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Machine Learning-Driven Prenatal Brain Anomaly Detection: A Review using Ultrasound Imaging

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***Abstract*— Artificial intelligence is essential to prenatal medicine because it assist in preventing congenital fetal defects. Despite advancements in ultrasound technology, accurately identifying irregularities remains challenging and time-consuming for medical professionals. Evaluating the algorithms being used to streamline screening for prenatal brain abnormalities is the aim of the current investigation. ML and DL algorithms may be used to optimize fetal diagnostic (ultrasonography) examinations in order to boost the precision of diagnoses for fetal abnormalities, decrease examination time, and alleviate the doctor's burden. This review examines the importance of detecting anomalies in prenatal ultrasound images for the health of the fetus and mother. Additionally, it contrasts the effectiveness and quality of different ML algorithms for detecting fetal brain anomalies. The potential for these revolutionary technologies to improve pre-natal abnormality identification is emphasized, along with the need for further research in this area to improve clinical applications and outcomes.**

***Index Terms*— Machine Learning, Fetal Brain Anomalies, Pregnancy, Artificial Intelligence.**

I. INTRODUCTION

Anomalies refers to deviations from the norm or irregularities in data, behavior, or conditions. Fetal abnormalities are unusual or unanticipated events in the development of the fetus during pregnancy [1]. “An anomaly scan, also known as the 20-week scan or the mid-pregnancy scan, takes a deep look at your baby and your womb (uterus)” [2]. The sonographer performing the scan will examine the placenta's position and make sure your baby is developing normally. The sonography expert will examine your baby's organs and take measurements. At this stage anomalies are try to find such as for brain shape and structure of head. Anomalies in face of baby is try to identify to check for a cleft lip. Baby’s bone and its length, its cross section also identified to check anomalies of bone. Any anomaly during the crucial prenatal stage of human development can result in serious health issues. Misdiagnoses can occur when ultrasound image interpretation is vulnerable to subjectivity and errors.

Brain abnormalities are indicated by deviations from the normal developmental trajectory, which has been widely utilized to assess normal brain development using magnetic resonance imaging based brain age prediction. Developmental disturbances at various phases of developmental or fetal development can result in birth defects referred to as congenital brain malformations [3]. Numerous disorders are caused by the brain dysfunction.

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The interconnected fields such as Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning plays a crucial role in healthcare and medicine area. AI refers to the capability of a machine to perform tasks that typically require human intelligence. For anomalies detection in fetus, certain steps in artificial intelligence are applied such as the problem-solving, reasoning, learning, and understanding natural language. Machine Learning and Deep Learning are parts of Artificial Intelligence which are recognize while artificial intelligence detect or predict any remarkable task. Recent trend of image detection in deep learning is use of convolution neural network. Convolutional Neural Networks (CNNs) play a crucial role in computer vision applications, including image classification, object detection, and segmentation. Today, CNNs are typically developed with programming languages such as Python and incorporate sophisticated methods i.e. feature extraction from images [10]. Many analytical result shows that CNN works better in comparative analysis. The use of sophisticated deep learning methods, which use enormous datasets to increase diagnostic precision, is a crucial component of prenatal abnormality diagnosis. Algorithms such as Convolutional Neural Networks (CNNs) have surfaced as powerful tools due to their proficiency in analysing complex medical images, significantly enhancing the identification of anomalies during prenatal scans. Furthermore, strategies like Recursive Feature Elimination (RFE) are considered in the field of anomaly detection by considering image as input eventually enhancing the interpretability and performance of the model.

As a class of deep learning algorithms, Convolutional Neural Networks (CNNs) are a particularly well-suited for image analysis, making them highly effective in detecting fetal anomalies from ultrasound images. Prenatal care is progressively incorporating this technology to improve anomaly detection's precision and effectiveness. While detecting anomalies in image analysis CNN works on the basis of three layers. Three layers of CNN consist of Convolution, Pooling and Fully Connected Layers. Each layer has its own special feature which helps to improve the efficiency of algorithm. From data collection to deployment CNN is applied to special data set for detecting deficiency in processing of data. In next study, briefed CNN's challenges and working. [9]. Next to CNN advanced model of deep learning designed for real time object detection is YOLO. It works for real time object detection. While working on ultrasonography images of foetus You Only Look Once algorithm identify and classify various fetal structures for prenatal care. In real time applications such as fetal anomaly detection this algorithm optimized the performance [10].

