Child and Maternal Mortality Risk Factor Analysis Using Machine Learning Approaches

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Abstract— **Global attention is now being paid to maternal and child mortality. The incidence of maternal mortality is high in low and middle-income countries, particularly among adolescents and young adults. Healthcare professionals can monitor the mother's heartbeat during pregnancy to determine fetal viability using CTGs to prevent these deaths. To reduce child and maternal mortality, this work presented a risk factor analysis using machine learning approaches. As part of this study, this work evaluated seven machine learning algorithms. To assess the performance of different categorization algorithms, accuracy, precision, and recall were used. The random forest has achieved the highest 99.98% accuracy among the other algorithms. Initially, the dataset was imbalanced, after applying undersampling and oversampling methods, all algorithms performed excellently. A major focus of the present study was to predict the risk factor of child and maternal mortality using clinical data. Sending an ultrasound pulse and reading the response is how ultrasound devices work. To prevent child and maternal mortality, this analysis is an effective and cost-effective option for healthcare professionals.**

Keywords— maternal mortality, child mortality, CTG, machine learning, healthcare, risk factor, fetal health.

I. INTRODUCTION

One of humanity's greatest health problems is the child and maternal mortality, which accounts for almost all infant and maternal deaths worldwide. Women's health and human rights are highly influenced by it. It is more common for women in low- and middle-income countries to die from maternal diseases. According to the World Health Organization, there were an estimated 295000 deaths among women during pregnancy and childbirth worldwide; one quarter occurred in low-resource settings [1]. The UN Sustainable Development Goal 16, which aims to stop premature childbirth, stillbirths, and preterm births, also emphasizes this. In 2030, the UN estimates that countries must reduce maternal mortality to 10 per 100000 births. In the world today, over 20% of women and children are malnourished, stunted, or suffer from vitamin A deficiency (VAD) [2].

Child and maternal mortality remain one of the most pressing health challenges facing humanity today. This tragic issue affects women's health and human rights, particularly in low- and middle-income countries where maternal diseases are more prevalent. One promising solution to this global health crisis is cardiotocography (CTG) [3], a cost-effective ultrasound technique that can help prevent child and maternal mortality. CTG monitors the unborn child's heart rate and sends an ultrasound pulse to read its response. By analyzing the resulting data, healthcare professionals can track the mature human heartbeat during pregnancy, providing vital information to determine fetal viability if complications arise during pregnancy or delivery [4]. The advent of machine learning has greatly impacted the field of cardiotocography, allowing for more accurate and efficient analysis of CTG data. By employing machine learning algorithms, researchers can delve deeper into the dataset and gain a better understanding of the complex factors that influence child and maternal mortality. These algorithms can help identify patterns and trends that may not be apparent to the human eye, enabling healthcare professionals to make more informed decisions and intervene earlier when necessary. In addition to improving the analysis of CTG data, machine learning can also enhance the overall quality of prenatal care. By leveraging vast amounts of data, machine learning models can predict potential complications and recommend personalized interventions for pregnant women [5]. These models can also assist healthcare providers in optimizing resource allocation, ensuring that pregnant women in low-resource settings receive the necessary care and support. The use of machine learning in cardiotocography and prenatal care holds immense potential for reducing child and maternal mortality rates. By integrating advanced algorithms and data-driven insights into medical practice, healthcare professionals can better identify, monitor, and address the risk factors associated with pregnancy and childbirth. Child and maternal mortality are a critical global health issue that disproportionately affects women in low- and middle-income countries. The application of cardiotocography, bolstered by the power of machine learning, offers a promising avenue for addressing this problem. By harnessing the insights and predictive capabilities of advanced algorithms, healthcare professionals can provide more effective prenatal care and interventions, ultimately reducing child and maternal mortality rates and contributing to the achievement of the UN's Sustainable Development Goals.

With cardiotocography (CTG), healthcare professionals can prevent child and maternal mortality in a cost-effective manner. This ultrasound technique also monitors the unborn child's heart rate and sends an ultrasound pulse to read its response. During pregnancy, the mature human heartbeat can be monitored using the resulting information. A viability test can assist in determining fetal viability if complications occur during pregnancy or delivery. The dataset has been examined in depth, so we have gained a better understanding of it. Additionally, this work has developed algorithms that reduce child and maternal mortality.

