Bridging Prenatal Diagnostics and AI: A Systematic Review and Meta-Analysis of the Efficacy of Advanced Algorithms in Identifying Congenital Fetal Abnormalities

ABSTRACT

Congenital fetal abnormalities have emerged as a major cause of infant mortality globally. About 3% of pregnancies are reported as fetal structural anomaly through ultrasound, ranging from minor defect to severe organ system anomalies. Our study aimed to evaluate effectiveness of Artificial intelligence (AI) algorithms in prediction of fetal heart and brain abnormalities by using meta-analysis approach.In this study, the “Reporting Items for Systematic Review and Meta-Analysis (PRISMA)" guidelines were applied for screening and selection of research articles. We searched the research articles according to research aims from Google scholar, PubMed, and Ovid MEDLINE. The data search was limited to January 2015 to May 2024.Two researchers independently screened the studies to detect research aim oriented studies. After screening of titles, those researchers assessed all abstract for eligibility.The risk bias of included studies was assessed by two researchers who used Cochrane library tool (version 5.4.0). Using the DerSimonian-Laird technique, a bivariate random effect model that generated SROC plots, we pooled test estimates. This method is particularly helpful in visualizing variability in the sensitivity and specificity across studies, accounting for the heterogeneity. This improves the reliability of the SROC plot, offering a clear summary of diagnostic performanceUsing the software RevMan 5.4, we carried out every statistical analysis, particularly heterogeneity through the Q test.About 243,456 screened fetus or pregnant women of 11-32 gestational weeks through 10 studies based on AI algorithms (machine learning, deep learning and AI diagnostic tool). The imaging protocols including ultrasound and MRI were used to take visuals of fetal brain and heart abnormalities in all of including studies. DL and ML algorithms provided high-performance diagnostic predictions, mostly include CNN models that assist in providing accurate diagnostic results with high sensitivity and specificity. The AI algorithm model showed a generally good accuracy scores for detection of brain and heart abnormalities and reference machine learning findings, with sensitivity ranging from 82 to 99% and specificity from 78 to 99%. Figure 5's area under the SROC curve was 0.960. In contrast to the general detection, ML

and DL seems to be more sensitive in diagnosing fetal brain and heart abnormalities.Our study provided the scientific evidence that AI models including deep learning and Machine learning are effective in generating highly reliable detection or classification results for diagnosis of fetal brain and heart anomalies. These strategies can help in reducing infant mortalities, improving treatment outcomes, and postpartum outcomes among women.

Keywords: Artificial Intelligence, Deep Learning, Congenital fetal abnormalities, Meta-analysis

1. INTRODUCTION

1.1 Background

Congenital fetal abnormalities are appeared as one of major cause of infant mortalities globally. About 3% of pregnancies are reported as fetal structural anomaly through ultrasound, ranging from minor defect to severe organ system anomalies (1). Usually, these fetal structural abnormalities are detected or identified through morphology ultrasound scans that comprised standard planes of visible organs or other body parts (2). In developed countries,congenital heart disorders (CHDs) and fetal central nervous system (CNS) abnormalities are most common type of fetal abnormalities with high prognosis rates. These can vary from mild to severe. Currently, early prenatal ultrasonography is a widely accepted method for identifying fetal defects and tracking the development or emergence of intrauterine congenital illnesses. Diagnosing these diseases require careful interpretation of the ultrasound or MRI images. Despite advances in ultrasound and fetal MRI, some abnormalities are difficult to detect due their subtle presentation or late onset. Most often these cases are misdiagnosed and that leads to delayed clinical interventions at birth.Prenatal diagnosis of severe abnormalities during pregnancy can prevent the occurrence of different diseases,quickening postpartum intervention, improvement of treatment outcomes, and stabilizing the long-term neurodevelopment of the newborns (3). Similarly, fetal CNS and CHD significantly cause the postnatal morbidity and utero mortality (4). The findings of previous studies emphasized the detection of severe anomalies before 24 weeks of gestation among pregnant women (5).

