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Integrating Local Binary Pattern Image Transformations and Customized Deep Learning Models for Enhanced Fetal Cardiac Anomaly Detection

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Abstract
This research focuses on developing a deep learning diagnostic model for diagnosing fetal cardiac anomalies from real time ultrasound scan images. The dataset framed in the previous research is transformed using Local Binary Pattern (LBP) technique which is trained with the deep learning models to create the classifiers. These models are used to classify the Real Time images captured by ultrasound scanning machines. The LBP is a texture image feature. LBP captures the local structure and patterns within an image by comparing the intensity values of each pixel with its surrounding neighbours. The LBP operator assigns a binary code to each pixel based on the comparison results, resulting in a texture representation of the image. The FetaEcho_V05 dataset is transformed into an LBP image dataset titled as FetalEcho_V0501. This dataset is used for creating the classifiers by training the custom CNN(CCNN), AlexNet, VGG16 and ResNet50 deep learning models. The classifiers are evaluated for its overall classification performance and class wise evaluation performance using the metrics the precision, recall, accuracy and F1 score metrics. When the overall performance is considered, the CCCNN model performed the best on the FetalEcho_V0501 dataset.

Category: Smart and intelligent computing

Keywords: Deep learning, Diagnosis , Fetal cardiac anomaly, Image transformation, Local Binary Pattern,

I. Introduction

Fetal cardiac structural anomalies refer to abnormalities in the structure and function of the heart that are present in an unborn baby. These anomalies can range from minor defects to severe malformations, potentially affecting the normal development and functioning of the heart. Detecting and diagnosing these anomalies during the prenatal period is of utmost importance as it allows for appropriate medical interventions, counselling, and planning to ensure the best possible outcomes for both the baby and the mother [16].

During the second trimester of pregnancy, typically between the 18th and 22nd week, prenatal diagnosis becomes a critical tool in identifying fetal cardiac structural anomalies. This period is ideal for screening as the fetal heart undergoes significant development and becomes more visible through ultrasound examinations. Timely detection of these anomalies enables healthcare providers to intervene, provide appropriate counselling, and guide parents in making informed decisions regarding the management of their pregnancy.

The importance of prenatal diagnosis for fetal cardiac structural anomalies lies in several key factors. Firstly, it allows for the identification of potentially life-threatening conditions early on, ensuring prompt medical attention and the implementation of necessary interventions. For example, certain cardiac anomalies may require immediate postnatal surgical procedures or specialized medical care soon after birth. Early detection can significantly improve the chances of successful treatment and a positive outcome for the baby. The prenatal diagnosis helps in providing parents with vital information about their baby's condition, enabling them to emotionally prepare and make well-informed decisions about the pregnancy. It allows for discussions with healthcare providers, specialists, and support networks, aiding in developing appropriate care plans and considering potential treatment options. This knowledge empowers parents to understand the prognosis, potential challenges, and available resources, ensuring they can provide the best possible care and support for their child.

In addition to these, prenatal diagnosis facilitates coordination among a multidisciplinary team of healthcare professionals, including obstetricians, fetal medicine specialists, paediatric cardiologists, genetic counsellors, and neonatologists. These experts collaborate to assess the severity of the cardiac anomaly, develop comprehensive management strategies, and plan the appropriate level of care and monitoring both during pregnancy and after delivery. This collaborative approach enhances the overall healthcare experience and improves outcomes for both the mother and the baby.

The prenatal diagnosis during the second trimester plays a pivotal role in identifying fetal cardiac structural anomalies. The early detection of these anomalies provides an opportunity for timely medical interventions, informed decision-making, and appropriate planning to optimize the health and well-being of both the baby and the mother. By harnessing the power of modern diagnostic techniques, healthcare professionals can significantly improve outcomes, enhance the quality of care, and provide crucial support to families facing the challenges of fetal cardiac anomalies.

Ultrasound imaging technology (USIT) is frequently employed due to its accessibility, safety, and ability to provide real-time imaging of the developing fetus. It allows healthcare providers to visualize the fetal heart, assess its structure, and evaluate its function. During the second trimester, ultrasound can provide detailed information about the cardiac anatomy, detect any abnormalities or malformations, and assess blood flow through the heart and major vessels.

The diagnosis rate of fetal cardiac anomalies can vary depending on several factors, including the population studied, the expertise of the healthcare providers, and the availability of advanced imaging techniques. Studies have reported a wide range of diagnosis rates, typically ranging from 20% to 50% for major cardiac anomalies. In cases where anomalies are suspected, additional diagnostic tests such as fetal echocardiography, fetal MRI, or genetic testing may be performed to provide a more detailed evaluation. However, it's essential to acknowledge that despite advancements in prenatal diagnosis, there are still cases where cardiac anomalies may go undetected or misdiagnosed prenatally. Factors such as fetal position, gestational age, operator expertise, and the complexity of the anomaly can influence the diagnostic accuracy.

Using Machine learning techniques [7] [11]and image classification can contribute to the improvement of diagnosing fetal cardiac anomalies by providing automated analysis and decision support. Utilizing large datasets of ultrasound images, machine learning algorithms can be trained to recognize patterns and features associated with both normal and abnormal cardiac structures. Employing convolutional neural networks (CNNs) for image classification enables automated analysis of ultrasound images, facilitating the identification of potential anomalies. This can help in detecting subtle abnormalities that may be missed by human observers and improve the overall diagnosis rate. Also, the Machine learning models can continually learn and improve over time. By regularly updating the algorithms with new data and incorporating feedback from experts, these systems can adapt to emerging trends and variations in cardiac anomalies, further improving their diagnostic capabilities. Continuous learning ensures that the models stay up-to-date and maintain high accuracy rates in diagnosing fetal cardiac anomalies.

While machine learning techniques and image classification can offer numerous benefits in improving the diagnosis of fetal cardiac anomalies, there are certain potential disadvantages also. Machine learning models require large and diverse datasets to train effectively. However, obtaining a sufficient amount of high-quality labelled data for fetal cardiac anomalies can be challenging. Accessing datasets representative of diverse populations or containing rare or complex anomalies can pose challenges. Limited or biased training data may result in suboptimal performance and reduced generalizability of models. The accuracy of machine learning models in diagnosing fetal cardiac anomalies is heavily contingent upon the quality of input images. Factors such as fetal position, gestational age, image resolution, and image artifacts can impact the performance of the models. Poor-quality images may lead to misdiagnosis or false negatives, emphasizing the importance of standardized imaging protocols and skilled sonographers.

