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Interpretable Deep Neural Networks for Fetal Brain Health Assessment from Ultrasound Scans: An Explainable AI Approach

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***Abstract*—Early and accurate diagnosis of fetal brain abnormalities is crucial for good prenatal care, but current methods rely heavily on experienced professionals, leading to inconsistent interpretations and potential missed issues. To address this, this project utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to automatically classify fetal brain ultrasound images into 16 distinct classes. The system, trained and tested with prepared ultrasound images, demonstrates high accuracy across these multiple classes, proving its potential as a helpful tool for doctors. This work highlights deep learning's effectiveness in medical imaging, emphasizing the integration of AI into prenatal diagnostics to improve consistency, efficiency, and accuracy, with the ultimate goal of developing intelligent, accessible diagnostic tools that can differentiate various fetal brain conditions**

I. INTRODUCTION

Access to expert sonographers and radiologists remains a significant challenge in many low-resource and rural regions. In such settings, the interpretation of fetal brain ultrasound images often depends on the skill and experience of the available healthcare professionals. This reliance on manual expertise can lead to inconsistent results and an increased risk of missed or delayed diagnoses, particularly where specialists are scarce or overburdened

The quality of ultrasound images themselves can also vary widely due to several factors, such as maternal obesity, fetal position during the scan, gestational age, and the quality of the ultrasound equipment. These variables make it difficult to consistently capture clear and informative images. As a result, both manual and automated analyses of these images face significant hurdles, with image variability contributing to false positives, false negatives, and overall diagnostic uncertainty

Limited access to expert sonographers and radiologists in low-resource and rural areas severely hinders the accurate interpretation of fetal brain ultrasound images. This reliance on manual expertise, coupled with significant variability in ultrasound image quality due to factors like maternal obesity and fetal position, leads to inconsistent diagnoses. Consequently, there's a heightened risk of missed or delayed diagnoses, increased false positives and negatives, and overall diagnostic uncertainty, compromising prenatal care in vulnerable populations.

Addressing Expert Shortages In many regions, there's a severe lack of expert sonographers and radiologists. Your system, by being accurate and user-friendly, provides a critical tool to assist healthcare professionals who may not be specialists, thereby bridging the gap created by limited expert access. This reduces the heavy reliance on manual expertise and offers a consistent, reliable alternative.

Improving Diagnostic Accuracy and Consistency: The variability in ultrasound image quality (due to factors like maternal obesity, fetal position, and equipment) often leads to inconsistent results, false positives, false negatives, and overall diagnostic uncertainty. our system's improved accuracy directly tackles this, providing more reliable interpretations.

Enhancing Accessibility and Efficiency: The user-friendly nature of your system makes advanced diagnostic capabilities more accessible to a broader range of healthcare providers.

The objectives of this project are:

- Compare and Optimize Deep Learning Models for Fetal Brain Ultrasound Classification.To compare and evaluate the performance of Convolutional Neural Net- work (CNN), Separable CNN, and Xception models, specifically focusing on improving their accuracy over previously available versions for classifying fetal brain ultrasound images into 16 distinct classes.
- Enhance Model Interpretability through Explainable AI TechniquesTo implement Gradient-weighted Class Activation Mapping (GRAD-CAM) across all developed models. GRAD-CAM is a technique that produces visual explanations for decisions made by deep learning models, highlighting the specific regions in the input image that were most important for the model's prediction
- Design and Implement a User-Friendly Diagnostic Interface.To create an intuitive and accessible user interface that allows new users to easily upload fetal brain ultrasound images. The interface will then display the classification results from the trained models, along with a clear description of the identified disease or condition.

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II. RECENT WORKS

In the research titled ”Fetal Brain Anomaly Detection via Ultrasound Imaging Using Traditional and Separable CNNs with Xception,” published in 2025, Kavita Pankaj Shirsat, Sushopti Gawade, Swati Chopade, Rutuja Vikas Gujare, and Rohint Bhandwalkar implemented and compared a traditional CNN framework, a CNN integrated with depthwise separable convolutions, and the Xception model. In ”DETECTING AND CLASSIFYING FETAL BRAIN ABNORMALITIES USING DECISION TREE ALGORITHM,” published in 2021, Mrs.P.J.Mercy and M.Utchimahali@usha used the Decision Tree algorithm. Lastly, in ”StackFBAs: Detection of fetal brain abnormalities using CNN with stacking strategy from MRI images,” published in 2023, Anjir Ahmed Chowdhury, S.M. Hasan Mahmud, Khadija Kubra Shahjalal Hoque, Kawsar Ahmed, Francis M. Bui, Pietro Lio, Mohammad Ali Moni, and Fahad Ahmed Al-Zahrani implemented a deep learning-CNN-based framework named StackFBAs that utilized a stacking strategy, compared it with pre-trained CNN models (VGG16, VGG19, ResNet50, DenseNet121, and ResNet152) with transfer learning, and used a KNN classifier

