

NeuroTrace AI: Intelligent Fetal Brain Plane Identification with Explainable Decision Support and Secure Medical Record Traceability

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ABSTRACT

Accurate identification of standard fetal brain ultrasound planes is essential for prenatal diagnosis and early detection of neurological abnormalities. However, manual interpretation of ultrasound images is often challenging due to image noise, low contrast, and dependence on operator expertise. This paper presents NeuroTrace AI, an intelligent framework for automated fetal brain plane identification using deep transfer learning, Explainable AI decision support, and secure medical record traceability. The proposed system employs a VGG19-based transfer learning model to classify fetal brain ultrasound images into four categories: Trans-cerebellum, Trans-thalamic, Trans-ventricular, and Other. Image preprocessing and data augmentation techniques are applied to improve model robustness and generalization across diverse ultrasound imaging conditions. Following classification, an Explainable AI module generates clinically meaningful explanations to support healthcare professionals in understanding the predicted anatomical plane and its diagnostic relevance. To enhance security and transparency, blockchain technology is integrated to store prediction outcomes, confidence scores, timestamps, and associated metadata in a tamper-resistant manner, ensuring data integrity and traceability. A web-based interface enables real-time image upload, automated analysis, and report generation for clinical use. Experimental evaluation demonstrates that the proposed framework achieves reliable classification performance while improving interpretability, security, and trustworthiness. NeuroTrace AI offers an intelligent and scalable solution for AI-assisted prenatal fetal brain assessment and supports more consistent clinical decision-making.

Keywords: Fetal Brain Ultrasound, Deep Transfer Learning, VGG19, Explainable AI, Blockchain, Medical Image Classification, Prenatal Diagnosis, Clinical Decision Support, Medical Data Traceability.

I. INTRODUCTION

Prenatal imaging plays a vital role in evaluating fetal development and detecting abnormalities during pregnancy. Among the available diagnostic modalities, ultrasound remains the preferred imaging technique because it is non-invasive, safe, cost-effective, and capable of providing real-time visualization of fetal anatomy. One of the key objectives of prenatal ultrasound examinations is the assessment of the fetal brain, as early identification of structural abnormalities can significantly improve clinical management and pregnancy outcomes. Standard fetal brain ultrasound planes, including the trans-thalamic, trans-ventricular, and trans-cerebellar views, provide essential anatomical information required for evaluating normal brain development and diagnosing neurological disorders and congenital anomalies [1]. Accurate recognition of these standard planes is fundamental for reliable prenatal diagnosis. In routine clinical practice, radiologists and sonographers manually identify the appropriate imaging plane based on their expertise. However, ultrasound images are often affected by speckle noise, low contrast, fetal motion, and variations in probe orientation, making interpretation challenging. Furthermore, manual assessment of large numbers of ultrasound scans is time-consuming and may introduce inconsistencies between observers. These limitations emphasize the need for intelligent computer-assisted systems that can automatically identify fetal brain planes while improving diagnostic consistency and reducing clinical workload [2]. Recent developments in artificial intelligence have transformed medical image analysis by enabling automated extraction of meaningful features from complex imaging data. In particular, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in applications such as disease detection, anatomical structure recognition,

organ segmentation, and medical image classification. Unlike conventional machine learning approaches that depend on handcrafted features, CNN-based models automatically learn hierarchical image representations directly from training data. Their ability to capture subtle anatomical differences has made them highly effective for fetal ultrasound plane classification and decision support in obstetric imaging [3]. Transfer learning has further enhanced the applicability of deep learning in medical imaging, especially in scenarios where annotated datasets are limited. Instead of training models from scratch, pre-trained architectures such as VGG19, ResNet, and EfficientNet can be fine-tuned for specific clinical tasks, resulting in faster convergence and improved classification performance. Among these models, VGG19 provides a robust architecture with deep convolutional layers capable of extracting fine-grained spatial features from fetal ultrasound images, enabling accurate discrimination between different fetal brain planes [4]. Although deep learning models achieve high predictive performance, their adoption in healthcare requires greater transparency, interpretability, and secure management of diagnostic information. Explainable Artificial Intelligence (XAI) addresses this challenge by generating human-readable explanations that help clinicians understand the rationale behind model predictions and support informed clinical decision-making. In parallel, blockchain technology offers a secure and tamper-resistant framework for storing diagnostic records, prediction outcomes, confidence scores, timestamps, and related metadata, thereby ensuring data integrity, traceability, and accountability throughout the healthcare workflow [5]. Motivated by these advancements, this work proposes NeuroTrace AI, an integrated framework for automated fetal brain ultrasound plane identification that combines deep transfer learning, Explainable AI decision support, and blockchain-enabled medical record traceability. The proposed system employs a VGG19-based transfer learning model to classify fetal brain ultrasound images into four categories: Trans-cerebellum, Trans-thalamic, Trans-ventricular, and Other. Following classification, an Explainable AI module generates clinically meaningful explanations to improve result interpretability, while blockchain securely records diagnostic information for transparent and reliable data management. By integrating intelligent image classification with explainability and secure record management, NeuroTrace AI aims to improve the accuracy, reliability, and clinical usability of AI-assisted prenatal fetal brain assessment.

