International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
Peer Reviewed, Referred & Indexed Journal
ISSN: 3068-272X www.ijdim.com Original Research Paper

A Hybrid Deep–Ensemble Intelligence Framework for Early Stratification of Pregnancy-Associated Risk Dynamics

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ABSTRACT

Maternal health complications are still a major concern worldwide, particularly in areas with limited medical resources where early risk identification is difficult. Existing methods mostly depend on manual checks and fixed threshold values, which often miss the complex and changing patterns seen during pregnancy. The system works with important health indicators such as age, blood pressure, glucose levels, and heart rate. To ensure that high-risk cases are properly identified, SMOTE is applied to balance the dataset. The model integrates a stacking approach, using RFC and GBC, along with an LSTM network to capture deeper patterns in the data. The final prediction is obtained by merging the outputs of both components through a soft voting method. The results show that this combined approach performs significantly better than individual models, achieving 99.03% accuracy along with equally strong precision, recall, and F1-score, while ETC and RFC achieve lower performance. The system is also designed with a simple Tkinter interface, making it easy for healthcare professionals to use it in real-time. This solution supports quicker and more accurate decision-making, helping doctors take early action and improve outcomes for both mothers and babies.

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

1. INTRODUCTION

Maternal Health Risk (MHR) refers to the various conditions and factors that can negatively affect a woman's health during pregnancy, childbirth, and even after delivery. These risks are strongly connected to maternal mortality, making early identification and proper management extremely important. If these risks are not detected and addressed on time, they can lead to serious complications or even death. It is therefore essential to take preventive measures throughout pregnancy, while also recognizing that a mother's health remains vulnerable even in the postpartum period. Ensuring continuous care before, during, and after childbirth plays a key role in improving both maternal and neonatal outcomes.

Despite advancements in healthcare, maternal health continues to be a major global challenge. Every day, hundreds of women lose their lives due to complications related to pregnancy and childbirth, highlighting the urgent need for better monitoring and intervention systems. In addition, millions of newborns fail to survive beyond the first few weeks of life, which further emphasizes the importance of timely medical care. Studies have shown that simple measures such as access to contraception and proper birth spacing can significantly reduce both maternal and child mortality rates. However, a large proportion of these deaths still occur in low- and middle-income countries, particularly in regions like Sub-Saharan Africa and South Asia, where access to quality healthcare services is limited.

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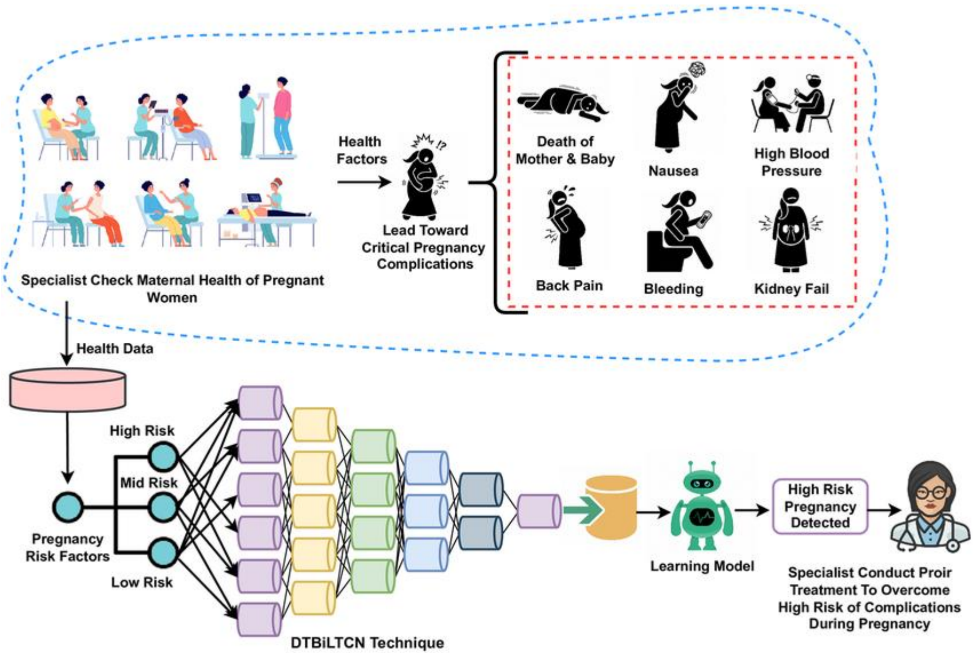

Figure 1. Maternal health risk analysis.

