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RESEARCH

Machine learning-based approach for predicting low birth weight

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Abstract
Background Low birth weight (LBW) has been linked to infant mortality. Predicting LBW is a valuable preventative tool and predictor of newborn health risks. The current study employed a machine learning model to predict LBW.
Methods This study implemented predictive LBW models based on the data obtained from the "Iranian Maternal and Neonatal Network (IMaN Net)" from January 2020 to January 2022. Women with singleton pregnancies above the gestational age of 24 weeks were included. Exclusion criteria included multiple pregnancies and fetal anomalies. A predictive model was built using eight statistical learning models (logistic regression, decision tree classification, random forest classification, deep learning feedforward, extreme gradient boost model, light gradient boost model, support vector machine, and permutation feature classification with k-nearest neighbors). Expert opinion and prior observational cohorts were used to select candidate LBW predictors for all models. The area under the receiver operating characteristic curve (AUROC), accuracy, precision, recall, and F1 score were measured to evaluate their diagnostic performance.
Results We found 1280 women with a recorded LBW out of 8853 deliveries, for a frequency of 14.5%. Deep learning (AUROC: 0.86), random forest classification (AUROC: 0.79), and extreme gradient boost classification (AUROC: 0.79) all have higher AUROC and perform better than others. When the other performance parameters of the models mentioned above with higher AUROC were compared, the extreme gradient boost model was the best model to predict LBW with an accuracy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. According to the feature importance rank, gestational age and prior history of LBW were the top critical predictors.
Conclusions Although this study found that the extreme gradient boost model performed well in predicting LBW, more research is needed to make a better conclusion on the performance of ML models in predicting LBW.
Keywords Low birth weight, Fetal weight, Birth weight, Machine learning, X gradient boost model

Background

Birth weights less than 2500 g are called low birth weight (LBW). LBW has been linked to infant mortality and its consequences [1]. Predicting LBW is thus a valuable preventative tool and predictor of newborn health risks. Previous research has found that maternal demographics, preexisting health conditions, and prenatal care level are all linked to LBW [2, 3]. Thus, pinpointing which pregnant patients are most likely to have a baby with LBW during the preconception or early pregnancy stages is

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critical for saving neonatal lives and reducing potentially avoidable medical costs through direct clinical and health policy interventions. There are some documented studies on using ML in perinatal care and maternal health. Previous LBW prediction studies achieved good performance in predicting LBW; however, all previous studies recommended more studies due to study limitations such as small sample size or limited feature selection [4–7]. In this study, we aimed to evaluate the performance of eight different ML algorithms in predicting LBW.

Methods

The findings of this retrospective cohort study are based on birth records obtained from the "Iranian Maternal and Neonatal Network (IMaN Net)," a legitimate national system, from January 2020 to January 2022. IMaN Net is a comprehensive system for registering maternal and newborn information on the outcomes of each delivery, which is completed daily by midwives in all birth centers and hospitals throughout Iran in an integrated manner. All patients’ personal information was deidentified and not disclosed.

Women with singleton pregnancies above the gestational age of 24 weeks who gave birth during a study period were included. The target population in this study was divided into LBW ("d 2499 g) and not LBW ("e 2500 g), which is the national standard definition [8]. Exclusion criteria included multiple pregnancies and fetal anomalies.

A predictive model was built using eight statistical learning models, including logistic regression, decision tree classification, random forest classification, deep learning feedforward, extreme gradient boost classification (XGBoost), light gradient boost (LGB), support vector machine (SVM), and permutation feature classification with k-nearest neighbors (KNN). Expert opinion and prior observational cohorts were used to select candidate LBW predictors for all models [9, 10]. Predictor factors included maternal age, educational level, maternal occupation, place of residence, inadequate prenatal care (less than three prenatal care visits), smoking, drug addiction, maternal anemia, cardiovascular disease, chronic hypertension, hepatitis, COVID-19, overt diabetes, gestational diabetes and thyroid dysfunction, parity, preeclampsia, fetal gender, method of childbirth, previous history of LBW, supplementary and vitamins intake were obtained from patient medical records. We used Chi-square test to evaluate the association between predicting factors mentioned above and LBW. Then we performed ML analysis approach. We followed the Guidelines for Developing and Reporting Machine Learning Predictive Models in Biomedical Research: A Multidisciplinary View to report our findings. The programming language Python was chosen to create the machine learning model. Scikit-learn was used to implement the ML algorithm. Scikit-learn is a machine-learning library written in Python. It includes an extensive collection of cutting-edge machine-learning algorithms for both supervised (including the multi-output classification and regression algorithm) and unsupervised problems [11].

Internal validation was carried out with the help of k-fold cross-validation. The cases were randomly assigned to either the “training set” (70%) or the “test set” (30%) using a random number generator. The original dataset kept the rate of LBW and non-LBW groups in the training and test sets constant. Using the training set, we arranged the parameters of the prediction models and evaluated their performance using the "test set". The average performance was calculated by repeating these ten times.

Metrics, including area under the receiver operating characteristic curve (AUROC), accuracy, precision, recall, and F1 score, were used to assess the predictive power of the models. The accuracy metric calculates how often a model is correctly predicted across the entire dataset. Precision measures how many of the model's "positive" predictions were correct. The model's recall estimates how many positive class samples in the dataset were correctly identified. The F1 score combines precision and recall by using their harmonic mean, and maximizing the F1 score implies maximizing both precision and recall simultaneously. As a result, researchers have chosen the F1 score to evaluate their models in conjunction with accuracy. We used AUROC as the primary performance metric because it is a widely used index to describe the ML model's ability to predict outcomes. The metrics were scaled from 0 to 1, with higher values indicating a better model [12].

Results

Of 8850 eligible cases, we found 1280 women with a recorded LBW, for a frequency of 14.5%. The demographic and clinical characteristics of study population is given in Table 1. As it shown, maternal age, living residency, gestational age, parity, access to prenatal care, maternal anemia, chronic hypertension, preeclampsia, drug addiction, COVID-19, previous LBW, and newborn gender was linked to LBW.

In this study, we attempt to evaluate parameters and feature selection based on performance parameters using various ML algorithms. A plot ROC chart, as shown in Fig. 1, and calculate AUROC as a plot that allows the user to visualize the tradeoff between the classifier's sensitivity. Deep learning (AUROC: 0.86), random forest classification (AUROC: 0.79), and XGBoost classification

(AUROC: 0.79) all have higher ROC_AUC and perform better than others, as shown in Fig. 1.

