Explainable Fetal Ultrasound Classification Using CNN And MLP Models

A Project Report submitted in the partial fulfillment of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the project that is entitled with the name **"EXPLAINABLE FETAL ULTRASOUND CLASSIFICATION USING CNN AND MLP MODELS"** is a bonafide work done by the team **Y.Sowmya (21471A05E0), Y.Madhavi (21471A05D9), SK.Chand Asmi (21471A05B9)** in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2024-2025.

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DECLARATION

We declare that this project work titled **EXPLAINABLE FETAL ULTRASOUND CLASSIFICATION USING CNN AND MLP MODELS** is composed by ourselves that the work contain here is our own except where explicitly stated otherwise in the text and that this work has not been submitted for any other degree or professional qualification except as specified.

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The graduates of the programme are able to:

PEO1: Apply the knowledge of Mathematics, Science and Engineering fundamentals to identify and solve Computer Science and Engineering problems.

PEO2: Use various software tools and technologies to solve problems related to academia, industry and society.

PEO3: Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

PEO4: Pursue higher studies and develop their career in software industry.

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Program Outcomes (PO'S)

1. **Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. **Problem analysis:** Identify, formulate, research literature, and analyse complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. **Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. **Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activitieswith an understanding of the limitations.

6. **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. **nvironment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. **Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. **Life-long learning**: Recognize the need for, and have the preparation and ability to engagein independent and life-long learning in the broadest context of technological change.

Project Course Outcomes (CO'S):

CO421.1: Analyse the System of Examinations and identify the problem.

CO421.2: Identify and classify the requirements.

CO421.3: Review the Related Literature

CO421.4: Design and Modularize the project

CO421.5: Construct, Integrate, Test and Implement the Project.

CO421.6: Prepare the project Documentation and present the Report using appropriate method.

Course Outcomes – Program Outcomes mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
C421.1		√											√		
C421.2	√		√		√								√		
C421.3				√		√	√	√					√		
C421.4			√			√	√	√					√	√	
C421.5					√	√	√	√	√	√	√	√	√	√	√
C421.6									√	√	√		√	√	

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
C421.1	2	3											2		
C421.2			2		3								2		
C421.3				2		2	3	3					2		
C421.4			2			1	1	2					3	2	
C421.5					3	3	3	2	3	2	2	1	3	2	1
C421.6									3	2	1		2	3	

Note: The values in the above table represent the level of correlation between CO’s and PO’s:

1.Low level

2.Medium level

3.High level

Project mapping with various courses of Curriculum with Attained PO’s:

Name of the course from which principles are applied in this project	Description of the device	Attained PO
C2204.2, C22L3.2	Gathering the requirements and defining the problem, plan to develop a model for recognizing image manipulations using CNN and MLP	PO1, PO3
CC421.1, C2204.3, C22L3.2	Each and every requirement is critically analyzed, the process model is identified	PO2, PO3
CC421.2, C2204.2, C22L3.3	Logical design is done by using the unified modelling language which involves individual team work	PO3, PO5, PO9
CC421.3, C2204.3, C22L3.2	Each and every module is tested, integrated, and evaluated in our project	PO1, PO5
CC421.4, C2204.4, C22L3.2	Documentation is done by all our four members in the form of a group	PO10
CC421.5, C2204.2, C22L3.3	Each and every phase of the work in group is presented periodically	PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementation is done, and the project will be used for fetal ultrasound image classification, with future updates for improved accuracy and XAI integration.	PO4, PO7
C32SC4.3	The physical design includes website to check whether an image is Valid or Invalid	PO5, PO6

ABSTRACT

Artificial Intelligence has greatly influenced healthcare, most particularly in medical imaging. This paper represents a review in large form that classifies fetal ultrasound images with the use of convolutional neural networks and multi-Layer Perceptrons. While CNN is very good at spatial feature extraction in image classification, their lack of interpretability presents challenges toward applications in health. In this regard, we include methods of Explainable AI (XAI), more precisely Local Interpretable Model-Agnostic Explanations (LIME), for giving more transparency and confidence in the decision-making process of such models. The research here utilizes 12,400 fetal ultrasound images, which were classified under six anatomical structures. The CNN and MLP models showed very promising classification performances of 93.24% and 91.17%, respectively. LIME was implemented to interpret model predictions and to more clearly identify factors contributing to the classification. The results also show that explainability enhances not only trust in AI-based diagnostics but also model reliability in clinical settings.

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1 INTRODUCTION

Artificial Intelligence (AI) has revolutionized the field of medical imaging, playing a crucial role in automating and improving diagnostic processes. Among the various AI techniques, deep learning has gained significant attention for its ability to analyze complex medical data with high accuracy. Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional performance in image classification, making them a powerful tool for medical image analysis. Their ability to automatically extract features from images has enabled advancements in diagnostic applications, reducing human error and increasing efficiency in medical decision-making[1].

Fetal ultrasound imaging is an essential diagnostic tool in obstetric care, providing real-time visualization of the developing fetus. It helps in assessing fetal health, detecting abnormalities, and monitoring growth and development. Despite its importance, interpreting fetal ultrasound images remains a challenging task due to variations in fetal position, image quality, and operator expertise. Traditionally, sonographers and radiologists rely on manual evaluation, which is time-consuming and prone to subjective interpretation. The introduction of AI-based solutions aims to standardize and improve the accuracy of fetal ultrasound image classification, reducing reliance on manual assessments.[2]

Deep learning models, especially CNNs, have proven to be highly effective in medical image analysis due to their ability to extract hierarchical features. These models employ convolutional layers to detect patterns in ultrasound images, pooling layers to reduce dimensionality, and fully connected layers to classify images into different categories. However, one of the main concerns associated with deep learning models is their lack of interpretability. CNNs function as "black boxes," meaning their decision-making process is not easily understood by humans. This lack of transparency raises concerns about reliability and trust, particularly in medical applications where accurate and explainable decisions are critical.

Explainable AI (XAI) has emerged as a solution to address the interpretability issue in deep learning models. XAI techniques provide insights into how AI models make predictions, allowing medical professionals to understand and validate model outputs. One widely used XAI method is Local Interpretable Model-agnostic

Explanations (LIME). LIME works by perturbing input data and analyzing the effects of these changes on model predictions. By highlighting the most influential features that contribute to a classification decision, LIME enhances transparency and builds trust in AI-assisted diagnoses.

In this research, a hybrid deep learning approach is proposed for classifying fetal ultrasound images. The model combines CNNs for feature extraction with Multi-Layer Perceptrons (MLPs) for classification. CNNs are responsible for identifying and extracting spatial features from images, while MLPs process these features to generate classification outputs. This hybrid approach aims to improve classification accuracy while ensuring computational efficiency. Furthermore, LIME is incorporated to provide interpretable explanations, enabling clinicians to understand how and why a particular classification is made.[3]

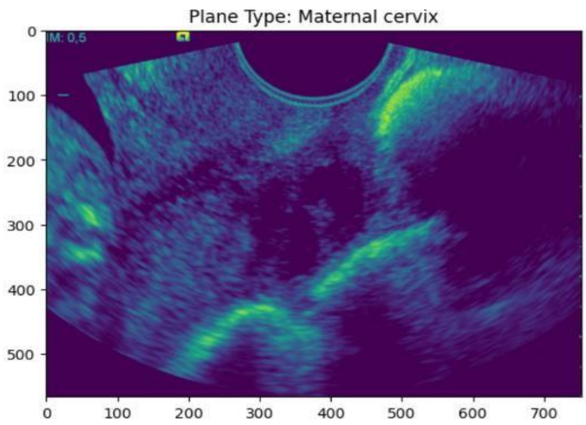


Fig 1.1: Fetal Ultrasound Image

Fetal ultrasound image classification presents unique challenges due to the variability in imaging conditions and the complexity of fetal anatomy. Differences in maternal body composition, fetal movement, and ultrasound machine settings contribute to variations in image quality. Additionally, class imbalance in fetal ultrasound datasets can impact model performance, as some fetal structures are more frequently represented than others. To address these challenges, robust preprocessing techniques and data augmentation strategies are implemented to enhance model generalization and accuracy.

To improve model performance, preprocessing steps such as resizing, normalization, and contrast enhancement are applied. These techniques standardize image inputs, making it easier for the deep learning model to learn relevant features.

Data augmentation methods such as rotation, flipping, and scaling are used to artificially expand the training dataset, mitigating class imbalance and enhancing the robustness of the model. Transfer learning is also employed by fine-tuning pre-trained CNN models on fetal ultrasound images, leveraging previously learned features to accelerate training and improve classification accuracy.[4]

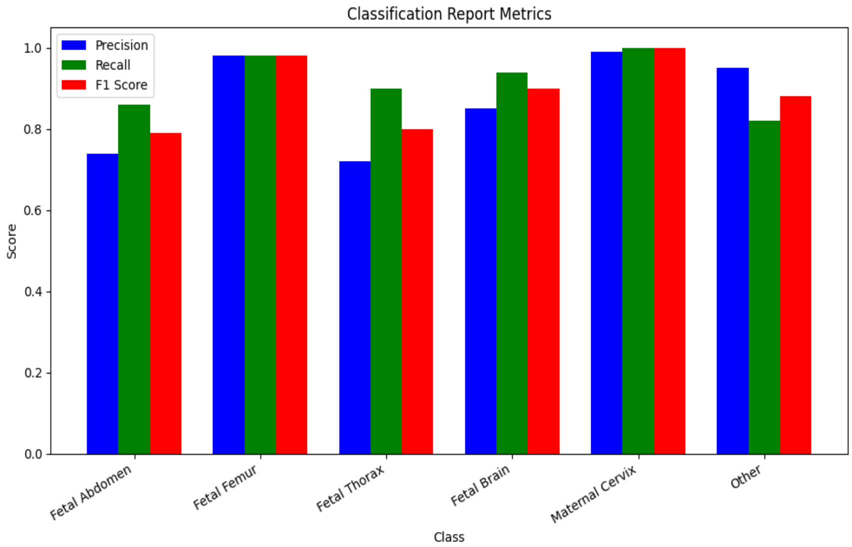
The integration of XAI techniques in medical imaging has significant implications for clinical decision-making. By making AI models more interpretable, explainability fosters trust and adoption among medical professionals. Regulatory bodies emphasize the importance of AI transparency, ensuring that AI-driven medical applications adhere to ethical guidelines and safety standards. Additionally, interpretability helps in error analysis and debugging, allowing researchers to identify biases in the model and improve its overall performance.

Applying explainable deep learning models in fetal ultrasound classification represents a step toward AI-assisted prenatal diagnostics. The proposed CNN-MLP architecture, coupled with LIME, provides an efficient and interpretable framework for classifying fetal ultrasound images. As Shown in Fig:1.2. This approach not only enhances classification accuracy but also ensures that AI-driven decisions can be understood and validated by medical practitioners. The ability to explain AI predictions is crucial in medical contexts where transparency and reliability are paramount.[5]

The use of AI in fetal ultrasound imaging can lead to significant advancements in prenatal healthcare. Automated classification of fetal structures can assist sonographers in identifying abnormalities early, enabling timely medical interventions. By reducing the subjectivity associated with manual evaluation, AI-powered ultrasound analysis can provide more consistent and objective results. This is particularly beneficial in resource-limited settings where access to highly skilled radiologists may be restricted.

Multi-modal data integration can enhance model performance by combining ultrasound images with other clinical data, such as patient demographics and medical history. This holistic approach can provide more comprehensive diagnostic insights, improving overall accuracy and reliability. Additionally, advancements in federated learning could allow AI models to be trained across multiple institutions without compromising patient privacy, facilitating large-scale deployment in medical settings.

As AI continues to transform healthcare, the development of explainable deep learning models will remain a priority. High classification accuracy alone is not sufficient; AI models must also be transparent and interpretable to gain acceptance in clinical practice. The success of AI-driven diagnostics depends on balancing model performance with interpretability, ensuring that medical professionals can trust and rely on AI-generated insights.



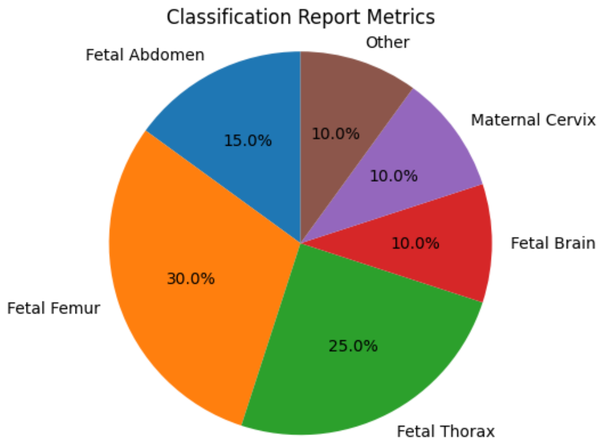


Fig 1.2: Statistics for fetal Ultrasound

The proposed explainable deep learning framework contributes to the responsible adoption of AI in fetal ultrasound classification. By bridging the gap between accuracy and interpretability, this research provides a foundation for integrating AI into prenatal diagnostics. The insights gained from explainable AI can lead to further improvements in medical imaging, ultimately benefiting both healthcare providers and patients. [6]

The increasing role of AI in medical imaging underscores the need for continuous advancements in model transparency and performance. As deep learning techniques evolve, the emphasis on interpretability will grow, ensuring that AI remains a trustworthy and valuable tool in healthcare. Collaboration between AI researchers, medical professionals, and regulatory bodies will be crucial in shaping the future of explainable AI in medical diagnostics. This research serves as a step in that direction, demonstrating how deep learning and explainability can be effectively combined to enhance fetal ultrasound classification and improve prenatal healthcare outcomes.

While deep learning has significantly improved medical image classification, challenges related to dataset quality and size persist. Medical imaging datasets often contain noise, artifacts, and variations in image acquisition protocols. These inconsistencies can affect model generalization, leading to biased or inaccurate predictions. To address this, high-quality datasets with diverse and well-annotated images are essential. In fetal ultrasound classification, ensuring balanced representation of different fetal structures helps prevent model bias and enhances the robustness of AI-based diagnostic systems.

Another key consideration in AI-driven medical imaging is real-time processing capability. Ultrasound imaging is commonly used in clinical settings for real-time fetal monitoring, necessitating AI models that can process and classify images instantly. Efficient deep learning architectures optimized for speed and accuracy are crucial for deployment in real-world medical applications. Edge computing and cloud-based AI solutions can further support real-time image analysis, enabling seamless integration of AI into ultrasound imaging workflows without compromising performance.

