Volume 10, Issue 05, May 2025 ISSN (online): 2456-0006
International Journal of Science Technology Management and Research
Available online at: www.ijstmr.com

Enhancements in Prenatal Anomaly Identification via Ultrasonography: An Exploration of Machine Learning Approaches

Mr. Sagar U. More
Research Scholar, Dept. of Computer Science and Engineering, SAGE University, Indore, Asst. Professor at RCPIT, Shirpur
E-mail: moresagar.sum@gmail.com

Dr. Ritu Tondon
Associate Professor
Dept. of Computer Science and Engineering
SAGE University, Indore
E-mail: ritu.tondon@sageuniversity.in

Dr. R. B. Wagh
Associate Professor
Dept. of Computer Engineering
RCPIT, Shirpur

Abstract: ***This review examines the importance of detecting anomalies in prenatal ultrasound images for the health of the fetus and mother. Despite advancements in ultrasound technology, accurately identifying irregularities remains challenging and time-consuming for medical professionals. The review discusses recent advances in machine learning (ML) techniques applied to prenatal ultrasound pictures, incorporating picture categorization, object identification, and segmentation. The potential for these revolutionary technologies to improve prenatal abnormality identification is emphasized, along with the need for further research in this area to improve clinical applications and outcomes.***

Keywords: Machine Learning, Fetal Anomaly, Deep Learning, CNN, YOLO technique

I. INTRODUCTION

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. Fetal anomalies are defects in the structure of the developing fetus that manifest in various important anatomical areas, including the heart, lungs, kidneys, and central nervous system (CNS). Multifactorial illnesses, which are caused by a combination of environmental as well as genetic variables, can produce several malformations, which can manifest at different stages of pregnancy. Examples of prenatal diagnostic and screening methods that can assist in identifying these anomalies at an earlier gestational age include genetic testing and ultrasound. A kid's health can be affected by fetal anomalies in a variety of ways, from problems that are easily treated to conditions that cause the child to pass away during pregnancy or soon after birth. The frequency of prenatal abnormalities varies among various groups; roughly 3% of pregnancies result in the detection of fetal structural defects [1]. The most popular and reliable a secure method of checking for prenatal abnormalities when pregnant is ultrasound, however it is error-prone and strongly dependent on sonographer skill. Furthermore, poor quality and indistinct borders in ultrasound images can result in incorrect diagnoses. There have been notable advancements during the past few years in the application of machine learning algorithms in ultrasonography to diagnose prenatal abnormalities. In reviewing these developments, this paper emphasizes real-time picture plane detection, automated fetal parameter measurement, deep learning, and neural networks.

ENSEMBLE OF MULTIPLE NEURAL NETWORKS

An ensemble of several neural networks has been applied to improve the analytical performance for complex tasks such as assessment of fetal echocardiography. This method addresses machine-learning purposes by combining the predictions of several neural networks. A group of several neural networks working together usually performs better than anyone network acting independently.

II. APPLICATION OF DEEP LEARNING AND MACHINE LEARNING

The accuracy of fetal abnormality diagnosis in ultrasound pictures has been enhanced by utilizing machine learning and deep learning approaches. This involves training models that can recognize particular screening views in prenatal ultrasounds using convolutional neural networks (CNNs) [2].

A. Convolutional Neural Networks (CNNs)

CNNs are the most popular deep learning model at the moment and have demonstrated the most potential for medical image analysis. CNN is being increasingly widely used for illness classification, organ segmentation, and anomaly detection. A CNN is composed of pooling and convolution layers. In order to extract visual features, convolution combines small kernels to the available pixels to produce feature maps [3]. CNNs excel at jobs like distinguishing edges and forms because of their quickness in capturing visual patterns. A CNN is composed of pooling and convolution layers. Through the use of tiny kernels on input pixels, convolution extracts information from images and generates feature maps.

