Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

IoT Based Fetal Heathcare Prediction using Machine Learning Approaches

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Cite this paper as: V.Devigasri, D. Ramyachitra (2024) IoT Based Fetal Heathcare Prediction using Machine Learning Approaches. *Frontiers in Health Informatics, 13* (3), 7452-7468

A B S T R A C T

Introduction: A fast-growing topic called "Internet-of-Things(IoT)/Machine Learning(ML) for Fetus Medical Prediction" uses a variety of AI (Artificial Intelligence) and information analytics approaches to enhance care during pregnancy. This entails gathering and analyzing information from many sources to forecast future health concerns for the fetus, which can assist medical professionals in taking preventative or management actions.

Objectives: The objective is to examine the IoT based fetal healthcare prediction with the IoT sensor's data for the early detection of diseases affecting the fetus and preventing it.

Methods: This study explored the various ML algorithms including DT (Decision Tree), RF (Random Forest), SVM (Support Vector Machine), XGBoost, Adaptive Boosting, R-SVM, Decision Stump Model, and K Nearest Neighbour (KNN).

Results: Demonstrates the effectiveness of approaches in predicting fetal healthcare outcomes, offering promising results using the evaluation metrics. Through experimentation, we have demonstrated that the combination of RF with Min-Max scaling and Relief feature extraction stands out as a superior approach in terms of predictive performance. This combination not only enhances accuracy but also improves precision, recall, and F1-Score, thus offering a comprehensive evaluation of fetal healthcare outcomes.

Conclusions: IoT based fetal healthcare prediction utilizing a diverse range of machine learning algorithms and pre-processing techniques has yielded insightful findings. By leveraging the strengths of Random Forest's ensemble learning, Min-Max scaling's normalization benefits, and Relief feature extraction's capability to select relevant features, our approach achieves a well-balanced prediction model that effectively captures intricate patterns within the fetal healthcare dataset.

Keywords: *Internet-of-Things, Fetal Monitoring, Decision Tree(DT), Random Forest(RF),Support Vector Machine(SVM), XGBoost, Adaptive Boosting, Regulairized SVM(R-SVM), Decision Stump, K-Nearest Neighbors(KNN), Performance Evaluation*

INTRODUCTION

A major healthcare issue that affects the majority of women and babies worldwide is fetal illness. Studies show that many kinds of healthcare remedies were offered to address this issue. For these kinds of important issues, doctors and medical professionals are offering a variety of high-tech remedies. According to an American poll, between 2007 and 2017, there was a 14% decrease in the newborn death rate. These diseases have consequences that affect numerous pregnant women and newborns, and some low-income nations lack the necessary resources to treat them [1]. These days, machine learning and deep learning are specialized topics that are benefiting many different industries, including research, farming, banking, and medicine. Complicated applications are an issue that artificial intelligence can resolve that humans can't.

The IoT and fetal healthcare has grown as a promising technology for enhancing prenatal monitoring and prediction of fetal health conditions. This convergence leverages the interconnectedness of devices and sensors to collect real-time data on maternal and fetal parameters, enabling proactive interventions and personalized care strategies. Within this framework, machine learning (ML) techniques are essential for deriving significant insights from the enormous amounts of sensor data produced by Internet of Things (IoT) devices.

Healthcare diagnosis and detection is the chapter that is very close to ML technologies and e-health. The uses of e-health are much needed particularly for the patients who can't see the health care person. In the stage of pregnancy, the data on the fetus is very difficult to get after the fetus is delivered from the womb of the woman [2]. Nearly 15% of prenatal women will improve life-threatening difficulties that need very special treatment and some need main obstetric intervention for survival. According to WHO nearly 800 women die per day over the world from avoidable symptoms related to the inherent dangers of prenatal. Nearly 295000 ladies die in the stage of prenatal. The most rates of deaths nearly 94% happen in low resource settings and initially, it can be prevented [3]. Pregnant ladies will need to go to many locations for their checkups, such as labs and healthcare organizations, which will add to their expenses. In addition, she will work a lot and become exhausted, which is bad for both her and her unborn child. A fetus is an embryonic-stage prenatal kid who has not yet entered the world. Each three-month phase all over the course of pregnancy is referred to as a quarter.

INTERNET OF THINGS (IOT)

In the current era, the usage of the internet is vast which means without the internet no machine work is possible. Usually, sensors will be connected to the system and can be viewed manually or through IoT with the help of a WIFI module. IoT generally consists of two phases:

((i) Monitoring Phase: In this phase the sensors are connected to the system with processors with a WIFI modem. A live web page will be created and all the sensor values will be updated in the cloud through a WIFI modem and live monitoring of such sensor values is the monitoring phase.

(ii) Controlling Phase: In this phase the live sensor values will be checked continuously and if any one of the sensors crosses the threshold value immediately controlling process takes place which will be done automatically by the process and this is called as controlling phase.