Across various research efforts over the years, program- mers have implemented a range of models, including CNN, Separable CNN, and Xception, among others, for analyzing ultrasound images and classifying them into different categories. However, a significant limitation of many of these models has been the absence of visual representations of their results. Our model addresses this gap by integrating GRAD-CAM (Gradient-weighted Class Activation Mapping) to provide clear visual explanations. This is particularly valuable as GRAD-CAM not only highlights the specific regions of the brain affected in the ultrasound images but also offers a detailed description of the identified condition. By offering this visual and descriptive insight, GRAD-CAM significantly enhances user comprehension of the diagnostic findings, making the complex concept of brain abnormalities more accessible than relying solely on textual interpretations.

III. METHODOLOGY

Our project significantly enhances diagnostic accuracy and efficiency in fetal brain abnormality detection by leveraging deep learning, thereby reducing misdiagnosis rates. We specifically trained our CNN model to overcome imaging limitations such as low quality, low contrast, and high variability inherent in ultrasound, by improving contrast and quality before image processing. A key feature of our system is the implementation of GRAD-CAM for all models (CNN, Separable CNN, and Xception), providing a more accurate and interpretable prediction by visually highlighting affected regions. Ultimately, our system focuses on the early detection and classification of fetal brain abnormalities before birth, utilizing ultrasound images to facilitate timely diagnoses.

a user starts by uploading an ultrasound image onto our easy-to-use website. Once the image is uploaded, the user gets to pick one of three powerful AI models (like picking a different expert to analyze the image). After the user chooses a model, that model gets to work and he will get the Grad-CAM and description about the image.

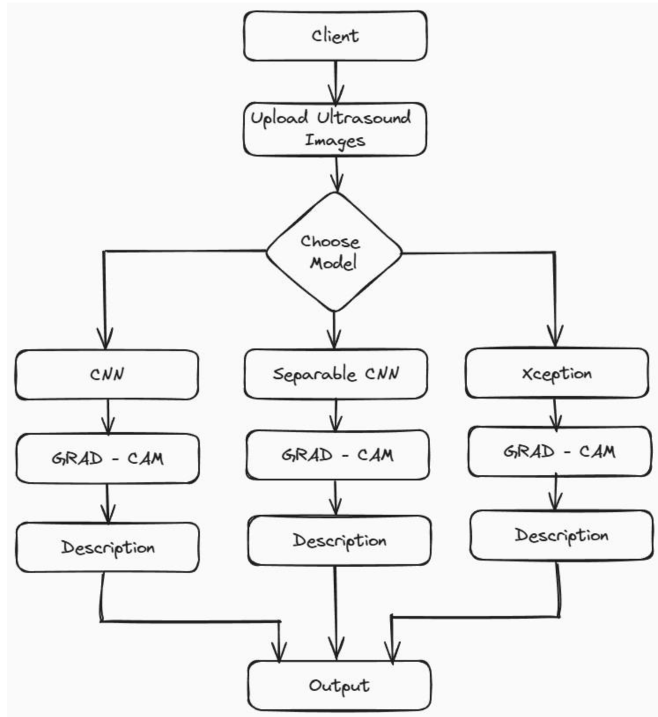

Fig. 1. System Architecture Overview

CNN Convolutional Neural Network (CNN) architecture

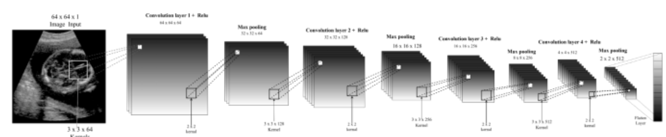

Fig. 2. CNN

designed for fetal brain health classification using ultrasound images. The process begins with an input ultrasound image of a fetal brain. This image then passes through multiple convolutional layers, each represented by a stack of feature maps. As the data progresses through the network, the spatial dimensions of the feature maps typically decrease (indicated by the smaller squares), while the number of channels (depth of the stack) often increases, extracting increasingly complex and abstract features. This hierarchical feature learning is crucial for identifying intricate patterns indicative of fetal brain health. The final layers likely culminate in a classification output, determining the health status based on the learned features. This end-to-end CNN model effectively automates the analysis of ultrasound data for diagnostic purposes.