II. RELATED WORKS

Artificial intelligence has become an important component of modern medical image analysis, particularly in obstetric ultrasound, where automated techniques assist clinicians in fetal assessment. Over the past few years, researchers have investigated numerous machine learning and deep learning approaches to improve the accuracy, reliability, and efficiency of fetal ultrasound interpretation. A major research focus has been the automatic identification and classification of standard fetal ultrasound planes, which are essential for evaluating fetal development and detecting congenital abnormalities. Earlier methods primarily employed conventional machine learning algorithms that depended on handcrafted features such as texture patterns, shape descriptors, and pixel intensity statistics. Although these techniques achieved acceptable performance, they were often limited by ultrasound noise, anatomical variability, and complex image characteristics. The adoption of deep learning has largely addressed these limitations by enabling automatic extraction of discriminative features directly from raw ultrasound images, resulting in improved classification accuracy and robustness [6]. Several studies have demonstrated the effectiveness of convolutional neural networks for fetal ultrasound plane recognition. Burgos-Artizzu et al. performed one of the pioneering large-scale studies on automatic classification of maternal and fetal ultrasound images using deep convolutional architectures. Their evaluation of models including ResNet and Inception on a comprehensive annotated dataset achieved high classification performance across multiple anatomical views. The authors also emphasized the importance of diverse training datasets and effective preprocessing techniques to ensure reliable model generalization under different imaging conditions and across various ultrasound devices [7]. Transfer learning has been widely adopted to overcome the challenge of limited annotated medical datasets. Qu et al. evaluated several pre-trained convolutional architectures, including VGG16, VGG19, and ResNet50, for fetal brain ultrasound plane classification. Their findings demonstrated that fine-tuning pre-trained models consistently outperformed training from scratch. The study also highlighted the capability of deeper neural networks to distinguish subtle anatomical differences between closely related fetal brain planes. Furthermore, data augmentation methods such as image rotation, flipping, and brightness adjustment were shown to improve model robustness by increasing variability in the training dataset [8]. Researchers have also proposed lightweight neural network architectures suitable for real-time deployment in portable ultrasound systems and resource-constrained clinical environments. Yu et al. introduced LPC-SonoNet, a computationally efficient model that integrates Light Pyramid Convolution modules into the conventional SonoNet architecture. This design enables effective multi-scale feature extraction while considerably reducing computational complexity. Their experimental results demonstrated that the lightweight architecture maintained competitive classification accuracy while improving inference speed. The incorporation of Gradient-CAM visualization further enhanced model interpretability by identifying the image regions that contributed most significantly to the classification process