In fetal medicine, artificial intelligence plays a crucial role in preventing congenital prenatal malformations. Artificial Intelligence (AI) is the capacity of a computer to perform tasks normally performed by intelligent creatures, such as acquiring knowledge, analyzing information, and interacting. AI includes machine learning and deep learning (DL), which are based on artificial neural networks (ANNs) (6). Standard planes in prenatal ultrasonography and MRI have been shown to be recognizable, detectable, and localizable by ML algorithms and CNNs. However, very few studies have created artificial intelligence (AI) algorithms that are capable of carrying out in-depth analyses of abnormal structures in fetus pictures in order to categorize and forecast congenital abnormalities; instead, almost all current research that have used AI in fetal imaging have focused on identifying normal fetal structures (7).

Recent advancements in AI algorithms have enabled the healthcare providers to detect and examine the medical images as powerful tool (8). Various types of AI algorithms including deep neural networks and machine learning effectively manage the medical picture segmentation (9). In medical science, AI helps in detection, localization, classification, segmentation and recording of medical images. Among types AI deep learning algorithms, a convolutional neural network (CNNs) is most common type which progressed the image recognition extensively (10). 2D and 3D obstetric ultrasound assisted by AI algorithm may precisely detect the particular fetus structures among pregnant women on the basis of gestational weeks.Additionally, throughout the past few decades, AI-based automatic measurements and assessments have been used to improve diagnosis accuracy and reduce measurement variability within and among observers. Furthermore, advancements in AI in recent years have made it possible to create AI-based methods for fetal anomaly detection (11). It is important to realize that artificial intelligence (AI) relies on computational algorithms, and that the quality and amount of the data it uses to deliver information affects its accuracy in addition to the algorithm (12).

Ahmad et al., 2024 (13) conducted a study to evaluate predictability of AI algorithms in detection and classification of heart as well as brain fetal abnormalities among pregnant women. The findings reported AI as a potential screening method for detection of fetal anomaly that become possible due to significant advancements in last few years. The capacity of AI improved to detect or identify heart and brain fetal anomalies during pregnancy through analysis of ultrasound images. Studies reveal AI's potential for accurate brain and heart structure recognition. Research has indicated that when it involves prediction and similarity, CNNs beat specialists, especially when it comes to distinguishing between normal growth and cardiac or brain disorders. However, the research lacked appropriate pooled analysis to explain specificity, sensitivity and accuracy of AI algorithms.

1.2 Research Objectives

The primary objectives of this review are to:

1. Evaluate effectiveness of Artificial intelligence (AI) algorithms in prediction of fetal heart and brain abnormalities by using meta-analysis approach.

2. Evaluate the sensitivity and specificity of AI models in identifying common fetal abnormalities such as Congenital Heart Defects (CHSs), Central Nervous System (CNS) abnormalities, etc.
3. Analyze the strengths, limitations and clinical applicability of prenatal abnormality detection models

2. LITERATURE REVIEW

2.1 Machine Learning in Prenatal Diagnostics

Over the last 10 years, there has been considerable improvements in both imaging and AI applications in prenatal diagnostics. Traditionally, clinicians are responsible in going through the ultrasound or MRI fetal images and identify any fetal anomaly, which has often led to misclassifications. Due to the inconsistency in the anomaly outcomes, AI powered applications have taken the charge and have been performing extraordinarily in terms of accuracy of classifying fetal abnormalities.