One of the best ways to overcome this issue is to perform image transformations and the use of different image features can help overcome some of the challenges associated with diagnosing fetal cardiac anomalies using machine learning techniques. Image transformations, such as extracting and incorporating different image features, such as texture, shape, or spatial information, can provide complementary information and enhance the representation of the cardiac anomalies in the dataset. According to different research conducted in other problem domains, texture features can be valuable for ultrasound image classification in the context of fetal cardiac anomaly diagnosis. Texture analysis techniques capture variations in pixel intensities and patterns, providing information about the fine-grained details and texture characteristics within an image region.

Research on the utilization of artificial intelligence (AI) for the diagnosis of fetal cardiac anomalies assumes paramount significance by not only enhancing the well-being of future generations but also actively contributing to social welfare. This research endeavors to utilize AI to enhance the accuracy and effectiveness of diagnosing fetal cardiac anomalies, ultimately aiming to foster a healthier generation. By leveraging AI technologies, significant advancements in prenatal care can be achieved, ensuring a brighter and healthier future for unborn children and their families. Through this initiative, the research aims to make a meaningful contribution to social welfare and secure the well-being of future generations.

II. Literature Review

A literature review is conducted for understanding the scope of Local Binary Patterns for analysing medical images, class wise evaluation of performance of AI models and to establish the scope of the research. The following research had implemented the same concept in a similar domain and proved to be successful.

[1] Patil et. Al. focuses on the recognition of emotions, which plays a crucial role in human intellect, innovation, and

creativity. Real-time emotion identification faces challenges related to noise and hardware limitations To tackle this challenge, the researchers suggest a hardware configuration comprising an ECG sensor, a temperature sensor, and a signal processing circuit. The ECG data is utilized to compute RR intervals, and machine learning techniques are employed to forecast emotions based on these features. The proposed research introduces a hardware setup comprising an ECG sensor, a temperature sensor, and a signal processing circuit to visualize emotions on the Arduino serial port. Leveraging the WESAD benchmark dataset and various libraries, the study innovatively employs ECG for emotion detection, real-time capture of temperature and ECG data, and display of current emotions on the Arduino serial port. Performance evaluation metrics such as F1 score, macro average, and weighted average are utilized, with a comparison of different algorithms highlighting the advantages of probability-based Navies Bayes over traditional methods like KNN, SVM, and Random Forest.

Khasendar et al. [2] developed and validated a computerized model for classifying ovarian masses as benign or malignant using transvaginal 2D B mode static ultrasound images. Their study involved pre-processing and enhancing the images, extracting Local Binary Pattern Histograms, and training a Support Vector Machine (SVM) using stratified cross-validation. The SVM achieved significantly improved accuracy when images were pre-processed and treated with a Local Binary Pattern operator, demonstrating its effectiveness in accurately categorizing ovarian masses.

Nanni et al. [3] explored image-based machine learning techniques, focusing on various Local Binary Patterns (LBP) as texture descriptors in medical image analysis. Their comprehensive literature review discusses existing LBP variants' strengths and weaknesses while proposing novel texture descriptors tailored for biomedical images. Utilizing these descriptors, a support vector machine classifier is trained to enhance understanding and effectiveness in biomedical image analysis.

Zeebaree et al. [4] introduced a feature-based fusion scheme for breast cancer image pattern recognition, enhancing Local Binary Pattern (LBP) features and employing filtered noise reduction. Their method achieved high accuracy, sensitivity, and specificity by generating diverse features from pre-processed ultrasound images, showcasing potential for improving breast cancer image recognition and diagnosis accuracy.

In a meta-analysis by Holland et al. [12], the impact of prenatal versus postnatal diagnosis of cardiac anomalies on mortality rate was assessed, emphasizing the importance of prenatal diagnosis in reducing postnatal mortality associated with congenital heart defects (CHDs).

Suard et al. [13] conducted an observational study evaluating the accuracy of prenatal diagnosis of CHDs in South France, highlighting the need for improved prenatal and postnatal diagnosis to better manage CHDs.

Changlani et al. [14] examined the short-term outcomes of infants with prenatal diagnosis of CHDs, demonstrating favorable outcomes facilitated by prenatal identification and planned delivery in specialized cardiac care centers.

Vijayaraghavan et al. [15] compared the outcomes of prenatal and postnatal diagnosis of CHDs, emphasizing the importance of prearranged peripartum care, particularly in resource-constrained settings.

Research reviews in authenticated repositories explore opportunities in applying artificial intelligence techniques to diagnose fetal cardiac anomalies, emphasizing the importance of texture features and the relevance of LBPs in implementing new systems.

Dataset Creation

The development of the FetalEcho_V05 [8] dataset was a crucial aspect of an extensive research project aimed at identifying diverse structural heart defects in developing fetuses. This meticulously crafted dataset was not left to chance but deliberately created to ensure its exceptional quality. Impeccable attention was given to the data collection process, which involved meticulous sourcing from esteemed establishments such as specialized fetal clinics, repositories of esteemed clinical experts, and active forums in the field of fetal medicine. A prominent research repository, Radiopedia, was also extensively utilized, along with esteemed sources like various chapters of Fetal Medicine foundations (India, UK), the prestigious Society of Fetal Medicine, The revered Karnataka chapter.

To achieve utmost accuracy and reliability, every image within the FetalEcho_V01 dataset underwent rigorous manual classification and validation, expertly executed by a clinical specialist. The dataset, comprising a substantial collection of 1600 images, was intelligently categorized into 16 distinct groups, meticulously representing a wide range of structural heart defects. These encompassed critical anomalies such as Atrial Septal Defect, Aortic Atresia or Stenosis, AV Septal Defect, Tetralogy of Fallot, Ventricular Septal Defect, Truncus Arteriosus, Transposition of Great Arteries, Single Ventricle, Ebstein Anomaly, Double Outlet RV, Hypoplastic Left Heart Syndrome, Hypoplastic Right Heart Syndrome, Aortic Coarctation or Hypoplasia, Pulmonary Stenosis, Ectopia Cordis, Pentalogy of Cantrell and the normal (without any anomaly) images.

Crucially, the FetalEcho_V01 dataset was scrupulously balanced to provide equal representation for all 15 anomalies, rendering it an exceptional resource for in-depth studies on structural heart defects in developing fetuses. To further enhance the dataset's credibility, image standardization was meticulously conducted, expertly fine-tuning the resolution to a consistent 256 * 256 * 3 for all experiments. This stringent standardization ensured that every image within the dataset maintains uniformity and a reliable distribution of features.

