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PRENATAL VENTRICULAR SEPTAL DEFECT DIAGNOSIS USING VGG -16

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Abstract
Health has been the primary area of interest in human welfare, especially fetal health. Fetal heart abnormalities are the most widespread congenital anomaly that leads to the cause of infant mortality related to congenital disabilities. Several techniques have come into existence for this purpose. The deformed heart can be differentiated from the normal heart based on several parameters such as the size of auricles, ventricles, valve and position of heart, area, circumference, and perimeter. One of the methods to detect the anomalies in fetal heart is by applying advanced Image Processing techniques to enhance the properties of the image that could improve the performance of the artificial intelligence algorithms. This proposed system is the primary framework for diagnosing the prenatal ventricular septal defects (PVSD). The first step is to denoise the US images using enhanced anisotropic diffusion Enhanced Perona Malik Filter (EPMF), followed by K-means clustering segmentation method as the second step, and finally, VGG-16 architecture was implemented with the pre-trained weights from the database. The original image is compared with the reference image in terms of different parameters using a VGG16 deep learning algorithm to predict PVSD anomalies at the early stage of pregnancy. VGG-16 is the first attempt to diagnose prenatal ventricular septal defects to achieve an accuracy of 90%. This proposed system will give a second opinion for the doctors in diagnosing the abnormalities at the early stages.

Keywords:
Enhanced Perona Malik filter, K-means, VGG-16, CNN model.

I. Introduction

Congenital heart defects (CHD) are the major types of fetal structural and functional abnormalities, isolated or related to fetal anatomical defects. Simultaneously, specific investigation proves that congenital heart defects (CHDs) influence 10% of children per 1000 live births. CHD's were broadly classified as major and minor types, in which the major types of defects result in the termination of pregnancy [1]. While the minor types of CHD's may or may not corrected during fetus development, which can lead to surgery. More than one-third of malformations were found after the birth of the child. Regardless of continuous development in the medical field, screening congenital heart defects is still challenging. Although, 2D ultrasound provides good quality fallout at different gestation periods, it requires plenty of skills and experience to fine predict fetus abnormalities.

The foremost advantage of using ultrasound imaging is its non-invasive nature and its fewer radiation effects. Special tools for screening the medical images are 2D Echocardiography, color Doppler and sonography [8]. The prenatal detection of the fetal cardiac structure is difficult during the gestation period of 20-30 weeks due to its small size and rapid fetus movements. Around 2% of fetuses are ill with congenital anomalies, which may be the primary cause of the newborn's death. Cardiovascular

anomalies are usually associated with other congenital anomalies as the heart begins to enlarge from the third week after conception and develops until the end of the 8th week. As the heart is developing throughout the entire period of organogenesis, it is vulnerable to the growth of anomalies.
Abnormality in Fetal development has become a bane to society. The detection rates of these fetal abnormalities are low to date. Ultrasound is one of the tools used for determining the health of a fetus. Radiologists choose ultrasound as an essential tool because of its low cost, broad availability, real-time capabilities, and the lack of harmful radiation. Nevertheless, the accuracy of echocardiography is restricted due to its poor signal-to-noise ratio, poor penetration through bone or air, and also air or bowel gas prevents visualization.
In addition to that, the fetus may not have a favorable position in the womb to get a clear image of the required part. By performing edge location in fetal ultrasound pictures is non-minor because the nature of the fetal heart chamber divider is thin along the atrial and ventricular septum. This circumstance gives a higher effect on imagining a remarkable strategy to enhance the programmed outline of natural structures from ultrasound images. As a result, an advanced preprocessing method is implemented for image denoising and recovers the fine details present in the images. Finally, a computational intelligence model is proposed to diagnose the type of CHD's present in the US images. As congenital heart defects would sufficiently influence the fetus's life, the efficient prenatal diagnosis of the fetal heart is certainly essential [16].