Ethical and regulatory aspects also play a vital role in AI adoption for medical applications. Ensuring patient privacy and data security is paramount when working with sensitive medical data. Federated learning and secure AI models allow for collaborative training across institutions while maintaining patient confidentiality. Additionally, regulatory bodies such as the FDA and European Medicines Agency emphasize the need for AI models in healthcare to be interpretable, transparent, and clinically validated before widespread implementation.[7]

Despite the advancements in explainable AI, challenges remain in bridging the gap between AI-generated insights and clinical decision-making. Medical professionals require intuitive and user-friendly interfaces to interpret AI explanations effectively. Visual explanations provided by methods like LIME and Grad-CAM must align with human cognitive understanding to facilitate trust in AI-assisted diagnoses. Continuous collaboration between AI researchers and medical practitioners is essential to refine interpretability techniques and enhance clinical applicability.

Ultimately, integrating AI into fetal ultrasound imaging has the potential to transform prenatal diagnostics, improving early detection of fetal abnormalities and enhancing maternal-fetal healthcare. The combination of CNN-based classification, hybrid deep learning architectures, and explainability techniques offers a promising path forward. By ensuring accuracy, efficiency, and transparency, AI-driven medical imaging can provide valuable support to healthcare professionals, ultimately leading to better patient outcomes. As technology evolves, further research and innovation in explainable AI will be crucial in realizing the full potential of AI-assisted medical diagnostics.

2 LITERATURE SURVEY

Deep learning has significantly advanced the field of medical imaging, particularly in the classification of fetal ultrasound images. Traditional approaches relied on handcrafted features, which were often labor-intensive and less accurate. Convolutional Neural Networks (CNNs) have emerged as a powerful tool for automating feature extraction, leading to improved classification of anatomical planes such as the brain, abdomen, thorax, and femur. Studies like those by Ravishankar et al. and Baumgartner et al. demonstrated the potential of CNNs to achieve high accuracy in fetal ultrasound classification. However, challenges such as imbalanced datasets and the inherent complexity of CNNs underline the need for explainable and robust models.

The integration of Explainable AI (XAI) techniques in medical imaging has addressed the black-box nature of deep learning models. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) provide insights into the decision-making process by highlighting the regions of interest in an image that influence predictions. This has proven particularly useful in fetal ultrasound imaging, where understanding the model's focus is critical for clinical reliability. Ribeiro et al. and Selvaraju et al. have laid the groundwork for these XAI techniques, emphasizing their importance in enhancing trust and transparency in AI-driven healthcare systems.

Preprocessing techniques are essential for improving the quality and interpretability of ultrasound images. Methods such as resizing, normalization, and data augmentation have been widely used to address variations in image quality. Advanced techniques like edge detection and segmentation, as demonstrated by Lu et al., further enhance the visibility of anatomical structures, leading to better classification performance. These preprocessing steps, when combined with augmentation, also mitigate the challenges posed by limited and imbalanced datasets.[8]

To ensure model reliability, researchers have adopted strategies like cross-validation and transfer learning. Cross-validation provides a robust evaluation framework, especially for small datasets, while transfer learning leverages pre-trained models to improve performance with limited data. Studies like Howard et al. highlight the effectiveness of these techniques in reducing training time and boosting model generalization. Despite these advancements, future work must focus on developing more interpretable models and leveraging larger datasets to enhance the clinical applicability of AI in fetal ultrasound classification.

2.1 DEEP LEARNING AND NEURAL NETWORKS

Deep learning is a powerful branch of artificial intelligence that uses artificial neural networks to model and solve complex problems. It has transformed industries by enabling machines to process, understand, and act on data in ways that were previously impossible. Neural networks, the core of deep learning, are computational models inspired by the structure and function of the human brain. They consist of layers of interconnected nodes, or neurons, which process input data and extract meaningful features through a series of mathematical operations. These networks typically include an input layer that receives data, multiple hidden layers that perform feature extraction, and an output layer that generates predictions. [9]

The strength of deep learning lies in its ability to automatically learn hierarchical feature representations directly from raw data. This eliminates the need for manual feature engineering, which is often required in traditional machine learning. For example, in image analysis, deep learning models can identify low-level features like edges and textures in early layers and high-level features like shapes and objects in deeper layers. This hierarchical approach allows deep learning to excel in tasks such as image classification, object detection, speech recognition, and natural language processing.

Convolutional Neural Networks (CNNs) are among the most widely used architectures in deep learning, particularly for image-related tasks. They use convolutional layers to extract spatial features, making them highly effective for tasks like facial recognition, medical imaging, and autonomous driving. Another important architecture is the Recurrent Neural Network (RNN), which is designed for sequential data such as time-series and text. RNNs are commonly used in applications like speech recognition, language translation, and predictive modeling. More recently, transformer-based models have gained prominence for their exceptional performance in natural language processing and image analysis, leveraging attention mechanisms to focus on relevant parts of the input data.

Training a deep learning model involves a series of iterative steps. Data preprocessing is a critical first step, ensuring that the input data is clean and normalized for optimal performance. Once the model architecture is defined, it undergoes a training process where input data is passed through the network, and predictions are compared to the actual outcomes using a loss function. The model's weights are then adjusted using optimization algorithms such as Stochastic Gradient Descent or Adam to minimize the loss. This process, known as backpropagation, is repeated across many iterations, or epochs, until the model converges to an optimal solution. [10]

Despite its impressive capabilities, deep learning is not without challenges. It is computationally intensive, requiring significant hardware resources like GPUs or TPUs for training. Large datasets are often necessary to achieve high performance, which can be a barrier in domains where labeled data is scarce. Additionally, the black-box nature of deep learning models makes them difficult to interpret, raising concerns about transparency and trust, particularly in critical applications like healthcare.

Deep learning has found applications across diverse domains, revolutionizing industries with its ability to handle complex, high-dimensional data. In healthcare, it is used for disease diagnosis, medical imaging, and personalized treatment planning. In finance, it supports fraud detection and algorithmic trading. In autonomous systems, it powers self-driving cars and robotics. The continuous advancements in hardware and algorithms are enabling deep learning to address increasingly complex problems, making it a cornerstone technology in the era of artificial intelligence. [11]

2.2 APPLICATIONS OF EXPLAINABLE AI IN HEALTHCARE

Explainable AI (XAI) has become a transformative force in healthcare, addressing the critical need for transparency, trust, and interpretability in artificial intelligence systems. AI models in healthcare often involve complex algorithms, such as deep learning, which function as "black boxes," making their decision-making processes challenging to understand. XAI bridges this gap by offering explanations that make these models more interpretable to clinicians, researchers, and patients, thus enhancing their utility in medical applications. [12]

In diagnostics, XAI facilitates the adoption of AI tools by providing understandable insights into the decision making process. For instance, in medical imaging, deep learning models are employed to detect abnormalities like tumors, fractures, or other pathological features. However, clinicians often require a rationale for these predictions to trust the AI system. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Exp lanations (SHAP) highlight critical regions of the image that contribute to the AI's decision, allowing clinicians to validate the findings. In radiology, XAI-powered AI systems can detect early signs of diseases such as cancer, providing explanations for each diagnosis, thus improving acceptance and reducing diagnostic errors. [13]

Another critical application is in personalized medicine, where XAI helps tailor treatments to individual patients by explaining model predictions regarding treatment outcomes. AI models are often used to predict drug efficacy, possible side effects, or the progression of diseases based on patient data, including genetic information. XAI ensures that these predictions are interpretable, enabling clinicians to choose the most appropriate treatment strategies confidently. For example, in oncology, AI systems can recommend chemotherapy regimens, and XAI explains why specific regimens are chosen based on factors such as tumor markers, patient age, and genetic profiles.

XAI also plays a pivotal role in enhancing clinical decision support systems (CDSS). These systems analyze patient data to provide recommendations for diagnosis, treatment, or risk stratification. With XAI, CDSS can explain their recommendations, empowering clinicians to make informed decisions while maintaining accountability. For instance, in cardiology, CDSS can predict the risk of heart attacks based on a combination of patient data such as cholesterol levels, blood pressure, and medical history. By explaining which features contributed to the prediction, XAI fosters trust in the system and improves its adoption in clinical practice. [14]

In critical care and emergency medicine, XAI improves the management of acute conditions by providing real time, interpretable insights. AI models are used to predict sepsis, monitor vital signs, or determine the need for interventions such as mechanical ventilation. XAI techniques explain these predictions, allowing medical staff to act promptly and with greater confidence. For example, in the prediction of sepsis, XAI can identify key indicators such as abnormal white blood cell counts or elevated body temperature, thus assisting clinicians in initiating timely treatments.

Beyond diagnostics and treatment, XAI contributes significantly to healthcare administration and operational efficiency. In hospital resource management, AI models are used to predict patient admission rates, optimize staffing, and allocate resources efficiently. XAI ensures these predictions are transparent, enabling administrators to justify decisions and plan accordingly. Similarly, in medical insurance, XAI models help assess claims by explaining decisions about approvals or rejections, ensuring fairness and compliance with regulations.

Another growing application of XAI is in wearable health technologies and remote monitoring. Wearable devices equipped with AI algorithms monitor parameters such as heart rate, blood oxygen levels, and sleep patterns. XAI explains anomalies detected by these devices, helping users and healthcare providers understand the underlying causes and take appropriate action. For example, in detecting atrial fibrillation, XAI-powered wearables can highlight specific periods of irregular heartbeats, allowing for accurate diagnosis and follow-up.

XAI also addresses ethical concerns and biases in AI models used in healthcare. AI systems may unintentionally learn biases from training data, leading to unequal treatment of different patient groups. XAI methods expose these biases by clarifying how decisions are made, enabling developers to refine models to ensure fairness and equity. This capability is particularly important in ensuring that AI benefits diverse populations and avoids perpetuating health disparities. [15]

In summary, XAI enhances the reliability, transparency, and fairness of AI systems in healthcare. By providing interpretable insights, it bridges the gap between advanced AI models and their practical application in clinical settings. From diagnostics and personalized medicine to critical care and operational efficiency, XAI has the potential to revolutionize healthcare by empowering clinicians, improving patient outcomes, and fostering trust in AI technologies. As AI continues to advance, the integration of XAI will remain a crucial factor in ensuring its ethical and effective deployment in healthcare.

Applications of XAI in healthcare include:

- **Medical Diagnostics:** Assisting doctors in diagnosing diseases like cancer, cardiovascular conditions, and neurological disorders.
- **Personalized Treatment Plans:** Recommending tailored treatments by understanding patient-specific factors that influence model outcomes.

- **Drug Discovery:** Explaining how models predict the efficacy of potential drug compounds.
- **Fetal Ultrasound Analysis:** Identifying anatomical structures and abnormalities in fetal development, which is critical for prenatal care.

By making model predictions transparent, XAI enhances the credibility and adoption of AI systems in healthcare. However, challenges such as scalability, robustness, and integration with clinical workflows remain areas of active research.

2.3 CHALLENGES IN FETAL ULTRASOUND IMAGE ANALYSIS

Fetal ultrasound imaging is a vital tool in prenatal care, offering insights into fetal development and detecting abnormalities. However, several challenges limit its effectiveness in automated analysis:

A. **Image Quality Variability:** Ultrasound images are prone to noise, low resolution, and artifacts, which hinder accurate feature extraction and analysis. Variability due to operator expertise and device quality further complicates standardization.

B. **Complex Anatomy:** The small size and dynamic nature of fetal structures make it challenging to distinguish between different planes, such as the fetal brain, abdomen, and femur. Precise localization and classification require advanced segmentation and classification algorithms.

C. **Imbalanced:** Datasets often contain an unequal distribution of image categories, with some fetal planes being underrepresented. This imbalance affects model training and may lead to biased predictions.

D. **Interpretability:** Clinicians need to understand the rationale behind AI predictions to trust and use these systems. Black-box models pose a significant hurdle, necessitating the integration of XAI techniques.

3 EXISTING SYSTEM

The existing systems for fetal ultrasound image analysis predominantly rely on manual interpretation by trained sonographers and clinicians. These systems involve capturing two-dimensional (2D) or three-dimensional (3D) ultrasound images, which are then analyzed visually to assess fetal growth, detect abnormalities, and monitor overall health. While manual interpretation remains the gold standard, it is highly dependent on the operator's expertise, skill, and experience, leading to variability in diagnostic accuracy. Inconsistent interpretations can result from factors such as sonographer fatigue, suboptimal imaging conditions, or the complexity of fetal anatomy.

Automated systems have been developed to augment manual efforts by leveraging traditional image processing techniques and, more recently, machine learning (ML) models. These systems aim to perform tasks such as segmentation of fetal anatomical structures, plane classification, and anomaly detection. Traditional approaches rely on handcrafted features and rule-based algorithms, which are often limited in handling the high variability and noise in ultrasound images. Such systems struggle to generalize across different imaging conditions and patient populations.

Deep learning has emerged as a transformative technology, with Convolutional Neural Networks (CNNs) being widely used for fetal ultrasound analysis. These models have shown promising results in tasks like classifying standard planes, detecting fetal abnormalities, and estimating gestational age. Despite their success, existing deep learning-based systems face significant challenges, including the need for large annotated datasets, high computational resources, and a lack of interpretability. The "black-box" nature of these models limits their trustworthiness in clinical settings, where understanding the rationale behind a prediction is crucial.

Current systems also face challenges in real-time performance. Automated analysis needs to provide immediate feedback during scanning to assist clinicians, but achieving real-time capabilities often involves trade-offs in accuracy. Furthermore, the diversity in ultrasound machines, operator skills, and patient conditions makes it difficult for existing systems to perform consistently in all clinical environment.

4 PROPOSED SYSTEM

The proposed system for the project, Explainable Fetal Ultrasound Classification Using CNN and MLP Models, combines the power of Convolutional Neural Networks (CNNs) and Multilayer Perceptrons (MLPs) to create an accurate and interpretable solution for classifying fetal ultrasound images. The system leverages the strengths of both deep learning models while ensuring that the decision-making process is transparent and understandable through the integration of Explainable AI (XAI) techniques.

CNNs are employed for their capability to automatically extract meaningful features from the raw ultrasound images. These networks excel in recognizing complex patterns, such as anatomical structures and textures, which are crucial for identifying and classifying different fetal anatomical planes, such as the fetal brain, abdomen, femur, thorax, maternal cervix, and other categories. The CNN model processes the images through multiple convolutional layers, pooling, and activation functions to learn the hierarchical features that are essential for distinguishing between different planes.