The extensive measures taken throughout the dataset creation process, combined with the diligent validation conducted by a proficient clinical expert, solidify the accuracy and reliability of the data within the FetalEcho_V01 dataset. Consequently, this comprehensive dataset stands as a robust and dependable foundation for future research endeavours and advanced analyses in the field of structural heart defect identification in developing fetuses.

Extensive research endeavours delved into the optimization of pre-processing techniques, aiming to unlock the true potential of the newly minted FetalEcho dataset. These pre-processing techniques served as the gateway, diligently transforming raw image data into a format that machine learning algorithms could readily comprehend. The triumvirate of rescaling, normalization, and filtering emerged as the primary contenders for elevating the dataset to new heights.

Rescaling, the initial step in this transformative journey, bestowed uniformity upon the dataset. By resizing the images to a fixed size, either through explicit pixel values or judicious scaling factors, a harmonious equilibrium was achieved, unifying the dimensions of every image. Normalization, the second technique, unveiled its power, taming the unruly fluctuations of brightness and contrast that plagued the images. Through diligent scaling of pixel values to a standardized range, the ill-effects of variations were quelled, enhancing the robustness of subsequent analyses. Filtering, the final method, emerged as a key player, leveraging its prowess to bestow images with heightened clarity. By skilfully applying filters, noise was subdued, blurriness was banished, and the very edges of objects were emboldened, unveiling a world of refined details.

The FoetalEcho_V01 dataset underwent a metamorphosis with the objective was to disentangle the most potent pre-processing technique for this unique dataset, employing the venerable conventional AlexNet as the vehicle of analysis. The dataset's raw state, bereft of pre-processing, revealed a meagre 49% accuracy. Noise removal, the first contender, propelled the accuracy to a remarkable 87%, while blur removal propelled it further to an excellent 88%. Sharpening gave a comparatively modest 69% accuracy.

The alliance of blur removal and noise removal proved to be an unstoppable force, propelling the accuracy to an inspiring 89%. Yet, the dynamic of sharpening underwent a transformative shift in the presence of its allies. When paired with blur removal, the accuracy settled at a commendable 79%, while its collaboration with noise removal yielded a more subdued accuracy rate of 53%. However, when all three techniques converged, an unexpected decline ensued, with accuracy plummeting to a modest 57%. This unveiled the unsuitability of sharpening for the FetalEcho_V01 dataset, as its behaviour underwent a metamorphosis in the presence of noise and blur removal.

These findings, firmly rooted in previous research, propelled the adaptation of this winning pre-processing methodology i.e, by removing Noise and blur removal, in the current study, amplifying the dataset's potential and After the preprocessing the dataset used for further experiments was named as FetalEcho_V05.

III.Methodology

This research endeavours to investigate the merits of distinct texture image features in capturing intricate details within images. By extracting an extensive range of minute details from the images, the learning process becomes more informative and comprehensive. This, in turn, facilitates the development of a highly effective classifier. The exploration of diverse texture image features not only enhances the depth of analysis but also provides valuable insights that contribute to the refinement and optimization of the classification model. The culmination of these efforts results in a more sophisticated and powerful classifier, capable of making accurate distinctions and classifications based on the intricacies and nuances present in the image data. The overall research process is depicted in Fig.1. The FetalEcho_V05 dataset developed in the previous research is transformed to LBP [9] images. This dataset is versioned as FetalEcho_V0501 and splited into train and test data. Then the deep learning models are administered on this dataset. The models had undergone stringent optimization by tuning the hyperparameter of the models till the satisfactory performance metrics are achieved. Then model is built and evaluated to record the performance.

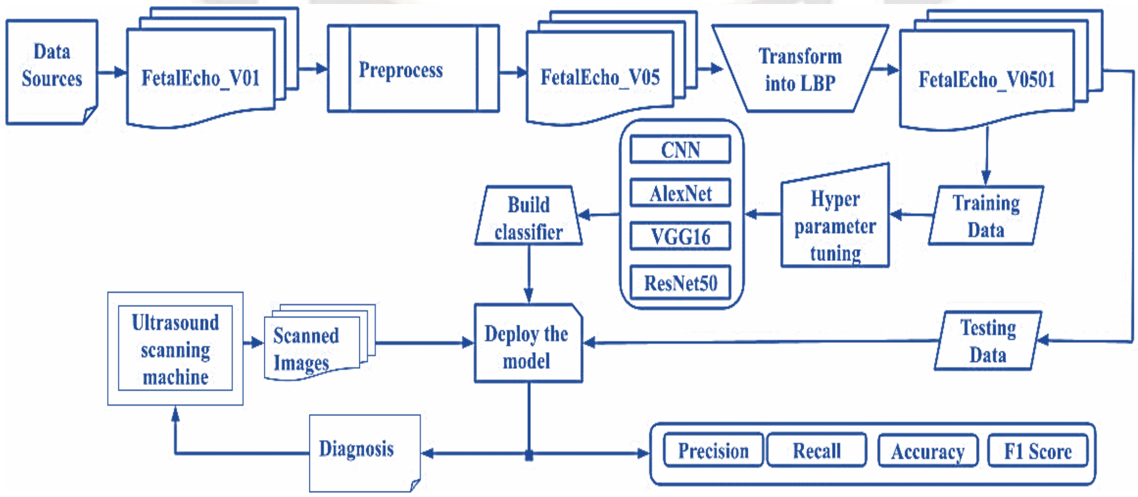

Fig.1. The research process flow

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Local Binary Pattern

Texture in any type of images refers to the visual patterns, assembly, and arrangement of object parts inside the image. It provides valuable information about the surfaces and their relationship with the surrounding environment. Analyzing texture features of USIT images can offer insights into the homogeneity and structural characteristics of the image.

Texture analysis plays a significant role in various image processing applications, including classification and segmentation of images such as face recognition. A widely used technique in texture examination [10] is the LocalBinaryPattern (LBP). LBP is known for its effectiveness in capturing texture information that is invariant to changes in grayscale intensity. LBP feature is selected for this research by referring to the outcome of various other research happening in the similar domain like for diagnosing thyroid nodule, for classifying the nodule is benign or malignant, and other similar medical image analysis. By leveraging texture analysis, practitioners can gain a deeper understanding of the underlying structures within static images. Hence the LBP transformation of FetalEcho_V05 is explored with the same deep learning models to appraise the diagnosis perfection. The models are evaluated using Precision, Accuracy, Recall, and F1 score parameters. After the models are evaluated, the model can be embedded in the USIT capturing device to classify and real time patient images.

