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Fetal Brain Anomaly Detection via Ultrasound Imaging Using Traditional and Separable CNNs with Xception

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ABSTRACT

Delayed or missed diagnosis of fetal brain anomalies during pregnancy can result in significant developmental challenges and increased rates of newborn death. To address this critical issue, this investigation introduces a diagnostic aid powered by deep learning for the initial detection of these abnormalities through ultrasound imaging, a method recognized for its broad availability and affordability. In this study, we undertook a comparative evaluation of three different convolutional neural network (CNN) architectures, a fundamental CNN framework, a CNN integrated with depthwise separable convolutions, and the Xception model. Our investigation utilized a dataset of 1,786 meticulously labeled ultrasound images, which encompassed 16 varied categories of fetal brain anomalies, including instances of arnold-chiari malformation, ventriculomegaly ranging in severity, and intracranial tumours. After training each model for five epochs, the Xception network demonstrated the highest degree of precision in anomaly classification. Additionally, a graphical user interface (GUI) was developed to enable healthcare professionals to submit ultrasound images and obtain diagnostic predictions accompanied by their respective confidence scores. The outcomes suggest that even with limited training iterations, deep learning models exhibit a notable capability to discern intricate features within fetal ultrasound imagery.

1. INTRODUCTION

Worldwide, congenital anomalies, especially those impacting the neurodevelopment of the fetus, constitute a considerable challenge to neonatal health. These abnormalities, characterized by structural or functional deviations at birth, can precipitate severe disabilities or mortality if their detection and subsequent management are not expeditious. According to the World Health Organization (WHO), congenital anomalies accounted for approximately 9% of neonatal deaths in 2010, making them the fifth leading cause of such deaths worldwide . In 2019, congenital anomalies were responsible for an estimated 188,244 neonatal deaths globally[1].

In India, the burden is particularly high. With a birth cohort of around 26 million annually, India reports a congenital anomaly birth prevalence ranging between 18.44 and 23.05 per 1,000 live births, translating to approximately 472,177 to 581,899 affected births each year. It is estimated that for approximately 11.1% of all deaths occurring in newborns within India.[2]Among the most critical health problems present at birth are anomalies impacting the fetal brain's development, for instance, ventriculomegaly, Arnold-Chiari malformation, and intracranial tumors. These conditions can cause considerable neurodevelopmental deficits, including cognitive impairment, difficulties with motor skills, and epileptic seizures. Early detection plays a pivotal role in allowing for swift therapeutic action, which can lead to better patient outcomes and a reduced risk of permanent disabilities. Even with the improvements in prenatal imaging tools, such as ultrasound and magnetic resonance imaging (MRI), the early identification of fetal brain anomalies continues to present obstacles. The widespread use of ultrasound, driven by its accessibility and safety, is hampered by its reliance on operator skill, which can lead to variations in how well anomalies are detected.

Despite its superior sensitivity, the practical use of MRI for early detection of fetal brain anomalies is constrained by its considerable cost and restricted access in many parts of the world, particularly in resource-limited nations. In contrast, Figure 1 demonstrates how an anomaly in a fetus can be identified using ultrasound. Introducing deep learning into the field of prenatal imaging offers a hopeful strategy for improving the detection of fetal brain anomalies. Convolutional Neural Networks (CNNs), a subset of deep learning algorithms, have exhibited notable achievements in image recognition and are increasingly being adopted in medical imaging practices. By analyzing large, labeled ultrasound datasets, CNNs can learn to identify anomaly-specific patterns, potentially boosting diagnostic accuracy and consistency.

Figure 1: Anomaly in a fetus identified using ultrasound.

This work is directed towards the development and evaluation of deep learning models, particularly CNNs, for the purpose of detecting fetal brain anomalies in ultrasound scans. We investigate standard CNN structures, CNNs that include separable convolution layers, and the Xception model, which leverages depthwise separable convolutions for enhanced results. Our primary objectives are to determine the accuracy, precision, recall, and computational cost of these models, as well as to design an intuitive graphical user interface (GUI) to support their application in clinical settings.