Reduction of maternal mortality, as global health data indicates that a large proportion of pregnancy-related complications can be prevented through early detection. Unlike traditional reactive approaches that respond only after complications arise, this system adopts a proactive strategy by predicting potential risks before they escalate into critical conditions. By automating the initial risk stratification process, the system empowers healthcare providers such as doctors and midwives to efficiently prioritize their attention, enabling them to focus more on patients identified as high risk, thereby improving timely intervention and overall maternal healthcare outcomes..

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 shows 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 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 operational flow of the proposed system begins with parallel processing, where the input data is simultaneously fed into both a Stacking Ensemble model and an LSTM network. Within the stacking layer, Random Forest (RFC) and Gradient Boosting Classifier (GBC) function as base learners, while the Extra Trees Classifier (ETC) serves as the meta-learner to combine and refine their predictions. In parallel, the deep learning layer utilizes the LSTM network to capture temporal dependencies and complex patterns within the data. As shown in figure 2 a soft voting (fusion) mechanism is applied, where the probability scores generated from both the stacking ensemble and LSTM components are averaged to produce a more accurate and reliable final risk assessment.

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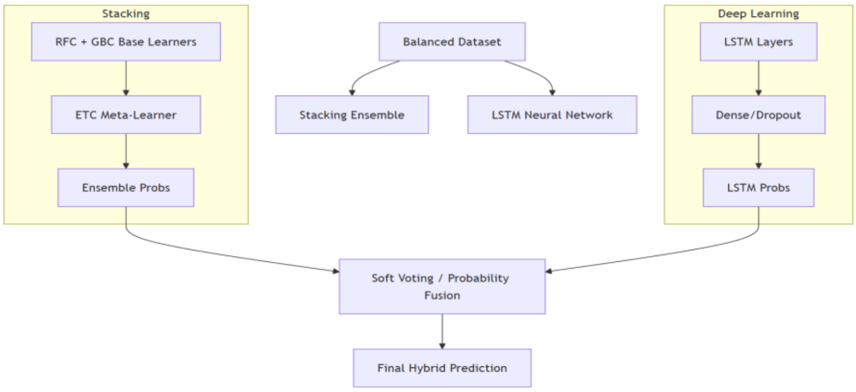

Figure 2. Proposed hybrid stack LSTM-ensemble workflow.

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 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 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.

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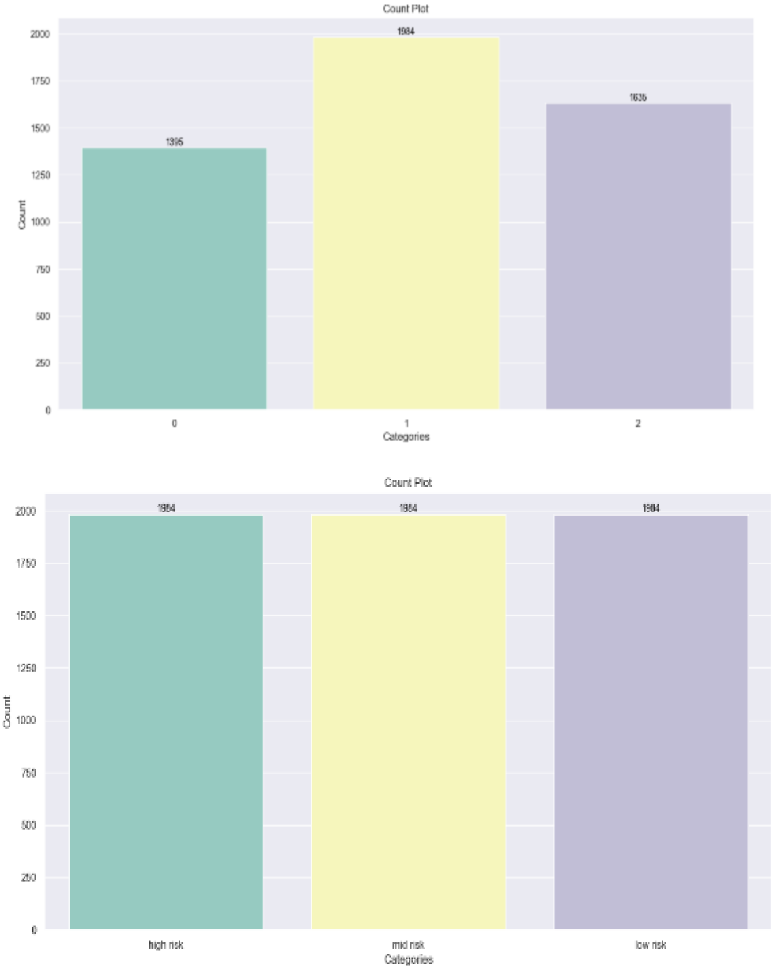

Figure 3. Count plots obtained before and after SMOTE.

Figure 4 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.

