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Original Article

Deep Learning-Based Detection of Fetal Brain Anomalies in Ultrasound Images: A Novel Approach

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Abstract *- Early detection of fetal brain anomalies is critical for ensuring appropriate medical care. This paper presents an improved deep learning approach integrating image super-resolution with advanced classification techniques. Unlike prior work, we introduce a custom fine-tuned deep learning pipeline that enhances low-resolution ultrasound images before classification. The novel proposed architecture incorporates a modified Enhanced SRGAN for super-resolution and an optimized CNN classifier integrating VGG16, ResNet, and DenseNet features. A dataset of 4,000 grayscale ultrasound images (512×512 pixels) was collected and categorized into four classes: normal, cerebellum anomalies, thalamic anomalies, and ventricular anomalies. To address class imbalance (1039 normal vs. 2961 abnormal), oversampling, augmentation, and class-weighted loss functions were applied. Unlike previous studies, we provide a comprehensive performance analysis using accuracy (92.94%), precision, recall, F1-score, and confusion matrices, demonstrating the impact of super-resolution on classification accuracy. This research significantly improves fetal brain anomaly detection and establishes a robust deep learning pipeline for clinical applications.*

Keywords *- Fetal brain ultrasound images, CNN, VGG16, ResNet, DenseNet, Image super resolution.*

1. Introduction

Fetal brain anomalies are among the most serious and life-altering congenital disorders, contributing to long-term neurological deficits, developmental delays, or even fetal demise. According to the World Health Organization, congenital anomalies affect approximately 1 in 33 infants globally, and brain abnormalities account for a significant proportion of these cases. Timely and accurate detection of such anomalies during pregnancy is crucial for early intervention, informed decision-making by parents, and appropriate perinatal care. Ultrasound remains the most widely used imaging modality in prenatal care due to its safety, affordability, and real-time imaging capability.

However, detecting subtle fetal brain abnormalities from ultrasound images is a challenging task due to low image resolution, operator dependency, and limited availability of expert radiologists. These challenges can result in missed diagnoses, particularly in resource-constrained clinical settings. Recent advancements in deep learning have shown great promise in automating medical image analysis. In particular, Convolutional Neural Networks (CNNs) have demonstrated high performance in classification and anomaly detection tasks. Yet, existing studies often overlook the impact of poor image resolution in fetal ultrasound scans, which hinders the ability of models to extract fine-grained structural features necessary for accurate classification.

1.1. Research Gap

Most existing approaches either focus solely on classification or apply generic super-resolution techniques without tailoring them to the characteristics of fetal brain images. There is limited work on integrating advanced super-resolution with optimized deep learning classifiers specifically designed for ultrasound-based fetal brain anomaly detection.

1.2. Objective

This study proposes a novel two-stage deep learning pipeline that first enhances image resolution using a modified Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) and then classifies the improved images using a custom CNN model that integrates the strengths of VGG16, ResNet, and DenseNet architectures. Our primary contributions include:

- A customized Enhanced SRGAN model for improving the resolution of fetal brain ultrasound images.
- A novel CNN classifier combining the best features of VGG16, ResNet, and DenseNet for accurate anomaly classification.
- Detailed comparison of model performance across original and super-resolved images.
- A new dataset with 4,000 labeled ultrasound images representing four specific categories: normal, cerebellum, thalamic, and ventricular anomalies.

2. Problem Formulation and Research Gap

Despite the progress in deep learning-based medical image classification, a significant challenge in fetal brain anomaly detection remains: the poor quality of ultrasound images and class imbalance in datasets. Moreover, existing models do not jointly optimize super-resolution and classification in an end-to-end or interdependent framework, often leading to suboptimal diagnostic Accuracy.

2.1. Problem Statement

How can we improve the diagnostic performance of deep learning models in fetal brain anomaly detection from low-resolution ultrasound images?

2.2. Research Gap

1. Lack of integration between image super-resolution and classification.
2. Insufficient handling of class imbalance and data augmentation.
3. Limited comparative performance analysis with existing CNN architectures.

2.3. Our Approach

To address these gaps, this research proposes a unified deep learning pipeline that performs image enhancement followed by robust classification, using:

- Modified ESRGAN integrated with perceptual loss from VGG16 for super-resolution.
- A custom CNN classifier trained using cross-validation and weighted loss functions.
- Comparative evaluations against VGG16, DenseNet, ResNet, and traditional CNNs using accuracy, precision, recall, F1-score, and confusion matrices.