II. Literature Review

Rahmayanti et al. examined [6] how fetal health was compared with a machine learning algorithm after classification, based on heart rate data. It is based on a dataset from the UCI Machine Learning Repository. And their data set is a type of public dataset. There are 2,126 pregnant women's data in this set. Their dataset consists of 21 features used in CTG to measure FHR and UC. Five out of seven algorithms were very successfully tested (89-99% accurate) in three scenarios with a total of seven algorithms tested in that paper. LGBM is the only algorithm that provides reliable results in all three scenarios.

Afridi and et al. studied [7] how cardiography data and known classifiers can be used to analyze fetal heart rate. A training set and a testing set are well separated in the datasets. Characteristic measurements of FHR and uterine contractions were obtained in cardiograms on CTG. There were also 23 traits associated with this and 2126 examples aligned into three embryonic states. Each cardiogram was graded by obstetricians and a consensus classification level was assigned. Their study achieved 85.50% f-measure, 84.88% assurance, 94.60% accuracy, 85.90% recall, and 94.60% precision under certain conditions. A NB approach has yielded more promising results.

Amin and et al. used [8] rough neural networks to analyze the Cardiotocography Classification. There are many different types of data mining algorithms used in their study such as RNNs, neural networks, decision tables, bagging, nearest neighbour, decision tree and support vector machines. The RNN algorithm provides high accuracy and low time consumption. The RNN is 92.95 percent accurate. The dataset comes from the UCI Machine Learning Repository. A dataset of 2126 samples of fetal health is used in their research. There are 21 attributes in the dataset. To improve accuracy and remove irrelevant features, they plan to apply other data mining techniques and selection algorithms in the future.

Comert et al. [9] used machine learning techniques for classifying fetal heart rate. Their study is based on 2126 instances of fetal health datasets. There are 21 features in the dataset. In this work, SVM, ELM, ANN, RBFN, and RF were used in this study. Based on the results of a 99.73% sensitivity and 97.94% specificity artificial neural network. It was found that the ANN performed better than other machine learning techniques in the study.

Mehbodnia et al. [10] analyzed cardiotocographic data using machine learning to classify fetal health. An automated fetal diagnosis framework based on machine learning is presented in this paper. In their dataset, 21 features are used, which are then preprocessed. The classification results clearly demonstrate that Random Forest outperforms all other classification algorithms. After SVM, the next highest performer had a 93% accuracy rate.

Bhowmik et al. analyzed [11] the data from cardiotocography to predict fetal health risks through tree-based ensemble learning. Data from CTG can be used to predict fetal well-being and make clinical decisions. A machine learning repository at UCI provided the data set used in this paper. There were 2126 observations in this data set. There are 1655 samples in the N-class, 295 samples in the S-class, and 176 samples in the P-class. Based on the Random Forest classifier algorithm, the accuracy rate was 93.46%. Using the same feature selection method and several features, this study improved by 2.59%.

The classification of fetal heart rates was analyzed by Krupa et al. [12] through the utilization of empirical mode decomposition and support vector machines. Two obstetricians with expertise in the field classified the datasets into two categories: 'normal' or 'at risk'. The cross-validation outcomes for the training dataset indicated an accuracy rate of 86%. A geometric mean of 94.8% was computed for the measures of sensitivity and specificity. Subsequent research endeavors will employ the suggested approach to fetal heart rate (FHR) signals of varying durations and integrate numerous classifications.

Warmerdam et al. evaluated [13] the contraction-dependent fetal heart rate variability can be used to detect distress in fetuses. In the second stage of labor, it examines whether separating contractions and rest periods improves the rate of detecting HRV features associated with fetal distress. An analysis of 100 recordings containing 20 adverse outcome fetuses was conducted by the authors. Using support vector machines, a genetic algorithm selected the most informative HRV features. There was an improvement in classification performance from 70% to 79% for segments closest to birth.

Das and et al. evaluated [14] the process for detecting periodic changes in fetal heart rate. It simultaneously records the Fetal Heart Rate (FHR) and the Uterine Contraction Pressure (UCP) of the mother. In the article, the authors propose methods to identify periodic changes, such as acceleration and deceleration. A data set of 556 CTG data was analyzed to find 987 accelerations and 1755 decelerations. For acceleration and deceleration, the three clinicians' estimates agreed 96.6% and 97.3%. In addition, they proposed a method for detecting Sinusoidal Heart Rates. SHR classification accuracy was 93% using Random Forests. There was 93% sensitivity and 86% specificity, and a 100% Positive Predictive Value (PPV) and Negative Predictive Value (NPV).