The mathematical formula for calculating the LBP is as explained. Let I(x, y) be the intensity value of a pixel located at coordinates (x, y) in the image. The LBP value at that pixel is computed as:

$$LBP(x,y) = \sum_{p-1}^{s=0} f(s) * 2^s \qquad (1)$$

where P is the number of neighbours considered in the circular neighbourhood around the central pixel, and f(s) is a binary function defined as:

$$f(s) = 1, \text{ if } I(x_s, y_s) \geq I(x, y) \qquad (2)$$

$$f(s) = 0, \text{ if } I(x_s, y_s) < I(x, y) \qquad (3)$$

In the above formula, (x_s, y_s) represents the coordinates of the s-th neighbouring pixel, arranged in a circular pattern around the central pixel (x, y). The sum is taken over all P neighbours.

Transforming the USIT into LBP image

The experiments were conducted using Python programming language, specifically Python version 3.10.12. Python served as the primary tool for data preprocessing, model development, and result analysis. The process to transform an ultrasound image into a LBP [5] image is explained with examples below. The LBP transformation operation will only be on gray scale images. Hence, the first stage is to convert the ultrasound image to grayscale. Fig.2 shows an original USIT of the fetal heart and the grayscale image of the same.

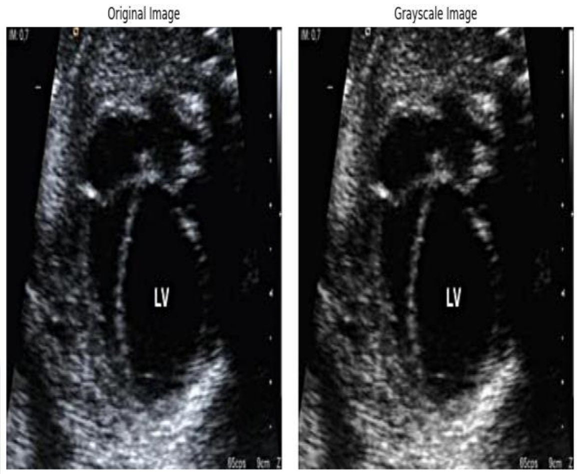

Fig.2 (a) Original fetal heart image, (b) Grayscale image

The second stage is to divide the grayscale ultrasound image into small, overlapping image regions called pixels. Typically, a central pixel of all 3*3 matrix and its surrounding neighbours are considered.

```
Image shape: (256, 256)
Pixel matrix:
[[  0,   0,   1,   0,   0,   1,  14,   0,   0,   1],
 [  0,   2,   0,  12,  23,  30,   0,  11,  24,   2],
 [  5,   2,  35,  69, 108, 147,   0, 114, 124,   0],
 [  1,   0,  36,  94, 125, 182,   0, 168, 131,  30],
 [  0,   0,  32,  99,  82, 145,  52, 148, 100,  28],
 [  2,   2,  50, 111,  74, 121, 138, 131, 104,   0],
 [  0,   1,  49,  93,  80,  80, 154,  88,  97,   7],
 [  2,   0,  58,  80,  92,  66, 129,  51,  87,  73],
 [  1,   1,   1,   0,   0,   0,   1,   1,   4,   3],
 [  0,   0,   0,   0,   0,   0,   0,   1,   2,   1]]
```

Fig.3 Part of the pixel array of the image in Fig1(b)

The above image, Fig.3 is a part of the pixel array of the image in Fig.2 (b).

For each pixel in grayscale image, compare its intensity value with the intensity of its neighbouring pixels. Assign a binary digit (0 or 1) to all neighbour pixel based on whether its intensity figure is greater or lesser than the threshold value. For example, if a neighbour's intensity is greater than or equal to the threshold, assign it a binary value of 1; otherwise, assign 0. Fig.4 depicts the LBP pixel array calculation for the first 3*3 matrix of Fig.4.

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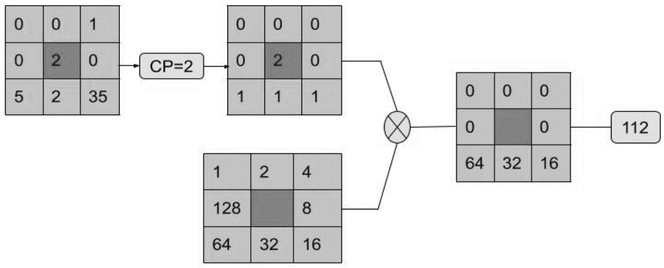

Fig.4 LBP pixel value calculation for the first 3*3 matrix

Implementing the transformation of an ultrasound image into an LBP image typically involves iterating through the pixels of the grayscale image and comparing their intensities with the neighbouring pixels. Construct an LBP pixel array by replacing each pixel in the grayscale image with the corresponding LBP code generated from its neighbours. Each pixel in the LBP image represents the local pattern around the corresponding pixel in the grayscale image
.

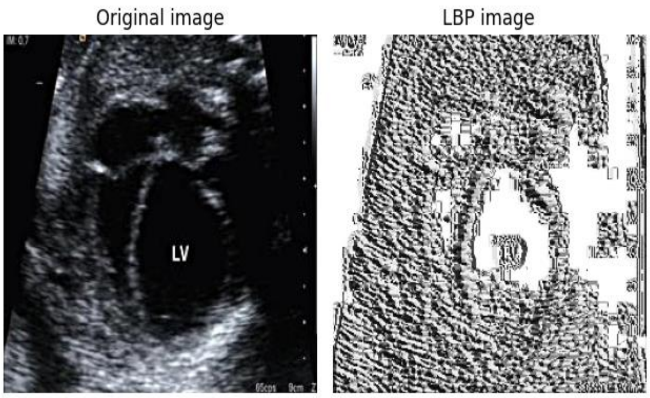

Fig.5. (a) Original image, (b) LBP image

Fig.5 shows the original and transformed image using the LBP technique. This pixel array can have an image representation also. The entire FetalEcho_V05 dataset undergoes the transformation iteratively and the resultant dataset is named as FetalEcho_V0501. Fig.6 shows some random images taken from the dataset for reference.

