PREDICTION OF CESAREAN SECTION USING CARDIOTOCOGRAPHY

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***Abstract*— Prediction of cesarean section delivery via computerized cardiotocography involves evaluating fetal heart rate patterns observed and its relation with uterine contractions and assessing fetal well-being for accurate prediction of delivery outcome. This paper investigates the application of machine learning techniques to improve the precision of C-section prediction based on cardiotocography data. We develop a model using a dataset of cardiotocography recordings of pregnant women in labor and use features such as baseline fetal heart rate, heart rate variability, accelerations, decelerations, and uterine contraction in frequency. We develop and assess various models based on machine learning including logistics regression, support vector machines, and neural network. The result indicates that advanced machine learning models, including neural network, have the capacity to enhance the prediction of C-section outcomes by a considerable degree compared to linear methods. Although the applicability of real-time machine learning is yet to be evaluated.This study focuses on c-section in healthcare using advanced machine learning techniques.The study utilizes a comprehensive dataset encompassing patient demographics, medical history, prenatal care, prelabour care and hospital-specific variables.The predictive models developed in this study are trained on historical data and can be updated in real-time with new patient information.**

Keywords*— *caesarean section, computerised cardiotocography, neural network, prenatal, prelabour

I. INTRODUCTION

Every mother rights to know the health of her foetus. Hence, the best way to monitor foetal health has always been sought, in past times also by means of auscultation. Nowadays, cardiotocography (CTG) is the methodology most widely used in prenatal diagnostic to know about the foetal health; this is an important and still challenging task both in the antepartum and in the intrapartum period; even more, in some countries, the cardiotocographic signal (sometimes simply CTG in the following) is a report with legal value. A CTG is actually composed by two signals, namely the Foetal Heart Rate (FHR) and the trend of Uterine Contractions (UCs). Their features and relationship have, in clinical environments, the main aim to allow the early detection of foetal hypoxia.

This technique was introduced in the Sixties in order to avoid foetal death and/or neonatal cerebral palsy; indeed, it has allowed a significant reduction in perinatal mortality and morbidity; however, its diagnostic accuracy is still far from being fully satisfactory. This is mainly due to the kind of evaluation of cardiotocographic traces, currently often performed by visual inspection; obviously, this kind of practice yields to an operator-based and qualitative interpretation with a high variability both among inter and intra-physician. The worst consequence of this situation is the number of false positives, still too high, which leads to a consequent high number of unnecessary operative deliveries or cesarean sections.

Fetal heart rate (FHR) monitoring is the most common procedure assessing the fetal health in the present-day obstetric practice. For this, various techniques are in practice including fetal stethoscope, intermittent auscultation(Doppler ultrasound) and electronic fetal monitoring (EFM).These techniques have the potential to determine intrauterine hypoxia, andalso make additional assessments leading to the identification of normal and abnormal births . Though fetal stethoscope is cheap and easy to use for monitoring purposes only, it lacks the

recording of FHR and also requires right expertise to interpret. Similarly, intermittent auscultation provides baseline FHR along with the baseline variability,
accelerations and decelerations, however, their quantification also remains daunting . On the contrary, the EFM, also named cardiotocography (CTG), provides not only the precise monitoring and recording of FHR but also captures maternal uterine contractions (UCs), making CTG a more attractive technique in obstetrics .

Fetal distress, a common occurrence and cause of concern for both patient and the treating obstetrician, can be the harbinger of perinatal morbidity and mortality. To minimize these untoward outcomes it is essential to determine the intrauterine fetal condition which can be achieved by intrapartum fetal monitoring. Intrapartum fetal monitoring not only gives the idea about fetal condition but also identifies fetuses at risk of hypoxic damage so that perinatal outcome can be optimized by appropriate and timely intervention. Admission test by Cardiotocography (CTG) is used to indicate not only the state of oxygenation of the fetus on admission of the mother non- invasively but also checks the fetal reserve by recording FHR during the phase of temporary occlusion of the utero-placental blood supply under physiological stress of repeated uterine contractions. Thus, taking a short recording of fetal heart rate on admission helps us to determine the ability of the fetus to withstand the stress of labor [2] For these reasons electronic fetal monitoring by cardiotocography is widely established obstetric practice .However critics of this method of fetal surveillance claim that it has led to rise in the rate of cesarean section due to false positive results (the false-positive rate for a reactive CTG is 2-5%, versus 50-80% for non-reactive CTG.) [3-5]. Economic constraints especially in developing countries like ours, is also a limiting factor for the use of cardiotocographic or electronic fetal monitoring (EFM) for all antenatal patients admitted to the labor room. This continuous EFM was recommended for high risk patients but FHR changes, fetal hypoxia and acidosis may occur with same frequency in low risk patients as in high risk ones. Busy labor rooms with limited CTG monitors make it difficult to select patients for continuous EFM.

