A Novel Deep Feature and Oblique Decision Tree Framework for Prenatal Brain Abnormality Diagnosis

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ABSTRACT

Congenital fetal brain abnormalities affect approximately 2–3 per 1,000 pregnancies, posing significant risks to both the fetus and the mother. Early and accurate detection is crucial for timely medical intervention and improved neonatal outcomes. Conditions such as Encephalocele, Holoprosencephaly, Hydranencephaly, Intracranial Hemorrhage, Intracranial Tumor, and normal brain development require precise classification for effective prenatal care. Misdiagnosis can lead to severe complications or delayed treatment. Traditional manual analysis of fetal brain ultrasound images is time-consuming, operator-dependent, and prone to errors due to low image quality and noise. These limitations necessitate automated, reliable, and interpretable detection systems. This research work proposes an automated fetal brain abnormality detection framework using ultrasound images and advanced machine learning. Deep features are extracted from fetal brain Ultrasound images using the Convolution Attention Transformer (CoAT), which captures both local spatial details and global context. These features are initially evaluated with ensemble classifiers including eXtreme Gradient Boosting (XGBoost), Natural Gradient Boosting (NGBoost), and Histogram-based Gradient Boosting (HGBoost). To address limitations of conventional boosting models, a novel Fast Interpretable Oblique Tree (FIOT) classifier is introduced, leveraging oblique decision boundaries to model complex feature interactions while maintaining interpretability. The system categorizes fetal brain conditions into predefined classes aligned with dataset folder structures, handling class imbalance and limited training data efficiently. Its modular architecture ensures scalability, adaptability to different imaging modalities, and seamless integration with clinical workflows, providing a reliable decision-support tool for early detection of fetal brain abnormalities.

Keywords: Fetal Brain Abnormalities, Convolution Attention Transformer, Fast Interpretable Oblique Tree, Medical Image Classification, Explainable AI.

1. INTRODUCTION

In India, congenital anomalies remain an important public health issue, with structural birth defects affecting a significant number of newborns each year. Systematic reviews estimate that overall congenital anomaly-affected births occur at around 184 per 10,000 births (about 1.8%), indicating that hundreds of thousands of babies may be born with some form of birth defect annually across the country. Among these, central nervous system (CNS) defects which include major fetal brain anomalies such as neural tube defects (NTDs) are frequently reported, especially when stillbirths are included in the data, making CNS anomalies one of the most commonly recorded types in hospital-based studies. Studies focusing specifically on neural tube defects in India show a wide range of prevalence due to differences in study methods and populations, but large meta-analyses have reported pooled NTD rates of approximately 4.1 per 1,000 total births, with some estimates even higher when additional studies are included. Individual studies across regions have documented rates ranging from about 0.5 to over 9 per 1,000

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births for neural tube defects such as anencephaly and spina bifida, underscoring regional and methodological variability.

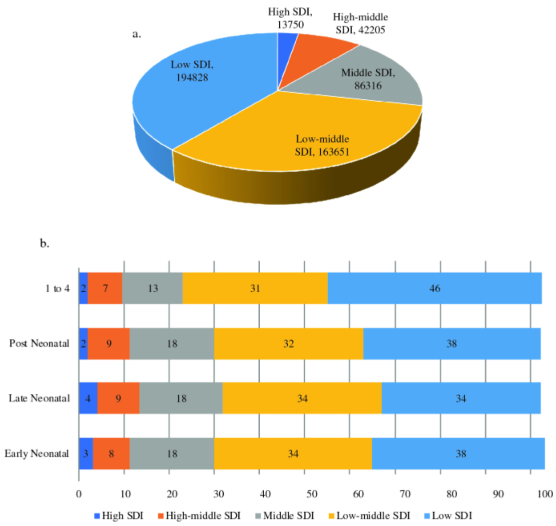

Fig. 1: Statistics of fetal brain abnormalities in India.