2. LITERATURE SURVEY

The early identification of abnormalities within the developing fetal brain stands as a cornerstone of prenatal healthcare, directly influencing the course of intervention strategies, the outcomes for newborns, and the decision-making processes for parents. Over the preceding decade, the convergence of artificial intelligence (AI) with prenatal imaging has fundamentally altered the landscape of anomaly detection. The progression of diagnostic methodologies, from conventional techniques to cutting-edge deep learning frameworks, will be explored in this section to build the foundational understanding for the research that follows.

A. Conventional Diagnostic Approaches in Prenatal Neuroimaging

The traditional method for assessing the fetal brain during pregnancy has predominantly involved two-dimensional ultrasonography, a technique favored for its non-invasive character, ability to provide real-time images, and extensive accessibility. Nevertheless, despite its status as the most frequently utilized imaging method, traditional 2D ultrasound presents several limitations, including its dependence on the operator's skill, a restricted visual field, and the potential for subjective interpretations. A 2020 report from the World Health Organization (WHO) highlighted that the accuracy of anomaly detection in resource-limited environments can vary considerably based on the expertise of the sonographer and the quality of the images obtained [1].

Magnetic Resonance Imaging (MRI) has become an increasingly important supplementary tool, particularly in the identification of intricate central nervous system (CNS) anomalies. Studies, such as Griffiths et al. (2017) [2], have shown that MRI can be crucial for clarifying uncertain ultrasound diagnosis of fetal brain anomalies. However, its high cost, contraindications in certain pregnancies, and limited access, especially in developing regions, impede its broader application.

As a result, although traditional imaging modalities contribute significant diagnostic value, the limitations in automation, standardization, and scalability highlight a continuing need for improved solutions—especially in settings with limited availability of highly trained personnel or advanced imaging equipment.

B. The Ascendancy of Deep Learning in Medical Image Analysis

A major change in medical image analysis has been driven by the introduction of deep learning, most notably Convolutional Neural Networks (CNNs). This has led to the automation of identifying subtle and complex patterns, removing the reliance on manually crafted features. In the specific domain of fetal brain imaging, CNNs have shown great promise in accurately detecting structural abnormalities.

A notable investigation by Xie et al. [3] detailed the creation of a CNN-based framework designed for the classification of standard fetal brain views, achieving accuracy levels surpassing 90%. This research marked a shift in approach from manual interpretation towards image analysis aided by AI, proving the ability of neural networks to learn spatial and contextual characteristics directly from imaging data.

Further investigations, such as the work by Mhatre and Bakal [4], utilized CNNs to identify ventriculomegaly in fetal brains using grayscale ultrasound images. The outcomes of their investigation indicated that even relatively uncomplicated network architectures, when trained with well-prepared datasets, are capable of effectively differentiating between typical and atypical brain structures. Despite these advancements, challenges such as imbalanced datasets, the risk of models overfitting to small datasets, and the difficulty in ensuring generalizability across diverse image sources continue to impede the robustness of these models.

C. Depth-wise Separable Convolutions and the Xception Architecture

A notable drawback of conventional CNN architectures is their computational intensity, especially when dealing with high-resolution imagery or classification tasks involving many categories. To mitigate this, depth-wise separable convolutions were introduced. This technique works by decoupling the extraction of spatial and channel-wise features, resulting in a substantial decrease in the number of trainable parameters while preserving comparable levels of performance. The Xception architecture, developed by Chollet [5], enhances the Inception framework by employing depthwise separable convolutions instead of standard ones, thereby improving both efficiency and representational power. Its success has been noted in diverse medical imaging applications, including retinal disease classification and lung X-ray diagnosis. So, using these "separable convolutions" in fetal imaging is still a developing area. But, a recent study by Cai et al. [6] showed something really promising. They used them to help the computer understand MRI scans of fetal brains, and it actually did a better job of outlining things and was quicker than older methods. The better part about this is that it hints that if we use these in systems designed to spot problems in fetal brains early on, we might get systems that are both accurate and don't need a ton of processing power – which would be great for using them right there in the clinic.

