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Original Article

AI-Enabled Early Detection of Fetal Gestational Age and CNS Anomalies in the First Trimester through Ultrasound to Support Rural Doctors in India

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Abstract - *Identification of Central Nervous System (CNS) abnormalities in fetuses is serious for timely medical intervention and improved perinatal outcomes. India stands as the most populous country in the world today, with a population of more than 1.484 billion. Of this 68.8% population is living in rural India, where the healthcare infrastructure facilities are sparse. Access to specialized fetal medicine experts and advanced diagnostic tools remains a significant challenge in rural India. According to a report published through NGO Transform Rural India besides Development Intelligence Unit, the doctor-patient proportion in India is approximately 1:1456, which remains under the World Health Organization (WHO) recommended ratio of 1:1000. Thus, the report also revealed a lack of diagnostic facilities in the form of a shortage of trained personnel. The report indicated that only 39% of survey respondents had access to a diagnostic facility within commutable distance. Ultrasonography in the first trimester of pregnancy aims to confirm viability, gestational age, position, and implantation of the gestational sac, as well as fetal anatomy, amongst other factors. Structural brain abnormalities are comparatively common and can be spotted in the first trimester. The study explores the potential of Artificial Intelligence in enhancing the initial Identification of central nervous system anomalies during first-trimester sonography, particularly to support rural healthcare providers. Thus, the reading concludes that a Deep Learning model of AI succeeded with an accuracy of 88% training and 87.76% in testing in detecting CNS abnormalities using the Head Circumference parameter in cm of the fetus in the first trimester. Henceforth, the AI-based diagnostic support can help as a transformative tool in linking the healthcare gap aimed at rural populations in India.*

Keywords - *Artificial Intelligence, CNS anomalies, Fetal US sonography, First trimester, Rural healthcare, Early detection.*

1. Introduction

Despite advancements in fetal medicine, the late diagnosis of CNS anomalies remains a critical challenge in low-resource settings. Many cases go undetected until the second or third trimester, when medical options become limited, increasing the risk of complications such as hydrocephalus, severe brain malformations, and pregnancy termination decisions at advanced gestational stages. Therefore, a proactive approach to first-trimester screening is essential for early detection, better management, and improved clinical outcomes.

1.1. Challenges Faced in the Early Detection of CNS

The first-trimester ultrasound (11–14 weeks) is crucial for detecting structural anomalies, including CNS defects. However, several challenges hinder its effectiveness: Limited Access to Specialists: Rural areas lack trained radiologists and fetal medicine specialists who can accurately interpret sonographic findings.

1.2. Role of AI in Addressing These Challenges

Artificial Intelligence (AI) has revolutionized the area of medical imaging, providing enhanced diagnostic accuracy, efficiency, and accessibility. With advancements in Deep Learning (DL) and Machine Learning (ML) [36] algorithms, AI has shown notable proficiencies in investigating difficult medical images, assisting radiologists and clinicians in detecting, classifying, and predicting various pathologies.

1.3. AI-Driven Medical Imaging Primarily Relies on Deep Learning Architectures Like

Convolutional Neural Networks (CNNs): Broadly aimed at examining ultrasound, MRI, and CT scans. Capable of detecting subtle structural anomalies in fetal brain development. Transfer Learning: Pre-trained models adapted for medical imaging datasets reduce the need for extensive labeled data, which is crucial for CNS anomaly detection. Generative Adversarial Networks (GANs): Enhance image resolution and quality, improving early-stage anomaly identification. Useful in generating synthetic fetal ultrasound images for training AI models. Radiomics and Feature Extraction: AI models extract quantitative imaging biomarkers to differentiate between normal and abnormal fetal brain structures. Helps in predictive analysis for developmental abnormalities. [33] This review study introduces the latest developments in AI applications in prenatal ultrasound, exploring the challenges and opportunities brought by AI to prenatal diagnostics.

AI-powered image recognition and deep learning algorithms can: Enhance Diagnostic Accuracy: AI models trained on large datasets can assist in the early Identification of CNS anomalies, reducing human error in interpretation. Provide Real-Time Decision Support: AI-integrated ultrasound machines can assist rural healthcare providers by flagging potential anomalies for further expert review. Increase Accessibility: AI-driven solutions enable portable and cost-effective screening tools, making early detection feasible in remote and underserved areas.

2. Literature Review

2.1. Importance of Early Identification of CNS Anomalies

In order to lower fetal morbidity and enable prompt clinical interventions, it is essential to identify Central Nervous System (CNS) abnormalities early in the first trimester. The effectiveness of early gestational ultrasound scans for this purpose has been validated by numerous studies. As an example, Ungureanu et al. [2] and Bağcı et al. [3] highlighted that the majority of significant fetal abnormalities can be detected by thorough First-Trimester (FT) CNS screening.