Garcia-Canadilla and et al. studied [15] the use of machine learning in the field of fetal cardiology. The authors review the potential of ML techniques to improve fetal cardiac function evaluations by improving image acquisition, quantification and segmentation, and aiding in the diagnosis of fetal cardiac abnormalities and remodeling during pregnancy.

III. Proposed Methodology

The importance of a child to a mother is the same as that of the child to that mother. The key objective of this research is to keep them both healthy. Fig. 1 illustrates the proposed model workflow of this research.

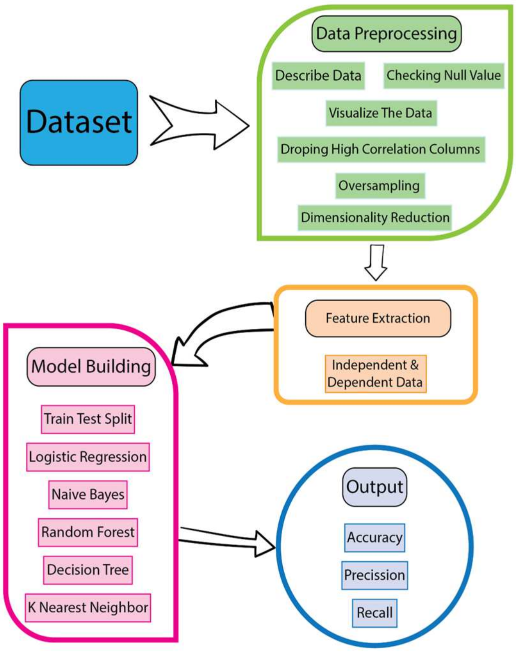

Fig.1. Proposed model workflow

This work preprocessed the raw data to ensure it is suitable for implementing various algorithms. After analyzing the data, it extracted relevant features to facilitate machine learning algorithms. To predict fetal health rates, here seven machine learning algorithms have used, including Logistic Regression[16], Naive Bayes [17], Decision Trees [18], Random Forests [19], K Nearest Neighbors [20], XGBoost [21], and Support Vector Machines [22]. The models were trained and evaluated using appropriate performance metrics to ensure accuracy and reliability. This workflow is designed to provide accurate and efficient fetal health monitoring, enabling healthcare providers to intervene promptly if necessary and ultimately improve pregnancy outcomes. As we continue to gather more data, this research aims to refine our models and further enhance the system's capabilities to meet the evolving needs of pregnant women and their healthcare providers.

A. Data Collection and Pre-Processing

The dataset used in this study was obtained from Kaggle [23], a public dataset repository. It is a combination of two datasets that each contain 2,126 and 1,488 records about pregnant women who are in their third trimester. The cardiotocography collection includes 21 characteristics for measuring fetal heart rate (FHR) and uterine contractions (UC). CTG Baseline heart rate, baseline variability, number of accelerations per second, number of early, late, variable, prolonged decelerations per second, and sinusoidal patterns are the most important factors in determining the fetal state based on FHR, as recommended by the National Institute of Child Health and Human Development. Uterine contractions can be diagnosed based on their intensity, regularity, length, and normal uterine tone [24]. Three obstetrics specialists rated the expectant women's CTG findings, and their opinions were used as the benchmark for further analysis. SisPorto 2.0 was used to conduct automated analysis of the CTG data. [25].

The dataset under consideration does not contain any missing values. The dataset was partitioned into two distinct components, namely x and y. The former represents the complete set of independent variables, while the latter denotes the dependent variable, specifically fetal health. In Fig. 2 visualizes the number of samples of each class.