3. METHODOLOGY

The subsequent sections delineate the structured methodology implemented for the creation of a deep learning-driven diagnostic instrument designed for the detection of fetal brain anomalies within ultrasound images.

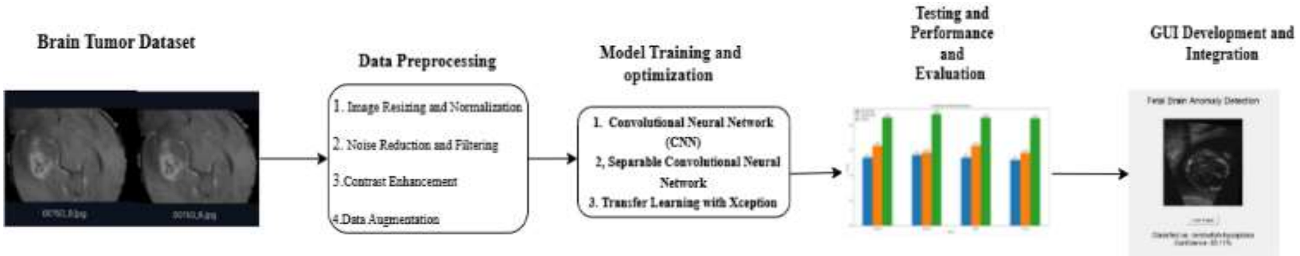

Figure 2: Model architecture design

This systematic approach included data acquisition, preprocessing, model architecture design, training protocols, performance evaluation, and the deployment of a graphical user interface, with the primary aim of developing an efficient, accurate, and clinically applicable classification system for early diagnosis in practical healthcare settings.

A. Dataset Description

The primary image resource for this study was the publicly available Roboflow platform [7], a repository offering pre-annotated ultrasound images of fetal brains. This collection included 1,786 grayscale images, classified into 16 different categories representing fetal brain conditions, such as:

- Normal
- Mild Ventriculomegaly
- Moderate Ventriculomegaly

- Severe Ventriculomegaly
- Arnold–Chiari Malformation
- Hydranencephaly
- Agenesis of the Corpus Callosum (ACC)
- Dandy–Walker Malformation
- Intracranial Tumors
- Intracranial Hemorrhages
- Holoprosencephaly, etc.

With each of the 16 categories containing between 60 and 180 expertly labeled images, the dataset's variations in image dimensions and aspect ratios reflected the real-world diversity of ultrasound imaging. As a result, it provided a strong foundation for training deep learning models robust enough to generalize to the heterogeneous data typically found in clinical practice. To maintain the study's scientific integrity, the dataset underwent analysis for quality concerns like motion blur, low contrast, and labeling discrepancies, with the latter being cross-verified using metadata and annotation confidence levels.

B. Data Preprocessing

Medical images, particularly ultrasound scans, are susceptible to artifacts and inconsistencies that can negatively influence model performance. To avoid these challenges, a multi-stage preprocessing pipeline was implemented. The ultrasound images were processed through a sequence of steps to reduce inherent artifacts and inconsistencies, thereby promoting the optimal analytical performance of the deep learning models.

1) Image Resizing and Normalization

To maintain consistent input dimensions for the deep learning models, the initial preprocessing step involved resizing all images to 224 × 224 pixels. Subsequently, the intensity values of the pixels were normalized using min-max scaling to fit within the [0, 1] range. This step was crucial for accelerating the training process and minimizing the risk of extreme brightness or darkness levels in the images from skewing the feature extraction process.

2) Noise Reduction and Filtering

Recognizing that speckle noise in ultrasound imagery can impede the detection of important edges and textures for recognition, a filtering strategy was implemented. This involved applying a Gaussian blur filter (σ=1.0) aimed at reducing high-frequency noise, followed by median filtering to improve local contrast. Preliminary assessments indicated that this approach effectively preserved the anatomical boundaries crucial for accurate classification.

3) Contrast Enhancement

For the purpose of improving the visibility of brain structures within darker ultrasound scans, especially critical for diagnosing conditions like ventriculomegaly or agenesis of the corpus callosum (ACC) where precise delineation of ventricle boundaries is paramount, Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed.