II. Deep Learning

Machine learning is a subdivision of artificial intelligence (AI), and deep learning is a subclass of machine learning (ML). Artificial intelligence (AI) is the entirety of things. When the similarity between the human visual system and the computer vision system is compared, a Human Visual System has eyes to see images, videos, or any objects and it is processed in our brain to make intelligent decisions [5]. While working in various domains like finance, healthcare, teaching, photo-editing and cybersecurity, Anomaly detection is crucial task. Deep learning's capacity to represent intricate patterns in huge datasets has made it a potent tool for anomaly detection. Three frameworks are considered for detection of anomaly in human computer vision applications. One of three model is auto encoder which is designed to learn efficient representation of input dataset through unsupervised learning. Next frame to auto-encoder is CNN which learn automatically from spatial features of input data images. Third framework for anomaly detection in deep learning is RNN (Recurrent Neural Network) which is feasible for sequential data analysis. While discussion about deep learning some difficult circumstances may occur which are: improper data set, improper selection of feature, and gaining trust for deployed anomaly detection model. In deep learning, most recent algorithmic models we are covering are: convolution neural network, and you only look once.

III. Convolution Neural Network

One of the most crucial deep learning architectures is the Convolutional Neural Network (CNN), especially for tasks involving image and video input. Highly effective algorithm for detection of anomalies in ultrasound images, the available algorithm is CNN (Convolution Neural Network). One type of deep neural network called a CNN is made especially to interpret structured grid-like input, such a 2D image. Manually feature engineering takes too much time, so CNNs eliminate that by using convolution operations to extract features from input given data, in contrast to typical fully connected networks. While working on CNN, some context are being considered for working, such as deep learning architecture, image modalities where both MRI and ultrasound images is being taken as input. While working with this module, challenges may occur which include rapid changes in image dataset [6].

A. Convolution Neural Network

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Out of many deep learning architecture, specific CNN architecture has been considered for anomalies in foetal brain such as automatic cortical plate segmentation in ultrasound images. Attentive convolution neural network was developed for plate segmentation in foetal brain. Following are different convolution models for fetal brain abnormalities detection:

FOAC-Net: An advanced deep learning architecture called the embryonic Organ Anomaly Classification Network (FOAC-Net) was created specifically to identify abnormalities in embryonic organs, with an emphasis on the fetal brain. This model's capacity to automatically detect and categorize abnormalities in fetal MRI images is improved by the use of sophisticated techniques like squeeze-and-excitation (SE) and naïve inception (NI) modules [6]. FOAC-Net targets fetal organ abnormalities by using a convolutional neural network (CNN) framework that is tailored for fetal brain picture classification tasks [7]. The model has demonstrated significant performance, achieving an 89% probability of correctly identifying brain anomalies in test images. In the initial stage this model developed for MRI imaging only, afterwards it adapted working for ultrasound imaging which having better efficiency than traditional. Using deep learning models such as FOAC-Net, healthcare providers can improve diagnostic accuracy and treatment outcomes.

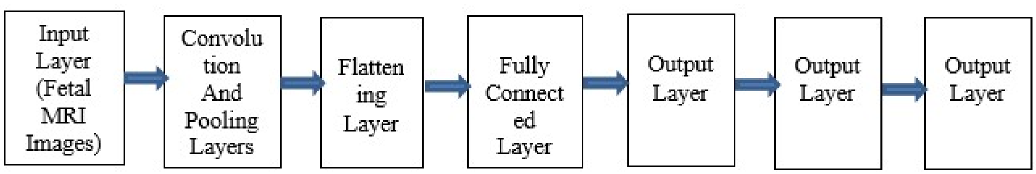

Figure 1. CNN Model: FOAC-Net schematic layout

B. ResNet-50

Another deep learning model for CNN is Residual Network family which is efficient in image classification hence improves the efficiency of neural network. Each of the five blocks that make up ResNet-50's 50 layers has a collection of residual blocks. The network's capacity to learn intricate traits is improved by these blocks, which are made to retain data from previous levels. Residual block is core block of this architecture.

