**Fatal Brain Anomaly Detection & Classification Using Deep Learning: An Approach for Early Diagnosis**

* **Introduction:**

Fetal brain anomalies are physical or functional abnormalities in the brain of a developing fetus. Secondary causes may develop during pregnancy due to infections, environmental factors, genetic factors, or other causes. Recent advances in medical imaging and artificial intelligence have revolutionized the detection of fetal brain anomalies, which remain a critical challenge in prenatal healthcare [1]. Congenital or acquired anomalies may occur in a pregnancy due to genetics, environmental factors, or infectious agents [2]. These abnormalities, if predicted early enough, can drastically change the prognosis many tests during pregnancy, including fetal ultrasound and fetal MRI, monitor fetal development. Fetal brain is a significant challenge in prenatal health care, as its early detection is crucial for the well-being of the mother and baby. Fetal diagnostic techniques rely on MRI and ultrasound, which might present challenges because of imaging quality, interpretation, and technology accessibility[3]. New approaches based on AI and ML have provided tools such as ResNet-50, VGG-19, and U-Net that have proved the ability to improve anomaly detection in general, through features extraction and classification [4]

Recent developments in artificial intelligence (AI) and machine learning (ML) have introduced new methodologies to improve detection and classification of fetal brain anomalies. Deep learning architectures such as Convolutional Neural Networks (CNNs), U-Net and pre-trained networks such as ResNet-50 and VGG-19 have shown potential in the automation of fetal image analysis [4]. These models allow for feature extraction and classification, which may enhance the accuracy and efficiency of diagnostics. The highest accuracy was attained by the K-NN classifier with 95.6 percent while ensemble models increased the identification rate of defects [5].Various approaches in the field include convolutional neural networks (CNNs), long short-term memory (LSTM) networks and segmentation algorithms including the U-net have been found to have an impressive performance in diagnosing fetal brain abnormalities (Khan et al., 2021). In addition, the incorporation of explainable AI (XAI) methods provide interpretability in model decision-making, a level of transparency required for clinical trust and use [11].

Despite these progresses, the field still faces several important problems:

* A limited number of complete, designated datasets are available for training models, and it's hard to make models work with different imaging methods and clinical settings. [7]
* To build professional trust, models need to be easier to understand through explainable AI (XAI).[10]
* Current techniques for segmentation had limitations particularly when it comes to finding irregular anomaly borders.[8]
* Complicated functions that affect real-time applications in settings with limited resources [9]

This study hopes to respond to these difficulties by focusing on these main objectives:

* Make and check strategies to increase the usefulness of deep learning models for images from many different types of equipment and clinical situations.
* Design metrics for evaluation that correspond to the main goals of diagnosing in the field
* Use explainable AI techniques to ensure the model is understandable to clinicians.
* The outcomes of the research add to the field of detecting brain irregularities in fetuses.
* Using new techniques to enhance how accurately and reliably we can diagnose diseases
* Ensuring AI-based diagnostic tools are both understandable and reliable for healthcare experts.
* Finding and using ways to assess how well AI models function in medical environments

The findings of this research will contribute to the field of fetal brain abnormalities prediction, which will benefit both mothers and newborns. Early actions will help both pregnant women and their unborn children, AI researchers will contribute to the development of medical imaging technologies, and healthcare will benefit from faster and more accurate diagnosis methods for physicians.

* **Methodology:**

This research employs MobileNetV2 as a convolutional neural network (CNN) architecture for detecting fetal brain abnormalities in ultrasound images. The approach combines transfer learning and data augmentation to address challenges in medical imaging, including small datasets and class imbalance.The workflow combines pre-processing, model architecture and performance evaluation, to handle the complexities associated with medical image analysis.

The dataset is derived from the Roboflow Universe ([Fetal Brain Abnormalities Ultrasound Dataset](https://universe.roboflow.com/hritwik-trivedi-gkgrv/fetal-brain-abnormalities-ultrasound/dataset/1)) and consists of 1,768 labelled ultrasound images of fetal brains. The dataset are medical ultrasonic images of abnormal fetal brains. These images are also annotated with unique categories corresponding to different syndrome symptoms. Modality The images are in general grayscale, with different contrasts and noise. The dataset is organized to mimic multiple scenarios under which fetal brain development can be compromised, enough to train the classifier.The images lack both size and resolution consistency, which needs to be normalized to address both consistency and make the model more generalize. There are 16 categories, including normal, ventriculomegaly (mild/moderate/severe), arachnoid cysts, and intracranial tumorsetc.

|  |  |  |
| --- | --- | --- |
|  |  | An ultrasound of a baby  AI-generated content may be incorrect. |
| Figure 1.1: moderate-ventriculomegaly | Figure1.2: mild-ventriculomegaly | Figure 1.3: Normal |
| A ultrasound of a baby  AI-generated content may be incorrect. |  |  |
| Figure 1.4: m-magna | Figure 1.5: intracranial tumor | Figure 1.6: intracranial hemorrdge |

Figure 01: Different classes for fatal brain anomalies.