The goal is to build a clinically viable model that can support radiologists in accurately diagnosing fetal brain anomalies, even in low-quality scans.

3. Review of Fetal Brain Anomalies

Fetal brain anomalies refer to a broad spectrum of structural, functional, and developmental abnormalities in a developing fetus's brain. These anomalies can arise due to various factors, including genetic mutations, environmental influences, or disruptions in normal brain development. The anomalies can vary widely in severity, from minor issues that may have little to no impact on the child’s future health to major malformations that can lead to significant neurological impairments or be incompatible with life. The consequences of fetal brain anomalies can range from mild developmental delays to severe disabilities, depending on the type and severity of the anomaly. Early detection through prenatal screening and diagnostic imaging is crucial for planning appropriate medical management and interventions. In some cases, prenatal therapy or surgery may be possible, while in others, the focus may be on managing the condition postnatally. Overall, fetal brain anomalies represent a significant area of concern in prenatal medicine due to their potential impact on the child’s future quality of life and the challenges they pose for both medical professionals and families.

A literature review focusing on brain fetal anomalies using deep learning approaches involves examining how advanced Artificial Intelligence (AI) techniques, specifically deep learning, are being leveraged to detect, classify, and potentially predict fetal brain anomalies. This review will explore the integration of deep learning models into prenatal imaging analysis, the outcomes of these approaches, and the challenges faced. Reviews of recent works on Deep Learning-Based Brain Fetal Anomaly Detection are included in this section.

The important problem of identifying fetal brain abnormalities-which can cause serious health problems and long-term complications-is discussed in Samhita Shivaprasad et al.'s study [1]. Early detection and management are critical to improving results. The researchers suggest a deep learning-based method to detect fetal brain abnormalities from ultrasound pictures. CNNs are employed in the procedure, and a subset of pre-trained models is expanded to include 100 more layers and optimised for improved anomaly classification performance. The 88-layer MobileNetV2, the 16-layer VGG16, the 50-layer ResNet50, and the 159-layer InceptionV3 transfer learning models are trained using two publicly accessible datasets of ultrasound pictures of the fetal brain. Of them, the MobileNetV2 architecture is particularly noteworthy, obtaining a noteworthy 90% classification accuracy in identifying fetal brain disorders.

Farzan Vahedifard et al. [2] created an automated workflow that uses a UNet-based Deep Learning (DL) model to measure the lateral ventricle in fetal brain MRI and classify cases as normal or ventriculomegaly (a diameter wider than 10 mm). They trained the DL model directly on the FeTA 2022 dataset, which was built for the purpose of performing image segmentation on brain tissue. During testing, they had 22 MRI cases in which the ventricle measurements were previously acquired, from which they subsequently obtained automatic measurements using their DL model. They achieved 95% accuracy for the classification of cases as normal vs ventriculomegaly, and they measured ventricle diameters with an error of less than 1.7 mm, which was consistent with the original radiologists' measurements. Specifically, the average difference between the DL model and the general and neuroradiologists' measurements was 0.90 mm and 0.82 mm, respectively. The AI model also produced 3D-reconstructed images of the anatomical structure for a better anatomical context.

Their statistical analysis demonstrated there was no significant difference in AI compared to radiologists' measurement as a group, although there was a significant difference between general and neuroradiologists. This is the first AI model to perform 2D linear measurements for ventriculomegaly using a 3D approach, with these findings suggesting the model's ability to provide accurate automated classifications of fetal brain MRIs. Ruowei Qu and others [3] Promising results were obtained in automatically identifying six standard planes of fetal brains in 2D ultrasound images using the developed Deep Learning-based approaches. These methods included a CNN and a CNN-based domain transfer learning approach.

In general, the Deep Learning-based frameworks fared better than other conventional techniques, indicating CNNs' enormous promise in this application. The study assessed the effectiveness of the suggested strategies using two datasets: one including 30,000 images from 155 individuals and another containing 1,200 images from a single subject over the course of the pregnancy. In contrast to a simple DNN or DNN combined with Support Vector Machine (SVM) framework, Kavita Shinde et al. [4] in this paper propose the Deep Hybrid Learning (DHL) method, which combines Deep Neural Network (DNN) with Random Forest (RF) classifier, to achieve better classification results for fetal brain abnormality detection. The DNN+RF model outperformed earlier state-of-the-art techniques with an Area Under Curve (AUC) of 94% for training and 87% for validation. According to T. Singh et al. [5] in this research, fetal abnormality detection and prenatal diagnosis depend heavily on the precise identification and visualisation of the fetal face. 3D ultrasonography is increasingly often employed in obstetric scans; nonetheless, it can be difficult and time-consuming for the sonographer and trained expert to choose the best plane for visualising the fetal face. In this study, we offer a unique method employing 3D ultrasound volumes for fetal face recognition and visualisation.