Once the CNN extracts the relevant features, the data is passed to an MLP, which acts as the decision-making layer of the system. MLPs are capable of learning complex, non-linear relationships between the features and the output labels, allowing for improved classification accuracy.

To address the need for transparency in deep learning models, LIME is a crucial addition, as it helps to interpret and explain the predictions made by the CNN and MLP models. By providing a localized explanation for individual predictions, LIME highlights the regions in the ultrasound images that contributed to the model's decision, thereby enabling clinicians to trust and understand the model's output. This is especially important in healthcare, where decision support systems must be interpretable to ensure they complement the expertise of medical professionals.

Real-time classification and feedback capabilities are integrated into the system, providing immediate assistance to clinicians during ultrasound examinations. This enables rapid and accurate classification of fetal anatomical planes and offers interpretable results to ensure that the clinicians can validate the AI’s suggestions effectively.

5 SYSTEM REQUIREMENTS

5.1 HARDWARE REQUIREMENTS:

- **System Type** : intel®core™i3-7500UCPU@2.40gh
- **Cache memory** : 4MB(Megabyte)
- **RAM** **:** 8GB (gigabyte)
- **Hard Disk** : 4GB

The selection of appropriate hardware is crucial for efficiently training and deploying deep learning models, especially in medical image classification tasks such as fetal ultrasound analysis. Deep learning models, particularly Convolutional Neural Networks (CNNs) combined with Multi-Layer Perceptrons (MLPs), require significant computational resources to process large datasets and perform complex mathematical operations. The choice of processor, memory, and storage plays a vital role in determining the performance and speed of model training and inference. A system equipped with an Intel Core i3-7500U CPU at 2.40 GHz provides moderate computational power to handle image preprocessing, feature extraction, and model evaluation tasks. However, for more demanding deep learning applications, utilizing a dedicated GPU such as an NVIDIA CUDA-enabled GPU is highly recommended, as it can significantly accelerate matrix multiplications and deep learning computations.

Memory and storage are equally important components in deep learning applications. The 4MB cache memory helps in reducing data access latency, enabling faster retrieval of frequently used variables during model execution. Additionally, 8GB of RAM ensures smooth operation by allowing parallel processing of data and computations. Since deep learning models often require handling large datasets and batch processing, having higher RAM capacity (16GB or more) is beneficial for avoiding memory constraints and improving training efficiency. The hard disk storage of 4GB is required for installing essential software, saving datasets, and storing trained models. Using a Solid State Drive (SSD) instead of a traditional HDD can further enhance system performance by improving data read and write speeds, leading to faster model loading and execution.

In deep learning projects involving medical imaging, the hardware requirements should align with the complexity of the models and dataset size. While the given hardware configuration is sufficient for training and testing a moderate-sized fetal ultrasound dataset, more complex architectures and larger datasets may require cloud-based solutions like Google Colab, AWS, or Azure, which provide access to high-performance GPUs and TPUs. Proper hardware selection ensures an efficient workflow, reducing the overall training time and improving model performance, which is crucial for developing an accurate and explainable AI-driven fetal ultrasound classification system.

5.2 SOFTWARE REQUIREMENTS:

- **Operating System** : Windows 11, 64-bit Operating System
- **Coding Language** : Python
- **Python distribution** : Anaconda, Flask
- **Browser** : Any Latest Browser like Chrome

The operating system plays a crucial role in the execution and management of software applications. Windows 11, a 64-bit operating system, is selected for this project due to its enhanced performance, security, and support for advanced computing tasks. With improved memory management and optimized processing capabilities, Windows 11 ensures smooth execution of deep learning models, enabling efficient handling of large datasets and complex computations required for fetal ultrasound image classification. The stability and compatibility of Windows 11 with various software tools and libraries make it an ideal choice for developing and deploying AI-based applications.

The coding language used for this project is Python, which is widely recognized for its versatility and ease of use. Python provides a rich ecosystem of libraries such as TensorFlow, Keras, NumPy, and OpenCV, making it highly suitable for deep learning and image processing tasks. Its simplicity and readability allow for rapid prototyping, debugging, and implementation of machine learning algorithms. Python’s extensive community support ensures access to various resources, updates, and troubleshooting solutions, which enhances the development process and facilitates the seamless integration of AI techniques in medical imaging applications.

To manage Python’s dependencies and streamline the development process, Anaconda is used as the primary Python distribution. Anaconda simplifies package management and supports various data science libraries required for deep learning. Additionally, Flask is utilized as a lightweight web framework to create a user-friendly interface for model deployment. Flask enables efficient interaction between users and the AI model, allowing medical professionals to upload ultrasound images and receive classification results in real time. The integration of Anaconda and Flask enhances the project's usability, ensuring smooth execution of AI-based fetal ultrasound image classification.

A web browser is essential for accessing and interacting with the deployed AI model. Any latest browser, such as Google Chrome, is recommended due to its speed, security, and compatibility with modern web technologies. Chrome provides an optimized environment for running Flask-based web applications, ensuring a responsive and efficient user experience. The browser also supports various debugging tools that aid in monitoring and improving the performance of web applications, making it an indispensable component of the system.

Overall, the combination of Windows 11, Python, Anaconda, Flask, and a modern web browser ensures a robust and efficient environment for developing and deploying an AI-driven fetal ultrasound image classification system. The selected software components provide the necessary computational power, flexibility, and accessibility required for processing ultrasound images, applying deep learning techniques, and presenting interpretable results to healthcare professionals. This well-integrated software stack enhances the reliability and accuracy of the system, contributing to improved prenatal diagnostics and medical decision-making.

6 SYSTEM ANALYSIS

6.1 DATASET DESCRIPTION

The dataset used in this project is focused on classifying fetal ultrasound images into different anatomical regions. It consists of a total of 9876 augmented images.

Class Details:

A. **Other:** This class includes ultrasound images that do not belong to any of the other specified categories as shown in Fig 6.6.

B. **Maternal cervix:** Images of the maternal cervix area, crucial for identifying pregnancy progression and health as shown in Fig 6.1.

C. **Fetal abdomen:** This class covers images of the fetal abdomen, important for assessing fetal growth and development as shown in Fig 6.2.

D. **Fetal brain:** This category contains images of the fetal brain, used for checking fetal neurological development as shown in Fig 6.3.

E. **Fetal femur:** These images focus on the fetal femur, typically used to estimate fetal size and growth as shown in Fig 6.4.

F. **Fetal thorax:** Images of the fetal thorax, often used for monitoring fetal heart and lung development as shown in Fig 6.5.

Fig 6.1: Fetal Abdomen

Fig 6.2: Fetal Brain

Fig 6.3: Fetal Femur

Fig 6.4: Fetal Thorax

Fig 6.5: Metarnal Cervix

Fig 6.6: Others

6.2 PREPROCESSING TECHNIQUES

In this project, the primary goal is to enhance the quality of the images and prepare them for the deep learning model As shown in Fig 6.7. This involves several key preprocessing steps :

A. **Resizing:** Since the original image dimensions vary, all images are resized to 224x224 pixels. This is essential because the CNN model expects input images of a consistent size to efficiently process them through layers.
B. **Normalization:** Images are normalized by scaling the pixel values between 0 and 1. This helps in speeding up the convergence of the deep learning model and stabilizes the training process.
C. **Feature extraction:** in this project is performed using ResNet-50, a deep convolutional neural network pre-trained on large datasets. It extracts deep features from fetal ultrasound images by leveraging residual learning and multiple convolutional layers.
D. **Splitting the Dataset:** The data is divided into training, validation, and testing sets, with a ratio of 4:1 for training and validation, ensuring a balanced approach to model validation.

These preprocessing techniques are essential in ensuring that the model has a diverse and well-prepared set of images for training and evaluation**.**

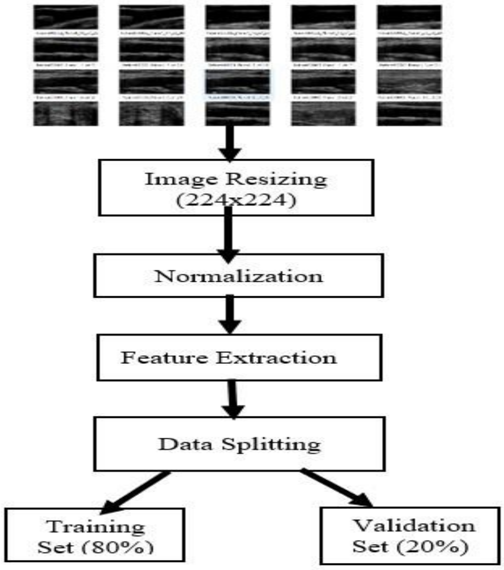


Fig 6.7: Preprocessing Techniques

6.3 IMPLEMENTATION OF CNN MODEL

The Convolutional Neural Network (CNN) model is a deep learning architecture specifically designed for image classification and feature extraction. It mimics the human visual system by identifying patterns and spatial hierarchies in images, making it particularly suitable for medical imaging tasks such as fetal ultrasound classification. The CNN model operates by automatically detecting features such as edges, textures, and complex structures within an image, enabling accurate classification. As shown in Fig 6.8, the CNN model used in this study consists of multiple layers, each serving a distinct function in processing the input images. These layers work together to progressively extract, transform, and classify important image features. The CNN model significantly reduces the need for manual feature engineering, making it an efficient and powerful approach for medical image analysis.

Model Architecture

The CNN model used in this study follows a structured architecture comprising multiple layers, including convolutional layers, pooling layers, fully connected layers, and an output layer. The input to the model consists of ultrasound images of size 224x224x3, where the three channels represent RGB color values. The model processes these images through a series of transformations, allowing it to extract and learn meaningful patterns from the data.

A. **Convolutional Layers:**The convolutional layers are the foundation of a CNN and play a crucial role in feature extraction. These layers apply multiple filters (kernels) to the input image to detect fundamental visual patterns such as edges, curves, and textures. Each filter slides over the image and performs element-wise multiplications, generating feature maps that represent the detected patterns. Stacking multiple convolutional layers allows the model to capture increasingly complex features, starting from simple edges in the initial layers to more detailed structures in deeper layers. The activation function used in these layers is typically ReLU (Rectified Linear Unit), which introduces non-linearity and helps the model learn complex relationships.
B. **Pooling Layers:** Pooling layers follow convolutional layers and serve to down-sample feature maps, reducing their spatial dimensions while retaining essential information. This process helps in making the model computationally efficient and prevents overfitting by reducing the number of parameters. In this study, max pooling is employed, where the highest value within a small window is selected and retained. This operation not only reduces dimensionality but also ensures that the most significant features are preserved for further processing. Pooling also provides translation invariance, allowing the model to recognize patterns regardless of their exact position in the image.
C. **Fully Connected Layers:** After the convolutional and pooling operations, the extracted features are passed to fully connected layers. These layers transform the spatially reduced feature maps into a one-dimensional vector representation, allowing the model to make predictions based on learned features. The fully connected layers act as a classifier by combining information from different neurons to produce a final decision. Dropout regularization is applied to these layers to prevent overfitting by randomly deactivating some neurons during training.
D. **Output Layer:** The final layer in the CNN architecture is the output layer, which determines the predicted class of the input image. This layer uses the softmax activation function, which converts raw prediction scores into a probability distribution over the predefined classes. The class with the highest probability is selected as the final output. In this study, the CNN model classifies

fetal ultrasound images into different categories such as fetal brain, fetal thorax, fetal abdomen, fetal femur, and maternal cervix.

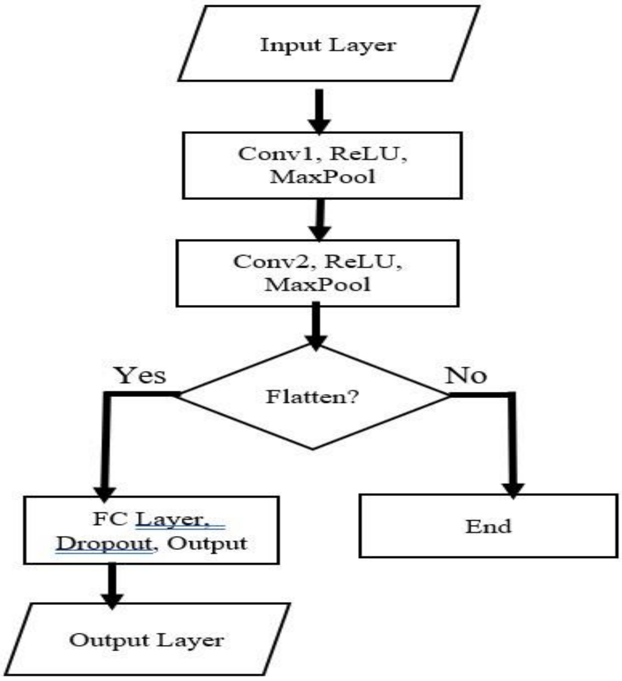


Fig.6.8: CNN Model Architecture

6.4 IMPLEMENTATION OF MLP MODEL

In addition to the CNN model, a Multi-Layer Perceptron (MLP) model was also tested for comparison in the classification of fetal ultrasound images. The MLP is a feedforward artificial neural network that consists of multiple layers of neurons, each connected to the next layer in a fully connected manner. Unlike CNNs, which utilize convolutional operations to detect spatial patterns in images, MLPs rely solely on fully connected layers, making them less effective for image processing tasks but useful for comparison and baseline performance evaluation. The MLP model was trained on the same dataset as the CNN model to analyze its ability to classify fetal ultrasound images accurately.

Model Architecture

The MLP model architecture consists of three main components: the input layer, multiple hidden layers, and an output layer. Each of these layers plays a crucial role in processing the input data and making predictions.

A. **Input Layer:** The input layer of the MLP model takes in the fetal ultrasound images, which have been resized to 224x224 pixels to match the input format used for the CNN model. However, unlike CNNs that maintain the spatial structure of the image, the MLP model flattens the image into a one-dimensional vector before passing it to the first hidden layer. Each pixel in the image is treated as a separate input feature, which increases the number of neurons in the input layer significantly. This flattening process results in $224 \times 224 = 50{,}176$ input features for each image.

B. **Hidden Layers:** The hidden layers in the MLP model perform the task of feature learning and representation transformation. In this study, two or more hidden layers were used to enhance the model's ability to learn complex relationships between input features. Each hidden layer consists of multiple neurons, each of which applies a mathematical transformation to the input received from the previous layer.The ReLU (Rectified Linear Unit) activation function was used in each hidden layer to introduce non-linearity, allowing the model to learn complex patterns in the data.The number of neurons in each hidden layer was determined experimentally to balance performance and computational efficiency.