So, an alternative way of short recording of FHR at admission for labor, called as the 'Admission Test'(AT) is used to select patients for continuous EFM and also to detect compromised foetuses on admission. Based on the postulation that the early uterine contractions of labour may put stress on the placental circulation; an AT might detect pre-existing intrauterine fetal hypoxia and also that hypoxia which develops in active labor thereby allowing early detection of such compromised foetuses and prompt intervention [6]. So we carried out this study to evaluate the predictive value of the admission CTG in detecting foetal hypoxia at the time of admission in labour and to correlate the results of the admission CTG with the perinatal outcome.

II. MATERIALS AND METHODS

This dataset contains 391 records of features extracted from patients which were then used to find whether the patient has complications or not.The data analyzed in the present study was taken from a freely available CTU-UHB intrapartum cardiotocography databasehttp://www.physionet.org/physiobank/database/ctu-uhb-ctgdb/

Hardware requirements of the project include

- Operating System (Windows/Linux)
- RAM (4 GB Minimum)
- Secondary Storage (256 GB Minimum)

Software requirements include

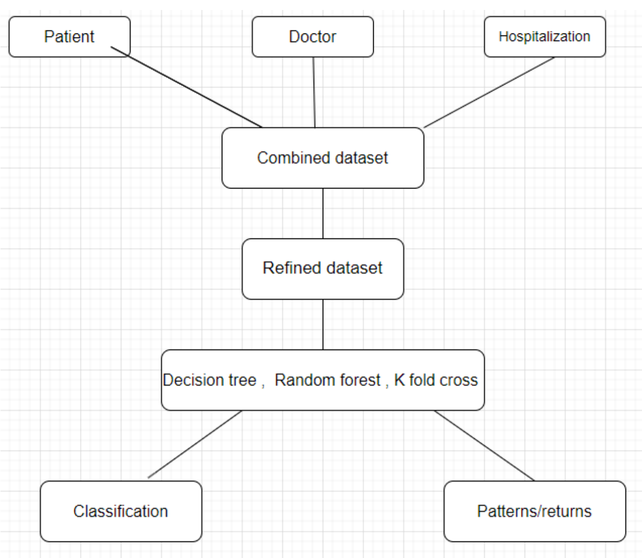
- Random forest algorithm,
- Jupyter Notebook
- Anaconda Navigator

III EXISTING SYSTEM

Cardiotocography is the method used during pregnancy and labor to monitor the fetal heart rate and uterine contractions. The CTG system is not used to predict the need for cesarean section. However, depending on the information obtained, health care providers can assess the well-being of the fetus and decide on the appropriate modality of delivery. The primary method used by the already existing system is the parameters obtained when analyzing the CTG monitoring session. These measurements include the following: FHR parameters mainly the baseline, variability,, presence of accelerations and decelerations; uterine contractions parameters such as the frequency, duration, and intensity of contractions; overall CTG tracing such as the patterns of reassuring and non-reassuring.

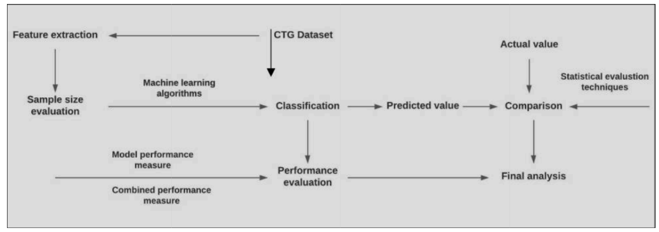
IV. PROPOSED SYSTEM

To the need for accurate prediction of scissor lift sections, This system utilising the Random Forest algorithm within machine learning techniques gives us a robust solution. This system aims to revolutionise the precision an efficiency of cesarean section predictions by leveraging the power of ensemble learning offered by Random Forest. By employing a multitude of decision trees, Random Forest effectively captures the intricate relationships between various parameters influencing scissor lift sections, such as material properties, dimensions, and load capacities. Through extensive training on a comprehensive dataset comprising diverse cesarean lift designs and configurations, the proposed system can learn complex patterns and correlations, enabling it to make highly accurate predictions. Moreover, the versatility of Random Forest allows for the inclusion of both numerical and categorical features, facilitating a comprehensive analysis of cesarean lift sections across different contexts. The proposed system holds the potential to streamline the design and optimisation processes of cesarean lift sections, contributing to enhanced safety, efficiency, and performance in diverse industrial applications. it will be generated below the camera space and also simultaneously a audio will be played deciphering or reading the generated text aloud for the users to hear and also thereby confirm.