The method for teaching a Deep Learning network to recognise, segment, and visualise fetal faces is innovative. The suggested method automatically recognises the location and orientation of important landmarks and the fetal facial surface, given a 3D ultrasound volume. The results show that the proposed method has outstanding detection accuracy while dealing with many foetuses, such as twins or triplets, as well as single foetuses.

4. The Proposed System

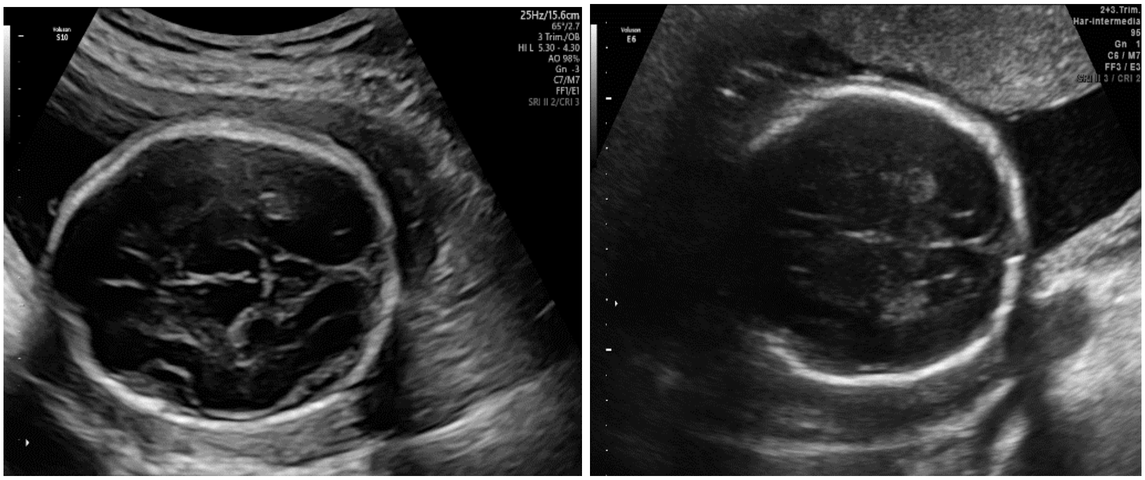
The proposed approach consists of two parts. Image Super resolution 2. Fetal Anomalies Detection. This proposed research methodology detects three important types of fetal brain anomalies. Initially, Image super-resolution was performed on the fetal brain ultrasound dataset, then fetal abnormalities were classified according to the three types. Finally, Accuracy is used to evaluate the model's performance.

4.1. Fetal Brain Ultrasound Dataset

- Dataset: 4,000 ultrasound images (512×512 pixels) from Vivaan Diagnostics and SDRC.
- Class Distribution: Class 1: Normal (1039), Class 2: Cerebellum Anomalies (1000), Class 3: Thalamic Anomalies (980), Class 4: Ventricular Anomalies (981).
- Data Augmentation: Rotation, flipping, Gaussian noise, and intensity normalization applied.
- Addressing Class Imbalance: Oversampling minority classes and using weighted loss functions.

Class-1 Normal Image

Class-2 Cerebellum Image



Class-3 Thalamic Image Class-4 Ventricular Image

Fig. 1 Sample fetal brain ultrasound images (Source: Text follows)

4.2. Image Super-Resolution

The images that are obtained or used for medical imagery are generally in low resolution. One technique that can be used to increase the image's resolution is Single Image Super Resolution [16-18]. Extensive research has been done in image super-resolution, but detecting fetal congenital anomalies using ultrasound is very challenging. So, image super-resolution techniques can be used to detect this anomaly using different deep learning algorithms [19, 20]. So, the proposed deep learning algorithm for image super resolution is Enhanced SRGAN with VGG16, which is represented in Figure 2 below.