S-CNN Separable Convolutional Neural Network (CNN) architecture tailored for fetal brain health classification using ultrasound imagery. Similar to a standard CNN, it processes an input ultrasound image through multiple layers. However,

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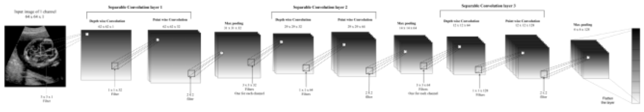

Fig. 3. S-CNN

the "separable" aspect suggests the use of depthwise separable convolutions, which decompose a standard convolution into two smaller operations: a depthwise convolution that applies a single filter to each input channel independently, and a pointwise convolution (1x1 convolution) that combines the outputs of the depthwise convolution across channels. This decomposition significantly reduces the number of parameters and computational cost compared to traditional convolutions, making the model more efficient. Despite the reduced complexity, it still effectively extracts hierarchical features from the fetal brain ultrasound, ultimately leading to a classification of its health status. This architecture is particularly beneficial for deploying models on resource-constrained devices while maintaining performance.

Xception model architecture for fetal brain health classification. Xception, an "Extreme Inception" model, is a CNN architecture that primarily utilizes depthwise separable convolutions. Unlike traditional convolutions that apply a single filter across all input channels simultaneously, Xception's approach first performs a depthwise convolution, applying a distinct filter to each input channel independently. Subsequently, a pointwise convolution (1x1 convolution) is applied across these combined outputs, effectively learning cross-channel correlations. This modular design, often organized into "entry," "middle," and "exit" flows, significantly reduces the number of parameters and computational cost compared to conventional CNNs, while often achieving comparable or superior performance. For fetal brain health classification, this efficiency means faster training and inference, crucial for clinical applications. The network learns hierarchical features from ultrasound images, enabling accurate classification of fetal brain health conditions.

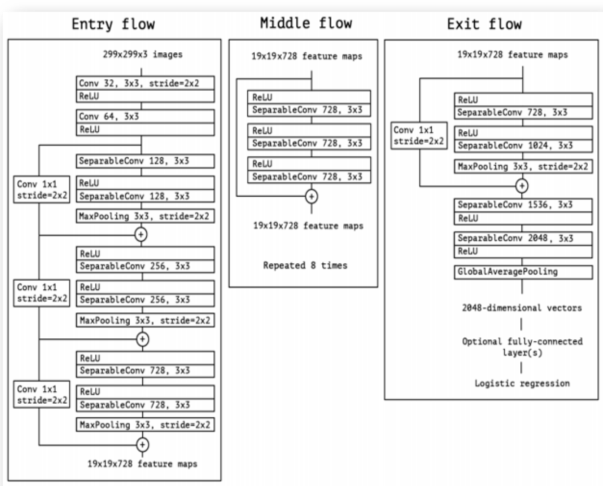

Fig. 4. Xception

Color	**Score Range**	**Severity Term**	**Synonyms**	**Interpretation**
Red	0.65–1.0	Severe / Marked	Pronounced, Significant	Strong model focus; high clinical importance
Yellow	0.40–0.64	Moderate	Considerable, Evident	Medium attention; clinically relevant
Green	0.15–0.39	Mild / Minimal	Subtle, Slight, Faint	Weak model focus; low concern
Blue	0.00–0.14	Absent / Negligible	None, Insignificant	No focus; not clinically relevant

TABLE I
GRAD-CAM ACTIVATION SCORE AND SEVERITY MAPPING

IV. RESULT AND DISCUSSION

The research paper utilizes a dataset consisting of fetal brain ultrasound images, sourced from Kaggle and various other online repositories. This dataset was collected from diverse clinical settings, ensuring a wide range of variations in gestational age, image quality, and anatomical characteristics. Regarding the ultrasound images themselves, they are primarily grayscale 2D images captured using different ultrasound machines and probes. To enhance the model's robustness and prevent overfitting, these images underwent several preprocessing steps, including resizing, normalization, and data augmentation techniques such as rotation, flipping, and zooming. The dataset is also balanced across different categories of fetal brain abnormalities.