According to Mandava et al. [6], first-trimester ultrasonography successfully identifies CNS abnormalities and provides parents with information regarding options for rehabilitation or termination. However, these conventional imaging techniques rely heavily on operator skill and equipment quality, both of which are frequently deficient in underserved and rural areas [12].

2.2. Difficulties in Rural and Clinical Contexts

Standard 2D and 3D ultrasound techniques can achieve detection accuracies of up to 85.7% [8, 9]. However, the lack of real-time decision-support systems, high equipment costs, and a lack of trained personnel limit their widespread adoption in low-resource settings.

The ISUOG guidelines [11] state that certain anatomical views and measurements are necessary for first-trimester CNS evaluations. However, these are not always possible with the equipment or personnel available in rural India. Missed interventions and delays in diagnosis are made worse by the lack of adequate healthcare infrastructure [12].

2.3. Artificial Intelligence in Prenatal Diagnostics

The analysis of fetal ultrasound images has greatly improved with recent developments in Artificial Intelligence (AI), especially Deep Learning (DL). Research by Xiao et al. [5] and Fiorentino et al. [4] showed that AI algorithms, like Convolutional Neural Networks (CNNs), can quickly and accurately automate the detection of fetal abnormalities. In order to aid in early diagnosis, AI also facilitates real-time segmentation and biometric measurement tasks such as Occipitofrontal Diameter (OFD), Biparietal Diameter (BPD), and Head Circumference (HC) [5, 14, 17].

AI models with diagnostic accuracy on par with that of skilled clinicians were proposed by Zhang et al. [8] and Lin et al. [26]. Their research demonstrated CNNs' ability to recognize structural CNS abnormalities from ultrasound pictures. These models are unsuitable for use in rural areas with portable, subpar ultrasound equipment because they were primarily trained on high-resolution datasets and validated in urban or tertiary care settings.

2.4. Existing AI Models' Limitations

- Many current AI applications have significant drawbacks despite their potential:
- Absence of First-Trimester Focus: The majority of research combines data from several trimesters without addressing the particular difficulties associated with early gestational CNS detection [20].
- Problems with Generalization: AI models developed on high-quality datasets frequently do not generalize to real-world, low-resolution scans from rural clinics [23, 35].
- Lack of Biometric-Driven Classification: Gestational age and head circumference measurements are crucial diagnostic inputs for early anomaly prediction, but they are not frequently included in models [10, 17].
- Lack of Rural Field Testing: Models are rarely evaluated in real-world rural clinical settings, which limits their scalability and practical application [18, 21].

2.5. Artificial Intelligence in Low-Resource Settings

The necessity for lightweight, explainable AI models that can run on portable devices with low computational demands has been underlined by a number of scoping reviews [19, 15, 22]. Furthermore, it is frequently emphasized how crucial it is to modify these tools in order to assist non-specialists, such as general practitioners and auxiliary nurse midwives. In order to close the healthcare gap in rural areas, AI-driven solutions that can operate offline or in places with limited bandwidth are especially helpful.

2.6. Gaps Identified from the Literature Review

- Absence of thorough AI assessment in CNS detection during the first trimester.
- No AI validation based on gestational age.

- No AI models that have been field-tested for use in rural areas.
- There is a need for low-resource, easily navigable AI tools for non-specialists.
- Absence of AI models tailored to biometrics for early CNS detection.

In order to fill these gaps, this study builds and tests a CNN-based AI model that uses biometric parameters from low-resolution ultrasound images to identify CNS abnormalities and predict gestational age. The model is specifically designed to be implemented in rural healthcare settings.

3. Objectives

This research paper aims to:

A. Evaluate the potential of AI in detecting CNS anomalies during the first trimester through ultrasound.
B. Provide assistance to rural healthcare providers in the early detection of CNS by using AI models.
C. Develop and evaluate AI models for detecting CNS anomalies of head circumference in early pregnancy.

4. Methodology

4.1. Experimental Setup

An AI-enabled trained model is proposed in this study to detect abnormalities in the Central Nervous System (CNS) early in the first trimester of fetal development. By offering real-time decision support, especially in settings with poor connectivity, the model seeks to help rural healthcare professionals.

4.2. Data Collection and Preparation

4.2.1. Dataset Sources

A variety of publicly accessible sources, such as Zenodo [27], Kaggle [28], and Mendeley [29], were used to gather ultrasound images of the fetal head regions.

4.2.2. Total Dataset

A total of 1,000 ultrasound pictures showing the anatomy of the fetal head during the first trimester were used.