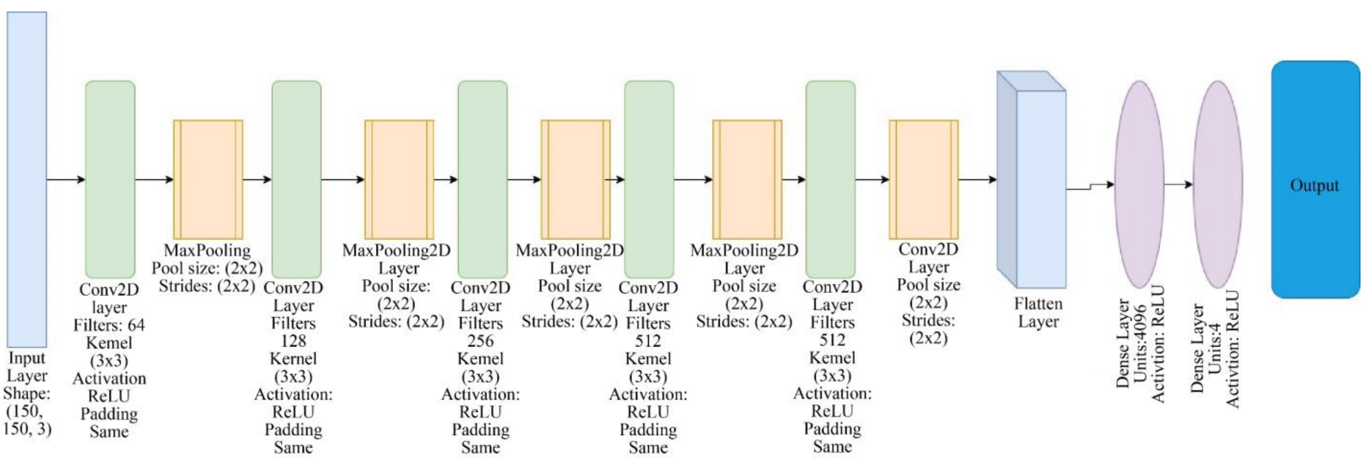


Fig. 2 The novel proposed system for image super resolution process

Figure 2 depicts a novel super-resolution architecture using deep learning

4.3. Key Components

1. Input Layer: Accepts 150×150×3 RGB images.
2. Convolutional Layers: Uses 3×3 kernels, ReLU activation, and "same" padding, with filters increasing (64→128→256→512→512).
3. MaxPooling Layers: Downsamples feature maps using 2×2 pooling with a stride of 2.
4. Flatten Layer: Converts feature maps into a 1D vector.
5. Fully Connected Layers:
   - Dense Layer 1: 4096 units with ReLU activation.
   - Output Layer: 4 units with Softmax for classification.

4.4. Relation to ESRGAN & VGG19

- VGG19 Backbone: Acts as a feature extractor.
- ESRGAN Role: Likely used for image super-resolution, with VGG19 aiding perceptual loss calculation.

4.5. Evaluation Method

- The generator creates HR images from LR inputs.
- These generated images are passed through a pre-trained VGG16 network to extract their feature maps.
- Simultaneously, the original high-resolution images are also passed through VGG16.
- The perceptual loss is computed as the difference between the feature maps of the generated and real images at various layers of VGG16.

- The generator is trained to minimize this perceptual loss while also trying to fool the discriminator.

4.6. Fetal Brain Anomalies Detection

In this study, we propose an automated approach for fetal brain anomaly diagnosis from ultrasound images, based on deep learning. This paper's primary contribution is the classification of brain anomalies in fetuses at an early stage, prior to birth. The suggested technique uses a straightforward, adaptable approach with minimal processing overhead to classify a range of anomalies from ultrasound images. The general architecture of the proposed system is shown in Figure 3.

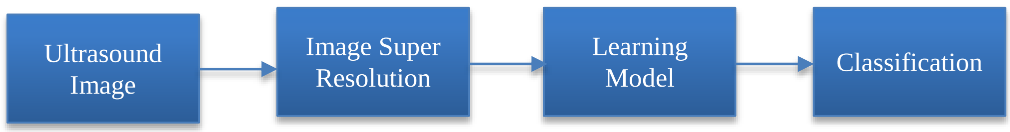


Fig. 3 General architecture of the proposed system

4.7. Classification Phase

Five deep learning classifiers are trained and tested during this stage using the fetal brain ultrasound dataset. CNN, VGG16, ResNet, Dense Net, and the proprietary algorithm are some of these classifiers. Five classifiers were validated using the 5-fold validation approach.

