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Classification of Fetal Development Based on Cardiac Imaging

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ABSTRACT: The fact is that children are the future of the world. Therefore, the business makes sure that they are born without any problems or disabilities. But unfortunately, some babies are born with one or more problems and some of them have fetal distress. This condition occurs due to lack of oxygen supply in their mother's womb and many other factors. This pain can lead to certain disorders like neurological disorders and sometimes it can even lead to death.

Electrocardiography (CTG) is an effective, efficient and widely used method to diagnose fetal heart rate (FHR), maternal uterine contractions, etc. This ECG plays an important role in the analysis of different conditions of fetal distress (normal, suspicious, pathological) and their possibilities. A total of 2126 measurements and fetal heart rate (FHR) signal outputs were analyzed to assess the different conditions of fetal distress, of which 1655 were normal, 295 were suspicious, and 176 were pathological samples indicating the presence of fetal distress. used to indicate.

There is a need for a computer-based approach to analyze the findings and observations made during the ECG and to assess the likelihood of fetal distress. To achieve this goal, custom reinforcement set learning algorithms and many other machine learning algorithms are used. You need a user interface to interact with Doc Forms. The user interface should have input fields and should also be able to print the desired output and the algorithm should analyze the output and the practitioner should take additional steps. The additional steps provided by the algorithm should be dynamic in different cases of embryos (normal, suspicious, pathological).

KEYWORDS: Fetal Distress, Electrocardiography, Fetal Heart Rate, Pathological.

I. INTRODUCTION

An emergency that arises during late pregnancy or during delivery can be called fetal distress. It is a type of problem that arises when the fetus does not receive oxygen (hypoxia) or when the oxygen supply is inadequate. These problems can lead to changes in the baby's heart rate, fetal motility, and sometimes low levels of amniotic fluid. To monitor fetal health, you will need an electrocardiogram. ECG is a technique used to monitor fetal and uterine abnormalities. This device simultaneously records the fetal heart rate and cervical abnormalities. In general, there are three stages of fetal distress: normal, suspicious, and symptomatic. A normal condition indicates that the heartbeat is stable and the probability of fetal distress is very low, but a suspicious condition indicates that the heartbeat is unstable and the crisis is likely to occur if the problem is not resolved immediately, and the stage indicates that the fetus is in the disease stage and needs immediate treatment. Therefore, the signs or symptoms of fetal distress should not be taken lightly and the medical team should be aware of these conditions before taking any immediate action. Nowadays, the goal of machine learning is to provide computational methods for gathering, diversifying, and updating systems knowledge in an ideal way that can help alleviate our problem. It includes some specialized knowledge-based learning methods that help to stimulate knowledge from data.

II. RELATED WORK

In general, when faced with large and extensive pathology reports generated by the latest medical examination equipment, the medical team has clinical difficulties in diagnosing the condition of the fetus. Here, the medical team takes notes from the scan machine and manually determines the condition of the fetus, which requires a lot of work to fully determine the condition of the fetus. However, a medical team can handle a small amount of fetal case analysis reports in a day. If the patient receives the report after an hour or half an hour. This will be fine once the fetus returns to normal. If, however, the patient's fetal condition is toxic, but the problem is reported late, it can lead to a dangerous condition. Delay in treatment of the patient can lead to serious disorders such as nervous



system disorders and sometimes infant death in pregnancy. If a dead baby is in its mother's womb, it can lead to dangerous conditions such as infertility and sometimes death in the future.

The main objective of launching this project is to overcome this problem through machine learning approach. Here, the method of machine learning helps the medical team to successfully assess the condition of the fetus in seconds and avoid misdiagnosis.

To solve the problems discussed in the previous section. We need a computer-based approach to evaluate the results and observations made during the ECG and to assess the likelihood of fetal distress. To achieve this goal, custom support set learning algorithms and many other machine learning algorithms are used. The algorithm should analyze the output and suggest what additional steps the physician should take. By presenting the analysis in a visual manner the user (physician) can easily understand where the problem is and how to solve it. Algorithms and additional measures provided by the visual material should be assembled in different cases of fetal distress (general, suspected, pathological).

III. METHODOLOGY

Project implementation is the next stage of the project, where projects and processes become reality. Sometimes, we need to change the project approach to achieve a goal. Each outcome and the steps taken to implement the process vary depending on the project.