The FetalEcho_V0501 had undergone experiments with the customized deep learning models identified in the previous research. The customized models that were ide-ntified in the previous research were CCNN, AlexNet, ResNet50 and VGGNet16.

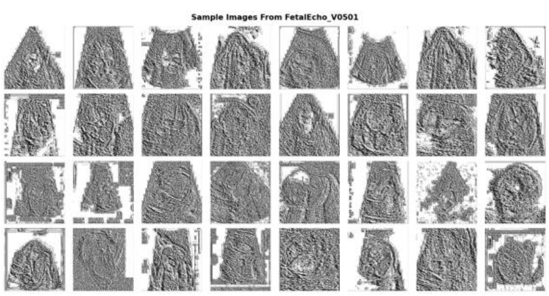

Fig.6 Sample images from the FetalEcho_V0501 dataset

The FetalEcho_V0501 dataset, comprises of a collection of 1600 images categorized into 16 distinct sets, representing 16 structural heart defects of fetus. Fig.6 shows some sample images from the dataset FetalEcho_V0501.

Model Development and Evaluation

Here the four deep learning models CNN, AlexNet, VGG16 and ResNet50 [12] are used with required customization in the layers and hyperparameters. These models are already proven to be performing consistently with the fetal echo datasets in the previous research conducted [6]. Each model configurations are explained below with individual hyper parameter setting.

The Sequential model stacks layers sequentially, starting with a Conv2D layer employing 64 filters and a 3x3 kernel size. This layer conducts convolutional operations on input images to extract features via learned filters. ReLU serves as the activation function, introducing non-linearity. Subsequently, another Conv2D layer with 32 filters and a 3x3 kernel size refines the extracted features. The Flatten layer converts 2D feature maps into a 1D vector, facilitating subsequent fully connected layers. A Dense layer with 16 units follows, fully connecting each neuron to those in the previous layer. The softmax activation function converts raw outputs into probabilities, predicting final class probabilities. The model is compiled using the SGD optimizer with a 0.001 learning rate, adjusting weights during training to minimize the categorical cross-entropy loss. This loss function gauges dissimilarity between predicted probabilities and true labels, suitable for multi-class classification. Employing convolutional layers for feature extraction, followed by flattening and fully connected layers for prediction, the model is trained using SGD optimizer and categorical cross-entropy loss.

The AlexNet model, developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in 2012, is a deep convolutional neural network architecture that gained significant acclaim for its performance in the ImageNet Large Scale Visual Recognition Challenge, thereby advancing computer vision research. This model comprises several key components. Initially, the first convolutional layer employs 96 filters with an 11x11 kernel size and a 4x4 stride, applying the ReLU activation function to input images with dimensions of 256x256x3 (representing RGB images). Subsequently, a max pooling layer with a pool size of 3x3 and a stride of 2x2 is applied to reduce the spatial dimensions of the feature maps. Following this, the second convolutional layer utilizes 256 filters with a 5x5 kernel size and ReLU activation, followed by another max pooling layer. The subsequent convolutional layers consist of 384, 384, and 256 filters, each with a 3x3 kernel size and ReLU activation. Finally, a max pooling layer with a 3x3 pool size and 2x2 stride is applied. The output from the last convolutional layer is flattened into a 1D vector, and a series of fully connected layers follows. The first fully connected layer comprises 4096 units with ReLU activation, while dropout layers with a

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dropout rate of 0.5 are incorporated to prevent overfitting. Another fully connected layer with 4096 units and ReLU activation is added, followed by a final fully connected layer with 16 units and softmax activation for multi-class classification. The model is compiled using the Adam optimizer with a learning rate set to 0.001 and categorical cross-entropy loss. Similarly, the ResNet50 architecture is utilized in this research, leveraging a deep convolutional neural network pre-trained on the ImageNet dataset. The model comprises pre-trained layers with frozen weights to retain learned features, while additional layers are added for fine-tuning. A Global Average Pooling 2D layer is included to reduce spatial dimensions, followed by a Dense layer with 1024 units and ReLU activation to capture higher-level patterns. Finally, a Dense layer with 16 units and softmax activation facilitates multi-class classification. The model is compiled with the Adam optimizer, a learning rate of 0.001, and categorical cross-entropy loss, evaluated based on accuracy. The VGG16 architecture, known for its effectiveness in image classification, is also employed in this research. It consists of convolutional blocks with increasing numbers of filters, followed by max pooling layers. Fully connected layers at the end perform classification, with dropout layers to prevent overfitting. The model is compiled with categorical cross-entropy loss, the Adam optimizer, and accuracy as the evaluation metric. Throughout the study, the FetalEcho_V0501 dataset is utilized for model building, where the dataset is divided into training and testing sets. Hyperparameters are carefully selected and adjusted to optimize model performance, considering factors such as train-test split ratio, learning rate, optimization algorithm, activation function, loss function, number of hidden layers, dropout rate, kernel filter size, pooling size, batch size, and epoch. Performance evaluation measures, including precision, recall, accuracy, and F1 score, are employed to assess the effectiveness of each model in diagnosing fetal cardiac anomalies.

IV. Results and Discussions

The previous research tested the FetalEcho_V05 dataset with identified traditional machine learning models and deep learning models. The results from the previous research can be kept as a benchmark for judging improvement in the classification performance of deep learning models.

Table 1. Hyper parameters settings

Models	Train-test split ratio	Learning rate	Optimization algorithm	Activation function	Loss function	Number of hidden layers	The drop-out rate	Number of iterations per epoch	Kernel or filter size in convolutional layers	Pooling size	Batch size	Epoch
CNN	0.8-0.2	0.001	Stochastic Gradient Descent (SGD)	ReLU	Softmax Cross-Entropy	10	0.5	20	3*3	Max-pooling	64	100
AlexNet	0.7-0.3	0.0001	Local Response Normalization	ReLU	Categorical cross entropy	40	0.4	20	11*11	Max-pooling	64	100
VGG16	0.7-0.3	0.0001	Momentum SGD	ReLU	Categorical cross entropy	50	0.4	20	3*3	Max-pooling	64	100
ResNet50	0.7-0.3	0.0001	Adaptive Moment Estimation	ReLU	Categorical cross entropy	10	0.3	20	3*3	Max-pooling	64	100

In this study, we employed MATLAB's DL toolbox to construct and connect neural network layers aimed at classifying 1600 USIT images into 16 distinct categories. To assess the performance of our models, we utilized essential metrics including Accuracy, Precision, Recall, and F1-score on the FetalEcho_V0501 dataset. We diligently prepared the dataset for further processing and leveraged pretrained models to construct classifiers tailored for classifying fetal echo USIT images based on the aforementioned dataset.