Other performance parameters for each algorithm are shown in Table 2. Other performance parameters indicate that the XGBoost classification performs more than all. Random forest classification and deep learning feedforward are also very close. When the accuracy, precision, recall, and F1 score of the models mentioned above with higher AUROC were compared, the XGBoost model was the best model to predict LBW with an accuracy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. The confusion matrix of the XGBoost classification model is shown in Fig. 2.

Figure 3 presents an analysis of the importance of variables in the XGBoost algorithm. As the feature importance rank was identified, gestational age and previous history of LBW were the top critical predictors.

Discussion

With the exponential growth in the quantity and dimension of healthcare data in recent years, ML approaches for dealing with complex and high-dimensional data have been introduced [13–15]. In this study, we aimed to evaluate the performance of eight different ML algorithms in predicting LBW. According to our findings, the XGBoost classification model had a more significant diagnostic performance parameter with an AUROC of 0.79, accuracy of 0.79, precision of 0.87, recall of 0.69, and F1 score of 0.77. XGBoost classification is a supervised machine learning algorithm based on a distributed gradient-boosted decision tree [16]. It can produce consistent

Table 1 Demographic and clinical factors associated with low birth weight

Outcome	Non-LBW (n = 7570)	LBW (n = 1280)	P-value
Maternal age			< 0.001
13–19	137 (1.8)	36 (2.8)	
20–35	6247 (82.5)	995 (77.7)	
Above 35	1186 (15.7)	249 (19.5)	
Education			0.348
Illiterate	480 (6.3)	73 (5.7)	
Primary	2344 (31.0)	378 (29.5)	
High-school/Diploma	3463 (45.8)	609 (47.6)	
Advanced	1283 (16.9)	220 (17.2)	
Occupation			0.299
Housewife	6798 (89.8)	1146 (89.5)	
Worker/employee	772 (10.2)	134 (10.5)	
Living residency			0.045
Urban	5056 (66.8)	823 (64.3)	
Rural	2517 (33.2)	457 (35.7)	
Gestational age			< 0.001
24–36^{+6}	429 (5.7)	801 (62.6)	
37–41	7141 (94.3)	479 (37.4)	
Parity			< 0.001
Primiparous	2056 (27.1)	439 (34.3)	
Multiparous	5517 (72.9)	841 (65.7)	
Access to prenatal care			0.030
Yes	7343 (97.0)	1255 (98.0)	

No	230 (3.0)	25 (0.2)	
Maternal anemia			0.047
No	7364 (97.2)	1233 (96.3)	
Yes	209 (2.8)	47 (3.7)	
Chronic hypertension			0.005
No	7501 (99.0)	1256 (98.1)	
Yes	72 (1.0)	24 (1.9)	
Cardiovascular disease			0.803
No	7492 (98.9)	1267 (99.0)	
Yes	81 (1.1)	13 (1.0)	
Diabetes			0.276
No	6420 (84.8)	1094 (85.5)	
Yes	1153 (15.2)	186 (14.5)	
Preeclampsia			< 0.001
No	7196 (95.0)	1083 (84.6)	
Yes	377 (5.0)	197 (15.4)	
Drug addiction			< 0.001
No	7530 (99.4)	1251 (97.7)	
Yes	42 (0.6)	29 (2.3)	
Previous low birth weight			< 0.001
No	7479 (98.8)	1089 (85.1)	
Yes	94 (1.2)	191 (14.9)	

Data are presented as n (%)

Table 1 (continued)

Outcome	Non-LBW (n = 7570)	LBW (n = 1280)	P-value
COVID-19			0.020
No	7465 (98.6)	1250 (97.7)	
Yes	108 (1.4)	30 (2.3)	
Thyroid dysfunction			0.999
No	6778 (89.5)	1146 (89.5)	
Yes	795 (10.5)	134 (10.5)	
Hepatitis			0.079
No	7543 (99.6)	1279 (99.1)	
Yes	30 (0.4)	1 (0.1)	
Newborn gender			< 0.001
Male	3942 (52.1)	599 (46.8)	
Female	3631 (47.9)	681 (53.2)	
Supplementary intake			0.078
No	4 (0.1)	5 (0.4)	
Yes	7569 (99.9)	1275 (99.6)	

results while minimizing overfitting by employing a parallel tree-boosting strategy. Furthermore, XGBoost can use the importance score to determine the importance of each feature. Previous studies evaluating different ML machines for predicting LBW will also have promising results. According to Ahmadi et al., the random forest model performed well in terms of diagnostic performance, with an accuracy of 0.95, recall of 0.72, and AUROC of 0.89 [5]. Another study by Desiani et al. found that naive Bayes had excellent diagnostic performance, with an accuracy of 0.85 and a recall of 0.72 [17]. However, both studies were limited by a small sample size (less than 1000 participants).

Recent studies with larger sample sizes also demonstrated good performance. For example, in a survey by Eliyati et al., with a sample size of 12,500 study participants, SVM showed high diagnostic performance in predicting LBW with an accuracy of 0.93 [18]. Ren et al. used a more extensive study in this field, with a sample size of 266,687 birth records over six years. According to their findings, the XGBoost classification model had the highest recall score of 0.85, but the AUROC score was only 0.61 [19].

Although our study did not have the largest sample size of any study in this field, we believe that using hospital records made our feature selection rich enough to make a reasonable conclusion on identifying LBW risk factors. In our study, we surveyed maternal age, educational level, place of residence, inadequate prenatal care (fewer than three prenatal care visits), drug addiction, maternal anemia, cardiovascular disease, chronic hypertension, pyelonephritis, hepatitis, COVID-19, overt diabetes, gestational diabetes and thyroid dysfunction, parity, preeclampsia, and history of LBW. Among all the potential predisposing factors of LBW, gestational age and previous history of LBW were the top critical predictors. In line with previous findings [20, 21], gestational age is the highest predictor of LBW. Being born too soon (premature birth) is the most common cause of LBW. The prior history of LBW was another weighted factor in predicting LBW. It has been reported that the risk of LBW recurs between pregnancies. Women with a

Fig. 1 AUROC of ML models

Table 2 Performance parameters of models with the highest AUROC

Row	Algorithms	Accuracy	Precision	Recall	F_1 Score
1	Random Forest Classification	0.78	0.85	0.70	0.77
2	XGBoost Classification	0.79	0.87	0.69	0.77
3	Deep Learning- Feed Forward	0.78	0.84	0.70	0.76

Fig. 2 XGBoost classification confusion matrix

Fig. 3 Feature importance of the XGBoost classification in the prediction of low birth weight previous LBW baby have been identified as potential carriers of the recurrent risk and have a higher recurrence risk of LBW in their subsequent pregnancy than those with a previous normal birth weight baby [22]. Other factors, such as maternal comorbidities, sociodemographic characteristics, and fetal gender, were not among the weighted factors in predicting LBW, in contrast to previous studies. In one study, Bekele et al. found that fetal gender, marriage to birth interval, mother's occupation, and mother's age were all weighted factors in predicting LBW [23]. Another study found that maternal pre-pregnancy weight, mother's age, number of doctor visits during the first trimester, and previous preterm labor were the most significant risk factors for LBW [4]. The differences in findings could be attributed to study design, the type of ML models used, geographical differences, or imbalances in each study's dataset. It should be noted, however, that clinicians can use the key findings of each study to identify high-risk pregnant patients early in their pregnancy using early prenatal care screening tools.