C. Dropout regularization was applied to prevent overfitting by randomly deactivating a fraction of neurons during training.As the image passes through these layers, the MLP model attempts to learn distinctive patterns that help differentiate between various fetal ultrasound image classes. However, due to the lack of spatial feature extraction mechanisms, MLP models generally perform sub optimally compared to CNNs when handling image classification tasks.

D. **Output Layer:** The final layer of the MLP model is the output layer, which is responsible for making the final classification decision. This layer consists of neurons corresponding to the number of image categories in the dataset.

- The softmax activation function was used in the output layer to convert the raw scores into a probability distribution over the predefined classes.

- The class with the highest probability was selected as the predicted category for the input image.
- The categorical cross-entropy loss function was used to measure the discrepancy between the predicted and actual labels during training.

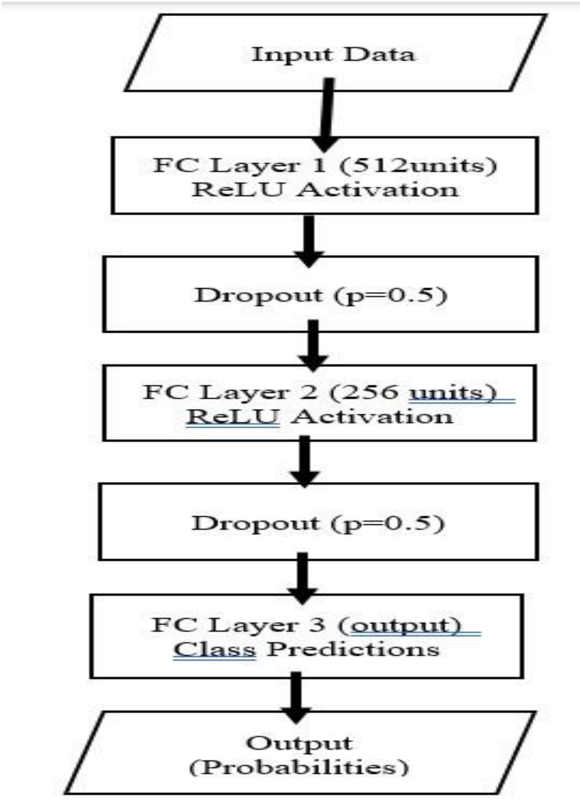


Fig 6.9: Mlp Model Architecture

6.5 CLASSIFICATION RESULTS

After training both the CNN and MLP models, the combined results are as follows:

- Training Accuracy: 93.24%
- Validation Accuracy: 91.17%

The classification results obtained from the trained CNN and MLP models demonstrate the effectiveness of the deep learning approach in identifying fetal ultrasound image planes. With a training accuracy of 93.24% and a validation accuracy of 91.17%, the model shows a strong ability to generalize well on unseen data. These results highlight that the CNN has successfully extracted meaningful features from the ultrasound images, while the MLP classifier has effectively distinguished between different fetal structures. The high accuracy achieved on both training and validation datasets indicates that the model has learned relevant patterns and variations present in fetal ultrasound images, making it a reliable tool for automated classification.

The slight difference between training and validation accuracy suggests that the model is well-trained without significant overfitting. The use of data augmentation, regularization techniques such as dropout, and hyperparameter tuning has contributed to improving model generalization, ensuring that it does not memorize training data but instead learns robust features applicable to new images. The consistent validation accuracy of 91.17% indicates that the model maintains its classification capability across diverse ultrasound images, reinforcing its potential for real-world applications in prenatal diagnostics. Additionally, the explainability techniques, such as LIME, help in interpreting the model's predictions, ensuring that healthcare professionals can trust its decisions.

6.6 EXPLAINABILITY WITH LIME

One of the core objectives of this project is to implement Explainable AI (XAI) to understand how the model makes decisions. As shown in **Fig 6.10** LIME (Local Interpretable Model-agnostic Explanations) is applied to the CNN model to generate explanations for individual predictions.

A. **LIME Explanation Process:** LIME explains the model's predictions by perturbing the input image and observing how the predictions change. It fits a simple interpretable model (e.g., a linear model) to these perturbed data points, highlighting which parts of the image are most influential in the model's decision.

B. **LIME Visualizations:** LIME produces heatmaps that highlight the regions of the image that most influenced the prediction. For instance, in fetal ultrasound images, LIME can show which parts of the fetal abdomen or brain the CNN model focused on while making a classification.

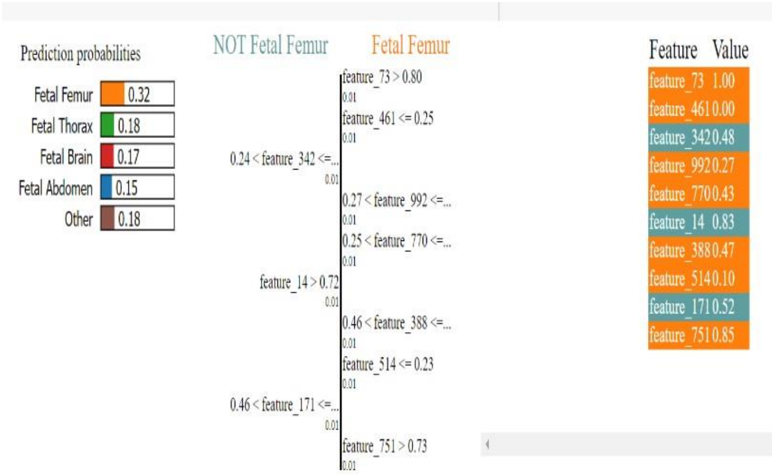


Fig 6.10: Lime Visualization

C. **Insights from LIME:** By using LIME, we gain better insight into the CNN's decision-making process. For example, it might highlight certain fetal anatomical structures (like the femur or brain) that are critical for distinguishing between classes. As shown in Fig 6.11 This improves the trust and transparency of the model, particularly important in medical applications where interpretability is crucial.

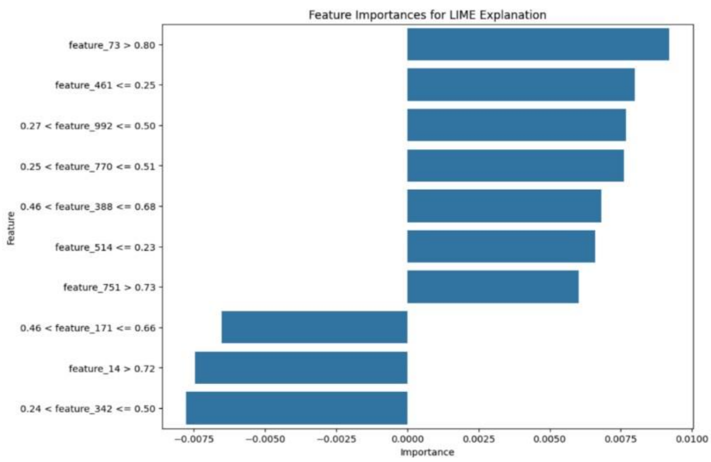


Fig 6.11: Lime Prediction

7 SYSTEM DESIGN

The design of the fetal ultrasound image classification involves resizing images for CNN and MLP compatibility, followed by normalization to enhance training stability. Feature extraction is performed using CNN, capturing spatial patterns and textures, which are then processed by an MLP for classification. As shown in **Fig 7.1** The dataset is split into 80% training and 20% validation to ensure effective learning and performance assessment. LIME is integrated for model interpretability, providing transparency in fetal ultrasound image classification, making the system both accurate and explainable for medical use.

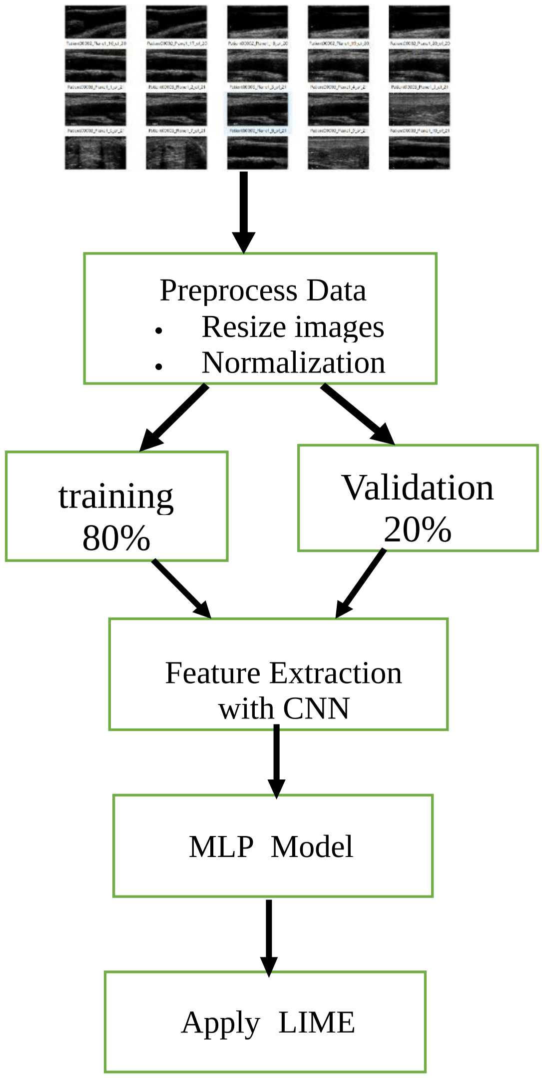


Fig 7.1 Design Overview

8 IMPLEMENTATION

IMPORT LIBRARIES

import numpy as np # Imports NumPy for numerical operations.
import pandas as pd # Imports Pandas for data manipulation and analysis.
import matplotlib.pyplot as plt #Imports Matplotlib for plotting and visualization.
import tensorflow as tf #Imports TensorFlow for deep learning.
from tensorflow.keras.models import Sequential # Imports Sequential model for building neural networks.
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout # Imports layers for building a CNN.
from tensorflow.keras.preprocessing.image import Image Data Generator #Imports a tool for image augmentation.
from lime import lime_imag # Imports LIME for explaining image classification models.
from skimage.segmentation import mark_boundarie # Imports function to highlight image segmentation boundaries.

SAMPLE CODE

```
# Step 1: Load and Preprocess the Dataset
# Replace this with your dataset path
data_dir = 'path_to_your_fetal_ultrasound_dataset/'
# Data Augmentation
datagen = ImageDataGenerator(
    rescale=1.0/255.0,
    validation_split=0.2,
    horizontal_flip=True,
    zoom_range=0.2
)
train_generator = datagen.flow_from_directory(
    data_dir,
```

```
    target_size=(128, 128),
    batch_size=32,
    class_mode='binary',  # Use 'categorical' for multi-class
    subset='training'
)
val_generator = datagen.flow_from_directory(
    data_dir,
    target_size=(128, 128),
    batch_size=32,
    class_mode='binary',
    subset='validation'
)
```

 # Step 2: Build the CNN Model

#A CNN extracts features using convolutional layers, reduces dimensions with pooling, and classifies through fully connected layers.

```
cnn_model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')  # Use 'softmax' for multi-class
])
cnn_model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
# Train the CNN model
history = cnn_model.fit(train_generator, validation_data=val_generator, epochs=10)
```

 # Step 3: Feature Extraction and MLP Model

#An MLP is a fully connected neural network that transforms inputs through multiple dense layers with activation functions to learn complex patterns and make predictions.

```
def extract_features(generator, model):
    features, labels = [], []
    for inputs, label in generator:
        features.append(model.predict(inputs))
        labels.append(label)
        if len(features) >= len(generator):
            break
    return np.vstack(features), np.vstack(labels)
feature_model = tf.keras.Model(inputs=cnn_model.input, outputs=cnn_model.layers[-3].output)
train_features, train_labels = extract_features(train_generator, feature_model)
val_features, val_labels = extract_features(val_generator, feature_model)
mlp_model = Sequential([
    Dense(64, activation='relu', input_shape=(train_features.shape[1],)),
    Dropout(0.5),
    Dense(1, activation='sigmoid')  # Use 'softmax' for multi-class
])
mlp_model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])
mlp_model.fit(train_features, train_labels, validation_data=(val_features, val_labels),
epochs=10)
```

 # Step 4: Apply LIME for Explainability

#LIME explains model predictions by generating perturbed samples and analyzing their impact on the output to create interpretable local approximations.

```
lime_explainer = lime_image.LimeImageExplainer()
# Select a sample image
sample_image, _ = val_generator[0]
```

```
image = sample_image[0]
# Define the prediction function
def predict_fn(images):
    return cnn_model.predict(images)
explanation = lime_explainer.explain_instance(
    image.astype('double'),
    predict_fn,
    top_labels=1,
    hide_color=0,
    num_samples=1000
)
# Visualize the explanation
temp, mask = explanation.get_image_and_mask(
    explanation.top_labels[0],
    positive_only=True,
    num_features=5,
    hide_rest=False
)
plt.imshow(mark_boundaries(temp / 255.0, mask))
plt.title("LIME Explanation")
plt.show()
# Save the Model and Results
cnn_model.save('cnn_model.h5')
mlp_model.save('mlp_model.h5')
```

APP.PY CODE

 # Implementation Of FrontEnd Code Using Flask

```
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
```

```
import cv2
from flask import Flask, render_template, request, jsonify
from werkzeug.utils import secure_filename
from torchvision import transforms
from PIL import Image
# Initialize Flask app
app = Flask(__name__)
# Configure Upload Folder & Allowed Extensions
UPLOAD_FOLDER = 'static/uploads'
ALLOWED_EXTENSIONS = {'png', 'jpg', 'jpeg'}
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER
# Ensure the upload directory exists
if not os.path.exists(UPLOAD_FOLDER):
    os.makedirs(UPLOAD_FOLDER)
# Model Definition
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1)
        self.bn1 = nn.BatchNorm2d(32)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1)
        self.bn2 = nn.BatchNorm2d(64)
        self.fc1 = nn.Linear(64 * 56 * 56, 512)
        self.fc2 = nn.Linear(512, 256)
        self.fc3 = nn.Linear(256, 6)
    def forward(self, x):
        x = self.pool(F.relu(self.bn1(self.conv1(x))))
        x = self.pool(F.relu(self.bn2(self.conv2(x))))
        x = x.view(x.size(0), -1)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