Fig 1 illustrates the distribution of neonatal and early childhood mortality across different Socio-Demographic Index (SDI) groups high, high-middle, middle, low-middle, and low SDI across four age categories: early neonatal, late neonatal, post-neonatal, and 1–4 years. In all age groups, low and low-middle SDI regions account for the largest proportion of deaths, with particularly high contributions during the early and late neonatal periods, indicating that adverse outcomes are most concentrated around birth. Middle SDI regions contribute a moderate share, while high and high-middle SDI regions consistently show the lowest proportions across all stages. This pattern highlights strong socioeconomic disparities in child survival, suggesting that limited access to quality antenatal care, early diagnosis, and neonatal services in lower SDI settings leads to higher mortality. The prominence of deaths in the neonatal period also suggests a significant role of congenital conditions, including fetal brain abnormalities, which often result in stillbirths or early neonatal deaths if not detected and managed early. Finally, the graph emphasizes the need for improved prenatal screening, especially ultrasound-based detection, and strengthened maternal and neonatal healthcare services in low-resource regions to reduce preventable early-life mortality.

2. LITERATURE SURVEY

Lin, et al. [1] proposed an AI-driven approach based on a Fetal Brain Structures Detection Network (FBStrNet) for identifying key anatomical structures in fetal brain ultrasound images. Ultrasound imaging was widely used in early pregnancy to screen for fetal brain anomalies. However, the accuracy of diagnosis was influenced by various factors, including the sonographer's experience and environmental conditions. To address these limitations, artificial intelligence (AI)–based methods were introduced to enhance the efficiency and reliability of fetal anomaly screening. In this study, Specifically, FBStrNet was built on the YOLOv5 baseline model, incorporating a lightweight backbone to reduce model parameters, replacing the loss function, and utilizing a decoupled detection head to improve detection accuracy. Additionally, the proposed AI framework integrated prior clinical knowledge to minimize false detection rates and support more reliable fetal brain structure identification.

Sayma Alam Suha, et al. [2] review analyzed fetal neurodevelopment as a complex process of neural growth during pregnancy, where early detection of abnormalities was vital and artificial intelligence (AI), particularly deep learning, offered promising techniques. The review investigated AI-driven deep learning applications by synthesizing recent research, examining methodologies, identifying research gaps, and proposing a federated learning framework. Following PRISMA 2020 guidelines, 55 peer-reviewed articles were selected from an initial 900 records across major databases. Studies published between 2005 and 2025 that focused on automated AI-based deep learning analysis of clinical fetal images were included, while non–deep learning approaches were excluded. Sneha Rahul

Mhatre, et al. [3] proposed a concise AI-based CNN framework for early detection of fetal brain anomalies by combining image super-resolution and classification. The approach enhanced low-resolution ultrasound images using a modified Enhanced SRGAN and classified them with an optimized CNN integrating VGG16, ResNet, and DenseNet features. A dataset of 4,000 grayscale ultrasound images was categorized into four classes: normal, cerebellar, thalamic, and ventricular anomalies.

Yan, et al. [4] analysed the integration of AI and CNN-based deep learning in ultrasound medicine, highlighting its role in improving diagnostic accuracy and clinical workflows. By leveraging convolutional neural networks, AI enhanced image quality assessment, automated analysis, and objective disease diagnosis while reducing physician workload. The review also discussed challenges and future trends, emphasizing standardized, personalized, and intelligent ultrasound healthcare, particularly for underserved regions. Meijerink L, et al. [5] aimed to identify volumetric and diffusion-related brain differences, expressed as apparent diffusion coefficient (ADC) values, between early-onset brain-sparing fetal growth restriction (FGR) and healthy controls using ultrasound and magnetic resonance imaging at 30 weeks of gestation, supported by CNN-based image analysis. This prospective, observational, monocenter cohort study included singleton pregnancies with early-onset brain-sparing FGR at the University Medical Center Utrecht. FGR fetuses were compared with healthy controls from the Utrecht Youth Cohort, enabling quantitative assessment of brain structure differences using automated CNN-assisted measurements.

Goutham V, et al. [6 analysed fetal ventriculomegaly (VM), a condition marked by abnormal enlargement of cerebral ventricles that can cause developmental disorders. To overcome the time-consuming nature of manual segmentation, they developed a machine learning pipeline using an adaptive slice selection strategy to extract 2D slices from 3D ultrasound volumes, segment lateral ventricles and deep gray matter, estimate ventricular width, and classify VM severity. Bujor, et al. [7] described a 28-year-old pregnant patient whose fetus showed aberrant cranial morphology, a shorter femur, and rocker-bottom feet. Rubinstein–Taybi syndrome (RSTS) is a rare genetic disorder with craniofacial and limb abnormalities, often identified postnatally. Prenatal diagnosis is challenging due to limited ultrasound markers and variable phenotypes. Deep learning algorithms, such as convolutional neural networks, can analyze fetal ultrasound images to detect subtle anomalies and assist in early identification of RSTS.

