Fetal Distress Classification based on Cardiotocography using Machine learning

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Abstract - **Children are the future of the world. It is important to make sure that they are delivered safely to this world. One of the complicated prenatal and neonatal problems faced by pregnant woman and new born infants is fetal distress. It is a condition where the fetus does not receive enough oxygen for respiration, which results in an unhealthy and dangerous condition in the fetus. If left untreated fetal distress may result in stillbirth. The fetal distress can be diagnosed by monitoring the heartbeat of the baby. Any abnormal spike or deceleration in the fetus' heartbeat is the indication of the problem. The main objective is to use machine learning algorithm to predict the condition of fetal distress from the test results of a cardiotocogram. The decision tree classifier algorithm has been used to predict the abnormal fetus. Various parameters such as light decelerations, severe deceleration, prolonged deceleration, repetitive deceleration, baseline value, fetal movements and uterine contraction are analysed and the fetal distress is predicted by the algorithm in decision tree classifier. The main purpose of this decision tree classification method is to classify and determine the fetal state class code consisting of normal, suspicious or pathologic. The histogram means median, mode and standard deviations for those parameters and effectively is calculated and used in the algorithm to get high accuracy. Totally 2126 measurements and classifications of fetal heart rate (FHR) signal output were analyzed to predict the fetal distress. 80% of data is given as train dataset and 20% as test dataset. The algorithm also have predicts the suitable food to be taken by the women during the time of her pregnancy by giving the input as the total number of her pregnancy month. Thus using ML (machine learning) algorithm the possibility of fetal distress in pregnant women is predicted.**

Index Terms - **Decision tree classifier, histogram mean, median, mode and standard deviations, normal, suspicious, pathologic.**

I. INTRODUCTION

Machine Learning (ML) aims at providing us the computational methods for collecting, varying and updating knowledge of systems in intelligent manner, and in particular learning mechanisms that will help us to induce knowledge from examples or data [4]. Generally, clinical difficult for doctors exist to diagnose the diseases while facing the enormous and tremendous amounts of disease inspection reports generating from the latest medical examination equipment. Here machine language (ML) successfully assists medical diagnosis (by prediction) and prevent misdiagnosis [2].

Aim of this work is to classify fetal distress using machine learning techniques based on high dimensional CTG data and patient's medical history. Research will provide solutions to so called third world or remote places where obstetricians are not accessible in terms of prior detection of fetal risks as well as its categorization

The term fetal distress indicates the abnormal of fetal during the time of pregnancy. Fetal distress, defined as progressive fetal hypoxia and/or academia secondary to inadequate fetal oxygenation, is a term that is used to indicate changes in fetal heart patterns, reduced fetal movement, fetal growth restriction, and presence of meconium stained fluid [6]. Although fetal distress may be associated with neonatal encephalopathy, the generic term has poor predictive value for neonatal outcomes; most neonates will be vigorous and healthy at birth despite a diagnosis of fetal distress. Fetal distress can only be observed indirectly, usually via electronic fetal heart rate monitoring which is subject to high intra- and inter-observer variability in data interpretation. For this reason, many experts recommend abandoning the term fetal distress, and adopting the term non-reassuring fetal status to describe clinical interpretation of fetal well-being. Mostly fetal distress is confused by the term asphyxia birth whereas many people use fetal distress and birth asphyxia as interchangeable terms but the Committee of Obstetric Practice of American Congress of Obstetricians and Gynecologists (ACOG) had expressed its concern which led to replacement in the term of fetal distress. Conditions commonly associated with non-reassuring fetal status include maternal cardiovascular disease, anemia, diabetes, hypertension, infection, and placental abruption, abnormal presentation of the fetus, intrauterine growth restriction and umbilical cord compression, among other obstetric, maternal or fetal conditions.

