Prenatal Detection of Fetal Birth Weight and Bone Density using AI and ML techniques

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ABSTRACT

The newborn's low birth weight, which can have a detrimental effect on the infant's health and even cause its death in more extreme conditions, is one of the most critical problems in prenatal care. The high infant mortality rates observed worldwide are caused by this disorder. Artificial intelligence approaches, particularly those based on machine learning (ML), can anticipate health issues that may arise throughout the entire gestation, including at birth. As a result, our project suggests analyzing several (ML) techniques that can determine whether a fetus would be born with less weight than expected for its gestational age. The potential for an increase in gestation days through prompt intervention underlies the significance of early detection of issues related to fetal development. With such an intervention, it would be possible to increase fetal weight at birth, which would lead to a reduction in newborn morbidity and mortality. So in this project we are going to predict the fetal birth weight in early stage also classified them as low weight if weight is less than 2.5kg, normal weight if weight is greater than 2.5kg and less than 4.5kg and abnormal weight if weight is greater than

4.5kg. To estimate the fetal birth weight in this situation, we employed ML approaches and algorithms including Linear and Random Forest Regressor, with Random Forest Regressor predicting more accurately than Linear Regression

Keywords: infant mortality rates, gestational age, neonatal morbidity, Linear Regression, Random Forest Regressor**.**

INTRODUCTION

Today, there are more babies born with low birth weights than ever before. A fetus with intrauterine growth restriction (IUGR) has a lesser stature than other fetuses of the same gestational age. The organ and body growth of the infant is constrained by this condition. Birth issues for neonates with IUGR can include low oxygen levels, a poor Apgar score, respiratory issues brought on by me conium aspiration, or hypoglycemia. In severe circumstances, the fetus may die or experience long-term growth issues. Although it is still very difficult to distinguish between the various types of hypertension that can occur during the pregnancy-puerperal cycle, maternal hypertension is the main cause of IUGR. In this way, the most severe prenatal development problems are caused by persistent arterial hypertension, regardless of its genesis. One of the sectors that has profited most from the adoption of machine learning (ML) techniques is the health care sector. In order to find patterns and trends that are hidden from human observers, machine learning (ML), a subfield of artificial intelligence (AI), utilizes vast volumes of data. Incorporating fresh data and learning from experience in this way enables a system to behavioral predictions. The learning capacity of the systems increases with the size of the databases. This paradigm enables AI systems to learn, for instance, hundreds of diagnoses and treatment recommendations for the widest range of ailments. Clinicians can enter case characteristics when examining their patients to generate the most likely diagnostic hypotheses. In more complicated cases, machine learning algorithms aid by reducing the number of possible diagnoses, which helps create suggestions for testing and treatments that are more accurate. Consequently, ML-based algorithms are a powerful tool for aiding the decision-making process for the health professional. It is possible, in terms of the Big Data paradigms, to analyze a substantial quantity of data from pregnant women and provide obstetricians and gynecologists with more in- depth knowledge about fetal health before, during, and after pregnancy by applying cutting- edge ML algorithms. Internet of Things paradigms for tracking patients utilizing a number of devices.

Cloud computing also makes it simple to store data and retrieve it remotely. Therefore, ongoing fetal health monitoring by improving both mother and baby's quality of life. Predicting the short- and long- term health effects of pregnancy requires knowledge of the fetal weight. . The (WHO) divides neonates into three categories based on birth weight (BW), including low birth weight (LBW, BW 2500g), normal birth weight (NBW, 2500g BW 4000g), and high birth weight (HBW, BW 4000 g), also known as macrosomia. Lesser weight at birth has been linked to prenatal and neonatal death, stunted growth, and long-term pediatric illnesses such mental retardation and learning difficulties. Additionally, macrosomia increases the risk of caesarean section, protracted labor, abnormal hemorrhage, and perinea trauma for mothers. It can also result in infant hypoxia and death. Yonghong Peng served as the editor's assistant who handled the manuscript's assessment and gave it the go- ahead for publishing. Long-term risks for obesity, diabetes, and heart disease are increased by macrosomia. It is important to precisely assess weight of fetus in pregnancy and recognize low birth weight fetuses or macrosomia. Once the risk has been identified, it is possible to reduce maternal or newborn morbidity and mortality by making the right clinical choices and adopting the necessary safety measures. Therefore, in this study, we will anticipate the fetal birth weight at an early stage and classify it as low, normal, or abnormal based on the expected birth weight. To forecast the fetal birth weight in this case, we used machine learning approaches and techniques including Linear and

