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Deep Learning Techniques for a Comprehensive Analysis of Fetal Biometric Parameters Across Trimesters

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ABSTRACT

The process of creating fetal images from the uterus using sound influence is known as fetal ultrasound imaging. During this scan, measurements such as the gestational sac, biparietal diameter, head circumference, abdominal circumference, and femur length can be taken from the mother, which are further analyzed by the radiologist or gynecologist. These factors allow us to quickly test for anomalies and monitor the fetal growth and development of a baby. This paper delves into the techniques utilized in previous studies for analyzing abnormalities from ultrasound images using machine learning and deep learning techniques. Specifically, we focus on two trimesters and three key fetal parameters: Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL). Our proposed method, the Unet segmentation method, not only performs segmentation but also predicts the parameters. We employ various transfer learning techniques for classification. The experiment involves 1,313 medical fetal images, comprising 563 from the second trimester and 750 from the third trimester. In terms of segmentation accuracy, the results for the second trimester's biometric parameters are as follows: AC = 69.09%, FL = 92.02%, and HC = 69.43%. For the third trimester, the accuracy for FL is 90.04%, and for HC, it is 69.76%. Regarding classification methods, MobileNet and XceptionNet yield comparable results. For the second trimester, MobileNet achieves

99.28%, and XceptionNet achieves 99.82%. For the third trimester, both MobileNet and XceptionNet achieve 99.86%.

Keywords: Anomaly detection, Abdominal circumference, Biparietal diameter, Deep learning techniques, Femur length, Head circumference, Machine Learning, MobileNet, Segmentation accuracy, Transfer learning, Ultrasound Fetal Images, XcepationNet

INTRODUCTION

Ultrasound stands out as the preferred prenatal diagnostic tool due to its myriad benefits, encompassing widespread accessibility, affordability, non-ionizing radiation usage, and mobility. It serves as the predominant approach for two primary objectives: screening fetal growth and evaluating pathological and physiological states [1] [2]. An anticipated 8 million children are born each year. Sober birth abnormalities of hereditary or largely inherited origin affect 6% of all babies globally. Sober birth abnormalities cause at least 3.3 million deaths in children under five every year, and most of those who survive may always have physical and mental disabilities [3]. According to a joint World Health Organization (WHO) and March of Dimes (MOD) meeting report, 3.3 million under-five fatalities and 7% of all neonatal deaths occur in India due to birth abnormalities. India has a 6% to 7% prevalence of birth abnormalities, which equates to about 1.7 million birth problems annually. [4]. The fact that birth abnormalities have been increasing in frequency annually in recent years is of more significant concern.

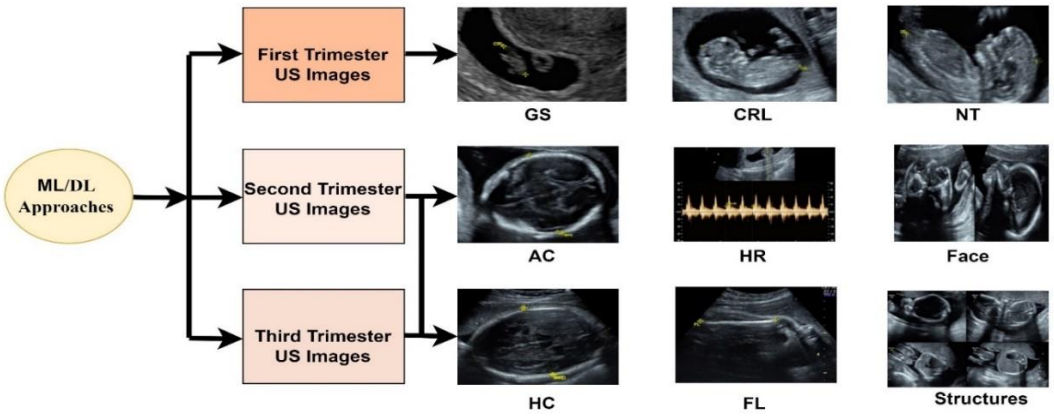


Fig 1: shows a diagram of biometric measurements for each trimester. US: ultrasound; GS: Gestational Sac; CRL: Crown-Rump Length; NT: Nuchal Translucency; HC: Head Circumference; AC: Abdominal Circumference; FL: Femur Length;

As a result, pregnancy outcome prediction becomes a vital study issue since it may assist in reducing congenital disabilities and improving population quality. Each of the three trimesters of pregnancy is characterized by distinct fetal development. At 40 weeks, a pregnancy is considered to be full-term. They are three trimesters. The first trimester lasts from 0 to 13 weeks, the second from 14 to 26, and the third from 27 to 40 weeks [6]. Gestational age (GA) estimation, crucial for monitoring fetal growth, relies on fetal biometric parameters [5]. Measuring parameters such as head circumference (HC), biparietal diameter (BPD), abdominal circumference (AC), and femur length (FL) is imperative for this purpose. These standard

biometric parameters, commonly evaluated during routine second-trimester scans, are defined based on fetal anatomy [5]. A biometric parameters diagram of different trimesters is shown in Fig. 1.

The first-trimester ultrasound assesses key biometric parameters are Gestational Sac (GS): Detected as early as 4.5 to 5 weeks, the GS surrounds the developing embryo with fluid, marking the initial stage of pregnancy [13] [14]. Nuchal Translucency (NT): This fluid-filled space at the back of the fetal skin is detectable between 11 and 14 weeks. Increased NT thickness may indicate chromosomal or non-chromosomal defects and is associated with various fetal abnormalities and poor perinatal outcomes [12][9] [14]. Crown Rump Length (CRL): Measuring the length of the embryo or fetus from top to bottom of the torso, CRL provides a precise estimate of gestational age, particularly in early pregnancy due to minimal biological variability [12].

Ultrasound measurements in the second and third trimesters include crucial biometric parameters, and they include the following: Head circumference (HC), biparietal diameter (BPD), abdominal circumference (AC), and femur length (FL) are key indicators of fetal size and development. These measurements, along with fetal heart rate (FHR), aid in estimating gestational age and expected delivery date (EDD) [14]. Fetal Heart Rate (FHR) typically ranges from 120 to 160 beats per minute during gestation, varying throughout pregnancy. Detectable via sonography as early as six weeks, FHR shows a gradual increase to about 170 bpm at ten weeks and then decreases to around 130 bpm at term [14]. Fetal biometric characteristics are essential for monitoring gestational age, size, weight, and identifying developmental abnormalities in various body systems, including the brain, spine, heart, abdomen, and placenta, as well as detecting complications such as bleeding in the first trimester or cesarean scar pregnancy.

Ultrasound imaging is often plagued by artifacts like motion blurring, missing borders, acoustic shadows, speckle noise, and low signal-to-noise ratio, posing challenges for accurate analysis. Current research extensively employs deep learning and machine learning techniques to detect adverse pregnancy outcomes, leveraging their automatic feature learning capabilities to aid in abnormality detection in ultrasound images. This paper presents a comparative analysis of image-processing methods for studying fetal abnormalities and proposes novel approaches for analyzing fetal biometric parameters (FBP), focusing on images from the second and third trimesters. Utilizing various deep-learning techniques, we employ the Unet method for accurate segmentation and explore different transfer-learning techniques for classification tasks.

Key Contributions:

Overall, the major contributions of this work are multifold as indicated here: 1) The fetal images were collected and categorized into trimesters. We arrived at this juncture by labeling and annotating the images based on FBP.2) Research the effectiveness of deep learning neural networks for segmentation and feature extraction from biometric fetal images.3) Prediction and classification from the biometric fetal images using transfer learning techniques.4) Verification of the best classification model for fetal biometric image classification.