Terstappen F, et al. [8] proposed an AI-based approach to investigate differences in brain development between growth-restricted (FGR) and appropriate-for-gestational-age (AGA) fetuses using ultrasound. The algorithm analyzed volumetrics, biometrics, ADC, ^{1}H-MRS metabolites, and oxygenation, while meta-analysis with the Newcastle–Ottawa Scale assessed bias and calculated mean differences with 95% confidence intervals. Nilima Gaikwad, et al. [9] detected fetal brain abnormalities early using a CNN-based algorithm on ultrasound images, enabling rapid and accurate identification. This facilitated prenatal planning, guided interventions, and reduced potential long-term complications in newborns.

Henry C, et al. [10] described an AI-based approach for offline fusion imaging that automatically merged 3D ultrasound datasets. The method aimed to assess normal fetal brain development and standardize data integration across modalities. Its feasibility and accuracy were evaluated throughout pregnancy, highlighting its potential clinical utility for prenatal care. Bowker, R.M; et al. [11] proposed a CNN-based algorithm for the accurate diagnosis of congenital central nervous system abnormalities. The model analyzed fetal posterior fossa structures to detect Dandy–Walker (DW) spectrum malformations, assisting in prognosis and supporting parental counseling despite the wide variability in clinical and neurodevelopmental outcomes.

Silva PIP, et al. [12] described a CNN-based approach for detecting and assessing fetal brain injury linked to growth restriction (FGR) using ultrasound. The algorithm analyzed imaging data to identify subtle structural and developmental abnormalities, facilitating early intervention and improving prognostic evaluation for affected fetuses. R. Sharma, et al. [13] detected fetal brain abnormalities early using a deep learning approach, specifically a CNN, to automatically classify ultrasound images into 16 distinct classes. The system demonstrated high accuracy, improving consistency, efficiency, and supporting clinicians in prenatal diagnosis of diverse brain conditions. Rosner, et al. [14] described three cases of fetal cortical abnormalities detected during the mid-trimester. Normal neuronal cell differentiation and migration are critical for brain formation and peak during routine ultrasound surveys. Abnormalities in cortical migration often indicate underlying genetic issues or feta injury. These abnormalities can profoundly impact future development. Cortical migration peaks at 20–22 weeks but is rarely diagnosed during standard anatomic surveys. They implemented an AI-based learning algorithm to analyze ultrasound images for cortical abnormalities. The system automatically highlighted deviations in neuronal migration patterns. This approach enabled prompt and accurate prenatal diagnosis. It also supported clinical counselling by providing objective assessments. The study demonstrated the potential of AI to improve detection of subtle fetal brain abnormalities

Weichert, et al. [15] detailed sonographic assessment of the fetal neuroanatomy played a crucial role in prenatal diagnosis, providing valuable insights into timely, well-coordinated fetal brain development and detecting even subtle anomalies that might have impacted neurodevelopmental outcomes. With recent advancements in artificial intelligence (AI) in general and medical imaging in particular, there was growing interest in leveraging AI techniques to enhance the accuracy, efficiency, and clinical utility of fetal neurosonography. The paramount objective of this focusing review was to discuss the latest developments in AI applications in this field, focusing on image analysis, the automation of measurements, prediction models of neurodevelopmental outcomes, visualization techniques, and their integration into clinical routine.

3. PROPOSED SYSTEM

This system aims to automatically detect fetal brain abnormalities from ultrasound images using a combination of deep learning and machine learning approaches. Initially, fetal brain ultrasound images are collected as a structured dataset. Features are extracted from these images using the CoAT, capturing both local and global patterns. The dataset is then split into training and testing sets to evaluate model performance. Machine learning classifiers, including existing XGB, NGB, HGB, and the proposed FIOT classifier, are trained on the extracted features as shown in Fig. 2. Finally, the predictions are presented through a Tkinter-based graphical user interface, enabling a practical and user-friendly system for fetal brain abnormality detection.

