multi-layered computational framework, it classifies patients into "Low," "Mid," or "High" risk categories. The system begins by loading a dataset containing patient vitals (age, systolic/diastolic blood pressure, blood sugar, body temperature, and heart rate). It employs Synthetic Minority Over-sampling Technique (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.

Figure 2. Proposed MHRSSS architecture.

Initially, data cleaning is performed by removing rows with missing values dataset.dropna(inplace=True) to avoid inaccurate predictions caused by incomplete medical records. Next, the dataset is separated into features (X), which include clinical parameters such as age, blood pressure, and heart rate, and the target variable (y), which represents the risk level to be predicted. Since machine learning models cannot process

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textual data directly, categorical values like "High Risk," "Mid Risk," and "Low Risk" are converted into numerical form using label encoding. To address class imbalance where low-risk cases are more common than high-risk ones—the SMOTE technique is applied to generate synthetic samples of minority classes and balance the dataset. After balancing, the dataset is divided using train_test_split into 80% training data for model learning and 20% testing data for evaluation. Finally, for the LSTM model, the input data is reshaped from a 2D format to a 3D structure (samples, time steps, features) using np.reshape, enabling the deep learning model to process the sequential input format properly. Model building and training focus on creating a robust classification system to predict maternal health risks accurately. The framework utilizes a combination of traditional machine learning and deep learning to capture both statistical trends and complex non-linear patterns. By leveraging SMOTE to balance the training data, the models are trained to be equally sensitive to all risk categories, specifically ensuring that "High Risk" cases are not overlooked. Each model is evaluated using a cross-section of performance metrics to ensure clinical reliability before deployment.

4. RESULT ANALYSIS

Figure 3 shows the login page served as the entry point to the system, providing separate access for both administrators and users. Administrators had the privilege to upload datasets, initiate training, and analyze models, while users directly accessed the prediction module. The interface ensured secure access and role-based functionality, streamlining the workflow of the project.

Figure 3. MHRSS Graphical user interface

Figure 4 shows that after the admin logs into the system using SQL authentication, the upload dataset interface is displayed. In this screen, the administrator selects the maternal healthcare CSV dataset from the local storage, and the system successfully loads and previews the records in the text panel. The displayed table confirms that features such as age, systolic BP, diastolic BP, body temperature, heart rate, and risk level are properly read by the application. This step verifies data availability before preprocessing and model training. It ensures that only authorized users can supply training data to the prediction system.

Figure 4. Upload dataset interface after admin login

Figure 5 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

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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.

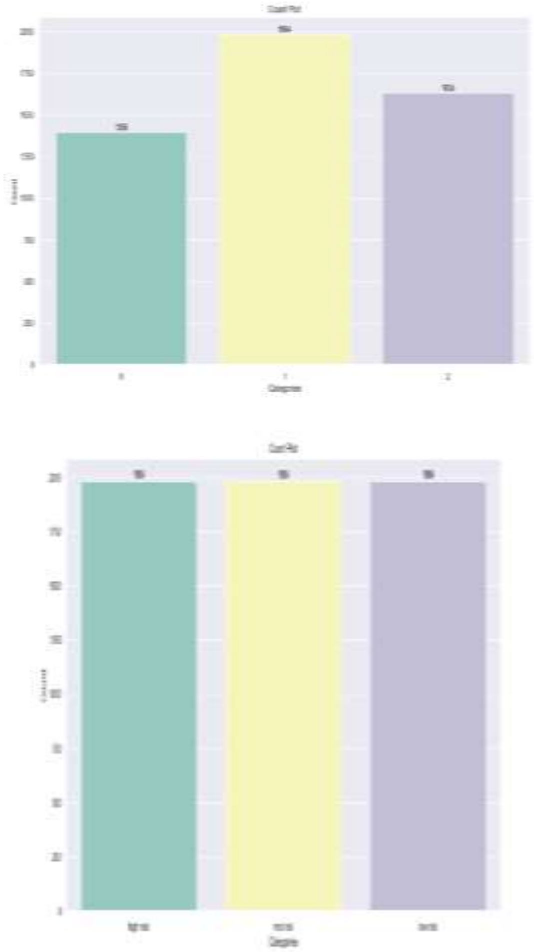

Figure 5. Count plots obtained before and after SMOTE.

Figure 6 shows the confusion matrix of the proposed hybrid stacked LSTM-ensemble model, which 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. Overall, this matrix confirms that the proposed approach provides superior accuracy and consistent maternal risk stratification.

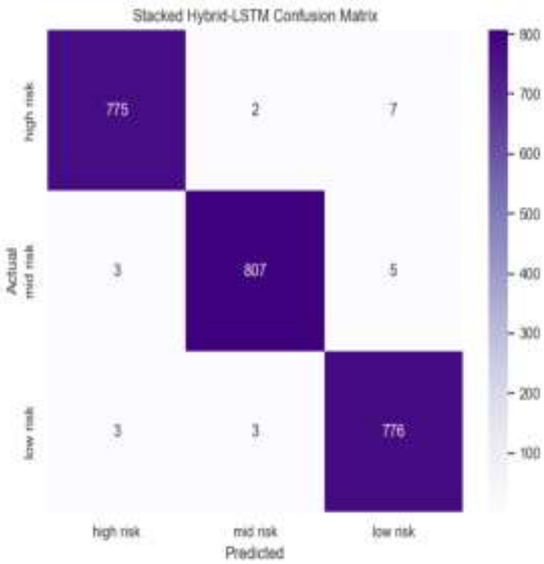

Figure 6. Confusion matrix obtained using the proposed hybrid stacked LSTM-ensemble model.

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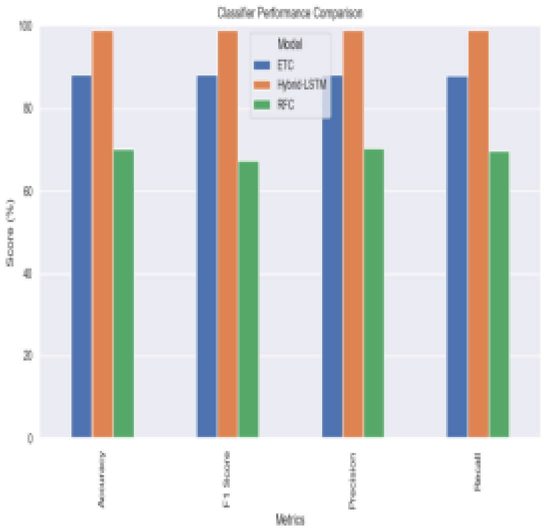

Figure 7. Performance comparison graph of existing and proposed models.

Figure 7 shows a performance comparison graph, clearly illustrates the effectiveness of the proposed hybrid stacked LSTM-ensemble model against the ETC and RFC across accuracy, precision, recall, and F1-score metrics. The hybrid stacked LSTM-ensemble model consistently achieves nearly perfect scores, close to 99%, in all evaluation measures, indicating highly reliable and balanced predictions for maternal risk levels. The ETC model performs moderately well, maintaining values around 88%, which shows good classification capability but still with noticeable prediction errors. In contrast, the RFC model records the lowest performance, with values near 70%, demonstrating weaker discrimination between risk categories. The graph visually confirms that integrating ensemble learning with deep learning significantly enhances prediction accuracy and stability compared to traditional machine learning approaches.

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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