The fetus experiences three stages of deterioration when oxygen levels are depleted: transient hypoxia without metabolic acidosis, tissue hypoxia with a risk of metabolic acidosis, and hypoxia with metabolic acidosis. Fetal response to oxygen deprivation is regulated by the autonomous nervous system, mediated by parasympathetic and sympathetic mechanisms. The fetus is equipped with compensatory mechanisms for transient hypoxia during labour, but prolonged, uninterrupted fetal hypoxia may lead progressively to acidosis with cell death, tissue damage, organ failure and potentially death. In response to hypoxia, fetal compensatory mechanisms include 1) a decrease in heart rate; 2) a reduction in oxygen consumption secondary to cessation of nonessential functions such as gross body movements; 3) a redistribution of cardiac output to preferentially perfuse organs, such as the heart, brain, and adrenal glands; and 4) a switch to anaerobic cellular metabolism. Prolonged fetal hypoxia is associated with significant peri natal morbidity and mortality with particular concern for short- and long-term complications including encephalopathy, seizures, cerebral palsy, and neurodevelopment delay.

The fetal heart rate changes markedly in response to prolonged oxygen deprivation, making fetal heart rate monitoring a potentially valuable and commonly used tool for assessing fetal oxygenation status in real time. Non-reassuring fetal heart rate patterns are observed in approximately 15% of labors [3].

Through abnormal reduction of labor time, fetal heart rate changes, the presence of dark green fecal liquid from the fetus (meconium) or other abnormal substances in the amniotic fluid, or fetal monitoring with an electronic device that shows a fetal scalp pH of less than 7.2 the fetal distress can be detected .The worldwide technique used to determine and to monitor the fetal distress is Cardiotocography. Fetal heart rate (FHR) and uterine contraction (UC) are the two main signals of CTG. The signals are recorded simultaneously using electronic fetal monitoring (EFM) devices. CTG relies upon FHR, UC, and fetal movement activity and it is employed to detect dangerous situations for the fetus. The aim of intrapartum fetal monitoring is to detect hypoxia or asphyxia and prevent fetal injury [4]. CTG contributes to the early diagnosing of undesirable events, such as cerebral palsy and intrapartum fetal hypoxia developing depend on the lacking of oxygen.

Severe sequel is caused due to fetal distress, the main purpose of this study is to establish models classification and to compare efficiency and accuracies among models to help obstetricians on diagnosis of fetal distress [2].

II. DATA

Some of the symptoms of fetal distress are:

1. Decreased movement felt by the mother

Cardiograph’s Width, Mode, Mean, Median and Variance are suitable for our research. Correlation between attributes and time dependent changes are analyzed by features selection method within CTG data. The cardiograph’s mean, median, mode and variance are calculated from the histogram which forms the root data for the prediction of fetal distress and based

2. Non-reassuring patterns seen on cardiotocography:
   a. Increased or decreased fetal heart rate (tachycardia and bradycardia), especially during and after a contraction
   b. decreased variability in the fetal heart rate
   c. late decelerations
3. Biochemical signs, assessed by collecting a small sample of baby's blood from a scalp prick through the open cervix in labor
   a. fetal metabolic acidosis
   b. elevated fetal blood lactate levels (from fetal scalp blood testing) indicating the baby has a lactic acidosis

To predict the fetal distress on the basis of the above symptoms cardiotocography data set is used. It contains the Fetal Heart Rate, measurements from Cardiotocography, and the diagnosis group classified by gynecologist. There are 21 attributes, including 11 continuous, 9 discrete and 1 nominal scales. Raw data has been collected and domain knowledge has gathered by literature review as well as identification of relevant features for research. Feature engineering is required to reduce complexity of data as well as to improve the model performance. [3] We are taking only two states of fetus normal or pathological into consideration under this research as suggested by literatures. We have proposed stacked generalized ensemble approach of ANN, SVM and RF. Individual performance of algorithms and model robustness can be analyzed by 10-fold cross validation. Model performance and accuracy can be improved by training several times the model. Feature selection has done before because research requires only selected features.