[9]. Attention-based deep learning models have also shown promising results in fetal ultrasound analysis. Sivasubramanian et al. proposed an EfficientNet-based framework enhanced with attention mechanisms to improve the detection of standard fetal ultrasound planes. The attention modules enabled the network to focus on clinically relevant anatomical structures while suppressing background noise and irrelevant regions. The proposed approach achieved high classification accuracy with a relatively compact model architecture, demonstrating its suitability for practical clinical deployment where computational efficiency is essential [10]. Beyond single-task learning, multi-task deep learning frameworks have attracted considerable attention for simultaneously performing multiple fetal ultrasound analysis tasks. Plotka et al. introduced the FetalNet framework, which combines ultrasound plane detection, anatomical segmentation, and biometric measurement within a unified architecture. By utilizing temporal information extracted from sequential ultrasound video frames, the proposed system improved both detection accuracy and measurement consistency. Such integrated learning strategies reduce computational redundancy and enhance the overall efficiency of prenatal ultrasound analysis [11]. Recent studies have further explored the integration of segmentation techniques with classification models to improve feature extraction from fetal brain ultrasound images. Hasan and Hossain proposed an ensemble transfer learning framework that first employs U-Net segmentation to isolate fetal brain structures before applying multiple deep learning classifiers, including InceptionV3, ResNet50V2, and DenseNet201. The final prediction is generated through an ensemble voting strategy, improving classification robustness and minimizing confusion between anatomically similar fetal brain planes. Experimental evaluation demonstrated that segmentation-assisted ensemble learning significantly enhances diagnostic reliability in fetal neurosonography [12]. In addition to improving predictive accuracy, recent research has increasingly emphasized the interpretability of artificial intelligence models used in healthcare. Explainable AI techniques, including Grad-CAM and saliency map visualization, enable clinicians to understand which image regions influence model predictions. Such visualization methods enhance transparency, improve clinician confidence, and facilitate the safe integration of AI-based diagnostic systems into routine clinical practice [13]. The integration of complementary technologies such as Explainable AI and blockchain has further strengthened intelligent healthcare systems. Explainable AI generates clinically meaningful explanations that assist healthcare professionals in interpreting automated predictions, thereby increasing trust in AI-assisted diagnosis. At the same time, blockchain technology provides a secure and immutable platform for storing diagnostic records, prediction results, confidence scores, and associated metadata. This combination improves data integrity, traceability, transparency, and accountability while supporting regulatory compliance within healthcare environments [14]. Overall, existing studies demonstrate that deep learning has substantially advanced automated fetal ultrasound analysis by improving classification performance and reducing dependence on manual interpretation. Nevertheless, important challenges remain regarding model explainability, seamless clinical integration, and secure management of diagnostic information. Addressing these challenges through the integration of deep transfer learning, Explainable AI, and blockchain-based traceability offers a promising direction for developing reliable, transparent, and clinically deployable fetal brain ultrasound analysis systems capable of supporting prenatal diagnostic decision-making [15].

III. DATASETS

The dataset utilized in this research comprises fetal brain ultrasound images obtained from a publicly accessible medical imaging repository available on Kaggle. It includes ultrasound scans representing standard anatomical planes of the fetal brain that are routinely examined during prenatal screening and fetal neurosonography. The images are organized into four categories: Trans-cerebellum, Trans-thalamic, Trans-ventricular, and Other. Each category corresponds to a specific anatomical view that provides valuable clinical information for assessing fetal brain development. The trans-thalamic plane is commonly used for measuring biparietal diameter and head circumference, the trans-ventricular plane facilitates evaluation of the lateral ventricles for abnormalities such as ventriculomegaly, while the trans-cerebellar plane is employed to assess the cerebellum and posterior fossa. The Other category includes ultrasound images captured from non-standard or oblique views that do not belong to the primary diagnostic planes. The dataset contains approximately 500 fetal brain ultrasound images acquired under diverse imaging conditions, including variations in fetal orientation, transducer positioning, image brightness, and ultrasound-specific noise artifacts. Such diversity reflects real-world clinical scenarios and enhances the model's ability to learn robust and generalized visual representations. Prior to model training, all images were resized to a fixed resolution of 224×224 pixels, ensuring compatibility with the VGG19 transfer learning architecture. To further improve generalization and minimize overfitting, several data augmentation techniques, including horizontal flipping, image rotation, zoom transformation, and brightness adjustment, were applied to generate additional training variations and strengthen the model's performance across different ultrasound imaging conditions.

IV. METHODOLOGY

The proposed methodology introduces NeuroTrace AI, an intelligent framework for automated fetal brain ultrasound plane classification by integrating deep transfer learning, Explainable AI, and blockchain-enabled traceability. The overall workflow consists of image acquisition, preprocessing, feature extraction, classification, explainable decision support, and secure data storage. Initially, fetal brain ultrasound images undergo preprocessing to enhance image quality and prepare the data for model training. A VGG19-based transfer learning model is then employed to extract discriminative features and classify the images into their respective fetal brain planes. Following prediction, an Explainable AI module generates clinically meaningful explanations to assist healthcare professionals in understanding the classification results. Finally, blockchain technology securely stores the prediction outcome along with confidence scores, timestamps, and associated metadata, ensuring data integrity, transparency, and traceability. Figure 1 illustrates the overall architecture and workflow of the proposed NeuroTrace AI framework.