2.2 Machine Learning & Deep Learning in Prenatal Diagnostics

Machine Learning (ML) models such as classification, detection, and prediction of several fetal symptoms that are indicative of fetal abnormalities have been used in several studies. Some of the traditional models such as Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, etc. have used characteristics from ultrasound images. In one of the studies, Attalah et al. (2018) (14) leveraged SVM and KNN models for fetal brain omental transfusion with an accuracy up to 79%. However, these models struggle in case of large dataset and lot of features are required for higher accuracy. Deep Learning (DL) models came to the rescue by providing higher hyperparameters to learn both linear and non-linear relationship thereby improving the accuracy to greater deal. Deep Learning models such as Convolutional Neural Network (CNN) models were popular among image-based predictions. For example, the study by Xie et al. (2020) (15) reported an accuracy of 90% in detection fetal abnormalities. using CNN model. and ultra sound images. Similarly, in a study by Arnaout et al (2021) (16), CNN-based models have achieved an expert level detection of fetal heart and brain anomalies. Furthermore, these models have performed well in case of 3D ultrasound images as well. Apart from ultrasound images, AI has leveraged MRI images for non-invasive prenatal testing diagnostically. For example, in a study by Huang et al. (202) (17), a 3D based CNN. Model architecture was trained on fetal MRI scans and did fairly well in segmenting different components of the brain with a recall score of 83%. Similarly, in another study by Zhang et al. (2022) (18), deep learning models were implemented on nuchal translucency images to analyze trisomy 21with a staggering specificity of over 95%.

2.3 Challenges and Limitations

Nonetheless, the process of using AI for prenatal diagnosis have several challenges. Over generalization of the models across different imaging populations is what many studies have reported as a potential concern. Models which are trained on limited dataset to clinical challenges usually do not perform well on images obtained in a different clinical set up. One of the most popular issues is the explainability of the DL models. However, with rising number of explainable AI (XAI), AI-assisted diagnosis is slowly getting adopted by the clinicians

3. METHODS

This systematic review of available studies on our topic was conducted according to the PRISMA guidelines ("Preferred Reporting Items for Systemic Reviews and Meta-Analysis")

3.1 Search Strategy

In this study, the "Reporting Items for Systematic Review and Meta-Analysis (PRISMA)" guidelines were applied for screening and selection of research articles (19). We searched the research articles according to research aims from Google scholar, PubMed, and Ovid MEDLINE by applying PRISMA guidelines. The keywords used for data search were "Machine learning" "deep learning" "artificial intelligence" "fetal MRI" "fetal heart", "brain abnormalities", "multi-modality" and "fetal anomalies". The data search was limited to January 2015 to May 2024.

3.2 Studies Selection

Two researchers independently screened the studies to detect research aim oriented studies. After screening of titles, those researchers assessed all abstract for eligibility. Disagreement among researchers was resolved by involving third reviewer. Only full text studies were included: having AI/ML model, pregnancy time, method used, and performance measures (Accuracy, specificity, and sensitivity). For each included study, the variables such as author, year, country, study population, fetal age, type of model, AUC values, sensitivity, specificity and findings.

3.3 Inclusion and Exclusion Criteria

The eligibility criteria for included studies were 1). Studies that addressed fetal abnormalities and pregnant women as population 2). Studies that involved the use of DL and ML algorithms in scanning of fetal ultrasound images 3). Studies investigating fetal brain and heart anomalies through primary analysis 4). Studies that were full text and published in English. The studies that did not meet inclusion criteria were excluded. The studies involving animals, other type of population (rather than fetus and pregnant women), articles published as abstracts, letters to the editor, reviews were excluded.

3.4 Risk Bias Assessment & Statistical analysis

The risk bias of included studies was assessed by two researchers who used Cochrane library tool (version 5.4.0). To determine the diagnostic accuracy of fetus ultrasound for the identification of significant cardiac and central nervous system abnormalities, data were retrieved and used to fill two-by-two tables and compute true-positive, false-positive, true-negative, and false-negative rates. In order to establish which cardiac abnormalities are most susceptible to abnormality detection, the procedure was carried out to measure the diagnostic accuracy for each type of cardiac abnormality separately. We computed the sensitivity and specificity for each research, pooled the values, and generated 95% confidence intervals in order to assess test accuracy. Using the DerSimonian-Laird technique, a bivariate random effect model that generated SROC plots, we pooled test estimates. Using the software RevMan 5.4, we carried out every statistical analysis, particularly heterogeneity through the Q test and sensitivity analysis (20).