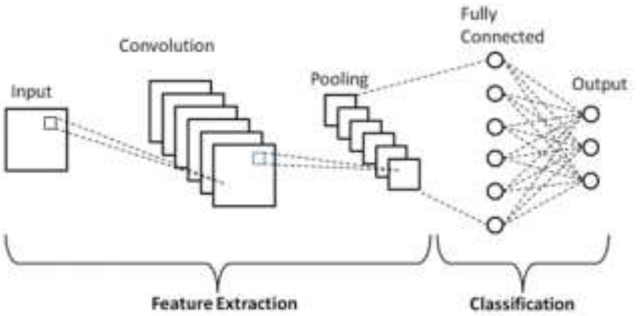

Figure-1**:** Architecture of CNN

B. Generative Adversarial Networks (GANs)

GANs have demonstrated potential in the synthesis, augmentation, and interpretation of medical images. Similar to CNN, GAN also produces medical images for anomaly identification and illness simulation [4, 5]. This new neural network design simultaneously trains two networks, one for picture creation and the other for distinguish between actual and fraudulent images. A noteworthy advantage of GANs is their ability to facilitate efficient anomaly detection, even when there is no training data for anomalous instances, such fetal echocardiograms, is scarce [6]. GANs gather real-time data by continuously learning in order to enhance performance analysis. Because the image varies with each week of gestation, this feature is especially helpful for fetal heart imaging.

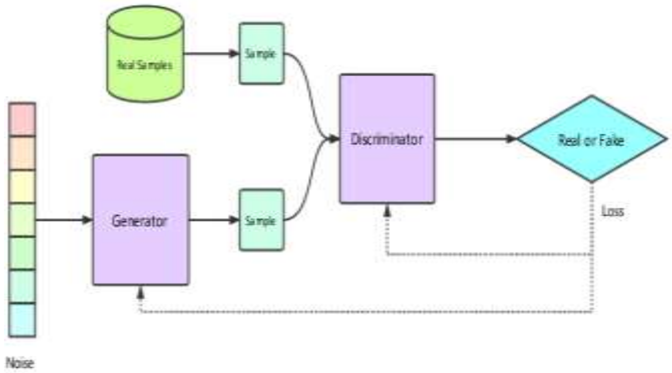

Figure-2: Architecture of GAN

C. Recurrent Neural Networks (RNNs)

When working with sequential data, like when examining time series or three-dimensional medical pictures, neural networks known as RNNs are utilized. Time series dependencies are recorded in RNNs and utilized for tasks such as long-term sickness modeling, video medical diagnostics, and heart motion analysis. Medical image processing tasks benefit from the use of LSTM, a class of RNN [7].

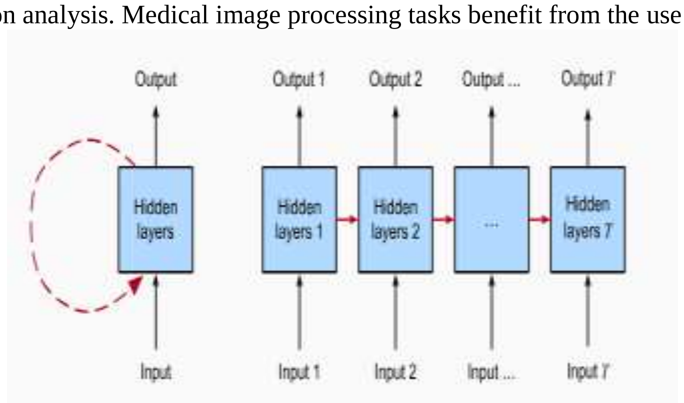

Figure: Recurrent Neural Network with Cyclic manner

III. DISCOVERY OF FOETAL DEVIATIONS

A. Birth Disorders of the Heart

Congenital heart disorders (CHDs) are prevalent and serious birth abnormalities that affect developing foetuses that impact 1 in 100 instances [13]. Since this disorder is the most prevalent, there is increased interest in its investigation. It is challenging to evaluate a fetus's heart activity due to factors such a fast heartbeat, erratic fetal movement, and restricted access during ultrasonography. It is commonly employed throughout pregnancy, and the acquired images can be utilized to train deep learning models, such CNN, to enhance and automate anomaly identification. While generative modeling and anomaly detection have demonstrated the usefulness of GANs, by training an ensemble of many neural networks and pooling their predictions, their analytical performance can be enhanced for more complicated tasks, such fetal echocardiography assessment. Recent advancements in the field of fetal congenital heart disease (FHD) screening have shown promising results. Gong introduced the DGACNN, a revolutionary model that surpassed earlier state-of-the-art networks with an FHD identification rate of 85%, in 2020. By utilizing the attention mechanism and Faster R-CNN, Zhang (2023) further refined this model and created an algorithm with improved classification accuracy [15]. Magesh (2023) achieved remarkable accuracy rates of 98.4% and 97.2%, respectively, in classifying fetal hearts into normal and diseased categories using a deep learning-based neural network. Collectively, these research demonstrates how cutting-edge technologies could increase the precision and effectiveness of FHD screening [16]. Research by Arnaout et al. (2020, 2021) and Magesh (2023) demonstrates the potential application of deep learning models to improve the detection of complex congenital heart disease (CHD) in fetuses [17].