The raw images used to create the datasets, must be pre-processed before feeding to the CNN model. Data cleaning procedure involves:

* Resizing: All images are resized to the same shape, usually 128x128 pixels, so that they can be input into the CNN without distortion.
* Missing Image Handling: If images are not available or corrupt, they are either dropped from the dataset or are replaced with some placeholder values.
* Noise Filtering: All the non-essentials data from the images i.e., extra background information, noise and artifacts are automatically removed or filtered.

CNN extracts important features from the input images, such as edges, shapes, and textures, with convolutional layers. These characteristics enable the model to capture the differences between various forms of fetal brain pathologies. The protocol of visualizing the feature maps produced by the convolutional layers can be found in.The more detail we can find in the feature maps, the greater understanding of what the network acts on to classify an image. These visualizations assist in understanding the decision-making process of the model and that it is learning from the appropriate areas of the images. Feature selection is the process of selecting the most informative features to the model performance. No feature except raw data is extracted in the process of extracting features in the CNN, and the most important features are automatically learned by the CNN, so that manual selection is reduced. But other methods such as principal component analysis (PCA) could also be applied if more dimension reduction was needed.

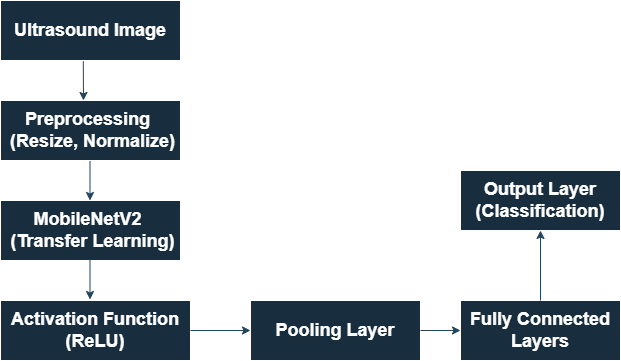


Figure 02: Workflow For Classification using CNN

A classification model is an algorithm used to categorize data into predefined classes or labels. In this case, the CNN is designed to classify ultrasound images of fetal brains into different categories based on the abnormalities detected in the images. The CNN learns patterns and features from labeled training data and applies them to classify new, unseen data. The classification in a CNN is typically based on the following equation:

Where:

* XXX is the input image.
* are the weight matrices for the convolutional and fully connected layers.
* ​ are the bias terms.
* The softmax function outputs a probability distribution over the classes, which is used for classification.

The “solving” in this model is to find the optimal solution function that minimizes the loss function between from the prediction to the class labels. The CNN has backpropagation and gradient descent that updates its weights and biases while minimizing the loss throughout the training. The last is the trained model for the prediction of class of new ultrasound images.

Model evaluation is the process to evaluate how well the model classify in the training dataset. This is important to understand how the model would generalize to new or unseen data. Model is evaluated using different metrics like Accuracy, Recall, Precision and F1-score.

The performance of the classification model is analysed through the confusion matrix. The following performance metrics are obtained from the confusion matrix:

1. **Accuracy (Acc):** The number of accurately classified images divided by the total images

Where:

* TP = True Positives
* TN= True Negatives
* FP = False Positives
* FN = False Negatives

1. **Recall (Sensitivity):** The ability of the model to correctly identify positive instances (i.e., correctly classify abnormal images).
2. **Precision:** The ability of the model to correctly identify only relevant positive instances (i.e., avoid false positives).
3. **F1-Score:** The harmonic mean of precision and recall, providing a balanced metric.

The confusion matrix and its derived metrics are presented “visually” as follows:

* **Heatmap**: A heatmap representing the confusion matrix is displayed to show how the model is performing for various classes.
* **ROC Curve**: The Receiver Operating Characteristic (ROC) curve is plotted to assess the trade-off between true positive rate and false positive rate.
* **Result and Analysis:**

Model performance and evalution

The convolutional neural network (CNN) model was evaluated using standard classification metrics. Below are the key evaluation results:  
  
1. Overall Accuracy: The model achieved an accuracy of 51% across the entire dataset, indicating a moderate ability to correctly classify fetal brain abnormalities.  
  