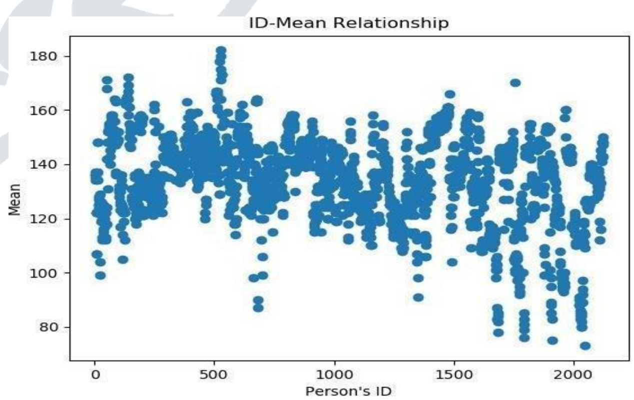

Figure 1: ID-Mean Relationship

Features like LB (FHR baseline beats per minute), FM (fetal movements per second), UC (uterine contraction per second), STV (short-term variability) and NSP (fetal state class), AC (acceleration), ASTV (), MSTV, ALTV, mLTV, DL (light deceleration), DS (slight deceleration), DP (prolonged deceleration), DR (repetitive deceleration) and on it the graph has been plotted for each case.

III. PREDICTION ALGORITM

A. Logistic Regression

Logistic model can be estimated through Logistic Regression; and also it is a form of binomial regression. According to mathematics a binary logistic model has a dependent variable with two possible values, such as pass/fail, win/lose, alive/dead or healthy/sick; these values can be represented by an indicator variable, where the two values are labeled "0" and "1". Discrete values can be easily estimated by logistic regression (usually binary values like 0/1) from a set of independent variables [5]. It helps to predict the probability of an event by fitting data to a legit function. It is also called legit regression.

313

$(\quad) = 313 + 9 + 4 = 0.96$

313

$(\quad) = 313 + 13 + 0 = 0.77$

$0.96 * 0.96$

$= 2 * 0.96 + 0.96 = 0.96$

	Predicted(Logistic Regression)			
		Normal	Suspect	Pathologic
Actual	Normal	313	9	4
	Suspect	13	43	2
	Pathologic	0	3	39

Table 1: Confusion Matrix of Logistic Regression

B. K-Nearest map

A non-parametric method is followed in K-nearest neighbor algorithm for classification and regression [2]. K-nearest map works based on the principle of minimum distance from training samples to query samples. In this algorithm the clustering of data occurs first and then it plots the query sample and checks for the minimum distance. This algorithm mainly analyses the neighbor point's information and predicts the query samples. The label for the query sample is determined with the help of neighbor or training samples.

314

$(\quad) = 314 + 9 + 3 = 0.96$

314

$(\quad) = 314 + 23 + 10 = 0.90$

$0.96 * 0.90$

$= 2 * 0.96 + 0.90 = 0.92$

	Predicted(K-Mean)			
		Normal	Suspect	Pathologic
Actual	Normal	314	9	3
	Suspect	23	35	0
	Pathologic	10	4	28

Table 2: Confusion Matrix of K-Nearest Map

C. Support-vector machine

By plotting points of raw data in an n-dimensional space (where n is the total number of available features) Support-vector machine algorithm is determined. Each feature value is then tied to a particular or specific coordinate, making the classification of data easier. Classifier Lines can be utilized for splitting of data and then the points are plotted on the graph. SVM distinctly classifies the data points in N-dimensional space to find the hyper planes. Optimal boundary between the possible outputs is found by taking the transfor~~mation of~~ data.

325

$(\quad) = 325 + 1 = 0.99$

325

$(\quad) = 325 + 54 + 39 = 0.77$

$0.99 * 0.77$

$= 2 * 0.99 + 0.77 = 0.86$

	Predicted(Support Vector Machine)			
		Normal	Suspect	Pathologic
Actual	Normal	325	1	0
	Suspect	54	3	1
	Pathologic	39	1	2

Table 3: Confusion Matrix of SVM D. Naive Bayes classifier

Naive Bayes classifier is a type of probabilistic algorithms that take benefits of probability theory and Bayes' theorem to predict the label value. They are probabilistic, which means that they calculate the probability of each label for a given train dataset, and then output the label with the highest one. By using Bayes' Theorem the naive bayes algorithm gets the probability value which describes the probability of a parameter, based on prior knowledge of conditions that might be related to that feature.