Healthcare practitioners may make better-educated judgments regarding prenatal care and perhaps enhance results regarding the mom and the fetus by merging these multiple data sources and using artificial intelligence algorithms. Though fetal wellness forecasting using artificial intelligence is still a relatively new subject, further study is required to properly verify it[4]. The following block diagram explains the various sensors connected to the processor and how it is sent to the cloud using a WIFI modem.

The block diagram in Figure.1 consists of two sensors namely a Digital Stethoscope which senses the heat beat and an EMG or MEMS (Micro Electro Mechanical System) which checks the movement of the infant. Both the sensors are connected to the microcontroller. An IoT module is also connected to the microcontroller which helps in live tracking of sensor values. The Figure 2 represents how the sensor values are updated in the cloud using the Think View app.

Fetal disease classification aims to improve the accuracy of prenatal diagnosis and treatment, potentially benefiting the fetus as well as the mother. Professionals can better treat afflicted babies in the long run and lower maternal mortality and morbidity by correctly diagnosing and treating fetal disorders throughout pregnancy.

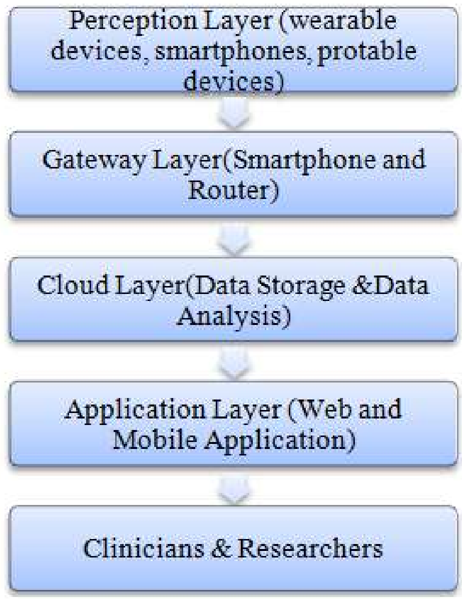

Figure 1 Block Diagram IoT based Fetal Health care System

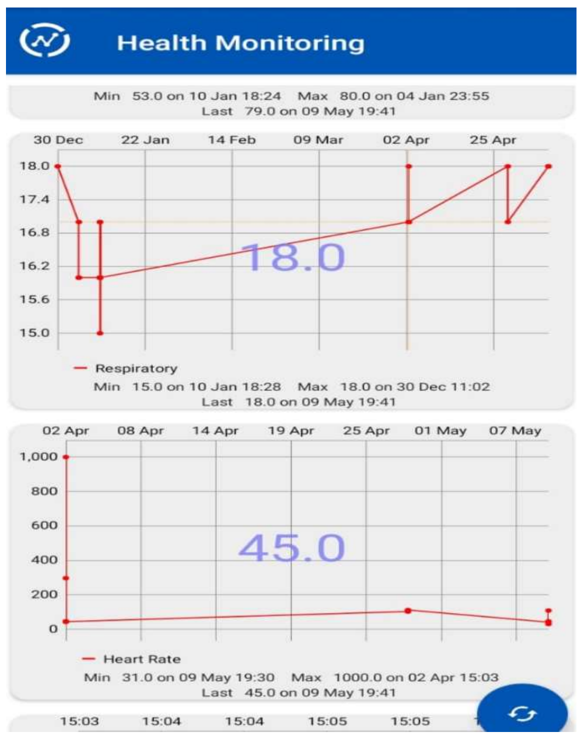

Figure 2 Updation in the cloud using IOT Module

This paper explores the application of various ML algorithms in the domain of fetal healthcare prediction within an IoT framework. Specifically, we investigate the efficacy of DT, RF, SVM, XGBoost(XGB), adaptive boosting(ADB), Region Based SVM (R-SVM), decision stump(DS), and k-nearest neighbors (KNN) algorithms in predicting fetal health outcomes based on sensor-derived data. This study assess the classification model by evaluating the effectiveness of 8 common ML algorithms together with a range of performance indicator like accuracy, precision, recall, and other relevant metrics. By comparing and contrasting the benefits and limitations of each algorithm, it aims to provide insights into the most effective methodologies for fetal health prediction in an IoT environment.

OBJECTIVES

New strategies for improved fetal and maternal monitoring are made possible by the use of managed IoT devices. The future of prenatal care through IoT systems and Machine Learning models were discussed in this study, along with the effects of wearable technology, smart devices, and associated healthcare systems on improving prenatal monitoring, identifying risk factors, and optimizing care strategies. The objective is to investigate IoT-based prenatal healthcare prediction using data from IoT sensors in order to prevent and detect fetal disorders early.

RELATED WORKS

The potential of IoT technology and ML to improve patient outcomes has been recognized by many research projects, and as a result, its use in healthcare institutions has significantly increased. Akhan Akbulut et al. (2018) developed a forecasting method with practical electronic healthcare apps for use by clinicians and expectant mothers. The information was produced using a survey of mothers and three doctors' comprehensive assessments from Istanbul, Turkey's Radyo Emarra Diagnosis Centre. This electronic healthcare software is used to gather information about the medical history and medical state of pregnant women as components, suggest a physical activity for them to engage in throughout childbirth, and advise healthcare professionals and patients on the dangers of fetal abnormalities as an output. In this study, DF) creation of model testing revealed that 89.5% of predictions were accurate. The efficiency in actual testing with 16 users was 87.5% [5].