II. Related Works

To focus on early diagnosis of prenatal CHD's, various authors' proposed different methodologies. Athira PK and Linda Sara Mathew [1] proposed a methodology that consists of four steps; first is to rescale the images and denoising, followed by image segmentation, and feature extraction and finally disease classification with a Machine Learning classifier ANN. Bindiya H M, Chethana Pavan Kumar S P [2] proposed an image processing and CNN model to classify the anomaly present in the US images. They had proved good results when compared to existing models.
Edgar Hernandez Andrade et al. [3], in their study, reported that assessment of fetal heart is because of family history, a child with CHD or an ultrasound decision related to cardiac anomalies. From 12 weeks of gestation, trans abdominal ultrasound shows reliable fetal cardiac images. Hence, the congenital heart defects can be easily identified from a four-chamber view or outflow tract view but with many challenges. Ping Chen, Yinhui Deng et al. [4] proposed an automatic detection of cardiac anomalies from the first trimester. As is it too early from the moving image, region of interest of the fetal heat is automatically selected, then the preprocessing method is applied to suppress the speckle noise and highlight the vital information for prenatal CHD detection.
PrabhakarRajiah [5] proposed that vascular and valvular lesions have found from Doppler imaging were used in the evaluation. 3D imaging enables the reform of several complex planes from a single transverse acquisition. 4D imaging enables the estimation of cardiac motion and function in multiple planes. Bronshtein and E Z Zimmer [6], in their study, discuss that out of 36326 fetus US images, 171 fetuses were detected with cardiac anomalies using transvaginal sonography dataset in various planes and directions giving an overall incidence of 1 in 200 pregnancies. From 72 cases, 27 cases were detected with abnormal cardiac karyotype and nuchal translucency, respectively.
Manoj Gupta et al.[7] focuses on implementing different filters for image denoising, and their performance is analyzed based on different parameters such as PSNR, MSE, and RMSE. The qualitative and quantitative results of different filters of the 2D ultrasound images were compared for better performance. MehidiMafi et al. [8] have proposed a Gaussian filtering method for image denoising. In line with specific coefficients, dual-tree complex wavelet transform is applied to the image to characterize the types of noise. Subsequently, thresholding was applied to remove the extracted coefficients, and the image is reconstructed using inverse wavelet transform. Oleg VMichailovich et al. [9] have proposed preprocessing method consisting of two stages; first, an image is passed during spectral equalization to reduce the correlation anatomy between sample images. Next,

the decorrelated image is subjected to shrinkage, thereby suppressing the peak component of additive noise.
Fodi M Barboza et al. [10] discussed in their study that many factors which visualize fetal cardiac anatomy are dependent on maternal body habitus, fetal activity and fetus position. Anomalies involving the outflow tracts of the aorta and pulmonary arteries were not seen in the 4 chamber view (4CV). From the base view of the heart, the outflow tracts can be visualized. As a result, sensitivity and accuracy in diagnosing the cardiac anomalies were improved. We have proposed a VGG-16 deep convolution neural network methodology that gives better results than the previous studies by observing all these studies.

III. Data Collection

This section describes the experimental dataset collected from the nearby private hospitals and some scanning centers and web sources. Owing to the ethical standards mentioned by Helsinki declarations, the patient's information and few data in the ultrasound images were kept confidential. This study, constructs a small dataset that comprises 564 US images collected over nearly 3 years. We collected the US images from the pregnant mothers during the gestational period of 0-30 weeks. Even though different visualization planes are available, in this article, we collected the dataset from 3 vessel views (3VV) and 4 chamber views (4CV).
Table 1 illustrates the dataset distribution based on the gestational period of the fetus. The ventricular septal defect was incepted from 4CV of the visualization plane. VSD is a small hole identified between the lower parts of the septum. According to the hole size, VSD was classified into small VSD, moderate VSD, and large VSD, which was clinically described by roger in 1879.