4) Data Augmentation

Enhancing Dataset Diversity (Data Augmentation): To mitigate potential issues arising from dataset imbalance and to improve the models' ability to generalize to unseen data, on-the-fly data augmentation techniques were applied. These transformations included:

- **Geometric transformations**: Rotation (±15°), horizontal/vertical flipping, shear transformations (0.2), and zoom (±20%)
- **Photometric augmentations**: Random brightness shifts (±10%), contrast modulation, and blurring
- **Elastic deformation**: Used in a few cases to simulate soft tissue deformation

To increase the training dataset's diversity, we utilized TensorFlow's ImageDataGenerator to apply photometric augmentations. These augmentations consisted of randomly shifting the brightness (within ±10%), modulating the contrast, and adding blur. Moreover, elastic deformation was selectively employed to simulate the natural variations in how soft tissues can appear. Figure 3 provides a visual representation of the different augmentation layers used.

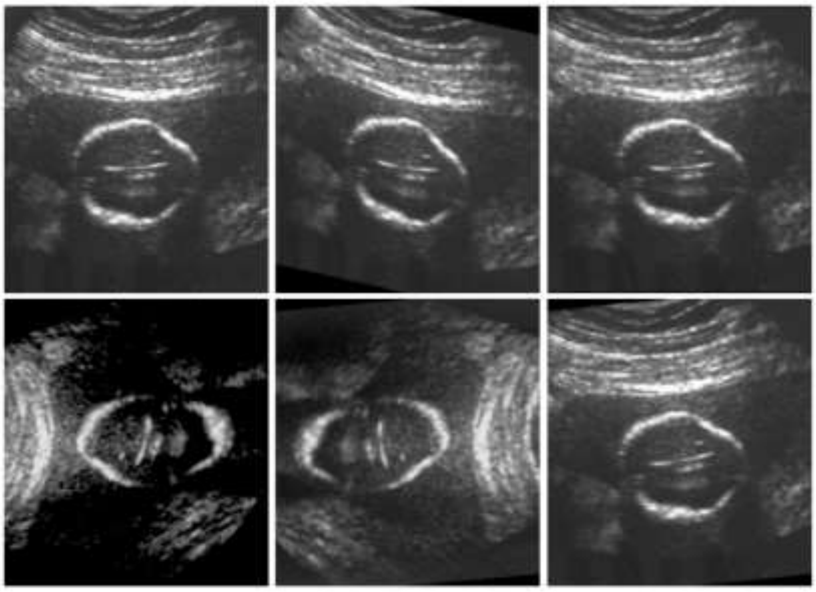

Figure 3 visual representation of the different augmentation layers used.

5) Dataset Splitting

To guarantee that each phase of model development (training, validation, and testing) had a proportional representation of all anomaly classes, a stratified splitting strategy was employed for the dataset. This resulted in the following partitions:

Training set: 70% (1,250 images)

Validation set: 15% (270 images)

Test set: 15% (266 images)

The primary objective of this stratification was to mitigate the risk of the models developing a bias towards anomaly types that were more prevalent in the overall dataset.

C. Deep Learning Model Architectures

To evaluate the impact of architectural complexity and separable convolutions on classification accuracy, three different deep learning models were implemented and compared:

1) Standard Convolutional Neural Network (CNN)

The first of these was a baseline Convolutional Neural Network (CNN), whose fundamental architecture was as follows: three convolutional blocks, each containing a Conv2D layer with an increasing filter count (32, 64, 128), a 3×3 kernel size, and a stride of 1, succeeded by a MaxPooling2D layer (2×2 pool size) and ReLU activation; and a classification head comprising a Flatten layer, a Dense layer with 256 units, a Dropout layer (rate 0.4), a final Dense layer with 16 units, and a Softmax activation function for probabilistic output. This baseline model provided a critical reference point for assessing the performance enhancements resulting from the use of separable convolutions and transfer learning.