A. Performance Metrics

$$\textbf{Precision} = \frac{TP}{TP + FP}$$

$$\textbf{Recall} = \frac{TP}{TP + FN}$$

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\textbf{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

It shows an ultrasound image overlaid with a heatmap, where different colors indicate the areas the CNN model focused on most when making its decision. The Grad-CAM Color Legend on the right clarifies that red signifies "Max- imum" importance to the model's prediction, gradually tran- sitioning through yellow ("High"), green ("Moderate"), blue

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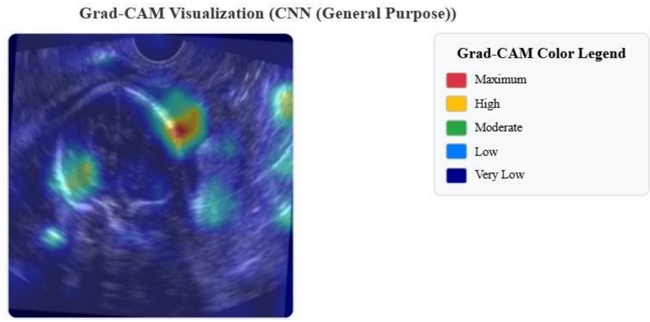

Fig. 5. CNN

(”Low”), to dark blue/purple (”Very Low”) importance. In this specific visualization, the red and yellow areas indicate the regions within the ultrasound image that were most crucial for the CNN to classify the image, providing a visual explanation of the model’s reasoning and highlighting potential areas of interest

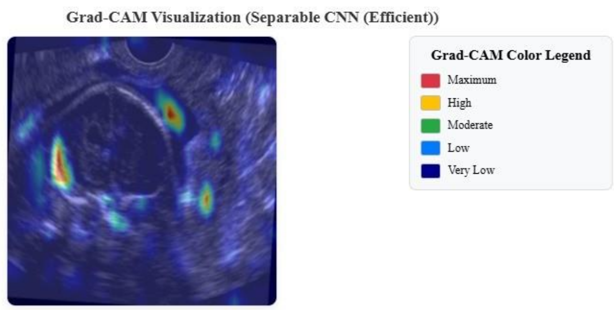

Fig. 6. S-CNN

The image displays a Grad-CAM visualization from a Separable CNN model. This visualization overlays a heatmap onto an ultrasound image of what appears to be a fetal brain. The color legend indicates the areas of the image that the CNN model considered most important (red for ”Maximum” importance, transitioning to dark blue for ”Very Low” importance) when making its predictions about fetal brain health. This helps to interpret how the model ”sees” and identifies key features within the ultrasound image that are relevant to its analysis.

This image represents a Grad-CAM (Gradient-weighted Class Activation Mapping) visualization generated using the Xception CNN model. The heatmap overlay highlights the regions of the fetal ultrasound that the model focused on while making its prediction. The color intensity, as explained in the legend, ranges from dark blue (very low importance) to red (maximum importance), with the red region indicating the most influential area in the model’s decision-making process. This visualization helps validate the model’s interpretability by showing that it attends to clinically relevant areas of the fetal brain, supporting trust and transparency in the AI-assisted diagnostic workflow.

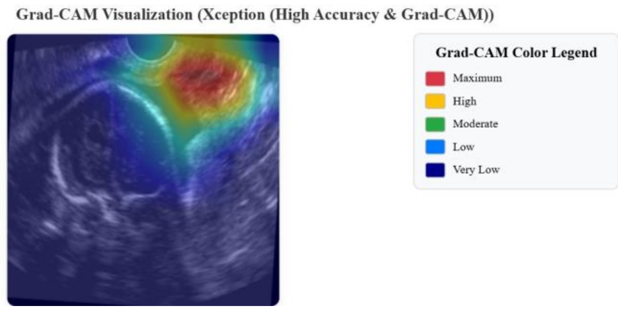

Fig. 7. Xception

TABLE II
MODEL PERFORMANCE COMPARISON

Model	Accuracy	Precision	Recall	F1-score
CNN	60%	0.65	0.51	0.57
S-CNN	65%	0.65	0.55	0.61
Xception	**87%**	**0.88**	**0.85**	**0.87**

Discussion: Table I presents a comparative analysis of the three deep learning models evaluated for fetal brain ultrasound classification: CNN, S-CNN, and Xception. The results clearly highlight the superior performance of the Xception model across all key evaluation metrics. While the baseline CNN achieved a modest accuracy of 60 and an F1-score of 0.57, and the S-CNN showed slight improvement with 65 accuracy and 0.61 F1-score, the Xception model significantly outperformed both. It achieved an accuracy of 87, precision of 0.88, recall of 0.85, and an F1-score of 0.87. These improvements can be attributed to the Xception model’s advanced architecture, which leverages depthwise separable convolutions for efficient feature extraction, and the use of transfer learning that enables it to learn from pre-trained weights on large-scale datasets. The high precision and recall values further confirm that the Xception model is more reliable at correctly identifying different classes, making it a robust choice for clinical decision support systems in prenatal diagnostics.