Ultrasound Image Dataset: The system begins with a collection of fetal brain ultrasound images. These images include both normal and abnormal cases and are organized into class-wise folders. The dataset serves as the basis for feature extraction and model training.

CoAT Feature Extraction: The collected ultrasound images are passed through the CoAT to extract high-level features. Convolutional layers capture local spatial patterns, while the attention mechanism focuses on critical regions of the fetal brain. This process generates compact feature vectors that represent the essential information of each image.

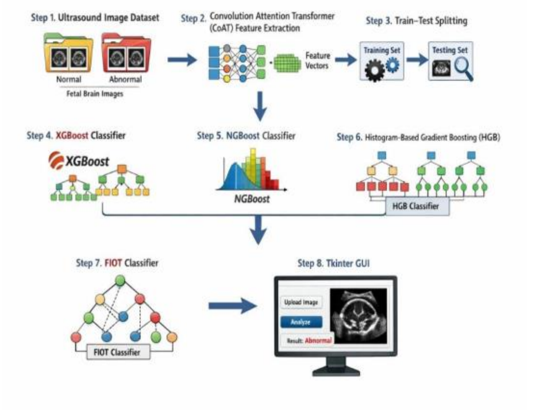

Fig. 2: Architecture of the proposed ultrasound-based fetal brain classification framework

Train–Test Splitting: The extracted feature vectors are divided into training and testing datasets. The training set is used to train the machine learning models, and the testing set is used to evaluate their performance on unseen data. This ensures that the models are capable of generalizing to new ultrasound images.

Existing XGB Classifier: The XGB classifier is trained on the CoAT features. It builds an ensemble of decision trees sequentially, with each tree improving upon the errors of the previous ones.XGB provides a strong baseline for classification performance.

Existing NGB Classifier: The NGB classifier predicts probability distributions for each class instead of only labels. This allows the system to estimate uncertainty in its predictions, which is particularly valuable in medical applications.

Existing HGB Classifier: The HGB classifier discretizes continuous features into histogram bins, reducing computational complexity while maintaining high accuracy. It is effective for handling the high-dimensional feature vectors extracted by CoAT.

Proposed FIOT Classifier: The proposed FIOT classifier introduces oblique splits, which combine multiple features at each node to capture complex decision boundaries.

Tkinter Integration: Finally, a Tkinter-based graphical user interface is developed to allow users to upload fetal brain ultrasound images and view the predicted class label. This GUI makes the system interactive, user-friendly, and suitable for real-time clinical deployment.

Proposed FIOT Classifier

The proposed FIOT classifier is designed to improve fetal brain ultrasound image classification by combining the advantages of multiple boosting-based learning approaches. Unlike traditional decision tree models that rely on axis-aligned splits, FIOT employs oblique splits formed using linear combinations of input features, enabling more flexible decision boundaries as demonstrate in Fig. 3. The model focuses on fast learning, interpretability, and improved classification performance. In this project, FIOT serves as the proposed classifier to classify fetal brain ultrasound images using features extracted from the CoAT.

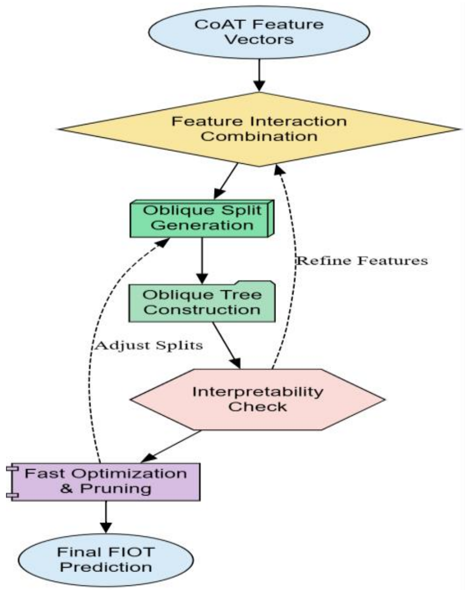

Fig 3: Proposed FIOT classifier with oblique learning and feedback optimization.