Table 1: Dataset distribution based on the gestational period of the fetus

SI. NO	US Image planes	Gestational periods in weeks					Total US images
		0 -21	21-23	23 -25	25 -28	28 -30	
1	4(4CV)	24	49	56	90	64	283
2	3(3VV)	23	67	71	65	55	281
3	Total US images	47	116	127	155	119	564

IV. Methodology

The main aim of this proposed work involves different image processing and segmentation algorithms, followed by the mechanism of transfer learning with VGG-16 architecture to diagnose and classify the anomalies present in the US images. The dataset comprises normal and abnormal 4CV ultrasound images.

4.1 Speckle Reduction Techniques

Pre-processing is to suppress the unwanted distortions or enhance image features from image data that are important for further processing. An image enhancement technique helps to denoise, sharpen or brighten an image and identify critical features of an image. Therefore, input images are pre-processed using various filtering techniques like Perona Malik filter, Lee filter, and Frost filter to remove noise present in the ultrasound images. Traditionally used non- linear filters offer the simplicity of implementation but fail to preserve minute edge details. Bilateral filters denoise by averaging the nearby pixels of the same color. The kernel shape depends on image content which avoids averaging across edges. Diffusion filters not only preserve the edges but enhance them by applying differential equations. Wavelet transform provides detailed information about the amplitude of a signal in horizontal, vertical, and diagonal orientation differs concerning frequency. Hence, it is observed that each filter has its own advantage and limitations.

4.2 LEE Filter

Lee filter is one of the non-linear filters that mainly focus on preserving the edges. Based on the multiplicative speckle model, it uses local statistics to preserve the details. Lee filter makes the speckle-noise reduction in a homogeneous region only, but the enhanced Lee filter performs well in homogeneous and heterogeneous areas. It purely works on the variance basis; for low variance, it performs smoothing operation, and for high variance, it preserves details in low and high contrast regions. From the result, it is clear that the Lee filter cannot effectively remove noise near the edges. It can be mathematically represented in equation 1.

$$I(X, Y) = I + W * (Cp - I) \tag{1}$$

4.3 Frost Filter

Frost filter is a linear convolution filter used to take away multiplicative noise from the images. Compared to non- linear filters, frost filter is adaptive in nature and also it meant for an exponentially-weighted averaging filter. It works based on the coefficient of variation, which is defined as the ratio of the local standard deviation to the local mean of the corrupted image. From the kernel size of n-by-n, the mean pixel value is replaced using a weighted sum of values of the neighborhood pixel. The weighting factor reduces as we move from the concerned pixel and boost its variance. Frost filter can be mathematically represented in equation 2.

$$DN=\Sigma n * xn * k * \alpha * e^{-|t|} \tag{2}$$

4.4 Enhanced Perona Malik Filter

Perona Malik diffusion is also known as anisotropic diffusion, widely used for image enhancement. The denoising effect is high and preserves all the vital parts of the image, like edges, lines, or other significant details for analyzing an image. In anisotropic diffusion, the output image is a convolution between an original image and the filter. As per the result, perona malik filter is a nonlinear and space-variant transformation of the original image. The mathematical representation of the perona malik filter is given in equation 3

$$\partial I(x, y, t)/\partial t = \nabla.[c(|\nabla I\sigma(x, y, t)|) * \nabla I(x, y, t)] \tag{3}$$

4.5 2D Wavelet Transform

The 2D wavelet transform is one of the image denoising methods. The first step is to apply the logarithmic function for the ultrasound images that contain speckle noise- followed by the implementation of a two-level decomposition of a logarithmic image using wavelet transform. The third step is to apply proposed adaptive thresholding in each level. To reconstruct the image, apply the inverse transform, followed by an exponential function. The final output is the denoised image by preserving all the fine details contained in the image. The mathematical expression of wavelet transform is given in equation 4 & 5.