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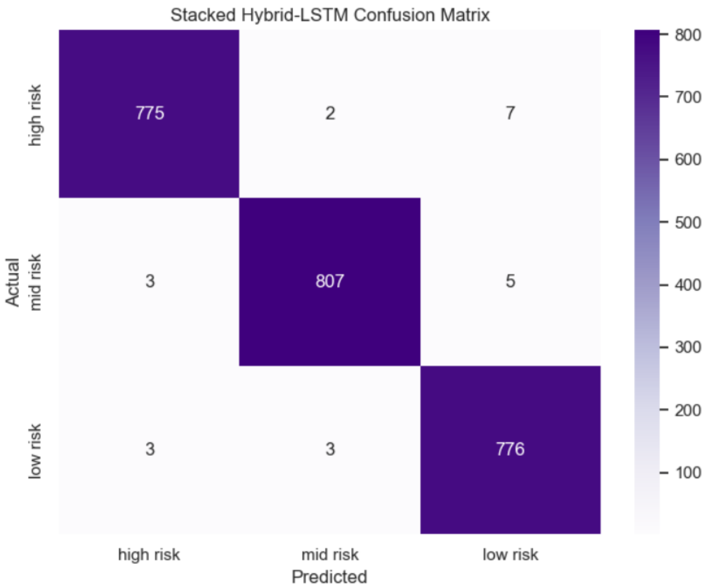

Figure 4. Confusion matrix obtained using the proposed hybrid stacked LSTM-ensemble model.

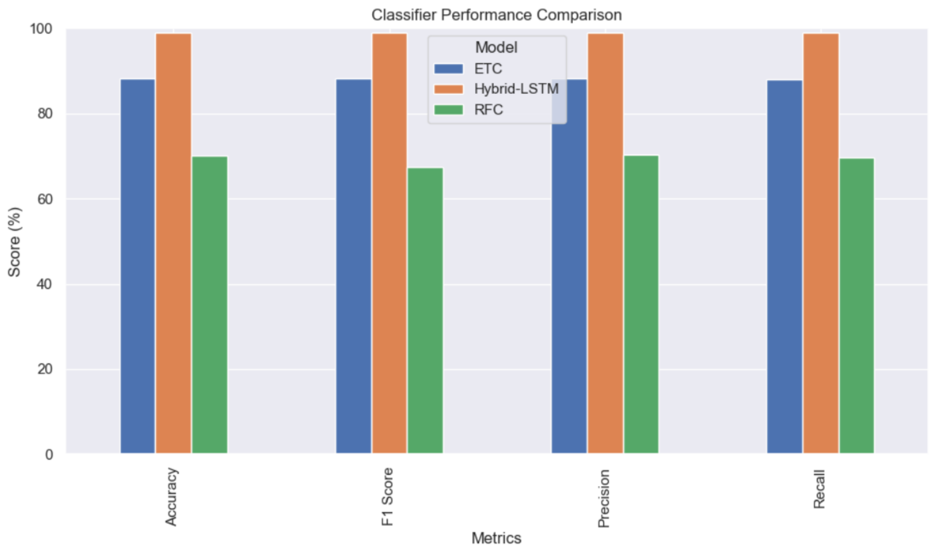

Figure 5. Performance comparison graph of existing and proposed models.

Figure 5 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 research represents an important step forward in using artificial intelligence for healthcare applications, especially in maternal health monitoring. Instead of relying on traditional rule-based methods, the study introduces a dynamic, data-driven approach that can better handle the complexity of pregnancy-related conditions. The proposed hybrid model, which combines a stacked ensemble with an LSTM network, highlights the strength of integrating machine learning and deep learning techniques. The results clearly support this approach, with the model achieving an impressive accuracy of 99.03%, significantly higher than individual models such as ETC (88.23%) and RFC (70.36%). Its high precision, recall, and F1-score show that the model is both accurate and well-balanced, effectively reducing critical errors like false negatives, aided by the use of SMOTE for handling class imbalance. Overall, the system acts as a reliable and scalable decision-support tool, offering healthcare professionals an additional layer of confidence. By enabling timely and accurate risk prediction, it helps support early medical intervention, ultimately contributing to improved maternal health and better outcomes for both mothers and newborns.

REFERENCES

[1]. Mapari, S.A.; Shrivastava, D.; Dave, A.; Bedi, G.N.; Gupta, A.; Sachani, P.; Pradeep, U. Revolutionizing Maternal Health: The Role of Artificial Intelligence in Enhancing Care and Accessibility. *Cureus* 2024, *16*, e69555.

[2]. Bertini, A.; Salas, R.; Chabert, S.; Sobrevia, L.; Pardo, F. Using Machine Learning to Predict Complications in Pregnancy: A Systematic Review. *Front. Bioeng. Biotechnol.* 2022, *9*, 780389.