Although we used a large dataset with a lot of maternal and neonatal information, a significant variable, like body mass index, was missing in most of the birth records, so we couldn't use this factor in our selection features, which is a significant limitation of the study.

Conclusion

Using ML approaches to predict LBW yielded promising results. As a result, this study might add to the current perinatal care literature. Although this study found that the XGBoost model performed well in predicting LBW, more research is needed to make a better conclusion on the performance of ML models in predicting LBW.

Abbreviations

LBW Low birth weight
ML Machine learning
XGBoost Extreme gradient boost
LGB Light gradient boost
SVM Support vector machine
KNN K-nearest neighbors

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Authors' contributions

F.D. and N.R. wrote the proposal. F.M. and V.M. contributed significantly to data collection. The findings were analyzed and interpreted by M.F. F.D., the primary contributor to the manuscript's commenting and editing. A.R. assessed the manuscript's scientific content critically. The final manuscript for submission was read and approved by all authors.

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None.

Availability of data and materials

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
This study complied with the Declaration of Helsinki and was performed according to ethics committee approval. The Ethics and Research Committee of the Hormozgan University of Medical Sciences approved the study. The records of all patients who provided informed consent for using their data for research purposes were analyzed. For those under the age of 18 the informed consent was taken from their gurdian. Statistical analysis was performed with patient anonymity following ethics committee regulations.
Consent for publication
Not applicable.
Competing interests
The authors declare no competing interests.
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 Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) ISSN: 2663-2187 https://doi.org/10.48047/AFJBS.6.14.2024.12243-12270 A systematic review on the applications *of* machine learning for fetal birth weight prediction Keerthana .P 1 , Dr. Sasidhar Babu Suvanam 2 1 Research Scholar School of CSE, REVA University, Bangalore, India 2 professor Department of CSE, Presidency University, Bangalore, India E-mail: 1 keerthiikeerthanayadav@gmail.com E-mail: 2 sasidharmails2@gmail.com Volume 6, Issue 14, Sep 2024 Received: 15 July 2024 Accepted: 25 Aug 2024 Published: 05 Sep 2024 doi: 10.48047/AFJBS.6.14.2024.12243-12270 Abstract In order to protect the maternal and infant safety, birthweight is an important indicator during fetal development. A doctor's experience in clinical practice, however, helps estimate birthweight by using empirical formulas *based* on the experience of the doctors. Recently, birth weights have been predicted *using* machine learning (ML) technologies. A *machine* learning model is built on the basis of a collection of attributes learns to predict predefined characteristics or results. Using *a* machine learning model, input and output are modeled together and then a set of models are trained on the data. It is possible to use machine learning for a variety of tasks such as predicting risks, diagnosing diseases, and classifying objects due to its scalability and flexibility, which are advantages over conventional methods. This research reviews *the* machine learning classification models used previously by various researchers to predict fetal weight. In this paper 85 studies were reviewed. *Machine* learning approach was considered as a better option to predict the fetal weight in all the studies included in this paper. *The* *findings* of this research show that the accuracy rate of *using* machine learning applications for fetal birth weight prediction is above 60% in all the studies reviewed. And also it can be found that ANN showed 100% accuracy when compared to other *machine* learning techniques. Keywords: Fetal *weight,* Machine learning, accuracy, birth weight, random forest, XG-Boost, SVM, Neural Network, Deep learning, binary classification, feature selection Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12244 to 10 1. Introduction: It is critical to achieve optimal health and survival from conception to early childhood. Fetal or intrauterine growth restriction is often considered an outcome of epidemiological interest due to its predominant role in shaping *the* risk of adverse perinatal outcomes, usually as small versus appropriate for gestational age. In addition, researchers are increasingly interested in quantifying the relationship between poor perinatal and childhood outcomes and fetal growth. Population health studies often use birth weight as a proxy for fetal weight since fetal (intrauterine) weight is not measured in populo. This practice, however, has been found to result in serious problems with missing data or selection bias, especially at early gestational ages. In order *to* determine the appropriate delivery method, it is imperative to correctly predict the birthweight. For both short-term and long-term health outcomes in neonates, reducing the incidence of overweight or underage babies will be very important. In addition to seizures, epilepsy, hyperbilirubinemia, polycythemia, thrombocytopenia and necrotizing enterocolitis, being born small for gestational age (SGA) increases your risk for hypoglycemia, hyperbilirubinemia, polycythemia, thrombocytopenia, and thrombocytopenia. In contrast, perinatal morbidity associated with large for gestational age infants (LGAs) relates to prolonged and complicated labor, including birth injuries, the need to undergo an operative vaginal or caesarean delivery, asphyxia and meconium aspiration as a result of the physical size of the infant. Hypoglycemia, hyperbilirubinemia, polycythemia, and respiratory distress are also common postnatal problems in LGA infants. In general, neonates born SGA and LGA need more medical care during delivery and afterward than neonates born appropriate for gestational age (AGA). To determine whether the fetal development is normal, it is necessary to estimate the birthweight during pregnancy. In addition, it serves as a guide in determining which mode of delivery to use during late pregnancy. A clinician's experience determines an approximate birthweight based on experience rather than directly measuring the birthweight before delivery. Pregnant women's B-ultrasound measurements are used as the basis of most empirical formulas. A fetal birth weight is a key indicator of the health of the mother and child during pregnancy. A correct *prediction* of the birthweight is certainly crucial to determining the most effective delivery method. Using machine learning methods, it is possible to predict fetal weight during the early stages of its birth. The *machine* learning models are comprised of linear regression, Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12245 to 10 decision tree-based systems, ensembles such as random forests, gradient-boosted trees, support vector machines, nearest neighbors, and Bayesian approaches, *based* on the function class used *to* create the input/output model. Data of the pregnant women can be analyzed using artificial neural networks *and* deep learning models, but convolutional neural networks tend to perform less well in this case than other methods. By analyzing external data such as x-rays, CT scans, various tests, and screenings, machine learning algorithms can improve the quality of treatments through self-learning algorithms. Additionally, it is an efficient and effective tool to assist pregnant women to monitor their own weight alongside traditional clinical practices for estimating fetal weight. 1.1.Aim The main aim of this study is to review the various existing *machine* learning models to predict fetal weight and to know to which of those models are used commonly and gives high accuracy, so that a new approach can be developed *based* on the gaps found in the previous researches. 