4.2.3. Data Augmentation

The training dataset was expanded using generative AI techniques to create more ultrasound images artificially to improve model generalization and increase dataset size.

4.2.4. Image Features

Every image is concentrated on the area of the fetal head, which is essential for the early Identification of CNS abnormalities.

Images were normalized to scale pixel values between 0 and 1 and resized to a fixed resolution of 256×256 pixels. Data augmentation techniques like rotation, flipping, and brightness adjustment were used to replicate real-world variability.

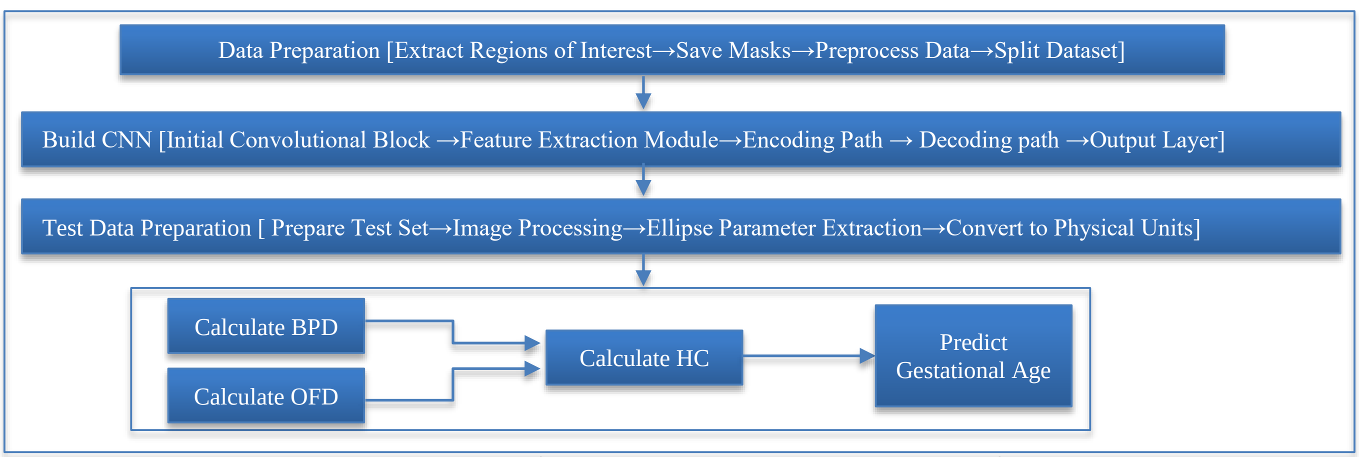

Fig. 1 Representation of prediction gestational age using CNN and ellipse fitting

As it is difficult to get such ultrasounds due to ethical and legal implications, the study uses ultrasound sonography images taken in the first trimester from an already available database.

The research uses the Deep Learning model to ultrasound the available images for estimating CNS anomalies.

The following are the steps for the proposed framework-

- Loading Data Set
- Extraction of regions of interest (presumably marked by contours in the training dataset images) and creation of masks for those regions.
- The masks are then saved to a destination directory.
- Resizing and applying transformations to input images and their corresponding mask images for training a model.
- Splitting the dataset into 0.7 for training and 0.3 for random validation.
- Built a CNN architecture

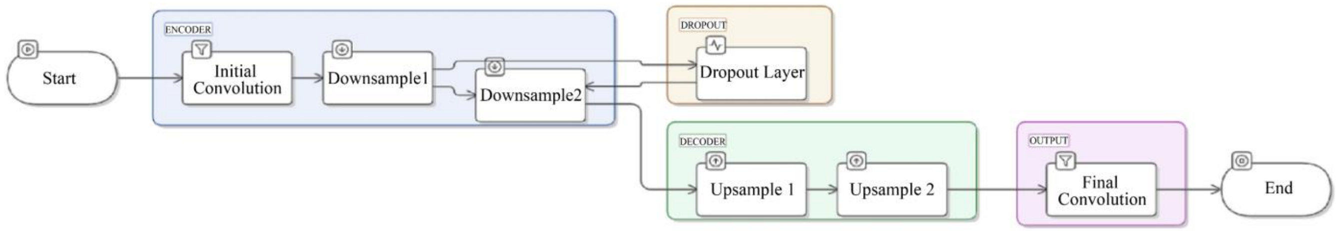

Fig. 2 CNN architecture

The designed CNN architecture consists of the following layers and operations:

A. Initial Convolutional Block
X1=ReLU (BN(Conv(X0,W1) +b1)) (1)

Where X0 is the Input image/feature map, W1, b1 are Weights and bias of the convolutional layer respectively, Conv stands for Convolution operation, and BN stands for Batch Normalization, which includes ReLU activation function, i.e. ReLU(x)=max(0,x)

B. Feature Extraction Module
X2=ReLU(BN(Conv(X1,W2)+b2)) (2)

X3=ReLU(BN(Conv(X2,W3)+b3)) (3)

The two consecutive convolution operations with batch normalization and ReLU activation are performed. Here, W2, W3 and b2,b3 are weights and biases for each convolutional layer.