B. Anomaly in Respiratory System

The growth and operation of the lungs are vital to the health and survival of fetuses. Anomalies in the structure of the lungs can be fatal or seriously dangerous for infants. The respiratory problems that newborns have are strongly correlated with undeveloped fetal lungs [8]. Given the significance of these conditions, further research is required to examine ML and DL's potential in the field of medical picture analysis. The ability of ultrasound-based radiomics technology to forecast infant respiratory morbidity has been shown in a number of investigations. Bonet-Carne (2014) and Palacio (2017) developed and evaluated methods for this purpose; the latter reported an accuracy of 86.5% with good sensitivity and specificity [20]. Jiao (2021) demonstrated a novel method for radiomics that produced excellent results in terms of sensitivity, specificity, and accuracy. It was founded on skewed few-shot images from prenatal lung scans. The great potential of ultrasound-based radiomics technology for forecasting respiratory morbidity in neonates is demonstrated by all of these studies [21]. In the training cohort (0.99) and validation cohort (0.90), the random forest model yielded the highest score. Promising outcomes have been shown when fetal lung texture is investigated in pregnancies impacted by gestational diabetes and/or pre-eclampsia using ultrasound-based radiomics technology. Ultrasound signs of placental tissue, fetal lungs, and liver tissue are related to gestational age; these findings were analyzed and compared using ultrasound-based radiomics technology in pregnancies complicated by pre-eclampsia and/or gestational diabetes mellitus, as well as in otherwise healthy pregnancies at various gestational ages [22].

C. Head Anomalies

The first 18 to 21 weeks of pregnancy are when the fetal brain develops. If a fetus has anomalies in its head, several repercussions could result. Learning capacities and language interpretation abilities, among other things, may be affected. Measurements of the cerebrum, midbrain, and brainstem are necessary to detect abnormalities in certain areas of the brain [9]. Sreelakshmy et al. created a model (ReU-Net) based on U-Net and ResNet for the segmentation of fetuses' cerebellum utilizing 740 fetal brain US images in order to identify fetal brain abnormalities. [10]. Xie et al. (2020) and Shivaprasad et al. (2023) are looking into using deep learning methods to identify abnormalities in fetus ultrasound pictures. Xie's work focuses on the feasibility of this method, whereas Shivaprasad's study achieves a high classification accuracy of 90% by combining pre-trained CNN models [18, 19].

D. Genetic Chromosomal Disorders

Chromosome abnormalities are a frequent genetic disorder that causes birth malformations differences in a person's cells' chromosomal quantity or composition generate these disorders, which lead to severe health issues and disabilities that are visible from birth. As previously said, there are several approaches to identify anomalies, some of which are included below.

- Measuring the thickness of the gap filled with fluid at the fetus's neck back
- Fetal echocardiography is a diagnostic tool used to identify cardiac abnormalities by assessing the structure and function of the developing heart.
- Absence of Nasal bone also marks the down syndrome in chromosome.
- Certain hereditary diseases can be detected by facial traits [11].

Finding Nuchal Transparency is a difficult task that can be detected throughout the 11–13 week scanning period. Medical professionals can detect anomalies on specific sites like the palate, nasal bone, and tip of the nose. Chromosome abnormalities can also be detected early with NT image segmentation using sing ML. Zhang et al. used US pictures from 822 fetuses to build a CNN-based model to detect trisomy 21. In addition to being limited to the NT thickness, their model was able to identify trisomy 21 in the validation set with an accuracy of 89% using pictures from the fetal head area [12]. Verma et al. (2022) and Jamshidnezhad et al. (2022) have proposed unique techniques that yield high accuracy rates of 98.642% and 97.58%, respectively, for the classification of fetal anomalies. While Verma et al. employ an Adaptive Stochastic Gradient Descent Algorithm, Jamshidnezhad et al. employ an integrated genetic-neural network [23]. Moreover, Hoodbhoy (2019) investigates the application of XGBoost, a machine learning method, to precisely detect high-risk pregnancies by estimating fetal risk using cardiotocographic data. Collectively, these studies demonstrate how machine learning may be applied to boost the accuracy and efficacy of risk assessment and fetal anomaly classification [24].