4. RESULTS

4.1 Study selection

The electronic databases yielded 6090 research articles and 4139 citations were removed due to duplicates, automation tool rejection and non-full text availability. About 1951 research articles were screened. Only 305 research articles were full text and assessed for eligibility criteria. The included studies were published between 2015 and 2020. Among those, only 9 studies met inclusion criteria (16-24), as mentioned in figure 1.

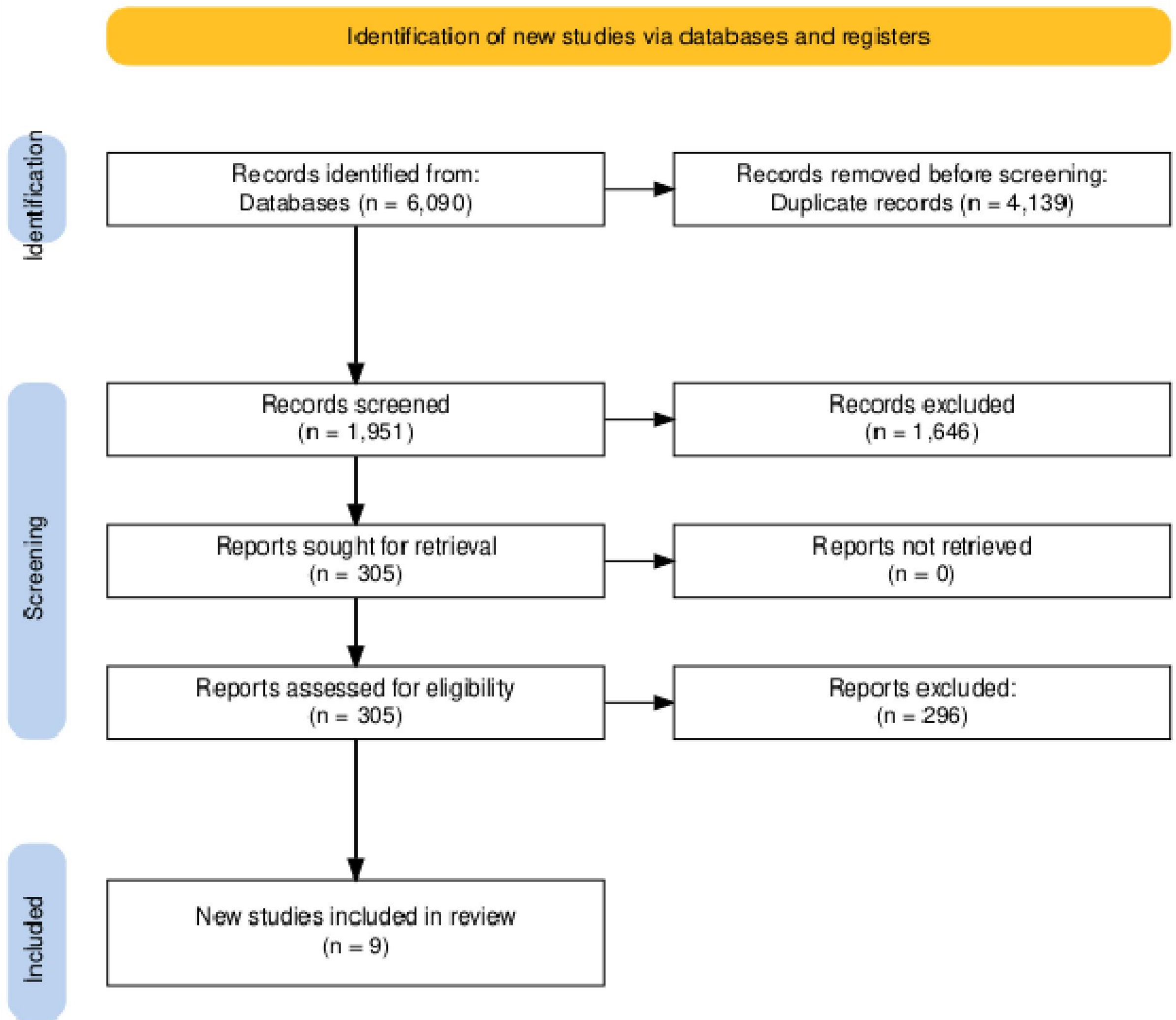


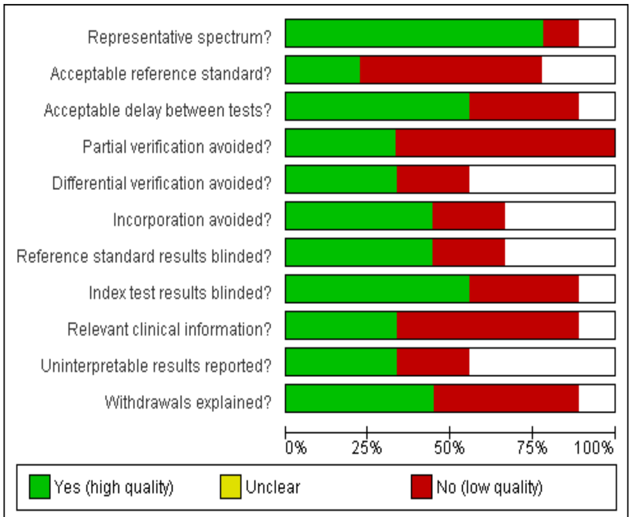
Figure 1: The PRISMA flow diagram for the systematic review detailing the database searches, the number of records screened and the full texts retrieved for the study.

4.2 Study characteristics