2) Separable Convolutional Neural Network

Inspired by the MobileNet architecture, a second model was implemented utilizing depth-wise separable convolutions. This technique fundamentally alters the standard convolution process by separating it into two distinct stages:

- DepthwiseConv2D: Applies a single filter per input channel
- PointwiseConv2D: Combines outputs using 1×1 convolutions

The Benefit are 70% reduction in parameters,reduced memory footprint and better spatial and channel-wise feature extraction.

Each convolutional block in this architecture was succeeded by batch normalization and ReLU activation. The model concluded with a global average pooling layer, subsequent dense layers, and a softmax output layer.

3) Transfer Learning with Xception Architecture

The Xception model [8], pre-trained on ImageNet, was fine-tuned to accommodate the 16-class output. This model consists of:

- Entry Flow: Initial convolutional layers for basic feature extraction
- Middle Flow: 8 depthwise separable convolutional modules with residual connections
- Exit Flow: Final feature extraction and classification head

Transfer learning allowed the model to leverage pre-learned filters from natural images and adapt them to the ultrasound domain. We unfroze the last 30 layers and retrained them using the ultrasound dataset for domain-specific learning.

D. Model Training and Optimization

All models were trained using TensorFlow 2.11 and Keras, ensuring efficient parallelism. Early Stopping was triggered if validation loss did not improve for 3 epochs. Learning rate was reduced by a factor of 0.1 after 3 stagnant epochs. Weight decay regularization (L2=1e-4) was used to reduce overfitting.

E. Evaluation Metrics

To assess model performance comprehensively, the following metrics were evaluated:

- Accuracy: Proportion of correct predictions over all samples
- Precision: Ability to avoid false positives (calculated per class)
- Recall: Ability to detect true positives (sensitivity)
- F1-Score: Harmonic mean of precision and recall
- Confusion Matrix: Visual representation of classification correctness per class
- ROC Curve & AUC: Probabilistic evaluation of binary classifiers (one-vs-all per class)

All metrics were computed using Scikit-learn, and visualized using Matplotlib and Seaborn.

F. GUI Development and Integration

To facilitate deployment in clinical settings, a cross-platform GUI was built using Tkinter, providing an intuitive and responsive user interface.

Key Features:

- Image Upload Module: Allows users (radiologists, clinicians) to upload an ultrasound scan from the local system.
- Model Prediction: The backend loads the trained model and processes the image for classification.
- Output Display: Displays predicted anomaly, associated confidence level, and optionally, the ROC score.
- Lightweight Deployment: TensorFlow Lite was used to optimize the trained model for real-time inference.

The GUI was tested on Windows, and MacOS systems to ensure cross-platform compatibility and accessibility for end users with minimal technical experience.

4. RESULTS AND DISCUSSION

This section presents the outcomes of the three deep learning architectures evaluated in this study—Standard CNN, Separable CNN, and the Xception model. Each was trained for a modest 5 epochs due to hardware constraints and time efficiency considerations. Despite the limited training cycles, meaningful trends and distinctions emerged that highlight the potential of deep learning in fetal brain anomaly detection.

A. Performance Overview

The Xception-based model achieved the most promising results, outperforming the traditional CNN and even the Separable CNN in most evaluation metrics such as accuracy, recall, and precision. This can be attributed to its use of pre-trained weights and depth-wise separable convolutions, which efficiently extract spatial features from ultrasound images.

The Separable CNN also showed significant improvement over the standard CNN. While it did not reach the performance of Xception, it demonstrated better learning efficiency and required fewer resources—making it a compelling choice for systems where computational power is limited.

