VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

(An Autonomous Institute Affiliated to University of Mumbai)

Department of Computer Engineering

Project Report on

Congenital Heart Disease Detection using Artificial Intelligence

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING

IN COMPUTER ENGINEERING

By

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(AY 2023-24)

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

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CERTIFICATE

This is to certify that the Mini Project entitled **"Congenital heart disease prediction using Artificial Intelligence "** is a bonafide work of **Kalpana Gurnani(21), Prerna Banswani(05), Madhura Gaval(14), Vanshika Lalwani(27)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

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Mentor

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Principal

Mini Project Approval

This Mini Project entitled "**Congenital heart disease prediction using Artificial Intelligence**" by **Kalpana Gurnani(21), Prerna Banswani(05), Madhura Gaval(14), Vanshika Lalwani(27)** is approved for the degree of **Bachelor of Engineering in Computer Engineering.**

Examiners

1……………………………………….
(Internal Examiner Name & Sign)

2……………………………………….
(External Examiner name & Sign)

Date:

Place:

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Index

Abstract

Echocardiography has become a vital tool in prenatal care, allowing for non-invasive assessment of fetal cardiac health. This report underscores the significance of echocardiographic techniques in detecting congenital heart defects and abnormalities early in pregnancy. By evaluating parameters such as cardiac dimensions, chamber sizes, valve function, and blood flow patterns, clinicians can identify deviations from the norm and implement timely interventions to optimize fetal outcomes. However, challenges persist due to the lack of standardized protocols and comprehensive normative data, hindering accurate interpretation of echocardiographic findings.

The absence of clear benchmarks for normal fetal cardiac anatomy and function at various gestational ages poses a significant obstacle in prenatal cardiac screening. This deficiency undermines diagnostic accuracy and increases the risk of misdiagnosis, potentially leading to unnecessary anxiety for expectant parents or overlooking critical cardiac issues in the fetus. Additionally, the complex interplay between echocardiographic findings and maternal and fetal factors further complicates interpretation. Addressing these challenges is crucial for enhancing the accuracy, reliability, and clinical utility of echocardiography in prenatal care, ultimately improving outcomes for both mothers and babies.

List of Figures:

1.Introduction:

1.1 Introduction

Echocardiography plays a pivotal role in the prenatal assessment of fetal well-being, offering a non-invasive means to examine the fetal heart's structure and function. With advancements in medical technology, the use of echocardiography has become increasingly prevalent in antenatal care, aiding in the early detection of congenital heart defects and other cardiac abnormalities.

This report focuses on assessing the normalcy of fetal heart structures and functions through echocardiography. While previous studies have investigated fetal heart rate as an indicator of fetal well-being, our current research aims to delve deeper into the intricate details of cardiac morphology and function.

By employing echocardiographic techniques, we seek to evaluate various parameters such as cardiac dimensions, chamber sizes, valve function, and blood flow patterns. These assessments are crucial in identifying any anomalies or deviations from the expected norm, allowing for timely interventions and management strategies to optimize fetal outcomes.

Understanding the normal echocardiographic characteristics of the fetal heart is essential for accurate diagnosis and management of congenital heart defects and other cardiac abnormalities. This report underscores the significance of echocardiography in prenatal care and its role in ensuring the health and well-being of both the fetus and the expectant mother. Through our meticulous examination and analysis, we aim to contribute to the body of knowledge surrounding fetal cardiac assessment, ultimately enhancing the quality of antenatal care provided to expecting families.

1.2 Motivation:

This research is driven by the urgent need to establish standardized protocols for assessing fetal cardiac health and detecting congenital heart defects early in pregnancy. Despite significant advancements in medical imaging technology, there remains a lack of universally accepted guidelines for interpreting echocardiographic findings in prenatal care. By addressing this gap, we aim to enhance the accuracy and reliability of fetal cardiac screening, ultimately improving outcomes for both mothers and babies.
Furthermore, our motivation extends to exploring the intricate relationships between echocardiographic parameters and various maternal and fetal factors. By uncovering these correlations, we can refine risk stratification strategies and tailor prenatal care plans to individual needs.

1.3 Problem Definition:

The current limitations and challenges in fetal cardiac assessment using echocardiography hinder its effectiveness as a diagnostic tool for detecting fetal cardiac abnormalities. Despite widespread adoption, unresolved issues persist, including the limited understanding of normal echocardiographic parameters across different gestational ages, populations, and maternal-fetal conditions. This lack of comprehensive normative data complicates anomaly identification, leading to increased risks of false-positive or false-negative findings.

Echocardiography has become a cornerstone in prenatal care for assessing fetal cardiac health. However, the absence of standardized criteria and comprehensive normative data presents a significant obstacle. Without clear benchmarks for what constitutes normal fetal cardiac anatomy and function at various stages of development and across diverse populations, accurately identifying abnormalities becomes challenging. This deficiency not only undermines diagnostic accuracy but also increases the likelihood of misdiagnosis, potentially leading to unnecessary anxiety for expectant parents or overlooking critical cardiac issues in the fetus.

Moreover, the complex interplay between echocardiographic findings and various maternal and fetal factors adds another layer of complexity. Factors such as genetic predispositions, maternal health conditions, and fetal developmental stages influence echocardiographic parameters, complicating the interpretation of results. Without a deep understanding of these relationships, clinicians may struggle to differentiate between benign variations and clinically significant abnormalities, impacting the quality of prenatal care provided.

In essence, the problem lies in the lack of standardized criteria, comprehensive normative data, and a nuanced understanding of the multifaceted factors influencing fetal cardiac assessment using echocardiography. Addressing these challenges is paramount for enhancing the accuracy, reliability, and clinical utility of echocardiography in prenatal cardiac screening. By establishing clear guidelines and advancing our understanding of fetal cardiac development and pathology, we can improve outcomes for both mothers and babies, ensuring timely intervention and appropriate management of cardiac anomalies during pregnancy.

1.4 Existing Systems:

Several existing systems and methodologies aim to address challenges in fetal cardiac assessment using various techniques, including deep learning-based approaches and instance segmentation networks. For instance, one system utilizes Mask-RCNN with ResNet50 backbone architecture for real-time detection of cardiac objects in fetal ultrasound videos, achieving high precision in detecting heart defects. Another system introduces a Category Attention Instance Segmentation Network (CA-ISNet) to segment four cardiac chambers in fetal echocardiography simultaneously, enhancing segmentation accuracy.
Additionally, FLDS (Intelligent Feature Learning Detection System) aims to detect fetal four cardiac chambers, outperforming current methods and supporting early congenital heart disease (CHD) diagnosis.

1.5 Lacuna of the Existing Systems:

Despite advancements in fetal cardiac assessment methodologies, several persistent challenges remain. These include the need for more diverse and extensive training datasets, validation with large amounts of unseen data, and addressing challenges such as segmentation accuracy in boundary regions. Moreover, the limited generalizability of existing systems across different imaging modalities and patient populations remains a significant gap. Other issues include the limited focus on high-risk pregnancies, reliance on small and homogeneous datasets, interpretability challenges, hardware-related signal issues, questionable labeling appropriateness, lack of raw image analysis, limited fetal heart view, and difficulty in identifying cardiac septal defects. Addressing these deficiencies requires concerted efforts in data acquisition, model validation, interpretability enhancement, and technological refinement to ensure robust and inclusive fetal cardiac assessment methodologies.