4.7.1. Basic CNN Model

A basic CNN model applies multiple layers of convolution, pooling, and fully connected layers to extract hierarchical features from input images and make accurate predictions.

The architecture is well-suited for tasks such as image classification, object detection, and segmentation, making it a powerful tool in medical imaging, including fetal brain anomaly detection.

4.7.2. VGG 16 Model

VGG-16 is a deep and powerful convolutional neural network architecture that significantly advances the field of image classification. Its simplicity in design (consistent use of 3x3 convolutional filters) and depth make it an excellent choice for tasks requiring detailed feature extraction. However, it comes with challenges related to computational complexity and memory usage.

4.7.3. ResNet Model

Residual Networks (ResNet) is a deep learning architecture designed to address the problem of training very deep neural networks. The key innovation of ResNet is the residual learning framework, which allows for the construction of extremely deep networks (hundreds or even thousands of layers) without suffering from the vanishing or exploding gradient problems typically associated with deep networks.

4.7.4. DenseNet Model

DenseNet is a powerful deep learning architecture that addresses some of the key challenges faced by traditional CNNs, such as vanishing gradients and parameter inefficiency. By introducing dense connections, DenseNet improves gradient flow, enables feature reuse, and requires fewer parameters, making it a highly effective model for a wide range of computer vision tasks. Despite its increased computational complexity, DenseNet remains a popular choice for applications requiring deep architectures with strong performance.

4.7.5. The Novel Deep Learning Model

Figure 4 shows the proposed deep learning model for image classification in four different classes.

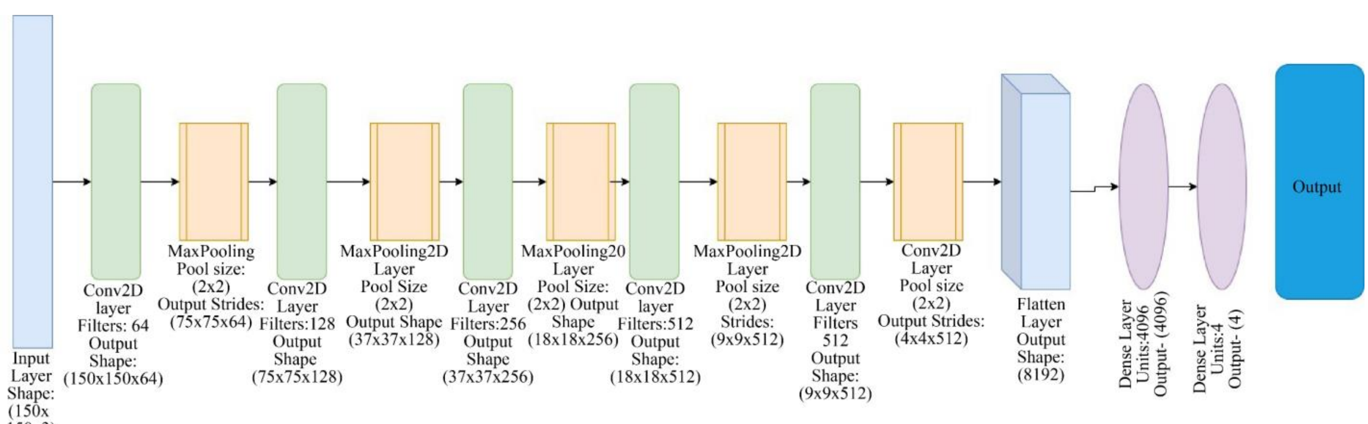


Fig. 4 Proposed deep learning algorithm for image classification model

This deep learning model processes input images through convolutional layers for feature extraction, pooling for dimensionality reduction, and fully connected layers for classification.

4.8. Key Components

a) Input Layer: Accepts 150×150×3 RGB images.

b) Convolutional Layers: Extract features using 3×3 filters with ReLU activation. Filter count increases:
   - Conv1: 64 filters (150×150×64)
   - Conv2: 128 filters (75×75×128)
   - Conv3: 256 filters (37×37×256)
   - Conv4 & Conv5: 512 filters (18×18×512 → 9×9×512)

c) MaxPooling Layers: Downsamples feature maps (2×2 pool size, stride 2) to reduce complexity and enhance feature extraction.

d) Flatten Layer: Converts the 3D feature map (4×4×512) into a 1D vector (8192 elements).

e) Fully Connected Layers:
   - Dense1: 4096 units (ReLU activation).
   - Output Layer: 4 units (Softmax activation) for classification.

f) Output: Provides final predictions with class probabilities.