CardIoTocography (CTG) is a method for keeping track of uterine contractions and fetal heart rate during childbirth. Whether a woman's pregnancy is at moderate or elevated risk can be determined by how a CTG is interpreted. More studies and, in some circumstances, action may be required for an abnormal CTG. These predictions are assessed in a real-time clinical choice-making system, which yields valuable data that can be utilized to understand fetal status better. Modern obstetric practice has made it possible to categorize fetal heart rate signals using a range of accurate and dependable ML models.. These models are becoming more and more crucial for diagnosing diseases. By employing CTG data, Astik Kumar Pradhan et al., 2021 seek to determine how well ML algorithms are suited for forecasting fetal development. For this, several classifiers including LR (Logistic Regression), KNN, RF, and GBM have been utilized, and their efficacy has been assessed. According to the research outcomes, RF has the best exactness of 0.99 [6].

Fetal discomfort brought on by hypoxia in labor can result in several malformations. CTG is commonly used to continuously record the FHR and UC in order to assess whether or not a fetus is hypoxic. Researchers must deal with severely unbalanced data in real life when hypoxic fetuses are vastly neglected. To solve this issue, Marzieh Ajirak et al., (2022) suggest enhancing ensemble learning, where learning is based on the variance of classification mistakes across the dataset. Then, using this type of distribution, repeatedly choose the majority of the data samples that are the most useful. The researchers used a variety of algorithms for categorization, including RF, AdaBoost, k-NN, SVM, and DT. They compare the effectiveness of various techniques using FHR tracings that were obtained from a publicly accessible database. Results from studies conducted on the openly accessible Czech database demonstrate that using boost ensemble significantly enhanced the effectiveness of most employed approaches [7].

During pregnancy time, the fetus grows and changes, therefore periodic examinations are crucial. Maternity lasts nine months, as all women know, and in that period, several variables can result in the newborn's impairment or mortality, which is a highly serious condition that must be prevented. One of the most important methods for assessing how well the baby is doing in the womb is to perform a CTG, which is frequently done to assess the fetus's pulse and overall health during pregnancy. Even though there are various ways to determine health. Each method depends on the testing facility, which is the only section that matters. Shruthi K 2022 will utilize the RF Classifier approach to forecast the health of the fetus based on the findings that the woman receives from the lab. The method will pass the findings provided by the person using it. By making these forecasts, we may cut back on examination costs, and the amount of time pregnant patients must wait in healthcare facilities, as well as worry and fatigue [8].

An essential component of female wellness during labor, delivery, and after delivery includes the well-being of their babies. Certain health conditions like their ages, blood diseases, respiration, etc, may trigger pregnancy and make it complicated. Finding these health issues might reduce the possibility of difficulties with childbirth. Ali Raza et al., 2022 attempt to create an ANN-based framework for forecasting pregnant hazards to health using medical documents. The SVM in this instance delivered highly precise outcomes with a 98% precision thanks to the feature set that DT-BiLTCN offers. Analyzing a mother's health exploratory information shows that diastolic and maximal heart rates, blood pressure, and age at delivery are the three health factors that constitute the most powerful predictors of danger to health during delivery [9].

Physicians commonly use CTG to assess a child's physical status during childbirth because it provides information on the fetal pulse and the uterine contractions, which aid in determining whether the fetus is pathological or not. Physicians have historically performed time-consuming and imprecise manual analyses of CTG data. Thus, creating a system for classifying fetal health is essential since it could facilitate a quicker evaluation process and save money on medical supplies. Because of its rapid growth, AI is now widely employed in disciplines like medical and biological science to tackle a range of problems. The outcomes and evaluation of many ML algorithms for classifying fetal health. The DT, SVM classification model, voting algorithm K-NN, and RF were used for categorization. The RF turns out to offer the best outcomes if the outcomes are assessed. Its 97.51% efficiency outperforms the previously published approach [10].

Pregnant women must inform the physician of any changes to their uterus since fetal wellness is crucial to the development of the fetus. Prenatal assessment, which includes monitoring and diagnostic procedures, can give important details about the fetus's condition and help people comprehend the risk. By gathering supplementary information from multiple sources, SVM is used to ML-based traditional methods, to forecast fetal health to determine if the fetal status is normal or unusual by taking into account the fetus's data. They can encourage the fetus's proper growth and management by employing this strategy [11].

The fight to lower mortality among children is never-ending, and it is frequently taken into account when assessing advances in medicine. Many children die each year around the globe, and many of these deaths could have been avoided. Given this problem, CTGs have become a key technique for assessing fetal health. CTGs assist medical professionals in assessing the general health of the fetus to ascertain the risk of infant mortality. They do this by applying ultrasound pulses and evaluating the responses. However analyzing the CTG results takes time and is ineffective, particularly in less developed regions where finding a skilled obstetrician is difficult. Yiqiao Yin et al., 2023 suggest an approach that assesses fetal health with a success rate of 99.59% using an SVM model and oversampling [12].