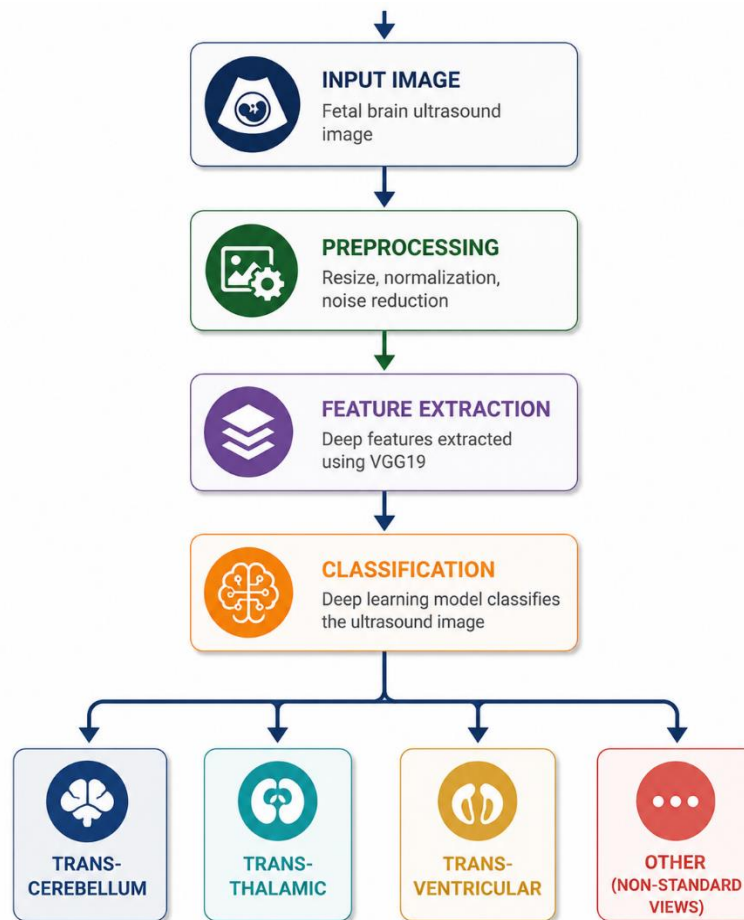


Fig. 1. Proposed NeuroTrace AI framework for automated fetal brain ultrasound plane classification using deep transfer learning architecture.

A. Data Collection

Data collection forms the initial stage of the proposed NeuroTrace AI framework and provides the foundation for developing a reliable fetal brain ultrasound classification system. In this study, fetal brain ultrasound images were collected from a publicly available dataset hosted on the Kaggle platform. The dataset consists of ultrasound scans representing four clinically significant fetal brain planes, namely Trans-cerebellum, Trans-thalamic, Trans-ventricular, and Other. Each anatomical plane provides unique diagnostic information that assists clinicians in evaluating fetal brain development and detecting neurological abnormalities during prenatal examinations. The images were acquired under diverse imaging conditions, including variations in fetal position, probe orientation, ultrasound machine settings, image brightness, and the presence of speckle noise. These variations closely

resemble real-world clinical environments and improve model generalization across diverse patient populations during practical clinical deployment.

B. Image Preprocessing

Image preprocessing is performed to improve the quality and consistency of fetal brain ultrasound images before they are used for training and testing the deep learning model. Ultrasound images often contain speckle noise, intensity variations, artifacts, and low contrast, which may reduce classification accuracy. To overcome these limitations, every image is resized to 224×224 pixels, matching the input dimensions required by the VGG19 architecture. Pixel values are normalized to stabilize numerical computations during optimization. Data augmentation techniques including horizontal flipping, rotation, zooming, brightness adjustment, and minor shifting are applied to increase dataset diversity and improve model robustness. These preprocessing operations reduce overfitting by exposing the network to different image variations while preserving clinically significant anatomical features required for accurate fetal brain plane classification.