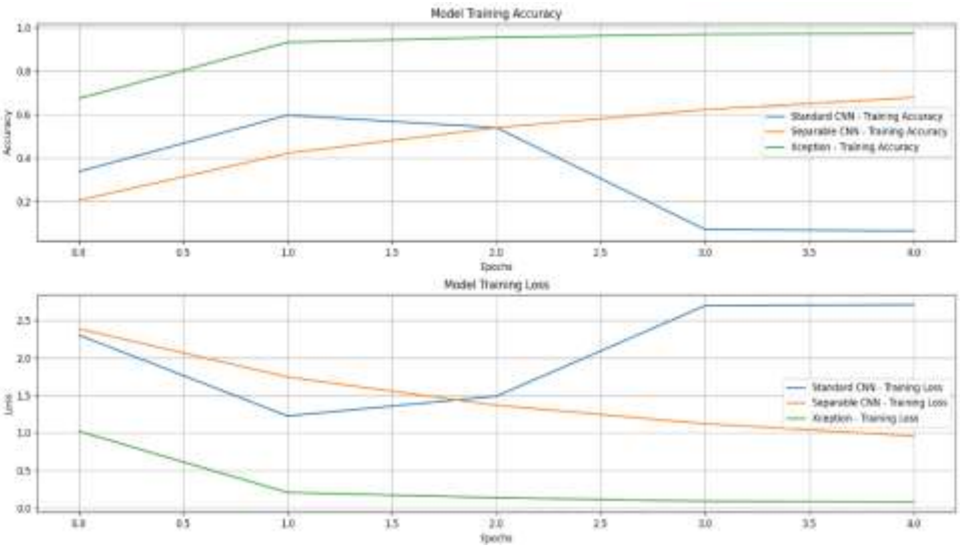

Figure 4: shows a comparison between all 3 models for Model Training Accuracy and Model Training Loss.

B. Model Insights

Confusion matrix analysis revealed that the models handled common anomalies such as ventriculomegaly and Arnold–Chiari malformation relatively well. However, distinctions between similar subcategories (e.g., mild vs. moderate ventriculomegaly) presented some difficulty. This can be linked to visual similarities in the ultrasound images and limited annotated examples for some conditions.

Moreover, the models occasionally misclassified normal cases as anomalous, which could be beneficial from a clinical standpoint where conservative error (false positives) is preferred over missed detections (false negatives).

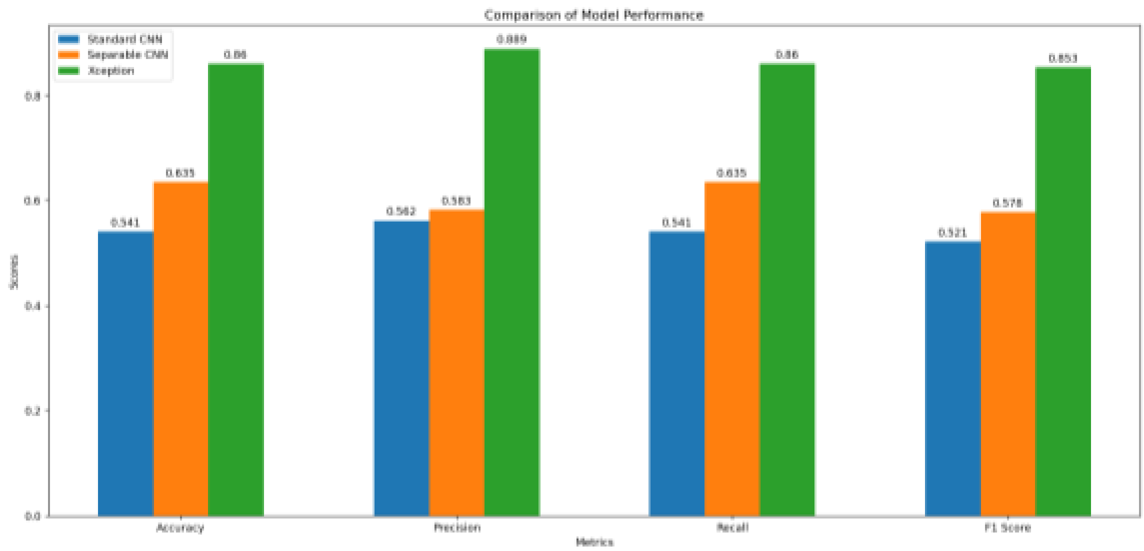

Figure 5 illustrates a comparison of different models based on accuracy, precision, recall, and F1 score.