V. METHODOLOGY

Our system uses random forest algorithm for training the model with the given image samples and recognising them. The following steps are included to describe the flow of training the samples and recognizing the signs respectively.



A. Data Wrangling:

In this section of the report will load in the data, check for cleanliness, and then trim and clean given dataset for analysis. Make sure that the document steps carefully and justify for cleaning decisions.

B.Data collection

The data set collected for predicting given data is split into Training set and Test set. Generally, 7:3 ratios are applied to split the Training set and Test set. The Data Model which was created using Random Forest, logistic, Decision tree algorithms and Support vector classifier (SVC) are applied on the Training set and based on the test result accuracy, Test set prediction is done

C.Data Pre-processing:

Validation techniques in machine learning are used to get the error rate of the Machine Learning (ML) model, which can be considered as close to the true error rate of the dataset. If the data volume is large enough to be representative of the population, you may not need the validation techniques. However, in real-world scenarios, to work with samples of data that may not be a true representative of the population of given dataset. To finding the missing value, duplicate value and description of data type whether it is float variable or integer. The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyper parameters. The evaluation becomes more biased as skill on the validation dataset is incorporated into the model configuration. The validation set is used to evaluate a given model, but this is for frequent evaluation. It as machine learning engineers use this data to fine-tune the model hyper parameters. Data collection, data analysis, and the process of addressing data content, quality, and structure can add up to a time-consuming to-do list. During the process of data identification, it helps to understand your data and its

properties; this knowledge will help you choose which algorithm to use to build your model. A number of different data cleaning tasks using Python's Pandas library and specifically, it focus on probably the biggest data cleaning task, missing values and it able to more quickly clean data. It wants to spend less time cleaning data, and more time exploring
and modelling.Some of these sources are just simple random mistakes. Other times, there can be a deeper reason why data is missing. It's important to understand these different types of missing data from a statistics point of view. The type of missing data will influence how to deal with filling in the missing values and to detect missing values, and do some basic imputation and detailed statistical approach for dealing with missing data. Before, joint into code, it's important to understand the sources of missing data. Here are some typical reasons why data is missing:

• User forgot to fill in a field.
• Data was lost while transferring manually from a legacy database.
• There was a programming error.
• Users chose not to fill out a field tied to their beliefs about how the results would
be used or interpreted.

Variable identification with Uni-variate, Bi-variate and Multi-variate analysis:

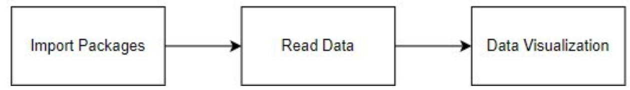
➢ import libraries for access and functional purpose and read the given dataset
➢ General Properties of Analysing the given dataset
➢ Display the given dataset in the form of data frame
➢ show columns
➢ shape of the data frame
➢ To describe the data frame
➢ Checking data type and information about dataset
➢ Checking for duplicate data
➢ Checking Missing values of data frame
➢ Checking unique values of data frame
➢ Checking count values of data frame.
➢ Rename and drop the given data frame
➢ To specify the type of values
➢ To create extra column

..

D.Building the classification model

The prediction of diabetic, a high accuracy prediction model is effective because of the following reasons: It provides better results in classification problem. It is strong in preprocessing outliers, irrelevant variables, and a mix of continuous, categorical and discrete variables. It produces out of bag estimate error which has proven to be unbiased in many tests and it is relatively easy to tune with.

