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Fetal Risk Analysis Using Cardiotocographic Data

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ABSTRACT: Child mortality is on an increasing scale and preventing them is the main indicator for progress in the medical domain. A majority of these deaths is due to improper monitoring of the fetal condition which is a result of less access to the resources necessary for monitoring. Cardiotocogram (CTG) is an economical and practical solution for fetal monitoring. CTGs monitor the movement, heart rate, uterine contractions, sudden heart rate changes and other health metrics of the fetus which are generally interpreted visually by physicians and can lead to errors that may result in increased fetal health risk. The aim of this study is to identify which features have the most impact using modelling processes on baseline models on fetal health being either normal or distressed. Using these features, we also aim to tune a model that provides the best predictions of fetal health class. The motive of this study is to develop a model that has high precision and other metrics and can predict these features to a greater effect than the standard visual analysis and therefore help in the precise classification of fetal distress and improve the overall child mortality rate by reducing risk through human error.

KEYWORDS: Cardiotocogram, Child mortality, fetal health risk, modelling process.

I.INTRODUCTION

Child mortality is a common problem in day-to-day life. With the advancement in medical technology, there is a decrease in child mortality. A key goal in the growing society and human progress as a whole is the prevention of child mortality and thereby reducing the child mortality rate. Even though there is a huge evolution in medical technology that has reduced the mortality rate, they are not globally available. A preterm baby is a child which is born before the 37 weeks gestation period. Preterm birth is of three subclasses based on the gestation age: extremely preterm (less than 28 weeks), very preterm (28 to 32 weeks) and moderate to late preterm (32 to 37 weeks). According to WHO, it is estimated that 15 million i.e., 5 to 18% preterm babies are born and this rate keeps rising. Around 2.4 million neonates were dead in the year 2019 which counts to up to 6700 deaths each day. A majority of these neonates' death is due to preterm birth. The mortality rate has been globally decreased from around 5.0 million in the year 1990 to 2.4 million in the year 2019 however, the rate of decline of neonatal mortality is still considered low. An analysis by WHO states that three-quarters of these deaths could have been prevented using simple cost-effective solutions. Therefore, it is necessary to perfect and apply readily available and cost-effective solutions to improve the mortality rates. Cardiotocography is the most oblique and practical way of interpreting the foetal condition.

Cardiotocogram is the fetal monitor used to measure two important signals: the fetal heart rate (FHR) and the uterine contractions (UC). The pathological condition of the fetus is identified by the information obtained by the CTG. Other health metrics such as the fetal movement and extreme variations in heart rate are also observed from the cardiotocograph by obstetricians. C – Sections (Caesarean) are usually done if there are extreme variations in the fetal heart rate. Obstetricians rely on the visual analysis of these cardiotocograph data which may lead to erroneous interpretations at times. CTGs are generally successful for low-risk pregnancies. In spite of its practicality, there are certain discrepancies as to its utility. Incorrect analysis of the Cardiotocographs may lead to complications that may have the highest impact on the death of both the mother and the child. One such complication is opting to go for C – section which may lead the mother's life to danger as well. For these reasons, fetal distress cannot be detected visually and is limited by human errors.

In order to enhance the interpretation of distressed fetus and thereby reduce the mortality rate, machine learning and automation has become a feasible option. On training a model well using different machine learning algorithms, our model will be able to identify which attributes with respect to the fetal heart rate will have the greatest influence on the fetal health. The Machine Learning model must not only be able to classify the fetal conditions precisely but also be accurate enough to prevent any unnecessary surgical procedures.

A standard procedure done during the third trimester is fetal monitoring. Fetal monitoring is checking the health of the unborn baby. Fetal growth entirely depends on the mother's health. To avoid such complications, a continuous measuring of fetus health and growth rate is done with cardiotocography. The cardiotocography aims to track the fetus' heartbeat and parallelly measure the mother's uterine contractions. This process would be performed during the final trimester, once the fetus' growth functions fully with heart rate. This method is considered cost-effective and straightforward, and hence, it is to be carried out by medical experts for early detection of fetal status and to reduce fetal mortality. The result of Cardiotocographic (CTG) will trace uterine contraction of the mother, most importantly heart rate of fetus, occurrence of acceleration, series of deceleration, and much more complicated measure of fetus. There are many ML techniques available for classifying the fetus's normal, suspected, and pathological stages. The results show that the ML technique will form a framework widely used for the automated system in analysing early fetal health.