About nine studies based on AI algorithms for diagnosis of fetal brain and heart abnormalities during gestation were included. These studies involved 243,456 fetuses and their images of fetal brain and heart abnormalities which were taken during 16 to 32 gestation weeks. Three type of AI algorithm models including machine learning, deep learning (Convolutional neural networks) and Prenatal ultrasound diagnosis Artificial Intelligence Conduct System (PAICS).

4.3 Risk bias Assessment & Pooled Analysis

The risk bias of included studies was assessed by using Cochrane library tool and results are shown in figure 2 and 3.



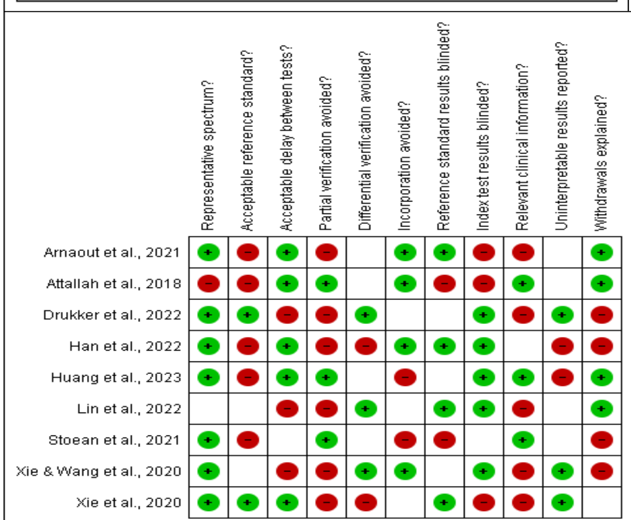


Figure 2: Risk bias graph of included studies Figure 3: Risk bias summary of included studies