1) Data Collection:

In this project, we used the CTG dataset, which is available to everyone in the "University of California Irvine" ML repository. There are 21 columns in the dataset that have no target class. Using these features of the data, the position of the fetus should be classified. The condition of the fetus is divided into three stages: normal, suspicious and pathological. The CTG dataset contains 2126 observations, of which 1655 are general, 295 are suspicious and 176 are pathological. These observations indicate the condition of the fetus. Attribute information is as follows:

LB	FHR baseline
AC	Accelerations
FM	Fetal Movements
UC	Uterine Contractions
DL	Light Decelerations
DS	Severe Decelerations
DP	Prolonged Decelerations
ASTV	Abnormal Short-Term Variability
MSTV	Mean Value of Short-Term Variability
ALTV	Abnormal Long-Term Variability
MLTV	Mean Value of Long-Term Variability
Width	Width of Histogram
Min	Minimum of Histogram
Max	Maximum of Histogram
Nmax	No: of Histogram Peaks
Nzeroes	No: of Histogram Zeroes
Mode	Histogram Mode
Median	Histogram Median
Variance	Histogram Variance



Tendency Histogram Tendency

NSP Fetal State (Normal – N, Suspicious – S, Pathological – P)

The below screenshot represents the sample data:

Screen 3.1 Cardiocotography Dataset

2)Data Pre-Processing:

Preprocessing means to create accurate data which helps us to get accurate results. One of the main steps in preprocessing is handling missing values, removing unwanted features, and modifying the data in the dataset. In this data set, we have removed unwanted features and unnecessary columns in the data set. We did not find any invalid values in the data.

- **Feature Scaling:** It is a technique used to validate the value of features in datasets from long to short. In this project, we used a standard scaling procedure to scale the features. After validation, the values range from 0 to 1. The basic principle of authentication is:

$$Z=(x-\mu)/ \sigma$$

x = Value
 μ = Mean
 σ = Standard Deviation

	count	mean	std	min	25%	50%	75%	max
baseline value	2126.0	133.303857	9.840844	106.0	126.000	133.000	140.000	160.000
accelerations	2126.0	0.003178	0.003866	0.0	0.000	0.002	0.006	0.019
fetal_movement	2126.0	0.009481	0.046666	0.0	0.000	0.000	0.003	0.481
uterine_contractions	2126.0	0.004366	0.002946	0.0	0.002	0.004	0.007	0.015
light_decelerations	2126.0	0.001889	0.002960	0.0	0.000	0.000	0.003	0.015
severe_decelerations	2126.0	0.000003	0.000057	0.0	0.000	0.000	0.000	0.001
prolonged_decelerations	2126.0	0.000159	0.000590	0.0	0.000	0.000	0.000	0.005
abnormal_short_term_variability	2126.0	46.990122	17.192814	12.0	32.000	49.000	61.000	87.000
mean_value_of_short_term_variability	2126.0	1.332785	0.883241	0.2	0.700	1.200	1.700	7.000
with_abnormal_long_term_variability	2126.0	9.846660	18.396880	0.0	0.000	0.000	11.000	91.000
mean_value_of_long_term_variability	2126.0	8.187629	5.628247	0.0	4.600	7.400	10.800	50.700
histogram_width	2126.0	70.445908	38.955693	3.0	37.000	67.500	100.000	180.000
histogram_min	2126.0	93.579492	29.560212	50.0	67.000	93.000	120.000	159.000
histogram_max	2126.0	164.025400	17.944183	122.0	152.000	162.000	174.000	238.000
histogram_number_of_peaks	2126.0	4.068203	2.949386	0.0	2.000	3.000	6.000	18.000