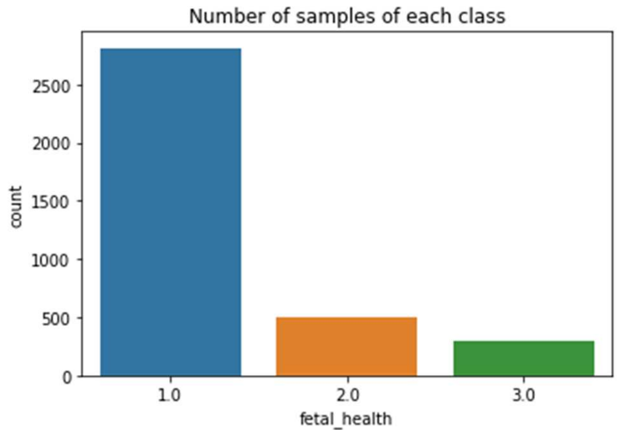

Fig. 2. Number of samples of each Class

As we can see from Fig. 2 the count plot of the dataset reveals a significant imbalance. Fig. 3 shows the results of the analysis of the characteristics with the highest interaction.

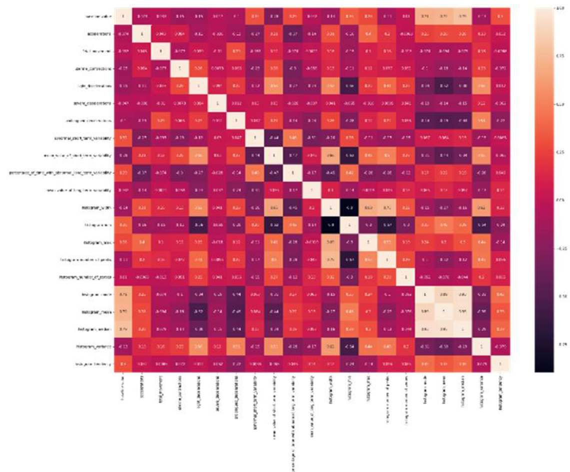

Fig. 3. Graphical representation of all features

The heatmap illustrates a strong correlation between the mean, median, and mode of the histogram. The decision has been made to remove these particular features from the dataset. In order to optimize the dataset, a combination of under-sampling the majority class and oversampling the minority class has been employed. In machine learning, under-sampling is used to even out skewed datasets by decreasing the number of samples from the dominant class [26]. In an imbalanced dataset, one or more classes may have considerably more instances than the others, which can create bias towards the dominant class during model training. To combat this, under-sampling attempts to make the minority class smaller through the random removal of examples until the number of instances in each class is roughly equal. This reduces the model's potential for bias against the minority group and can boost the group's total success. On the other hand, oversampling generates artificial instances in underrepresented classes until they are numerically comparable to the majority classes. This helps ensure that the model is not skewed towards the dominant class, which can lead to better results for the minority classes. Oversampling was performed using the SMOTE method in this study [27].

Finally, from the previous research study & author's understanding, seven machine learning algorithms have been used in this research to check how well these algorithms will perform on the child & maternal mortality dataset.

IV. Experimental Result

A. Performance Measurement Unit

The present study employed seven distinct machine learning algorithms to achieve optimal performance. In order to assess the efficacy of the trained model, this study has employed a range of performance measurement metrics, which are outlined below:

a) Accuracy

Classification accuracy measures the effectiveness of a classification model. It is the percentage of instances that are correctly classified and is frequently utilized as a performance benchmark for various models. The formula to calculate accuracy is:

Accuracy = (True Positive + True Negative) / (Total Number of Tuples) (1)

b) Precision

The proportion of true positive predictions among all positive predictions can be measured with precision. A model with a higher precision is well-designed. Using a formula to calculate precision:

Precision = (True Positive) / (True Positive + False Positive (2)

c) Recall

Recall measures the completeness of the classification model. It depicts the proportion of instances where the model identified true positives. The formula to calculate recall is:

Recall = (True Positive) / (True Positive + False Negative) (3)

B. Result

Random Forest ranked first in terms of accuracy on the imbalanced dataset with a score of 96%, followed by Decision Tree & XGBoost in second place with a score of 94% accuracy. K Nearest Neighbor finished in third with a score of 93% accuracy. Support Vector Machine placed in fifth with a score of 91% accuracy. Following that, Logistic Regression have achieved 89% accuracy. With a score of 85%, Naive Bayes placed last. In this work in terms of the imbalanced data, Random Forest had the highest accuracy, precision, and recall which is 96%, while Naive Bayes had the lowest score (85%). The result of all machine learning algorithms before balancing the dataset is displayed in Table I below.