Table 1: Characteristics of included studies

Author, year	Country	Study population	Fetal age	Type of model	AUC				Sensitivity	specificity	Findings
Attallah et al., 2018 (21)	Egypt	113 normal and 114 abnormal for fetal brain	16-39 weeks	**machine learning model:** with segmentation, enhancement, feature extraction and classification	Linear discriminate analysis (LDA) P: 0.72 A: 0.79	support vector machine (SVM) P: 0.74 A: 0.79	K-nearest neighbor (KNN) P: 0.67.5 A: 0.73	Ensemble Subspace Discriminate P: 0.72 A: 0.80	0.93	0. 78	Machine learning algorithm has successfully detected the fetal brain abnormalities with images of different fetal GA
Drukker et al., 2022 (22)	Israel	16,297 pregnant women	18–40 gestational weeks	Prenatal ultrasound diagnosis Artificial Intelligence Conduct System	internal validation image dataset P: 0.933 A: 0.977	external validation image dataset P: 0.902 A: 0.898	real-time scan setting P:0.969 A: 0.981		0.876 (0.596–1.000)	0.99 (0.95–1.000)	The PAICS achieved excellent diagnosis results for various fetal CNS abnormalities.
Huang et al., 2023 (23)	China	80 fetal brain MRI scans	20 to 35 weeks	3D network structures					0.848	0.8379	The neural networks provided excellent results in terms of diagnosis of fetal abnormilities
Arnaout et al., 2021 (24)	USA	107,823 images	18- to 24-week	Ensemble learning model	0.99				0.95	0.96	Ensemble learning models have significantly improved detection of

											fetal CHD
Xie et al., 2020 (25)	China	92,748 women	18 to 32 weeks	deep convolutional neural networks					0.942	0.96	Our algorithms proved potentially helpful in diagnosis of fetal brain abnormalities
Xie & Wang et al., 2020 (26)	China	10 251 normal and 2529 abnormal pregnancies	18 to 32 weeks	Deep-learning algorithms	Segmentation precision: 97.9%,	Recall: 90.9%	DICE: 94.1%		0.969	0.959	Deep-learning algorithms can detect normal and abnormal fetal brain lesions through ultrasound images
Stoean et al., 2021 (27)	Romani a	7251 fetal heart images	18 to 32 weeks	convolutional neural networks	0.9958				0.82	0.91	CNN improved the detection of fetal heart and brain abnormalities through ultrasound
Lin et al., 2022 (28)	China	16297 pregnancies	18-32 weeks	Prenatal ultrasound diagnosis Artificial Intelligence Conduct System (PAICS)	0.933	0.977	0.863		0.883,	0.891	PAICS resulted into excellent diagnostic performance for various fetal CNS abnormalities

											in less time
Han et al., 2022 (29)	China	204 fetuses	18-32 weeks	artificial intelligence (AI) segmentation algorithm					0.515	0.99	AI algorithm has improved the diagnostic efficiency of fetal heart abnormalities during pregnancy.

Diagnostic accuracy values for the interpretation of fetal brain and heart abnormalities through AI algorithms (Machine learning, deep learning and AI diagnostic model) are presented in the forest plot (Figure 4) and SROC plot (Figure 5). As shown in figure 4, the SORC revealed the high sensitivity scores for AI algorithms by ML and DL, exhibiting it as highly accepted scanning tool. The AI algorithm model showed a generally good accuracy scores for detection of brain and heart abnormalities and reference machine learning findings, with sensitivity ranging from 82 to 99% and specificity from 78 to 99%. Figure 5's area under the SROC curve was 0.960which indicates a high ability to discriminate between true positives and true negatives. In contrast to the general detection, ML and DL seems to be more sensitive in diagnosing fetal brain and heart abnormalities.