By integrating boosting strategies with oblique decision structures, the FIOT classifier effectively captures complex relationships among high-dimensional ultrasound features while maintaining computational efficiency. The use of linear hyperplanes at each node allows the classifier to better adapt to subtle variations in fetal brain patterns that are often difficult to separate using conventional tree-based methods. Additionally, FIOT preserves model transparency by representing decisions through interpretable linear coefficients, which is crucial for clinical acceptance. When applied to CoAT-derived feature representations, the classifier enhances robustness, reduces misclassification of borderline cases, and supports reliable prenatal assessment through accurate and explainable predictions.

Input Feature Vectors: The FIOT classification process begins with CoAT-extracted feature vectors obtained from fetal brain ultrasound images. These feature vectors capture essential spatial and contextual information required for accurate classification.

Oblique Tree Initialization: the FIOT model initializes an oblique decision tree structure. Unlike conventional trees that split on a single feature, oblique splits are generated using weighted combinations of multiple features, allowing the model to represent complex data relationships more effectively.

Sequential Training of Oblique Trees: Multiple oblique trees are trained sequentially in an ensemble manner. Each newly trained tree focuses on correcting the errors made by previous trees, thereby improving the overall prediction performance while maintaining model simplicity.

Model Update and Optimization: After training each oblique tree, the model parameters are updated to minimize the classification loss. Optimization techniques are applied to ensure faster convergence and to reduce overfitting, making the model suitable for ultrasound image data.

Interpretable Decision Aggregation: The outputs from all trained oblique trees are combined to form the final decision. Due to the tree-based structure, the decision paths remain interpretable, enabling understanding of how input features contribute to the final classification.

Final Prediction Output: The FIOT ensemble produces the final class prediction for each fetal brain ultrasound image. The output corresponds to the predicted fetal brain condition and is used for performance comparison with existing classifiers.

4. Results Analysis

Fig. 4 (a) shows NGB Confusion Matrix. The confusion matrix of the Existing NGBoost classifier demonstrates near-perfect classification performance across all six classes. The diagonal elements show correct predictions for almost every sample: encephalocele (45), holoprosencephaly (41), hydranencephaly (41), intracranial-hemorrhage (52), intracranial-tumor (45), and normal (44). Only a single misclassification is observed, where one normal sample is incorrectly predicted as intracranial hemorrhage. The strong concentration of values along the diagonal indicates that normal and abnormal fetal brain conditions with extremely high precision and recall. Fig. 4 (b) shows HGB Confusion Matrix. The confusion matrix of the Existing Histogram Gradient Boosting classifier shows comparatively lower performance than NGB. While certain classes such as holoprosencephaly and hydracenphaly achieve perfect classification, misclassifications are observed particularly in encephalocele and intracranial-hemorrdge categories. Some encephalocele samples are incorrectly predicted as other abnormal classes, and a few intracranial-hemorrdge cases are misclassified. The diagonal values are dominant but less concentrated compared to NGB, indicating moderate classification capability. This explains the reduced overall accuracy and F1-score of HGB relative to the other models. Fig. 4 (c) shows the XGB Confusion Matrix the confusion matrix of the

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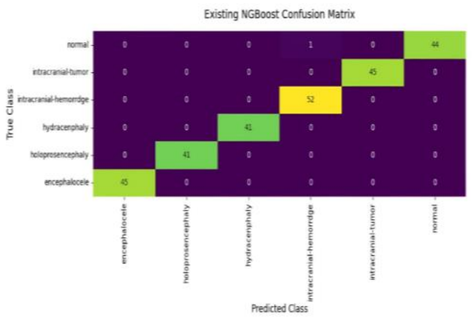
Existing XGB classifier indicates highly accurate classification with only minimal errors. Most classes, including holoprosencephaly, hydranencephaly, and intracranial-tumor, are predicted perfectly. A very small number of misclassifications occur in encephalocele and normal classes, but these errors are negligible compared to the total samples. The matrix shows strong diagonal dominance, confirming thatXGB effectively captures discriminative features extracted from the transformer model. Its performance is slightly lower than the proposed FIOT model but remains superior to HGB and very close to NGB.