5. Results and Discussion

The output of this proposed work will be either normal or abnormal images. The classification of the fetus is based on the 4000 fetal brain pictures. First, 1039 photographs are captured as typical cases and 2961 images as anomalous cases.The samples are split into three segments sequentially, as 497 images, for example, 80% of a train set, 10% of a test set, and 10% of a validation set. The following Figure 5 represents the training accuracy of different classification models:

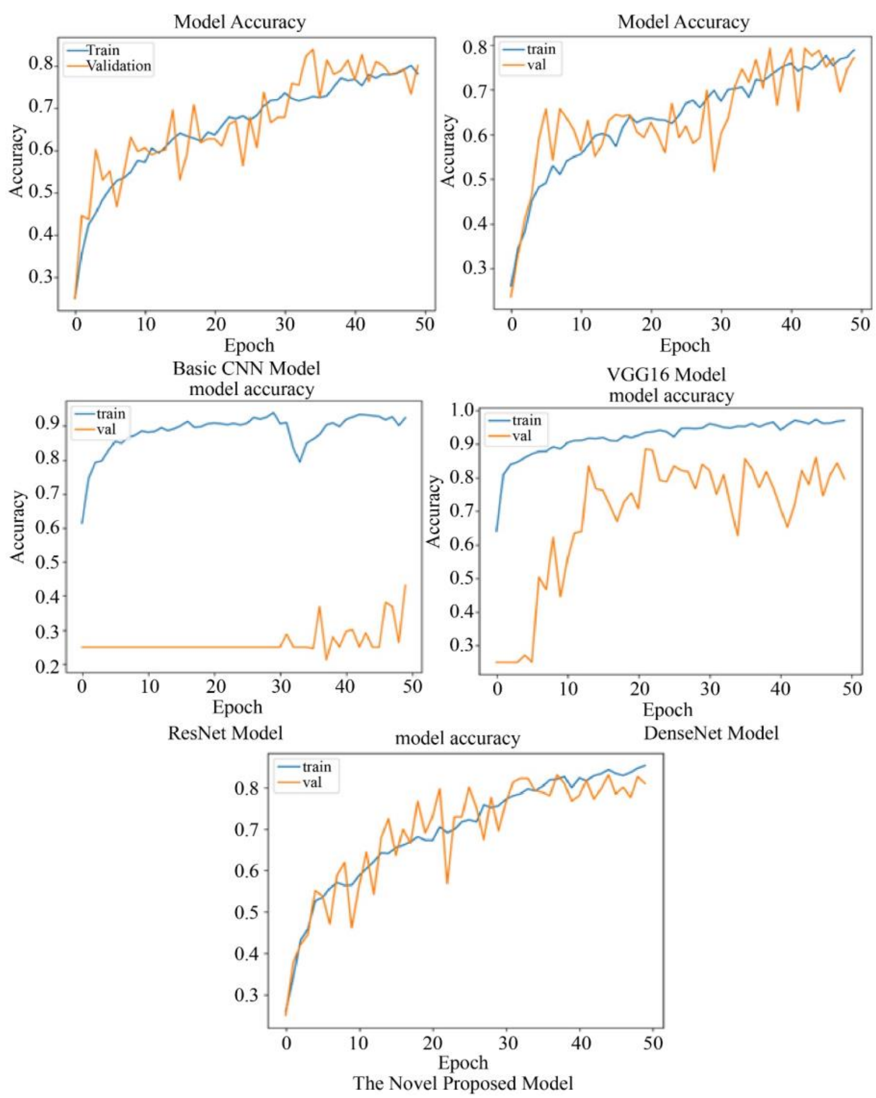


Fig. 5 Model accuracy of different algorithms

5.1. Performance Measure

In this section, the proposed system's image super-resolution and image classification are compared to other CNN algorithms, which were analysed in the literature review section. Table 1 compares the proposed method of image super-resolution to the ESRGAN algorithm with respect to PSNR value in detail.