Study	TP	FP	FN	TN	Sensitivity	Specificity
Arnaout et al., 2021	9590	3302	612	79244	0.94 [0.94, 0.94]	0.96 [0.96, 0.96]
Attallah et al., 2018	38	41	3	145	0.93 [0.80, 0.98]	0.78 [0.71, 0.84]
Drukker et al., 2022	1418	147	212	14521	0.87 [0.85, 0.89]	0.99 [0.99, 0.99]
Han et al., 2022	20	2	19	164	0.51 [0.35, 0.68]	0.99 [0.96, 1.00]
Huang et al., 2023	7	12	1	59	0.88 [0.47, 1.00]	0.83 [0.72, 0.91]
Lin et al., 2022	5737	1076	782	8703	0.88 [0.87, 0.89]	0.89 [0.88, 0.90]
Stoean et al., 2021	1130	529	248	5345	0.82 [0.80, 0.84]	0.91 [0.90, 0.92]
Xie & Wang et al., 2020	3936	308	164	5843	0.96 [0.95, 0.97]	0.95 [0.94, 0.96]
Xie et al., 2020	8904	4174	371	79300	0.96 [0.96, 0.96]	0.95 [0.95, 0.95]

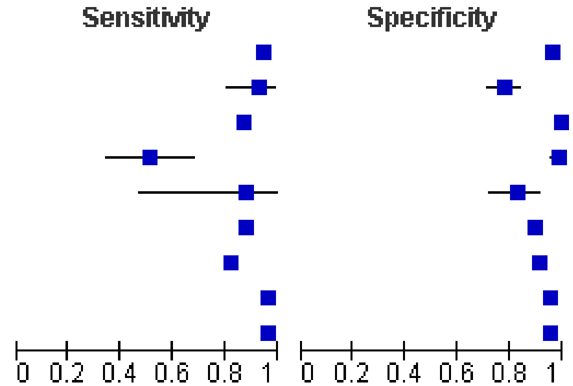


Figure 4: Forest plot of specificity and sensitivity of AI algorithms for detection of fetal and brain abnormalities

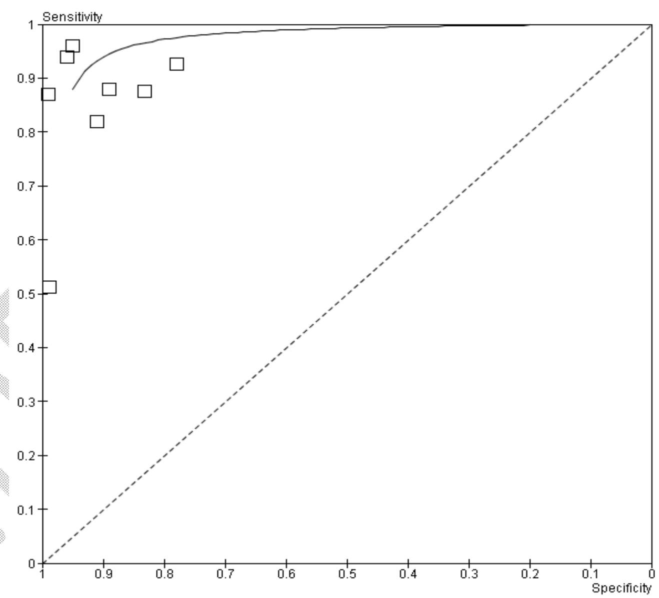


Figure 5: SROC plot of sensitivity and specificity of fetal abnormalities

5. DISCUSSION

This study aimed to evaluate the predictive ability of Fetal Brain and Heart Abnormalities using Artificial Intelligence (AI) Algorithms by using approach of meta-analysis. About 243,456 screened fetus or pregnant women of 11-32 gestational weeks through 10 studies based on AI algorithms (machine learning, deep learning and AI diagnostic tool). The imaging protocols including ultrasound and MRI were used to take visuals of fetal brain and heart abnormalities in all of including studies. DL and ML algorithms provided high-performance diagnostic predictions, mostly include CNN models that assist in providing accurate diagnostic results with high sensitivity and specificity (30). The neural networks are designed to enhance fetal imaging assessment processes by optimizing the detection of fetal heart and brain. It has reduced examination time and increased procedure accuracy (20). The examined studies covered a wide range of methods, and all of them achieved their objectives by finding fetal brain and heart defects or related biometric measures with accuracy rates greater than 90%.