1.2. Objectives of the study: 1. To evaluate the current state *of* machine learning applications for fetal birth weight prediction. 2. To analyze the efficacy *of* *machine* learning models for predicting fetal birth weight. 3. To compare *the* performance of different *machine* *learning* models with traditional methods of fetal birth weight prediction. 1.3.Problem Statement: During pregnancy and postpartum, it is important to estimate the fetal weight. It is even more critical to estimate fetal weight after the second trimester of pregnancy, since perinatal complications are more likely in cases where the weight of the baby is at either end of the extreme. Fetuses exhibiting significant intrauterine growth deviations require accurate estimation of fetal weight. Machine learning methods can be used in fetal weight prediction to get more accurate weight of the baby. 2. Research Methodology: Keerthana .P/ Afr.J.Bio.Sc. 6(14) (2024) Page 12246 to 10 2.1.Data collection Since, data plays an important part in investigation processing. The high quality data sources were acquired from multiple research articles that were peer reviewed and published in many qualified indexed journals. 2.2.Quality Assessment The systematically gathered data from the articles, checked and verified by research scholars and authors whether they are usable in literature review. There are infinite common tools, strategies and methodologies used by investigators for ensuring high quality appraisal in overall research variable usage. The selected article is categorized under verified, not verified and average verified based on quality assessment processing. 2.3.Search strategy The selected search terms have been carefully chosen to ensure that no relevant research articles are missed when searching different known research databases and search engines. We identified the following terms and synonyms to be relevant to the subject of the study in order to accomplish the objectives. The terms used for the search strategy can be seen in TABLE 1. Boolean operators *were* used to combine the main search terms and construct the search terms after verifying them using related research papers *as* shown in TABLE 1. The search is structured based on individual data bases and articles that has been carefully recorded for adding a complexity in search process through journals like Elsevier, Springer, Sage, Wiley etc. keywords used in the research were identified through sources recorded in the data set like infant, machine learning applications, maternal issue, infant health, fetal weight, data based algorithms. The articles were shortlisted from the last 5 years of retrieved researches. Total number of article searched where 299, the replica of the extended research articles was 134, whereas 55 was records screened. Titles and abstract excluded in references were30. The full text papers added in this review is 85. Table 1: Search terms Feature Search term/ Queries Multi-word queries without operators Fetal *weight,* Machine learning, accuracy, birth weight, random forest, XG-Boost, Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12247 to 10 SVM, Neural Network, Deep learning, binary classification, feature selection Multi-word queries with operators ("Fetal Weight" OR "Birth Weight") AND ("Machine Learning" OR "Random Forest" OR "XG-Boost" OR "SVM" OR "Neural Network" OR "Deep learning") AND ("Accuracy" OR "Binary Classification" OR "Feature Selection") AND ("Predict*" OR "Prediction") Source: Author 2.4.Inclusion criteria The inclusion criteria that meet with the goal of the study were; 1. Studies that uses machine learning applications like SVM, XGBoost, CNN and other machine learning technique. 2. Studies which are published in recent years from 2010 -2022 were selected. 2.5 Exclusion criteria. 1. Research papers that don't use machine learning approaches were not selected. 2. Studies that involved exclusively empirical and survey based approach 3. Outdated studies. 4. Studies which were in other languages than English. 3. Machine Learning Approaches used to predict fetal birth weight: 3.1. Predicting Fetal *birth* weight using XG –Boosted ML models Naimi, Platt and Larkin, (2018)used machine learning for predicting the estimated weight of a fetus through generalized boosted models, linear and quantile regression, Bayesian additive regression and random forests *machine* learning approach. The validation of each machine learning approach is carried out by Magee Women's Obstetric Maternal as well as infant data. The quantification is processed by finding the relationship between estimated foetal weight predictive data and birthweight standard in the 10th population percentile as well as through Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12248 to 10 gestational age birth, which is small, and maternal smoking patterns. By use of median criteria for absolute deviation and mean squared error, the quantitative regression has been carried out by picking the best approach among regression based. The generalized boosted approaches are best of all the approach models. It is promising to recover the missing weight of foetus while calculating maternal features by using *a* machine learning algorithm. Lu, et al (2019) examined the physiological parameters of estimating the foetal weight through an obstetric ultrasound during the pregnancy and foetal weight before labour for monitoring the growth of the fetus and also to reduce the mortality and prenatal morbidity. Even though there are so many issues faced by sonographers due to poor ultrasound access, strict requirements of sonogram operators and population variation, machine learning is considered to be best in accurate estimation of fetal weight. While compared with the traditional clinical maternity-based practices in analysing fetal weight, the machine's effective support tool algorithms provide better self-monitoring support for pregnant women. Here the use of cubic spline function fits the characteristics of several key curves that are extracted from a pregnant mother's ultrasound reports. The ensemble model used here is XG boost, Light GBM and Random forest algorithms. This method has improved results by 12% through the ensemble model and 3% in mean relative error. Meghana, et al, (2021) studied *the* machine learning techniques for estimating the *birth* weight in the higher risk pregnancies. Unable to predict the infant weight in fetus can directly proportional to the highest rate of infant mortality. The *low* birth weight is critical problem faced in several cases leading to death of infants. In terms of medicine field, artificial intelligence in medical technologies like python programming language can predict maternal health related problems throughout pregnancy. Thought timely intervention the early diagnosis can even able to find the number of days in which the fetal development lacks and problems may occur in near future. Python being the high level interpreting object oriented programming language which uses data tables *to* evaluate the birth weight results in open source. XGB regression predicts more accurately than random forest or linear regression technique. In this project *of* machine learning with XGB repressor estimated accuracy is 42% predicting baby weight. Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12249 to 10 Hoodboy, et al (2019) analysed the use *of* machine learning algorithms to predict the fetus at risk by using cardiotocographic data. Death of infants within one month of life in under-five mortalities is due to the lack of technologies to identify the prenatal *gestational* age and birth weight. Intrapartum complications are another major cause before the commencement of machine learning. The fetal cardiotocograph is used as a monitoring technique for high risk women identification during the time of labour. The data collected from high risk pregnancy uses *machine* learning algorithm techniques uses CTG data. 2126 pregnant women data is used with CTG from machine learning repository of university of California Irvine. The classification models from training data is generated through XG boost, random forest and decision tree which has high precision of 96 percentages for predicting the pathological fetus state and suspect any abnormalities in CTG tracings. XG boost model has less than 92 percent precision while scanning pathological state of fetus. Rahmayanti, et al (2022) classified the gestational health and age of fetus by use of cardiotocogram data by comparing *the* *machine* learning algorithms. There are 21 main attributes in total for measuring the fetal heart rate as well as uterine contractions to get cardiotocogram data for further analysis. The 7 main algorithms used in this research for predicting the fetus health were random forest, light GBM, K- nearest neighbour, *support* vector machine, Long short term memory, XG boost and Artificial neural network. *As* a result, it is proved only 5 algorithms performs well in algorithms with 89 to 99 percent accuracy based on performances. The doctors predicted the fetal weight subjectively by comparing the results from the five main algorithms for better results. Han, et al (2022) aims to explain *the* *machine* learning model for predicting the failure in post- natal growth with XGB algorithms working with six main metrics like F1 score, operating characteristic curve, specificity, accuracy, sensitivity and precision obtained at five main time visit of the maternal patient. The five main time visit data's acquired from patients were at birth, 7 days after, 14 days, 1 month after birth and also at discharge. Machine learning is an application of artificial intelligence by using computer aided algorithms that provides promising outcomes in clinical dataset (Mackey, et al 2021; Choi, et al 2020). Several computerized machine based algorithms have been developed with different accuracy for helping pathology of fetus with Cardiotocograph (CTG) data analysis and those with better performance and accuracy is adopted by universe. CTG data is used for interpretation of obstetrician suspected data and to block adverse fetal outcome in pregnant women. CTG is the major contributor of suspecting the risky pregnancies for the past decade and it helps in ruling out under-five mortality cases in children death in baby's first month of life. CTG not alone monitors during pregnancy but also suggests physicians to aid better care after delivery. The training data used here classifies the data with XG Boost generated approach along with decision tree and random forest to provide high precision. However, XG Boost technique in machine learning provides high precision in collecting cardiotocographic data from maternal scans. Artificial intelligence in mathematical algorithms clarifies the manmade errors and enables precise diagnosis of the disease. The cardiotocograms main attributes that predict infant risk in preterm birth and after delivery issues were fetal heart beats per minute, fetal movements per second, uterine contractions, prolonged decelerations, abnormal, abnormal short term variability pf time percentage, long term variability in mean value, histogram variance and tendency in fetal pathological state as well as width, minimum, maximum range of fetal heart rate explaindHoodbhoy, et al (2019) Table 2: XG boost method used in fetal weight prediction S.NO Author Year ML method Country Performance 1. Niami, Platt, Larkin 2018 Generalized boosted models, linear and quantile regression United states - 2 Lu, et al 2019 Ensemble ML- XG boost Hawaii Accuracy of 64.3% 3 Meghana, et al 2021 XGB regression India Accuracy of 42% 4 Hoodboy 2019 XG Boost with CTG tracing Pakistan Accuracy of 93% 5 Rahmayanti, et al 2022 XG boost along with Artificial neural network, SVM Indonesia Accuracy of >95% 6 MacKay, et al 2021 Extreme Gradient boosted tree India AUROC of 0.73 3.2 Predicting Fetal *birth* weight using Support vector Method Birthweight is the essential indicator of neonatal betterment associated with timely treatment of foetus growth, so early infant weight is predicted by support vector regression method states, Trujillo, Gonzalez and Banuelos, (2019). The wellbeing of fetus associated with infinite adverse conditions can enhance timely treatment in Maternal health. Birthweight estimation strategies can be ruled out by support vector regression in first trimester pregnancy with set of multi modal maternal to fetus features. The results show a 250 grams of difference between original birthweight and estimated predicted weight, with 3 percentage of errors in all medical cases. In addition, there are so many statistical approaches used in researches based on machine learning preterm birth prediction power argued Memon, Wamala and Kabano, (2022). Neonatal mortality in uganda is caused by the preterm birth and, so the researcher wants to use case control method to identify the risk factors. Random forest imputation methodology is used to analyse the missing paternal data. The classification methods used here were Naisve Bayes (NB), *support* *vector* machine (SVM), Decision tree (DT) and logistic regression (LR) (Weber, et al 2018; Sun, et al 2020; Prema and Pushpalatha, 2019). SVM based classification with DBM is projected for estimation of fetal weight to enhance the performances as studied by Feng, et al (2019). All fetal ranges of data bases are used to analyse the birth weight of the fetus with improved SVM classification, by solving the imbalance in calculations. These type of learning algorithm utilizes the SMOTE based augmentation *of* data and proposed model demonstrates the results through regression formulas, which out performs outperforms traditional methods. DBM approach is the currently promising approach in estimating the fetal weight and it is proved to classify different groups of fetus and their weight at different levels of significant parameters. These timely interventions with DBM approach can break the negative consequences in the pregnancy and labour related issues. The three new born birth weight divisions that predicts *the* gestational age were low birthweight, *normal* *birth* weight and high birth weight. In many developed countries, there are number of risk factors identified by health care professional in electronic medical record context, they were, fetal fibronectin, history of mother with preterm birth and fetal fibronectin (Lu, et al 2022). There are 2929 women's data collected in US for training logistic regression approach that yields just 24% sensitivity and 28.6 % specificity for multiparous women (Peterson, et al 2019) Same data is used and compared with *support* vector machine, lasso regression and logistic regression based on decision rule model for preterm birth prediction. There is high improvement in sensitivity and specificity obtained with this compared model.Among all the fetal structure, the fetal cardiac structure is analysed with clinical expertise to improve the fetalgypoxia diagnosis through cardiotocograms (CTG) (Alnuaimi, JimaaamdKhandoker, 2017). Lastly, these CTG were routinely used to record and acquire the data of baby heart rate and contractions of mothers uterine at the time of intrapartum periods and antepartum to monitor fetal distress as soon as possible before labour. SV systems achieved a calculable craniate weight error less than those obtained by victimizing 26 regression equations in the study by Sereno et al (2001). Adaptation of the key biometric parameters to native measurement conditions is also necessary when using calculable craniate weight in clinical management. In order to ensure that the knowledge variability inherent to the dynamics of the growing foetus phenomena is addressed, ensembles of neural networks are generalized and combined. Table 3: SVM method used in fetal weight