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AN EXPLAINABLE DEEP LEARNING FRAMEWORK FOR FETAL ULTRASOUND IMAGE PLANE CLASSIFICATION

Y. Sheela
Professor, Dept. of CSE,
Jayaraj Annapackiam CSI College of Engineering, Nazareth, India
sheelajabez@gmail.com

M. Sivasankari
PG Scholar, Dept. of CSE,
Jayaraj Annapackiam CSI College of Engineering, Nazareth, India
sankari102002@gmail.com

***Abstract* - Fetal ultrasound image plane classification plays a crucial role in prenatal diagnosis, enabling clinicians to assess fetal growth and detect abnormalities. However, ultrasound images often suffer from low contrast, noise, and high similarity between different anatomical planes, making manual classification challenging and time-consuming. To address these issues, this study proposes an explainable deep learning framework for automatic fetal ultrasound image plane classification using advanced convolutional neural networks. The proposed model leverages a deep learning architecture to accurately classify key fetal planes such as brain, abdomen, femur, thorax, and maternal cervix. To enhance model transparency and clinical trust, the framework integrates Local Interpretable Model-Agnostic Explanations (LIME) as an explainability technique. LIME provides visual interpretations by highlighting important regions in the ultrasound images that influence the model's predictions. Experimental results demonstrate that the proposed approach achieves improved classification accuracy compared to traditional methods, while also offering meaningful visual explanations. These explanations help clinicians understand the decision-making process of the model, thereby increasing reliability and usability in real-world clinical settings. Overall, this framework combines high-performance deep learning with interpretability, making it a valuable tool for computer-aided diagnosis in prenatal healthcare**

Keywords: Fetal Ultrasound Imaging, Image Plane Classification, Deep Learning, Convolutional Neural Networks (CNN) , Explainable AI (XAI) , LIME (Local Interpretable Model-Agnostic Explanations) , Medical Image Analysis

I. INTRODUCTION

Fetal ultrasound imaging is one of the most important and widely used techniques in prenatal care. It helps doctors monitor fetal growth, detect abnormalities, and ensure the health of both the mother and the baby. During an ultrasound scan, different standard anatomical planes such as the brain, abdomen, femur, thorax, and maternal cervix must be accurately identified for proper diagnosis. However, manual identification of these planes is often difficult due to low image quality, noise, and the high similarity between different fetal structures.

With the advancement of deep learning, especially Convolutional Neural Networks (CNNs), automated image classification has shown significant improvement in medical image analysis. These models can learn complex patterns from large datasets and provide accurate classification results. However, one major limitation of deep learning models is their "black-box" nature, meaning that the decision-making process is not easily understandable by humans. This lack of transparency reduces trust among medical professionals. To overcome this challenge, Explainable Artificial Intelligence (XAI) techniques are introduced. In this project,LIME (Local InterpretableModel-Agnostic Explanations) is used to provide visual explanations for model predictions. LIME highlights important regions in the ultrasound images that contribute to classification decisions, making the model more transparent and interpretable.This project proposes an explainable deep learning framework for fetal ultrasound image plane classification, combining high accuracy with interpretability. The system not only classifies different fetal planes but also generates meaningful explanations, helping clinicians better understand and trust the model's predictions. This approach aims to improve the reliability and efficiency of computer-aided diagnosis in prenatal healthcare.