E. MODULE DIAGRAM



GIVEN INPUT EXPECTED OUTPUT
Input: data
Output: removing noisy data

F. Algorithm implementation:

It is important to compare the performance of multiple different machine learning algorithms consistently and it will discover to create a test harness to compare multiple different machine learning algorithms in Python with scikit-learn. It can use this test harness as a template on your own machine learning problems and add more and different algorithms to compare. Each model will have different performance characteristics. Using resampling methods like cross validation, you can get an estimate for how accurate each model may be on unseen data. It needs to be able to use these estimates to choose one or two best models from the suite of models that you have created. When have a new dataset, it is a good idea to visualize the data using different techniques in order to look at the data from different perspectives. The same idea applies to model selection. You should use a number of different ways of looking at the estimated accuracy of your machine learning algorithms in order to choose the one or two to finalize. A way to do this is to use different visualization methods to show the average accuracy, variance and other properties of the distribution of model accuracies. In the next section you will discover exactly how you can do that in Python with scikit-learn. The key to a fair comparison of machine learning algorithms is ensuring that each algorithm is evaluated in the same way on the same data and it can achieve this by forcing each algorithm to be evaluated on a consistent test harness.

G. Performance Metrics to calculate:

False Positives (FP):. if the actual class says this passenger did not survive but the predicted class tells you that this passenger will survive.
False Negatives (FN): . if actual class value indicates that this passenger survived and predicted class tells you that passenger will die.
True Positives (TP):. if actual class value indicates that this passenger survived and predicted class tells you the same thing.

True Negatives (TN):if actual class says this passenger did not survive and the predicted class tells you the same thing.

True Positive Rate (TPR) = TP / (TP + FN)

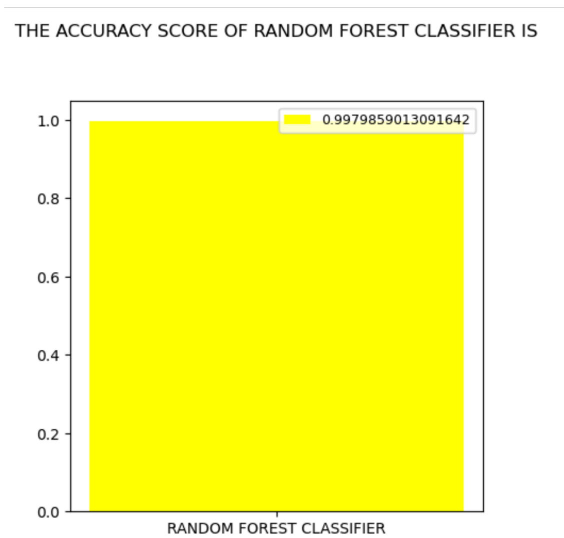
False Positive rate (FPR) = FP / (FP + TN)

Accuracy: It give a accurate value for how the outcome comes.

Accuracy calculation:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Accuracy is the most performance measure and it is a ratio of predicted observation to the total observations. One will get high accuracy only when you have symmetric datasets where values of false positive and false negatives are almost same.



Precision: The proportion of positive predictions that are actually correct.

Precision = TP / (TP + FP)

Precision is the ratio of predicted positive observations to the total predicted positive observations. The question that this metric answer is of all passengers that labelled as survived, how many actually survived? High precision relates to the low false positive rate. We have got **0.788** precision which is pretty good.

Recall: The proportion of positive observed values correctly predicted. (The proportion
of actual defaulters that the model will correctly predict)

Recall = TP / (TP + FN)

Recall (Sensitivity) - Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes.

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall.

General Formula:

F- Measure = 2TP / (2TP + FP + FN)

F1-Score Formula:

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

RESULTS

Thus our website was able to provide a swifter response than the other systems that we referred to. Also as the website has an intuitive User interface that can be accessed by people of any age, the target audience for our project has been expanded to a greater extent.