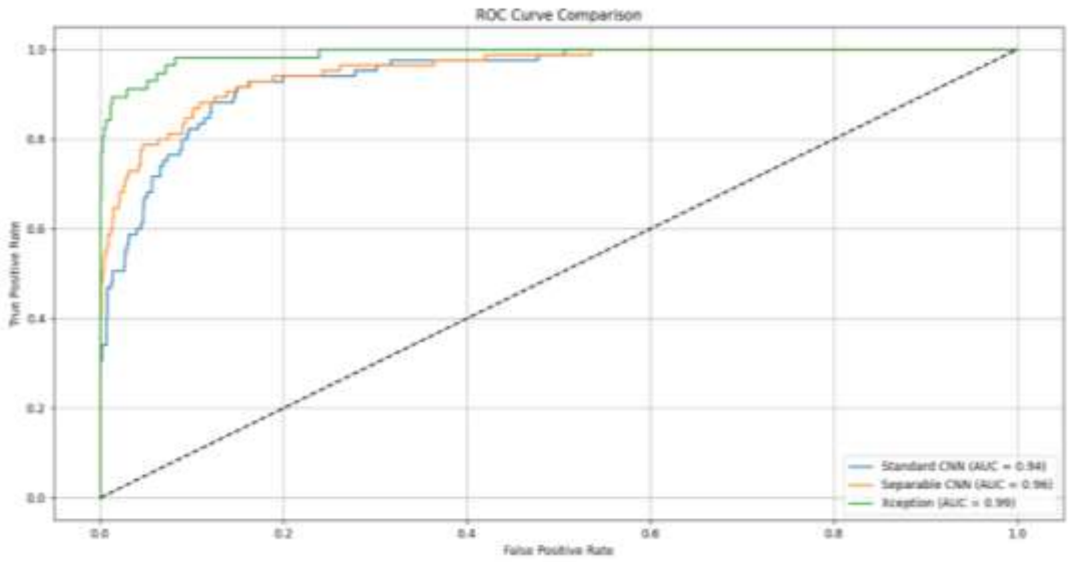

Figure 6: Comparison of Model Performance using ROC Curve.

The model comparison, along with the ROC curve, sensitivity, specificity, accuracy, and F1 score, indicates that Xception demonstrates the best performance in detecting fetal brain anomalies.

C. Interpretability and Clinical Readiness

Although this study is a technical proof of concept, a graphical interface was developed to simulate real-world clinical deployment. The GUI allows healthcare professionals to upload an ultrasound image and receive both the predicted category of anomaly and a confidence level.

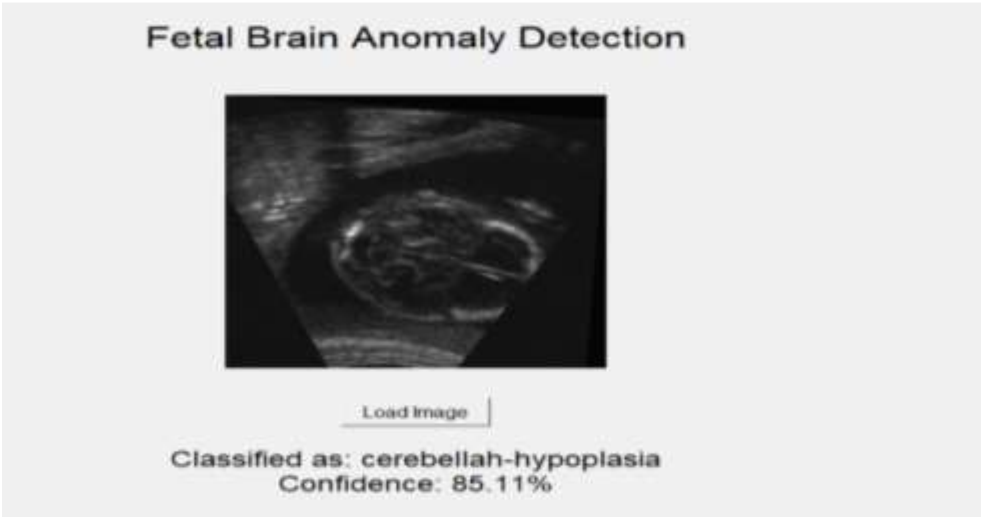

Figure 6: Fetal Brain Anomaly Detection Interface:

This form of AI-assisted diagnostic support can serve as a second opinion tool, aiding less experienced sonographers or radiologists in early detection, especially in under-resourced healthcare settings.