C. Encoding Path (down)
X4=MaxPool(X3) (4)

X5=ReLU(BN(Conv(X4,W4)+b4)) (5)

MaxPool is a Max-pooling operation performed for down-sampling. It is followed by the double_conv block.

D. Decoding Path
X6=UpSample(X5) (6)

X7=ReLU(BN(Conv(X6, W5)+ b5)) (7)

Upsampling operation is done to restore spatial dimensions. It is also followed by the double_conv block.

E. Final Output Layer
Y=Conv(X7, W6)+b6 (8)

In the Equation (8), Conv is a 1×11 times 1 convolution to reduce the output to the desired number of channels. Y is the final output, suitable for segmentation or classification.

F. Overall Network Operation
Y=outconv(up(down(inconv(X0)))) (9)

This mathematical formulation provides a clear understanding of each layer's contribution to feature extraction, down-sampling, up-sampling, and final output generation in the CNN architecture.

G. Test data is prepared.
H. Applied image thresholding, contour detection, and ellipse fitting on the test dataset.
I. Calculation of Head Circumference
The generalized formula for calculating the head circumference is as follows:
HC=1.62×(BPD+OFD)3 (10)
In the above Equation (10), BPD is 2×b, and OFD is 2×a. Here, a = semi-major axis (mm),b = semi-minor axis (mm). HC=31.62×(BPD+OFD)3/10 (11)
Here, (11) HC is the head circumference in centimetres. This formula provides a robust estimation of head circumference using elliptical measurements, which is particularly useful in medical imaging and fetal growth assessments.
J. A condition to predict the Gestational age of a fetus. (Table1)

Table 1. Prediction of gestational age

Head Circumference (cm)	Gestational Age
< 8.00	Less than 8 Weeks
8.00 - 9.00	13 Weeks
9.01 - 10.49	14 Weeks
10.50 - 12.49	15 Weeks
- 13.49	16. Weeks

5. Results and Discussion

5.1. Image Processing and Measurement of Head Circumference

In order to precisely identify and isolate the fetal head region for the Head Circumference (HC) measurement, the masking technique was applied over ultrasound images. The process comprised:

- Preprocessing to improve the visibility of the image.
- Fetal head segmentation using edge detection methods.
- Creation of a binary mask that highlights the area of the head.
- To determine the Head Circumference, fit an ellipse to the segmented border.

This method enables reliable and repeatable measurement, which is essential for identifying CNS anomalies early in pregnancy.

5.2. Model Training Progress

Key metrics are monitored for both training and validation datasets, and the deep learning model's training progress over four epochs is shown in Table 2 and Figure 2.

Table 2. Representation of training progress and evaluation metrics (for epochs=4)

Epoch	Train Loss	Validation Loss	Train Accuracy (%)	Validation Accuracy (%)
1	0.388498	0.590885	80.78	74.54
2	0.672555	1.147903	84.1	79.01
3	0.90027	1.792497	86.1	79.74
4	1.09194	1.96487	87.54	82.75