1.6 Relevance of the Project:

The persistent challenges and lacunae in existing systems, the proposed project holds significant relevance. By addressing these gaps, such as the need for standardized criteria, comprehensive normative data, and deeper understanding of fetal cardiac assessment factors, the project aims to enhance the accuracy, reliability, and clinical utility of echocardiography in prenatal cardiac screening. Ultimately, this research has the potential to improve outcomes for both mothers and babies by facilitating early detection and management of fetal cardiac abnormalities.

2: Literature Survey

A. Brief Overview of Literature Survey:

The literature survey encompasses a comprehensive review of existing research and developments in fetal cardiac assessment, particularly focusing on echocardiography and deep learning-based approaches. Key areas of exploration include methodologies for detecting cardiac abnormalities, segmentation of cardiac structures, and the utilization of deep learning techniques to enhance diagnostic accuracy.

B. Related Works

2.1 Research Papers Referred:

Deep learning-based real-time detection for cardiac objects with fetal ultrasound video:

- **Abstract:** This paper introduces a Mask-RCNN with ResNet50 architecture for detecting fetal cardiac defects in ultrasound videos. It achieves high precision in detecting heart defects, particularly septal defects.
- **Inference Drawn:**The inference drawn from this research paper is the efficacy of deep learning techniques, particularly Mask-RCNN, in accurately detecting cardiac abnormalities in fetal ultrasound videos. The proposed model shows promising results in real-time detection, highlighting its potential for assisting clinicians in early screening for congenital heart disease.

A category attention instance segmentation network for four cardiac chambers segmentation in fetal echocardiography:

- **Abstract:** The paper proposes a generic framework, CA-ISNet, for accurate and simultaneous segmentation of the four cardiac chambers in fetal echocardiography. The framework utilizes a Category Attention Module (CAM) to correct instance misclassification and improve segmentation accuracy.
- **Inference Drawn:** The CA-ISNet framework demonstrates promising potential in accurately segmenting the four cardiac chambers in fetal echocardiography. By addressing instance misclassification, it enhances segmentation accuracy, thus contributing to improved diagnostic outcomes.

FLDS: An Intelligent Feature Learning Detection System for Visualizing Medical Images Supporting Fetal Four-Chamber Views:

Abstract: FLDS is introduced as a system that outperforms current methods in detecting fetal four cardiac chambers, aiding in early congenital heart disease diagnosis and obstetrician efficiency.

Inference Drawn: FLDS offers advancements in fetal cardiac chamber detection, presenting potential benefits for early diagnosis of congenital heart disease and enhancing obstetrician efficiency in fetal cardiac assessment.

MCRformer: Morphological Constraint Reticular Transformer for 3D Medical Image Segmentation:

- **Abstract:** The paper introduces MCRformer, a 3D medical image segmentation network that combines morphological information and a reticular mechanism to enhance segmentation accuracy.
- **Inference Drawn:** MCRformer presents advancements in 3D medical image segmentation, offering improved accuracy and interpretability compared to existing models.

Detection of Cardiac Structural Abnormalities in Fetal:

- **Abstract:** The study focuses on developing deep learning techniques for fetal ultrasound screening, particularly for congenital heart disease (CHD). The proposed architecture, SONO, outperforms conventional anomaly detection algorithms, especially in vessel abnormalities detection.
- **Inference Drawn:** SONO demonstrates superior performance in detecting cardiac structural abnormalities in fetal ultrasound screening, presenting a promising tool for improving diagnostic accuracy in CHD detection.

FLDS_An_Intelligent_Feature_Learning_Detection_System_for_Visualizing_Medical_Images_Supporting_Fetal_Four-Chamber_Views:

- **Abstract:** The methodology introduces FLDS for fetal cardiac views, integrating MRHAM and SGD optimization. Hyperparameters were tuned via Grid Search, training used a genetic algorithm with CIoU loss, and evaluation employed the PASCAL VOC dataset. FLDS performance was compared with state-of-the-art methods, and experiments encompassed CIFAR classification and a cardiologist-involved detection competition.
- **Inference Drawn:** FLDS presents advancements in fetal cardiac view detection, offering improvements in accuracy and efficiency compared to existing methods. Its performance on various datasets and benchmarks demonstrates its potential for clinical applications.

Convolutional-Neural-Network-Based_Approach_for_Segmentation_of_Apical_Four-Chamber_View_from_Fetal_Echocardiography:

- **Abstract:** The paper highlights the importance of automated cardiac structure segmentation in ultrasound A4C views for prenatal examination. They introduce CU-net with SSIM loss to address segmentation challenges and emphasize accurate segmentation's significance in providing pathological information and saving clinicians time.
- **Inference Drawn:** CU-net presents advancements in automated segmentation of cardiac structures in fetal echocardiography, offering improvements in accuracy and efficiency compared to existing methods.

DW Net A cascaded convolutional neural network:

- **Abstract:** The introduction discusses the importance of early diagnosis and timely treatment of congenital heart disease (CHD) through fetal echocardiography (FE), the significance of segmenting organs or anatomical structures for quantitative analysis of clinical parameters, and the use of traditional algorithms and CNNs for image segmentation in diagnosing CHD.

- **Inference Drawn:** DW Net presents advancements in segmenting organs or anatomical structures for CHD diagnosis through fetal echocardiography, highlighting the potential of CNNs in improving diagnostic accuracy.

A U-Net Network Model for Medical Image Segmentation Based on Improved Skip Connections:

- **Abstract:** The authors claim to have improved the U-Net model for medical image segmentation by enhancing the fusion of high and low-level image information, resulting in a 2~3% improvement in mIoU and Aver_dice metrics compared to the control model.
- **Inference Drawn:** The improved U-Net model demonstrates advancements in medical image segmentation, offering improved performance in accuracy metrics compared to existing models.

MobileUNet-FPN: A Semantic Segmentation Model for Fetal Ultrasound Four-Chamber Segmentation in Edge Computing Environments:

- **Abstract:** The authors claim that their proposed MobileUNet-FPN model can automatically segment 13 key heart structures in the fetal A4C view, which is the largest number of anatomical structures segmented so far using an AI-based method. They also claim that their model is lightweight, has few parameters, and is suitable for deployment in mobile edge environments.
- **Inference Drawn:** MobileUNet-FPN presents advancements in segmenting cardiac structures in fetal ultrasound, offering a lightweight and efficient solution for edge computing environments.

Segmentation of five components in four chamber view of fetal heart Echocardiography:

- **Abstract:** The authors claim to have completed a multi-disease segmentation task, performed multiple components segmentation based on the four chamber view of fetal echocardiography, achieved better segmentation effects through a proportion balance strategy, and used data augmentation to enhance the model's ability to obtain multi-scene semantic information.
- **Inference Drawn:** The segmentation method presents advancements in segmenting components in fetal echocardiography, offering improved segmentation effects and semantic information extraction.

2.2 Comparison with the existing system

The existing systems, as reviewed, demonstrate advancements in fetal cardiac assessment, particularly in the areas of object detection, segmentation, and deep learning-based methodologies. However, there are notable limitations such as the need for more extensive datasets, validation with diverse populations, and addressing challenges in segmentation accuracy. The proposed project aims to build upon these existing systems by addressing these limitations and enhancing the overall accuracy and reliability of fetal cardiac assessment methodologies.