These findings show that automated and accurate fetal parameter assessments are becoming more common. Congenital cardiac disorders are the most common birth defects in the heart (31). Accurately detecting congenital cardiac problems is the aim of including ML and DL into ultrasonography examinations. Regardless of gestational age, research demonstrates that AI systems can successfully recognize embryonic features among 16-32 weeks old fetus. This sets the foundation for the development of a dependable protocol utilizing Deep Learning (DL) architectures to produce a clinical decision support system that is computerized and intelligent, particularly for fetal echocardiography in the early stages (32, 33).

Artificial intelligence (AI) algorithms have been providing promising outcomes as detection and classification of fetal or brain abnormalities during prenatal pregnancies. In segmenting and analyzing the fetal brain MRI images, deep learning models and convolutional neural networks (CNN) have provided high accuracy results across various gestational ages (30, 34). Artificial Intelligence (AI) can help in brain pathology preprocessing, reconstruction, and classification. It can also help with one-week gestational age prediction. AI technologies have the potential to increase scan effectiveness and precision in ultrasound imaging by automatically identifying conventional fetal brain planes and detecting aberrations in real-time. Fetal position and maternal variables are two constraints of conventional ultrasonography that these technologies may help to address. When it comes to identifying embryonic brain abnormalities, deep learning approaches—such as CNN—have demonstrated superior accuracy than conventional machine learning approaches. For the advancement of artificial intelligence in fetal imaging, large-scale, labeled dataset generation is still essential (35).

This approach demonstrates the efficacy of AI algorithms as practical tools that can significantly improve diagnostic proficiency for inexperienced medical professionals. The artificial intelligence used to recognize the fetal abnormalities in ultrasound pictures and assess the future disorders in fetus with abnormalities (36).

In this study, we have evaluated the diagnostic accuracy of AI models which scanned the fetal ultrasound images to predict fetal brain and heart anomalies. The study was conducted using meta-analysis approach to only analyze the studies of machine learning and deep learning models for detection of fetal anomalies of all trimesters, focusing on 16-32 gestation weeks. Similar to findings of other studies (11, 13), our study proved that AI models can revolutionize the diagnosis and detection ability of 2D ultrasounds or MRI for fetal abnormalities. Our comprehensive analysis encompasses a broad spectrum of ML and DL algorithms, existing literature, advantages and disadvantages of each, possible challenges, and anticipated applications of these algorithms in gynecology. This comprehensive study demonstrates the significant potential of AI for prenatal diagnosis, particularly in cases of fetal anomalies. It has the potential to improve patient outcomes in fetal medicine by removing barriers to diagnosis and increasing the range of possible treatments (37).

6. CONCLUSION

Artificial Intelligence has lately been making substantial leap in delivering high accuracy due to increase in the complexity of the models and availability of multi-modal data. AI has been showing promising results in early detection, diagnosis and management of fetal abnormalities.Our study provided the scientific evidence that AI models including deep learning and Machine learning are effective in generating highly reliable detection or classification results for diagnosis of fetal brain and heart anomalies. These strategies can help in reducing infant mortalities, improving treatment outcomes, and postpartum outcomes among women. Future fetal screening initiatives should adhere to a consistent anatomical evaluation process and acknowledge that certain defects change naturally throughout pregnancy and that not all anomalies may be detected. This should have a significant positive influence on the early diagnosis of fetal heart defects when paired with suitable training and the establishment of referral pathways.

7. LIMITATIONS

With advantages, there were few limitations in our meta-analysis. Firstly, the number of studies was limited, as large number of studies is needed to yield effective results. Secondly, we missed subgroup analysis of all AI methods such as deep learning, machine learning and AI diagnostic tools. The subgroup analysis can provide the comparative efficacy of each method separately for detection of fetal anomalies. Thirdly, the quality assessment of studies has been done with single tool that could not provide reliable results. There is need to implement JBI or CASP for quality assessment of included studies.

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

Option 2:

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

1.

2.

3.

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