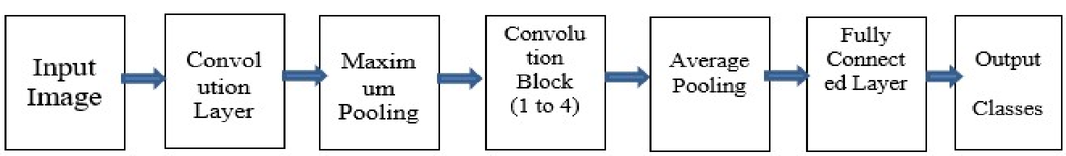

Figure 2. CNN Model: Res-Net-50 schematic layout

C. YOLO algorithm

A well-liked real-time object identification system, the YOLO (You Only Look Once) method can be used for a number of uses, such as fetal abnormality diagnosis and medical imaging. YOLO predicts bounding boxes and class probabilities directly from complete photos in a single evaluation, treating object identification as a single regression issue. So for quick responses task this algorithm plays vital role [8]. Particularly YOLO is used in anomalies detection in prenatal imaging, i.e. in ultrasound analysis. This enables to early diagnosis and monitoring. In order to identify diseases like malformations or developmental anomalies early on, YOLOv5 has been utilized to identify structural deviations in fetal brain ultrasound pictures [8]. Its single-stage detection system maintains high accuracy while enabling real-time analysis.

As research goes on for anomalies there are certain key features are elaborated. In the context of fetal brain anomalies detection below are certain key features.

- Single Neural Network: To accomplish both object identification and classification in a single forward pass, YOLO uses a single convolutional neural network (CNN). Multiple models are not necessary since healthcare providers can obtain entire information in a single step by simultaneously predicting bounding boxes and identifying anomalies. The model is able to efficiently learn spatial hierarchies and correlations between features that are pertinent to embryonic brain structures since the entire detection process is tuned concurrently.
- Grid Division: An S × S grid is created from the supplied image. For objects whose centres fall inside a grid cell, that cell is in charge of forecasting bounding boxes and class probabilities. For the purpose of detecting subtle aspects of the fetal brain structure and possible abnormalities, this divide enables the model to concentrate on particular areas of the ultrasound image. Variations in gestational age or fetal position may cause different brain regions to show up in different places on the ultrasound imaging. The model can better adjust to these changes because to grid division. The ability of each grid cell to anticipate numerous bounding boxes improves the likelihood of finding distinct kinds of brain abnormalities (such as cysts or malformations) that could manifest in different sizes or places.
- Forecasts for Bounding Boxes: A predetermined number of bounding boxes are predicted by each grid cell, together with the corresponding confidence scores that show the likelihood that the box contains an object. In the implications of bounding box, localization of precise in ultrasound images.
- Post Processing of Input: Here non max suppression takes place where elimination of redundant bounding boxes is takes place. By eliminating redundant bounding boxes accuracy get improves. To eliminate forecasts with low confidence that are not likely to be actual anomalies. Also in this phase, assignment of class labels is performed in which normal, abnormal 1 and abnormal 2 tagging is done. It generates the reports of detected anomalies on original image for further analysis by medical professionals.