LITERATURE SURVEY

The advancement of deep learning (DL) algorithms in fetal ultrasound image analysis has sparked significant research interest. Fiorentino et al. [1] provided a comprehensive review, categorizing studies into fetal standard plane detection, anatomical structure analysis, and biometry parameter estimation. They highlighted limitations, applications, open issues, publicly available datasets, and DL algorithms. Meanwhile, Vidhi Rawat et al. [2] emphasized automated techniques for interpreting fetal abnormalities, focusing on segmentation techniques like probabilistic boosting trees and fuzzy logic. Li et al. [8] proposed a novel deep neural network for fetal head segmentation and accurate biparietal diameter (BPD) and occipitofrontal diameter (OFD) prediction. They achieved significant results using 1334 ultrasound images from the HC18 challenge, with an accuracy of approximately 90%. Rueda et al. [11] automated segmenting of fetal anatomical structures, evaluating methods for obstetric biometric parameter measurement across different gestational ages. While numerical accuracy rates were not explicitly mentioned, the study demonstrated improvements in segmentation accuracy compared to existing methods. Micucci et al. [15] discussed machine learning (ML) and DL algorithms for ultrasound image analysis, achieving high accuracy rates with various models, including Linear, Logistic, SVM, UNet, AlexNet, and ResNet. However, specific accuracy values were not provided. Nithya et al. [16] proposed an algorithm for measuring abdominal circumference using a segmentation active contour model, achieving accurate fetal weight and growth restriction analysis. No specific accuracy rates were mentioned, but the method demonstrated effectiveness in analyzing fetal parameters. Carneiro et al. [21] presented a method for the automatic detection and measurement of fetal anatomical structures, employing a probabilistic boosting tree classifier. Accuracy rates for this method were not explicitly stated in the text. Shrimali et al. [23] discussed ultrasound fetal biometry using morphological operators for improved measurement consistency. While numerical accuracy rates were not provided, the study focused on addressing inconsistency and subjectivity in fetal ultrasound measurements. Singh et al. [24] developed a fetal face detection and visualization approach using 3D ultrasound volumes, achieving high accuracy even in multiple fetus pregnancies. However, specific accuracy rates were not mentioned in the text. Feng et al. [25] proposed a learning-based approach for automatic fetal face detection in 3D volumes, focusing on refining detection performance. Although no specific accuracy rates were provided, the study emphasized the need for further improvement in detection performance. Baumgartner et al. [27] introduced a real-time framework for detecting standard views in freehand fetal ultrasound, achieving high accuracy in classification and localization tasks, with an average F1-score of 0.798 in classification and 77.8% accuracy in localization. Meng et al. [28] focused on detecting acoustic shadows in ultrasound images, generating pixel-wise confidence maps for segmentation tasks. Specific accuracy rates for this method were not mentioned. Selvathi et al. [30] evaluated abnormalities in fetal images using CNN, GoogleNet, and AlexNet, achieving high classification accuracies, with AlexNet achieving an accuracy of 90.43%, GoogleNet achieving 88.70%, and CNN achieving 81.25%. Jardim et al. [32] addressed unsupervised contour estimation in fetal ultrasound images, facing challenges with noise sensitivity. Specific accuracy rates were not provided in the text. Attallah et al. [33] proposed a low computational cost method for classifying fetal brain abnormalities, achieving promising results with various classifiers, with SVM achieving 84% accuracy, Linear Discriminate Analysis achieving 86% accuracy, K-nearest neighbor achieving 80% accuracy, and Ensemble Subspace Discriminates

achieving 84.5% accuracy. Cerrolaza et al. [35] developed a fully automatic framework for segmenting fetal skulls in 3D ultrasound, integrating contextual information for accurate reconstruction. Specific accuracy rates were not mentioned in the text. Rawat et al. [37] employed an ANN model for fetal position detection, aiming for real-time and accurate analysis. Specific accuracy rates for this method were not provided. Skeika et al. [40] adapted a deep learning method for fetal skull segmentation, achieving improved segmentation accuracy, with up to 97.92% correct segmentation. Oghli et al. [42] focused on automatic biometric parameter prediction, achieving high accuracy with the MFP-Unet model, with a Dice Similarity Coefficient (DSC) of 0.98 and 100% accuracy in achieving good contours. Lee et al. [59] estimated fetal gestational age accurately using machine learning methods and biometry measurements, achieving a mean absolute error of 3.0 days in the second trimester and 4.3 days in the third trimester. Zhu et al. [60] discussed automatic femur length measurement in ultrasound images, achieving high accuracy with random forest regression and SegNet methods, with the random forest regression model achieving an average error of 1.23 mm and the SegNet-based method achieving an average error of 0.46 mm. Deepika et al. [65] defended against fetal abnormalities using CNN-U-Net, achieving exceptional identification accuracy of 99.7%. Prieto et al. [66] developed a fully automated framework for recognizing and measuring fetal structures, achieving accurate predictions with RESNET and RUNET models. Specific accuracy rates for this method were not provided. Bano et al. [68] automated fetal biometry estimation using segmentation models, achieving accurate parameter estimation, with specific accuracy rates not mentioned. Sahli et al. [72] integrated biometric features for diagnosing fetal brain abnormalities, achieving high classification accuracies with SVM, MNN, and KNN methods, with the SVM classifier achieving 87.10% accuracy, KNN achieving 71.70%, and MNN achieving 78.87% accuracy. Lee et al. [76] developed AI models for sonographic assessment of gestational age, showing potential for higher estimation accuracy. Specific accuracy rates for this method were not provided.

To check the preceding work the following selection is considered from 2010 onwards publication for analysis. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement to select the research publications. Focusing on prenatal anomalies analyzed using machine learning and deep learning techniques. After reviewing the titles, abstracts, and full texts. Nearly 120 research studies were taken into consideration for this investigation. Around 120 records, were considered, with 33 reviews excluded due to unclear objectives, irrelevance to our research area, inadequate use of machine learning, or unrelated focus on prenatal anomalies. The PRISMA flow diagram (Fig 2) summarizes our literature review process, while Table 1 outlines the main inclusion and exclusion criteria for the study.