Random Forest Regressor, with Random Forest Regressor predicting more accurately than Linear Regression. Ease of Use :Low birth weight is the main determinant of neonatal morbidity and death. Small for gestational age (SGA) care is the designation given to neonates who weigh less than 2,500g by the World Health Organization (WHO). This cutoff level was set for worldwide comparison because epidemiological research indicates that babies weighing less than 2,500g have a 20 times higher chance of dying than those weighing more. By using Random Forest and other requirements, predict baby weight accurately. Fetal weight is frequently estimated from birth weight Random. Through this algorithm we can predict accurate result of weight of the baby. Recently, issues with this approach have come to light. We investigate if estimated fetal weight can be predicted from data available at delivery using a variety of machine learning algorithms.

Proposed System: With the help of ML techniques like linear regression and random forest regressor on the basis of various parameters, we suggested a system to predict fetal birth weight and split them into 3 categories based on the expected birth weight: lower, average, and severe.

LITRATURE SURVEY

1. The authors, to enhance the effectiveness of EFW across all fetal weight ranges, they developed a novel fetal weight estimate model in this study that combines SVM-based classification with DBN. They also used SMOTE- based data augmentation to address the imbalanced learning problem. The outcome proved that the suggested model performed better than the regression formulae. The study showed that DBN is a true method for estimating fetal weight. It also demonstrated the effectiveness of grouping fetuses into different groups and estimating their birth weight using a number of essential traits.

2. According to the authors, the employment of cutting-edge technologies and artificial intelligence approaches can lower the high rates of sickness and death around the world, particularly in poor nations. The article compared multiple ML techniques with the help of database of pregnant women who had some type of hypertension sickness while pregnant. The findings demonstrated that hybrid approaches built on ensemble learning are effective at forecasting the anticipated birth weight of the fetus.

3. The authors suggest that using the EFSVR to determine fetal weight for LBW newborns. Numerous issues need to be taken into account for accurate weight calculation for LBW fetuses. The ultrasound measurement data that were utilized to develop the model are usually erroneous because of the low quality of ultrasound pictures and the variation in observer quality. The FSVR is suggested as a means of reducing the impact of erroneous data on model training and so improving the resilience of the weight estimation procedure. The last issue is that the best configuration of a number of empirical factors has a significant impact on how well the FSVR model generalizes. They offer a technique for choosing the best FSVR parameter settings based on the NSGA-II.

4. The authors uses SV method in their article which results in estimated fetal weight errors that are lower than those attained by employing 26 regression equations. Additionally, the estimated fetal weight must be adjusted to the local measurement conditions of the important biometric data before it may be employed in clinical care. The generalization and combining of neural network ensembles to ensure that data variability resulting from the dynamics of the phenomenon of the developing fetus is taken into account.

4. The authors examined how well the ANBLIR could classify and quantitatively describe prenatal cardiotocographic signals to predict the likelihood of a low fetal weight birth. Along with assessing various ANBLIR learning techniques, we also looked at the impact of patient data distribution and the underrepresented abnormal class on prediction accuracy. The results of the trials indicate that it is preferable to implement the plan with a single CTG trace per patient. The results collected also show that as fetal gestational age decreases, the likelihood of low fetal birth weight prediction increases. Using actual information collected over a two-year period, the scientists developed a simple and efficient mathematical model to predict the delivery weight for low birth weight infants. A multi-linear regression model was used to analyze only actual recorded data in order to determine the impact of various variables. The most significant reduced model is constructed for the prediction using the p-values associated with each attribute. The research discovered that 60% of the variance in neonatal weight for LBW neonates may be accounted for by regression using just the baby's height, gestational age, and head circumference. The hybrid LSTM-based birth weight prediction model developed by the authors creates a continuous model of the characteristics pertaining to the pregnant women and fetal physical examination. The experimental outcomes demonstrate that the proposed birth weight prediction model boosts model convergence rate while also boosting birth weight prediction accuracy by 6%.To increase the precision and usefulness of the model prediction, there is potential for improvement in the deep neural network model.