$$D = Wm * I * (Wn)^\wedge T \tag{4}$$

$$R = (Wn)^T * D * Wm \tag{5}$$

For image reconstruction, the following equation can be used

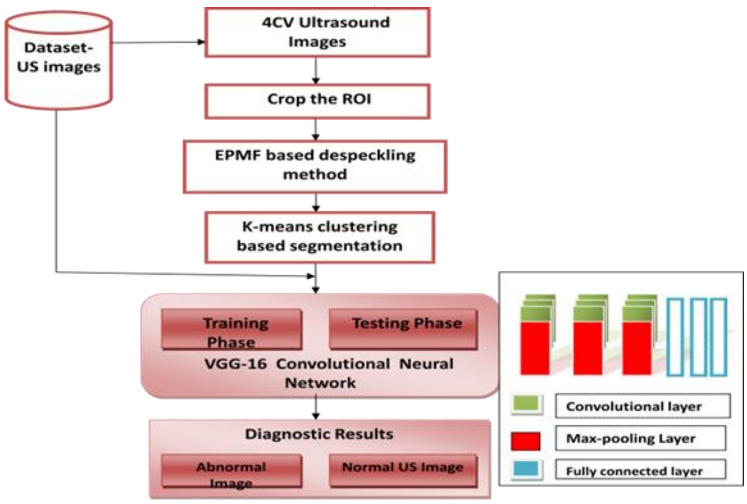

Figure.1. Flow diagram of VGG-16 Architecture to diagnose the VSD in US images.

V. Results

5.1 Qualitative performance of different filters

Figure 2 shows the qualitative performance of different filters. The visual inception of the Enhanced Perona Malik filter shows a clear delineation of heart chambers compared to other filter methods. From the residuals, it is clear that benchmarking method gives more residuals while denoising the images.

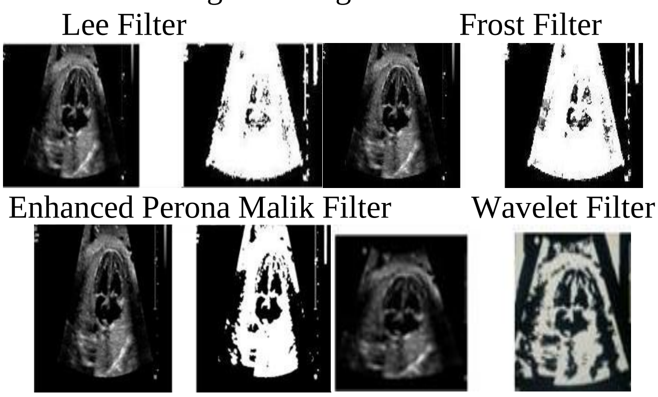

Figure.2. Illustration of qualitative results of different filters.

The outcome of the proposed filters offers the simplicity of implementation but fails to preserve the edges. Bilateral filter denoise by averaging pixels of the same color. The kernel shape depends on image content which avoids averaging cross edges. Non-local mean filter denoises by averaging nearby pixels of similar textures. Wavelet transform provides detailed information and near-optimal for compression, denoising, and detecting a broad class of signals. Anisotrophic diffusion filter not only preserves the edges but even enhances them by applying partial differential equations.

5.2 Segmentation

Segmentation is a robust method where it protects the particular region of an image. The main objective is to segment an image into a few regions where image pixels do not overlap and have common characteristics with the ground truth, and it separates the high contrast pixels from the light background called thresholding. Various advanced segmentation algorithms used for feature extraction are Region-based active contour, Graph cut, Level set, and K mean clustering.

5.3 Region-based active contour method

Active contour mainly uses 2D and 3D images from different medical modalities. Active contour is a type of segmentation technique that uses energy forces and constraints to isolate the pixels of importance from the image for advanced processing and examination. Generally, this model finds the contour to represent the boundary of objects in an image by minimizing an energy function Deforming of the contour is described by a collection of points that finds a contour. The fundamental concept of

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this model is the minimization of energy-based segmentation that uses both local and global region information of the image to define the image fitting energy functional. Hence, the energy function mathematically represented in equation 6

$$F(c1, c2, c) = \lambda 1 \int |I(y) - c1|^2 \, dy + \lambda 2 \int |I(y) - c2|^2 \, dy + \mu(c) \quad (6)$$

Tian Yun. et al. proposed an active contour model of the images for the stopping process, and the model is robust to noise as well. To re-initialization, an energy function and level set function was introduced [11].