II.LITERATURE REVIEW

Machine Learning (ML) techniques can help medical experts make early decisions during complex situations like diagnosis, effectively decreasing the MMR and high complications during labour. Classifying the stages of fetal health is a challenging task, but this can be outstandingly handled by ML classification techniques (Arif, 2015). Some of the standard methods used for classification are SVM, neural networks (NN), and random forest (RF) (Quilligan & Paul, 1975). RF classifier gives better performance in classifying the stages of fetal health with higher accuracy. Monitoring fetus even in the second trimester can reduce prenatal mortality randomly (**Signorini et al., 2020**).

Artificial Intelligence (AI) techniques have recently provided a significant decision for early diagnosis and multi-classifications. A significant comparison was made between 15 ML techniques defending healthy vs. affected foetuses (**Sharanya & Venkataraman, 2020**). The features are extracted from CTG signal recording. These effectively evaluate large amounts of real-time data to provide better solutions and develop a framework for other models to perform classification (**Comert et al., 2019**). CTC signals to directly assess the heart rate of the patients and give accurate results and updates to the medical experts. The effectiveness of using cardiotocography is discussed for the wellbeing of the fetal during labour. CTG is responsible for measuring the fetal heart rate and the contraction of the womb; hence this plays a vital role in assessing fetal before birth and also during labour. This would also measure the frequency of baby movement.

A recent rush in the deployment of four ML techniques, namely NN, K-nearest neighbours (k-NN) Classifier, SVM, and Decision Tree, which are evaluated on high dimensional data, proves that the classifier SVM dominates all other techniques in giving accurate diagnostic indices (**Akhtar et al., 2019**). All the Classifiers work well and use 30 ranked features to determine common risk factors in the prediction model (Stoean & Stoean, 2013). While using ML algorithms, feature extraction and selection are among the most used methods to select optimized features for prediction in the model. This would even help in giving top priority in feature selection (Lu et al., 2014). The algorithm's performance can be validated by different metrics, namely Accuracy, Specificity, Precision, and Recall (Azar, 2014).

The overview of using ML for assessing fetal changes with optimizing the image acquired and the effectiveness of classifying cardiac abnormalities (**Garcia-Canadilla et al., 2020**). Using CTG signals and their principles is described with evaluating historical data, and the process is used (Magenes & Signorini, 2021). The image data set has been taken with the implementation of CNN architecture in Deep Learning (DL) which motives to validate the data from CTG signals with that of the image acquisition dataset (Sridar et al., 2019).

Paper: “Predicting risk of stillbirth and preterm pregnancies with machine learning”
Author: Aki Koivu, Mikko Sairanen
Year: 2020

In this study, machine learning methods have been used for the purpose of predicting early and late stillbirths and preterm birth. Two datasets were used in this experimental analysis– CDC (Centers for Disease Control and Prevention) dataset and NYC (New York City) dataset. The CDC dataset was used for tasks like feature extraction and parameter optimization and for verifying the proposed models. Whereas the Predicting risk of stillbirth and preterm pregnancies with machine learning NYC dataset was used for validation purposes. Four different algorithms were used for constructing the classifiers – logistic regression, two artificial neural networks (SELU and Deep NN), and GBDT (Gradient Boosting Decision Tree). The output of the best performing model in this study had the highest AUC of 0.75, 0.76 for early stillbirth, and an AUC of 0.64, 0.67 for preterm birth in the NYC and CDC dataset respectively.