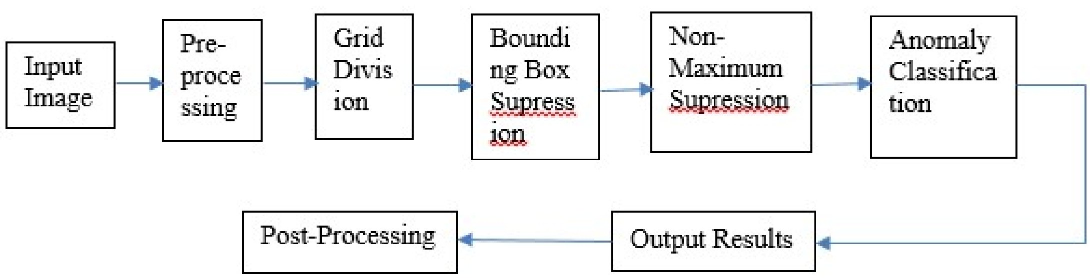

Figure 3. YOLO schematic workflow

IV. LITERATURE SURVEY

Shahrivar et al. (2024) examined developments in machine learning for the identification of prenatal abnormalities in ultrasound pictures. They emphasized how abnormalities in prenatal pictures make it difficult to accurately identify anomalies. To increase diagnosis accuracy, the study investigated a number of machine learning (ML)-based strategies, such as segmentation, classification, and object recognition methods. The authors highlighted how deep learning models can improve the effectiveness of anomaly detection. They also talked about the necessity for more study to close the gap between clinical application and AI developments. The paper emphasized how medical personnel might benefit from machine learning approaches by lowering diagnostic errors. They also looked at the present shortcomings of ultrasound-based AI models, emphasizing the significance of interpretable models and high-quality data. The study shed light on how cutting-edge computational techniques can enhance prenatal care [11].

A deep learning algorithm called IVY was created by Tran et al. (2019) to forecast the likelihood of fetal heart pregnancy using time-lapse movies without the need for physical morphological assessment. With an AUC of 0.93 in cross-validation, their retrospective analysis of 10,638 embryos from several IVF facilities showed the predictive power of the model. The results imply that by lowering inter-reader variability, deep learning can enhance embryo selection. The study does point out certain drawbacks, though, such as its retrospective design and the requirement for additional clinical validation. The findings suggest that AI-driven embryo evaluation may improve the quality of pregnancies [12].