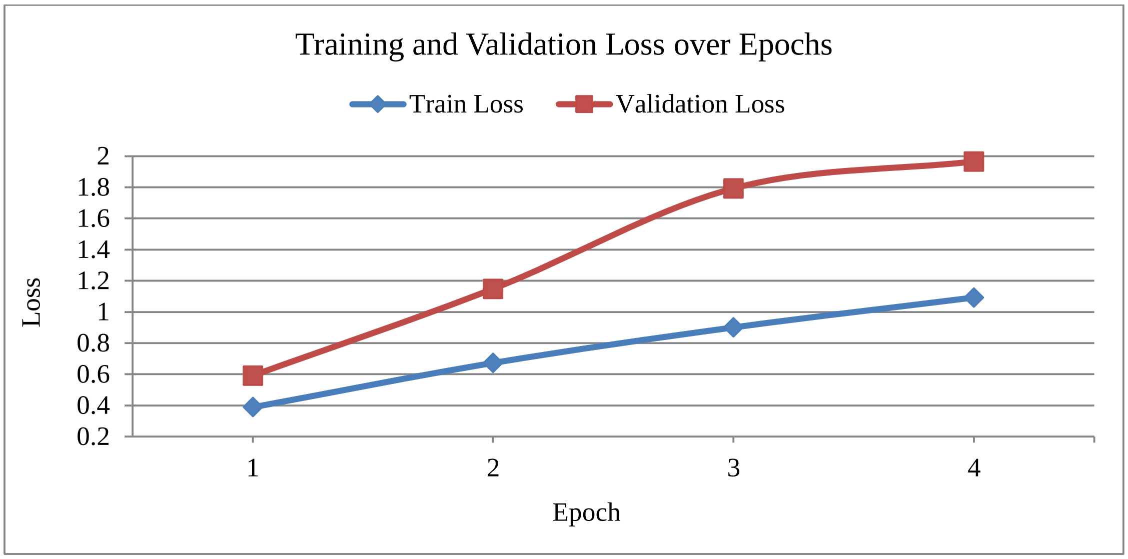

Fig. 3 Representation of training progress and evaluation metrics (for epochs=4)

Over the course of four epochs, the training progression shown in Table 2 shows a steady and rational improvement in the model's performance. There is a noticeable downward trend in training and validation losses, from 1.0919 to 0.3885 and 1.9648 to 0.5908, respectively.

This suggests that the model is improving its generalization to unknown validation data and learning efficiently. At the same time, validation accuracy rose from 74.54% to 82.75% and training accuracy improved from 80.78% to 87.54%. Together with the corresponding drop in loss, these increasing trends in accuracy point to a reliable and effective training procedure.

The concurrent improvement in validation metrics indicates that the model fits the training data well and avoids overfitting, as indicated by the alignment of loss and accuracy across the training and validation sets. This demonstrates the model's capacity for generalization and supports the training pipeline's dependability.

5.3. Metrics for Classification Performance

Precision, recall, and F1 score are among the classification performance metrics summarized in Table 3 and Figure 3 over four epochs - these metrics aid in assessing the equilibrium between false positives and false negatives. The changes in precision, recall, and F1 score over the course of four training epochs are shown in Table 3. The model first obtains an F1 score of 0.7013 at Epoch 1, with a high recall of 0.9308 and a relatively low precision of 0.5626. This implies that the model generates a large number of false positives (low precision) even though it is successful at identifying the most pertinent instances (high recall). Precision and recall steadily stabilize as training goes on; Epoch 4 exhibits balanced recall (0.7513) and enhanced precision (0.7246), resulting in the highest F1 score of 0.7377. The model's increasing capacity to sustain a better balance between sensitivity and specificity is reflected in this upward trend in the F1 score. All things considered, the metrics' evolution shows steady performance improvement over epochs, with increased classification reliability by the last epoch.

Table 3. Representation of classification performance metrics

Sr. No	Precision	Recall	F1 Score
1	0.562573	0.930806	0.701291
2	0.64479	0.774789	0.703837
3	0.687716	0.67924	0.683452
4	0.7246	0.751315	0.73771