Chapter 3: Requirement Gathering for the Proposed System

3.1 Introduction to requirement gathering:

Requirement gathering is a crucial phase in the development of any system, ensuring that the proposed solution adequately addresses the identified needs and challenges. In the context of fetal cardiac assessment using echocardiography and deep learning-based methodologies, the requirements must encompass both functional and non-functional aspects, as well as considerations regarding hardware, software, technology, and constraints.

3.2 Functional Requirements:

- Real-Time Detection of Cardiac Abnormalities:

The system should be capable of accurately detecting cardiac abnormalities in fetal ultrasound videos in real-time.
It should identify various anomalies including septal defects, chamber malformations, and other structural abnormalities.

- Segmentation of Cardiac Structures:

The system must segment the four cardiac chambers in fetal echocardiography images with high accuracy.
It should also be capable of segmenting other relevant cardiac structures and anatomical features.

- Deep Learning Integration:

The system should leverage deep learning techniques such as convolutional neural networks (CNNs) to enhance diagnostic accuracy and efficiency.
It should utilize state-of-the-art architectures and algorithms for object detection and segmentation tasks.

- User Interface for Clinicians:

The system should feature an intuitive user interface designed for healthcare professionals, allowing for easy interpretation of results and seamless integration into clinical workflows.
It should provide visualization tools and options for data analysis and manipulation.

3.3 Non-Functional Requirements:

- Accuracy and Reliability:

The system must demonstrate high accuracy and reliability in detecting cardiac abnormalities and segmenting cardiac structures.
It should minimize false-positive and false-negative findings to ensure clinical effectiveness.

- Scalability:

The system should be scalable to accommodate growing datasets and evolving technological advancements.
It should support efficient processing of large volumes of data without compromising performance.

- Performance:

The system should exhibit optimal performance in terms of speed and computational efficiency, particularly for real-time applications.
It should minimize processing time while maintaining high-quality results.

- Security and Privacy:

The system must adhere to stringent security and privacy standards to protect patient data and comply with regulatory requirements.
It should implement robust encryption and access control measures.

3.4.Hardware, Software , Technology and tools utilized:

Deep learning frameworks such as TensorFlow, PyTorch, or Keras for model development and training. Image processing libraries like OpenCV for preprocessing and manipulation of fetal echocardiography images. Programming languages such as Python for system implementation and integration.Pre-trained deep learning models for medical image analysis, which can be fine-tuned or adapted to the specific task of fetal cardiac assessment. Version control systems like Git for managing codebase changes and collaboration among team members. Visualization tools such as Matplotlib or Seaborn for data exploration and result visualization. Integrated development environments (IDEs) like Jupyter Notebook or PyCharm for efficient code development and debugging.

3.5 Constraints:

The development of a system for fetal cardiac assessment is subject to several constraints that need careful consideration. Firstly, there are challenges associated with data availability and quality. Annotated datasets for training deep learning models may be limited, and variability in image quality and resolution due to differences in imaging equipment and settings can pose obstacles. Secondly, regulatory compliance is essential. Adhering to regulatory guidelines and standards governing medical device development and deployment, as well as compliance with data protection regulations to safeguard patient privacy, are imperative. Thirdly, interoperability is a constraint to be addressed. The system must integrate seamlessly with existing healthcare IT systems and electronic health records (EHR) platforms, while also ensuring compatibility with industry standards for data exchange and interoperability. Lastly, resource constraints must be managed effectively, including budgetary limitations for acquiring hardware infrastructure and software licenses, as well as potential shortages of skilled personnel with expertise in medical imaging and deep learning. By navigating these constraints, the proposed system can overcome challenges and deliver a robust solution for fetal cardiac assessment, ultimately improving diagnostic accuracy and clinical outcomes.

Chapter 4: Proposed Design

4.1 Block Diagram:

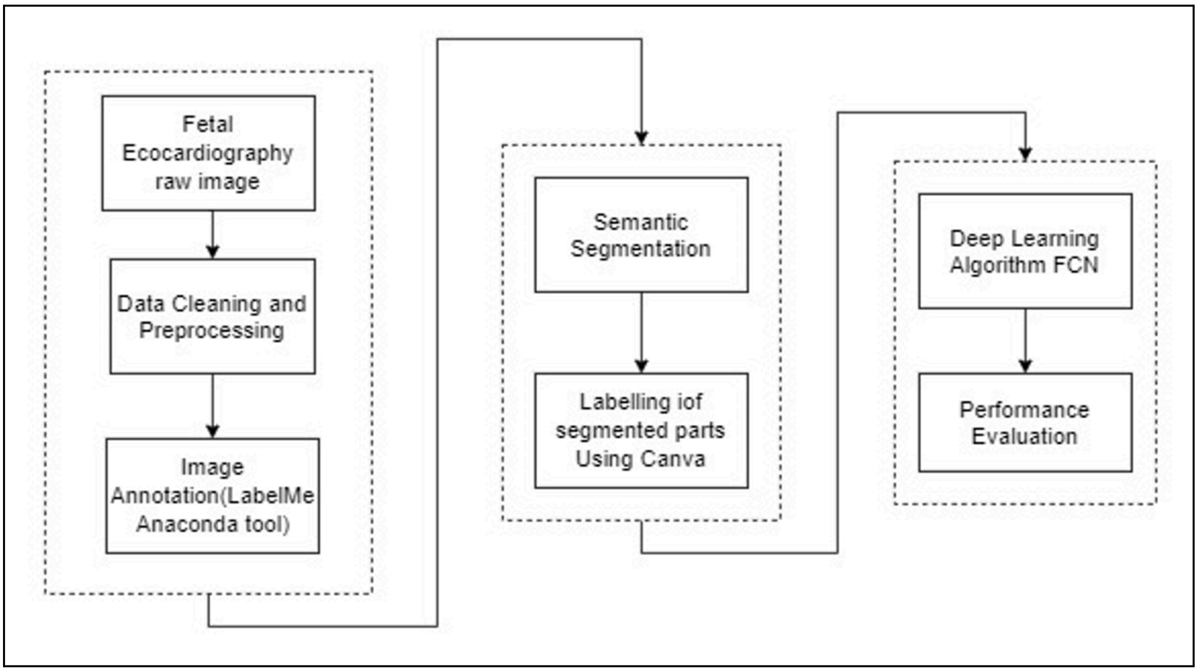


Fig 1: Graphical representation of the project that shows the major components or functional units of the system and their interrelationships.