Abhinay Kumar Singh, Poshitha Dinesh, Lohith Datta M, Devanshi Pokalkar, Aayan Khan, and Apoorva Reddy Bagepalli provide a machine learning-based method for early prenatal abnormality diagnosis using ultrasound pictures. Their research focuses on the first trimester and uses cutting-edge methods to increase classification accuracy, such as Ada Boosting and Gradient Boosting. Early detection of congenital abnormalities is intended to aid in prenatal diagnosis. In addition to discussing healthcare disparities despite technological developments, the research emphasizes the significance of cardiotocography in prenatal health assessment [13].
A deep learning-based method for identifying fetal anomalies from ultrasound pictures is presented by D. Selvathi and R. Chandralekha. Manually identifying fetal features is difficult and time-consuming in traditional 2D ultrasound examinations, which need for specialized skills. The suggested technique automatically detects the region of interest (ROI) in fetal ultrasound pictures using deep convolutional neural networks (CNN), such as AlexNet and GoogleNet. The approach increases classification accuracy by adding local phase information to input data. The study shows the efficacy of automated deep learning techniques for prenatal diagnosis by achieving classification accuracies of 90.43%, 88.70%, and 81.25% utilizing CNN, GoogleNet, and AlexNet, respectively [14].
A prospective investigation on the efficiency of prenatal sonography in identifying fetal abnormalities was carried out by N. Anderson, O. Boswell, and G. Duff. They compared the defects found with postnatal outcomes and previous published studies after analysing 7880 foetuses at 16–20 weeks gestation. Of the 157 malformations identified in the study, 93 (60%) were discovered during pregnancy, and in 50% of these cases, the pregnancy was terminated. The detection success rates were 92% for CNS deviations, 31% for cardiac anomalies, and 25% for facial anomalies, depending on the kind of aberration. With prenatal detection rates ranging from 16.6% to 74.4%, the study showed variation in anomaly detection rates among earlier studies, highlighting the necessity of uniform screening methods [15].
Md Rafiul Hassan, Sadiq Al-Insaif, M. Imtiaz Hossain, and Joarder Kamruzzaman present a machine learning-based approach to predict pregnancy outcomes following IVF treatment. The study used a hill-climbing feature selection approach in conjunction with machine learning techniques to enhance prediction accuracy, considering the intricacy of IVF success determinants. Five models—MLP, SVM, C4.5, CART, and RF—were evaluated for performance using data from 55 attributes [16].
In the absence of ultrasonography, Yu Lu, Xianghua Fu, Fangxiong Chen, and Kelvin K. L. Wong suggest a machine learning-based method for estimating fetal weight at different gestational ages. Inaccurate weight estimation can have a detrimental effect on prenatal outcomes because of operator dependence and restrictions in ultrasonography accessibility. The study models fetal growth patterns using a cubic spline function on a dataset of 4212 intrapartum recordings. A new intersection-over-union (IoU) measure is used to train and assess an ensemble learning model that combines Random Forest, XGBoost, and LightGBM. Given the great accuracy of the results, machine learning may be a viable substitute for fetal weight estimation in environments with limited resources [17].
J. Jayashree, Harsha T., Anil Kumar C., and J. Vijayashree propose an optimal feature selection technique for fetal risk prediction using machine learning algorithms. The study focuses on cardiotocography (CTG), which measures the health of the fetus by recording uterine contractions and the fetal heart rate (FHR). Notwithstanding its benefits, CTG data is still complicated and challenging to understand, therefore better feature selection techniques are required. In order to improve classification accuracy in fetal risk prediction using Python, the research presents the Minimum Redundancy Maximum Relevance (MRMR) feature selection approach. This method seeks to help physicians detect fetal distress and enhance prenatal care outcomes by enhancing the analysis of CTG data [18].
In order to classify fetal health using CTG data, this study investigates a number of machine learning algorithms, including support vector machines, random forests, multi-layer perceptrons, and k-nearest neighbors. Random forests are shown to be the most successful method after evaluating these models' performance in terms of accuracy, precision, recall, and F1-score. The contribution of feature engineering to better classification results is also covered in the paper [19].
To evaluate the sensitivity and specificity of first-trimester ultrasonography in identifying fetal abnormalities, J. N. Karimi, N. W. Roberts, L. J. Salomon, and A. T. Papageorghiou carried out a systematic review and meta-analysis. The study evaluated variables such gestational age, ultrasonography modality, and healthcare settings by analyzing data from 225 pertinent publications. According to the results, detection rates varied, ranging from over 60% in high-risk groups to 32% in low-risk ones. With higher rates in high-risk pregnancies, the pooled detection rate was 46.10%. The results emphasize how crucial standardized anatomical procedures are to raising the accuracy of first-trimester screening [1].

A common ultrasound test provided during prenatal treatment to evaluate fetal development and identify particular congenital problems is the 20-week anomaly scan, which is performed between 18 and 21 weeks of gestation. In order to detect anomalies including cleft lip, spina bifida, and congenital heart defects, this comprehensive scan examines the baby's anatomy, including the brain, heart, spine, face, kidneys, and limbs. To guarantee the best possible fetal support, the scan also looks at the placenta's position. It is crucial to remember that not all conditions can be identified during pregnancy, even though the treatment is usually safe and gives peace of mind regarding the health of the unborn child. When abnormalities are discovered early on, prompt medical measures and well-informed choices for expectant parents are made possible [2].

The developments in fetal brain magnetic resonance imaging (MRI) methods were evaluated by L. Mf. Tee et al. 44 pertinent publications were found by the study's analysis of MEDLINE articles published after 2010. Findings imply that ultra-quick sequences and single-shot fast spin-echo T2-weighted imaging increase anatomical delineation, whereas newer approaches boost contrast resolution. MRI offers superior structural features that are helpful in identifying twin problems, callosal abnormalities, and ventriculomegaly, although lacking sonography's real-time capabilities. According to the analysis, MRI is a safe prenatal diagnostic procedure that has no known negative effects on the fetus [3].