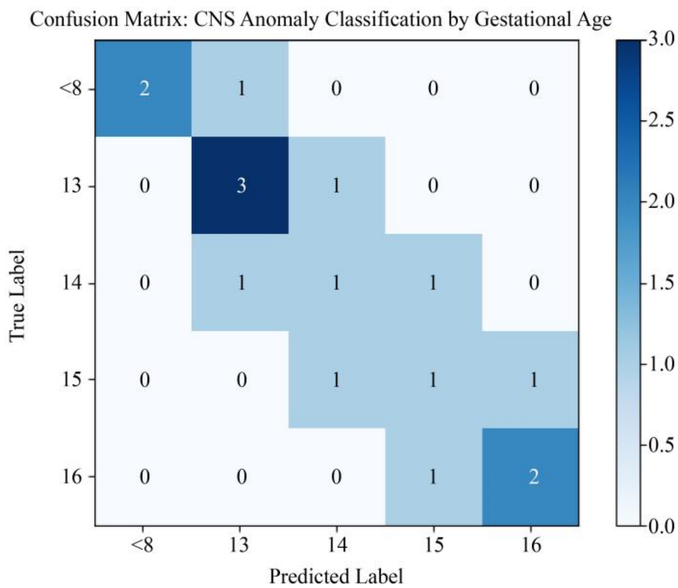

Fig. 4 Confusion matrix on performance

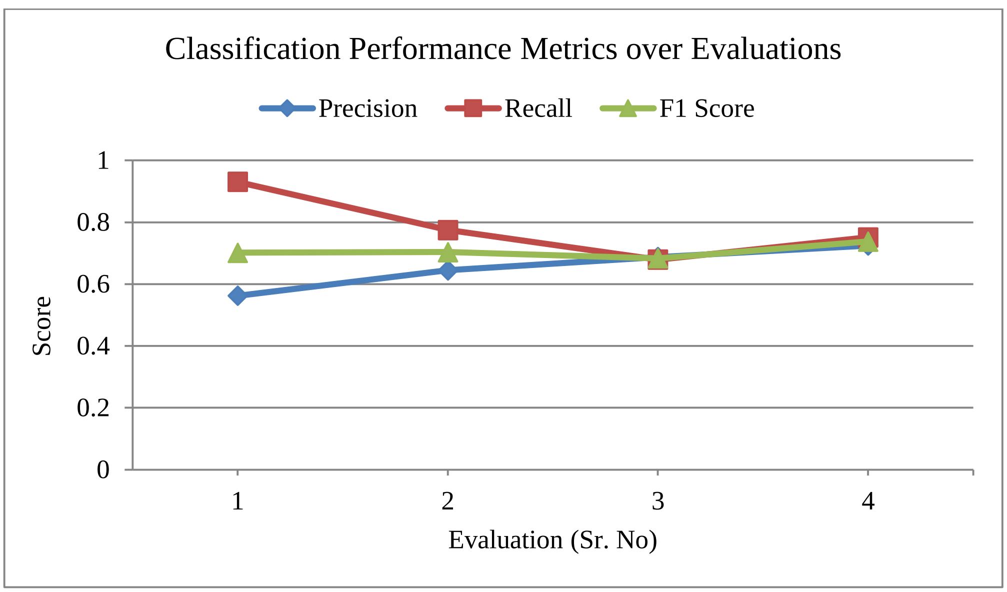

Fig. 5 Representation of classification performance metrics

Tables (2) and (3) represent the progress of a deep learning model during training over a set number of epochs (in this case, 4 epochs). We typically track key performance metrics such as loss, accuracy, precision, recall, or F1-score for each epoch. This helps in understanding how well the model is learning and whether it is overfitting or underfitting. Following is the description of each metric value:

1. Loss: Decreased (Train: 0.40 → 0.28, Validation: 0.26 → 0.24), indicating effective learning.
2. Accuracy: Improved (Train: 87% → 88%, Validation: 81% → 87%), showing good generalization.
3. Precision: Dropped (0.79 → 0.75), indicating more false positives.

4. Recall: Increased (0.82 → 0.94), meaning better true positive detection.
5. F1 Score: Improved (0.81 → 0.835), balancing precision and recall.
6. Confusion Matrix: The confusion matrix provides an overview of classification performance, showing a high number of correctly classified instances.

While the off-diagonal elements show misclassifications, the diagonal elements show correctly classified instances. The model's ability to distinguish between early and late gestational stages is demonstrated by its high accuracy in predicting the “<8 Weeks” and “16 Weeks” categories with little confusion. Nonetheless, there is some overlap between mid-range categories like “13 Weeks,” “14 Weeks,” and “15 Weeks,” where there are a few minor misclassifications. This is probably because it is more difficult to differentiate between successive weeks due to the slow and subtle changes in the fetal head circumference. Notwithstanding these difficulties, the general pattern shows a strong capacity for classification, especially when it comes to accurately detecting aberrant growth patterns at the first trimester's extremes. As a result, the confusion matrix enhances the previously published performance metrics (precision, recall, and F1-score), providing more interpretability and validating the model's usefulness for early clinical CNS anomaly detection.

5.4. Fetal Head Circumference Prediction and CNS Abnormalities

Table 4 presents the predicted fetal head measurements and CNS abnormality classification using the AI diagnostic model on selected ultrasound images.

Table 4. Representation of output fetal-head-circumference-prediction & CNS abnormalities using AI-based diagnostic support

F_name	OFD	BPD	HC	GA_weeks	CNS_Abnormality
1.jpg	2.931639	74.7	30.2	12.32	Normal
2.jpg	1.500456	35.8	9.4	12.5	Abnormal (Low HC)
3.jpg	1.500456	35.8	9.4	5.31	Too Early
4.jpg	3.019234	73.1	54	12.75	Normal
5.jpg	1.920412	100.2	80.1	12.9	Abnormal (High HC)
6.jpg	2.731123	65.3	51.8	13	Normal