Classifier	Person status	Precision	Recall	F1 Score	Execution Time (ms)	Accuracy
Logistic	Normal	0.96	0.96	0.96		
Decision Tree	Normal	0.96	0.96	0.96	489	0.924
	Suspect	0.80	0.74	0.77		
	Pathologic	0.85	0.93	0.89		

$(\ ) = \frac{258}{258 + 5} = 0.98$

$(\ ) = \frac{258}{258 + 51 + 17} = 0.79$

$= 2 * \frac{0.98 * 0.79}{0.98 + 0.79} = 0.874$

	Predicted(Naïve Bayes Classifier)		
Actual	Normal	Suspect	Pathologic
Normal	258	51	17
Suspect	5	50	3
Pathologic	0	15	27

Table 4: Confusion Matrix of Nave Bayes

D. Decision Tree Classifier

One of the most popular machine learning algorithms in use today, this is a supervised learning algorithm that is used for classifying problems. It uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modelling approaches used in statistics, data mining and machine learning. It works well classifying for both categorical and continuous dependent variables [7].

	Predicted(Decision Tree Classifier)		
Actual	Normal	Suspect	Pathologic
Normal	312	9	5
Suspect	13	43	2
Pathologic	1	2	39

Table 5: Confusion Matrix of Decision Tree

$(\ ) = \frac{312}{312 + 13 + 1} = 0.96$

$(\ ) = \frac{312}{313 + 9 + 5} = 0.96$

$= 2 * \frac{0.96 * 0.96}{0.96 + 0.96} = 0.96$

IV. SELECTION OF DECISION TREE

Decision tree consists of root, decision nodes, branch nodes, and leaf nodes. The root node is the node with the largest gain which is calculated using the following:

Information gain:

$(\ ,\ ) = -\frac{}{} \log_2 \frac{}{} - \frac{}{} \log_2 \frac{}{}$

Entropy: $(\ ) = \sum \frac{+}{+} * (\ ,\ )$

Gain: $(\ ) = (\ ,\ ) - (\ )$

It begins with the root, and each branch is a new decision node or a new leaf node of the tree. Each decision node represents a decision with respect to the attribute of classification observation. And each leaf node reflects one possible classification result. The attribute with maximum information is chosen to develop the next node based upon the information gain from information theory. And the specific value for this attribute is determined to set up the branch. [1] On continuing these steps to develop the decision tree until satisfying the predetermined stopping criteria. The following steps describe the details of building the decision tree:

Step 1: Split the whole dataset into training and testing sets.

Step 2: Use the training set as the input for tree root.

Step 3: Grow the tree by selecting one best attribute based upon the information gain theory for each node.

Step 4: Prune the grown tree by using the testing set until each node has only one node.

Step 5: repeat step 1 to 4 until all the nodes are leaf nodes.

Thus by using these methods in our prediction of fetal distress the results and the accuracy of each algorithm is shown in the below-picture.

Table 6: Precision, Accuracy, recall Execution time

For the above given datasets the accuracy for decision tree classifier is more than the other algorithms. Due this main reason we have decided to go with Decision Tree Classifier algorithm for the prediction of fetal distress in pregnant women.