Halima Hamid N. Alrashedy et al. proposed BrainGAN, a framework that combines GAN architectures and CNN models for brain MRI image generation and classification. The work uses GANs like DCGAN and Vanilla GAN to enhance training datasets in order to offset the shortage of medical imaging data because of privacy concerns. CNN, MobileNetV2, and ResNet152V2 were used to classify the generated images; ResNet152V2 performed the best (99.09% accuracy, 99.12% precision, 99.08% recall, and 99.51% AUC). This study demonstrates how well GAN-based data augmentation works for deep learning in medical imaging [6].

Justin Lo et al. introduced a deep learning-based architecture, FOAC-Net, for identifying fetal organ anomalies in MRI. The model automatically distinguishes between normal and abnormal embryonic brain, spinal cord, and heart anatomy using squeeze-and-excitation (SE) and naïve inception (NI) modules. By using 3D SSFP MRI sequences from 36 people, the model was able to classify spinal cord defects with up to 89.29% accuracy. FOAC-Net showed better F1 and accuracy scores than alternative topologies. This study demonstrates how DL models can help with observer-independent prenatal diagnosis [7].

Mary Stella et al. presented a method for early detection of fetal brain abnormalities using the YOLO V5 model, a state-of-the-art object detection algorithm. In order to improve therapy and results, the study highlights how crucial early anomaly diagnosis is in prenatal healthcare. The method improves the precision and dependability of fetal brain imaging analysis by combining deep learning with computer vision. With the goal of promoting improved decision-making and patient care in the detection of fetal abnormalities, the suggested model assists doctors in making prompt diagnoses [8].

V. Comparative Analysis

TABLE I

Author	Methodology	Analysis/Accuracy	Limitations
Ramin Yousefpour Shahrivar, Faremah Karami, Ebrahim Karami	Review of machine learning (ML) techniques applied to fetal ultrasonography for anomaly detection.	The study reviews classification, object recognition, and segmentation methods for prenatal diagnosis using ultrasound imaging.	Accuracy of detection in ultrasound remains challenging due to variability and complexity in prenatal image patterns.
D. Tran, S. Cooke, P.J. Illingworth, D.K. Gardner	Developed a deep learning model named IVY capable of predicting fetal heart (FH) pregnancy without requiring manual annotations, using time-lapse imagery of embryos for training.	With an AUC of 0.93–0.94 in 5-fold cross-validation and constant accuracy across labs, the model demonstrated high predictive ability. By automating embryo selection, the method may improve IVF results.	The study is retrospective and does not confirm embryo implantation viability. Variability in lab processes may affect model generalization. Further prospective trials are needed for clinical application validation.
N. Anderson, O. Boswell, G. Duff	A two-year prospective research that used prenatal sonography at 16–20 weeks to analyse 7880 pregnancies. Compared the results and published data with the abnormalities that were found.	144 infants had 157 abnormalities; the detection rate was 11.8 out of 1000 screened. The type of abnormality affected the detection success. Although thresholds varied, detection rates were comparable to previous investigations. The RADIUS experiment revealed fewer negative consequences.	Methodology, anomaly type, and threshold all affected the detection rates per 1000. Pregnancy outcome per 1000 and detection rate did not correlate. Restricted by retrospective comparison and regional scope.