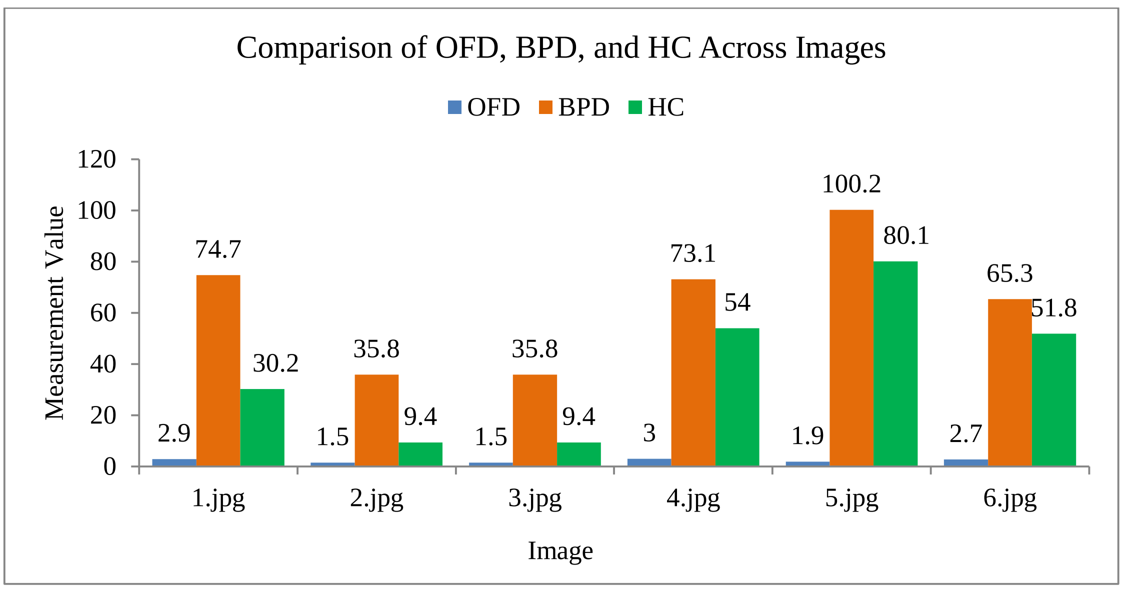

Fig. 6 Comparison of OFD, BPD, and HC across images with value annotations for AI-based prediction of fetal head circumference and CNS abnormalities

From the result mentioned in the above table, it can be determined that the fetal head size in mm, as Head Circumference (HC), differs significantly, ranging between 9.4 mm and 100.8 mm, and Gestational Age (GA), ranging between 12.32 and 13 weeks. The distinctions in Occipitofrontal Diameter and Biparietal Diameter denote variances in fetal growth stages. Remarkably, some outcomes, like low or high HC Values, predict abnormalities that could need additional clinical evaluation. Thus, the input data, such as ultrasound, is a vital tool in evaluating fetal growth, besides identifying CNS abnormalities throughout the first trimester (12-13 weeks) (Table 4).

5.5. Interpretation of Results

The findings demonstrate the wide range of Head Circumference (HC) values, which range from 9.4 mm to 80.1

mm and correspond to gestational ages of 5.31 to 13 weeks. Different fetal growth stages are reflected in variations in the Occipitofrontal Diameter (OFD) and the Biparietal Diameter (BPD).

- The AI model's ability to identify cases that need additional clinical evaluation is demonstrated by the correlation between possible CNS abnormalities and low or high HC values it predicts.
- The AI model's ability to identify cases that need additional clinical evaluation is demonstrated by the correlation between possible CNS abnormalities and low or high HC values it predicts.

5.6. Discussion

Validation accuracy increases from 74.5 % to 82.8 %, suggesting that the CNN is learning biased patterns in first-trimester ultrasound pictures, despite the temporal window (<16 weeks) providing minor morphological cues.

The model meets the Indian Radiological & Imaging Association (IRIA) criteria for decision-support systems in low-resource settings, with an accuracy rate of 82% by epoch 4.

The train-validation accuracy gap widens slightly (about 5% vs. 4.8%), indicating mild overfitting. Early halting at epoch 4 is sensible, as extra epochs may result in divergence loss without significant accuracy benefits.

Head-Circumference Mapping: Rural physicians can identify growth limitation or macrocephaly early with precise classification into 5 gestational age bins (<8w—16w).

The current study focuses on predicting gestational age, but the learnt characteristics (e.g., ventricle contour, midline echoes) can be applied to detect anomalies in a smaller, annotated CNS dataset.