C. Feature Extraction Using Deep Transfer Learning

Feature extraction is accomplished using the VGG19 convolutional neural network through a transfer learning strategy. Instead of manually designing image descriptors, the model automatically learns hierarchical visual representations directly from fetal brain ultrasound images. The initial convolutional layers identify fundamental image characteristics such as edges, contours, and texture patterns, whereas deeper layers capture complex anatomical structures associated with different fetal brain planes. Pre-trained ImageNet weights provide generalized visual knowledge that is subsequently fine-tuned using the ultrasound dataset, enabling efficient adaptation to the target application. This approach minimizes the requirement for extensive medical training data while improving convergence speed and classification accuracy. The extracted feature maps provide discriminative information that enables the classifier to distinguish between visually similar fetal brain anatomical views effectively.

D. Classification and Prediction

Following feature extraction, the generated feature vectors are passed to fully connected layers responsible for identifying the anatomical category of each fetal brain ultrasound image. A Softmax activation function calculates the probability distribution across the four predefined classes, and the class with the highest probability is selected as the final prediction. Model optimization is performed using the Adam optimizer together with the categorical cross-entropy loss function to achieve stable convergence during training. Performance evaluation is carried out using multiple validation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. This automated prediction process significantly reduces manual effort, improves diagnostic consistency, and provides healthcare professionals with reliable classification results for supporting prenatal fetal brain assessment and clinical decision-making.

E. Explainable AI Decision Support

After the fetal brain ultrasound image is successfully classified, the proposed framework activates an Explainable AI (XAI) module to generate clinically meaningful interpretations of the prediction. The generated explanation describes the identified anatomical plane, summarizes its clinical significance, and provides supporting information that assists healthcare professionals in understanding the model's decision. This additional decision-support mechanism improves transparency by presenting predictions in a human-readable format rather than displaying only numerical probabilities. Explainable AI enhances clinician confidence by increasing trust in automated diagnostic systems and reducing uncertainty during prenatal assessment. The interpretable output enables radiologists and sonographers to validate model predictions more effectively, supporting informed clinical decisions while promoting responsible adoption of artificial intelligence within modern healthcare environments.

F. Blockchain-Based Data Storage

Blockchain technology is incorporated into the proposed framework to provide secure, transparent, and tamper-resistant storage of diagnostic information generated during fetal brain ultrasound analysis. Following prediction, important details including the identified fetal brain plane, confidence score, timestamp, and associated metadata are securely recorded as blockchain transactions. Each record is linked to the previous block using cryptographic hash functions, ensuring that stored information cannot be modified without authorization. This decentralized

storage mechanism maintains data integrity, improves traceability, and enables secure auditing of diagnostic records throughout the healthcare workflow. Blockchain integration also facilitates trustworthy sharing of medical information among authorized healthcare providers while supporting regulatory compliance, protecting sensitive patient information, and enhancing confidence in AI-assisted prenatal diagnostic systems.

G. Web-Based Result Visualization

The final stage of the proposed NeuroTrace AI framework provides an interactive web application that enables healthcare professionals to perform automated fetal brain ultrasound analysis through a simple graphical interface. Users can upload ultrasound images directly into the system, after which the trained deep learning model processes the input and generates classification results within a short time. The interface displays the predicted fetal brain plane, confidence score, and Explainable AI generated clinical interpretation in an organized format. Simultaneously, blockchain securely records the diagnostic information in the background for future verification and auditing. The web application improves usability, simplifies clinical workflows, reduces manual effort, and supports efficient deployment of intelligent fetal brain ultrasound classification systems in healthcare environments.

V. EXPERIMENT

A. Evaluation Metrics

The performance of the proposed NeuroTrace AI framework is assessed using several standard evaluation metrics to determine its effectiveness in fetal brain ultrasound plane classification. Since the proposed model addresses a multi-class classification problem, multiple performance measures are employed to provide a comprehensive evaluation. Accuracy is used as the primary metric to determine the percentage of correctly classified ultrasound images among all test samples. Although accuracy provides an overall measure of model performance, it does not completely reflect the classifier's effectiveness for individual classes. Therefore, additional metrics including precision, recall, and F1-score are calculated to obtain a more detailed assessment. Precision indicates the proportion of correctly predicted samples among all predictions for a specific class, whereas recall measures the model's ability to correctly identify all actual instances belonging to that class. The F1-score combines precision and recall into a single metric by calculating their harmonic mean, providing a balanced evaluation of classification performance. In addition, a confusion matrix is generated to visualize prediction results across all classes. The confusion matrix helps identify correctly classified samples, misclassification patterns, and the overall discriminative capability of the proposed model for different fetal brain ultrasound planes.