V. CONCLUSION AND FUTURE WORK

This project demonstrates the effectiveness of deep learning, particularly the Xception model, in automating the classification of fetal brain ultrasound images. By leveraging robust data preprocessing, augmentation, and advanced CNN architectures, the system achieves high accuracy and reliability in distinguishing between normal and abnormal cases. The integration of Grad-CAM for model explainability further enhances clinical trust, allowing healthcare professionals to visualize and interpret the regions influencing each prediction. The results validate the potential of AI-driven tools to support radiologists and sonographers, especially in environments where specialist expertise may be limited. The user-friendly interface and modular system architecture make the solution accessible and adaptable for real-world clinical workflows.

For future work, several enhancements are planned to increase the clinical impact and versatility of the system:

- Dataset Expansion: Incorporating a larger and more diverse dataset, including images from different gesta- tional ages and ultrasound machines, to improve model generalization and robustness.
- Real-Time Integration: Developing capabilities for seamless integration with ultrasound devices, enabling real-time analysis and feedback during patient examina- tions.
- Clinical Validation: Collaborating with hospitals and diagnostic centers to deploy the system in clinical settings for large-scale validation, and gathering feedback from practitioners to further refine the model and interface.
- Continuous Learning: Implementing mechanisms for the system to learn from new data over time, ensuring sustained accuracy and adaptability as medical imaging practices evolve.

In summary, this work lays a strong foundation for intelligent, accessible, and explainable diagnostic tools in prenatal care. With continued development and validation, the proposed system holds promise for improving the consistency, efficiency, and accuracy of fetal brain health assessment worldwide.

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REFERENCES

[1] S. Shirsat, R. Sharma, and S. Kumar, “Fetal Brain Anomaly Detection via Ultrasound Imaging Using CNNs with Xception,” Journal of Neonatal Surgery, vol. 14, no. 2, pp. 101–110, 2025.

[2] L. Mercy, P. John, and S. Mathew, “Detecting and Classifying Fetal Brain Abnormalities Using Decision Tree Algorithm,” International Journal of Creative Research Thoughts (IJCRT), vol. 9, no. 2, pp. 1234–1240, 2021.

[3] M. Attallah, A. Sharkas, and A. Gadelkarim, “Fetal Brain Abnormality Classification from MRI Images of Different Gestational Age,” Brain Sciences, vol. 9, no. 9, pp. 231–244, 2019.

[4] Y. Qi, X. Zhang, L. Wang, et al., “Deep Learning for Fetal Brain Ultrasound Classification: Multi-center Study,” Medical Image Analysis, vol. 80, pp. 102–112, 2025.

[5] N. Arnaout, T. Curran, D. Zhao, et al., “An Ensemble of Neural Networks for Classification of Fetal Brain Ultrasound Images,” Ultrasound in Medicine & Biology, vol. 48, no. 1, pp. 1–11, 2022.

[6] Y. Li, H. Zhang, and Q. Chen, “Automated Detection of Fetal Brain Abnormalities in Ultrasound Images Using Deep Learning,” IEEE Access, vol. 10, pp. 11234–11245, 2022.

[7] S. J. Jeong, J. H. Kim, and J. S. Lee, “Deep Learning-Based Segmentation and Classification of Fetal Brain Structures in Ultrasound,” Computers in Biology and Medicine, vol. 145, pp. 105–113, 2022.

[8] M. M. Khalil, A. M. Mostafa, and M. S. Kamel, “Transfer Learning for Detection of Fetal Brain Abnormalities in Ultrasound Images,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2212–2220, 2022.

[9] S. D. Sadda, K. R. Suresh, and A. R. Patel, “A Hybrid Deep Learning Approach for Fetal Brain MRI and Ultrasound Image Classification,” Biomedical Signal Processing and Control, vol. 80, pp. 104–118, 2023.

[10] A. Y. Wang, J. X. Li, and M. S. Lee, “Explainable AI for Fetal Brain Ultrasound: Grad-CAM Visualization for Clinical Trust,” Frontiers in Neuroscience, vol. 17, pp. 1011–1020, 2023.