[3]. Bruno, V.; D'Orazio, M.; Ticconi, C.; Abundo, P.; Riccio, S.; Martinelli, E.; Rosato, N.; Piccione, E.; Zupi, E.; Pietropolli, A. Machine Learning-Based Methods Applied in Recurrent Pregnancy Loss Diagnostic Work-Up: A Potential Innovation in Common Clinical Practice. *Sci. Rep.* 2020, *10*, 7970.

[4]. Jhee, J.H.; Lee, S.; Park, Y.; Lee, S.E.; Kim, Y.A.; Kang, S.W.; Kwon, J.Y.; Park, J.T. Prediction Model Development of Late-Onset Preeclampsia Using Machine Learning-Based Methods. *PLoS ONE* 2019, *14*, e0221202.

[5]. Zhao, Z.; Deng, Y.; Zhang, Y.; Zhang, Y.; Zhang, X.; Shao, L. DeepFHR: Intelligent Prediction of Fetal Acidemia Using Fetal Heart Rate Signals Based on Convolutional Neural Network. *BMC Med. Inform. Decis. Mak.* 2019, *19*, 286.

[6]. Kopanitsa, G.; Metsker, O.; Kovalchuk, S. Machine Learning Methods for Pregnancy and Childbirth Risk Management. J. Pers. Med. 2023, 13, 975.

[7]. Moreira, M.W.L.; Rodrigues, J.J.P.C.; Marcondes, G.A.B.; Neto, A.J.V.; Kumar, N.; Diez, I.D.L.T. A Preterm Birth Risk Prediction System for Mobile Health Applications Based on the Support Vector Machine Algorithm. In Proceedings of the 2018 IEEE International Conference on Communications (ICC), Kansas City, MO, USA, 20–24 May 2018; pp. 1–5.

[8]. Wang, C.; Johansson, A.L.V.; Nyberg, C.; Pareek, A.; Almqvist, C.; Hernandez-Diaz, S.; Oberg, A.S. Prediction of Pregnancy-Related Complications in Women Undergoing Assisted Reproduction, Using Machine Learning Methods. Fertil. Steril. 2024, 122, 95–105.

[9]. Raza, A.; Siddiqui, H.U.R.; Munir, K.; Almutairi, M.; Rustam, F.; Ashraf, I. Ensemble Learning-Based Feature Engineering to Analyze Maternal Health During Pregnancy and Health Risk Prediction. PLoS ONE 2022, 17, e0276525.

[10]. Rahman, M.A.; Noor, R.M.; Mallik, S.; Santa, N.K.; Deb, S.; Pathak, A. Classification of Health Risk Levels for Pregnant Women Using Support Vector Machine (SVM) Algorithm. IOSR J. Comput. Eng. 2024, 26-7, 17.

[11]. Allahem, H.; Sampalli, S. Framework to monitor pregnant women with a high risk of premature labour using sensor networks. In Proceedings of the 2021 IFIP/IEEE Symposium on Integrated Network and Service Management (IM), Lisbon, Portugal, 8–12 May 2021; pp. 1178–1181.

[12]. Moreira, M.W.; Rodrigues, J.J.; Oliveira, A.M.; Saleem, K. Smart mobile system for pregnancy care using body sensors. In Proceedings of the 2022 International Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT), Cairo, Egypt, 11–13 April 2022; pp. 1–4.

[13]. Lopez, B.D.B.; Aguirre, J.A.A.; Coronado, D.A.R.; Gonzalez, P.A. Wearable technology model to control and monitor hypertension during pregnancy. In Proceedings of the 2018 13th Iberian Conference on Information Systems and Technologies (CISTI), Caceres, Spain, 13–16 June 2018; pp. 1–6.

[14]. Azimi, I.; Oti, O.; Labbaf, S.; Niela-Vilén, H.; Axelin, A.; Dutt, N.; Liljeberg, P.; Rahmani, A.M. Personalized Maternal Sleep Quality Assessment: An Objective IoT-based Longitudinal Study. *IEEE Access* 2019, *7*, 93433–93447.

[15]. Kumar, S.; Gupta, Y.; Mago, V. Health-monitoring of pregnant women: Design requirements, and proposed reference architecture. In Proceedings of the 2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 11–14 January 2019; pp. 1–6.

[16]. Grym, K.; Niela-Vilén, H.; Ekholm, E.; Hamari, L.; Azimi, I.; Rahmani, A.; Liljeberg, P.; Löyttyniemi, E.; Axelin, A. Feasibility of smart wristbands for continuous monitoring during pregnancy and one month after birth. *BMC Pregnancy Childbirth* 2019, *19*, 34