Screen 3.2: Dataset Before Feature Scaling

	count	mean	std	min	25%	50%	75%	max
baseline value	2126.0	1.069490e-15	1.000235	-2.775197	-0.742373	-0.030884	0.680604	2.713428
accelerations	2126.0	-6.015804e-17	1.000235	-0.822388	-0.822388	-0.304081	0.730133	4.093929
fetal_movement	2126.0	-1.336863e-17	1.000235	-0.203210	-0.203210	-0.203210	-0.138908	10.106540
uterine_contractions	2126.0	-1.336863e-16	1.000235	-1.482465	-0.803434	-0.124404	0.894142	3.610264
light_decelerations	2126.0	-5.347452e-17	1.000235	-0.638438	-0.638438	-0.638438	0.375243	4.429965
severe_decelerations	2126.0	6.684315e-18	1.000235	-0.057476	-0.057476	-0.057476	-0.057476	17.398686
prolonged_decelerations	2126.0	1.336863e-17	1.000235	-0.268754	-0.268754	-0.268754	-0.268754	8.208570
abnormal_short_term_variability	2126.0	-7.352747e-17	1.000235	-2.035639	-0.872088	0.116930	0.815060	2.327675
mean_value_of_short_term_variability	2126.0	6.684315e-17	1.000235	-1.282833	-0.716603	-0.150373	0.415857	6.417893
with_abnormal_long_term_variability	2126.0	-5.347452e-17	1.000235	-0.535361	-0.535361	-0.535361	0.062707	4.412293
mean_value_of_long_term_variability	2126.0	2.406354e-16	1.000235	-1.455081	-0.637583	-0.139975	0.464263	7.555172
histogram_width	2126.0	-3.007942e-17	1.000235	-1.731757	-0.858765	-0.075640	0.758838	2.812936
histogram_min	2126.0	-4.679021e-17	1.000235	-1.474609	-0.899376	-0.019608	0.893996	2.213648
histogram_max	2126.0	-1.203177e-16	1.000235	-2.342558	-0.670314	-0.112899	0.555999	4.123453
histogram_number_of_peaks	2126.0	-1.671079e-16	1.000235	-1.379664	-0.701397	-0.362263	0.655137	4.272438
histogram_number_of_zeros	2126.0	2.757280e-17	1.000235	-0.458444	-0.458444	-0.458444	-0.458444	13.708003

Screen 3.3: Dataset After Feature Scaling



model. This single model sends inputs to 3 models to evaluate the results when the results are as expected, then a final estimate is made based on most of the results. The majority vote is determined by meta-classification..

Random Forest:

The random forest mass is a method of ML. The RF algorithm can be used for both classification and regression. In this project, we will use the taxonomy algorithm because the dataset is in a taxonomy distribution. We planted 12 depth trees in a random forest and used almost all the features available in the dataset without any work. The algorithmic estimators selected 150 parent trees that met the entropy criteria..

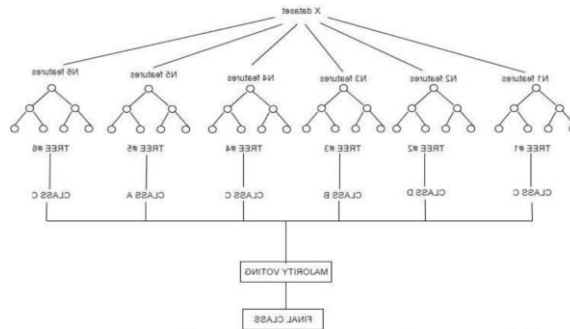


Fig 3.3 A Random Forest Structure.

1. Randomly select some features from yesterday. Make sure that the features selected are less than the total number of facilities.
2. From the given properties, calculate the best nodes using best methods called best distribution points.
3. Again, split the node (we came to step 2) in the same way to split the children into nodes.
4. Repeat the first three steps until you reach the nodes generated by the algorithm.
5. Next, create a random forest by repeating a random number 1-4 n times to form a decision tree.
6. Take the test data and features and use decision trees to estimate the result and save the result in some variable.
7. Count the votes for each estimate and take the majority as the final estimate.

After modeling with random forests using the hyper-parameters under discussion, the trainee is trained with the data set and evaluated using the test set.

		Predicted(Random Forest)		
		Normal	Suspect	Pathological
Actual	Normal	327	4	2
	Suspect	11	51	2
	Pathological	2	3	24

Table 3.1 Random Forest Confusion Matrix

From the above confounding matrix, we can see that the model is not well trained with pathological class condition. To overcome this, we need to train the model with some other hyperparameters. At this point, the hyper parameter is useful in determining the optimal hyper parameter for the tuning model.



