ISSN: 2995-3286

Research Article

International Journal of Media and Networks

A Systematic Review on the Applications of Machine Learning for Fetal Birth Weight Prediction

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Submitted: 2024, Jan 22 **Accepted:** 2024, Feb 19 **Published:** 2024, Feb 28

Citation: Mane, D. T., Mante, J., Bakare, A. A., Gandhi, Y., Khetani, V., et al. (2024). A Systematic Review on the Applications of Machine Learning for Fetal Birth Weight Prediction. *Int J Med Net, 2*(2), 01-12.

Abstract

In order to protect the maternal and infant safety, birth weight is an important indicator during fetal development. A doctor's experience in clinical practice, however, helps estimate birth weight 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.

Keywords: Fetal Weight, Machine Learning, Accuracy, SVM, CNN.

1. Introduction

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, 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.

2. Research Methodology

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 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 articles 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.

2.4. Inclusion Criteria

The inclusion criteria that meet with the goal of the study were;

• Studies that uses machine learning applications like SVM, XGBoost, CNN and other machine learning technique.

2.5 Exclusion Criteria

• Research papers that don't use machine learning approaches were not selected.
• Studies that involved exclusively empirical and survey-based approach

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 [1]. 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 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 [2]. 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 [3]. 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.

Hoodboy, et al (2019) analysed the use of machine learning algorithms to predict the fetus at risk by using cardiotocographic data [4]. 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 [5]. 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 [6]. The five main time visit data 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 [7,8].

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 explaind Hoodbhoy, et al (2019) [9].

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

Table 1: XG Boost Method Used in Fetal Weight Prediction

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) [10]. 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 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) [11]. 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) [12-14].

SVM based classification with DBM is projected for estimation of fetal weight to enhance the performances as studied by Feng, et al (2019) [15]. 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. This 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 [16]. 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 [17]. 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) [18]. 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) [19]. 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.

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% to 21.01%

Table 2: SVM Method Used in Fetal Weight Prediction

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 [20]. 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 mother's 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 [21]. 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 mother's 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) [22]. 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 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 [23,24]. Later singleton pregnancy was identified and used with data mining techniques with diverse ethnicity class, 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 [25]. 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.

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

Table 3: Random Forest Method Used in Fetal Weight Prediction

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 [26]. 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 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, and highly used CTG traced databases [27].

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 [28,29]. 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 [30]. 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.

Analysis based on the GA-BP neural networks for predicting the fetal weight is explained by Zhu, et al (2018) [31]. 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, and 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 [32]. 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 [33]. 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 [34]. To predict twin fetuses' weights, Mohammedi et al. (2011) used an artificial neural network [35].

S. No	Author	Year	ML method	Country	Performance
1.	Shawwa	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	Nicolidas, 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%

Table 4: Neural Network Method Used in Fatal Weight Prediction

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 [36]. 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 [37]. 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 techniques 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.

S. No	Author	Year	ML method	country	Performance
11..	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

Table 5: Binary Classification Method Used in Fetal Weight Prediction

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 [38]. 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 [39-41]. Feng et al (2019) used deep belief network, a deep learning model for prediction of fetal weight with multiple layers of Boltzmann machines [15]. 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 by the process of DL algorithms [42]

S.no	Author	Year	ML method	Country	Performance
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	Barcelona	Accuracy of 91.5%

Table 6: Deep Learning Method Used in Fetal Weight Prediction

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 [43]. 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 [12,44]. 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 [45,46].

3.8. Other Machine Learning Methods Used for Fetal Weight Estimation

In a study conducted by Moreira et al (2019), fetal birth estimation was performed using machine learning in high-risk pregnancies [47]. 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 [48]. 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 [49]. 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 [50]. 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 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 [27]. 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 [1]. 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.