Table 1. PSNR comparison: ESRGAN algorithm Vs Proposed method

	Average PSNR Value in dB			
Image Classes	Normal Images	Class 1-Cerebellum Images	Class 2-Thalamic Images	Class 3-Ventricular Images
ESRGAN Algorithm	12.02 dB	12.91 dB	12.06 dB	12.21 dB
Novel Image Super Resolution Algorithm	31.47 dB	32.70 dB	32.86 dB	32.49 dB

After image super resolution, ultrasound images get classified into 4 classes as class 1-Normal images, class 2-Cerebellum images, class 3- Thalamic images, and class 4-ventricular images using the Proposed CNN algorithm. Table 2 shows a comparison of the proposed method of image classification with other existing CNN algorithms.

Table 2. Accuracy comparison: Basic CNN, VGG16, DenseNet, ResNet and Proposed method

Algorithms	**Basic CNN Model**	**VGG16 Model**	**DenseNet Model**	**ResNet Model**	**Custom Model**
Model Testing Accuracy	76%	75%	75%	26%	**92.80%**

Table 3 summarizes the performance (Accuracy in %) of five models (Basic CNN, VGG16, DenseNet, ResNet, and Custom Model) on two types of images:

1. Original images
2. Super-Resolution (SR) images

The goal is to compare how well these models perform on standard images versus enhanced SR images to determine the impact of super-resolution preprocessing on classification accuracy.

Table 3. Comparison of model performance on original and Super-Resolution (SR) images

Algorithms/Type of Images	**Basic CNN Model**	**VGG16 Model**	**DenseNet Model**	**ResNet Model**	**Custom Model**
Original images	76%	46%	58%	25%	77%
SR images	76%	75%	75%	26%	**92.80%**

So, in the table above, our proposed system will give better testing accuracy at 92.80% to classify images into the normal or abnormal class using the Deep Learning model. Also, the result is compared with existing Deep Learning algorithms.

5.2. Confusion Matrix & Metrics

Table 4 compares VGG16, ResNet, DenseNet, and our Custom Model on these metrics:

Table 4. Comparison of precision, recall, and F1-Score of CNN models

Model	**Precision**	**Recall**	**F1-Score**
VGG16	0.78	0.76	0.77
ResNet	0.80	0.79	0.79
DenseNet	0.79	0.78	0.78
Custom Model	0.91	0.89	0.90

- The Proposed Model outperforms others, with higher precision, recall, and F1-score, meaning it effectively balances correct anomaly detection and minimizes errors.
- Recall is critical in medical diagnosis (fewer missed anomalies), making our model highly effective.
- The F1-score (90%) confirms that the model maintains a strong balance between precision and recall, making it reliable in real-world applications.

6. Conclusion

Early detection of fetal brain anomalies is vital for ensuring that affected pregnancies are managed with the highest level of care. It allows for timely medical interventions, helps parents make informed decisions, and ultimately leads to better health outcomes for both the mother and the child. As prenatal diagnostic technologies continue to advance, the importance of early detection in managing fetal brain anomalies will only grow, making it a cornerstone of modern prenatal care. This research paper presents a Deep Learning-based approach for the detection of fetal brain anomalies using ultrasound images. Following ethical approval, a clinical dataset comprising 4,000 grayscale ultrasound images with a resolution of 512x512 pixels was collected from two diagnostic centers, Vivaan Diagnostics Center and Siddhi Diagnostics and Research Center (SDRC). The dataset was divided into four classes: normal (Class 1) and three types of fetal brain abnormalities-cerebellum anomalies (Class 2), thalamic abnormalities (Class 3), and ventricular anomalies (Class 4). Each class consisted of 500 images for training, 200 for validation, and 200 for testing. The proposed Deep Learning model was designed to classify these ultrasound images into the four defined categories automatically. The study focused on optimizing the model's Accuracy and robustness in detecting subtle structural differences in fetal brain anomalies. Extensive experiments were conducted to assess the model's performance, which demonstrated high Accuracy in distinguishing between normal and abnormal fetal brain conditions. The results showed promise for integrating deep learning techniques into clinical practice to assist in early detection and diagnosis of fetal brain anomalies, potentially improving prenatal care and outcomes. An Accuracy of 92.80% is attained in this proposed research, which is better than the existing system.

6.1. Future Work

- Expansion of the dataset with diverse ultrasound sources.
- Incorporation of self-supervised learning for better generalization.
- Real-time deployment in clinical ultrasound systems.

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