TABLE I. Result of all Machine Learning Algorithms Before Balancing the Dataset

Algorithms	***Accuracy***	***Precision***	***Recall***
LR	0.89	0.83	0.96
NB	0.85	0.86	0.82
DT	0.94	0.91	0.85
RF	**0.96**	**0.99**	**0.86**
KNN	0.93	0.96	0.94
XGBoost	0.94	0.89	0.99
SVM	0.91	0.90	0.87

It is widely acknowledged that imbalanced data can adversely affect machine learning methodologies. Therefore, the present study employed both undersampling and oversampling techniques on the dataset in question. Fig. 4. displays the distribution of sample sizes for each class subsequent to the implementation of undersampling on the majority class.

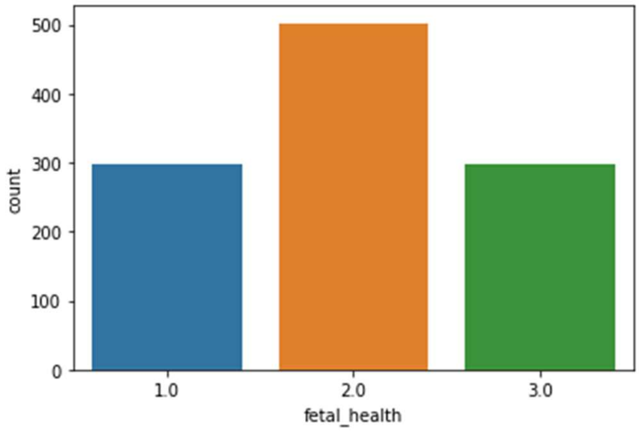

Fig. 4. After undersampling the number of samples of each class

In below, Table II displays the outcomes of machine learning algorithms subsequent to the implementation of undersampling. Here, Random Forest & XGBoost came in first with a score of 92% accuracy, while Decision Tree came in second with a score of 90%. Then came Support Vector Machine with a score of 88%. Then in fourth place came K Nearest Neighbor & Logistic Regression with a score of 86%. Naive Bayes came last with a score of 81%. When it came to precision & recall, Random Forest & XGBoost had the greatest score of 92% & Naive Bayes had the lowest score of 81%.

TABLE II. Result of all Machine Learning Algorithms After Undersampling the Dataset

Algorithm	***Accuracy***	***Precision***	***Recall***
LR	0.86	0.87	0.90
NB	0.81	0.86	0.84
DT	0.90	0.92	0.96
RF	**0.92**	**0.98**	**0.87**

Algorithm	*Accuracy*	*Precision*	*Recall*
KNN	0.86	0.79	0.81
XGBoost	0.92	0.86	0.98
SVM	0.88	0.78	0.96

The number of examples from each class after the dataset has been oversampled is shown in Fig. 5. This is extremely important because the work's initial collection was imbalanced.

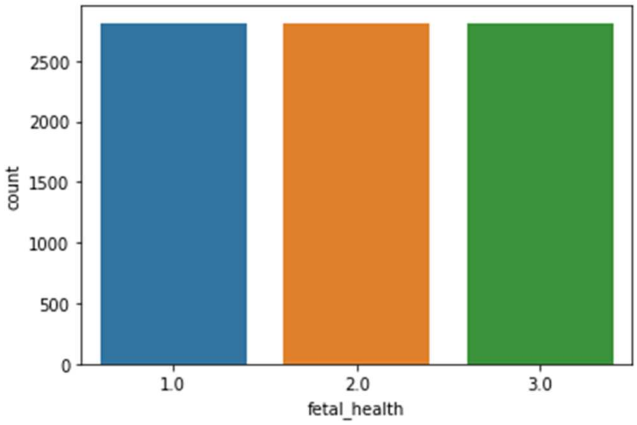

Fig. 5. After oversampling the number of samples of each class

The outcome is exhibited in Table III. The Random Forest algorithm achieved the highest accuracy score of 99.98%, followed by the Decision Tree algorithm with a score of 99%. Afterwards, the K Nearest Neighbor algorithm achieved a 98% accuracy score. Following that, XGBoost obtained a score of 97%, placing it in fourth position. The Support Vector Machine algorithm achieved an accuracy score of 94%. Logistic Regression achieved a score of 85%, placing it in sixth position. The Naive Bayes algorithm obtained a performance score of 81%. In terms of precision and recall metrics, the Random Forest algorithm demonstrated the highest score of 99.98%, while the Naive Bayes algorithm exhibited the lowest score of 81%.