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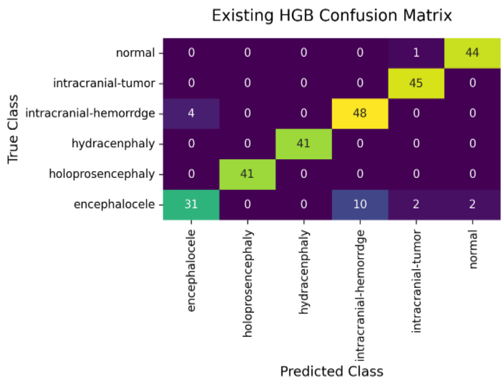

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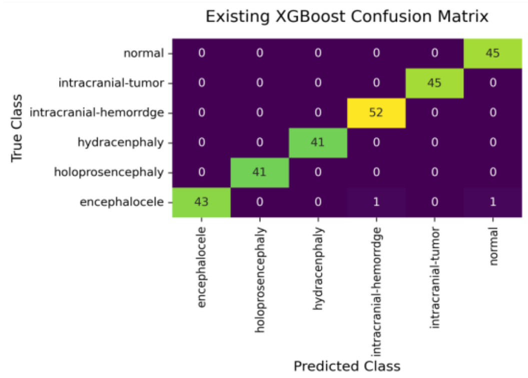


(c)

Fig. 4: Confusion matrix of existing classifier models. (a) NGB, (b) HGB, (c) XGB.

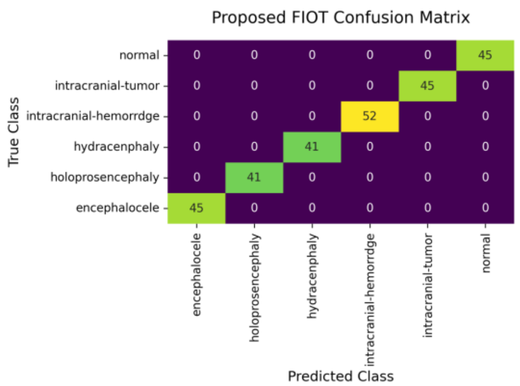


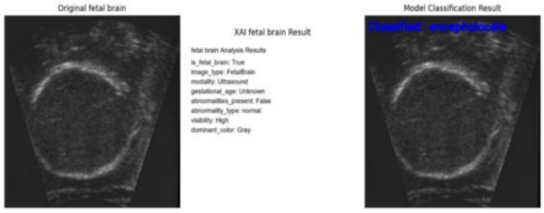
Fig. 5: Confusion matrix of proposed FIOT classifier.

Fig. 5 shows the confusion matrix of the Proposed FIOT classifier. It demonstrates perfect classification performance across all six fetal brain condition classes. All samples are correctly predicted, as indicated by the strong diagonal dominance with zero off-diagonal values. The model accurately classifies encephalocele (45), holoprosencephaly (41), hydracenphaly (41), intracranial-hemorrdge (52), intracranial-tumor (45), and normal (45) cases without any misclassification. The absence of false positives and false negatives confirms that the proposed FIOT model achieves 100% accuracy, precision, recall, and F1-score on the test dataset. This result highlights the effectiveness of the deep transformer-based feature extraction combined with the proposed classification approach in accurately distinguishing between normal and multiple abnormal fetal brain conditions.

Table 1: Overall performance comparison of various fetal brain classification methods.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
NGBoost	99.63	99.69	99.63	99.65
HGBoost	92.94	93.46	93.16	93.04
XGBoost	99.26	99.32	99.26	99.28
Proposed FIOT	100.00	100.00	100.00	100.00