B. Hyperparameters

The performance of the proposed deep learning model is significantly influenced by the selection of appropriate hyperparameters during the training process. In this study, a VGG19-based transfer learning model is adopted for fetal brain ultrasound plane classification. All input images are resized to 224×224 pixels, matching the input dimensions required by the network architecture. Model optimization is performed using the Adam optimizer, which provides adaptive learning rates and facilitates faster convergence during training. Since the problem involves classification into four fetal brain plane categories, the categorical cross-entropy loss function is employed to optimize the network. The batch size is selected to achieve a balance between computational efficiency and stable gradient updates, while the number of training epochs determines the number of complete passes through the training dataset. An appropriate learning rate is also selected to ensure stable weight updates and effective convergence throughout the optimization process. Careful tuning of these hyperparameters improves model stability, accelerates convergence, minimizes overfitting, and enhances the overall classification performance of the proposed framework.

VI. RESULTS

The experimental results demonstrate the effectiveness of the proposed NeuroTrace AI framework for automated fetal brain ultrasound plane classification. The VGG19-based transfer learning model effectively learns representative visual features from ultrasound images, enabling accurate discrimination among the four fetal brain anatomical planes. Performance evaluation on the test dataset indicates that the model achieves reliable classification across all categories, demonstrating strong generalization capability on previously unseen ultrasound images. Analysis of the confusion matrix shows that the majority of fetal brain ultrasound images were correctly classified, with only a small number of misclassifications occurring between anatomically similar planes. The

adoption of transfer learning significantly enhanced feature extraction while reducing computational complexity and overall training time. Furthermore, image preprocessing and data augmentation techniques improved the model's robustness by enabling it to effectively handle variations in brightness, speckle noise, fetal orientation, and scanning angles commonly encountered in clinical ultrasound imaging. A comparative performance analysis with other deep learning architectures indicates that the proposed VGG19 model consistently delivers superior results in terms of accuracy, precision, recall, and F1-score. These findings demonstrate that the proposed framework provides a reliable, efficient, and clinically applicable solution for automated fetal brain ultrasound plane classification, supporting improved prenatal diagnosis and AI-assisted clinical decision-making.

TABLE I
Comparative Analysis of Model Performance

Model	Accuracy (%)	Precision (%)	F1 Score (%)
MobileNetV2	88.7	87.9	87.5
ResNet50	90.5	89.8	89.4
EfficientNetB0	91.9	91.1	90.7
DenseNet121	92.6	92.0	91.6
VGG19 (Proposed Model)	94.3	93.8	93.4