```
# Load Trained Model
model = SimpleCNN()
model_path =
'C:\\Users\\LENOVO\\Desktop\\project\\save_model\\trained_model.pth'
try:
    model.load_state_dict(torch.load(model_path, map_location=torch.device('cpu')))
    model.eval()
    print("✅ Model loaded successfully.")
except Exception as e:
    print(f"❌ Error loading model: {e}")
```

 # Image Preprocessing

```
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
])
# Helper function to check allowed file extensions
def allowed_file(filename):
    return '.' in filename and filename.rsplit('.', 1)[1].lower() in
ALLOWED_EXTENSIONS
# Classification Categories
CATEGORIES = ["Fetal Abdomen", "Fetal Brain", "Fetal Thorax", "Fetal Femur",
"Maternal Cervix", "Others"]
```

 # Image Validation

```
def is_fetal_ultrasound(image_path):
    try:
        image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
        if image is None:
```

```
            return False
        height, width = image.shape
        if height < 100 or width < 100:
            return False
        avg_intensity = np.mean(image)
        if avg_intensity < 30 or avg_intensity > 200:
            return False
        return True
    except Exception as e:
        print(f"Error in image validation: {e}")
        return False
```

 # Flask Routes

```
@app.route('/')
def home():
    return render_template('home.html')
@app.route('/about')
def about():
    return render_template('about.html')
@app.route('/predictions')
def predictions():
    return render_template('predictions.html')
@app.route('/evaluationmetrics')
def evaluationmetrics():
    return render_template('evaluationmetrics.html')
@app.route('/flowchart')
def flowchart():
    return render_template('flowchart.html')
@app.route('/prediction_result', methods=['POST'])
def prediction_result():
    try:
        if 'file' not in request.files:
            return render_template('error.html', message='No file uploaded.')
```

```
        file = request.files['file']
        if file.filename == '' or not allowed_file(file.filename):
            return render_template('error.html', message='Invalid file format.')
        filename = secure_filename(file.filename)
        filepath = os.path.join(app.config['UPLOAD_FOLDER'], filename)
        file.save(filepath)
        # Validate if the uploaded image is a fetal ultrasound
        if not is_fetal_ultrasound(filepath):
            os.remove(filepath)
            return render_template('error.html', message='Uploaded image is not a fetal
ultrasound.')
        image = Image.open(filepath).convert('RGB')
        image_tensor = transform(image).unsqueeze(0)
        # Perform Prediction
        with torch.no_grad():
            output = model(image_tensor)
            predicted_class = torch.argmax(output, dim=1).item()
        result = CATEGORIES[predicted_class]
        return render_template('prediction_result.html', result=result,
image_file=filename)
    except Exception as e:
        return render_template('error.html', message=str(e))
# Run Flask App
if __name__ == '__main__':
    app.run(debug=True)
```

PREDICTION_RESULT.HTML CODE

```
!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
```

```
<title>Prediction Result - Fetal Ultrasound Classification</title>
<style>
  body {
    margin: 0;
    font-family: 'Helvetica Neue', Arial, sans-serif;
    background-color: #f0f4f8;  /* Light grayish-blue background */
    display: flex;
    flex-direction: column;
    align-items: center;
    justify-content: center;
    min-height: 100vh;
  }
  header {
    display: flex;
    align-items: center;
    justify-content: flex-start;
    width: 100%;
    padding: 20px;
    background-color: #5f7a85;  /* Cool, calming blue */
    position: fixed;
    top: 0;
    z-index: 10;  /* Ensures header is on top */
  }
  header img {
    width: 100px;
    height: 100px;
    margin-right: 20px;
  }
  h1 {
    color: white;
    margin: 0;
    font-size: 24px;
  }
  /* Navbar Styling */
```

```
.navbar {
    display: flex;
    justify-content: center;
    background-color: #3b4e58;
    overflow: hidden;
    width: 100%;
    position: fixed;
    top: 70px;
    z-index: 5;  /* Ensures navbar stays below the header */
}
.navbar a {
    display: block;
    color: white;
    text-align: center;
    padding: 16px 20px;
    text-decoration: none;
    font-size: 18px;
    font-weight: 600;
    border-radius: 5px;
    margin: 5px;
    background: linear-gradient(145deg, #4f6b77, #3a4f58);
    box-shadow: 0 6px 10px rgba(0, 0, 0, 0.1);
    transition: background 0.3s ease, transform 0.2s ease, box-shadow 0.2s ease;
}
.navbar a:hover {
    background: linear-gradient(145deg, #3a4f58, #4f6b77);
    transform: scale(1.05);
    box-shadow: 0 10px 20px rgba(0, 0, 0, 0.15);
}
.navbar a.active {
    background-color: #2d3b41;
    color: white;
    box-shadow: 0 8px 12px rgba(0, 0, 0, 0.3);
    transform: scale(1.05);
```

```
    }
    .navbar a:active {
      transform: scale(0.98);
      box-shadow: 0 4px 8px rgba(0, 0, 0, 0.2);
    }
    .prediction-result-container {
      max-width: 900px;
      padding: 20px;
      background-color: white;
      border-radius: 10px;
      box-shadow: 0 4px 10px rgba(0, 0, 0, 0.1);
      margin-top: 140px;  /* Adjust margin-top to account for the fixed header and
navbar */
      text-align: center;
      z-index: 1;  /* Ensure content is above the background */
    }
    .prediction-result-container h2 {
      color: #3b4e58;
      font-size: 32px;
    }
    .result p {
      color: #555;
      font-size: 18px;
      margin: 20px 0;
    }
 .image-container img {
      width: auto;  /* Ensures the image's natural width is maintained */
      height: auto; /* Ensures the image's aspect ratio is maintained */
      max-width: 200px; /* Sets a smaller size for the image */
      max-height: 200px; /* Ensures the image doesn't exceed the specified
dimensions */
      margin-bottom: 30px;
    }
    .button-container a {
```

```
            display: inline-block;
            text-decoration: none;
            padding: 10px 20px;
            background-color: #5f7a85;
            color: white;
            border-radius: 5px;
            font-weight: bold;
            margin: 5px;
            transition: background 0.3s ease, transform 0.2s ease;
        }
        .button-container a:hover {
            background-color: #4f6b77;
            transform: scale(1.05);
        }
        .back-button {
            background-color: #3b4e58;
        }
        .button-container a:active {
            transform: scale(0.98);
        }
    </style>
</head>
<body>
    <header>
        <img src="{{ url_for('static', filename='images/NEC.png') }}" alt="Banner">
        <h1>Explainable Fetal Ultrasound Classification Using CNN And MLP
Models</h1>
    </header>
    <!-- Navbar -->
    <div class="navbar">
        <a href="{{ url_for('home') }}">Home</a>
        <a href="{{ url_for('about') }}" class="active">About</a>
        <a href="{{ url_for('predictions') }}">Predictions</a>
        <a href="{{ url_for('evaluationmetrics') }}">Evaluation Metrics</a>
```