IV. EXPERIMENTAL RESULTS

After building a stacking model using the default parameters to classify fetal pain using ECG, we achieved 96.04% accuracy. The bar graph shown below represents the quality of each improved model in the test data set.

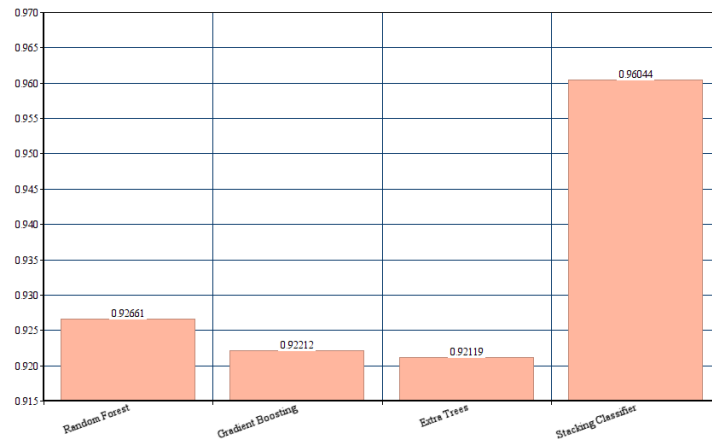


Fig 4.1 Precision Bar Graph

As we have already seen in the performance evaluation, the additional tree model has a lower accuracy value than the other models, and the random forest always comes before and after the hyperparameter set. Next, we included three algorithms using comprehensive learning stacking. The main reason to go with stacking classification is the high stacking accuracy value as compared to other algorithms. This is why we consider accuracy as a diagnostic measure due to category imbalance. The bar graph plot shown below indicates the accuracy of each optimized model in the test data set.

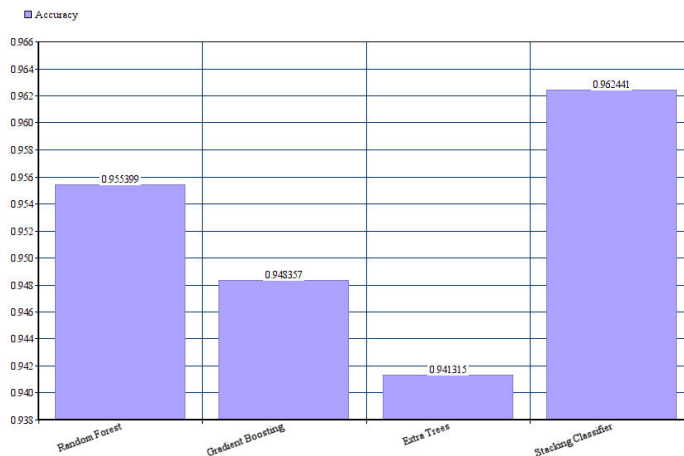


Fig 4.2 Accuracy Bar Graph

From the graph above, the results of random forest accuracy and gradual improvement are close to each other, about 95%. However, the accuracy of the rear trees is about 994.13%. Furthermore, the maximum improvement in accuracy through the stacking classifier is achieved with approximately 2% progress. One percent makes sense because the model approximately correctly estimates 21 other patients.

V. CONCLUSION

ECG data is useful for obstetricians to diagnose fetal abnormalities and is used to decide on medical treatment before a serious condition develops. Major developments in the medical field have been largely based on systemic

decision support. This project analyzes fetal ECG data and uses machine learning strategies using anisymbol learning techniques to build taxonomic models to assess sexual dysfunction. For classification, we used 3 algorithms, namely Random Forest, Gradient Boosting and Extra Tree with 95% accuracy (approx). The accuracy obtained from Stacking 3 algorithm is (approximately) 96% higher than any other algorithm. The results of this project indicate that sexual machine learning methods can be used to classify fetal positions. In short, we can say that this development requires a significant contribution of technologies to prevent human error and improve the quality of medical treatment.

In the future, this machine learning model can be combined with other software or machines such as ECG machines. Therefore, this software can be used directly with other software as a main subset of software. These days, the age of the mobile phone is increasing anywhere in the world. Therefore, a mobile application can be developed for the classification of fetal pain, which is accessible to everyone and can be accessed by everyone from anywhere. With technology developing day by day, anyone can use this software to improve scalability and flexibility of applications through advanced technology.

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