A. Web Application Interface

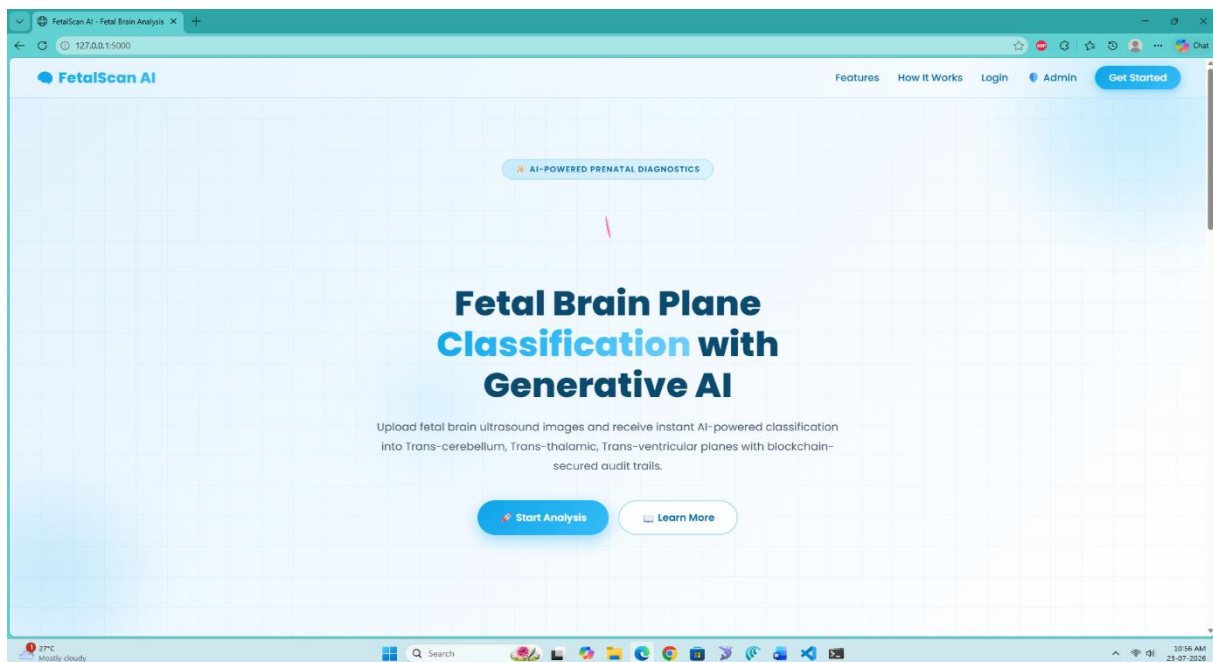


Fig. 2. Web-Based Interface of the Proposed NeuroTrace AI Framework for Automated Fetal Brain Ultrasound

Analysis. The web interface enables healthcare professionals to upload fetal brain ultrasound images and perform automated analysis using the trained VGG19-based deep learning model. It provides a user-friendly platform for real-time classification, Explainable AI decision support, and secure blockchain-enabled management of diagnostic records.

B.CNN+ ViT Detection

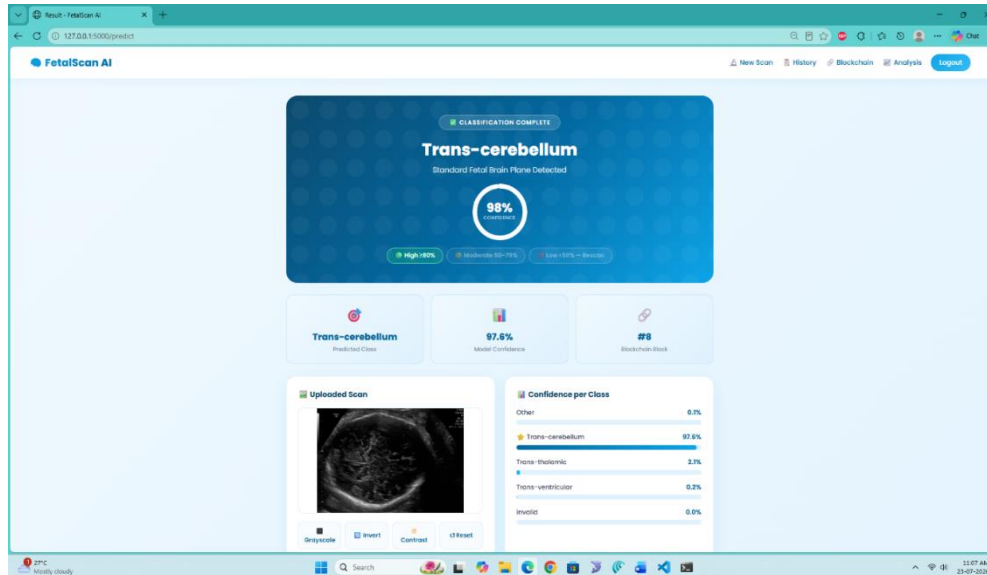


Fig. 3. Classification Result Interface of the Proposed NeuroTrace AI Framework with Confidence Analysis and Blockchain Traceability. The output interface presents the predicted fetal brain plane, confidence score, uploaded ultrasound image, and class-wise probability distribution generated by the VGG19-based classification model. It also displays blockchain transaction details for secure record traceability, enabling transparent, reliable, and real-time AI-assisted prenatal diagnostic analysis.