The cornerstone of developing an effective classifier lies in identifying the optimal combination of hyperparameters. This involved conducting multiple iterations to fine-tune each model with various hyperparameter combinations. Following meticulous evaluation, we determined the best hyperparameter settings that resulted in the highest classifier performance.

For our CCNN model, we adopted a train-test split ratio of 80%/20%, whereas for AlexNet, VGG16, and ResNet50, we utilized a split ratio of 70%/30%. We set the learning rate to 0.001 for CCNN and 0.0001 for AlexNet, VGG16, and ResNet50. The optimization algorithms varied across models, with Stochastic Gradient Descent (SGD) employed for CCNN, Local Response Normalization for AlexNet, Momentum SGD for VGG16, and Adaptive Moment Estimation for ResNet50.

ReLU activation function was chosen for training all models, accompanied by Softmax Cross-Entropy for CCNN and Categorical Cross-Entropy for AlexNet, VGG16, and ResNet50 as the loss functions.

Each model featured a different number of hidden layers, with CCNN having 10, AlexNet with 40, VGG16 with 50, and ResNet50 with 10. Dropout rates were set at 0.5 for CCNN, 0.4 for AlexNet and VGG16, and 0.3 for ResNet50. All models underwent 20 iterations per epoch, with varying kernel filter sizes (3x3 for CCNN, 11x11 for AlexNet, and 3x3 for VGG16 and ResNet50). We applied max-pooling as the pooling technique, while the batch size was fixed at 64, and the number of epochs deemed suitable was 100. Detailed hyperparameters for the selected models are outlined in Table 1.

Following multiple iterations and hyperparameter tuning, we found that the CCNN model emerged as the best-performing model for the FetalEcho_V0501 dataset. Its precision, recall, accuracy, and F1-score were 0.94, 0.91, 0.93, and 0.93, respectively. Other models, such as AlexNet, VGG16, and ResNet50, also demonstrated competitive results, albeit slightly lower than CCNN.

Considering the overall performance, the CCNN model showcased superior performance on the FetalEcho_V0501 dataset. We present the results, including precision, recall, accuracy, and F1-scores for each model, in Table 2. Additionally, we provide evaluation results for different classes of fetal cardiac anomalies, shedding light on the models' capabilities in distinguishing between various cardiac anomalies.

Table.2 Performance results of various classifiers

Models	Precision	Recall	Accuracy	F1 Score
CCNN	0.94	0.91	0.93	0.93
AlexNet	0.92	0.88	0.89	0.89
VGG16	0.91	0.87	0.87	0.89
ResNet50	0.93	0.91	0.93	0.93

Table 3 Class wise performance

Sl No	Defect	Class Name	Precision	Recall	Accuracy	F1-Score
1	Aortic Atresia or Stenosis	AA	91	88	90	89
2	Aortic Coarctation or Hypoplasia	AC	90	89	90	89
3	Atrial Septal Defect	ASD	88	84	85	86
4	AV Septal Defect	AVSD	89	84	84	86
5	Cardiomyopathies	CM	90	90	88	90
6	Double Outlet RV	DORV	93	89	88	91
7	Ebstein Anomaly	EA	92	89	89	90
8	Ectopia Cordis and Pentalogy of Cantrell	EC	90	87	88	88
9	Hypoplastic Left Heart Syndrome	HLHS	83	79	80	81
10	Hypoplastic Right Heart Syndrome	HRHS	84	80	80	82
11	Pulmonary Stenosis	PS	90	87	89	88
12	Single Ventricle	SV	86	82	81	84
13	Transposition of Great Arteries	TA	88	85	85	86
14	Truncus Arteriosus	TGA	89	84	85	86
15	Ventricular Septal Defect	VSD	90	88	89	89
16	Normal Heart	Normal	89	84	86	86

Analyzing the performance metrics for individual classes can offer valuable insights into the strengths and weaknesses of the model. For instance, high precision in certain classes indicates the model's proficiency in correctly identifying those classes. Conversely, low precision in some classes suggests challenges in accurately classifying instances of those classes. Table 3 summarizes the average performance evaluation of the Fetal_Echo_V0501 dataset.

The evaluation results for different classes of fetal cardiac anomalies are detailed below:

- Aortic Atresia or Stenosis (AA): Precision 91%, Recall 88%, Accuracy 90%, F1-score 89%
- Aortic Coarctation or Hypoplasia (AC): Precision 90%, Recall 89%, Accuracy 90%, F1-score 89%
- Atrial Septal Defect (ASD): Precision 88%, Recall 84%, Accuracy 85%, F1-score 86%

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- AV Septal Defect (AVSD): Precision 89%, Recall 84%, Accuracy 84%, F1-score 86%
- Cardiomyopathies (CM): Precision 90%, Recall 90%, Accuracy 88%, F1-score 90%
- Double Outlet RV (DORV): Precision 93%, Recall 89%, Accuracy 88%, F1-score 91%
- Ebstein Anomaly (EA): Precision 92%, Recall 89%, Accuracy 89%, F1-score 90%
- Ectopia Cordis and Pentalogy of Cantrell (EC): Precision 90%, Recall 87%, Accuracy 88%, F1-score 88%
- Hypoplastic Left Heart Syndrome (HLHS): Precision 83%, Recall 79%, Accuracy 80%, F1-score 81%
- Hypoplastic Right Heart Syndrome (HRHS): Precision 84%, Recall 80%, Accuracy 80%, F1-score 82%
- Pulmonary Stenosis (PS): Precision 90%, Recall 87%, Accuracy 89%, F1-score 88%
- Single Ventricle (SV): Precision 86%, Recall 82%, Accuracy 81%, F1-score 84%
- Transposition of Great Arteries (TA): Precision 88%, Recall 85%, Accuracy 85%, F1-score 86%
- Truncus Arteriosus (TGA): Precision 89%, Recall 84%, Accuracy 85%, F1-score 86%
- Ventricular Septal Defect (VSD): Precision 90%, Recall 88%, Accuracy 89%, F1-score 89%
- Normal Heart (Normal): Precision 89%, Recall 84%, Accuracy 86%, F1-score 86%

These results are visualized in Fig.6 for better clarity, providing a comprehensive understanding of the diagnostic model's performance across specific fetal cardiac anomaly classes. Fig.7 further illustrates the class-wise performance metrics, offering insights into precision, recall, accuracy, and F1-score variations.