TABLE III. RESULT OF ALL MACHINE LEARNING ALGORITHMS AFTER UNDERSAMPLING THE DATASET

Algorithm	*Accuracy*	*Precision*	*Recall*
LR	0.85	0.95	0.86
NB	0.81	0.79	0.72
DT	0.990	0.895	0.990
RF	**0.9998**	**0.9959**	**0.9945**
KNN	0.98	0.96	0.92
XGBoost	0.97	0.99	0.88
SVM	0.94	0.98	0.89

V. DISCUSSION

In this research using clinical data the researchers wanted to see if they could make predictions about infant and maternal fatalities. The operation of ultrasound equipment consists of transmitting an ultrasonic pulse and analyzing the reaction it receives. Seven different machine learning techniques were utilized throughout the study of this research and found excellent results of random forest algorithm. This analysis provides healthcare practitioners with an alternative that is both successful and cost-effective in reducing the risk of infant and maternal mortality. In Table IV, we compare this work with other existing work related to this domain.

TABLE IV. COMPARISON WITH PREVIOUSLY PUBLISHED WORK

Ref	Contribution	Dataset	Algorithms	Best Accuracy
This Work	Analysis of Maternal and Child Mortality Rates via Machine Learning	Kaggle	LR, NB, DT, RF, KNN, XGBoost. SVM	99.98% - RF
[6]	Comparison of machine learning algorithms for classification of fetal health based on heart rate data	UCI Machine Learning Repository	XGB, SVM, KNN, LGBM, RF, ANN, LSTM	99% - LGBM
[7]	Study of fetal heart rate analysis methods	Not specified	J48, IBK, SMO, RF, NB	85.88% - NB
[9]	Classification of fetal heart rate using different machine learning algorithms	UCI Machine Learning Repository	ANN, SVM, ELM, RBFN, RF	99.73% - ANN
[10]	Cardiotocography classification based on machine learning	UCI Machine Learning Repository	SVM, RF, MLP, K-NN	94.5% - RF
[28]	Risk assessment for prenatal health using ensemble learning trees	UCI Machine Learning Repository	DT, RF, Forest, Extra Trees, Deep Forest, Ensemble Learning	96.05% - Ensemble Learning
[13]	Analysis of contraction-dependent fetus heart rate variability: a feasibility study for prenatal distress detection	Analysis of 100 recordings with 20 adverse outcome fetuses	SVM with Genetic Algorithm	79%
[14]	Detection of periodic changes in fetal heart rate	556 CTG data	Random Forest	93%

From Table IV, it is clearly visible that there are a lot of work have already published on this domain. Maximum of the work was performed with open access dataset. Authors applied different machine learning and deep learning algorithms to get the best accuracy. Sometimes it achieves above 90% accuracy. Among these presented works, our research is quite stronger because of its number of machine learning approach. In this work, seven machine learning algorithms have applied to get the best accuracy. Among these seven algorithms Random Forest have achieved 99.98% accuracy which is greater than all other presented works in Table IV. There is quick fight between the RF and DT in this work after oversampling the dataset, but at the end RF placed first.

VI. Conclusions and Future Work

Fetal heart rate (FHR) monitoring during pregnancy is essential for ensuring the health of both the fetus and the mother. Cardiotocography (CTG) is a useful method for identifying fetal anomalies and determining whether intervention is required to prevent permanent harm. The main goal of this research was to provide supervised machine learning services to pregnant women and clinicians. Among all the classifiers tested, the Random Forest classifier based on patient data exhibited the highest accuracy. This study analyzed various clinical parameters of pregnancy and statistically correlated them with the presence of fetal anomalies. The limitation of this research is collecting more quality data and collecting primary data. Moving forward, this research aims to collect more data and develop an application in future which can be particularly beneficial in low-income countries with limited access to medical resources or specialists. This work has the potential to make a significant impact on healthcare research and development, leading to improved pregnancy outcomes and better maternal and fetal health. Ultimately, our goal is to empower pregnant women and their healthcare providers with accurate and efficient tools for monitoring fetal health and detecting potential anomalies.