II. LITERATURE REVIEW

Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization was proposed by Ramprasaath R. Selvaraju et al. in 2017 as an Explainable AI technique for interpreting Convolutional Neural Networks (CNNs). The method works by using the gradients of a target class flowing into the last convolutional layer to identify important regions in an image. These gradients are combined with feature maps to produce a heatmap that highlights the areas most influential in the model's decision. Grad-CAM is widely used because it provides clear visual explanations, does not require changes to the model, and is especially useful in medical imaging applications. However, it produces low-resolution heatmaps and depends on CNN architectures. Evaluation of Deep CNNs for Automatic Classification of Common Maternal Fetal Ultrasound Planes presents a study on the use of deep Convolutional Neural Networks (CNNs) to automatically classify standard fetal ultrasound planes. The methodology involves training multiple CNN architectures on a large dataset of ultrasound images containing different anatomical planes such as brain, abdomen, femur, and thorax. The models are evaluated based on classification accuracy and compared with expert-level performance. The study demonstrates that deep learning models can achieve high accuracy, sometimes comparable to human experts, in identifying fetal planes. However, the research highlights limitations such as lack of interpretability and dependency on large annotated datasets, emphasizing the need for explainable AI techniques in medical imaging. Clinical XAI Guidelines for Medical Image Analysis focuses on providing practical guidelines for applying Explainable Artificial Intelligence (XAI) techniques in clinical settings. The methodology involves reviewing existing XAI methods and evaluating their suitability for medical imaging tasks based on factors such as interpretability, reliability, and clinical relevance. The study emphasizes that explanations should be accurate, consistent, and easily understandable by clinicians. It highlights the importance of validating explanations with medical experts and ensuring that models do not provide misleading interpretations. The paper concludes that while XAI has great potential in healthcare, proper guidelines and evaluation standards are essential to build trust and ensure safe deployment in real-world clinical applications. Self-Supervised Learning for Medical Image Analysis explores the use of self-supervised learning techniques to improve medical image analysis without requiring large amounts of labeled data. The methodology involves pretraining deep learning models using automatically generated labels from the data itself (such as image transformations, contrastive learning, or reconstruction tasks), and then fine-tuning the model for specific tasks like classification or segmentation. This approach helps in learning meaningful feature representations from unlabeled medical images. The study shows that self-supervised learning can significantly improve performance, especially when labeled data is limited. However, the effectiveness depends on the choice of pretext tasks and training strategy.

III. METHODOLOGY

The proposed system focuses on developing an Explainable Deep Learning Framework for fetal ultrasound image plane classification. The methodology involves multiple stages including data collection, preprocessing, model development, prediction, and explanation using LIME.

A. Proposed Method

The system takes fetal ultrasound images as input and processes them using a Convolutional Neural Network (CNN) to classify different anatomical planes such as brain, abdomen, femur, thorax, and maternal cervix. To overcome the black-box nature of deep learning models, LIME is integrated to provide visual explanations. LIME highlights the important regions in the image that influence the prediction, making the model more transparent and interpretable for clinical use.

B. Algorithm Used

CNN is used for feature extraction and classification of ultrasound images. It automatically learns patterns such as edges, textures, and shapes through convolution and pooling layers, followed by classification using fully connected layers. LIME explains individual predictions by generating perturbed samples and identifying which parts of the image contribute most to the output. It produces visual explanations in the form of highlighted regions.

C. Dataset

The dataset used in this project consists of fetal head ultrasound images collected from publicly available sources such as the HC18 Challenge Dataset and datasets from Kaggle. The dataset includes images focusing only on the fetal head region, which are commonly used for analyzing brain structures and measuring head circumference. Each image is labeled according to its respective plane or category, enabling supervised learning. The dataset contains variations in image quality, orientation, and noise, which reflect real-world clinical conditions. This dataset is used to train and evaluate the deep learning model for accurate classification of fetal head ultrasound images.