5.4 Graph cut method

It is a semiautomatic segmentation technique. In order to segment an image into foreground and background elements, graph cut method was proposed. Sketch lines on the image, known as scribbles, to spot which pixels should highlight in the foreground and background of the given image. The segmented segments the image repeatedly based on scribbles in the image and shows the segmented image. The Graph Cut technique applies graph theory to the images. This method creates a graph on the image where each pixel is a node associated with weighted edges. This method breaks along weak edges, achieving the segmentation of objects in the image.

The feature distribution estimation is done in two steps

1. Estimate the color distribution on scribbles
2. Each pixel is assigned a probability that belongs to F or B

Energy minimization using the graph cut method is mathematically proven by,

$$E(f) = E_{smooth}(f) + E_{data}(f) \quad (7)$$

$$E_{smooth}(f) = \sum_{\{P,Q\} \in N} u\{P, Q\} * T \quad (8)$$

$$Edata(f) = \sum_{p \in P}, Dp * fp \quad (9)$$

5.5 Level Set Method

It is a conceptual framework that uses level sets as a tool for mathematical analysis of surface and shape. The advantage of the level-set is that it can perform mathematical computations relating curves and surfaces on a fixed Cartesian grid devoid of parameterizing the object. The level- set method makes it extremely easy to track shapes that change topology. The closed curves in a two-dimensional surface are regarded as a continuous surface of a three- dimensional space. The smoothing function is defined as ϕ (x, y, t), which stands for the surface, whereas the set of ϕ (x, y, t) = 0 stands for the curves. The level set methods represent a closed curve Γ using an auxiliary function ϕ, known as the level set function in two dimensions. The level set method (Γ) is represented as the zero level set of ϕ and is given in equation 10.

$$\Gamma = \{(x, y) \mid \phi(x, y) = 0\} \quad (10)$$

5.6 K-means clustering

K-means is an unsupervised clustering algorithm that is similar to classification algorithms, but the basis is different

Based on the similarities, the given image is divided into various classes or clusters. Data points in one group are same when compared data points in the other groups. Here, k indicates the number of clusters. The flow chart of the K-means clustering algorithm is shown in figure 3

Qualitative Performance of various Segmentation Methods

The qualitative performance of various segmentation methods is discussed in this section. Different parameters are considered to validate the performance of proposed work (K- means clustering), such as the dice coefficient, jaccard index and conformity coefficient.

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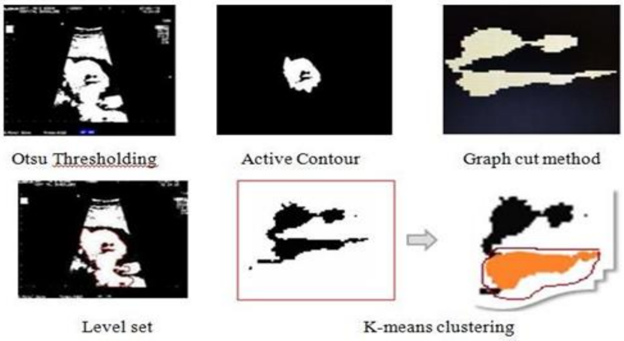

Figure. 3. Shows the qualitative results of different Segmentation methods.

To remove the isolated points and unwanted pixels generated due to noise, one of the morphological operations like clean, is implemented after the segmentation step. The proposed method gives better performance in segmenting the particular part of the four-chamber view of the ultrasound images. The visual inception of the proposed work proves that the given US image is prone to have higher efficiency in segmenting the heart chambers.