Relevance to current Research

No.	Paper Title	Author Name	Key Points	Remark
1	Maternal hemodynamic and computerized Cardiotocography during labor with epidural analgesia	Stefano Raffaele Giannubilo, Mirco Amici, Simone Pizzi, Alessandro Simonini & Andre a Ciavattini,2022	Measurements of the main hemodynamic parameters using a non-invasive ultrasound system (USCOM-1A). Total vascular resistances (TVR), heart rate (HR), stroke volume (SV), cardiac output (CO) and arterial blood pressure were measured before epidural administration (T0), [1]	Maternal hemodynamic status at the onset of labor can make a difference in fetal response to the administration of epidural analgesia.
2	Predicting risk of stillbirth and preterm pregnancies with machine learning	Aki Koivu, Mikko Sairanen,2020	Algorithms were used for constructing the classifiers – logistic regression, two artificial neural networks (SELU and Deep NN), and GBDT (Gradient Boosting Decision Tree) [2].	Best performing model in this study had the highest AUC(Area under curve) of early stillbirth.
3	Machine Learning Methods for Neonatal Mortality and Morbidity Classification	Joel Jaskari, Janne Myllarinen, Markus Leskinen, Ali Bahrami Rad, Jaakko Hollmén, Sture Andersson, Simo Sarkka, 2020	Different classifiers were used in the process: Logistic Regression (LR), Linear Discriminate Analysis classifier (LDA), Quadrant Discriminate Analysis classifier (QDA), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Gaussian Process (GPRBF, M32, M52), Random Forest (RF) [3].	Prediction of mortality, bronchopulmon-ary dysplasia, necrotizing enterocolitis and retinopathy of prematurity
4	Classification of the Cardiotocogram data for anticipation of fetal risks using machine learning techniques	Hakan Sahin, Abdulhamit Subasi, 2015.	Algorithms were used in the process: ANN,KNN,LR,RF,DT,Radial Basis Function Network (RBFN), Classification and Regression Trees (CART) [4].	Evaluation metrics which are the F1-measure and ROC area were found to be the highest for the Random Forest algorithm
5	Maternal and fetal risk factors for stillbirth	Jason Gardosi, Vichithranie Madurasinghe, epidemiologist, M andy Williams,2013	Gestation related optimal weight standard (GROW) .Weight that is small for gestational age after such adjustment by growth potential has been shown to represent pathological smallness and is referred to as fetal growth restriction [5].	Spectral estimates in preterm fetuses was probably due to increased sympathetic and parasympathetic modulation

In summary, the work presented in this paper is built on previous research to detecting on the risk in fetus. While earlier work focused on different ML algorithm, we focus on the contribution to detect Fetal and maternal health which will reduce the fetal death rate and preterm birth. The monitoring fetal health conditions are essential for maintaining good health for both mother and child. CTG is the prenatal test for monitoring uterine contractions and fetal heartbeat during pregnancy and child birth.

III.METHODOLOGY OF PROPOSED SURVEY

Training Dataset:

The dataset belongs to the Cardiotocography and it has the measurements of FHR and uterine contraction (UC) features on CTG classified. The dataset gathered is suffering with imbalanced problem. Initial dataset has 22 columns and 2126 instances and three target classes namely healthy, suspect and pathological. Class healthy has 295, class suspect has 1655, class pathological has 176 instances. The suspect and pathological were combined into a single class as distressed for easy identification.

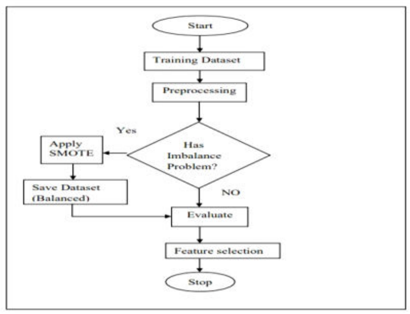

Figure 1. Flow chart of Cardiotocography Data

Data Partitioning:

The training dataset is partitioned into two subsets on the basis of the target class. The target class is decided based on the morphological pattern or the Fetal Heart Rate (FHR) content of the dataset. The target class of the FHR data can have a count of three values as tabulated in table below.

Table 1 .Class Description of Cardiotocography Dataset Based on fetal heart rate

Sl.No	Class Values	Class Description
1	N	Normal
2	S	Suspect
3	P	Pathological state

Data Pre-Processing:

The training dataset is partitioned into two subsets on the basis of the target class. The two subsets are stored as two separate Excel spreadsheets. The predictor and target attributes of each subset are specified and stored as files. Each file is visualized to ensure accurate loading of the attribute values. After the data is pre-processed, the classification algorithms are executed on the dataset..