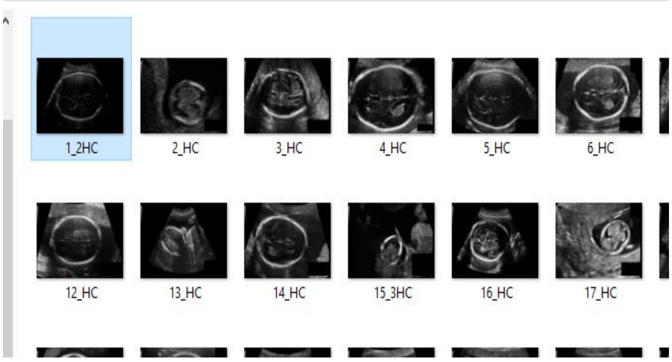

Figure 1. Dataset

D. Preprocessing

The preprocessing stage is essential to prepare fetal head ultrasound images for effective model training. Initially, all images are resized to a fixed dimension (e.g., 224×224 pixels) to ensure uniform input to the Convolutional Neural Network (CNN). The pixel values are then normalized to a range of 0 to 1 to improve training stability and convergence. To increase dataset diversity and reduce overfitting, data augmentation techniques such as rotation, flipping, and zooming are applied. Additionally, basic noise reduction methods are used to enhance image quality, as ultrasound images often contain speckle noise. Finally, the dataset is divided into training and testing sets, enabling proper evaluation of the model's performance.

IV. IMPLEMENTATION

The implementation of the proposed system is carried out using deep learning techniques to classify fetal head ultrasound images and generate interpretable results using LIME. The complete process is divided into multiple stages as shown in the system architecture.

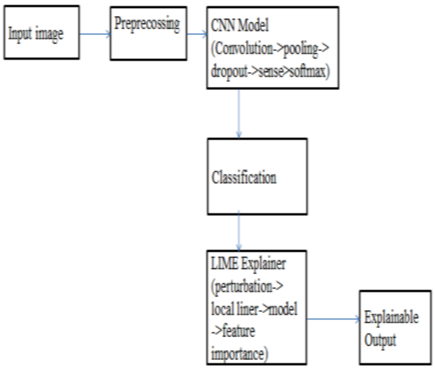

Figure 2. Block Diagram

A. *Input Image*

The input to the proposed system consists of fetal head ultrasound images collected from the dataset. These images represent different views of the fetal head and may vary in size, quality, orientation, and noise levels due to real-world scanning conditions. Before processing, all input images are converted into a standard format with dimensions of 224 × 224 × 3, ensuring compatibility with the Convolutional Neural Network (CNN) model. These standardized images serve as the initial input for the preprocessing stage, where further enhancements are applied to prepare them for accurate classification.

B. *Preprocessing*

The preprocessing stage is performed to prepare the fetal head ultrasound images for effective training and classification. Initially, all input images are resized to a uniform dimension of 224 × 224 × 3 to ensure consistency across the dataset. The pixel values are then normalized to a range of 0 to 1, which helps in improving model convergence and stability during training. To enhance the diversity of the dataset and reduce overfitting, data augmentation techniques such as rotation, flipping, and zooming are applied. Additionally, basic noise reduction methods are used to minimize speckle noise commonly present in ultrasound images, thereby improving image quality. These preprocessing steps ensure that the input data is standardized, clean, and suitable for the Convolutional Neural Network (CNN) model.

C. CNN Model Implementation

The Convolutional Neural Network (CNN) model is used as the core component for feature extraction and classification of fetal head ultrasound images. The model consists of multiple convolutional layers with filters (such as 3×3 and 5×5) that automatically learn important features like edges, textures, and anatomical structures from the input images. These feature maps are then passed through pooling layers, which reduce the spatial dimensions and computational complexity while retaining essential information. A dropout layer is included to prevent overfitting by randomly deactivating neurons during training. The extracted features are then fed into fully connected (dense) layers, which perform the final classification. The output layer uses a softmax function to generate probability scores for each class, and the class with the highest probability is selected as the predicted fetal head plane. This CNN model enables accurate and efficient image classification in the proposed system.

D. Classification

The classification stage is responsible for identifying the category of the input fetal head ultrasound image. After feature extraction by the Convolutional Neural Network (CNN), the learned features are passed through fully connected layers, which analyze and map them to predefined classes. The final output layer uses a softmax function to assign probability scores to each class. The class with the highest probability is selected as the predicted label, representing the type of fetal head plane. Along with the predicted class, a confidence score is also generated, indicating how certain the model is about its prediction. This step provides the final decision of the system before applying explainability techniques.