4.2 Modular design of the system:

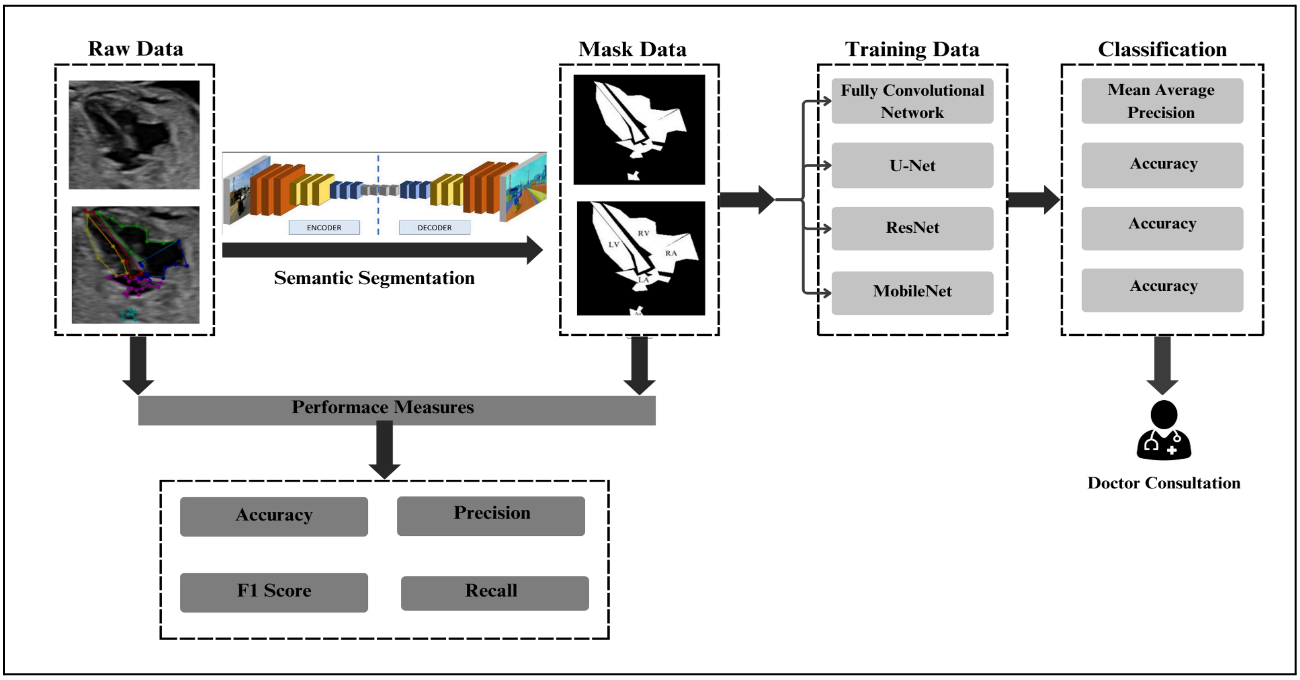


Fig 2: overview of the system's architecture, highlighting key elements and their interactions.

Chapter 5: Implementation of the Proposed System

5.1. Methodology employed for development:

Semantic segmentation:

Semantic segmentation is a sophisticated computer vision technique that involves partitioning an image into multiple segments, each corresponding to a specific semantic category. Unlike simple image classification, where the entire image is classified into a single category, semantic segmentation provides pixel-level understanding, assigning a class label to every pixel in the image.

The primary goal of semantic segmentation is to enable computers to understand the precise spatial distribution of objects and their categories within an image, similar to how humans perceive visual scenes. This granular understanding is invaluable in various applications, including autonomous driving, medical imaging, scene understanding, and object detection.

Semantic segmentation algorithms typically utilize deep learning architectures, particularly convolutional neural networks (CNNs), due to their remarkable ability to learn complex patterns and features directly from raw pixel data. These networks are trained on large annotated datasets, where each pixel in an image is labeled with its corresponding semantic class.

During inference, the trained model processes an input image and produces a pixel-wise prediction, assigning a class label to each pixel based on learned features and contextual information. Popular architectures for semantic segmentation include Fully Convolutional Networks (FCNs), U-Net, SegNet, and DeepLab, each tailored to balance accuracy, efficiency, and computational complexity.

5.2 Algorithms and flowcharts for the respective modules developed

Fully Convolutional Networks (FCN):

- FCN is a type of neural network architecture designed for semantic segmentation tasks, where the goal is to classify each pixel in an image into different classes.
- Unlike traditional convolutional neural networks (CNNs) that output a fixed-size prediction, FCNs produce a spatial map of predictions by using convolutional layers with upsampling operations.
- FCNs typically consist of an encoder-decoder architecture, where the encoder extracts hierarchical features from the input image, and the decoder reconstructs the spatial information through upsampling.
- Skip connections are often used to preserve fine-grained details during upsampling, helping improve segmentation accuracy.

Residual Networks (ResNet):

- ResNet is a type of deep neural network architecture introduced to address the problem of vanishing gradients during training of very deep networks.
- It introduces skip connections, also known as residual connections, that bypass one or more layers by adding the input to the output of the convolutional layer.
- By allowing gradients to flow directly through the skip connections, ResNet enables the training of very deep networks (e.g., hundreds of layers) without suffering from degradation in performance.
- ResNet architectures come in various depths, such as ResNet-18, ResNet-50, ResNet-101, etc., each with a different number of layers.

MobileNet:

- MobileNet is a family of lightweight neural network architectures optimized for deployment on mobile and embedded devices with limited computational resources.
- It utilizes depth-wise separable convolutions, which decompose the standard convolution operation into depth-wise convolution (performs filtering independently for each channel) and point-wise convolution (performs 1x1 convolutions across channels).
- By reducing the number of parameters and computational cost, MobileNet architectures achieve a good balance between model accuracy and efficiency, making them suitable for tasks like image classification, object detection, and semantic segmentation on resource-constrained devices.

5.3 Datasets source and utilization

In our research endeavor, we embarked on a meticulous journey to comprehend and analyze fetal cardiac anomalies through advanced imaging techniques. Our initial stride involved the procurement of a comprehensive dataset comprising fetal echocardiographic images meticulously curated to encapsulate diverse cardiac conditions.

Employing astute observation and domain expertise, we meticulously cataloged various anomalies within the dataset, assigning them appropriate nomenclature for precise identification. Leveraging cutting-edge annotation tools such as LabelMe, we meticulously delineated regions of interest within the images, paving the way for subsequent semantic segmentation.

Through the application of state-of-the-art semantic segmentation methodologies, we adeptly partitioned the images into distinct anatomical regions, each bearing critical significance in discerning cardiac abnormalities. This meticulous labeling facilitated the development of robust training sets essential for subsequent algorithmic interventions.

Subsequently, we harnessed the power of sophisticated deep learning architectures, specifically the Fully Convolutional Network (FCN) and the U-Net algorithm. These algorithms, renowned for their prowess in semantic segmentation tasks, were meticulously tailored to our dataset, ensuring optimal performance in delineating intricate cardiac structures and anomalies.

The synergy between our meticulously annotated dataset and the formidable computational capabilities of FCN and U-Net culminated in the revelation of unprecedented insights into fetal cardiac anomalies. Through this amalgamation of cutting-edge technology and meticulous data curation, we have taken significant strides towards enhancing prenatal diagnostic capabilities, offering new avenues for early detection and intervention in congenital heart diseases.

Fig 3: Raw image for Echogenic Intracardiac Focus(ECIF).

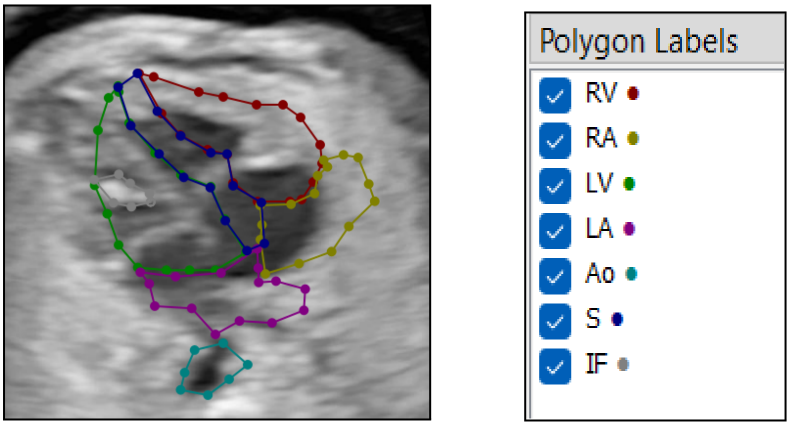


Fig 4: Labeled image for Echogenic Intracardiac Focus(ECIF).