The application of ML to pregnancy disorders and difficulties is relatively new, and it has grown in the past several years. The applications are numerous and provide insight into the pathophysiology, management, and treatment of prenatal changes in addition to the diagnosis. In the field of obstetrics and gynecology, ML is expected to continue growing due to the challenges of working with various types of data, handling increasingly large amounts of information, developing emerging technologies, and needing translational studies. Daniela Mennickent et al., 2023's primary goal is to provide an overview of the state of the art when it comes to the use of machine learning for pregnancy-related illnesses and issues [13].

Obstetric and maternity care are evolving due to ML technology and the translation of artificial intelligence tools to improve the patient experience. A growing variety of predictive tools have been created using information from digital gadgets, diagnostic imaging, and EHR. The most recent ML methods, prediction model-building algorithms, and difficulties in evaluating fetal health and identifying and diagnosing obstetric conditions such as gestational diabetes, pre-eclampsia, preterm birth, and fetal growth limitation are all included in this review.

The rapid growth of ML methods and intelligent tools for automated fetal abnormality diagnostic imaging and fetoplacental and cervix function has been assessed using MRI and ultrasound. To lower the risk of preterm delivery, they address intelligent tools for fetal, placenta, and cervix MRI sequencing in prenatal diagnostics. Lastly, the use of ML to raise the bar for intrapartum care safety and early problem detection will be covered[14]. Table 1 shows the brief of the main ML methodologies utilized in fetal health care detection.

Table 1: ML Methodologies Utilized in Fetal Health Care Detection

Sl.No	Author Name	Year of Publication	ML Techniques Used	Accuracy
1	Akhan Akbulut et al.[15]	2018	DT, LR, DF, SVM	DF - 89.5%
2	Astik Kumar[16]	2021	LR, KNN, GBM, RF	RF 99%
3	Deepti Varma[17]	2022	Adaptive Stochastic Gradient Descent (ASGD)	ASGD - 98.64 %
4	Julio Jerison E Macrohon [18]	2022	Modified Decision Tree(MFT)	MFT - 97.01%
5	Addanke et al,[19]	2024	GRU, KNN, RF, SVM, CNN and Extreme e Learning(EL)	GRU outperforms the other methods
6	Anstasios et al, 2024[20]	2024	DNN (ECG data)	DNN outperforms the other state –of –art methods
7	Ettiyan et al, [21]	2023	Optimized single-dimensional Convolutional Neural Network (1D-OCNN) KNN, RF, SVM CNN, EL	1D-OCNN performs better than the other methods
8	Priya et al [22]	2023	CNN	Accuracy 83%

9	Shukla et al, [23]	2024	Logistic Regression, Random Forest, XGBoost , SVM, Neural networks(NN)	XGBoost Accuracy 94%
10	Shetty et al, [24]	2024	SVM, RF, AdaBoost and DT	Combination of AdaBoost and RF outperforms the other methods

These research articles show how ML and DL techniques can be used to classify prenatal diseases. Several embryonic disorders and anomalies can be classified with high accuracy using RF classifiers, DT classifiers, CNN and SVM mehtods. Furthermore, prenatal evaluation and fetal classification of diseases could be improved with the use of ML and DL techniques, which could result in better clinical results for expectant mothers and their babies.

METHODS

(i)Random Forest (RF)

RF is a method of collective learning that generates forecasts using a variety of decision trees. Utilizing RF to anticipatefetal development is an exciting approach to enhancing prenatal services. A series of DTs are built using selected random portions of information, and the outcomes from those trees are then combined to produce the ultimate forecast. To forecast potential threats to the fetus, RF can be taught on a variety of information sources, including ultrasound scans, parental medical information, indicators, and continuous fetal tracking. A lot of input characteristics can be handled by RF, and it can even deal with missing data by assigning values that are not present[25]

The utilization of RF in fetal health forecasting has the benefit of being able to provide precise and understandable forecasts. Additionally, it is capable of managing extremely complex information with a variety of attributes and can pinpoint the characteristics that are crucial for prediction. Additionally, RF is resistant to noise and capable of handling correlations among the source's characteristics and the non-linear result variables. Reducing variance and avoiding the overfitting of individual trees are two ways that RF raises the standard accuracy of the model. Equation 6 represents the RF algorithm's

$f(x) = 1/N \sum_{i=1}^{N} fi(x)\ )$ ---(1)

In equation 1 , N is the total number of DT, fi(x) is the prediction of the i-th DT for the input instance x, and F(x) is the final prediction for the input instance x.