Imbalanced Dataset:

To balance the complete dataset, 45% synthetic instances are created using SMOTE for class healthy, 75% synthetic instances are created for class pathological state. As a result of this process, total 4773 instances have been generated, out of these, Class label healthy has 1622, suspect has 1655, and pathological has 1496 instances in new dataset (Balanced). Since a class imbalance was found to occur in the dataset, oversampling was done using SMOTE and hyperparameter tuning was done for the best performing models using GridsearchCV. Now the new dataset has almost balanced class labels. As SMOTE uses the K-Nearest Neighbour algorithm for sampling the dataset.

Feature Selection:

After applying the SMOTE over the imbalanced dataset, some of the feature selection techniques (Vanilla Model and Experimental Model) are applied over the balanced and imbalanced datasets. Vanilla modelling process involves working with an unaltered dataset i.e., without making changes to the original dataset. Whereas in experimental modelling, the original dataset is altered by adding additional features and by creating dummy variables.

The baseline models were experimented in both the vanilla and experimental models and checked for the evaluation metrics. The baseline models which were chosen were checked if they were compatible with the dataset and surprisingly, they all produced a good result. The baseline models which are taken for this analysis are: K-Nearest Neighbour (KNN) Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and XgBoost.

Table 2 Evaluation Metrics for the baseline models

Algorithm	Accuracy (%)	Recall (%)	F1-score (%)	Precision (%)
KNN	**92.10**	96.82	94.96	93.17
LR	87.21	87.21	91.99	88.66
DT	92.87	95.11	**95.34**	**95.57**
RF	90.97	**99.02**	94.40	90.20

Table2 gives an in-detail explanation of the evaluation metrics found out for the baseline models. The evaluation metrics are accuracy, recall, F1-score and precision. Accuracy was the highest for KNN, recall for RF and F1-score and precision for DT algorithms. Best performing models using GridsearchCV is done in both the vanilla and the experimental modelling process to check if both the modelling process produced the same results.

Two modelling process was created in this study:

- Vanilla modelling process.
- Experimental modelling process.

Vanilla modelling process involves working with an unaltered dataset i.e., without making changes to the original dataset. Whereas in experimental modelling, the original dataset is altered by adding additional features and by creating dummy variables. The baseline models were experimented in both the vanilla and experimental models and checked for the evaluation metrics.

Since a class imbalance was found to occur in the dataset, oversampling was done using SMOTE and hyperparameter tuning was done for the best performing models using GridsearchCV. This step was done in both the vanilla and the experimental modelling process to check if both the modelling process produced the same results. Figure 2 explains the methodology for selecting the key features from the best performing model.

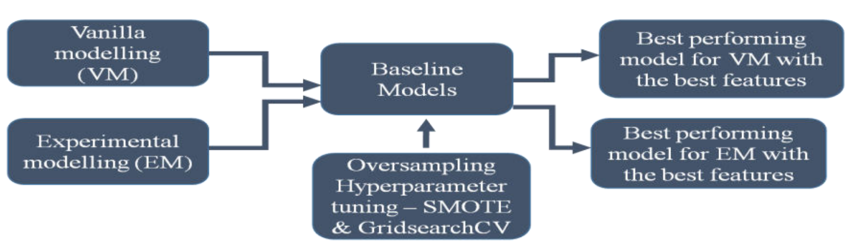

Figure 2 . Block diagram explaining the modelling process and selection of the key features from the modelling process.

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Exploratory data analysis of CTG data:

The CTG data sourced from UCI repository are very rich and clean, with no missing values. The dataset contains 21 features to monitor the health state of the fetus. It is essential to study the nature of data and the degree of contribution of the attribute towards fetal health. RA and CA are done to explore insights from the various qualities. EDA refers to the initial analysis of the data set, which is done before preprocessing. EDA helps discover the correlation between the data and perform the impact of irrelevant data in the dataset. Data visualization helps the researcher to investigate the nature of the dataset being deployed for the model. This will also help improve the model's performance by summarizing the critical feature of the dataset. The significant implications from the EDA analysis are listed below.