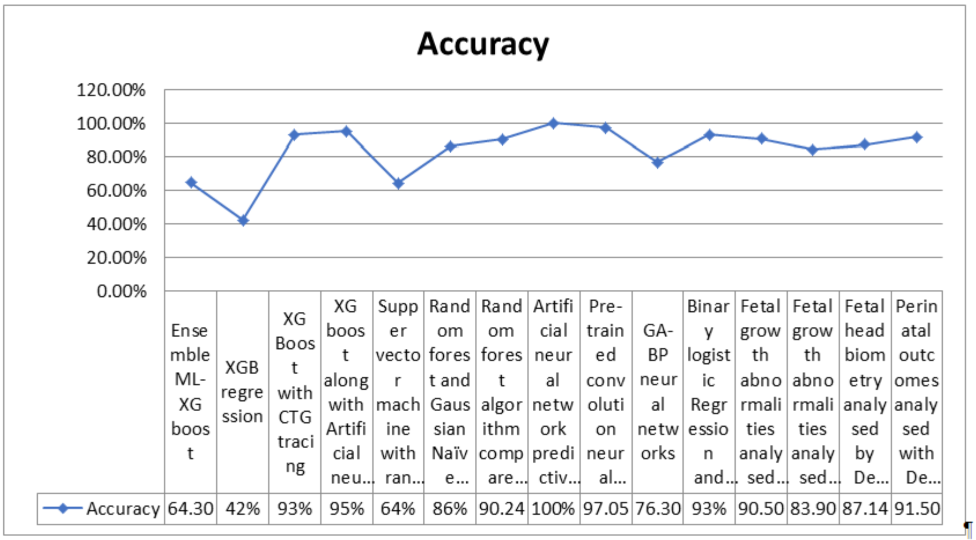

Figure 1: The Accuracies of the ML Techniques used to Predict Fetal Weight
Source: Author

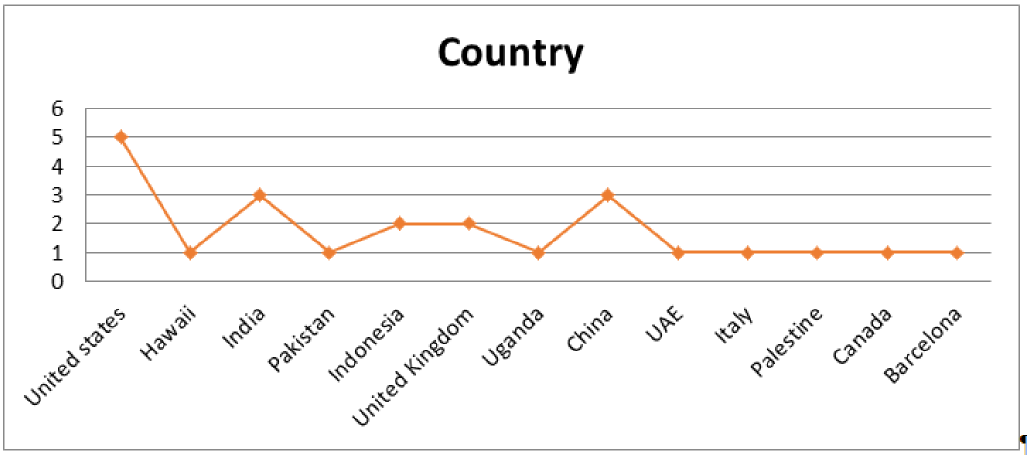

Figure: 2 Country-Wise Segregation of Studies Using Machine Learning to Predict Fetal Weight
Source: Author

5. 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.

Acknowledgement

We would like to express our sincere gratitude to our colleagues for their support and mentors for their valuable guidance throughout the research process. We also wish to thank the Dr.Vishwanath Karad MIT World Peace University for providing the required resources, as and when required. Finally, we are grateful to all the other participants who generously gave their input in terms of idea and co-operation towards successfully completing the review process.

Conflicts of Interest

The authors declare that we have no conflict of interest.

Author Contribution

The authors participated in research work and manuscript preparation.
[1]***Deepak T. Mane:*** Conceptualization, formal analysis and writing original draft
[*2]***Jyoti Mante:*** Reviewing, editing, and supervision
[3]***Anuradha Amar Bakare:*** Editing, reviewing and validation
[4]***Yatin Gandhi:*** Conceptualization, Data curation, Formal analysis, Investigation
[5]***Vinit Khetani:*** Methodology, Project administration, Resources
[6]***Dr.Rupali Atul Mahajan:*** Supervision, Validation, Visualization
All authors read and approved the final manuscript.

Data Availability Statement

The data used to support the findings of this study are included in the article.

Funding

The authors received no financial support for the research, authorship and/ or publication of this article.

Disclosure Statement

No potential competing interest was reported by the authors.

Ethical Approval and Consent to Participate

This article does not contain any studies with human participants or animals performed by any of the authors.

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