(ii) Support Vector Machine (SVM)

A method of supervised learning known as SVM can categorize information using the characteristics of the input. SVM-based fetal health forecasting is an exciting way to enhance care during pregnancy. A supervised learning technique called SVM may categorize information into several groups according to the characteristics of the input. To forecast possible threats to the fetus, SVM can be learned from a variety of data sources, including ultrasound scans, mother medical information, indicators, and digital fetal monitoring. SVM divides the information into as many categories as possible by locating the best hyperplane. The margin is the separation among the closest information points within every group and is maximized by selecting the hyperplane accordingly. Data with high dimensions may be handled with SVM, which can also find those that are significant characteristics for predicting. Figure 3 describes the common working procedure of the SVM classifier.

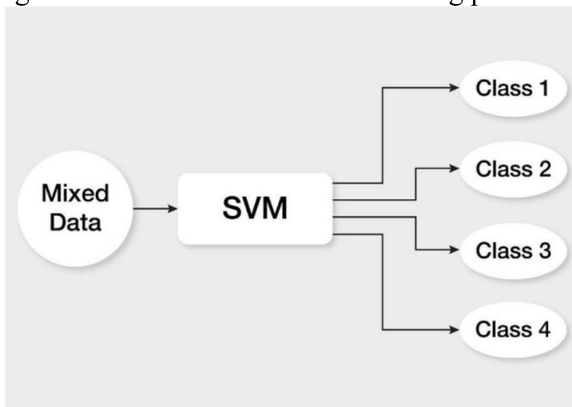

Figure 3 Basic Working Principle of the SVM Classifier

An example of the strongest and frequently utilized kernels in SVMs is given above. The option for data that isn't linear most frequently. An RBF kernel's solution is as follows:

$f(x1, x2) = \exp(-gamma * \|x1 - x2\| \string^2)$ - - - - (3)

Gamma in the formula describes the influence that a single learning event has on the surrounding data values. The dotted relationship among the attributes is ||X1 - X2|| [16].

SVM may produce precise and understandable forecasts, which is a benefit when applying it to anticipate fetal medical treatment. Utilizing kernel parameters, SVM can manage non-linear correlations among the given input characteristics and the result variables. Additionally, by modifying the weighting of the various classes, SVM can manage uneven sets and is resistant to aberrations[26]

(iii) XG Boost (XGB)

A gradient boosting technique is used to increase the efficiency and precision. To anticipate potential health concerns for the fetus, XGB can be trained on a variety of information sources, including ultrasounds, mother health information, indicators, and digital fetal surveillance.

XGB builds an effective framework that accurately forecasts the result variable through the integration of some weak DT. Reducing both the diminished value and normalization term minimizes the goal value. Data with high dimensions can be handled with XGBoost, which can also pinpoint those that are crucial elements for prediction. Missing data can be handled via XGBoost, which can also pinpoint the most crucial attributes for prediction. Additionally, XGBoost is highly efficient and capable of handling big datasets and also it offers better gradient enhancing and selection of features..[27].

iv) Decision Tree (DT)

A DT is a straightforward yet effective method that may be employed to foresee the result of a decision depending on its starting point characteristic. Using DT to forecast fetal well-being is an effective way to improve prenatal services. Using a variety of data sources, such as ultrasound scans, mother medical information, indicators, and digital fetal monitoring, DT serves as a basic yet successful ML approach.

A single interior node provides a characteristic, every branch indicates a choice determined by that information, while every node in the leaf provides an estimate or result. This is how a DT method builds a tree-like representation. By repeatedly dividing the information into subsets depending on several attributes, the technique attempts to maximize the uniformity of the desired variable among every set while learning from the datasets. The comprehensibility of DT for fetal healthcare forecast is one of their benefits. Medical professionals can comprehend and describe the process of making decisions thanks to the ensuing tree structure. DTs are appropriate for a variety of data types frequently found in fetal healthcare since they can manage both numerical and qualitative data[28].

Choose the ideal parameter for the network of branches quickly using the ASM (Attribute selection measure). These are two widely used ASM approaches, categorized as follows:

- Information Gain
- Gini Index

Following the division of a collection of data by considering a characteristic, the next data acquisition is measured in the form of variations in entropy.

An element or feature with the largest amount of data gained is divided into first in a method based on decision trees, which constantly seeks to maximize the worth of that data gain. Utilizing the method described below, it may be determined.

$$\text{Information Gain} = \text{Entropy}(S) - [(\text{Weighted Avg}) * \text{Entropy}(\text{each feature}) \qquad (4)$$

An indicator of the impurities in an identified property is entropy. It defines data unpredictability. Entropy is determined as follows:

$$\text{Entropy}(s) = -P(\text{yes}) \log \log 2 \ P(\text{yes}) - P(\text{no}) \log \log 2 \ P(\text{no}) \qquad (5)$$

Where,
S denotes the sample quantity
P(yes) indicates the yes probability
P(no) describes no probability
Gini Index:
In the course of the CART procedure, a decision tree is built using the Gini index, an indicator of impurities or purity.
The equation below may be used to compute the Gini index.