Step 1: Majority of the fetal heart rate is in the range of 130 bpm -140 bpm.
Step 2: The dataset is highly imbalanced with majority of the normal fetal records.
Step 3: Only very low cases exhibit variance in the histogram values
Step 4: Light decelerations are most common even among normal fetal records, whereas prolonged and severe decelerations indicate an abnormal FHS.
Step 5: The fetal heart rate displays more S-TV. The long-term variance is interpreted as a warning sign of abnormal fetal health.
Step 6: The uterine contractions towards the value of 0.012 and above are an indication of abnormality.

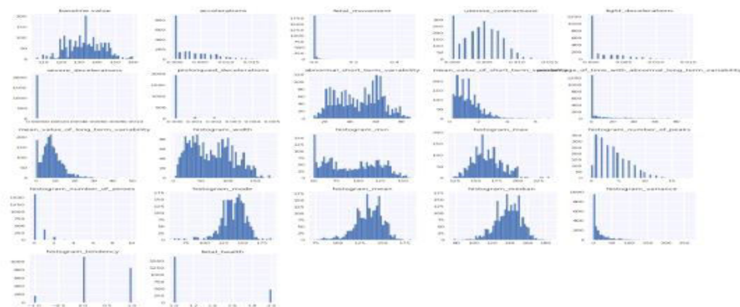

FIGURE 3 . Data analysis of the attributes of Cardiotocographic (CTG) dataset for classifying fetal health state (FHS)

CLASSIFICATION METRICS:

The ML models are used to predict the class labels, and their performance is validated on the resulting metrics: Accuracy, Precision, Recall, F1-score, and Support. A detailed analysis of the metrics is given below: There are four methods for determining whether or not the predictions are correct:

A. **True negative rate**: The case was predicted to be negative. In other words, these are the correctly predicted negative values, denoting that neither the actual class value nor the predicted class value is positive. For example, if the actual class discloses that this patient died and the predicted class indicates the same thing.
B. **True positive rate**: The case was positive, and the outcome was expected to be positive. In other words, these are the correctly predicted positive values, indicating that both the actual class value and the predicted class value are indeed positive. For example, if the patient's actual class value and predicted class both proved that patients survived, the results are in accordance. These values occur when our class value contradicts the predicted class.
C. **False negative rate**: The case was positive, but the outcome was negative as predicted. When the actual class value is YES, but the predicted class value is NO. For example, if the actual class value shows that this patient survived, the correctly classified value indicates that the individual will die.
D. **False positive rate**: Although the case was negative, it was predicted to be positive. When the predicted class is yes, but the actual class is no. For example, if the actual class reports that this patent did not survive, but the predicted class predicts that it will.

Will predict the Accuracy, Precision, Recall, F1-score and Support which gives the visual analysis of fetal health classification of machine learning (ML) algorithms.

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IV.RESULTS AND DISCUSSION

Classification of FHS using various ML algorithms is done, and the outcomes are charted in Table 2.

From the classification results, it is evident that RF outperforms all the other classifiers. This ensemble algorithm gains the best from the individual learners. The next best performer is SVM, with 93% accuracy and same F1-score. All the algorithms show same support value, which indicates the purity of classes

This work deploys the fundamental ML algorithms, each with unique qualities, to assess the performance of classification status. Though the results are promising, there is still room for improvement. Intensive feature engineering and creating models with less training data can be viewed as the future direction of this work. Image Datasets (ID) are considered for monitoring the fetal movement, and the efficiency can be compared with the data generated from CTG signals. The work may extend to utilizing DL techniques to deal with the ID. The comparative study proved the difference between the ID and statistical dataset taken from UC Irvine repository. The EFM system is used to find out fetal health inside the womb. The work can be extended by analysing the other lifestyle disease that affects the fetal growth and variations on the measurements generated by the CTG signals are compared with the old dataset. This enhances the system and extends the work to the next level. Since the lifestyle disease such as diabetes, obesity and heart failure during the pregnancy can be related to the fetal growth can also be monitored, and required suggestion can be given to the medical experts. The EFM system can be quantified based on the validating measure used in the process. Output can be compared with the real-time decision, and live validation can be performed to reveal the accuracy of the model implemented.