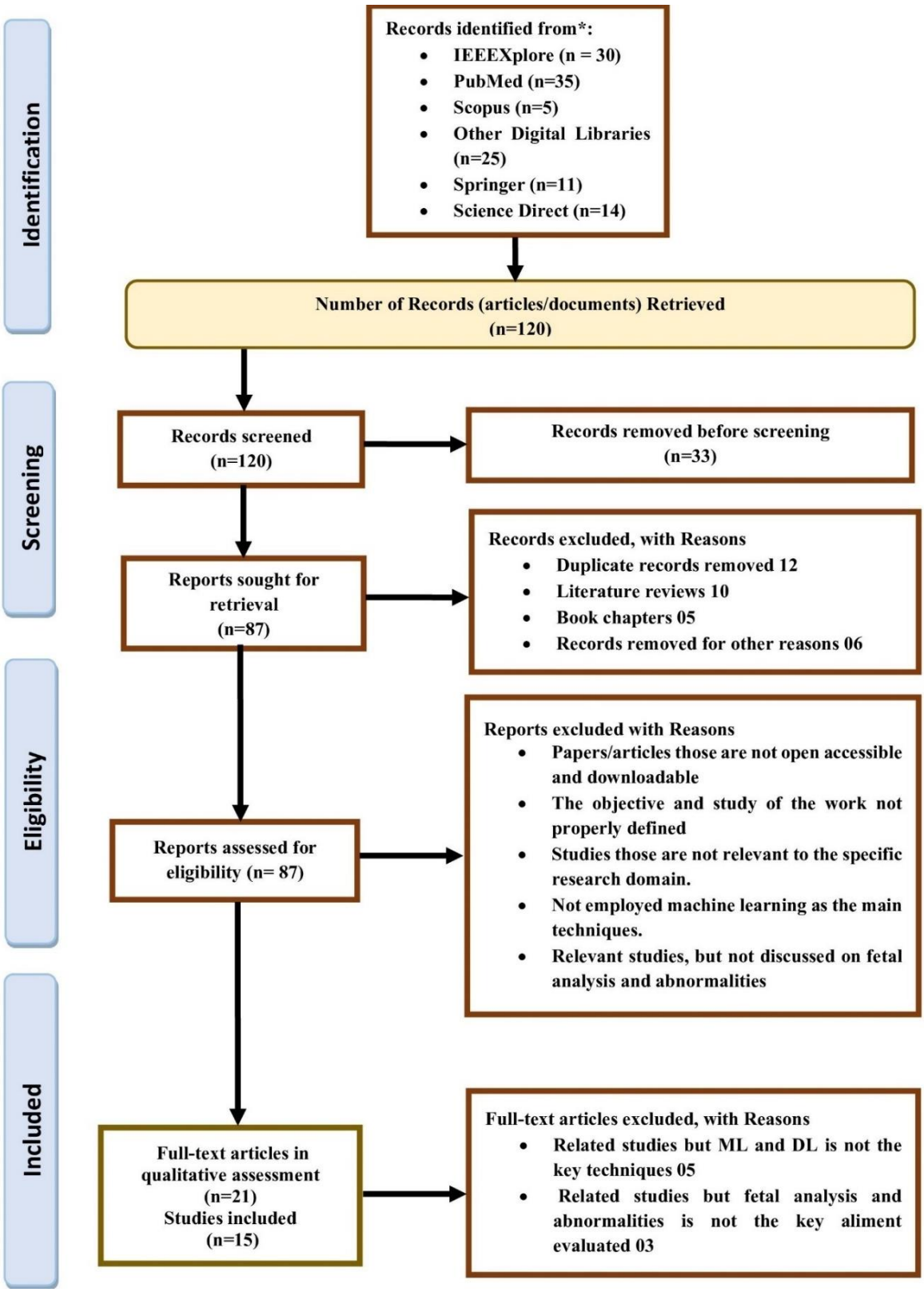


Fig 2: illustrates the summary systematic literature review process using the PRISMA flow diagram

Table 1: Inclusion and Elimination Measures of The Study

Inclusion Measures for the Study	Exclusion Measures for the Study
➢ Available articles are in the English language. ➢ Available articles are chosen from the last decades. ➢ Papers/articles that are open accessible and downloadable. ➢ Studies that utilized behavioral Biometric parameters data i.e. publicly available datasets. ➢ Research work related to machine learning as the main technique. ➢ Research work related to analysis and abnormalities in fetal ultrasound images	➢ Articles which are written/published in non-English languages ➢ Papers/articles that are not open-accessible and downloadable ➢ The objective and study of the work are not properly defined ➢ Studies that are not relevant to the specific research domain. ➢ Studies those are not employ machine learning and deep learning as the main techniques. ➢ Relevant studies, but not based on fetal analysis and abnormalities.

Challenges

From the clinician's perspective, analysis of the fetus is challenging in scanning because of poor image quality, fetal position, poor visualization, acoustic shadows, etc.

- It continues to be very difficult to access massive datasets of prenatal ultrasound images. Because of this, collecting high-quality ultrasound images separating those images according to the biometric parameters, and also labelling those images is the big challenge [1,2,7,15,38-39,83-84,91].
- Fetal face analysis and detection of face position and visualization is the big challenge [1,24-26,40,22].
- As biometry-parameter estimation includes gestational sac(G.Sac)[56,59,61,64,66,73-74,77,85], biparietal diameter(BPD)[49,51-54,67], head circumference (HC)[7,8,18-21,44-47,57-58], abdominal circumference(AC)[16,17,22,31,41,79]and femur length (FL)[1,60,78], hence considering these parameters in second and third trimester to detection and classification of fetal abnormalities is necessary and emerging research area. [1,2,7,15,30,33,37,42-43,65,72,83-84,87,89].
- There have not been any proposals for unified frameworks for biometry estimation from multiple anatomical locations. The primary obstacle in this case is the extreme form fluctuation. Clinicians may find it helpful to determine the scan plane before calculating the biometrics related to that plan. [1,27,75,81]
- Determining the parameters is difficult, and multiple or twin pregnancies require longer computing times and iterations. [1,2,32,91].
- The difficult task in fetal imaging is to identify gestational diabetes and preterm birth problems and recognize standard planes in the fetal brain, abdomen, and heart. [1,28-29,33-35,62-63,69-71,82,86,92-93].
- An acoustic shadow created by opaque sound may obscure important anatomical information in 2D ultrasound, making it difficult to analyze ultrasound data, from anatomy segmentation to landmark detection. [1,28,29,55]

PROPOSED METHODOLOGY

In the current literature study, most of the researchers focus on the HC biometry parameter, other biometry parameters need to be analyzed such as FL and AC. To fill the research challenge, this work focuses on the analysis of HC, FL, and AC biometric parameters for both second and third trimesters. This research introduces a deep-learning method for fetal ultrasound images. The proposed model uses the U-Net method for segmentation and the classifications have used transfer learning methods [42]. The model predicts the given parameter and classifies the parameters.Fig.3. shows the process flow diagram.

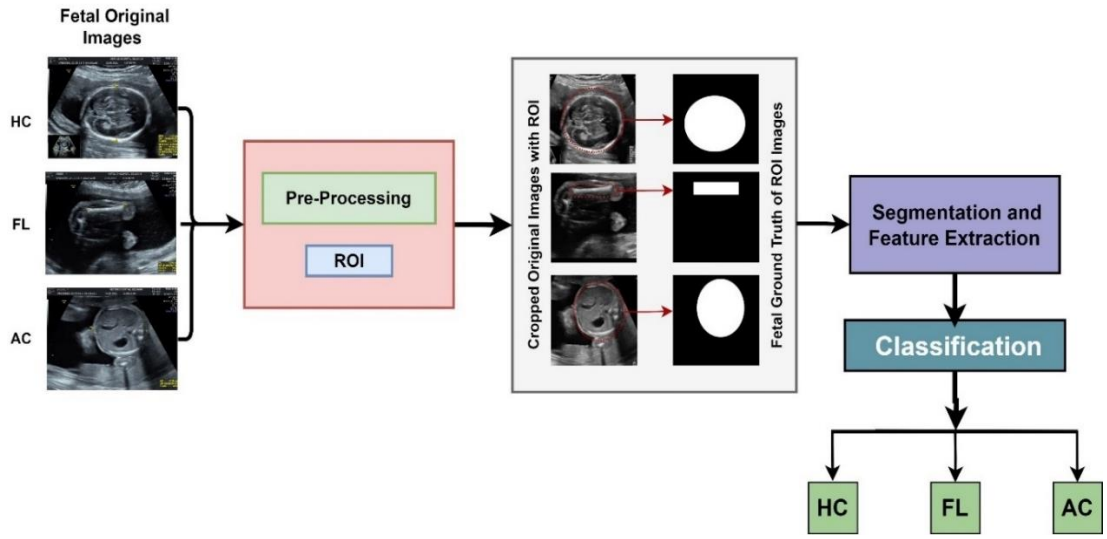


Fig.3: The Process Flow Diagram.

Pre-Processing

The Pre-Processing step enhances the quality of the image by suppressing unwanted distortions and highlighting the data of interest. In this process first step, divided the collected raw images into three trimesters bifurcated them parameter-wise (AC, FL, HC), and also labeled the images. In the Region of Interest (ROI), the image cropping function for extracting the region of interest and resizing the images 300*300 pixels.

Platform Implementation

GIMP (GNU Image Manipulation Program) is a tool used for annotating the medical images and generating the ground truth images. [94] The model is executed in the Anaconda navigator, which is a graphical user interface.it is compatible with many different implementation platforms. Jupyter Notebook (7.0.6) is used for computing, it is an online interactive execution environment. Python is used for coding and importing libraries such as TensorFlow, Keras, sklearn, pandas, NumPy, and Matplotlib.

Segmentation and Feature Extraction

The segmentation process of images gives qualitative and quantitative image analysis. The weak edges and wrong edges are inherent in the Ultrasound images. The digital image processing segmentation techniques like Edge-based, Otsu's, Threshold-based segmentations, morphological operation dilation, and erosion methods for segmenting the images. Different

filtering techniques have been applied to reduce the noise and enhance the quality of ultrasound images. Fig 4 shows the results of various segmentation techniques. The above-mentioned technique's results do not haveaccurate outcomes of ultrasound images. Therefore, the deep-learning Unet model is used for segmentation [95] [96].