References

[1] I. L. Horon, "Underreporting of maternal deaths on death certificates and the magnitude of the problem of maternal mortality," *Am J Public Health*, vol. 95, no. 3, pp. 478–482, Mar. 2005, doi: 10.2105/AJPH.2004.040063.

[2] A. Kurjak, M. Stanojević, and J. Dudenhausen, "Why maternal mortality in the world remains tragedy in low-income countries and shame for high-income ones: Will sustainable development goals (SDG) help?," *J Perinat Med*, vol. 51, no. 2, pp. 170–181, Feb. 2023, doi: 10.1515/JPM-2022-0061/MACHINEREADABLECITATION/RIS.

[3] I. Ben M'Barek, G. Jauvion, and P. F. Ceccaldi, "Computerized cardiotocography analysis during labor – A state-of-the-art review," *Acta Obstet Gynecol Scand*, vol. 102, no. 2, pp. 130–137, Feb. 2023, doi: 10.1111/AOGS.14498.

[4] V. Paladugu, S. Sreedhar, R. Chitra, S. T. Mannava, S. Sreekumar, and J. Mangalakanthi, "Association of CTG Diagnosis of Intrapartum Fetal Distress and Immediate Postpartum Acidemia in Foetal Umbilical Artery," *Journal of Obstetrics and Gynecology of India*, vol. 73, no. 1, pp. 28–35, Feb. 2023, doi: 10.1007/S13224-022-01702-2/METRICS.

[5] M. T. Alam *et al.*, "Comparative Analysis of Different Efficient Machine Learning Methods for Fetal Health Classification," *Appl Bionics Biomech*, vol. 2022, 2022, doi: 10.1155/2022/6321884.

[6] N. Rahmayanti, H. Pradani, M. Pahlawan, and R. Vinarti, "Comparison of machine learning algorithms to classify fetal health using cardiotocogram data," *Procedia Comput Sci*, vol. 197, pp. 162–171, Jan. 2022, doi: 10.1016/J.PROCS.2021.12.130.

[7] M. Khan, R. Afridi, Z. Iqbal, A. Ahmad, and R. Naseem, "Fetal Heart Rate Classification and Comparative Analysis Using Cardiotocography Data and Known Classifiers," *Article in International Journal of Grid and Distributed Computing*, vol. 12, no. 1, pp. 31–42, 2019, doi: 10.33832/ijgdc.2019.12.1.03.

[8] B. Amin, M. Gamal, A. A. Salama, I. M. El-Henawy, K. Mahfouz, and I. M. El-Henawy, "Classifying Cardiotocography Data based on Rough Neural Network COVID-X & Neutrosophic Systems View project A Conceptual Model for Visual Monitorting Information System (VMIS) for the Strategic Plan View project Classifying Cardiotocography Data based on Rough Neural Network," *Article in International Journal of Advanced Computer Science and Applications*, vol. 10, no. 8, 2019, doi: 10.14569/IJACSA.2019.0100846.

[9] Z. Cömert and A. F. Kocamaz, "Comparison of Machine Learning Techniques for Fetal Heart Rate Classification," vol. 132, 2017, doi: 10.12693/APhysPolA.132.451.

[10] A. Mehbodniya *et al.*, "Fetal health classification from cardiotocographic data using machine learning," *Expert Syst*, vol. 39, no. 6, p. e12899, Jul. 2022, doi: 10.1111/EXSY.12899.

[11] P. Bhowmik, P. Chandra Bhowmik, U. A. M. E. Ali, and M. Sohrawordi, "Information Technology and Computer Science," *Information Technology and Computer Science*, vol. 5, pp. 30–40, 2021, doi: 10.5815/ijitcs.2021.05.03.

[12] N. Krupa, M. A. MA, E. Zahedi, S. Ahmed, and F. M. Hassan, "Antepartum fetal heart rate feature extraction and classification using empirical mode decomposition and support vector machine," *Biomed Eng Online*, vol. 10, no. 1, pp. 1–15, Jan. 2011, doi: 10.1186/1475-925X-10-6/FIGURES/8.

[13] G. J. J. Warmerdam *et al.*, "Detection rate of fetal distress using contraction-dependent fetal heart rate variability analysis," *Physiol Meas*, vol. 39, no. 2, p. 025008, Feb. 2018, doi: 10.1088/1361-6579/AAA925.