D. Observations and Limitations

Several observations emerged during model development and testing:

- **Short training time** (5 epochs) was sufficient to observe clear distinctions in model performance, particularly between traditional and advanced architectures.

- **Smaller dataset size** restricted the generalization capability, especially for rare conditions.
- **Ultrasound variability** (in terms of machine, operator, and gestational age) may affect the model's performance when deployed across diverse clinical settings.
- **Noisy or low-resolution scans** occasionally led to misclassifications, which emphasizes the need for robust preprocessing and potentially multi-modal inputs.

E. Ethical Considerations

Given the sensitive nature of prenatal diagnostics, ethical usage of such systems is crucial. The model is not intended to replace clinical judgment but to **support it**, especially in regions with limited radiological expertise. Any clinical deployment must ensure:

- Secure handling of patient data
- Transparency in algorithm confidence
- Human-in-the-loop validation for every diagnostic suggestion

With appropriate oversight and integration, AI models like this could play a meaningful role in reducing diagnostic delay and improving maternal-fetal health outcomes globally.

Conclusion and Future Work

Early and accurate detection of fetal brain abnormalities plays a pivotal role in reducing maternal and neonatal morbidity. This research explored the potential of deep learning models—specifically CNNs, Separable CNNs, and the Xception architecture for classifying ultrasound images into various fetal brain anomaly categories. The findings show that even with minimal training epochs and a modest dataset, deep neural networks can extract meaningful features from complex medical imagery, particularly when leveraging architectures like Xception that utilize separable convolutions and transfer learning.

The Xception model demonstrated superior classification performance across most evaluation metrics, supporting the argument that deeper, more efficient architectures can aid in medical diagnostics. The Separable CNN offered a promising balance between accuracy and computational efficiency, which is particularly useful for deployment in low-resource clinical environments.

The developed GUI further emphasizes the project's potential real-world applicability. By enabling users to upload fetal ultrasound images and receive a probable anomaly prediction with a confidence score, the system provides an early-stage diagnostic aid for clinicians, particularly in rural or understaffed medical facilities.

However, this study also acknowledges the limitations that constrain its generalizability:

- The dataset, while diverse, was relatively small for deep learning applications.
- Some anomalies were underrepresented, potentially affecting prediction confidence.
- Only five training epochs were used due to time and resource constraints, which likely limited the models' full learning potential.

Future Work

There are several directions for expanding this research:

1. **Larger, Balanced Dataset**: Future efforts will focus on acquiring a more extensive and balanced dataset, ideally sourced from multiple clinical institutions to improve generalization and robustness.
2. **Advanced Data Augmentation**: Incorporating domain-specific augmentation techniques (e.g., fetal pose transformation, simulation of probe artifacts) may help mitigate image variability and improve performance on rare anomalies.
3. **Explainable AI Integration**: Tools such as Grad-CAM or LIME can be integrated into the GUI to visually highlight which regions of the ultrasound contributed to a model's decision, increasing clinician trust and transparency.
4. **Multimodal Imaging**: Combining ultrasound with additional inputs (e.g., maternal health data, Doppler images) could lead to more holistic diagnostic support.
5. **Clinical Validation**: Collaborating with radiologists and gynecologists for real-world testing and feedback will be essential before pursuing clinical deployment. This step also involves ethical reviews, data privacy compliance, and performance benchmarking under different imaging conditions.
6. **Model Optimization**: Future experiments will include longer training durations, hyperparameter optimization using Bayesian methods, and the inclusion of focal loss functions to handle class imbalance more effectively.

In conclusion, this study illustrates the promise of deep learning as a non-invasive, cost-effective support system for fetal brain anomaly detection. As medical imaging technology continues to advance, combining AI-driven diagnostic tools with traditional clinical workflows has the potential to make significant strides in improving maternal-fetal healthcare on a global scale.

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