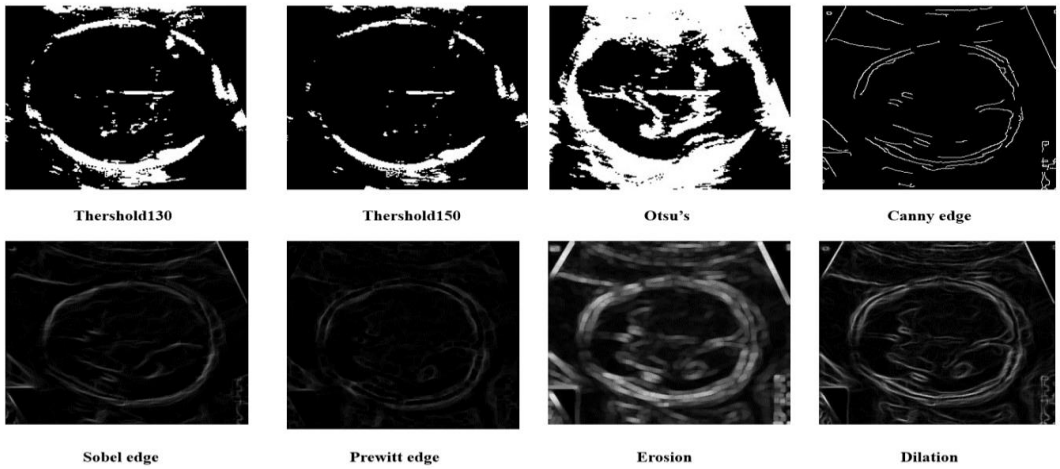


Fig 4: Results of Traditional Digital Image Processing Techniques.

U-Net:

For accurate segmentation, the deep-learning techniques U-net model used for image segmentation.

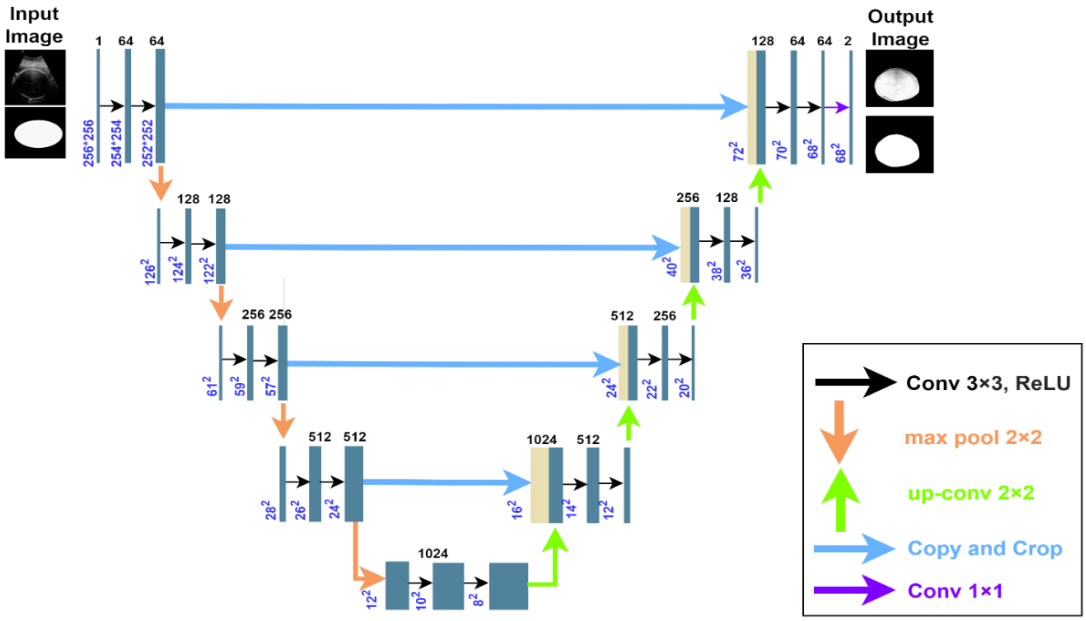


Fig 5: U-net Architecture

Fig 5. shows the U-Net model. This model takes an input image of size 256*256 and 1 single channel and the output of segmented size is 68*68. The convolution layer with Rectified Linear Unit (ReLU) activation function is used for feature extraction and 2*2 max-pooling layers are

used for spatial dimension reduction. The network hits a bottleneck where the feature channels are maximal but the spatial dimensions are limited after multiple down-sampling steps. To avoid overfitting, dropout layers are used. To expand the spatial dimensions of the feature maps, up-sampling layers are employed. Concatenation is used to obtain high-resolution features for segmentation by combining the corresponding feature maps from the down-sampling path. The last layer creates a binary mask that indicates if the target object is present in each pixel by using a 1x1 convolution with sigmoid activation. The binary cross-entropy loss function and Adam optimizer are used to compile the model. A metric for assessing the performance of the model is accuracy. [96]

Classification

To identify segmented images based on trimester parameters, we investigated a wide range of classification approaches in this study, each of which represented a unique convolutional neural network (CNN) architecture. CNN, DNN, ResNet50, LenNet, InceptionV2, XceptionNet, DenseNet121, MobileNet, MobileNetV2, and VGG16 are some of the categorization models used. Since each method has its special qualities and skills, we can assess each method's effectiveness in classifying fetal biometric parameters in great detail. To improve prenatal diagnoses and healthcare, these models were thoroughly contrasted and examined to ascertain how well they could classify traits unique to each trimester. [98-107]

Convolutional Neural Networks (CNN):

A popular deep-learning technique for image classification Convolutional layers are used to extract features from images, and pooling layers are used to minimize dimensionality. CNNs are renowned for their capacity to automatically figure out feature spatial hierarchies. To introduce non-linearity, they frequently employ activation functions such as Rectified Linear Unit (ReLU). Images with translation invariance can be used to train CNNs to recognize patterns. They have proven essential in helping numerous computer vision tasks achieve state-of-the-art performance. For training, CNNs need a lot of labeled data and are computationally demanding. It is common practice to fine-tune pre-trained CNN models for particular tasks through transfer learning [98] [99].

A Deep Neural Network (DNN):

A deep neural network (DNN) has several hidden layers in between the input and output layers. They can deduce intricate patterns and representations from data. To reduce prediction errors, DNNs employ weight adjustments during training via backpropagation. DNNs usually use activation functions like sigmoid, tanh, or ReLU. Numerous fields, including voice and picture recognition, have seen their successful use. For training, DNNs need a lot of processing power and big datasets. Regularization strategies are frequently used to solve overfitting, a significant problem with DNNs. Numerous sophisticated neural network designs are built on top of DNNs. They may be tailored to various tasks and data kinds because of their versatility. [98] [100].

A Residual Network (ResNet50):

A Residual Network (ResNet50) is a convolutional neural network design. The vanishing gradient problem is tackled by utilizing skip links or shortcuts. Deep networks can be trained with skip connections, which provide a more direct gradient flow. ResNet50 uses residual

blocks with identity mappings and has 50 layers. In the ImageNet Large Scale Visual Recognition Challenge, it performed remarkably well. Image categorization is one of the many computer vision applications where ResNet50 is widely used. Because transfer learning using pre-trained ResNet50 models is so successful, it is widely used. It is useful for numerous applications because it strikes a compromise between computational performance and model complexity. Beyond picture categorization, advances in neural network design have been sparked by ResNet50's architecture [98] [101] [102]

LeNet-5(LeNet):

LeNet-5(LeNet) one of the first convolutional neural network (CNN) designs, created by Yann LeCun, transformed the area of deep learning. Convolutional, pooling and fully connected layers make up LeNet's architecture, which is specifically designed for handwritten digit recognition. In presenting ideas like convolutional layers and max-pooling, which are currently essential to CNN architecture, it was a trailblazer. LeNet demonstrated how neural networks can handle complex real-world data by demonstrating impressive performance in pattern recognition tasks. LeNet established a vital groundwork for later developments in deep learning, despite its relative simplicity in comparison to contemporary designs. Beyond just digit identification, it also influences how CNNs are designed for different picture classification tasks. Thus, LeNet represents a significant turning point in the development of computer vision and deep learning. [98] [103]

Incepation-ResNet-V2(InceptionV2):

Incepation-ResNet-V2(InceptionV2) is based on the original Inception design, is a major development in convolutional neural network (CNN) architectures, and was developed by Google. With factorized convolutions and batch normalization, for example, InceptionV2 aims to improve performance and efficiency by cutting computing costs without sacrificing accuracy. Its architecture revolves around inception modules, which allow filters of varying sizes to be processed in parallel to efficiently capture a variety of properties. Through benchmark testing, InceptionV2 proved to be more accurate than its predecessor, proving its usefulness for a range of computer vision tasks. Notable is the dimensionality reduction it introduces in the intermediary layers, which improves computational efficiency without sacrificing performance. Because of its sensible architecture, InceptionV2 is a good option for real-world applications since it places a high priority on balancing model complexity and processing resources. Using pre-trained InceptionV2 models to facilitate transfer learning [98] [104].