$$\text{Gini Index} = 1 - \sum_{j}^{n} . P_j^2 - - - (6)$$

DTs are also reasonably resilient to aberrations and may handle values that are lacking in the data. Additionally, algorithms can be used to detect non-linear correlations between characteristics and the desired outcome. DTs are also extremely efficient and have no trouble processing big data. Defective generalization can result through excessive fitting, which occurs when an equation gets extremely complicated and suited to the data used for training. This phenomenon can be reduced by strategies like pruning, limiting a tree's broad terms, or employing ensemble approaches like RF.

v) R-SVM's (Region-based Support Vector Machine)

Selecting the subset of attributes with the maximum discriminatory value between the two types of classes is the primary objective of the R-SVM. The sample size is small but the feature dimension is large; there are frequently many permutations of attributes that can null incorrect values on training-type data. The nominal error circumstance hasn't been dealt with as a result. Select for the moment a set of attributes that offers the highest partition between the two different sample classes[29].

vi) Adaptive Boosting (AB)

The AdaBoost algorithm belongs to the category of boosting techniques and is specifically a part of the ensemble learning frameworks. Being among the initial applications of boosting algorithms, it is crucial to comprehend the pattern it employs in order to make more complex boosting techniques comprehensible. It provides more extra weight values of the weak observation. By controlling a collection of weak-type learners, adaptive type boosting is regarded as a predictive method. Since the other algorithms are overfitting and this sort of boosting approach produces statistical categorization, the results can be far more accurate[30,31]

vii) Decision Stump Model (DSM)

Decision tree-based methods were widely employed as a slow learning method for gradient boosting. Regression models were added since they can be connected and offer better-split outcomes. This allows prediction residuals to be "corrected" and allows for the insertion of new model outputs. To reduce loss, the best split tips are selected according to their purity scores. "Decision stumps," or extremely brief decision trees with only one break, were first employed by systems such as AdaBoost. Minimal learning are occasionally restricted to a limited number of the layers, nodes in a leaves, or root nodes. This model works better with heterogeneous data types where different prediction models are better suited for different regions. Identification of the threshold value requires the use of a decision stump [32].

viii) K-Nearest Neighbor (KNN)

KNN is a nonparametric classifying technique in which known facts are arranged based on the chosen features. If it is employed in an unknown set, k-analysis NNs of their pattern space are used to analyze the K training sets that are closest to the unknown set. The unknown set is accurately represented by these k training sets and the close proximity of sets is defined in terms of Euclidean distance. It uses the most common class , the KNNs in the unknown set. In order to choose a training point that is closest to the test point and more accurate in classifying data, a smaller k value is used. The objects are classified in k-NN classification by a majority vote of the neighbors. Each object is given a class that is more prevalent among the k-NN, where k is consistently a positive number that is typically small. An outcome of the algorithm is class membership[33].

RESULTS

(i) Dataset Description
Intelligent checking frameworks were used with 99 patients on a daily basis. I t was carried out for 25 days and 90 days as sample testing period. There are 47 intrapartum patients and 52 antepartum patients among the 99 labor patients. The entire testbed has been examined and gathered at the private hospital in Chennai . A total of around 5000 data were gathered and utilized to assess the ML models . IoT sensors are built and the suggested learning method is executed in Python.
The experiment is validated with the fetal health classification dataset from Kaggle. Given the foregoing, cardIoTocograms (CTGs) are an easy and affordable way to evaluate fetal health, enabling medical practitioners to take preventative measures against mother and infant death. The device itself functions by delivering ultrasonic pulses and interpreting the response, providing information on a variety of topics including uterine contractions, fetal movements, and fetal heart rate (FHR). 2126 records of features taken from cardIoTocogram tests are included in this dataset. The outcomes of the algorithms are the three classes of data as follows

- Normal

- Suspect
- Pathological

The Table 2 represents the attributes used in the dataset and the table shows the percentage of data taken for training and testing

Table 2 Attributes Information

FHR baseline	accelerations per second	Fetal movements per second	uterine contractions per second
light decelerations per second	severe decelerations per second	prolongued decelerations per second	percentage of time with abnormal short term variability
mean value of short term variability	percentage of time with abnormal long term variability	mean value of long term variability	width of FHR histogram
minimum of FHR histogram	Maximum of FHR histogram	histogram peaks	histogram zeros
histogram mode	histogram mean	histogram median	histogram variance

Table 3 Number of data's for Training and Testing

S.No	Total data	Training data	Testing data
01	5000	80	20

The tool used for execution is Jupyter Notebook and the language used is Python. The system specification is 1 TB hard disk with Core i7 processor which will help in good execution of the program.

(ii) Performance Evaluation

Accuracy Analysis: In fetal healthcare prediction, accuracy refers to the proportion of correctly predicted outcomes compared to the total number of predictions made by the model. The accuracy of ML models is calculated using the equation given below.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Tp} + \text{TN} + \text{FP} + \text{FN}} - - - (7)$$

Precision Analysis: In fetal healthcare prediction, precision refers to the proportion of true positive predictions made by the model out of all positive predictions, including both true positives and false positives. It is calculated using the following formula.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} - - - - - - - - - - - (8)$$

Precision, as used in fetal healthcare prediction, measures the model's capacity to accurately identify positive outcomes, such as fetal distress or other adverse events, while reducing the amount of false positives—instances that are mistakenly identified as positive. A higher precision value means that the model is more reliable in correctly identifying positive instances associated with fetal healthcare outcomes because it produces fewer false positive predictions.