The risk classification of various categories of birth weight was also studied in this work, we were able to do so with greater accuracy than other approaches, which is important for clinical applications. In this work, we provided a comprehensive performance evaluation of several ML models for infant weight estimate and LBW classification using the maternal information gathered from pregnant women. Ten ML models with various feature subsets and combinations of subsets with and without the imputation of missing values were employed for weight estimation. Multiple FS approaches were also used to identify key features, which helps with LBW classification and weight calculation. Here, relevant features are chosen via a combination of FS approaches that use majority voting. A data balancing strategy based on SMOTE was used to oversample the minority class sample in order to improve classification outcomes. The best weight estimate and classification performance were both

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achieved by the RF technique, which had an MAE value of 294.53 g.

METHODOLGY

Dataset of Fetal Birth Weight is added.

- Thedataset is preprocessed and loaded using a variety of machine learning methods.
- Thepreprocessed data are segregated from the testing and training data.
- The approaches to machine learning The prediction model is built using a combination of linear and the Random Forest Regressor.
- The model must be tested after it has been effectively trained using the training dataset.
- Thetesting dataset is used to gauge the trained model's correctness.
- We use analgorithm that provides the highest level of accuracy as ourfinal predictionmodel.
- Afterbeing finalized stores the model as a pickling version (binary format data).
- Flask and HTML are used to create a Front End.
- Our developed algorithm uses the user- collecteddata as input to forecast the fetal birth weight.
- Now categorize them as Low Birth Weight if their expected birth weight is less than 4.5 kg and as Abnormal Birth Weight if it is greater than 4.5 kg.
- Finally the predicted Birth Weight and Classified Category both output is displayed on the front end.

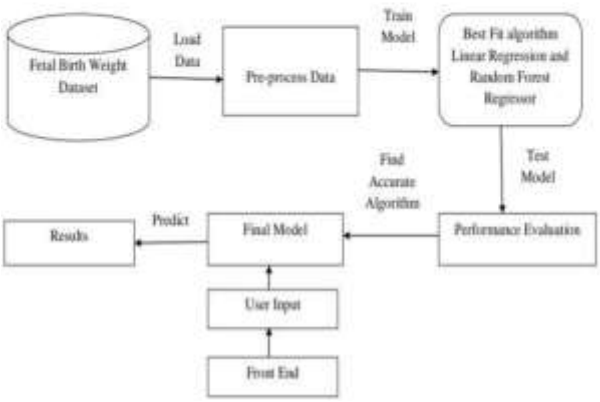

Figure1: Flow Diagram.

- The data is preprocessed to boost accuracy by filling in missing values, removing duplicate entries from the dataset, etc.
- The model was created using two machine learning algorithms: linear regression and the Random Forest Regressor.
- With the preprocessed data, it is trained.
- The model is assessed, and the accuracy for various ML methods is computed.
- The algorithm with the maximum degree of accuracy has been completed, and it will make use of fresh information to forecast the user's fetal birth weight.
- The process of fetal birth weight prediction using AI and ML follows.