Extreme Inception (XceptionNet):

As an acronym for "Extreme Inception," which represents its progression from the Inception framework, Google invented XceptionNet, a revolutionary convolutional neural network (CNN) architecture. Unlike its predecessors, XceptionNet allows the independent capturing of spatial and channel-wise dependencies by substituting depth-wise separable convolutions for typical inception modules. By drastically reducing the number of parameters compared to conventional convolutional layers, this innovative architectural design improves computing efficiency. XceptionNet has proven to be effective in real-world applications by achieving state-of-the-art performance on multiple picture categorization benchmarks. Its accomplishment serves as a reminder of how important effective model design is in actual deployment settings.

Because pre-trained XceptionNet models are successful and can be easily adapted to a variety of applications and datasets, transfer learning with these models is widely used. Moreover, XceptionNet's architecture has accelerated the creation of thin and effective neural networks, highlighting [98] [105]

Densely Connected Convolutional Networks (DenseNet):
A novel convolutional neural network (CNN) architecture called DenseNet121 is characterized by its dense connections between layers, in which every layer is feed-forwardly coupled to every other layer. Both feature reuse and smooth gradient flow throughout the network are facilitated by these tight connections. Because DenseNet121 is composed of several dense blocks followed by transition layers, it promotes feature propagation and solves the vanishing gradient issue that deep networks frequently face. The usefulness of dense connection patterns in deep neural networks is demonstrated by DenseNet121, which has remarkably attained competitive performance across a variety of image classification tasks. About deep learning model optimization, its architecture emphasizes the significance of information flow and connectivity patterns. The fact that transfer learning using pre-trained DenseNet121 models is common demonstrates its effectiveness by allowing adaption to a variety of datasets [98][106].

MobileNet:
Convolutional neural network (CNN) architecture has advanced with MobileNet, a breakthrough designed for mobile and embedded devices that prioritizes low computational cost and efficiency without sacrificing accuracy. By utilizing depth-wise s arable convolutions, MobileNet effectively reduces both computational complexity and model size by factorizing ordinary convolutions into distinct depth-wise and pointwise convolutions. This cutting-edge architecture is a popular option in mobile and edge computing scenarios because it is especially well-suited for applications with constrained compute resources or strict latency requirements. The efficacy of MobileNet in transfer learning, which permits fine-tuning particular tasks with pre-trained models, further facilitates its widespread use. Furthermore, the design concepts of MobileNet have greatly impacted the creation of lightweight neural network architectures, which in turn has influenced the continuous search for effective deep learning models [98] [107].

MobileNetV2:
Which focuses on improving both efficiency and performance, is a major improvement over the original MobileNet architecture. To effectively capture complicated features while minimizing computing costs, it incorporates inverted residual blocks with linear bottlenecks. To improve gradient propagation and information flow, MobileNetV2 also includes shortcut connections. This results in lower computing overhead and increased accuracy over its predecessor. This design strikes a compromise between model complexity and deployment efficiency for resource-constrained situations, making it ideal for real-time applications on embedded and mobile devices. The practical applicability of MobileNetV2 is further highlighted by its success in transfer learning with pre-trained models. It has been widely implemented across numerous computer vision tasks, including object identification and image classification. Additionally, the advancement of lightweight design has been significantly impacted by its design advancements [98] [108].

Visual Geometry Group 16-layer model (VGG16):

The Visual Geometry Group at Oxford created VGG16, which is well known for its ease of use and efficiency in picture classification applications. VGG16, which consists of several convolutional layers and max-pooling layers, demonstrated the potential of deeper architectures by achieving competitive performance in the ImageNet Large Scale Visual Recognition Challenge. Its success can be attributed to its design principles, which place a high priority on preserving feature hierarchy and spatial resolution across the network. Notably, the durability and effectiveness of VGG16 are largely due to its uniform architecture, which includes modest receptive fields in convolutional layers. Because of its efficacy, VGG16's architecture is frequently used in transfer learning and has influenced later deep learning designs. VGG16 is still a benchmark for picture classification even though it is simpler than most recent architectures, demonstrating the importance of architectural decisions in deep learning [98] [109]

RESULTS AND DISCUSSION

Description of Data

As mentioned in the challenges section 2.3, the collection, labeling, and annotation of high-quality fetal images based on biometric parameters are significant challenges of fetal research. The publicly available benchmark dataset contains one biometric parameter, the dataset name is HC18. The proposed model needs biometric parameters like HC, FL, and AC fetal images to analyze. To address this limitation, we have collected fetal images and created our dataset for experiments. The images were collected from the VOLUSON P6 Ultrasound Machine in JPG format from Metgud Hospital - Advanced Laparoscopy Centre and IVF, Belagavi, Karnataka, India. The original image size is 640*480.

In this work, the image size is 300*300. The dataset contains 1,313 images, these images are divided into two categories the Second and Third trimesters. Each sonographic fetal image is manually annotated and labeled as per the biometric parameters by the guidance of doctors. In the second trimester, have 563 images and 563 ground truth images. These images are the three parameters HC=228 images, FL=232 images, and AC=101 images. In the third trimester, have used 750 fetal images and 750 ground truth images. These images are the two parameters HC=355 images and FL=395 images. In our experiments, we have split each biometric parameter dataset into 70:20:10 ratios for training, testing, and validation purposes.

Segmentation Results

The objective of this work is an analysis and prediction of biometric parameters of fetal images. The quality of fetal images depends on the machine and the radiologist’s ability to find good images. These images involved various types of noises.it is essential to differentiate noise and parameter information. Radiologists may make the wrong prediction; it may give the wrong analysis and treatment. So, the deep learning approach has proposed to accurate prediction of the fetus.

A total of 1,313 images were preprocessed and used for the training of the U-Net model for segmentation. Each parameter is split into a 70:20:10 ratio for training testing and validation. These parametric datasets are applied for the segmentation task, where our pre-trained model

undergoes rigorous evaluation to produce robust and reliable results. and results have been stored in the pre-trained model.

The segmentation accuracy for the second-trimester results is HC= 69.43%, AC=69.09%, and FL=92.02%. Third-trimester results are HC= 69.76%, and FL=90.04%, Fig 6. and Fig 7. show the segmentation results of the second and third trimesters. In the results figures a) Input the original image b) ground-truth image c) Segmented output mask image d) Segmented output image.