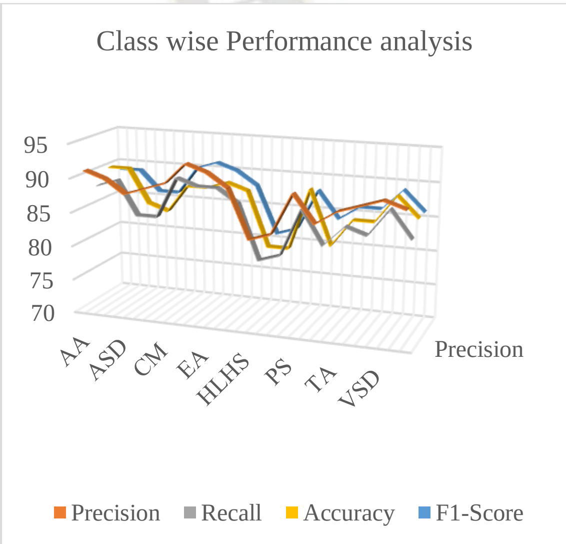
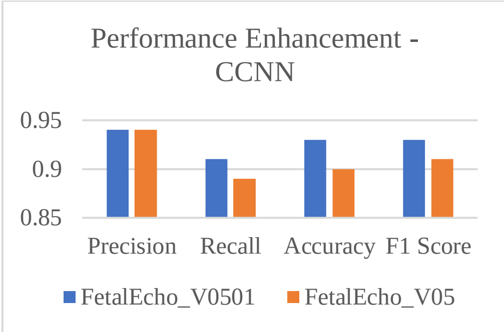
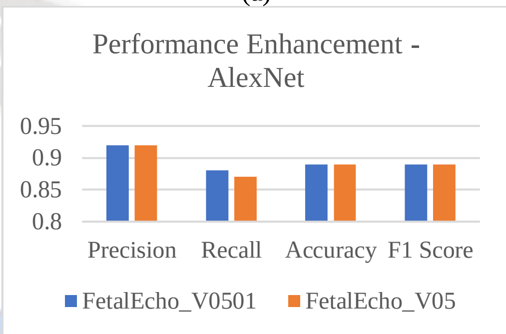


Fig.7 Overall performance analysis

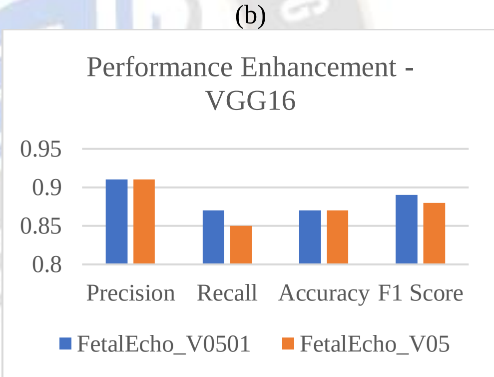
The comparison of the performance of LBP images and the original images' dataset i.e, FetalEcho_V0501 dataset and FetalEcho_V05 is plotted in the below charts.



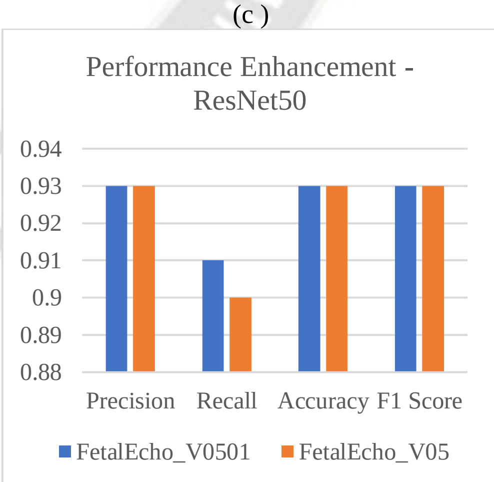
(a)



(b)



(c)



(d)

Fig. 8 FetalEcho_V05 performance for different models
Fig.8 FetalEcho_V0501 performance with FetalEcho_V05 using (a) CCNN, (b) AlexNet, (c) VGGNet16, (d) Resent50 models

As plotted in the chart Fig.8, the FetalEcho_V0501 shows more perfection in classifying.
In the previous research the FetalEcho_V05 dataset was used for training the deep learning models. For the CCNN model the overall precision remains the same, 94%. There is an improvement in recall from 0.89 in FetalEcho_V05 to 0.91 in FetalEchoV0501 for the CCNN model. This suggests that the CCNN model is better at capturing positive instances in FetalEcho_V0501 compared to FetalEcho_V05. The accuracy for CCNN is improved from90% to 93%. The F1 score for CCNN also improved from 91% to 93%. It is observed that there are improvements in recall, accuracy and precision for the CCNN model and precision remains the same. The AlexNet model performs consistently with 92%, when precision is taken into concern for FetalEcho_V05 and FetalEcho_V0501. There is a improvement in recall from 87% to 88% and both Accuracy and F1 score remain the same as 89%. This shows that there is a slight improvement in the AlexNet classifier performance trained with FetalEcho_0501. The VGG16 model demonstrates the same precision and accuracy with consistent values of 91% and 87% respectively. There is remarkable improvement in recall from 85% to 87% and F1-score also improved from 88% to 89%. The model has improvement in the performance metrics for the FetalEcho_V0501. The ResNet model showed consistent measures for precision, accuracy and F1-score with 93% for all three metrics with both the datasets. The recall value has improved from 90% to 91% for the FetalEcho_V0501.

Findings

The overall precision remains the same for the CCNN model across both FetalEcho_V05 and FetalEchoV0501, indicating consistent performance in correctly identifying true positives relative to the total predicted positives. The recall, accuracy and F1-score also improved with FetalEcho_V0501 dataset. The FetalEcho_V0501 shows clearly better performance while analysing the class wise performance metrics also. The Alexnet model improved in the recall metrics and the precision, accuracy and F1-score was consistent. The VGG16 classifier performed with improved score in recall and F1-score with a consistent score in precision and accuracy. The ResNet50 model performed for achieving consistent scores in precision, accuracy and recall along with an improved score in recall. Hence all the four classifiers developed by training FetalEcho_V0501 dataset has got an improve classification power. Amongst all the four models the CCNN and ResNet50 models demonstrate the highest overall performance across all metrics, while AlexNet and VGG16 exhibit slightly lower scores. However, the class wise evaluation will provide more insights on computational efficiency to provide a complete analysis of the models. The class wise performance metrics of the FetalEcho_V05 dataset was showing poor performance for HLHS, HRHS, SV, TA and Normal classes when compared to the other classes. This is due to the variability in the images within a specific class can impact the model's ability to generalize effectively. If there is a wide range of appearances or variations within a class, it can lead to misclassifications and lower performance metrics. The FetalEcho_V0501 dataset shows improved performance in the above-mentioned classes since the LBP images capture the details of the image more intensely and helps the deep learning models to learn better.