E. Automated Fetal Parameter Measurement

Fetal parameter measurement has shown considerable increase in accuracy and reproducibility due to the development of automated techniques. These automated methods overcome the difficulties presented by manual measurements by streamlining workflow and assisting in the accurate measurement of fetal parameters.

F. Clinical Workflow and Future Opportunities

Developments in machine learning could enhance medical ultrasonography illness detection and characterization as well as clinical workflow. Medical ultrasound image analysis is anticipated to be significantly impacted by these developments, especially when it comes to deep learning.

CONCLUSION

The field has advanced significantly with the development of ultrasonography-assisted fetal abnormality detection, which offers the possibility of more precise, effective, and timely diagnosis of anomalies in fetal pictures. In this article, we studied some of the newest techniques for spotting chromosomal abnormalities, lung disease, heart problems, head and neck deformities, and other fetal defects. ML-based models for biometric assessment and identification of the most efficient standard planes were also investigated, in addition to anomaly detection. Although recent advances are encouraging, it's critical to comprehend the barriers inhibiting the development of models in this sector that can be used therapeutically. It is expected that this sector will improve more as machine learning techniques continue to advance.

REFERENCES

1. D. Selvathi and R. Chandralekha, "Fetal biometric based abnormality detection during prenatal development using deep learning techniques," *Multidimensional Systems and Signal Processing*, Mar. 23, 2021. https://dl.acm.org/doi/abs/10.1007/s11045-021-00765-0
2. J. Jayashree, H. T, A. K. C, and J. Vijayashree, "Enhanced Optimal Feature Selection Techniques for Fetal Risk Prediction using Machine Learning Algorithms," *International Journal of Engineering and Advanced Technology*, vol. 9, no. 3, pp. 4364–4370, Feb. 2020, doi: 10.35940/ijeat.c6502.029320.
3. Sarvamangala, D.R.; Kulkarni, R.V. Convolutional neural networks in medical image understanding: A survey. Evol. Intell. 2022, 15, 1–22.
4. Yi, X.; Walia, E.; Babyn, P. Generative adversarial network in medical imaging: A review. Med. Image Anal. 2019, 58, 101552.
5. Skandarani, Y.; Lalande, A.; Afilalo, J.; Jodoin, P.-M. Generative Adversarial Networks in Cardiology. Can. J. Cardiol. 2022, 38, 196–203.
6. Alrashedy, H.H.N.; Almansour, A.F.; Ibrahim, D.M.; Hammoudeh, M.A.A. BrainGAN: Brain MRI Image Generation and Classification Framework Using GAN Architectures and CNN Models. Sensors 2022, 22, 4297.
7. Rajeev, R.; Samath, J.A.; Karthikeyan, N.K. An Intelligent Recurrent Neural Network with Long Short-Term Memory (LSTM) BASED Batch Normalization for Medical Image Denoising. J. Med. Syst. 2019, 43, 234.
8. Ahmed, B.; Konje, J.C. Fetal lung maturity assessment: A historic perspective and Non-invasive assessment using an automatic quantitative ultrasound analysis (a potentially useful clinical tool). Eur. J. Obstet. Gynecol. Reprod. Biol. 2021, 258, 343–347.
9. Hu, Y.; Sun, L.; Feng, L.; Wang, J.; Zhu, Y.; Wu, Q. The role of routine first-trimester ultrasound screening for central nervous system abnormalities: A longitudinal single-center study using an unselected cohort with 3-year experience. BMC Pregnancy Childbirth 2023, 23, 312.
10. Sreelakshmy, R.; Titus, A.; Sasirekha, N.; Logashanmugam, E.; Begam, R.B.; Ramkumar, G.; Raju, R. An Automated Deep Learning Model for the Cerebellum Segmentation from Fetal Brain Images. BioMed Res. Int. 2022, 2022, 8342767.
11. Lord, J.; McMullan, D.J.; Eberhardt, R.Y.; Rinck, G.; Hamilton, S.J.; Quinlan-Jones, E.; Prigmore, E.; Keelagher, R.; Best, S.K.; Carey, G.K.; et al. Prenatal exome sequencing analysis in fetal structural anomalies detected by ultrasonography (PAGE): A cohort study. Lancet 2019, 393, 747–757.
12. Zhang, L.; Dong, D.; Sun, Y.; Hu, C.; Sun, C.; Wu, Q.; Tian, J. Development and Validation of a Deep Learning Model to Screen for Trisomy 21 during the First Trimester from Nuchal Ultrasonographic Images. JAMA Netw. Open 2022, 5, e2217854.
13. Shi, B.; Han, Z.; Zhang, W.B.; Li, W. The clinical value of color ultrasound screening for fetal cardiovascular abnormalities during the second trimester: A systematic review and meta-analysis. Medicine 2023, 102, e34211.
14. Xiao, S.; Zhang, J.; Zhu, Y.; Zhang, Z.; Cao, H.; Xie, M.; Zhang, L. Application and Progress of Artificial Intelligence in Fetal Ultrasound. J. Clin. Med. 2023, 12, 3298.
15. Gong, Y.; Zhang, Y.; Zhu, H.; Lv, J.; Cheng, Q.; Zhang, H.; He, Y.; Wang, S. Fetal Congenital Heart Disease Echocardiogram Screening Based on DGACNN: Adversarial One-Class Classification Combined with Video Transfer Learning. IEEE Trans. Med. Imaging 2020, 39, 1206–1222.
16. S. Magesh and P. S. R. Kumar, "Fetal Heart Disease Detection Via Deep Reg Network Based on Ultrasound Images," *Journal of Applied Engineering and Technological Science (JAETS)*, vol. 5, no. 1, pp. 439–450, Dec. 2023, doi: 10.37385/jaets.v5i1.3226.