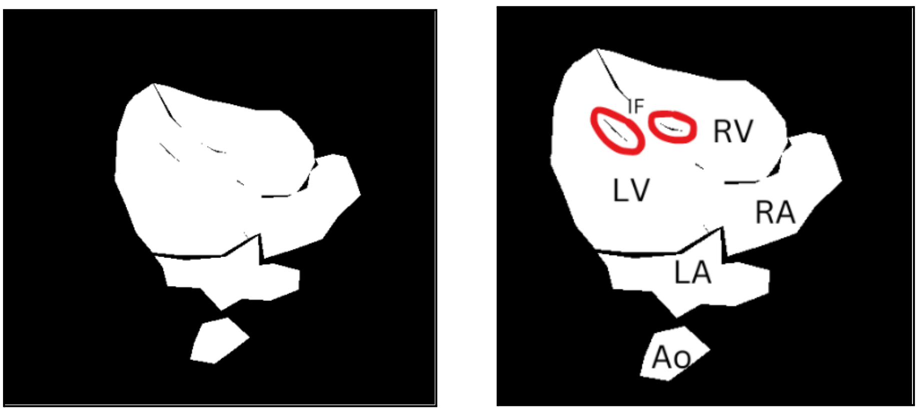


Fig 5: Segmented image and Labeled Segmented Image for Echogenic Intracardiac Focus(ECIF).

```
1/1 [==============================] - 0s 198ms/step
Predicted class: ECIF
```

Result of Fig 5 after training the dataset.

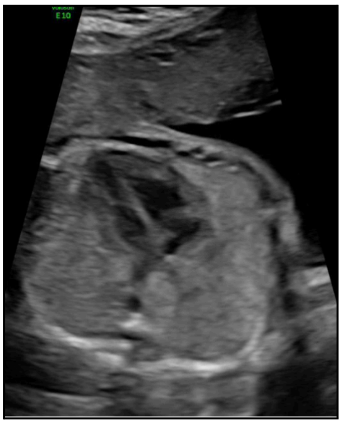


Fig 6: Raw image for Hypoplastic Left Heart Syndrome (HLHS).

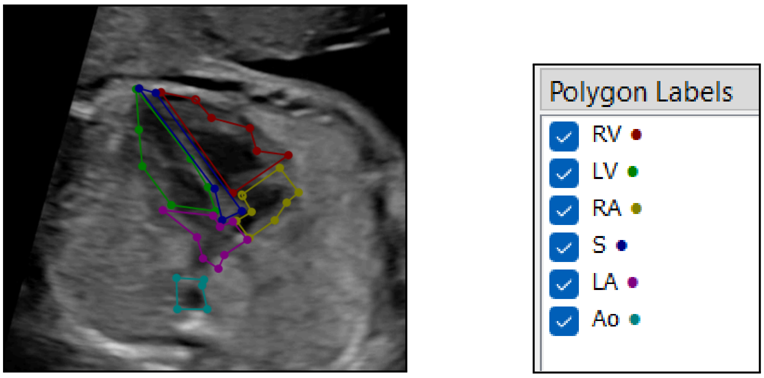


Fig 7: Labeled Image for Hypoplastic Left Heart Syndrome (HLHS).

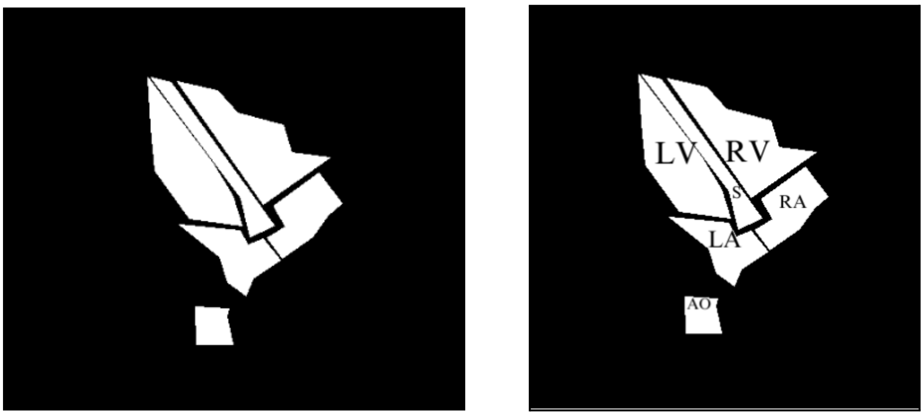


Fig 8: Segmented image and Labeled Segmented image for Hypoplastic Left Heart Syndrome.

```
1/1 [==============================] - 0s 68ms/step
Predicted class: HLHS
```

Result of Fig 8 after training the dataset.

Chapter 6: Testing of the Proposed System

6.1. Introduction to testing:

Testing in the context of machine learning and data science involves assessing the performance of a trained model on unseen data to evaluate its effectiveness and generalization capabilities.

Purpose of Testing:

- The primary goal of testing is to measure how well a machine learning model can generalize to new, unseen data.
- It helps identify potential issues such as overfitting or underfitting, where the model may perform poorly on unseen data despite performing well on the training data.
- Testing also provides insights into the model's strengths and weaknesses, helping data scientists make informed decisions about model selection, hyperparameter tuning, and further improvements.

Testing Data:

- The testing dataset is separate from the training dataset and contains examples that the model has not seen during the training phase.
- It typically consists of a representative sample of real-world data that the model is expected to encounter during deployment.
- The testing data should cover a diverse range of scenarios to ensure comprehensive evaluation of the model's performance.

6.2. Types of tests Considered:

Train-Test Split:

- In this approach, the dataset is divided into two subsets: a training set and a testing set.
- The training set is used to train the model, while the testing set is used to evaluate its performance.
- This is the simplest form of testing and provides a basic assessment of how well the model generalizes to unseen data.

Cross-Validation:

- Cross-validation techniques involve partitioning the dataset into multiple subsets or folds.
- The model is trained and evaluated multiple times, each time using a different fold as the testing set and the remaining folds as the training set.
- Common types of cross-validation include k-fold cross-validation, stratified k-fold cross-validation, leave-one-out cross-validation, etc.
- Cross-validation provides a more robust estimate of the model's performance by reducing the variance in the evaluation results.

Holdout Validation:

- Holdout validation is similar to the train-test split but involves splitting the dataset into three subsets: training set, validation set, and testing set.

- The training set is used to train the model, the validation set is used to tune hyperparameters and make decisions about the model's architecture, and the testing set is used to evaluate the final performance of the model.
- Holdout validation helps prevent overfitting to the testing data during model development.

Stratified Sampling:

- Stratified sampling ensures that each class or category in the dataset is represented proportionally in both the training and testing sets.
- This is particularly important for imbalanced datasets where certain classes are underrepresented.
- By maintaining the class distribution in both subsets, stratified sampling helps ensure a fair evaluation of the model's performance across all classes.