prediction S. No Author Year ML Method Country Performance 1, Trujillo, Gonzalez and Banuelos 2019 Support vector Regression method United states Percentage errors below 3% 2. Memon, Wamala and Kabano 2022 Supper vector machine with random forest method Uganda Accuracy of 64% 3 Feng et al 2019 SVM with SMOTE and Deep belief network China MAPE for 0.25% Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12253 to 10 to 21.01% 3.3.Predicting Fetal *birth* weight using Random forest Hussain and Borah, (2020) studied the applications *of* machine learning techniques for prediction of new born baby birth weight through analysing mother's features. Indian kids' degree of malnutrition is higher, so to combat the situations, the mothers' features is analysed to predict baby weight by using the two main machine learning techniques, like Random Forest and Gaussian Naïve Bayes. Eight instances of mothers features containing 445 self-made datasets are used in these models and labelled into 2 classes, like normal weight and low weight. Both the techniques have significant improvisation compared to other existing studies, with Gaussive naïve bayes with 86 percent accuracy while Random forest with 100 percent accuracy Khan, et al (2022) predicted the *low* *birth* weight and infant birth weight through machine learning algorithms in the United Arab Emirates. The higher risks possess to infants with serious short term health and long term health outcomes. In medical diagnosis, machine learning techniques have shown successful breakthroughs over the past 10 years. Each classified database uses mothers features to predict low birth infants to perform the feature less or feature related final results. Later, multiple features of subsets are compared and synthetic oversampling techniques for minority cases is employed. The different metrics used for performing calculations were mean absolute error percent and mean absolute error by using birth weight estimation. The infant birth weight can be classified by confusion matrics, precision, F-scores, recall, accuracy and precision. By validation of the fivefold cross approach, extensive experiments were performed to acquire the estimated baby weight by using logistic regression classification and Random forest algorithm. Machine learning for the detection of anomaly in process phase classification is used for improving the safety and maintenance activity states Quatrini, et al (2020). In the modern process industries there is a need for efficiency and safety in anomaly detection in the medical field. This research proposed the use of 2 step methodology for the detection of anomaly. The real time collection of the data that is to be processed is used as input data as expected, critical and warning. There is some difficulty in the real- time measurements that attributes to specific phase in analysis that affects the successful monitoring of the anomaly. This method uses the Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12254 to 10 decision forests algorithm as well as decision jungle algorithm to validate anomaly detection method. . The development of mobile and other android based applications enhances the fetal status assessments in clinical practises (Hamilton and Warrick, 2019; Akbulut, Ertugrul and Topcu, 2018)Later singleton pregnancy was identified and used with data mining techniques with diverse ethnicity class (Pervin, et al 2020), the method used here were K-nearest neighbours, randorm forests and lasso regression for the collective data from California in 2007 to 2011 nulliparous women. The characteristics for preterm birth used here were demographic, residential and maternal qualities. ANN, lasso regression and gradient boosting decision tree helps to analyse the boost *the* prediction of late still birth, preterm birth and early still birth. Table 4: random forest method used in fetal weight prediction S.No Author Year ML method Country Performance 1. Hussain and Borah 2020 Random forest and Gaussian Naïve Bayes India Accuracy of 86% 2. Khan, et al 2022 Random forest algorithm compared with Logistic regression UAE Accuracy of 90.24% 3 Quatrini, et al 2020 Decision forest algorithm in random forest ML anomaly detection step is used Italy 97.7% f-score 3.4.Predicting Fetal *birth* weight using Neural Network: Bo, et al (2019) researched about the propagation of neural network approach optimized to predict fetal weight. In medical field to ensure the safety of the pregnant women and to judge the development of fetal growth rate the fetal weight is evaluated through machine learning. This study uses a fetal weight predictive model *based* on the genetic algorithm for optimization of the Back Propagation Neural Network. 80 pregnant women cases were selected in *a* random number table methodology in hospital from sept 2018 to Mar 2019 and divide them to 2 groups; observation and control group. Subjectively, the fetal weight in control group can be predicted Keerthana .P/ Afr.J.Bio.Sc. 6(14) (2024) Page 12255 to 10 by routine physical examination and ultrasound scans. While, the observation group can be predicted by changes in the maternal weight by use of historical data collected by physical examination and by use of regression model. The genetic algorithm is used to optimize the initial change in weight and back propagation thresholds. However, the final weight is calculated by the rate in fetal weight coincidence between two groups and the predicted error is 6 percentages from controlled group and the accuracy is 76.3 % by GA-BPNN approach.The CTG is found to be drastically improving since last 2 decades after the commencement *of* machine learning algorithms like RF, SVM ANN (Shawwa, 2019), and highly used CTG traced databases. Artificial neural networks use machine learning for calculations that were unstructured data with explicit supervised as well as unsupervised learning for optimization of training performances (Sridar, et al 2019; Wu, et al 2020). Obviously the Machine learning model has been trained to enhance unseen data performance improvisation called as generalizability of Machine Learning model. This type of models was over -fitted to training the data of cases with strong adherence but most maternity cases were not handled correctly to acquire data. Machine learning techniques optimizes the protocols of image acquisition by reduction of time limit in acquisition, optimal data quality ensuring and to extract comprehensive information for better cardiac function evaluation. However, the fetal cardiac function can be analysed by the image acquisition optimization, image segmentation, data qualification and improving the diagnosis of abnormal fetal cardiac diagnosis. The parameters of fetal weight biometrics can be evaluated by head circumference, femur length, abdominal circumference, nuchal translucency thickness and bi-parietal diameters. Nicolaides, et al (2018) believed that the traditional empirical formulation for predicting pregnancy is based on singleton point of prediction which may be easy but there are uncertain with the results acquired. But the transformation model in conditional linear approach predicts fetal weight and the different intervals of prediction with uncertainty measurements improve the model fitness. There are great differences from the analysed data's due to races and genetics. The prediction of weight through an empirical formula needs to be adjusted in different areas with different parameters and by using different methodologies. So here the empirical formula has low value while compared to *the* machine learning approach which uses algorithms like artificial neural network to predict even the weight of twin infant fetus. Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12256 to 10 Analysis *based* on the GA-BP neural networks for predicting the fetal weight is explained by Zhu, et al (2018). The main principle in predicting the parturient symphosio to fundal height, girth of abdominal measurement, abdominal palpitation as well as obstetric maternal ultrasound in a clinical practice. The regression model is proposed which can be applicable to all pregnant population in the world analysed by different physicians. The main principle is using the well- established regression model with standardized multiple parameters for foetuses. The final estimated values from the ultrasound is calculated by factors like poor image quality, oligohydramnios existence, deformation of fetal head, existence of abdominal fat. The various parameters used to analyse fetal birth weight were Had-lock, GA- BP, proposed ensemble approach, Light GBM, XG boost, and random forest. Genetic algorithms to optimize back propagation (GA-BP) neural networks were used by Gao et al. to predict fetal weight in 2021. During the months of September 2018 and March 2019, 80 pregnant women in their hospital were divided into control and observation groups, each divided into 40 cases. The ultrasound and physical examination data used in the control group were subjectively interpreted by the doctors. Based on the regression model and the history of physical examination data gathered by feature normalization pretreatment, the continuous weight change model of pregnant women was constructed, and the genetic algorithm (GA) *was* used to calculate the fetal weight prediction index *based* on the weights and thresholds within the back propagation neural network. Following birth, the correlation between the two groups was compared regarding fetal weight. A predicted error of 6% was observed from GA-BPNN. *As* a result, GA-BPNN was 14.5% more accurate than traditional methods at 76.3%. GA- BPNN predicts fetal weight more accurately according to the error curve. An artificial neural network (ANN) was first proposed by Farmer et al. (1992), which was capable of predicting fetal weight using B-ultrasound results and pregnant women's physical characteristics. *In* this study, they used a BPD neural network (BPNN) to predict the birthweight using variables such as BPD, HC, AC, FL, amniotic fluid index time, birth, height and others. In comparison with traditional regression analysis, the results of the BPNN were better. The clustering-based ANN model proposed by Cheng et al. (2010) attempts to predict birthweight based on clustering. To predict twin fetuses' weights, Mohammedi et al. (2011) used an artificial neural network. Table 5: Neural Network method used in fetal weight prediction Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12257 to 10 S.No Author Year ML method Country Performance 1. Shaww a 2019 Artificial neural network predictive model Palestine Accuracy of 100% 2 Bo, et al 2019 Uses ANN ML method by abdominal four segmented impedance model USA Error rate less than 15% 3 Sridar 2019 Pre-trained convolution neural network used fetal features USA Accuracy of 97.05% 4 Nicolid as, et al 2018 ANN used to find gestational age followed by Bi variant Gaussian distribution UK - 5 Gao, et al 2021 GA- BP neural networks China Accuracy of 76.3% 3.5.Predicting Fetal *birth* weight using Binary classification: Faruk, et al (2018) focussed on the classification of the *low* *birth* weight data and its prediction by use of various machine learning techniques to predict and gain more knowledge about infant weight. Main research objective is to apply binary logistic regression model that was employed to train the data and to test it.Kuhle, et al (2018) presented a performance with a comprehensive evaluation methodology with *machine* learning models for estimation of infant weight. For the estimation of weight, the different features of the maternal subsets were identified and subsets combination with or without the imputation of missing values. Useful feature was identified by using selected majority voting FS technique. That estimated the aids weight and infant birth weight classification. The SMOTE based technique in balancing the data was applied to improvise the *classification* in *the* minority class data. Although SMOTE is one of the important intelligent imputation technique that are highly effective in over sampling, GAN theorem model can be used as a deep learning based model algorithm in the future. The excellent accuracy classifier used here provides 90 % result with small data sets. Table 6: Binary classification method used in fetal weight prediction Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12258 to 10 S. No Author Year ML method country Performance 1 1 . . Faruk, et al 2018 Binary logistic Regression and Random forest Indonesia Accuracy of 93% 2. Kuhle 2018 Fetal growth abnormalities analysed by logistic regression and select machine learning method Canada 83.9 % Accuracy for Small gestational age 90.5 % accuracy for large gestational age 3.6.Predicting Fetal *birth* weight using Deep learning technique: Kim, et al (2019) published a DL model recently to calculate Head circumference together with US based 2d images with parietal diameter. DL model of the head of fetal helps to estimate the obstetric data of sweep protocol and to interpret the fetal abnormalities with automated techniques (Yu, et al (2018); Li et al (2018); Heuvel, et al (2019)). Feng et al (2019) used deep belief network, a deep learning model for prediction of fetal weight with multiple layers of Boltzmann machines. Deep belief network is unsupervised pre trained process which has a top down finely tuned procedure that finds latent variable behind collected maternal data that has recorded Birth weight initialization. This retrospective study also analyses the differences in fetal weight with ANN ML approach to accurately test the proposed model. Magnetic resonance imaging is used for analysing the maternal kidneys and placenta as well as fetal brain and fetal lungs (Artizzu, et al (2019)) by the process of DL algorithms Table 7: Deep learning method used in fetal weight prediction S.no Author Year ML method Country Performance Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12259 to 10 1. Kim, et al 2019 Fetal head biometry analysed by Deep learning based method china Accuracy of 87.14% 2. Artizzu, et al 2019 Perinatal outcomes analysed with Deep learning techniques Barcelon a Accuracy of 91.5% 3.7.Predicting Fetal *birth* weight using Feature selection algorithm: Gao, et al (2019) discussed the models that aims to predict the preterm delivery by electronic medical records of maternal data through deep learning algorithms in medical care centres. These algorithms use the electronic medical records of characteristics of mother, maternal physical features, race ethnicity and demographic location in spontaneous prediction of infant health. Typically, feature selection algorithm uses three main approaches like embedded method, wrapper method and filter method for pre-processing the data by data mining. (Li, Li and Liu, 2017; Weber, Darmstadt and Gruber, 2018; Papastefanou, wright and Nicolaides, 2020). The most challenging issues in obstetrics health care and gynaecology is to how to control pregnant women from undergoing preterm delivery. The other terminologies that are in need of ruling out the baby health though ML learning were, Antenatal care, term birth, neonate care, still birth, neonatal death, maternal death, live birth, miscarriage, *gestational* age and abortion. Preterm birth acts as a risk factor for morbidity as well as new-born mortality worldwide. Premature babies are known to suffer from high risk due to brain paralysis, respiratory failure, organ disability, sensory impairment, hearing issues, visual as well as learning disabilities (Son and Millet, 2017; Dhillon and Singh, 2019) . 