17. Arnaout, R.; Curran, L.; Zhao, Y.; Levine, J.C.; Chinn, E.; Moon-Grady, A.J. An ensemble of neural networks provides expert-level prenatal detection of complex congenital heart disease. Nat. Med. 2021, 27, 882–891.

18. H. N. Xie *et al.*, "Using deep- learning algorithms to classify fetal brain ultrasound images as normal or abnormal," *Ultrasound in Obstetrics & Gynecology*, vol. 56, no. 4, pp. 579–587, Oct. 2020, doi: 10.1002/uog.21967.

19. S. Shivaprasad, S. Shanbhog, and J. Medikonda, "Detecting Fetal Brain Abnormalities Using Deep Learning Technique," *2023 International Conference on Recent Advances in Information Technology for Sustainable Development (ICRAIS)*, Nov. 2023, Published, doi: 10.1109/icrais59684.2023.10367109.

20. E. Bonet- Carne *et al.*, "Quantitative ultrasound texture analysis of fetal lungs to predict neonatal respiratory morbidity," *Ultrasound in Obstetrics & Gynecology*, vol. 45, no. 4, pp. 427–433, Apr. 2015, doi: 10.1002/uog.13441.

21. J. Jiao, Y. Du, X. Li, Y. Guo, Y. Ren, and Y. Wang, "Prenatal Prediction of Neonatal Respiratory Morbidity: A Radiomics Method Based on Imbalanced Few-Shot Fetal Lung Ultrasound Images," Jun. 2021, Published, doi: 10.21203/rs.3.rs-654307/v1.

22. Y. Du *et al.*, "Application of ultrasound- based radiomics technology in fetal- lung- texture analysis in pregnancies complicated by gestational diabetes and/or pre- eclampsia," *Ultrasound in Obstetrics & Gynecology*, vol. 57, no. 5, pp. 804–812, May 2021, doi: 10.1002/uog.22037.

23. Verma, D.; Agrawal, S.; Iwendi, C.; Sharma, B.; Bhatia, S.; Basheer, S. A Novel Framework for Abnormal Risk Classification over Fetal Nuchal Translucency Using Adaptive Stochastic Gradient Descent Algorithm.

24. B. Hasan, Z. Hoodbhoy, M. Noman, A. Shafique, A. Nasim, and D. Chowdhury, "Use of machine learning algorithms for prediction of fetal risk using cardiotocographic data," *International Journal of Applied and Basic Medical Research*, vol. 9, no. 4, p. 226, 2019, doi: 10.4103/ijabmr.ijabmr_370_18.

25. N. P. S. Rathore and L. Prasad, "Hybrid Deep Learning Model to Detect Uncertain Diseases in Wheat Leaves," Journal of Uncertain Systems, vol. 15, no. 03, Aug. 2022, doi: 10.1142/s1752890922410045.