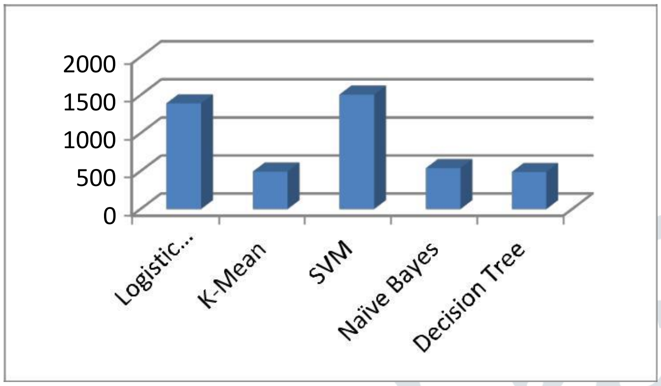

Figure 2: Execution Time Graph for all algorithms

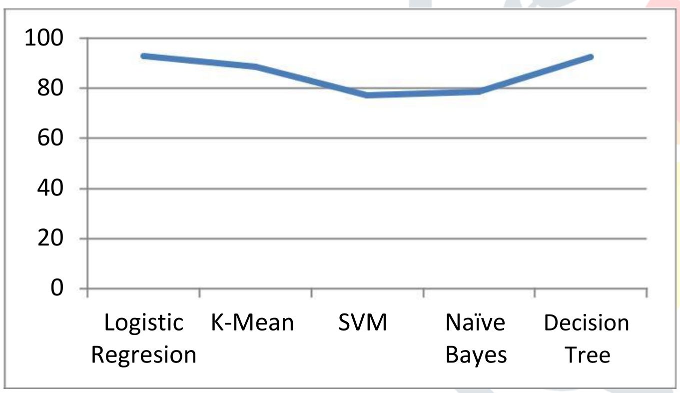

Figure 3: Accuracy Graph for all algorithms

V. CONCLUSION

This study analyses Cardiotocography data set for fetus and uses Machine Learning Repository website with, decision tree, and artificial neural network techniques to create the classification models to predict fetal distress. Similar study with ANN application of the exceptional accuracy 0.988 was done on breast cancer diagnosis. And the other study with the application of decision tree reached 0.801 accuracy was found on glaucoma diagnosis. The accuracy derived from the DT model is higher than the other algorithms and it shows the concise and effective decision rules to classify the situation of fetus. Those decision rules could support obstetrician determine whether the fetus is suffering fetal distress effectively and efficiently. This database contains 21 attributes, involving 11 continuous attributes and 10 discrete attributes. Since discrete attribute could not be applied in discriminant model, the continuous attributes were employed in this study. The future study will involve in evolving of this idea into product that is useful for doctors and pregnant women around the globe to predict fetal distress and prevent it from occurring.

VI. REFERENCES

[1]. Adhistya Erna Permanasari, Akhsin Nurlayli," Decision Tree to Analyze the Cardiotocogram Data for Fetal Distress Determination" 2017 International Conference on Sustainable Information Engineering and Technology (SIET), 459-463.

[2].Fetal distress prediction using discriminant analysis, decision tree, and artificial neural network by Mei-Ling Huang*, Yung-Yan Hsu

[3]. Application of Machine Learning Techniques to classify Fetal Hypoxia by Krishna Mohan Mishra

[4]. Machine Learning in Medical Applications by George D. Magoulas1 and Andriana Prentza.

[5]. Applications of Machine Learning in Cancer Prediction and Prognosis by Joseph A. Cruz, David S. Wishart.

[6]. Frank, A. and Asuncion, A. (2010) UCI Machine Learning Repository. University of California, School of Information and Computer Science. Irvine.

[7]. Huang, M.L. and Chen, H.Y. (2011) Glaucoma classification model based on GDx VCC measured parameter by decision tree. Journal of Medical Systems.

[8] J. D, "Cardiotocography - A Comparative Study between Support Vector Machine and Decision Tree Algorithms," vol. 4, no. 1, 2017.

[9] S. A. A. Shah, W. Aziz, M. Arif, and M. S. A. Nadeem, "Decision Trees Based Classification of Cardiotocograms Using Bagging Approach," Proc. - 2015 13th Int. Conf. Front. Inf. Technol. FIT 2015, pp. 12–17, 2016.

[10]. E. M. Karabulut and T. Ibrikci, "Analysis of Cardiotocogram Data for Fetal Distress Determination by Decision Tree Based Adaptive Boosting Approach," Comput. Commun., vol. 2, no. July, pp. 32–37, 2014.