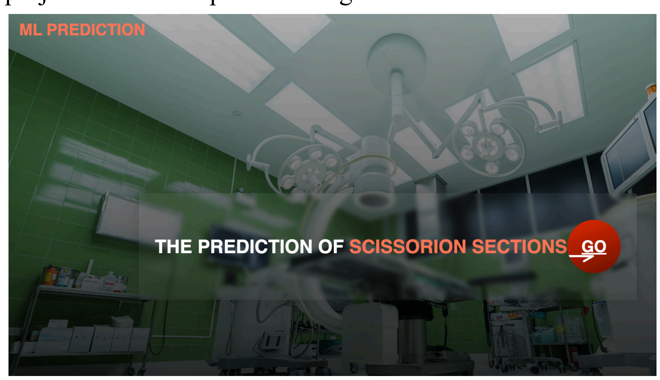


Figure 2. Output screenshot

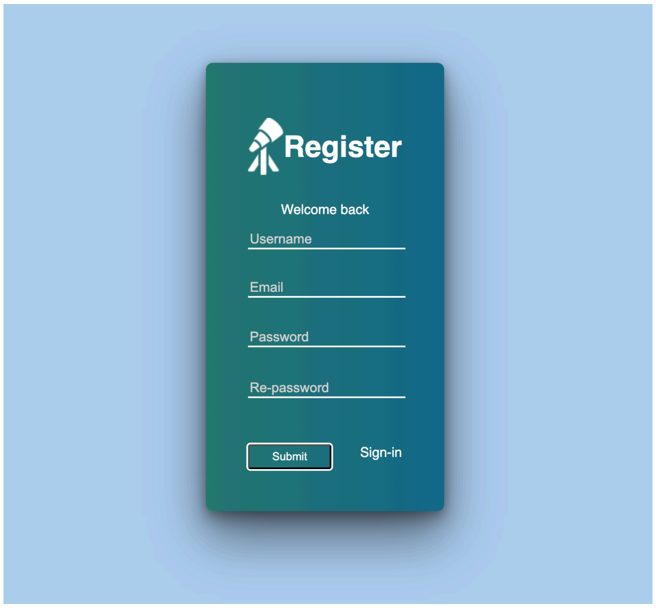


Figure 3.Input page

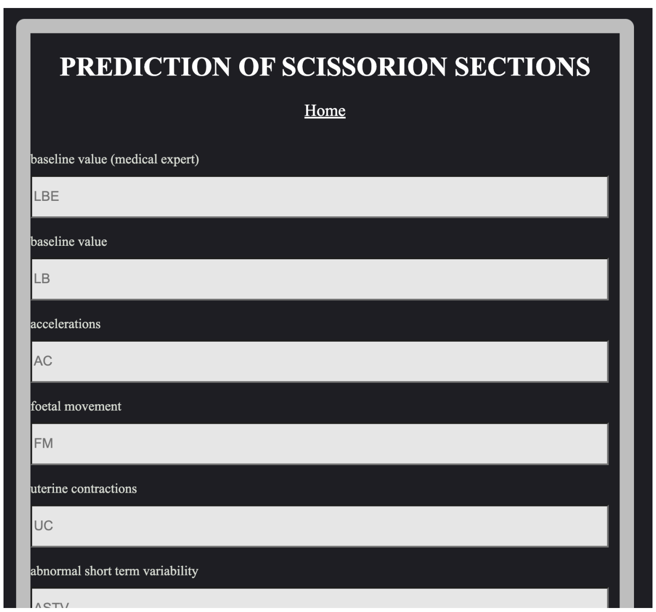


Figure 4 result page

DISCUSSION

The previous works that we considered mostly were constrained to specific categories of people

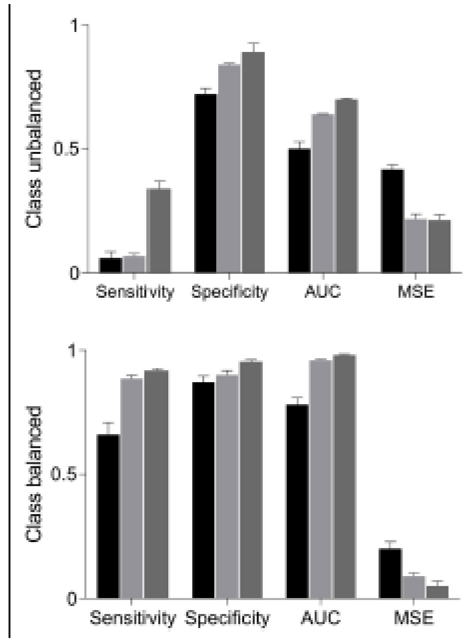


Figure 5. Comparison of previous research and their results (Accuracy and Rapidity in prediction) over the years

VIII CONCLUSION

In conclusion, the application of the Random Forest algorithm in predicting cesarean sections demonstrates its efficacy in addressing complex classification tasks within the real of machine learning. Through the utilization of ensemble learning and decision tree- based models, Random Forest exhibits robustness in handling high-dimensional data and mitigating over fitting. The accuracy and efficiency of this approach in predicting cesarean sections pave the way for its potential utilization in various other fields, ranging from medical diagnostics to industrial quality control. Furthermore, by leveraging the insights derived from this study, future research endeavors can explore further refinements and adaptations of the Random Forest algorithm, ultimately contributing to advancements in both theoretical understanding and practical applications of machine learning techniques.

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