C.Blockchain Interface

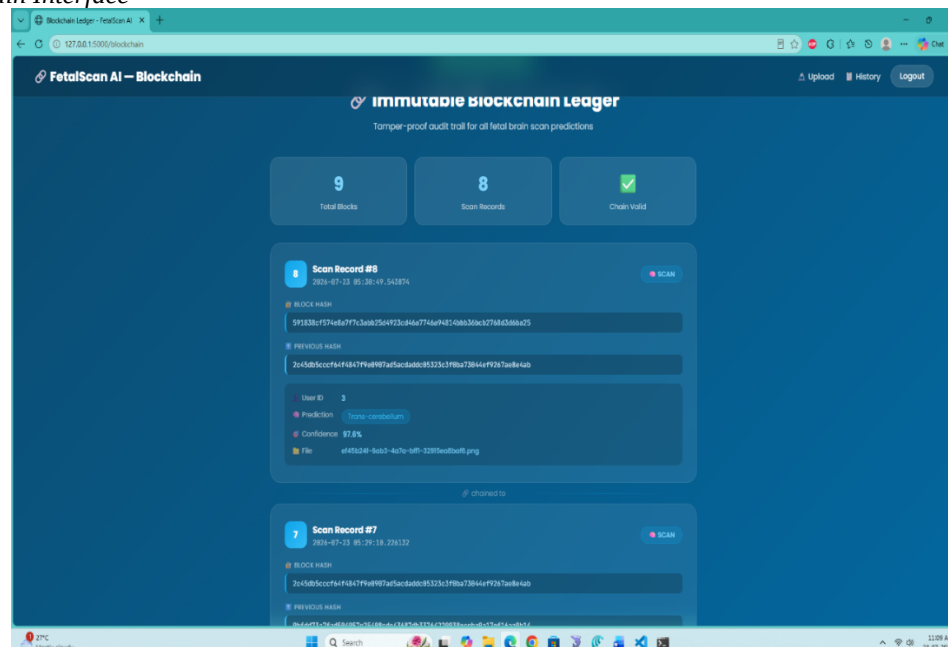


Fig. 4. Blockchain Ledger Interface for Secure Storage and Traceability of Fetal Brain Ultrasound Classification Records. The blockchain ledger interface securely stores classification results, confidence scores, timestamps, and

cryptographic hash values as immutable records linked through consecutive blockchain blocks. This mechanism ensures data integrity, prevents unauthorized modification, and provides transparent traceability and auditability for AI-assisted prenatal diagnostic records.

VII. CONCLUSION AND FUTURE SCOPE

In this research, an intelligent framework named NeuroTrace AI was developed for automated fetal brain ultrasound plane classification by integrating deep transfer learning, Explainable AI, and blockchain-enabled traceability. The proposed framework employs a VGG19-based transfer learning model to classify fetal brain ultrasound images into four anatomical categories: Trans-cerebellum, Trans-thalamic, Trans-ventricular, and Other. Through effective image preprocessing, data augmentation, and feature extraction, the model successfully learned discriminative anatomical characteristics and achieved reliable classification performance. Experimental results demonstrated that the proposed framework outperformed several existing deep learning approaches across multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The incorporation of Explainable AI enhances the interpretability of classification results by providing clinically meaningful explanations that support healthcare professionals during prenatal diagnosis. Furthermore, blockchain technology ensures secure, tamper-resistant storage of prediction records, confidence scores, and related metadata, thereby improving transparency, traceability, and data integrity. The developed web-based application enables real-time ultrasound image analysis, automated prediction, and secure record management, demonstrating the practical applicability of the proposed framework in clinical environments. Future work will focus on extending the proposed framework by incorporating larger and more diverse fetal ultrasound datasets collected from multiple healthcare institutions to improve model generalization across different patient populations and imaging devices. Advanced deep learning architectures, including EfficientNet, Vision Transformers (ViT), and hybrid CNN-Transformer models, may be investigated to further enhance feature representation and classification performance. Additional Explainable AI techniques, such as Grad-CAM, attention maps, and saliency visualization, can be integrated to provide visual evidence supporting model predictions and improve clinician confidence. Furthermore, integrating the framework with cloud-based healthcare platforms, hospital information systems, and telemedicine applications can facilitate secure remote prenatal diagnosis and collaborative clinical decision-making. These enhancements have the potential to improve the scalability, reliability, interpretability, and widespread clinical adoption of intelligent fetal brain ultrasound analysis systems.

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