E. LIME Explainer Implementation

The LIME (Local Interpretable Model-Agnostic Explanations) explainer is used to provide interpretability to the predictions made by the CNN model. After the classification of a fetal head ultrasound image, LIME analyzes the model's decision by creating multiple perturbed versions of the input image and observing how the predictions change. It then builds a simple, interpretable model locally around the prediction to identify the most important regions that influenced the output. The result is presented as a visual explanation, where key areas of the image are highlighted, indicating which parts of the fetal head contributed most to the classification. This helps in understanding the model's behavior and increases trust in its predictions, especially in medical applications.

F. Explainable output

The explainable output is the final stage of the system, where both the prediction and its interpretation are presented. After the CNN model classifies the fetal head ultrasound image, the LIME explainer generates a visual explanation by highlighting the most important regions that influenced the prediction. The output includes the predicted class label, the confidence score, and a highlighted image showing the key areas responsible for the decision. This combined output helps users understand not only what the model predicts but also why it makes that prediction. Such interpretability is especially important in medical applications, as it increases transparency, reliability, and trust among clinicians.

G. Performance Evaluation

The performance evaluation stage is used to measure the effectiveness of the proposed model in classifying fetal head ultrasound images. The trained Convolutional Neural Network (CNN) is evaluated using the test dataset to assess its accuracy and reliability. Various evaluation metrics such as accuracy, precision, recall, and F1-score are used to analyze the model's performance. Accuracy measures the overall correctness of predictions, while precision and recall evaluate the model's ability to correctly identify each class. The F1-score provides a balanced measure by combining both precision and recall. Additionally, a confusion matrix can be used to visualize the classification results and identify any misclassifications. This evaluation ensures that the model performs well and is suitable for practical medical applications

V. CONCLUSION

In this project, an Explainable Deep Learning Framework was developed for the classification of fetal head ultrasound images. A Convolutional Neural Network (CNN) was used to automatically extract features and accurately classify the images into their respective categories. To overcome the black-box nature of deep learning models, LIME (Local Interpretable Model-Agnostic Explanations) was integrated to provide visual explanations by highlighting important regions in the images. The proposed system achieved reliable performance in classifying fetal head images while also improving interpretability. The combination of accuracy and explainability makes the model more trustworthy and suitable for medical applications. Overall, this approach can assist clinicians in better understanding model predictions and supports effective decision-making in prenatal diagnosis

VI. FUTURE ENHANCEMENT

Although the proposed system achieves good performance in fetal head ultrasound image classification with explainability, several improvements can be made in the future to enhance its accuracy, robustness, and clinical usability. One major enhancement is the use of larger and more diverse datasets. Increasing the dataset size with images from different hospitals, ultrasound machines, and patient conditions can improve the generalization ability of the model. This will help the system perform better in real-world clinical environments. Another improvement is the integration of advanced deep learning architectures such as ResNet, EfficientNet, or Vision Transformers. These models can extract more complex features and may further improve classification accuracy compared to a basic CNN model. The project can also be extended to include multi-plane classification, where the system can classify not only fetal head images but also other planes such as abdomen, femur, and thorax. This would make the system more comprehensive and useful in complete fetal assessment.In terms of explainability, combining multiple XAI techniques such as LIME and Grad-CAM can provide better and more reliable visual interpretations. This hybrid approach can offer both local and global explanations, improving the understanding of model decisions. Another important enhancement is the development of a real-time system that can be integrated with ultrasound machines. This would allow instant classification and explanation during scanning, assisting clinicians in making quick decisions. Additionally, implementing self-supervised or semi-supervised learning techniques can reduce dependency on large labeled datasets, which are often difficult to obtain in medical domains. The system can also be improved by incorporating segmentation techniques (such as U-Net) to focus specifically on the fetal head region before classification. This can reduce background noise and improve model accuracy. Finally, creating a user-friendly interface or application (web or mobile-based) can make the system easily accessible to healthcare professionals. This will help in practical deployment and increase adoption in clinical settings.

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