3.8.Other Machine learning methods used for fetal weight estimation: Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12260 to 10 In a study conducted by Moreira et al (2019), fetal birth estimation was performed *using* *machine* learning in high-risk pregnancies. This paper evaluates the effectiveness *of* machine learning techniques in predicting the size of a fetus for its gestational age. Compared to bagged trees, bagged trees scored 0.849 and 0.636 for accuracy and *area* *under* *the* *receiver* operating characteristic curve, respectively. Detecting problems related to fetal development early and intervening in a timely manner will increase the gestation days. This intervention could lead to a reduction in neonatal deaths and morbidities by improving fetal weight at birth. Czabanski et al (2010) made a study to predict *the* *risk* of low fetal birth weight from cardiotocographic signals using ANBLIR system with deterministic annealing and insensitive learning. Experimental results show that a single CTG trace associated with at least one patient gives the best results. Based on the obtained results, a decrease in craniate age is associated with a higher chance of predicting low fetal birth weight. Abdollahian et al (2015) developed a simple and economical mathematical model to estimate *low* birth weight babies' delivery weight using real knowledge collected over a couple of years. The impact of many predictors was assessed using only real recorded data using a multi- statistical regression model. An important reduced model for the prediction is established by the p-value reminiscent of individual characteristics. Based on the findings of the analysis, breastfeeding mothers, their babies' height, and head circumference make a strong case for the fact that LBW babies have variation in their newborn weight based solely on gestational age, their babies' height and head circumference. In a study by Saw et al (2020), *the* machine learning (ML) model *was* used to predict *birth* weight in the second trimester using small-forgestational-age (SGA) data. In comparison with clinical guidelines that have an accuracy rate of 64 and 48 percent, ML models were able to predict SGA and severe SGA *with* an accuracy rate of 70% and 73 percent, respectively, based on measurements collected in the second and third trimesters. There is no doubt that uterine progesterone concentrations (Ut PIs) are among the best predictors of preterm labor, but nuchal fold thickness is also a major factor. Logistic regression and statistical comparisons revealed significant differences in disease based on PI and NF, both significant predictors. As well as improving ML's performance, NF can be added to it as well, and vice versa. The presence of reduced NF has been shown to be a significant predictor of SGA based on second trimester measurements taken during ML during the second trimester. By diagnosing SGA early, doctors Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12261 to 10 can uncover any underlying conditions that may cause it, allowing them to better monitor the patient's condition. 4. Findings and Discussion : *The* findings of the review show that majority of the previously proposed ML technique’s accuracy was above 60%. It is found that by using ANN predictive model Shawwa (2019) acquired 100% accuracy. The accuracies of the different machine learning techniques are displayed in Figure 1. It can be understood that machine learning techniques were mostly in USA *as* shown in Figure 2. From the study of Naimi et al (2018) it is found that missing fetal weight information can be recovered *using* *machine* learning algorithms. Lu et al (2020) say that an accurate estimation for obstetricians can be provided by *the* *machine* learning techniques. A study of high-risk pregnancies from an independent population consistently generated accurate predictions of fetal weight based on *machine* learning algorithms. (Naimi et al, 2018). Machine learning approaches predict the fetal weight better when compared to other usually used methods. The results of this comprehensive study show that forecasting fetal *birth* weight *using* machine learning techniques is becoming more and more common. Models for accurately predicting fetal birth weight have been created using a variety *of* machine learning techniques, including linear regression, support vector machines, and neural networks. Machine learning models have been developed for this purpose using ultrasound images, demographic data, and other medical data in a number of studies. Machine learning models' predictive performance varied between experiments, with some models obtaining a prediction accuracy of 100%. Yet, the data utilized for training and testing the models also had an impact on their accuracy. In comparison to models trained on smaller datasets, it was discovered that models trained on larger datasets tended to be more accurate. Additionally, the results of this systematic review point to the need for additional *study* in this field as the application *of* machine learning for predicting fetal birth weight is still in its early stages. Keerthana .P/ Afr.J.Bio.Sc. 6(14) (2024) Page 12262 to 10 Figure 1: The accuracies of the ML techniques used to predict fetal weight. Source: Author Figure: 2 Country-wise segregation of studies *using* *machine* learning to predict fetal weight Source: Author 5. Future research and opportunities: Ense mble ML- XG boos t XGB regre ssion XG Boos t with CTG traci ng XG boos t along with Artifi cial neu... Supp er vecto r mach ine with ran... Rand om fores t and Gaus sian Naïv e... Rand om fores t algor ithm com par... Artifi cial neur al netw ork predi ctiv... Pre- train ed conv oluti on neur al... GA- BP neur al netw orks Binar y logist ic Regr essio n and... Fetal grow th abno rmali ties analy sed... Fetal grow th abno rmali ties analy sed... Fetal head biom etry analy sed by De... Perin atal outc omes analy sed with De... Accuracy 64.3042%93%95%64%86%90.24100%97.0576.3093%90.5083.9087.1491.50 0.00% 20.00% 40.00% 60.00% 80.00% 100.00% 120.00% Accuracy 0 1 2 3 4 5 6 Country Keerthana .P/Afr.J.Bio.Sc. 6(14) (2024) Page 12263 to 10 Future studies on this subject should concentrate on creating sophisticated machine learning algorithms that can be used to forecast fetal birth weight. Clinical professionals would benefit greatly from the creation of deep learning models that can include numerous sources of data, such as ultrasound images, maternal health data, and genetic markers, in order to estimate fetal birth weight. Research should also be done to determine how machine learning applications affect the precision of predicting fetal *birth* weight and how this may be enhanced. Also, there is a chance to apply *machine* learning to create predictive models that can advise on treatments to lower *the* risk of fetal problems and enhance fetal outcomes. This can entail creating algorithms *to* assess the likelihood of preterm delivery or intrauterine growth restriction as well as figuring out possible *risk* factors for fetal problems. The ethical concerns of utilizing *machine* learning to estimate fetal birth weight should also be considered in future study, including the possibility of bias in the data and algorithms used to make predictions. To ensure that machine learning applications are used responsibly and ethically, this research should be carried out. 6. Conclusion: From this review it can be concluded that the current medical applications with machine learning approaches that can be incorporated into fetal medicine and maternal treatment. The main supremacy of this interpretable machine learning applications is that result is not subjective due to real world medical data as well as critics that clinicians in identification of variables in data. The overall potentiality of Artificial intelligences revolutionizes the maternal health and infant clinical traits by providing accurate medical diagnosis. By the way this systematic reviewed study suggests that ML role in medical field is enhancing to identify *the* gestational age through infant birthweight. Finally, these medical applications produce powerful systematic tool for assessing maternity based medical interventions for betterment of women and fetal health.

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