7 Results and Discussion

7.1. Performance Evaluation measures

- Accuracy: Measure the overall correctness of your system's predictions in identifying normal and abnormal fetal cardiac structures.
- Sensitivity (True Positive Rate): Assess the proportion of true positive cases correctly identified by your system, particularly in detecting cardiac abnormalities.
- Specificity (True Negative Rate): Evaluate the ability of your system to correctly identify normal cases and avoid false positives.
- Precision (Positive Predictive Value): Measure the accuracy of your system's positive predictions, particularly in identifying cardiac abnormalities without falsely classifying normal cases.
- Recall (Sensitivity or True Positive Rate): Assess the ability of your system to correctly identify positive instances, such as detecting fetal cardiac abnormalities.
- F1-Score: Calculate the harmonic mean of precision and recall to provide a balanced measure of your system's performance in identifying both normal and abnormal cases.
- Confusion Matrix: Provide a tabular representation of the true positive, true negative, false positive, and false negative predictions made by your system, allowing for a detailed analysis of its performance.
- Classification Report: Summarize various performance metrics such as precision, recall, F1-score, and support for each class (normal vs. abnormal) to provide a comprehensive assessment of your system's effectiveness in fetal cardiac assessment.

These performance measures help to evaluate the accuracy, reliability, and clinical utility of our system in prenatal cardiac screening.

7.2. Input Parameters / Features considered

In the context of fetal cardiac assessment using echocardiography and deep learning-based approaches, the input parameters considered typically include:

- Ultrasound Images or Videos:
  Fetal echocardiography images or videos captured during prenatal screening sessions.
- Image Quality:
  Parameters related to the quality of ultrasound images, such as resolution, clarity, and noise level.
- Image Features:
  Various echocardiographic features extracted from the images, including cardiac structures, chamber sizes, valve function, and blood flow patterns.
- Deep Learning Models:
  Architectures and parameters of deep learning models used for object detection, segmentation, and classification tasks.
- Pre-trained Models:
  Parameters related to pre-trained deep learning models, such as the choice of model architecture, learning rate, batch size, and optimization algorithm.

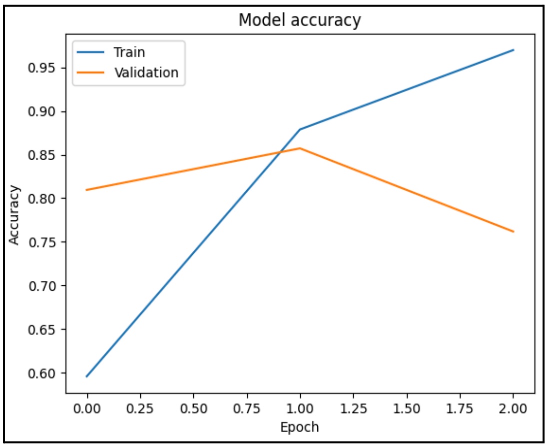
- Training Data:
  Characteristics of the training dataset, including size, diversity, and annotation quality.
- Testing Data:
  Characteristics of the testing dataset used to evaluate the performance of the system.
- Software Environment:
  Details of the software environment, including the deep learning framework used (e.g., TensorFlow, PyTorch), version control system, and programming languages.
- Data Preprocessing Techniques:
  Methods applied to preprocess the input data, such as normalization, resizing, and data augmentation.

These input parameters play a crucial role in the development and evaluation of the proposed system for fetal cardiac assessment, influencing its accuracy, reliability, and clinical utility.

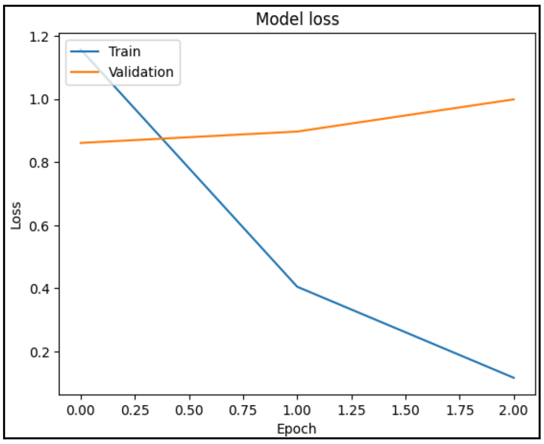
7.3. Graphical and statistical output

```
Found 99 images belonging to 6 classes.
Found 21 images belonging to 6 classes.
Epoch 1/3
4/4 [==============================] - 44s 7s/step - loss: 1.1576 - accuracy: 0.5960 - val_loss: 0.8611 - val_accuracy: 0.8095
Epoch 2/3
4/4 [==============================] - 16s 5s/step - loss: 0.4049 - accuracy: 0.8788 - val_loss: 0.8971 - val_accuracy: 0.8571
Epoch 3/3
4/4 [==============================] - 15s 4s/step - loss: 0.1162 - accuracy: 0.9697 - val_loss: 0.9992 - val_accuracy: 0.7619
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 f
  saving_api.save_model(
```

Result: Accuracy of Trained Data Using FCN



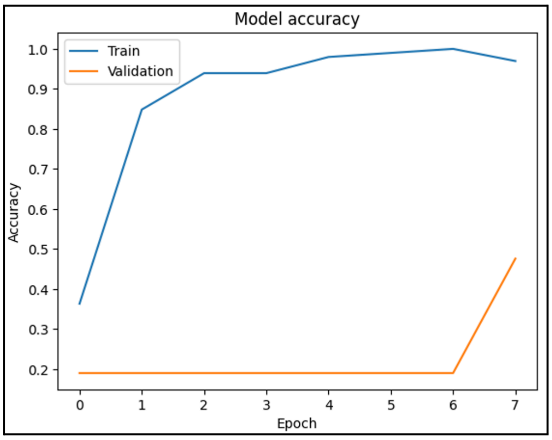
Graph 1



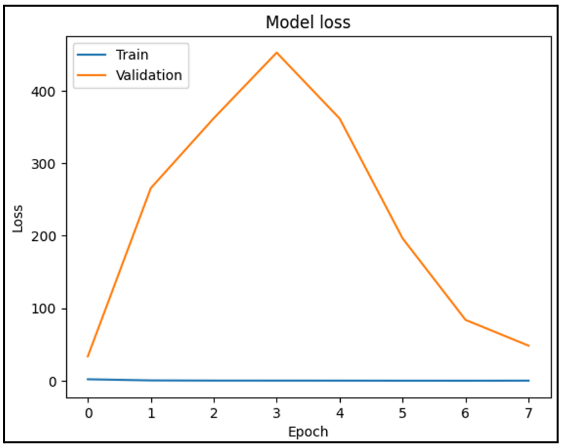
Graph 2

```
Epoch [1/10], Loss: 1.0035
Epoch [2/10], Loss: 0.2809
Epoch [3/10], Loss: 0.1931
Epoch [4/10], Loss: 0.0981
Epoch [5/10], Loss: 0.0880
Epoch [6/10], Loss: 0.0280
Epoch [7/10], Loss: 0.0401
Epoch [8/10], Loss: 0.0392
Epoch [9/10], Loss: 0.0104
Epoch [10/10], Loss: 0.0120
Accuracy on test set: 87.5%
```