```
        <a href="{{ url_for('flowchart') }}">Flowchart</a>
    </div>
    <div class="prediction-result-container">
        <h2>Prediction Result</h2>
        <!-- Display the predicted class -->
        <div class="result">
            <p><strong>Predicted Category: </strong>{{ result }}</p>
        </div>
        <!-- Display the uploaded image in the center -->
        {% if image_file %}
            <div class="image-container">
                <img src="{{ url_for('static', filename='uploads/' + image_file) }}"
alt="Uploaded Image">
            </div>
        {% endif %}
        <!-- Buttons to upload another image or go back to home -->
        <div class="button-container">
            <a href="{{ url_for('predictions') }}">Upload Another Image</a>
            <a href="{{ url_for('home') }}" class="back-button">Back to Home</a>
        </div>
    </div>
</body>
</html>
```

9 RESULT ANALYSIS

The result analysis of the fetal ultrasound image classification model, which used both Convolutional Neural Networks (CNNs) [7] and Multilayer Perceptrons (MLPs), highlights the performance and efficiency of the models in terms of training and validation accuracies.

The CNN model, after 10 epochs of training, achieved a remarkable training accuracy of 93.24% and a validation accuracy of 91.17%. This shows that the CNN effectively learned the features from the ultrasound images, leveraging its ability to capture spatial patterns in the data. The model's architecture, which included convolutional and pooling layers, allowed it to process the images in a hierarchical manner, extracting local and global features that are critical for classification. The high validation accuracy indicates that the model was able to generalize well to unseen data, avoiding overfitting, which is essential in a medical context where unseen data can have varied characteristics.

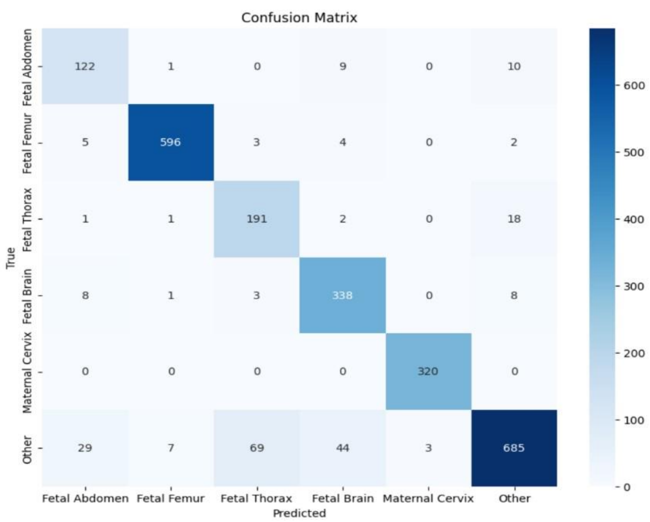


Fig 9.1: Confusion Matrix

Table 1.1: Classification Report

Class	Precision	Recall	F1 Score	Support
Fetal Abdomen	0.74	0.86	0.79	142
Fetal Femur	0.98	0.98	0.98	610
Fetal Thorax	0.72	0.9	0.8	213
Fetal Brain	0.85	0.94	0.9	358
Maternal Cervix	0.99	1.0	1.0	320
Other	0.95	0.82	0.88	837
Accuracy			0.91	2480
Macro avg	0.87	0.92	0.81	2480
Weighted avg	0.92	0.91	0.91	2480

To further evaluate the model's performance, a confusion matrix was generated, providing insights into the classification accuracy across different fetal ultrasound image categories. The confusion matrix as shown in Fig 9.1 helps in identifying false positives and false negatives, which are critical in medical diagnosis. The matrix showed that the model correctly classified the majority of images, with minimal misclassifications between similar categories such as the fetal abdomen and fetal thorax. The precision, recall, and F1-score as Shown in Table 1 derived from the confusion matrix confirmed the model's robustness in distinguishing different fetal ultrasound planes accurately.

10 TEST CASES

A. Unit Testing

Unit testing involves isolating and testing individual components of the project, such as image preprocessing steps, augmentation pipelines, and specific layers in the CNN model. Each module is validated independently to ensure it performs its intended function without dependency on other parts of the system. For example, unit tests could confirm whether the images are resized to 224x224, normalized properly, or if augmentation techniques are applied correctly. These tests help identify and fix errors early in the development process, ensuring the components are robust and reliable.

B. Integration Testing

Integration testing verifies that the different modules of the project, such as data preprocessing, model training, and XAI techniques like LIME, work together as intended. For instance, it checks if preprocessed data flows seamlessly into the model and whether LIME provides interpretable visual explanations for predictions. By testing these interactions, integration testing identifies any compatibility issues or errors in the communication between components.

C. Validation Testing

Validation testing uses a distinct validation dataset to evaluate the model's generalization ability during training. Metrics like accuracy, loss, precision, recall, and confusion matrix are analyzed to assess how well the model performs on unseen data. This phase helps identify issues like overfitting or underfitting, ensuring the model is neither too complex nor too simplistic. Validation testing provides critical feedback to improve the model's architecture, hyperparameters, or training strategy, leading to better overall performance.

D. System Testing

System testing evaluates the entire project's workflow from start to finish to ensure it meets all functional and non-functional requirements. It tests the model's ability to classify fetal ultrasound images accurately and generate explainable outputs using XAI techniques. The focus is on the complete integration of data preprocessing, training, validation, and interpretability.

Test case 1 :

"The system processes the input fetal ultrasound image Fig 10.1 and classifies it using CNN and MLP models. The expected behavior is identifying the image as 'Fetal Thorax,' and the actual classification result also predicts 'Fetal Thorax.' Since the prediction matches the expected outcome, the result Fig 10.2 is classified as a success."

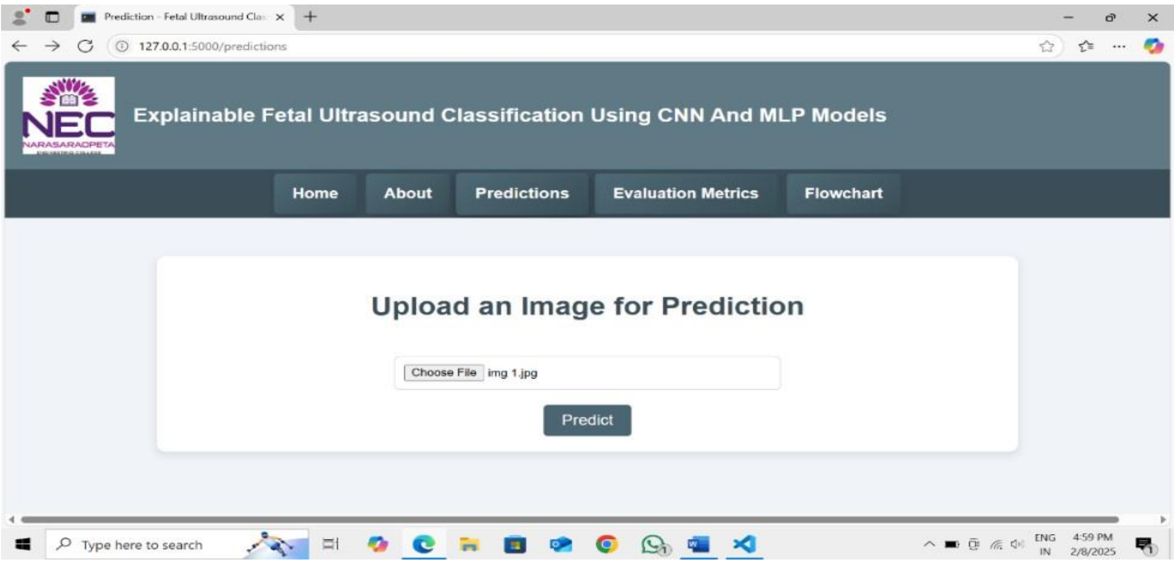


Fig 10.1:Fetal Thorax

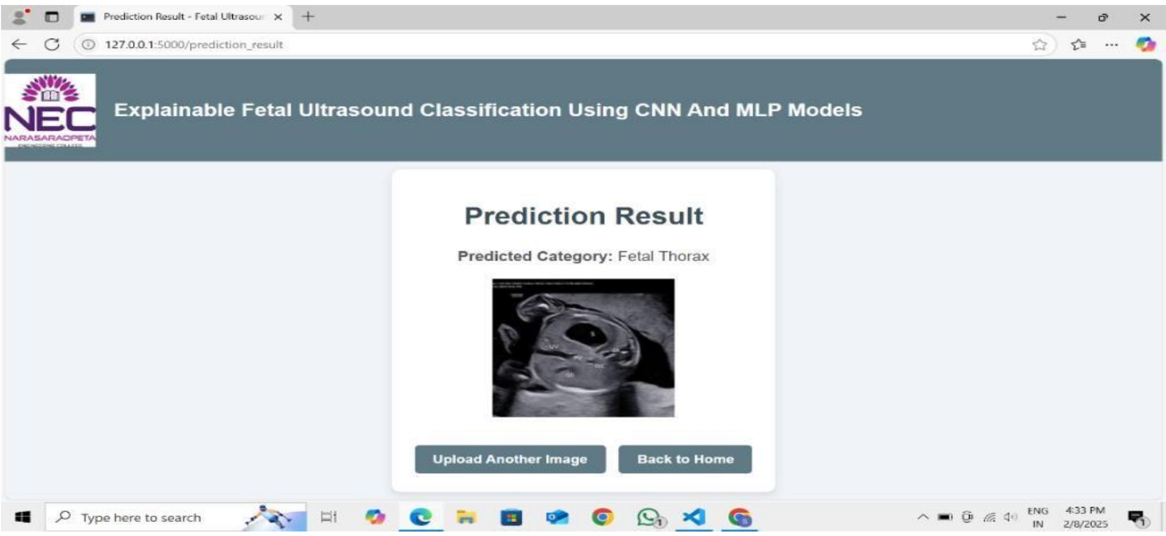


Fig 10.2: Fetal Thorax Image Detected

Test case 2 :

" The system processes a non-fetal ultrasound image Fig 10.3 using CNN and MLP models. The expected outcome is an error message indicating an invalid input. The actual result correctly detects the image as "Not a valid fetal image" Fig 10.4, confirming successful error handling."

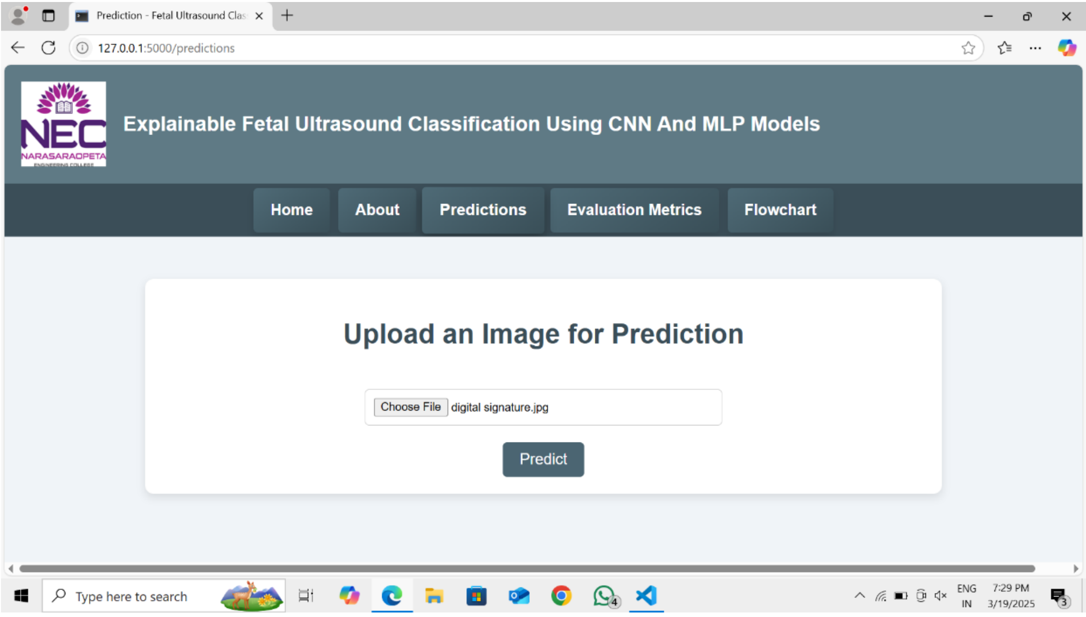


Fig10.3: Non-fetal image.

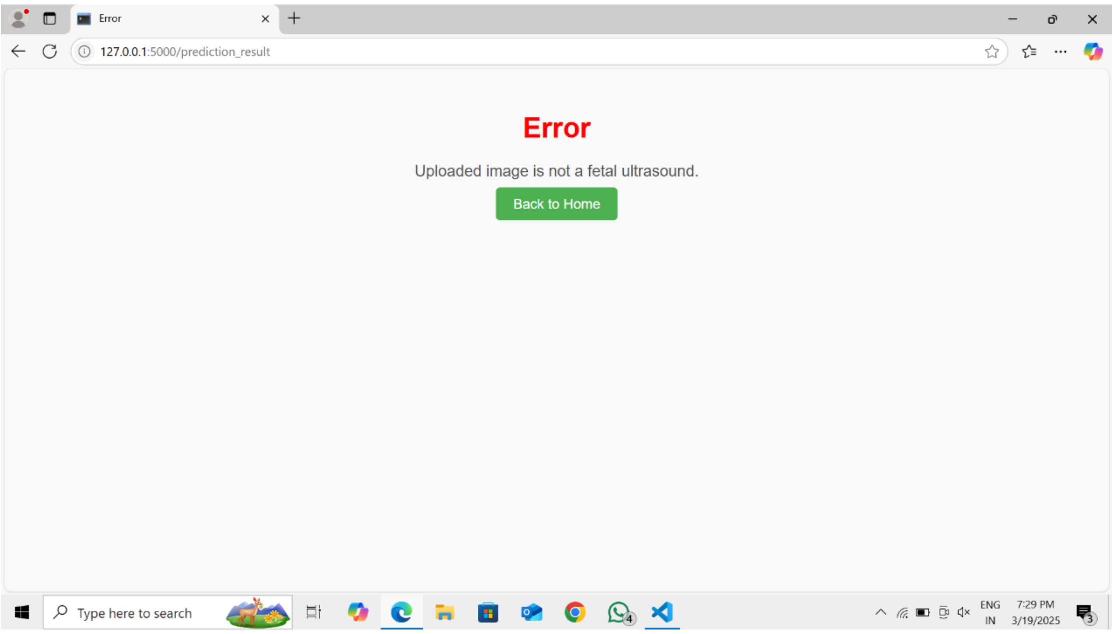


Fig 10.4: Error message indicating invalid

11 USER INTERFACE

This web application Fig 11.1 provides a user-friendly interface for classifying fetal ultrasound images using Convolutional Neural Networks (CNN) and Multi-Layer Perceptrons (MLP). It aims to enhance prediction transparency by integrating Explainable AI (XAI) techniques like LIME, making AI-driven decisions more interpretable and reliable for clinical use.

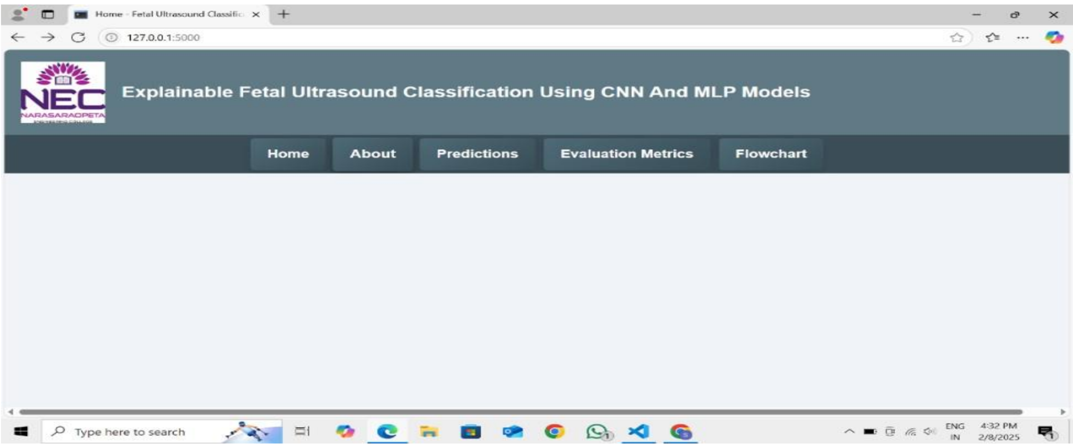


Fig 11.1 :Home Page

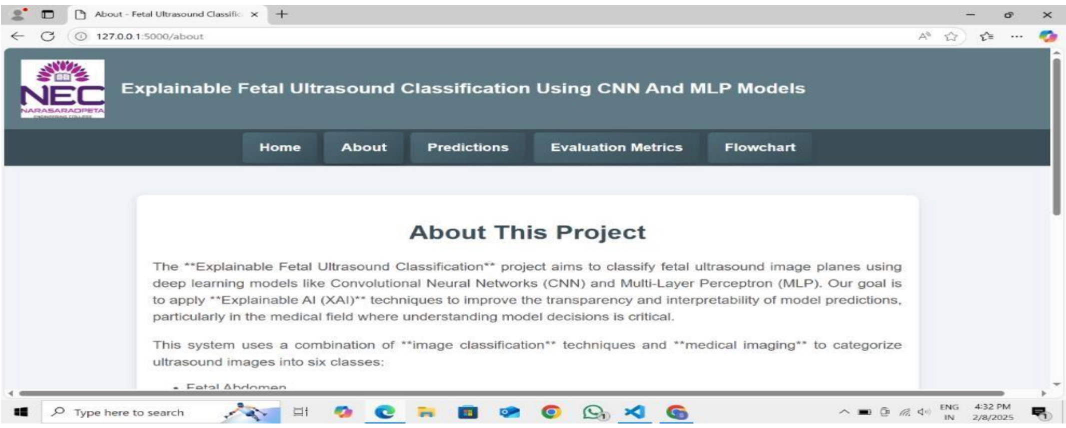


Fig 11.2: About Page

The Explainable Fetal Ultrasound Classification project Fig 11.2 focuses on classifying fetal ultrasound images into predefined categories using deep learning models (CNN and MLP). It leverages XAI methods to provide insights into model predictions, ensuring greater transparency and trustworthiness essential for medical diagnostics.

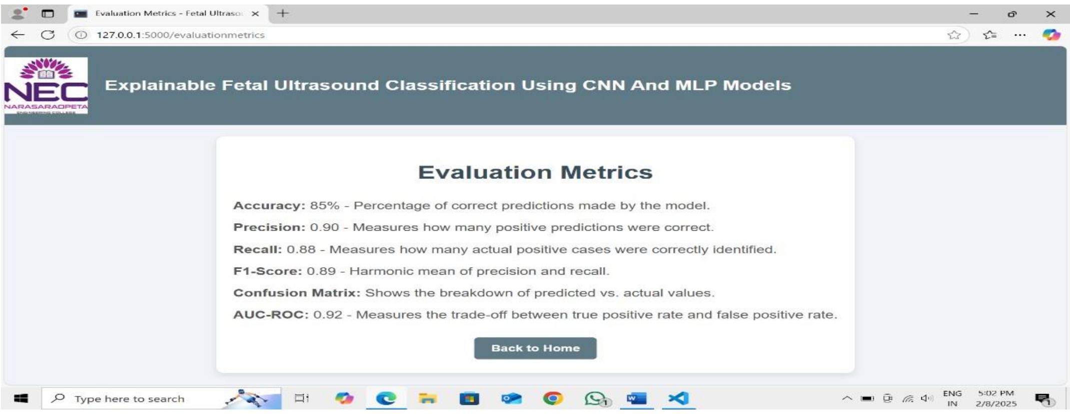


Fig 11.3: Evaluation Metrics Page

The performance of CNN and MLP models Fig 11.3 is evaluated using standard metrics: Accuracy, Precision, Recall (Sensitivity), and F1-Score. Additionally, a Confusion Matrix is used to visualize actual versus predicted classifications. These metrics ensure reliable and accurate classification of fetal ultrasound images.

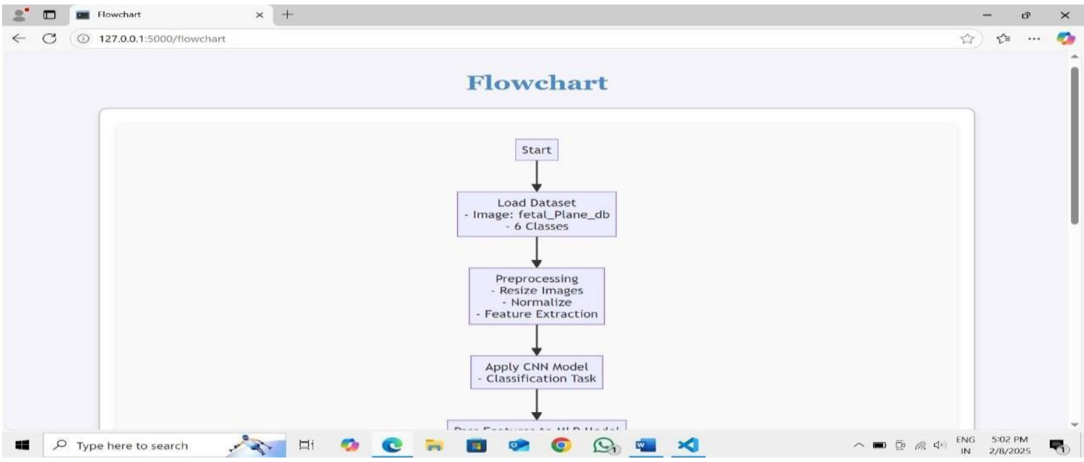


Fig 11.4: Flowchart Page

The flowchart Fig 11.4 outlines the process: Loading the fetal_plane_db dataset (6 classes), Preprocessing (resizing, normalization, feature extraction), and Applying CNN and MLP models for classification. Finally, predictions are generated and evaluated using performance metrics.

12 CONCLUSION

The project on Explainable Fetal Ultrasound Classification using CNN and MLP Models showcases the successful application of deep learning and explainable AI techniques to classify fetal ultrasound images accurately. By leveraging Convolutional Neural Networks (CNNs) and Multi-Layer Perceptrons (MLPs), the project achieves robust performance in identifying different fetal image planes, including fetal brain, thorax, femur, and abdomen. These models were trained and evaluated using rigorous preprocessing techniques, such as resizing, normalization, data augmentation, and feature extraction, ensuring high-quality inputs and reliable outputs.

Explainable AI methods, such as LIME, were integrated to enhance model transparency and interpretability. This addition allows healthcare professionals to understand the key features influencing the classification decisions, fostering trust in the model's predictions and enabling informed decision-making in clinical settings. By visualizing the areas of focus in ultrasound images, the project bridges the gap between complex AI models and practical medical applications.

Extensive testing, including unit, integration, validation, and system testing, ensures that all components of the project work seamlessly together. The combination of CNNs and MLPs provides complementary strengths, with CNNs excelling in feature extraction from images and MLPs handling complex decision-making layers effectively.

This work demonstrates the potential of combining multiple machine learning architectures to improve accuracy and interpretability in critical medical imaging tasks. It also highlights the importance of explainability in healthcare AI, where transparency and trust are essential. Future advancements could focus on expanding the dataset, optimizing model architectures, and incorporating real-time inference capabilities for clinical deployment.

In conclusion, this project successfully demonstrates how deep learning models like CNNs and MLPs, coupled with explainable AI techniques, can contribute to improving diagnostic accuracy and interpretability in fetal ultrasound classification, paving the way for safer and more reliable AI-assisted medical solutions.

13 FUTURE SCOPE

1. Advanced optimization techniques, hyperparameter tuning, and the use of more sophisticated deep learning architectures like Transformers or hybrid CNN-MLP models can further improve classification accuracy. Incorporating ensemble methods could also enhance model robustness and generalization to diverse datasets.
2. Beyond ultrasound images, the model can be extended to analyze other medical imaging modalities, such as MRI or CT scans. This would provide a broader scope for assisting in prenatal diagnostics and beyond. 3. Integration with edge computing or cloud platforms could enable real-time classification and explainability during live ultrasound sessions, assisting radiologists directly during patient consultations.
4. Incorporating advanced XAI methods, such as SHAP, Grad-CAM, or integrated gradients, can provide more detailed insights into the model's decision-making process. This would enhance trust and usability for healthcare professionals.
5. Using larger, more diverse datasets covering various demographics and rare abnormalities would improve the model's reliability and applicability in global healthcare scenarios. This could also include synthetic data generation using GANs to augment underrepresented categories.
6. Deploying the model in clinical settings with feedback mechanisms can allow for continuous learning and adaptation based on real-world data and user input. This would ensure the system remains relevant and effective over time.