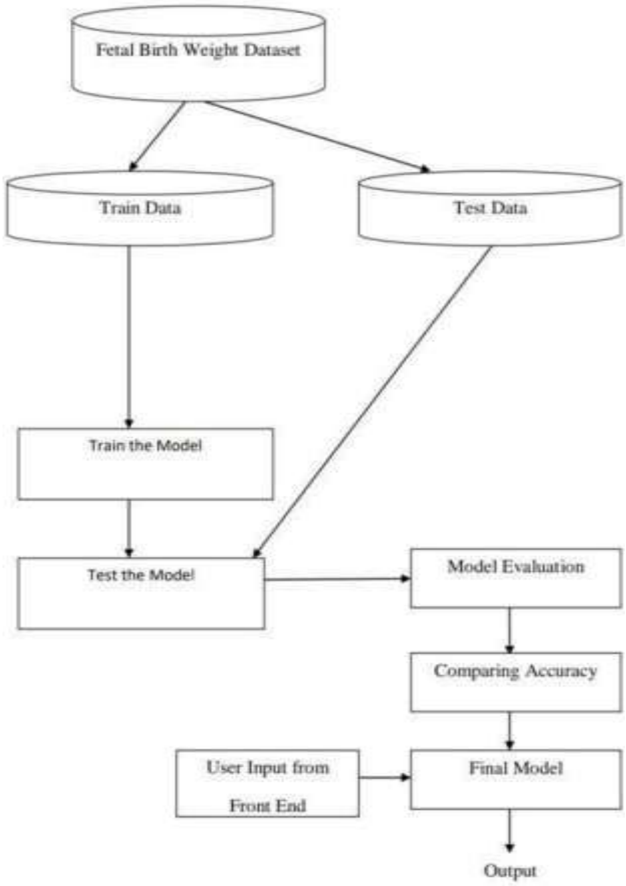

Figure2: System Architecture

- Thedata is cleaned and preprocessed to help with dataset comprehension.
- The data is divided into training and testing.
- The model was built using two machine learning algorithms: linear regression and the random forest regressor.
- Themodel has been trained using the preprocessed data.
- Themodel is assessed and the accuracy of several ml methods is estimated.
- The fetal birth weight dataset is loaded into the system.
- Machine learning algorithms, including Linear Regression and Random Forest Regressor, are used for training.
- The best-fit algorithm is chosen based on accuracy and performance.
- The trained model is tested to determine its accuracy and reliability.
- The most accurate model is finalized for predictions.
- The frontend collects user inputs related to maternal health parameters.
- The trained model processes the input data to predict fetal birth weight.
- The predicted birth weight is shown to the user.
- The model is connected to a user- friendly interface for accessibility.
- The user inputs the required maternal health parameters, and the trained model processes the data to predict the fetal birth weight.
- Once the data is prepared, the next phase is training the model, where machine learning algorithms such as Linear Regression and Random Forest Regressor are used to identify

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patterns in the dataset.

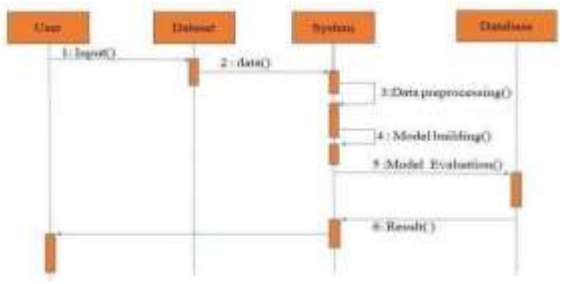

Figure3: Use Case Diagram

The user's data will be collected by the system.

- Thesystem will review the information gathered.
- Preprocessing and model construction will be done by the system.
- Theaccuracy of the constructed model is assessed and tested.
- Theuser will complete model as accurately as possible.
- The model will forecast results and present them after the user inputs fresh data into the system.
- Once the model is trained and performs well, it is saved for future use.
- This avoids the need to train the model every time a new prediction is needed.
- Thedataset is preprocessed to improve the model's precision.
- Themodel is constructed via several algorithms.
- The model is assessed, and the most accurate version is chosen to be used.
- The final model will forecast the outcomes.

Figure 4: Activity Diagram

The dataset will be supplied to the system by the user

- Thedataset is preprocessed to improve the model's precision.
- Themodel is constructed via several algorithms.
- The model is assessed, and the most accurate version is chosen to be used.
- The final model will forecast the outcomes.
- Handling missing values (e.g., mean/mode imputation, removal of incomplete records).
- Removing duplicate or irrelevant
- A machine learning algorithm is selected based on the problem type (e.g., regression, classification).
- The dataset is split into training and testing subsets (e.g., 80% training, 20% testing).
- Different algorithms (e.g., Linear Regression, Decision Trees, Neural Networks) may be tested.
- Hyper parameter tuning (e.g., Grid Search, Random Search) is performed to optimize the model.

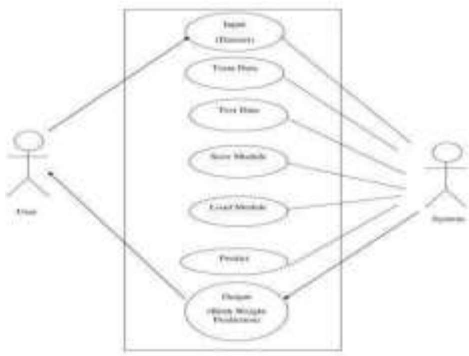

Figure 5 : Sequence Diagram

Theuserwill provide the system with a dataset as input.

- Thesystem will keep the dataset that the user provides in its database.
- Thesystem will preprocess the data that has been stored.
- Various ML techniques are utilized to make the model, and training is done using preprocessed data.
- The dataset transfers the collected data to the system.
- The system prepares the data for processing.
- Aftera model evaluation, the most accurate algorithm is chosen.
- Processes the data, builds the model, and evaluates performance.
- Stores the results of the model evaluation.
- The machine learning model is trained using the processed data.
- This sequence diagram outlines a structured pipeline for handling a machine learning task, from data input to final model evaluation. I
- Theresults will be predicted by the final model.