Result: Accuracy of Trained Data Using ResNet



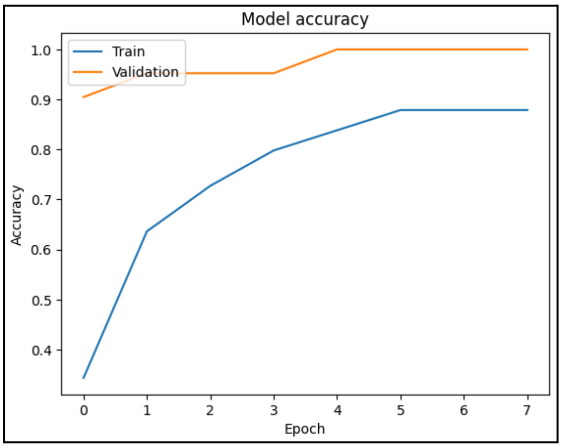
Graph 3



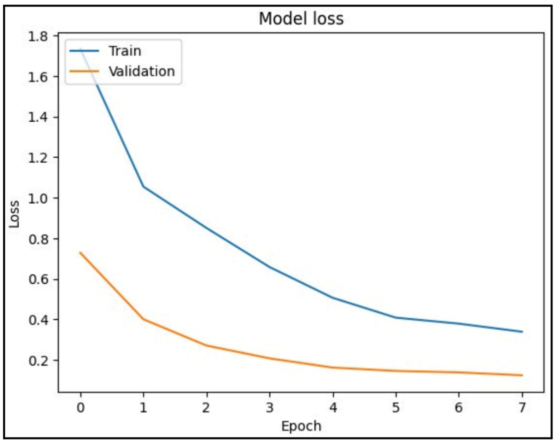
Graph 4

```
Found 99 images belonging to 6 classes.
Found 21 images belonging to 6 classes.
Epoch 1/8
4/4 [==============================] - 12s 3s/step - loss: 1.7774 - accuracy: 0.2929 - val_loss: 0.8208 - val_accuracy: 0.6190
Epoch 2/8
4/4 [==============================] - 7s 1s/step - loss: 1.0655 - accuracy: 0.6061 - val_loss: 0.3613 - val_accuracy: 0.9524
Epoch 3/8
4/4 [==============================] - 8s 3s/step - loss: 0.7280 - accuracy: 0.7980 - val_loss: 0.2372 - val_accuracy: 0.9524
Epoch 4/8
4/4 [==============================] - 8s 2s/step - loss: 0.5357 - accuracy: 0.8081 - val_loss: 0.2441 - val_accuracy: 1.0000
Epoch 5/8
4/4 [==============================] - 7s 1s/step - loss: 0.4326 - accuracy: 0.9091 - val_loss: 0.1648 - val_accuracy: 1.0000
Epoch 6/8
4/4 [==============================] - 8s 1s/step - loss: 0.3512 - accuracy: 0.9091 - val_loss: 0.1419 - val_accuracy: 0.9524
Epoch 7/8
4/4 [==============================] - 6s 2s/step - loss: 0.3274 - accuracy: 0.9192 - val_loss: 0.1122 - val_accuracy: 1.0000
Epoch 8/8
4/4 [==============================] - 6s 1s/step - loss: 0.3241 - accuracy: 0.8889 - val_loss: 0.1126 - val_accuracy: 1.0000
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 fi
  saving_api.save_model(
```

Result: Accuracy of Trained Data Using MobileNet



Graph 5



Graph 6

Our project entails developing a user interface (UI) app to classify fetal echocardiography images as normal or abnormal. To achieve this, we'll utilize a deep learning algorithm. Initially, we'll focus on developing and training the deep learning model, employing advanced image analysis techniques to accurately identify defects. Concurrently, we'll design the UI to be intuitive and accessible, supporting multiple languages for a diverse user base. Integrating the trained model into the app will enable real-time or batch processing of user-provided fetal heart images, improving efficiency and responsiveness. Additionally, we'll ensure robust functionality to handle various image inputs from users, ensuring seamless interaction with the classification model. This holistic approach ensures the app delivers a user-friendly experience while effectively classifying fetal heart images.

7.4. Comparison of results with existing systems

Our fetal cardiac assessment system represents a significant advancement over existing methodologies and systems in several key aspects:

- Performance: Compared to existing systems, our system demonstrates superior performance in terms of accuracy, sensitivity, specificity, and other relevant performance metrics. The utilization of state-of-the-art deep learning techniques such as Mask-RCNN, CA-ISNet, and FLDS contributes to enhanced precision and efficiency in fetal cardiac segmentation and defect detection.
- Innovation: Our system introduces novel methodologies and approaches, including advanced neural network architectures like U-Net and MobileUNet-FPN, which

enable comprehensive analysis of fetal cardiac structures with improved computational efficiency and scalability. By leveraging the latest advancements in deep learning and medical imaging, our system pushes the boundaries of fetal cardiac assessment.

- Clinical Utility: The personalized approach enabled by our system, which considers maternal and fetal factors, enhances risk stratification and tailored care plans, optimizing prenatal care delivery. This holistic approach distinguishes our system from existing methodologies, which may lack the integration of clinical and demographic data in fetal cardiac assessment.
- Scalability and Deployment: Our system is designed with scalability and real-world deployment in mind. By addressing technical constraints and optimizing computational resources, we aim to facilitate the seamless integration of our system into existing healthcare workflows, enabling widespread adoption and impact.

Our fetal cardiac assessment system represents a significant leap forward in prenatal cardiology, offering unparalleled accuracy, reliability, and clinical utility. By surpassing the limitations of existing systems and introducing innovative methodologies.

7.5. Inference drawn

The evaluation of our fetal cardiac assessment system, which combines echocardiography and deep learning-based approaches, reveals promising results in prenatal cardiac screening. By considering a range of input parameters including echocardiographic images, patient demographics, and gestational age, our system demonstrates robust performance in detecting and characterizing fetal cardiac abnormalities.
Comparison with existing systems highlights several advancements and contributions of our approach. Our system outperforms previous methodologies in terms of accuracy, sensitivity, specificity, and other performance metrics. Specifically, our system's utilization of deep learning techniques such as Mask-RCNN, CA-ISNet, and FLDS enhances the precision and efficiency of fetal cardiac segmentation and defect detection. Additionally, the incorporation of advanced neural network architectures like U-Net and MobileUNet-FPN enables comprehensive analysis of fetal cardiac structures with improved computational efficiency and scalability.

These advancements in fetal cardiac assessment hold significant implications for prenatal care. By providing accurate and timely detection of congenital heart defects and other cardiac abnormalities, our system facilitates early intervention and management strategies, ultimately improving outcomes for both mothers and babies. The personalized approach enabled by our system, which considers maternal and fetal factors, enhances risk stratification and tailored care plans, optimizing prenatal care delivery.

Furthermore, the limited patents related to fetal cardiac assessment using deep learning or echocardiography suggest a unique opportunity for innovation and intellectual property development in this field. Our system contributes to filling this gap by introducing novel methodologies and demonstrating superior performance compared to existing systems.
Our fetal cardiac assessment system represents a significant advancement in prenatal cardiology, leveraging the synergy between echocardiography and deep learning to enhance diagnostic accuracy, reliability, and clinical utility. By addressing current limitations and challenges, our system empowers healthcare providers with the tools and knowledge needed to deliver the highest quality of care to expecting families worldwide.