[14] S. Das, H. Mukherjee, K. C. Santosh, C. K. Saha, and K. Roy, "Periodic change detection in fetal heart rate using cardiotocograph," *Proc IEEE Symp Comput Based Med Syst*, vol. 2020-July, pp. 104–109, Jul. 2020, doi: 10.1109/CBMS49503.2020.00027.

[15] P. Garcia-Canadilla, S. Sanchez-Martinez, F. Crispi, and B. Bijnens, "Machine Learning in Fetal Cardiology: What to Expect," *Fetal Diagn Ther*, vol. 47, no. 5, pp. 363–372, May 2020, doi: 10.1159/000505021.

[16] M. P. LaValley, "Logistic Regression," *Circulation*, vol. 117, no. 18, pp. 2395–2399, May 2008, doi: 10.1161/CIRCULATIONAHA.106.682658.

[17] "Naïve Bayes", doi: 10.1007/978-1-4899-7502-7_581-1.

[18] X. Han, X. Zhu, W. Pedrycz, and Z. Li, "A three-way classification with fuzzy decision trees," *Appl Soft Comput*, vol. 132, p. 109788, Jan. 2023, doi: 10.1016/J.ASOC.2022.109788.

[19] S. J. Rigatti, "Random Forest," *J Insur Med*, vol. 47, no. 1, pp. 31–39, Jan. 2017, doi: 10.17849/INSM-47-01-31-39.1.

[20] A. J. Gallego, J. R. Rico-Juan, and J. J. Valero-Mas, "Efficient k-nearest neighbor search based on clustering and adaptive k values," *Pattern Recognit*, vol. 122, p. 108356, Feb. 2022, doi: 10.1016/J.PATCOG.2021.108356.

[21] T. Islam, A. Kundu, N. Islam Khan, C. Chandra Bonik, F. Akter, and M. Jihadul Islam, "Machine Learning Approaches to Predict Breast Cancer: Bangladesh Perspective," *Smart Innovation, Systems and Technologies*, vol. 302, pp. 291–305, 2022, doi: 10.1007/978-981-19-2541-2_23/COVER.

[22] M. Tanveer, T. Rajani, R. Rastogi, Y. H. Shao, and M. A. Ganaie, "Comprehensive review on twin support vector machines," *Ann Oper Res*, pp. 1–46, Mar. 2022, doi: 10.1007/S10479-022-04575-W/METRICS.

[23] "Child and Maternal Mortality | Kaggle." https://www.kaggle.com/datasets/ff191eccaacce8fb7860cecd930 16790f56e193d7197e91307dab5e2b2328dd2 (accessed Apr. 01, 2023).

[24] H. Rosen and Y. Yogev, "Assessment of uterine contractions in labor and delivery," *Am J Obstet Gynecol*, Mar. 2023, doi: 10.1016/J.AJOG.2022.09.003.

[25] J. Bernardes, "Computerized analysis of cardiotocograms in clinical practice and the SisPorto®system thirty-two years after: Technological, physiopathological and clinical studies," *J Perinat Med*, vol. 51, no. 1, pp. 145–160, Jan. 2023, doi: 10.1515/JPM-2022-0406/ASSET/GRAPHIC/J_JPM-2022-0406_FIG_001.JPG.

[26] T. Islam *et al.*, "Review Analysis of Ride-Sharing Applications Using Machine Learning Approaches : Bangladesh Perspective," *Computational Statistical Methodologies and Modeling for Artificial Intelligence*, pp. 99–122, Mar. 2023, doi: 10.1201/9781003253051-7.

[27] M. T. Islam, T. Ahmed, A. B. M. Raihanur Rashid, T. Islam, M. S. Rahman, and M. Tarek Habib, "Convolutional Neural Network Based Partial Face Detection," *2022 IEEE 7th International conference for Convergence in Technology, I2CT 2022*, 2022, doi: 10.1109/I2CT54291.2022.9825259.

[28] P. Bhowmik, P. Chandra Bhowmik, U. A. M. E. Ali, and M. Sohrawordi, "Information Technology and Computer Science," *Information Technology and Computer Science*, vol. 5, pp. 30–40, 2021, doi: 10.5815/ijitcs.2021.05.03.