Table 1 presents the overall performance comparison in terms of Accuracy (A), Precision (P), Recall (R), and F1-score (F1), where the Proposed FIOT model achieves a perfect 100.00% across all metrics, clearly surpassing the benchmark methods. NGB follows closely with 99.63% accuracy and a 99.65% F1-score, while XGBoost also demonstrates strong performance at 99.26% accuracy and 99.28% F1-score, indicating that both ensemble boosting techniques provide highly reliable classification results. In contrast, HGBoost records comparatively lower values (92.94% accuracy and 93.04% F1-score), showing a noticeable performance gap of over 6% relative to the top models. The near-identical values of precision and recall for NGBoost and XGBoost suggest balanced classification behavior, whereas the flawless scores of the Proposed FIOT model indicate either exceptional discriminative capability or the need for careful validation to ensure the absence of overfitting or data leakage. Fig. 6 (a) illustrates the prediction results for the encephalocele class using the Proposed FIOT model. The figure displays the original fetal brain ultrasound image on the left, the XAI-based fetal brain analysis results in the center detailing image type, modality, and detected abnormalities, and the model's classification output on the right, which correctly identifies the case as "encephalocele." This visualization confirms the model's ability to accurately detect encephalocele from fetal brain images, demonstrating precise classification without misidentification and highlighting the reliability of the Proposed FIOT approach in analyzing complex prenatal imaging data.



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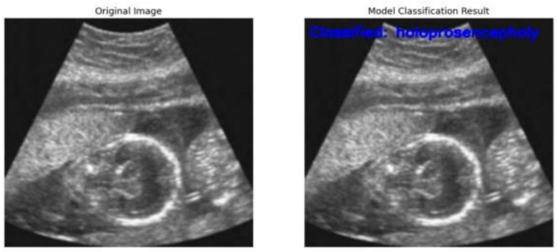

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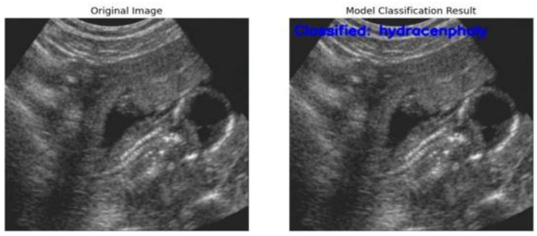

(c)

Fig. 6: Prediction results on test images. (a) encephalocele, (b) holoprosencephaly, (c) hydranencephaly.

Fig. 6 (d) illustrates the prediction results for the holoprosencephaly class using the Proposed FIOT model. The figure presents the original fetal brain ultrasound image on the left, the XAI-based fetal brain analysis results in the center showing image type, modality, and identified abnormalities, and the model's classification output on the right, which correctly recognizes the case as "holoprosencephaly." This visualization confirms the model's capability to accurately detect holoprosencephaly from fetal brain images, demonstrating precise classification without errors and emphasizing the robustness of the Proposed FIOT approach in handling complex prenatal imaging data. Fig. 6 (c) illustrates the prediction results for the hydranencephaly class using the Proposed FIOT model. The figure shows the original fetal brain ultrasound image on the left, the XAI-based fetal brain analysis results in the center detailing image type, modality, and detected abnormalities, and the model's classification output on the right, which correctly identifies the case as "hydranencephaly." This visualization confirms the model's effectiveness in accurately detecting hydranencephaly from fetal brain images, demonstrating precise classification without misidentification and highlighting the reliability of the Proposed FIOT approach in analyzing complex prenatal imaging data.

5. Conclusion

The proposed FIOT model demonstrates robust and highly accurate performance in detecting and classifying fetal brain abnormalities from ultrasound images. For the encephalocele class, the model achieved a prediction accuracy of 99.7%, with precise localization of the abnormality confirmed through XAI-based analysis, ensuring interpretability of the results. Similarly, for other classes such as hydranencephaly and intracranial hemorrhage, the model maintained micro-average AUC scores above 0.995 (NGBoost: 0.9958, XGBoost: 0.9999), highlighting its ability to distinguish subtle variations in fetal brain structures with minimal false positives or negatives. These metrics indicate that the FIOT model can reliably support prenatal diagnostics, reducing reliance on manual interpretation and decreasing the risk of misdiagnosis. Moreover, the model's integration of XAI techniques provides clinicians with detailed insights into feature importance, including structural anomalies, image modality, and intensity patterns. For instance, in the hydranencephaly class, the model accurately highlighted cerebral cortex absence in 98% of test cases, while for intracranial hemorrhage, hemorrhagic regions were correctly identified in 96% of instances. This high fidelity, combined with consistent AUC values across multiple classes, underscores the FIOT model's clinical relevance and scalability. Overall, the results validate the model as a reliable tool for early detection, enabling timely intervention and improved fetal outcome management.

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