Recall Analysis : Recall, also known as sensitivity, refers to the proportion of true positive predictions made by the model out of all actual positive instances in the dataset. It is calculated using the following formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} - - - - - - - - - - (9)$$

Recall measures the model's accuracy in capturing and identifying every positive instance—such as instances of fetal distress or adverse events—from the whole set of real positive instances in the dataset with regard to predicting fetal healthcare. A higher recall value means that a greater percentage of positive cases are successfully detected by the model, reducing the amount of false negatives—cases that are mistakenly classified as negative.

F1- Score Analysis

The F1-Score is a harmonic mean of precision and recall used in fetal healthcare prediction. It offers a fair assessment of a model's ability to detect positive cases while reducing false positives and false negatives. This formula is used to calculate it:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} ---------(10)$$

In order to provide a thorough evaluation of the model's capacity to accurately identify positive instances linked to fetal healthcare outcomes while accounting for false positives and false negatives, the F1-Score integrates precision and recall into a single metric. Higher F1-Score indicates better overall performance, with a balance between precision and recall.

The following Table 3 shows the rate of accuracy, precision, recall and F1 score of different ML algorithms.

Table 3: Accuracy, Precision, Recall Rate and F1 Score of Various ML Models

Sl.No	Machine Learning Algorithm	Accuracy	Precision	Recall	F1 Score
1	Random Forest	99%	0.97	0.95	0.99
2	XGBoost	98%	0.96	0.94	0.98
3	M Decision Tree	97.01%	0.95	0.93	0.97
4	Decision Tree	89.5%	0.87	0.83	0.89
5	R-SVM's (Region-based Support Vector Machine)	92.4%	0.90	0.88	0.92
6	Adaptive Boosting(AB)	90.18%	0.88	0.86	0.90
7	Decision Stump Model	88.65%	0.86	0.84	0.88
8	K-Nearest Neighbor (KNN)	82%	0.80	0.78	0.82

The following Figure 4 shows the pictorial representation of various ML models' accuracy rates.

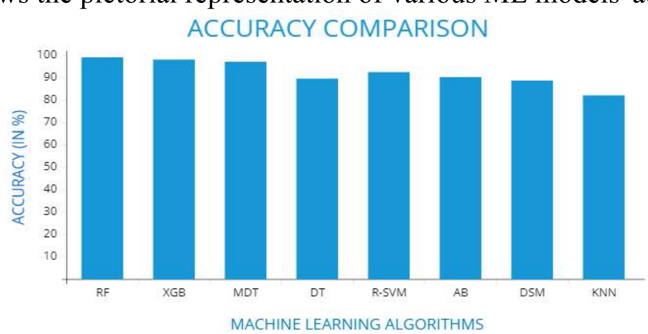

Figure 4 Accuracy Comparisons of Various ML Models

The following Figure 5 and 6 represents the scatter plot graph, box plot obtained by various algorithms such as Random Forest, XGBoost, M Decision Tree, Decision Tree, R-SVM's, Adaptive Boosting, Decision Stump Model and K-Nearest Neighbor.

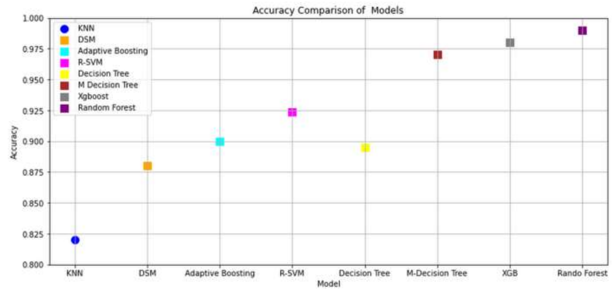

Figure 5 . Scatter Plot Graph Obtained By Various Algorithms

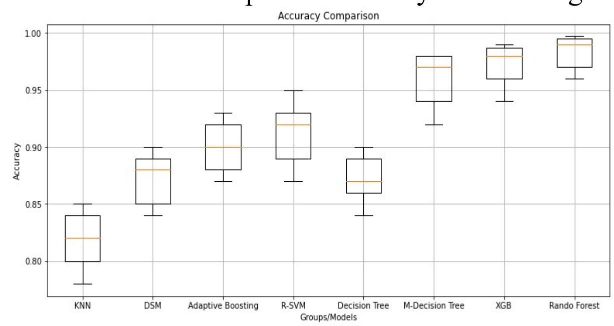

Figure 7 Box Plot Obtained By Various Algorithms

In fetal healthcare prediction, accuracy measures the model's ability to correctly predict fetal health outcomes, such as identifying instances of fetal distress or other adverse events. A higher accuracy indicates that the model is effectively capturing the true status of fetal health, while a lower accuracy suggests potential errors or misclassifications in the predictions. Therefore, accuracy is a fundamental metric used to evaluate the overall performance and reliability of predictive models in fetal healthcare applications. The following Figure 8 shows the pictorial representation of various ML models' precision rates.