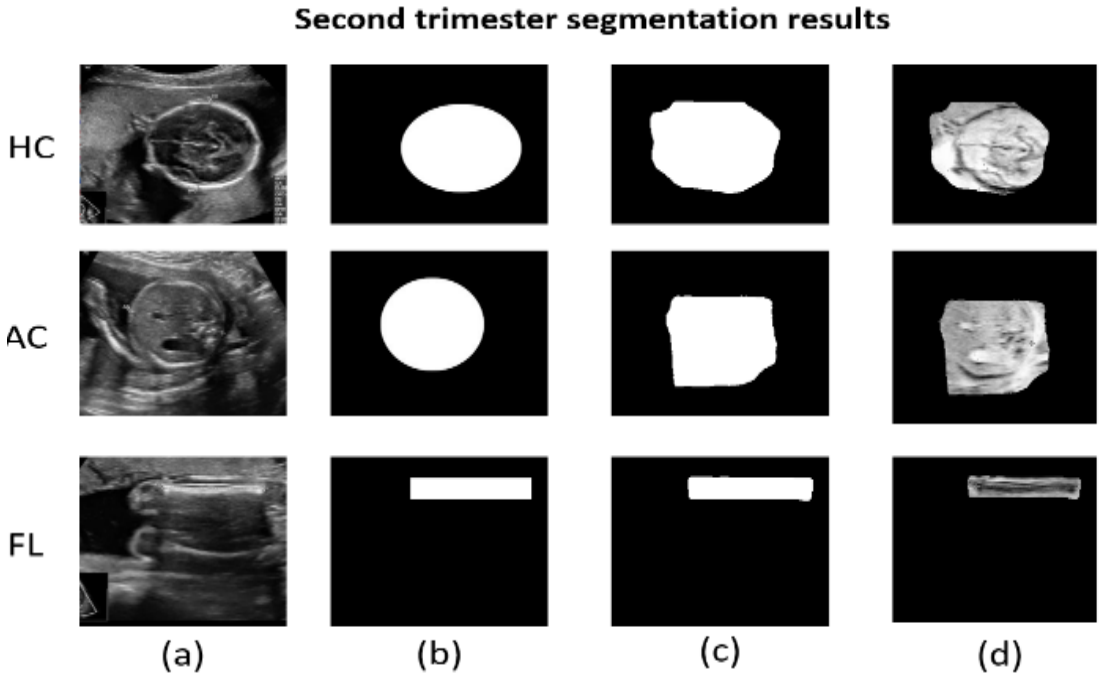


Fig 6: Segmentation Results of The Second Trimester

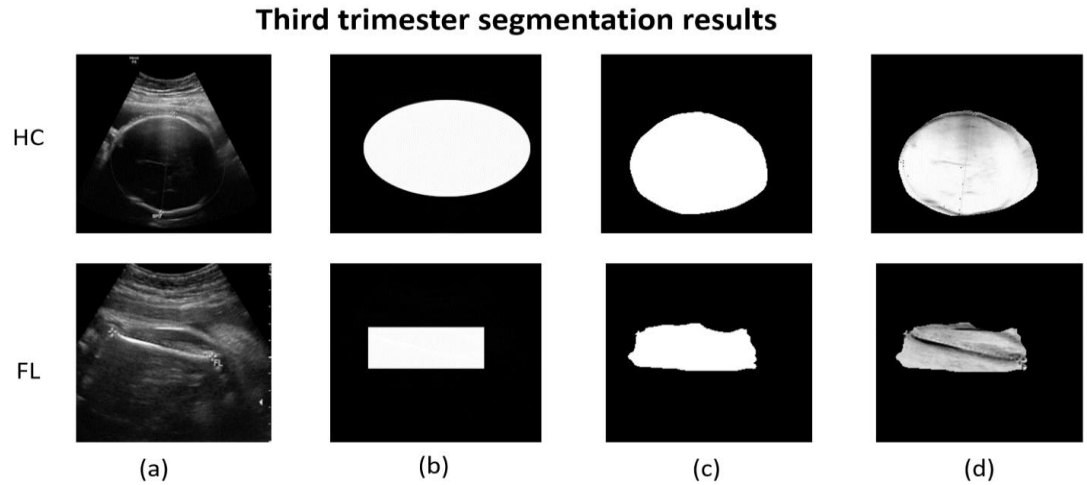


Fig 7: Segmentation Results of The Third Trimester

Classification Results

In the classification phase, the second-trimester dataset contains 1126 images for classification. This divided into three groups FL, AC, and HC. In these 563 images and 563 related annotated images. Similarly, there are two categories in the third-trimester dataset: FL and HC. These categories include 750 images and 750 images with annotations, for a total of 1500 images. For evaluation, these datasets were split into two sets: 20% for validation and 80% for training. To identify the segmented images based on trimester parameters, a variety of transfer learning classification approaches were used, including CNN, DNN, ResNet50, LenNet, InceptionV2, XceptionNet, DenseNet121, MobileNet, MobileNetV2, and VGG16.

Table 2. and Table 3. show the classification results of both the second and third trimesters and Fig 8 and Fig 9. show the classification accuracy chart of both trimesters. The good classification results of two methods MobileNet and XcepationNet. Results of the ROC curve and confusion matrix are shown in Fig 10. for the second trimester and Fig 11. for the third trimester. The evaluation of model performance measures used like confusion matrix, accuracy, precision, f1-score, recall-score, and Receiver Operating Characteristic (ROC) curve.

- Confusion Matrix: It is a table that is used to describe the performance of the classification model on a set of which the true values are known.it consists of four numbers:
  - True Positive (TP): The samples that the model correctly identified as belonging to a certain category based on parameters HC, FL, and AC.
  - True Negative (TN): The negative samples that the model correctly identified as not belonging to a certain category based on parameters HC, FL, and AC.
  - False Positive (FP): A sample identified as positive for a condition based on parameters HC, FL, and AC, when it doesn't have the condition.
  - False Negative (FN): A sample identified as negative for a condition based on parameters HC, FL, and AC, when it has the condition.
- Accuracy: It measures the proposition of correct predictions out of the total predictions made.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Sensitivity: It measures the proportion of actual positive cases that were correctly identified by the model.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- Precision: It measures the proportion of true positive predictions out of all positive prediction made by the model.

$$Precision = \frac{TP}{TP + FP}$$

- F1-Score: It is a harmonic mean of precision and sensitivity.it gives a balance between precision and sensitivity.

$$F1 - Score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity}$$

- Recall: It measures the proportion of actual positive cases that were correctly identified by the model, similar to Sensitivity.

$$Recall = Sensitivity = \frac{TP}{TP + FN}$$

- Receiver Operating Characteristic (ROC) Curve: It is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.it is created by plotting the True Positive Rate (Sensitivity) against the False Positive Rate(1-Specificity) at various threshold settings.
- Area Under the ROC Curve (AUC) is a measure of the area under the Receiver Operating Characteristic curve, which plots the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity). AUC quantifies the classifier's ability to discriminate between positive and negative classes, with values ranging from 0 to 1, where higher values indicate better performance.

Table 2: Classification Results for The Second Trimester

Classifier	Accuracy	Precision	F1-Score	Recall-Score
CNN	98.4	0.98	0.99	0.99
ResNet50	87.92	0.88	0.93	0.98
DenseNet121	98.22	0.97	0.98	1
VGG16	99.22	0.98	0.98	0.98
MobileNet	**99.28**	**0.99**	**0.99**	**0.99**
MobileNetV2	98.93	0.98	0.99	1
InceptionV3	98.75	0.99	0.99	0.99
XceptionNet	**99.82**	**0.99**	**0.99**	**1**
LeNet	97.51	0.97	0.98	0.99
DNN	98.93	0.99	0.99	0.98