IMPLEMENTATION

In this study we have used Python HTML, Linear regression and Random Forest Regressor as Machine Learning Algorithms. One type of supervised machine learning is linear regression. In this algorithm, the anticipated output is continuous and has a constant slope. It is a statistical tool that is extremely frequently used to build a relationship model between two variables. When using linear regression, there are five fundamental steps to follow**:** Add the classes and packages you require. Provide data to work with, then do the necessary transformations. Make a regression model, then fit the data to it. To determine whether the model is adequate, look at the results of model fitting. Use the model to make forecasts. A supervised learning algorithm is random forest. Both classification and regression can be done with it. It is also the most versatile and user-friendly algorithm. In a forest, there are trees. According to theory, a forest gets stronger the more trees it has. Random forests create decision trees on samples of data that are selected at random, get predictions from each tree, and then vote on the optimal course of action. In addition, it provides a reasonable indicator of the feature's applicability. Pick samples at random from the dataset provided. Each sample should be given a decision tree, and the predictions it yields should be examined. Cast a ballot for each anticipated result. The final prediction should be the outcome with the most votes.

RESULTS AND DISCUSSION

In accordance with the current guidelines for prenatal growth measurement using ultrasound, up to 15% of fetuses may be incorrectly categorized as SGA. Growth restriction is a symptom of serious health issues, frequently as a result of the fetus not getting enough nutrients or oxygen in the uterus. Many facets of embryonic growth and the biology of its restriction are still poorly understood. Several ultrasonic technology models have been developed as clinical ideas. There isn't yet a reliable way to diagnose the illness, though. It is well known that the severity increases with the degree of the initial growth limitation. A crucial tool for specialists to use in the early detection of this disturbance is machine learning (ML) methodology. With the use of machine learning techniques and methodologies,we present a system that can predict fetal birth weight with precision. So our project is predicted the fetal birth weight in early stage also classified them as low birth weight is weight is less than 2.5kg ,normal birth weight if weight is greater than 2.5kg and less than 4.5kg and abnormal birth weight if weight is greater than

4.5kg. To forecast the fetal birth weight in this case, we used machine learning approaches and algorithms including Linear Regression and Random Forest Regressor, with Random Forest Regressor predicting more accurately than Linear Regression.

PROGRAMMING

Dataset: This is the dataset used in this project and it has 13 columns in it and 101400 rows of data.

Back End Code: With the help of machine learning techniques and algorithms, this code trains our system. It also calculates the R2 score, finalizes the algorithm with high accuracy as the final model, and converts it into a pickle (binary format) file.

Front End Code: This code will generate a front end using HTML, Python, and Flask. Here, we will gather user information such as usernames and passwords for registration, which will only be stored in a local host database. Then, after collecting login information and verifying it against the database, the user will be directed to the prediction page if the credentials were successful. In the prediction page user will give different input parameters required to predict fetal birth weight. The overall workflow of the system begins with user interaction, where inputs are collected and formatted into a structured request. The frontend of a fetal birth weight prediction system serves as an interactive interface that allows users to input maternal health parameters and receive a predicted birth weight. The backend processes this request, runs the trained AI/ML model on the provided data, and returns the predicted outcome. Our machine learning algorithm's predicted fetal birth weight is displayed on the prediction front end webpage, along with a classification of the birth - weight into low, normal, and abnormal. The input parameters data serves as our machine learning algorithm completed, trained algorithm to predict the output.

CONCLUSIONS

Around 15% of fetuses may be not correctly classified as sga under current ultrasonography standards for fetal growth assessment. Many facets of embryonic growth and the biology of its restriction are still poorly understood. Several ultrasonic technology models have been developed as clinical ideas. There isn't yet a reliable way to diagnose the illness, though. It is well known that the severity increases with the degree of the initial growth limitation. A crucial tool for specialists to use in the early detection of this disturbance is machine learning (ML) methodology. We present a technique that uses machine learning techniques and algorithms to generate precise predictions of infant birth weight. So our project is predicted the fetal birth weight in early stage also classified them as low weight is weight is less than 2.5kg ,normal weight if weight is greater than 2.5kg and less than 4.5kg and abnormal weight if weight is greater than 4.5kg. To forecast the fetal birth weight in this case, we used ML methods and algorithms including Linear Regression and Random Forest Regressor, with Random Forest Regressor predicting more accurately than Linear Regression.

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