All the baseline models were experimented with both the altered and unaltered datasets. Random forest algorithm using GridsearchCV gave the best result in the vanilla modelling process with the key features as where abnormal_short term variability, acceleration, mean abnormal short term varitability and histogram mean as shown in Figure 4.

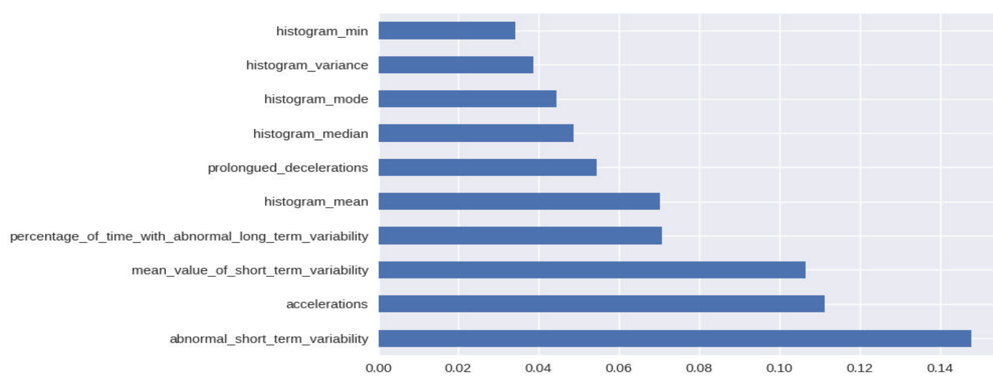

FIGURE 4. Key features obtained in Vanilla modelling using GridsearchCV Random Forest Algorithm

In the experimental modelling process, XgBoost algorithm using GridsearchCV gave the highest evaluation metrics producing the key features of importance as abnormal_short_term_variatability and the histogram mean, histogram min, histogram width and histogram mode is shown in Figure 5.

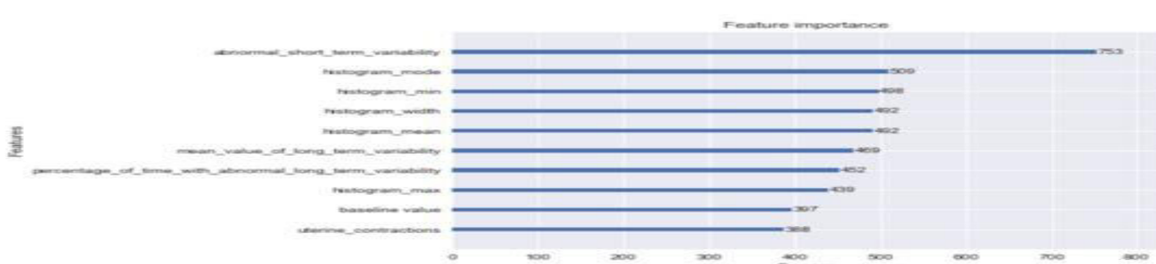

Figure 5. XgBoost using GridsearchCV variables of most importance

V.CONCLUSION AND FUTURE WORK

In this paper, we have proposed a Health complications during pregnancy time constitute a significant challenge confronted across the globe. Malnutrition among mothers, food habits, drug consumption, and congenital diseases are common health issues that affect the development of the fetus. This work assesses the influence of various factors measured through CTG to predict the health state of the fetus through algorithms like SVM, RF, MLP, and K-NN. This experimental study makes use of two modelling process to create the highest precision thereby reducing the false positive instances. The random forest of the Vanilla modelling set had the highest precision which was our target metric and XgBoost of our experimental modelling had the overall best metric with the highest precision. The variables of most importance are abnormal_short_term_variatability and the histogram mean, histogram min, histogram width and histogram mode. This research work will be helpful for the doctors in making timely decisions to save the life of both mother and child. Our future work is to include taking multi class predictor variables and using a larger dataset to train the model better. Other works also include taking other diagnostic metrics such as mother's health, heart rate, smoker or non-smoker, BMI, etc.

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