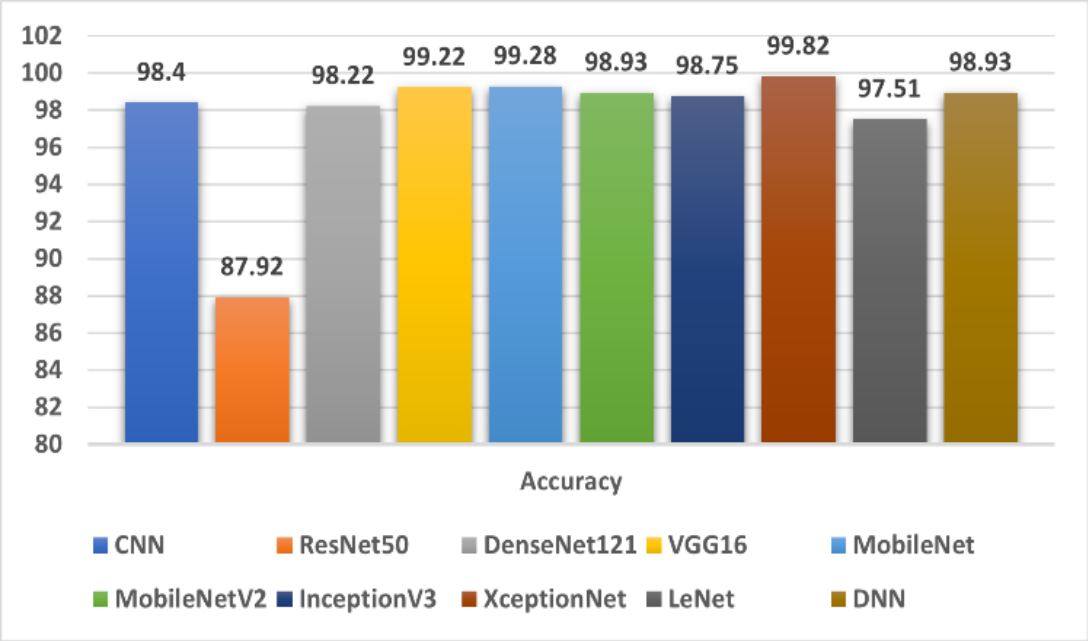


Fig 8: Classification Accuracy Chart for Second Trimester

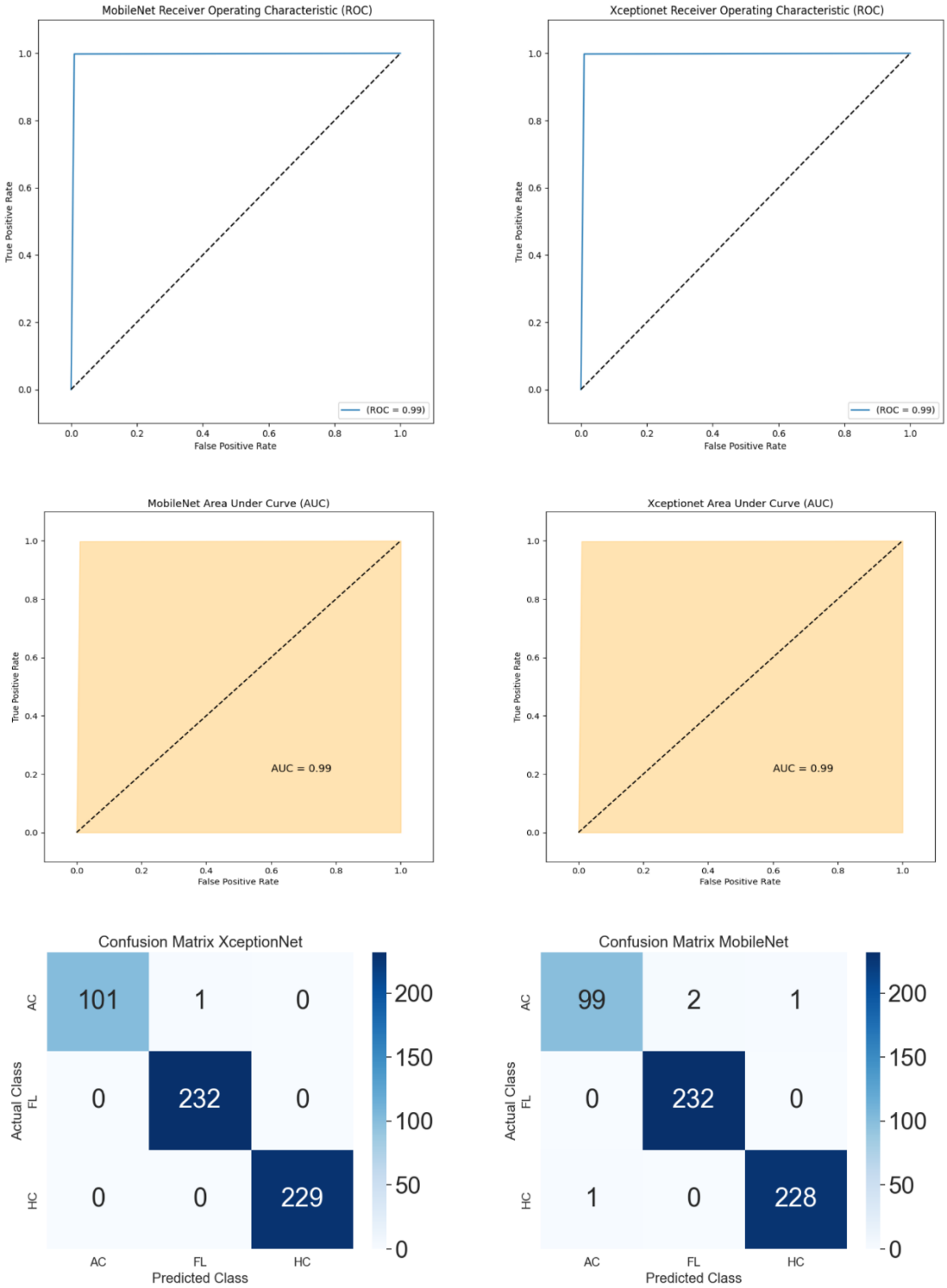


Fig 10: Confusion Matrix, ROC Curve, and AUC Curve

Table 3: Classification Results for The Third Trimester

Classifier	Accuracy	Precision	F1-Score	Recall-Score
CNN	90.66	0.86	0.91	0.96

ResNet50	96.66	0.94	0.96	0.99
DenseNet121	99.2	0.99	0.99	0.98
VGG16	99.73	1	0.99	0.99
MobileNet	**99.86**	**0.99**	**0.99**	**1**
MobileNetV2	99.2	0.99	0.92	0.98
InceptionV3	98.41	0.99	0.98	0.92
XceptionNet	**99.86**	**0.99**	**0.99**	**1**
LeNet	98.4	0.99	0.98	0.92
DNN	93.46	1	0.93	0.87

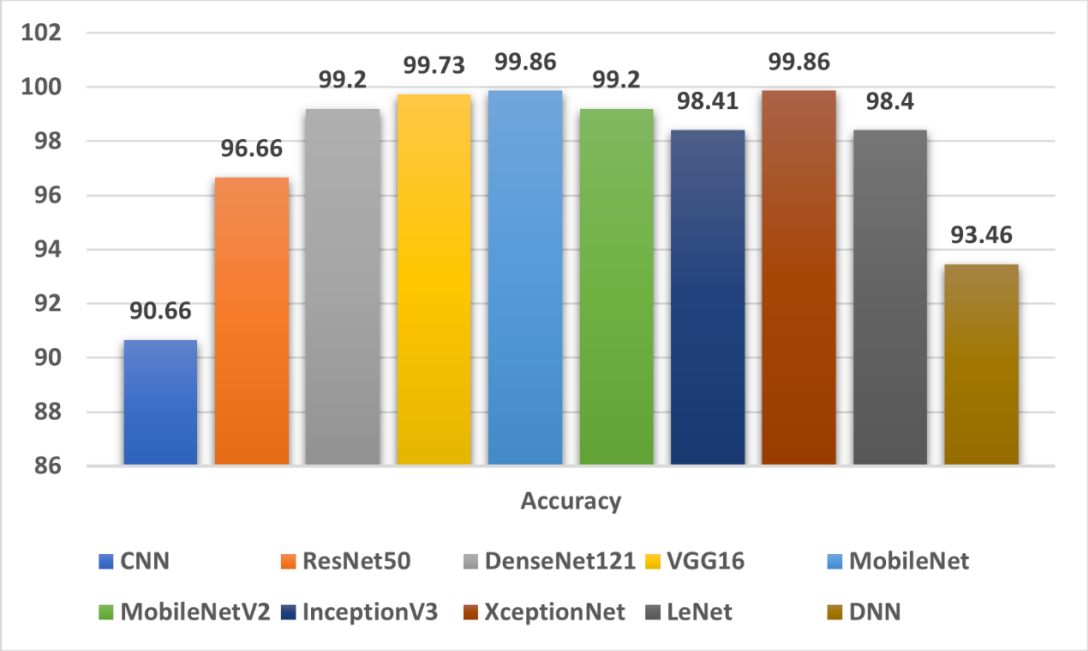
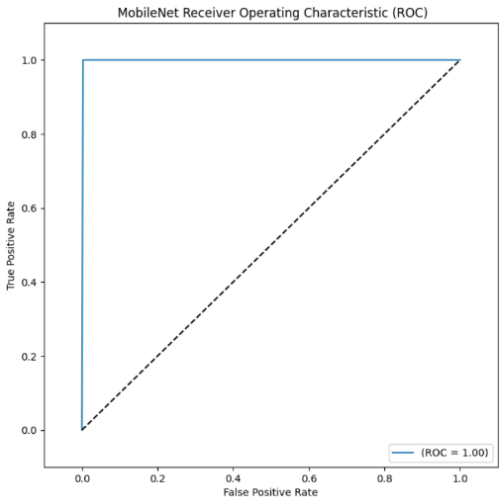
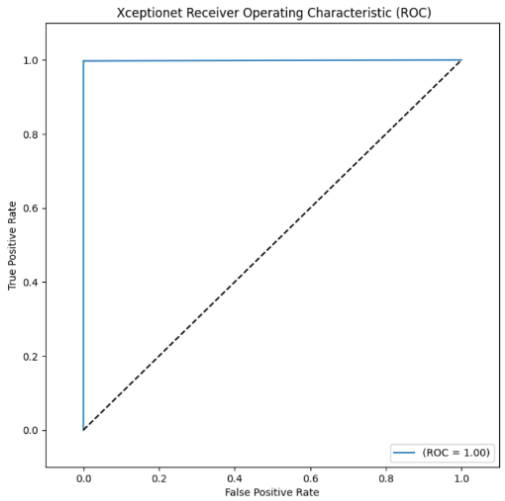