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Explainable Fetal Ultrasound Classification with CNN and MLP Models

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***Abstract*—Artificial Intelligence has greatly influenced healthcare, most particularly in medical imaging. This paper represents a review in large form that classifies fetal ultrasound images with the use of convolutional neural networks and multi-Layer Perceptrons. While CNN is very good at spatial feature extraction in image classification, their lack of interpretability presents challenges toward applications in health. In this regard, we include methods of Explainable AI (XAI), more precisely Local Interpretable Model-Agnostic Explanations (LIME), for giving more transparency and confidence in the decision-making process of such models. The research here utilizes 12,400 fetal ultrasound images, which were classified under six anatomical structures. The CNN and MLP models showed very promising classification performances of 93.24% and 91.17%, respectively. LIME was implemented to interpret model predictions and to more clearly identify factors contributing to the classification. The results also show that explainability enhances not only trust in AI-based diagnostics but also model reliability in clinical settings.**

***Keywords*—Fetal ultrasound classification, Convolutional Neural Networks, Multi-Layer Perceptron, Explainable AI, Local Interpretable Model-Agnostic Explanations.**

I. INTRODUCTION

Over the years, artificial intelligence (AI) has taken a significant role in changing the healthcare scene, especially in medical imaging. Deep learning has been one of the many AI methods but has become the one that healthcare workers can use to make diagnoses and treatment decisions that are more accurate. The main thing that makes CNNs (convolutional neural networks) [2] so special is that they can learn from the images themselves to find the relevant features, thereby making them suitable for image classification tasks and object detection.

One popular method of prenatal care is fetal ultrasound imaging. Through others, it can provide the medical

practitioners with as much as they need to know about the state of fetal development and ambler. The aforementioned pictures enable the attendants to evaluate the anatomy of the fetus, to supervise the growth, and to detect probable defects.

Relevant Pioneer of the fetal ultrasound image plane is the direct and most impactful pillar responsible for either a good or a bad health outcome of the mother or the fetus, so it is indeed a crucial point. Nevertheless, the complexity of ultrasound pictures and the need for a precise interpretation are the

difficulties. [1]

While CNN is great at getting high classification accuracy, the decision-making processes can be intransparent, causing difficulties for health care takers to comprehend and have trust in the model's predictions. This lack of interpretability, along with the broad judgment AI tools make in a clinical setting, becomes a real concern in the domain where transparency and accountability are essential. systems and gain their trust by being clear to them. Methods such as LIME [6] are making it possible for scientists to observe the roles of various features in the given data and the model's predictions, thus pointing out the path between the little downfall and the readability. This project has the support of both CNNs and Multi-Layer Perceptrons (MLPs) for classifying the fetal ultrasound image planes. To the point that the classification is exact while using the spatial hierarchies and patterns, they describe the features of the method with spatial description, the following appropriate and recognized by the computer: a big picture being reused. But at the same time, one can argue that the growing number of e courses, especially ones hands-on with technology, could soon make the traditional education system obsolete.

”These newly created and innovatively designed online engineering courses that are hands-on and use the latest technology that is generally not available in traditional face toface classes need to be called the Future of Engineering Education.” By both the CNNs and the MLPs architectures, we are the best model to solve the problem, which is both we are able to achieve high classification accuracy. The chief goal of the investigation at hand is the production of a reliable and interpretable classification model for the ultrasound images of the fetus that will use both the CNN model and the MLP models. Intrinsically, the algorithm’s capability has been promoted. The use of annotated fetal ultrasound images provides the AI assisted prenatal diagnostics process with more reliability and, with that, will alleviate the all too common concern, hence addressing the need for transparency in AI healthcare.

Explainable AI techniques (XAI) have been devised as a means of making deep learning models more transparent by providing insights for the model’s decisions. XAI is supposed to allow people to understand the inner workings of AI

II. LITERATURE REVIEW:

Befre Action that is most transformative for the deployment of pregnancy ultrasound category is the combination of convolutional networks and multilayer perceptrons with XAI tools and methods. Toward this end, we present a comprehensive list of relevant works and studies involving pretrained CNNs and MLPs in different AI applications to ultrasound images, as well as the general exploitation of XAI approaches in the deep learning context. Also, the possible pagination of the abstract with the keyword list is indicated in the main document. For example, Burgos-Artizzue et al. [7] mentioned automated maternal-fetal ultrasound abnormality classes that were generated using dense tissue segmentation. Their work highlighted the webcam, a CNN with an overall AUC of 1.0%, which significantly improved the performances in detecting different intrapelvic organs. Esteva et al. [3] in every alternative test copied the features of deep learning models in dermatology, reaching dermatologist-level classification of skin cancer. This work was the key point for the utilization of analogous techniques in different clinical imaging domains, such as fetal ultrasound analysis. The accomplishment of CNNs in identifying the diverse features of the picture in very fine detail has made them very popular in almost all of the medical imaging tasks. The applications include fetal biometry estimation as well as abnormality detection. CNNs have, in fact, become the most often used form of structure in the image-type tasks, but MLPs have still been recurrently utilized in clinical imaging applications. MLPs are distinguished for being both able to process and represent structured data in a proper manner and, therefore, can be an alternative approach to CNNs. For instance, MLPs have been used to analyze functions derived from CNNs, which leads to a more complete understanding of the information. Experiments have confirmed that the communication of MLPs with CNNs can be beneficial to the correct classification of data by both methods. Medical image interpretability and incorporation of Explainable AI (XAI) concepts into deep learning models are very important areas. LIME (local Interpretable model-agnostic explanations) can be referred to as one of the most recognized XAI approaches that have been used in many fields, including healthcare. The authors, Garreau and Luxburg [8], proposed a theoretical discussion on LIME in the medical field, the article of which paid attention to how the methods of LIME could help this department. Now and onwards, the same LIME article became the integral part of the discussion. Generally, XAI techniques are relatively new to fetal ultrasound imaging, but more and more people are gaining interest in this field. By using LIME researchers can pin down in an image where the most important points causing the model to decide like this are. Moreover, it is a must for the model to have the ability to provide logical decisions, as the latter tends to breed trust with healthcare professionals, who get the chance to acknowledge the basis of the prediction and hence make correct evaluations concerning the product of AI.

III. METHODOLOGY:

A. Dataset:

The dataset used to classify fetal ultrasound images consists of 12,400 images that are categorized into six main groups: AFD Fetal Abdomen, Fetal Femur, Fetal Thorax, Fetal Brain, Maternal Cervix, and Other. (https://zenodo.org/records/ 3904280). The csv dataset has basically 7 columns, i.e. patient num, Image name, Plane, Brain plane, Operator, US Machine and Train. and the images dataset contains the image name. All the images are a mix of RGB and Grayscale formats, and they have different resolutions and sizes. This complete dataset is not only helpful in classifying planes in the fetus but also it will function as a raw material for bringing out new and also confirming deep learning models in the context of prenatal healthcare.

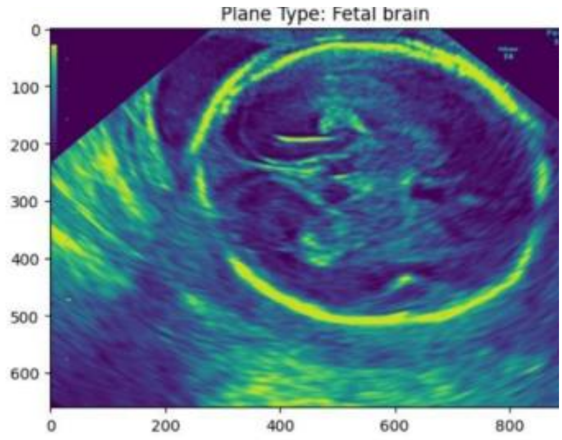

Fig1: Sample image

B. Data Preprocessing:

1) Resizing: All the pictures were changed to be the same measurement (224x224 pixels), which means that they are of the same size, and it is a must for the model's learning.

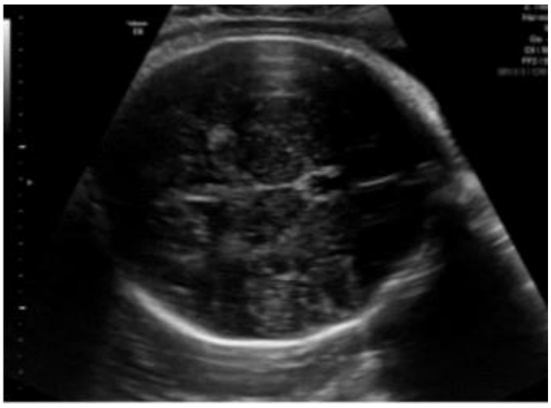

Fig2: Resized image

2.Normalization: Pixel values were reduced to a standard level of [0, 1]. This is a way of ensuring that the process is absolutely smooth and quick throughout the training of the model.

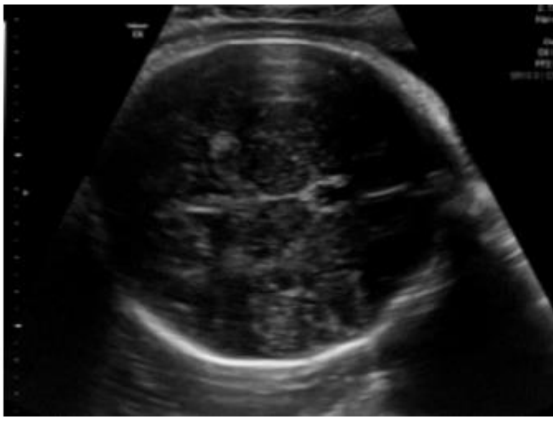

Fig3: Normalized Image

3) Feature Extraction: It is the code that makes use of the ResNet-50 model from torch vision. ResNet50 is a deep residual network honored for its strong performance and reasonable level of reliability in terms of image classification tasks. Functions such as the below mentioned code were performed for each image, passing the image into the ResNet50 model in order to extract its features. The model outputs the feature vector, which is then "printed" on the occasion of saving for further processing.

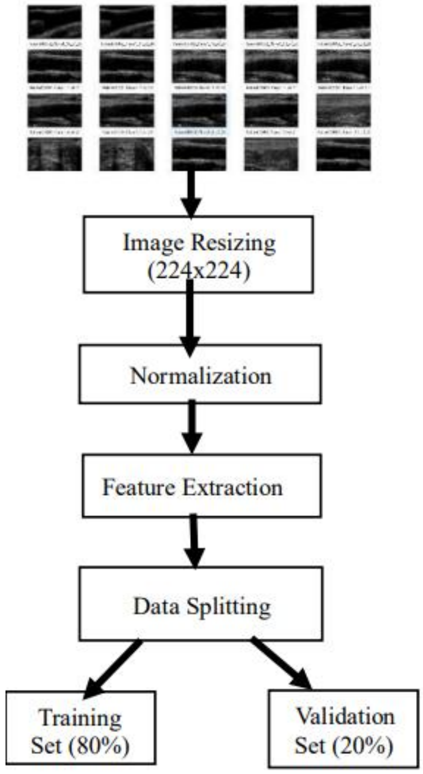

Fig 4: Data Preprocessing

C.Model Training:

Also, it is a design milestone to build a valid neural network that mixes CNN (Convolutional Neural Network) and MLP (Multilayer Perceptron)[7,8,9] models and manages the initial dataset. Data preparation is actually a process in which required procedures like normalization and transformation to tensors are implemented to ensure that the data entered is in a format model learning can use. Following the data loading process, we configure the two types of computational models: the first one for image data using CNN that obtains spatial features through the convolutional layers, and the second one, the so-called fully connected network that employs MLP for simpler input structures. [10,11] The first and the voice are the ones that are then being created, which is the initialization step. This approach keeps going unless the model achieves satisfactory production of the validation dataset.

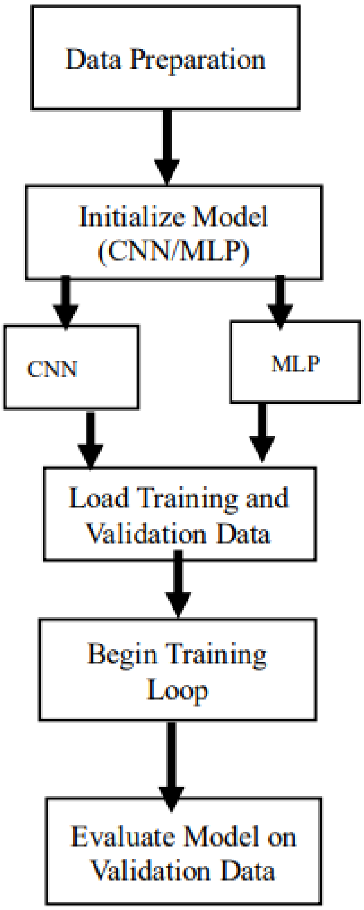

Fig 5:Model Training

1) Simple CNN Architecture:

