❖ Problem Background

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. Brain anomalies can be congenital or acquired. Examples are brain malformations, injury, or disease. These include alterations in brain size or shape, disruptions in neural activity, and structural cellular changes that lead to tumours, haemorrhages, strokes and aneurysms. Tumours are caused by rapidly proliferating cells, and they can be lethal unless treated (Narayanan,k., and Latifi,S. (2023)). These abnormalities, if predicted early enough, can drastically change the prognosis many tests during pregnancy, fetal ultrasound, amniocentesis and fetal MRI, monitor fetal development. Fetal brain MRI is especially useful for early detection of malformations. It is particularly useful for early detection of abnormalities, involving processes like image segmentation, feature extraction, and classification to determine the presence of anomalies. Machine learning techniques help detect, segment, and classify brain anomalies by analyzing medical images, but challenges arise due to variations in tumour location, structure, and size.

❖ Existing Study

A deep learning-based system using fused features from pre-trained ResNet-50 and VGG-19-GAP improves the automated classification of fetal ultrasound planes, outperforming existing methods in accuracy (Krishna, T.B., and Kokil, P. (2022)). Using MRI datasets, various deep-learning models have been proposed for brain tumour detection, segmentation, and classification. A CNN-based model achieved segmentation and classification accuracies of 96.2% and 97.4%, distinguishing between benign and malignant tumours. An advanced multimodal approach combining CNN and LSTM networks further improved accuracy to 98.6% and 99.1%. Other methods include Lee sigma filtered histogram segmentation for rapid detection, employing tanh activation and bimodal histogram analysis, and a Bayesian capsule network (BayesCap) framework, which outperformed CNNs by preserving spatial information during classification. These approaches highlight significant advancements in leveraging deep learning for brain tumour diagnosis (Sharma, V.K., and Ameta, G.K. (2024)). While existing models focus on specific imaging modalities such as ultrasound for fetal development and MRI for brain tumours, more research should be needed on techniques applicable to other types of medical imaging. While current models like CNNs and BayesCap highlight accuracy, they need explainable AI (XAI) processes that could enhance clinician trust and understanding of prediction.

❖ Research Objective

Having observed the research gaps in this article existing studies, we have identified a crucial area where we can expect the best results using explainable AI models. Therefore, our research objectives are of utmost importance:

- How can explainable AI (XAI) techniques enhance the interpretability and trustworthiness of DL models in diagnosing fatal brain anomalies?

Explainable AI (XAI) Enhances the interpretability and trustworthiness of deep learning models in the diagnosis of fetal brain anomalies. It does so by providing transparent visualizations, aligning predictions with clinical reasoning, and building clinician trust. It aids in error analysis, ensures regulatory compliance, and promotes ethical AI use. Most importantly, by reducing bias, XAI ensures that the diagnoses are accurate and trustworthy. (Ghnemat et al.,2023).

- How can Convolution Neural Network can show remarkable potential in transforming the medical sector, especially in the early detection and classification of fatal brain anomalies?

Convolutional neural Networks (CNNs) are revolutionizing the medical sector by enabling accurate and efficient analysis of medical images. Their ability to automatically extract and learn critical features from imaging data significantly reduces the manual effort required for the early detection and classification of fetal brain anomalies. This enhances diagnostic precision and brings relief and optimism about the efficiency of healthcare processes, thus revolutionizing prenatal healthcare. (Data Camp (2023)).

❖ Research Contribution

This research enhances prenatal healthcare by using AI for early detection of fetal brain abnormalities. It provides clinicians with accurate, automated diagnostic tools, reducing workload and improving outcomes. Hospitals can significantly reduce costs while increasing patient care, and families receive timely, reliable diagnoses for better health decisions. The primary audiences, including medical professionals, AI researchers, and policymakers, all benefit from these innovative solutions that advance maternal and newborn care and have the potential to reduce healthcare costs

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