V. Conclusion

The research work executed by applying the LBP transformation to the images and creating the new dataset FetalEcho_V0501. The pre-processed dataset was standardised and normalised before the experiments. The dataset was used for training customised deep learning models CCNN, AlexNet, VGG16 and ResNet50 and respective classifiers were developed with most appropriate hyperparameters. These classifiers were evaluated by calculating the precision, recall, accuracy and F1-score metrics and the outcomes were recorded. The experiment outcomes clearly indicate improved performance of classifiers developed after training the FetalEcho_v0501 dataset. The efficiency of all the four deep learning models has increased with the FetalEcho_V0501 dataset, indicating better classification results. The CCNN classifier was the best performing classifier and REsNEt50 classifier also stands along with very minute difference in performance. The other models AlexNet also VGG1 also showed improved performance on the FetalEcho_V0501 dataset compared to the earlier FetalEcho_V05 dataset. Therefore, based on the updated results, it can be concluded that the LBP transformation has enhanced the classification performance of the deep learning models for the FetalEcho USIT image classification task.

References

1. Patil, V. K., et al. ‘Real Time Emotion Recognition with AD8232 ECG Sensor for Classwise Performance Evaluation of Machine Learning Methods’. International Journal of Engineering, vol. 36, no. 6, 2023, pp. 1040–1047.
2. Khazendar, S., et al. ‘Automated Characterisation of Ultrasound Images of Ovarian Tumours: The Diagnostic Accuracy of a Support Vector Machine and Image Processing with a LocalBinaryPattern Operator’. Facts, Views & Vision in ObGyn, vol. 7, 2015.
3. Zeebaree, D. Q., et al. ‘Multi-Level Fusion in Ultrasound for Cancer Detection Based on Uniform LBP Features’. Uniform LBP Features. Computers, Materials & Continua, no. 3, 2021.
4. Iakovidis, Dimitris K., et al. ‘Fuzzy Local Binary Patterns for Ultrasound Texture Characterization’. Lecture Notes in Computer Science, Springer Berlin Heidelberg, 2008, pp. 750–759, https://doi.org10. 1007/978-3-540-69812-8_74. Lecture Notes in Computer Science.
5. Liu, Tianjiao, et al. ‘Classification of Thyroid Nodules in Ultrasound Images Using Deep Model Based Transfer Learning and Hybrid Features’. 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 2017, https://doi.org10.1109/icassp.2017.7952290.

6. Divya, M. O., and M. S. Vijaya. 'Artificial Intelligent Models for Automatic Diagnosis of Foetal Cardiac Anomalies: A Meta-Analysis'. Proceedings of the International Conference on Cognitive and Intelligent Computing, Springer Nature Singapore, 2023, pp. 179–192, https://doi.org10.1007/978-981-19-2358-6_18.
7. Divya, M. O., and M. S. Vijaya. "Optimizing Pre-processing for Foetal Cardiac Ultra Sound Image Classification." International Conference on Innovations in Bio-Inspired Computing and Applications. Cham: Springer Nature Switzerland, 2022.
8. Divya, M. O., and E. R. Vimina. 'Content Based Image Retrieval with Multi-Channel LBP and Colour Features'. International Journal of Applied Pattern Recognition, vol. 6, no. 2, Inderscience Publishers, 2020, p. 177, https://doi.org10. 1504/ijapr.2020.111524.
9. Vimina, E. R., and M. O. Divya. 'Maximal Multi-Channel LocalBinaryPattern with Colour Information for CBIR'. Multimedia Tools and Applications, vol. 79, 2020, pp. 25357–25377.
10. 'Diagnostic Models for Foetal Cardiac Anomalies Using Pattern Classification and FetalEcho_V01 Dataset (In Press)'. Proceedings of the Eighth International Conference on Computing, Communication and Security (ICCCS 2023, 2023.
11. MO, DIVYA, and M. S. Vijaya. "REVOLUTIONIZING FOETAL CARDIAC ANOMALY DIAGNOSIS: UNLEASHING THE POWER OF DEEP LEARNING ON FOETALECHO IMAGES." Journal of Theoretical and Applied Information Technology 101.16 (2023).
12. Holland, B. J., et al. 'Prenatal Diagnosis of Critical Congenital Heart Disease Reduces Risk of Death from Cardiovascular Compromise Prior to Planned Neonatal Cardiac Surgery: A Meta-Analysis'. Ultrasound in Obstetrics & Gynecology: The Official Journal of the International Society of Ultrasound in Obstetrics and Gynecology, vol. 45, no. 6, Wiley, June 2015, pp. 631–638, https://doi. org10.1002/uog.14882.
13. Suard, Cornélie, et al. 'Accuracy of Prenatal Screening for Congenital Heart Disease in Population: A Retrospective Study in Southern France'. PloS One, vol. 15, no. 10, Public Library of Science (PLoS), Oct. 2020, p. e0239476, https://doi.org10.1371/journal.pone.0239476.
14. Changlani, Trupti Deepak, et al. 'Outcomes of Infants with Prenatally Diagnosed Congenital Heart Disease Delivered in a Tertiary-Care Pediatric Cardiac Facility'. Indian Pediatrics, vol. 52, no. 10, Springer Science and Business Media LLC, Oct. 2015, pp. 852–856, https://doi.org10.1007/s13312-015-0731-x.
15. Vijayaraghavan, Aparna, et al. 'Prenatal Diagnosis and Planned Peri-Partum Care as a Strategy to Improve Pre-Operative Status in Neonates with Critical CHDs in Low-Resource Settings: A Prospective Study'. Cardiology in the Young, vol. 29, no. 12, Cambridge University Press (CUP), Dec. 2019, pp. 1481–1488, https://doi.org10. 1017/ S104795111900252X.