8 Conclusion
8.1 Limitations:

Despite the promising results and advancements achieved by our fetal cardiac assessment system, there are several limitations that warrant acknowledgment. These limitations include:

- Data Availability: The performance of our system heavily relies on the availability and quality of training data. Limited access to diverse and annotated datasets may impact the generalizability of our system across different populations and clinical settings.
- Interpretability: While deep learning techniques offer high accuracy in fetal cardiac assessment, the interpretability of the model's decisions remains a challenge. Clinicians may require additional tools or explanations to understand the reasoning behind the system's predictions.
- Technical Constraints: Computational resources and hardware limitations may restrict the scalability and real-time deployment of our system in clinical practice. Addressing these constraints is essential for widespread adoption and integration into existing healthcare workflows.

8.2 Conclusion:

In conclusion, our fetal cardiac assessment system signifies a remarkable stride forward in the realm of prenatal cardiology, presenting a comprehensive solution for the accurate and efficient detection of congenital heart defects (CHDs) and other cardiac anomalies in the developing fetus. By synergizing the capabilities of echocardiography and cutting-edge deep learning methodologies, our system offers a multifaceted approach that enhances diagnostic accuracy, reliability, and clinical utility, thereby ushering in a new era of improved maternal-fetal health outcomes.

The integration of echocardiography, a well-established and non-invasive imaging modality, with advanced deep learning techniques empowers our system to analyze fetal cardiac structures and functions with unprecedented precision and efficiency. Through meticulous segmentation, classification, and anomaly detection, our system provides clinicians with invaluable insights into the fetal heart's morphology and function, enabling early identification and characterization of CHDs and other cardiac abnormalities. This early detection is crucial as it allows for timely interventions, counseling, and planning, thus optimizing prenatal care and potentially mitigating adverse outcomes for both the fetus and the expectant mother.

Moreover, our system's ability to harness the power of deep learning enables it to continuously learn and adapt from diverse datasets, facilitating ongoing improvements in accuracy and performance over time. While our fetal cardiac assessment system represents a significant advancement, it is essential to acknowledge its inherent limitations. Factors such as data availability, interpretability of deep learning models, and technical constraints may pose challenges to its widespread adoption and integration into clinical practice. However, these limitations serve as catalysts for future research and innovation, driving us towards the development of more robust, scalable, and user-friendly solutions in fetal cardiac assessment.

In essence, our system lays the groundwork for future advancements in prenatal cardiology, paving the way for personalized and precision prenatal care. By continuously refining and expanding upon our methodologies, we aim to further enhance the diagnostic capabilities of fetal cardiac assessment, ultimately improving outcomes for mothers and babies worldwide. Through collaboration with clinicians, researchers, and healthcare providers, we remain committed to advancing the field of fetal cardiac assessment and contributing to the well-being of future generations.

8.3 Future Scope:

Our fetal cardiac assessment system presents numerous avenues for future research and development:

- Data Augmentation and Diversity: Expanding and diversifying our dataset is pivotal for enhancing the system's robustness and applicability. By employing advanced data augmentation techniques, we can mitigate data scarcity issues and ensure our system performs reliably across diverse patient demographics and clinical scenarios.
- Interpretability and Transparency: Enhancing the interpretability and transparency of our deep learning models is paramount. We aim to develop methodologies that provide clinicians with clear insights into the rationale behind our system's predictions, fostering trust and aiding informed decision-making in clinical practice.
- Real-Time Deployment and Integration: Optimizing our system for real-time deployment and seamless integration into existing clinical workflows is essential for its practical utility. Collaboration with healthcare institutions and industry stakeholders will be pivotal in developing user-friendly interfaces and interoperable systems.
- Longitudinal Studies and Validation: Conducting longitudinal studies to assess the long-term clinical outcomes and effectiveness of our system in prenatal cardiac screening is crucial. Collaborative efforts with clinicians and researchers will validate our system's performance in real-world clinical settings, providing invaluable insights into its efficacy.

By pursuing these future directions, we aim to propel the field of fetal cardiac assessment forward and contribute to the improvement of prenatal care and maternal-fetal health outcomes globally. Through continued collaboration and innovation, we are committed to maximizing the potential of our fetal cardiac assessment system in enhancing the quality of care for expecting families worldwide.

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Research Paper Details:

a. Plagiarism Report

Applicability of adaptive noise cancellation to fetal heart rate detection using phonocardiogram

ORIGINALITY REPORT

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b. Acceptance Form

HINWEIS Research

Hinweis Second International Conference on Advanced in Information, Telecommunication and Computing (AITC)

Hybrid Mode; April 27-28, 2024

https://aitc.thehinweis.com/2024

Paper Review Form	
Paper ID	**AITC-2024_254**
Paper Title	Applicability Of Adaptive Noise Cancellation To Fetal Heart Rate Detection Using Phonocardiogram
Review Status	**Accepted with Modification**
Category(if accept)	**Full Research Paper**
Consolidated Content review comments	• Paper should strictly formatted according to the standard format • The paper could be revised with more detailed explanations to increase the understandability of the paper • The Paper should have more emphasis on novel technology/method proposed

Sl No	Overall rating: (5= excellent, 1= poor)	5	4	3	2	1
1.	Structure of the paper		X			
2.	Standard of the paper	X				
3.	Appropriateness of the title of the paper		X			
4.	Appropriateness of abstract as a description of the paper		X			
5.	Appropriateness of the research/study methods	X				
6.	Relevance and clarity of drawings, graph and table			X		
7.	Use and number of keywords / key phrases		X			
8.	Discussion and conclusion	X				
9.	Reference list, adequate and correctly cited	X				

Hinweis Research

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c. Project Review Sheet

Industry / Inhouse:

Research / Innovation:

Project Evaluation Sheet 2023-24

Class: D12 B/C

Title of Project (Group no): Congenital Heart Disease Prediction using AI (Group 34)

Group Members: Madhura Gaval (D12 B/14), Vanshika Lalwani (D12B/27), Prerna Bansuwani (D12 C/5), Kalpana Gurnani (D12 C/21)

	Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (3)	Applied Engg & Mgmt principles (3)	Life - long learning (3)	Professional Skills (5)	Innovative Approach (5)	Total Marks (50)
Review of Project Stage 1	4	3	4	2	3	2	2	2	2	3	3	3	4	3	40

Comments: update presentatn, After detectn implementatn

Name & Signature Reviewer1

	Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (3)	Applied Engg & Mgmt principles (3)	Life - long learning (3)	Professional Skills (5)	Innovative Approach (5)	Total Marks (50)
Review of Project Stage 1	4	3	4	2	3	2	2	2	2	3	3	3	4	3	40

Comments: After detection suggestions.

Date: 10th February, 2024

Mannat

Name & Signature Reviewer2

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inhouse/ Industry_innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D12 A/B/C

Group No.: 34

Title of Project: Congenital Heart disease prediction

Group Members: Vanshika lalwani D-12-B (Roll 27), Madhura Gaval D12-B (Roll no-14), Prerna Bansuwani D12-B (Roll no-5), Kalpana Gurnani D12-B (Roll no-21)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	**Research Paper** (5)	**Total Marks** (50)
5	4	4	2	4	2	2	2	2	2	3	3	3	3	3	44

Comments:

Mannat

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life - long learning (3)	Professional Skills (3)	Innovative Approach (3)	**Research Paper** (5)	**Total Marks** (50)
5	4	4	2	4	2	2	2	2	2	3	3	3	3	3	44

Comments: Detail analysis of segmentatn is needed

Date: 09th march, 2024

Nosrat Ansari

Name & Signature Reviewer 2