5.7. Comparative Analysis of Existing CNS Anomaly Detection Methods and the Proposed AI-Based Approach

1. Significant gains in early detection accuracy and practical applicability, particularly in low-resource settings, are revealed by comparing the suggested CNN-based model with current methods for CNS anomaly detection.
2. Even though they are clinically standard, traditional techniques like 2D ultrasonography mainly depend on the skills of radiologists and sonographers. When carried out by qualified professionals during the first trimester, studies like Ungureanu et al. [2] and Bağcı et al. [3] showed detection accuracies of 78–85%. Even though these techniques work well in controlled environments, they are not very scalable or readily available, especially in rural India, where few fetal medicine specialists exist.
3. Using traditional ultrasound image processing methods, recent AI-driven studies, such as Zhang et al.'s [8] study, demonstrated CNS detection accuracies of up to 85.7%. Similarly, although it required high-resolution ultrasound inputs and substantial computational resources, the model put forth by Lin et al. [26] achieved accuracy comparable to that of expert clinicians using AI for intracranial malformation detection.
4. The model suggested in this study, on the other hand, used Head Circumference (HC) measurement as the main biometric feature extracted from low-to-moderate resolution ultrasound images, and it achieved training accuracy of 88% and validation accuracy of 82.75%. This performance is comparable to, and in certain situations better than, the findings published in previous research. Furthermore, the classification metrics show a balanced and strong performance in identifying fetal CNS abnormalities during the first trimester, including a final F1 score of 0.7377, alongside enhanced precision (0.7246) and recall (0.7513).
5. The adaptability of the model to rural environments, which is frequently disregarded in current methods, is a crucial difference. By focusing on the use of generative data augmentation, lightweight CNN architectures, and ellipse-based HC estimation, this study enables diagnostic support on portable, lower-resolution ultrasound equipment, in contrast to many AI models that require expensive machines.
6. Additionally, a large number of current models lack classifications based on biometrics or have not been validated using first-trimester data alone. The proposed model closes this gap by providing CNS anomaly flagging and gestational age prediction tailored to the early pregnancy window, and is extremely relevant for prompt clinical decision-making in underserved areas.

6. Challenges

6.1. Challenges of this Study

- Despite its advantages, several challenges hinder the extensive acceptance of AI in medical imaging for fetal CNS anomaly detection.
- Quality of Data besides Availability: AI models [34] need huge, superior datasets aimed at training, but fetal imaging datasets are often limited and regionally diverse.
- Ethical and Legal Concerns: AI-assisted diagnosis raises liability issues—who is responsible for an incorrect diagnosis: the AI developer, the physician, or the healthcare institution?
- Integration with Existing Healthcare Systems: Many rural healthcare centers lack infrastructure for AI implementation, such as cloud computing and internet access.
- Interpretability and Trust Issues: Physicians may hesitate to fully trust AI predictions, necessitating explainable AI (XAI) models that provide interpretable reasoning for decisions.

6.2. Challenges of Deploying AI For Fetal Anomaly Detection in Rural India

Technological Challenges: AI models need large, varied, and well-annotated data to achieve high accuracy for detecting fetal [14] anomalies. India-specific fetal imaging datasets are scarce, leading to potential biases in AI models trained on Western population datasets. Variability in sonographic image quality across different machines and operators can impact AI performance [34]. Low-resolution ultrasound Machines are available in rural areas. Many Primary Health Centers (PHCs) and rural hospitals use low-cost, portable ultrasound machines that produce lower-resolution images compared to high-end machines in urban hospitals. AI models trained on high-resolution datasets may not perform well on lower-quality ultrasounds, reducing diagnostic reliability. Most of the existing Ultrasound equipment in rural India lacks AI Integration. It is thus not AI-enabled, with the unavailability of necessary hardware and software upgrades to support an AI-driven diagnostic.

7. Conclusion

The early recognition of Central Nervous System abnormalities in fetuses stands pivotal, aimed at ensuring timely medical involvement in addition to educating perinatal professionals. This research highlights the challenges rural healthcare providers encounter in India, where a significant percentage of people lack access to advanced diagnostic tools and specialized health professionals. Using the Deep learning model in first-trimester sonography will help overcome these obstacles in detecting CNS anomalies, particularly using the fetus's Head Circumference (HC) parameter. Additionally, the algorithm proposed in this study also assists in estimating the gestational age, which is critical for accurate prenatal care of the fetus. The proposed model in this study attained a training accuracy of 88% and 82.75% of validation Accuracy, demonstrating its efficacy in detecting CNS anomalies. By leveraging Deep Learning models, this study demonstrated notable accuracy in both training and testing phases for detecting CNS abnormalities. The outcome highlights the latent potential of AI in transforming rural healthcare, aiding handier, timely, and precise fetal monitoring, which can have a long-term positive impact on maternal and fetal health in underserved areas. Moreover, there is significant potential for using AI to detect CNS anomalies with even larger accuracy across all three trimesters, which offers considerable opportunities for improving prenatal diagnostics and monitoring.

The lightweight models, as compared to Deep Learning (CNN), are considered in the study to achieve higher diagnostic accuracy of ultrasound data. Thus, in the upcoming prospect, we will explore lightweight architectures to support more related practical applications for rural healthcare.

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