Fig 9: Classification Accuracy Chart for the Third Trimester





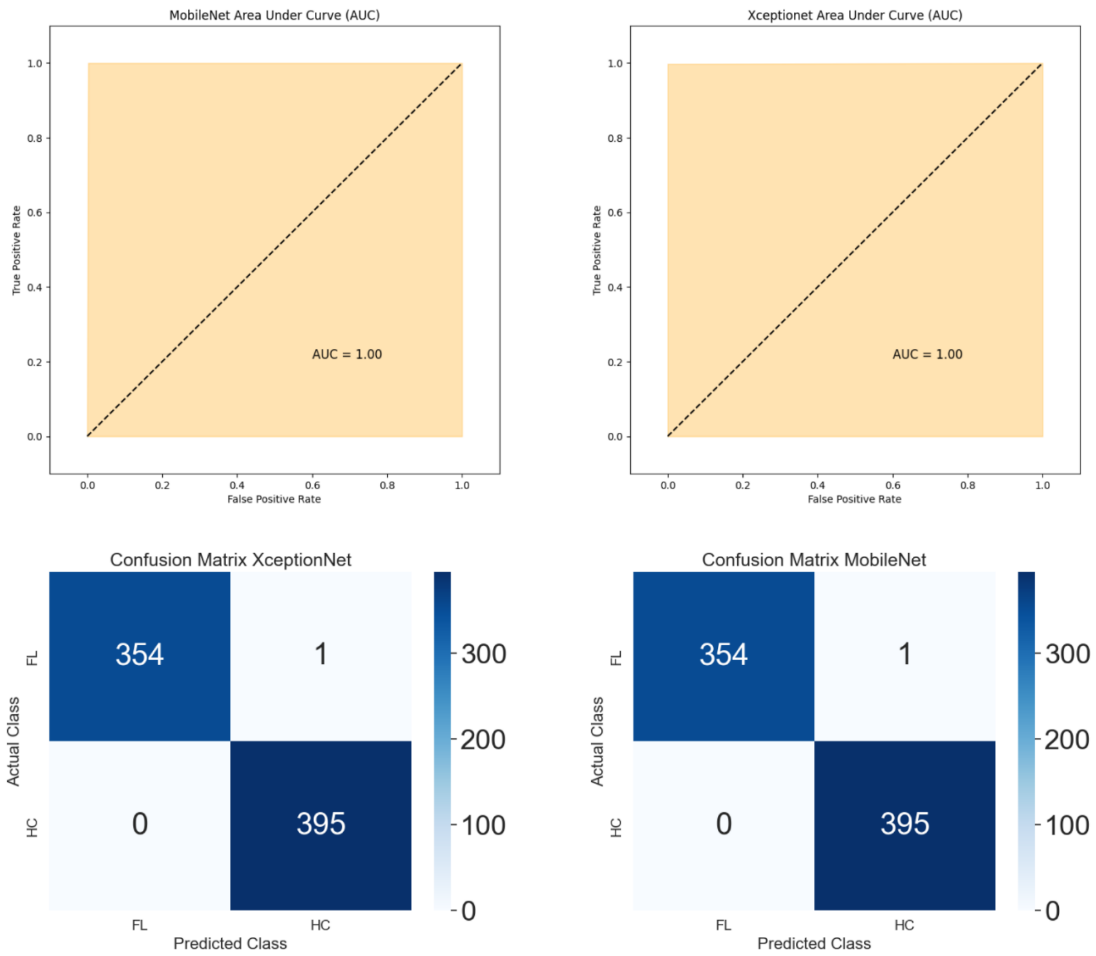


Fig 11: Confusion Matrix, ROC Curve, and AUC Curve

The validation and testing of our experiments were conducted at the Metgud Hospital - Advanced Laparoscopy Centre and IVF, located in Belagavi, Karnataka, India. The oversight of experienced professionals ensured the meticulous design and implementation of the validation and testing processes, thereby guaranteeing accuracy, reliability, and adherence to scientific standards. The outcomes derived from these rigorous experiments are robust and credible, highlighting their substantial contribution to the progress of research in our field. The invaluable insights gained from our collaboration with the expert professionals at Metgud Hospital further enhance the significance and reliability of our findings, fostering advancements in prenatal care and diagnosis

CONCLUSION

The application of deep learning and transfer learning techniques facilitates the automated segmentation and classification of fetal ultrasound images based on key biometric parameters such as Head Circumference (HC), Abdominal Circumference (AC), and Femur Length (FL). Our study encompasses a dataset comprising 1,313 images categorized into Second and Third trimesters. Each sonographic fetal image in our dataset is meticulously annotated and labeled by medical professionals according to the corresponding biometric parameters. Specifically, the Second trimester subset comprises 563 images, covering HC, FL, and AC, with corresponding

ground truth annotations. In contrast, the Third-trimester subset consists of 750 images, focusing on HC and FL parameters, each accompanied by ground truth annotations. Utilizing the deep learning architecture Unet, we achieved exceptional results in the segmentation process, accurately delineating fetal anatomy in ultrasound images. Additionally, we explored various transfer learning methods for classifying fetal images. Our proposed model demonstrated impressive performance, with MobileNet achieving an accuracy of 99.28% and XceptionNet achieving 99.82% for the Second trimester. Similarly, for the Third trimester, MobileNet and XceptionNet both achieved an accuracy of 99.86%. Looking ahead, our future research endeavors will delve into the analysis of fetal abnormalities through biometric parameters, transcending conventional measurements. Our goal is to enhance the accuracy and efficiency of fetal anomaly detection, paving the way for improved prenatal care and diagnosis. Despite the promising results achieved thus far, there remains ample room for further exploration and refinement in this field.

DATA AVAILABILITY STATEMENT

The data and codes utilized in this research study are available upon request. Access to and utilization of the data and codes are contingent upon citing the appropriate references to this paper. This provision aims to facilitate researchers and the wider community in accessing and utilizing the resources for further research and development endeavors.

CONFLICT OF INTEREST

The authors declare that the research was conducted without any commercial or financial relationships that could be constructed as a potential conflict of interest.

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