• Convolutional Layers: conv1: Gets the initial input, which is given to the basic 64 channels, on applying a 3x3 filter to it with a 1 zero-pad use. [13] conv2: It acquires the 64 channels from the previous layer and outputs a 128-channel layer by using a filter of the same size as the other and a zero-pad.

• Pooling Layer: pool: performing max pooling with a 2x2kernel, which reduces the feature map's length and width. • Fully Connected Layers: fc1: This is a linear layer thattakes the flattened output from the sets of features of the convolutional layers and connects it to 512 nodes. fc2: It is the last linear layer that maps 512 nodes to the number of classes (num-classes). [12] • Activation and Dropout: ReLU activations are placed inthe convolutional and fully connected layers. There lies after the first fully connected ReLU activations and dropouts for regularization to prevent overfitting there.

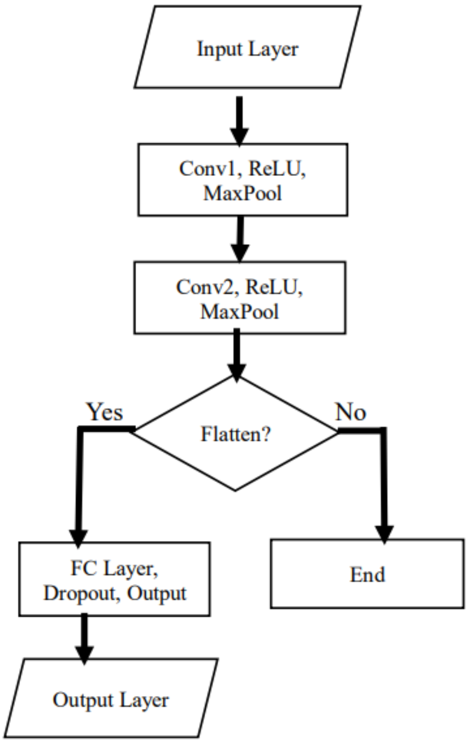

Fig 6: CNN model architecture

2) MLP Model Architecture And Explainability::

• Fully Connected Layers: fc1: The initial layer is as described. It's the very first linear layer that, when given the input features, maps the input features to 512 units. Fc 2: The second layer is further described. The number of units is decreased by the second linear layer, which is another feature of the MLP architectures. fc3: The very last layer is characterized by the following trait: The representation on the output layer that forms into the assigned categories (num-classes) is the last linear layer. • Activation and Dropout: Fully connected layers are separated by ReLu activations. ReLu activation layers are probably the best ones, and in between activation layers, they also do the job of breaking the symmetry too. Airplane.jpg are the users of the case of image classification, and my spatial data is the interpretation of it in 3-D with ReLu.

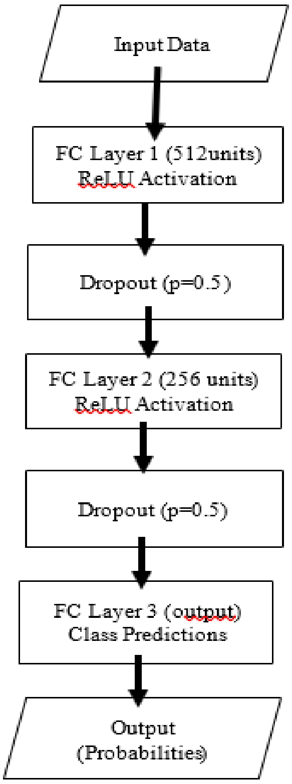

Fig 7: MLP model architecture

For this research, the Local Interpretable Modelagnostic Explanations (LIME) was employed to interpret forecasts of a highly advanced MultiLevel Perceptron (MLP) model executed using the PyTorch. The MLP model, the components of which are several fully connected layers with batch normalization and dropout, is one of the classification tasks. Generating modelunderstandable individual predictions with a simple and interpretable model is the primary idea of LIME. We can think of this procedure as building a simple model of a complex model to mimic the behavior of the complex model near a particular instance. The model is approximated by varying the input data along the features and monitoring the changes in the model's predictions. The explanation of the model's predictions is eventually based on the explanation of the specific feature. The diverse features and the relationship between them were noticed by the LIME model while generating the different versions of the input. Deploying LIME in this way is the mechanism by which the behavior of the model of the data can be examined in more detail from pred: production of choice. With the technique of LIME implementation, we were able to give indirect support to the whole process of generating interpretations through LIME. [14], [16] The visual presentations showed that the individual factors were of significant input to the classification, and the effect of the parameter change would be further encouraged; thereby, the reliability of the classification model was improved. This methodology not only helps to create a detailed central source model, but also facilitates crosschecking predictions and the existing domain knowledge. An example of this would be the MLP. When predicting an image as "fetal femur" with 32% probability, LIME pointed out the top positive features, which were feature-73 gt 0.80 and feature14 gt 0.72, as the main sources of the variance, thus giving a lucid elucidation of the model's prediction. The introduction of dizziness learning and interpretability supplied us with some salient information about the model's performance as well as their decision-making transparency, a crucial foreshadower of clinical applications.

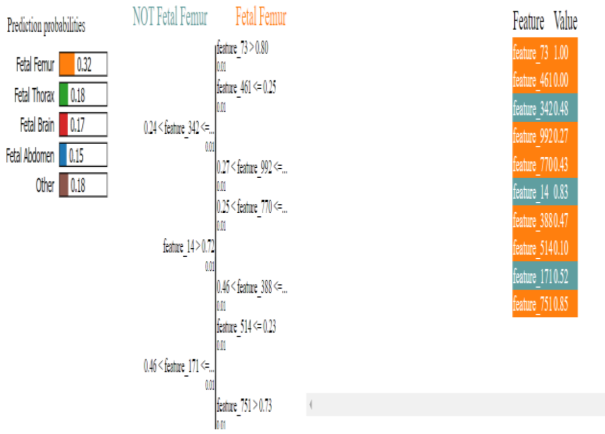

Fig 8:Lime Prediction

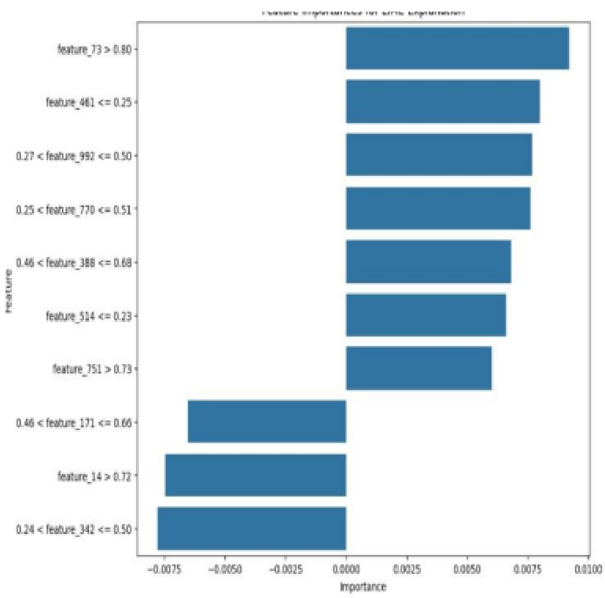

Fig 9: Lime Technique

IV. COMPARITIVE ANALYSIS AND DISCUSSION:

Comparative analysis of CNN and MLP clearly states the strengths and limitations of each method. The CNN's unbeatable means of working are in part thanks to the privilege of its construction. It can extract and process the spatial and hierarchical relationships in the fetal ultrasound images. The increased precision that was reached by CNN proves its effectiveness in this classification mission and thus makes it favorable for applied domains of medicine. [15] MLP is not prominently known for a baseline model, but it was toppled by CNN, which is the promise of its practical asset of finding the best models for specific forms of data. A high rating of the MLP is a visual mean to show that sometimes the tasks with the more complex models can be the bigger ones. The required model has enough to be a classifier by CNN; thus, this model fits for this purpose better than others. Implications for Medical Imaging New research findings that have taken place this study will have a huge impact on a variety of uses of artificial intelligence in the medical imaging field. According to the result, various abilities like high accuracy, as well as the capability to be independent across all samples, are restrained in the CNN model, choosing to like a ray ("/" from the tools"). It will be easy for radiologists and medical professionals to have a diagnosis and analysis of fetal ultrasound images with the help of this particular technological tool.

Thus, the classification in the process of diagnosis can be automated by the use of an accurate model that could help in verifying the diagnosis of a patient and also quickly proceed to more effective treatment by the doctors. Also, this is where medical conditions can become difficult to understand since patients will have trouble figuring out how a machine knows better than them. For example, using 'Explanation AI (AX) methods, which are the following. [9], [14] "CNN will help to unhide the models' and make them see through, thus providing an opportunity to perceive everything that the model has gone through to reach a decision. The medical field is specifically the one that Explainable AI (XAI) cannot work without as the understanding of the explanation of the prediction by models is the key to doctors' acceptance and trust. This is not only the support in the case of doctors but for patients also.

Perceptron (MLP) to determine the anatomical structures as well as classifying the fetal ultrasound images into different classes. The basic aim was to test the statistical reliability and efficacy of these models in the classification of images based on their anatomical structures and regions. Actually, the main reason the CNN model was chosen was that it is a model that can process and analyze images brilliantly. CNNs have such a way of design that convolutional layers can be used to get spatial hierarchies in images, which makes it really effective in image classification. The CNN model researchers used in the study was the one they had preprocessed.

V. RESULT

This experiment was performed by the application of a Convolutional Neural Network (CNN) and a Multi-Layer Perceptron (MLP) to determine the anatomical structures as well as classifying the fetal ultrasound images into different classes. The basic aim was to test the statistical reliability and efficacy of these models in the classification of images based on their anatomical structures and regions. Actually, the main reason the CNN model was chosen was that it is a model that can process and analyze images brilliantly. CNNs have such a way of design that convolutional layers can be used to get spatial hierarchies in images, which makes it really effective in image classification. The CNN model researchers used in the study was the one they had preprocessed.

Table 1: CLASSIFICATION REPORT

Class	Precision	Recall	F1 score	Support
Fetal Abdomen	0.74	0.86	0.79	142
Fetal femur	0.98	0.98	0.98	610
Fetal thorax	0.72	0.9	0.8	213
Fetal Brain	0.85	0.94	0.9	358
Maternal Cervix	0.99	1.0	1.0	320
Other	0.95	0.82	0.88	837
Accuracy			0.91	2480
Macro Avg	0.87	0.92	0.81	2480
Weighted Avg	0.92	0.91	0.91	2480

on with neglected steps like normalization and augmentation, among other carefully implemented preprocessing steps, so that the model's learning capability and its generalizability could be enhanced. The model trained using CNN underwent a hard training and validation process. To be specific, the accuracy of the model at the training stage was 93.24% and at the validation stage was 91.17%. This means that the CNN model was capable of acquiring ultrasound images' features with high effectiveness and utilizing the same capacity to sort out new images that have not been seen before with a high level of accuracy. The fact that the differences between training and validation accuracy are so small implies that the model is finetuned and thus doesn't tend to overfit, which is an often seen phenomenon in deep learning models. Instead, the MLP model, a distributed type of neural network, was also brought to serve as a gauge for a better comparison with a CNN. The convolving of the filter's weights with the input matrix produces a new feature map. Nonetheless, the MLP model, although selecting some of the possible responses, did not win against the CNN in the aspect of accuracy and overall performance. Moreover, the application of these layers means MLP could not fully match the intricacy of the set. MLPs, on the other hand, consider the image as a one dimensional line of pixels, which limits their capability to capture all of the spatial information the image inherently possesses.

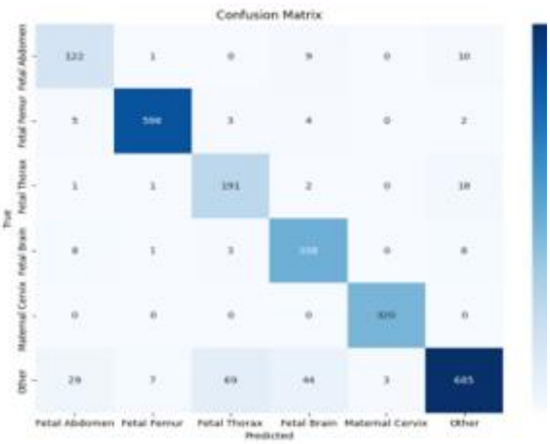

Fig 10:Confusion Matrix

VI. CONCLUSION :

Our study saw us carrying out the two models that we had designed that is the aftertaste of technology (CNN) and the Multilayer Perceptron (MLP) model aside for the classification of the fetus's ultra-sound images. The CNN model, with its capability to seize spatial hierarchies in images, was used to automatically morph the features and distinguish the images by the six superordinate classes which were the maternal cervix, fetal brain, fetal femur, fetal abdomen, and other. Additionally, we also utilized a MLP model for the process that the CNN model was applying but instead, it was doing it using fully connected layers. The MLP, on the other hand, was used to make the former approach by the feature vectors instead of image data, giving us an idea of the performance of the architecture on the task. Leveraging the LIME methodology, we obtained some explanations for the decisions that each model made which helped in achieving the interpretation so that humans can easily make sense of the models. Concerning the MLP model, LIME was able to diagnose the most critical features that altered its decision-making procedure.

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