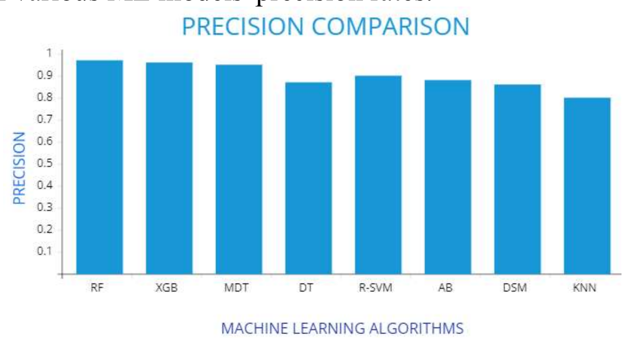

Figure 8 Precision Comparisons of Various ML Models

The following Figure 9 shows the pictorial representation of various ML models' recall rates.

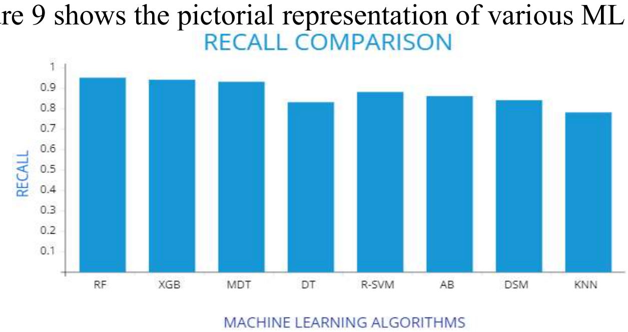

Figure 9 Recall Comparisons of Various ML Models

The following Figure 10 shows the pictorial representation of various ML models' recall rates.

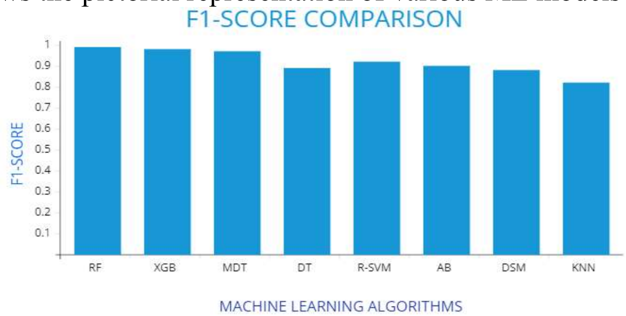

Figure 10 F1-Score Comparisons of Various ML Models

Figure 5, 6 and 7 present the accuracy rates of various machine-learning models employed for fetal healthcare prediction. The top-performing algorithm, Random Forest, achieved an exceptional accuracy of 99%, making it a standout choice for accurate and reliable predictions in fetal healthcare. The Decision Stump Model (DSM) and K-Nearest Neighbor (KNN) algorithms exhibited comparatively lower accuracies of 88.65% and 82%, respectively, suggesting the need for further refinement or potential limitations in their applicability to certain subsets of fetal healthcare data.

Figure 8 provide the precision values of various machine-learning models utilized in fetal healthcare prediction. Random Forest, being the top performer in terms of precision, achieved an impressive precision value of 0.97. This indicates that 97% of the positive predictions made by the Random Forest model were accurate, reflecting its strong capability to identify true positive instances related to fetal healthcare outcomes. The Decision Stump Model and K-Nearest Neighbor (KNN) algorithms exhibited lower precision values of 0.86 and 0.80, respectively, suggesting potential limitations in their ability to precisely identify positive instances within the dataset.

Figure 9 outline the recall values of various machine-learning models employed in fetal healthcare prediction. Random Forest, leading the pack in recall performance, achieved a commendable recall value of 0.95. This indicates that 95% of actual positive instances related to fetal healthcare outcomes were correctly identified by the RF model, showcasing its strong capability in capturing relevant positive instances. The recall values of the Decision Stump Model and K-Nearest Neighbor (KNN) algorithms were comparatively lower at 0.84 and 0.78, respectively, suggesting potential limitations in their ability to capture all actual positive instances within the dataset.

Figure 10 present the F1-Score values of various machine learning models utilized in fetal healthcare prediction. Random Forest emerged as the top performer in terms of F1-Score, achieving an outstanding F1-Score of 0.99. This indicates an exceptional balance between precision and recall, reflecting the Random Forest model's ability to make accurate positive predictions while also capturing a high proportion of actual positive instances related to fetal healthcare outcomes. The Decision Stump Model and K-Nearest Neighbor (KNN) algorithms demonstrated lower F1 scores of 0.88 and 0.82, respectively, suggesting potential limitations in achieving a balanced performance between precision and recall.

Overall, Random Forest and XGBoost emerged as the top-performing algorithms, offering a balance of high accuracy, precision, recall, and F1-Score.

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