2. Precision, Recall, and F1-Score: The model's performance across various classes is detailed below in terms of precision, recall, and F1-score:

|  |  |  |  |
| --- | --- | --- | --- |
|  | precision | recall | f1-score |
| Moderate ventriculomegaly | 0.35 | 0.67 | 0.46 |
| holoprosencephaly | 0.46 | 0.00 | 0.00 |
| arachnoid-cyst | 0.58 | 0.56 | 0.57 |
| anold-chiari-malformation | 0.33 | 0.14 | 0.20 |
| mild-ventriculomegaly | 0.50 | 0.51 | 0.51 |
| m-magna | 0.00 | 0.00 | 0.00 |
| severe-ventriculomegaly | 0.29 | 0.29 | 0.29 |
| cerebellah-hypoplasia | 0.67 | 0.27 | 0.39 |
| encephalocele | 0.46 | 0.42 | 0.40 |
| polencephaly | 0.29 | 0.27 | 0.28 |
| hydracenphaly | 1.00 | 0.25 | 0.40 |
| intracranial-tumor | 0.00 | 0.00 | 0.00 |
| normal | 0.95 | 0.87 | 0.91 |
| colphocephaly | 0.33 | 0.33 | 0.33 |
| intracranial-hemorrdge | 0.50 | 0.18 | 0.27 |
| accuracy |  |  | 0.50 |
| macro avg | 0.42 | 0.32 | 0.34 |
| weighted avg | 0.52 | 0.50 | 0.49 |

1. Precision: The model's precision varies widely across classes, with the highest precision for the 'Normal' class (0.87) and very low precision for rare conditions such as 'Holoprosencephaly' and 'M-Magna' (both 0.00).
2. Recall: The recall for certain classes, such as 'Moderate Ventriculomegaly' and 'Normal,'

is relatively high, while for others, like 'Holoprosencephaly,' it is extremely low.

1. F1-Score: The F1-scores reflect a balance between precision and recall. The highest F1-score was observed for 'Normal' (0.86), while the lowest was for 'Holoprosencephaly' (0.00).
2. Per-Class Accuracy:

The accuracy for each class is as follows:  
Moderate Ventriculomegaly: 0.73  
- Holoprosencephaly: 0.00  
- Arachnoid Cyst: 0.48  
- Severe Ventriculomegaly: 0.50  
- Normal: 0.85

- Other classes like 'Hydracenphaly' and 'Intracranial Tumor' showed no accurate classification (0.00).

The model performs well in identifying 'Normal' fetal brain scans, as evidenced by the high precision, recall, and F1-score.The model shows reasonable accuracy for more common abnormalities such as 'Moderate Ventriculomegaly' and 'Mild Ventriculomegaly.'The model struggles with rare abnormalities, such as 'Holoprosencephaly' and 'M-Magna,' which are likely underrepresented in the training data. These rare classes have precision, recall, and F1-scores close to zero.The imbalance in class distribution may cause the model to favor more frequent classes, resulting in lower performance on rare anomalies.

* **Conclusion**

This study aimed to develop a deep learning-based approach for the classification of fetal brain abnormalities using ultrasound images. The convolutional neural network (CNN) model was trained on a dataset containing 1,818 annotated ultrasound images, each classified into one of 16 abnormality classes. The model demonstrated a moderate overall accuracy of 51% but exhibited significant variation in performance across different classes.

The model performed well for certain classes, such as 'Normal' (accuracy of 85%) and 'Moderate Ventriculomegaly' (accuracy of 73%). These results highlight the model's ability to correctly classify more common conditions. However, the model struggled with rarer conditions, such as 'Holoprosencephaly' and 'M-Magna,' which showed very low precision, recall, and F1-scores. This issue was likely due to class imbalance in the dataset, with these rare conditions being underrepresented.The CNN model's ability to classify images is highly dependent on the balance and quality of the dataset.Future work should focus on addressing class imbalances, possibly through data augmentation, oversampling, or the inclusion of more diverse training examples for rare conditions.  
  
In conclusion, while the model shows promise for classifying common fetal brain abnormalities, further improvements are necessary for accurately detecting rarer conditions. The integration of more balanced datasets, advanced techniques like transfer learning, and refined model architectures could significantly enhance performance in future studies. The findings of this research lay the foundation for using deep learning in prenatal diagnostics, with the potential to assist medical professionals in identifying fetal brain abnormalities more efficiently.

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