Md Raflul Hassan, Sadiq Al-Insafi, M. Imtiaz Hossain, Joarder Kamruzzaman	used five machine learning models (MLP, SVM, C4.5, CART, and RF) and a hill-climbing feature selection algorithm to forecast the results of an IVF pregnancy based on 25 contributing factors.	Metrics such as accuracy, recall, precision, F-measure, and AUC are used to evaluate performance. Model performance was enhanced through feature selection. Compared to other models, MLP and RF demonstrated superior predictive power for IVF results.	The caliber and diversity of input features are critical to the model. Little information about the quantity and variability of the dataset. Uncertainty surrounds generalization to larger populations or clinics.
Yu Lu, Xianghua Fu, Fangxiong Chen, Kelvin K.L. Wong	Created a multi-parameter genetic algorithm-optimized ensemble learning model with Random Forest, XGBoost, and LightGBM. utilized 4212 intrapartum recordings as a dataset.	Without ultrasound, the model accurately estimates the weight of the fetus at different gestational ages. Used ensemble learning to achieve excellent outcomes, which were assessed using actual test data. Established a performance metric called intersection-over-union (IoU), which shown a high correlation.	In situations where visual evaluation is necessary, the generalizability may be impacted by the lack of ultrasound data. Prediction accuracy may be impacted by data quality and population variability.
J. Jayashree, Harsha T, Anil Kumar C, J. Vijayashree	The study use of cardiotocography (CTG) data, which comprises uterine contractions (UC) and fetal heart rate (FHR). The minimum Redundancy Maximum Relevance (MRMR) technique is used to optimize feature selection. Python is used for implementation.	The study emphasizes how crucial feature selection is to raising classification accuracy for predicting prenatal danger. In order to assess the health of both the mother and the fetus, it finds patterns in the CTG data. For analysis, four categorization models are used.	In clinical practice, the predictive ability of cardiotocography-based methods is still debatable and unreliable. For real-world applications, the techniques require additional verification and improvement.
Abolfazl Mehbodniya et al.	Used feature engineering approaches and machine learning algorithms (SVM, RF, MLP, and k-NN) to categorize fetal health conditions from CTG data.	Determined that random forests were the best model using criteria such as F1-score, recall, accuracy, and precision.	Restricted generalizability as a result of reliance on certain training datasets and a lack of real-world testing.
J. N. Karim, N. W. Roberts, L. J. Salomon, A. T. Papageorghiou	To evaluate the diagnostic precision of 2D transabdominal and transvaginal ultrasonography for identifying congenital fetal abnormalities prior to 14 weeks of gestation, a systematic review and meta-analysis of publications were conducted. Examined the effects of population characteristics, gestational age, and healthcare environment on detection rates.	Assessed the first-trimester ultrasound's sensitivity and specificity in identifying fetal abnormalities. To lessen the effect of study heterogeneity, data within subgroups were analyzed, with an emphasis on low-risk versus high-risk populations and major anomalies versus all anomaly categories.	The study recognizes that meta-analyses may have intrinsic limitations, including publication bias and heterogeneity among included studies, which may affect the findings' reliability and generalizability.
Prof. Mary Stella, Mohammad Yusuf, Mohammed Faizan Ali, Mohammed Thanzeem, Mohammed Sadath	Utilized the YOLO V5 model, a deep learning-based object detection system, to identify anomalies in the embryonic brain in pictures.	Although improving detection efficiency and reliability is mentioned in the abstract, no precise accuracy measurements or in-depth analysis are given.	It is possible to deduce general limits, such as reliance on data quality and difficulties common in medical imaging anomaly detection.

VI. CONCLUSION

By improving the early detection of fetal brain disorders, the combination of Artificial Intelligence (AI), namely Machine Learning (ML) and Deep Learning (DL) approaches, is transforming prenatal healthcare. Even with advances in ultrasound imaging technology, it is still difficult and time-consuming for medical experts to accurately identify fetal abnormalities.

The accuracy and efficiency of diagnosis have significantly increased with the use of AI-based techniques, particularly the usage of Convolutional Neural Networks (CNNs) and YOLO models. While YOLO offers real-

time object detection, which is essential for prompt clinical judgments, CNNs have proven to be exceptionally skilled at interpreting medical images.
By identifying the most important features, Recursive Feature Elimination (RFE) enhances model interpretability and further optimizes model performance.
By using these technologies, prenatal screenings are more reliable overall, take less time to do, and lighten the workload for clinicians.
To significantly improve results, however, sizable, high-quality datasets and algorithmic improvement are still essential. AI-based prenatal diagnostics research and development has enormous potential to improve maternal and fetal healthcare, improve clinical procedures, and increase patient safety.

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