VI. VGG-16 Convolution Neural Network

The VGG architecture was formed with the idea of investigating the effect of adding depth to a CNN, thereby evaluating its accuracy while applied to large-scale image recognition methods. As Vanessa Rezende [13] proposed a comparison method of using VGG-16 and VGG-19 for classifying plant diseases. This article proposed a new method CNN with VGG that uses small filters of size [3*3]. Unlike others methods like LeNet, Alexnet where it makes use of large filters. One of the importance of this CNN model is that it is a standardized architecture with pre-trained weights that challenge an efficient feature extractor. There are two models in VGG, which are 16 layered models and 19 layered models. The model used here is 16 layered models, and the architecture of the VGG16 model is shown in figure 5.

6.1 Implementation of VGG-16 Architecture

The ultrasound image of the fetal heart is classified usingtransfer learning with VGG16 network architecture. The flowof the algorithm is given in the following steps.

1. The segmented images are the input to the classifier; label the images and resize them so that they are reliable with the size of the input layer of VGG16.
2. Separate the dataset into training and testing sets, as 80% of the image are used for training and 20% for testing, training. Testing consists of subfolders in order to predict the normality and abnormality of VSD.
3. Transform the final layers of the pre-trained network by altering the last three layers of the pre-trained network with a set of “fc”, “softmax”, “classification output” for categorization of the images into normal and VSD classes.
4. Train the network with the training dataset. The training data is used to make sure the machine recognizes patterns in the data.
5. Test the classifier with the testing dataset. It is a step where the performance or accuracy of the system is determined.

Predict whether the given input is VSD or normal. After training and testing the 4CV ultrasound images, it is classified to predict whether the given input ultrasound image is VSD or not. The subfolders in the training and testing folders are in the order VSD and normal US images. For better prediction, the algorithm is designed in such a way that if the output falls among [1 0], then 1 indicates the image belongs to VSD, i.e., the given ultrasound fetal heart image has an abnormality that it is a VSD image and if the output is [0 1], then 1 indicates the given ultrasound fetal heart image is normal. This section describes the outcome of various preprocessing and segmentation methods. Even though we have many filters, EPMF highlights better when compared to existing methods. In order to justify the proposed results, various parameters are considered. The performance is validated using peak

signal to noise ratio (PSNR), structure similarity index measure (SSIM), edge preservation index (EPI), universal quality index (UQI).
The experimental analysis of different preprocessing methods concerning PSNR, SSIM, EPI, and UQI is shown in table 2. It shows that the Enhanced Perona Malik Filter stands higher when compared with the other algorithms. The processing time (shown in table 3) required for denoising the image shows that the proposed method performs better than other algorithms. For this reason, the output of the Perona malik filter becomes the input for segmentation for delineating the fetal heart chambers.
The segmentation is done using various algorithms such as region-based active contour, Graph cut, Level Set, K mean clustering, and the output is validated using various performance parameters such as dice coefficient, jaccard index, and conformity coefficient. From the results, it is highlighted that K means clustering gives better results than existing algorithms. Hence the output of K means clustering is used for the classification. Computational time is considered for both preprocessing and segmentation algorithms in order to prove the performance of the proposed work.

Table.2 Experimental analysis of pre-processing methods

	Lee	Frost	Median	Wavelet	Butterworth	Ideal	Proposed
PSNR	27.682	28.521	29.786	28.896	27.245	27.677	**33.452**
SSIM	0.931	0.8418	0.9104	0.9315	0.800	0.745	**0.9412**
UQI	0.9683	0.9854	0.9651	0.9893	0.9054	0.9732	**0.9934**
EPI (β)	0.9088	0.9343	0.9161	0.9347	0.8468	0.7851	**0.9522**

Table.3 Comparison of processor time for different preprocessing methods (sec).

	Lee	Frost	Median	Wavelet	Butterworth	Ideal	Proposed
PSNR	3.07515	2.72547	2.58261	2.08875	3.98745	3.58426	**2.46243**
SSIM	2.59590	3.45121	3.05485	60.41171	3.80861	4.84523	**2.94120**
UQI	2.56031	2.58470	2.25412	**60.5874**	2.96554	2.9732	**2.36528**
EPI (β)	3.93689	3.34395	2.99844	60.5412	2.58741	2.9635	**2.91114**

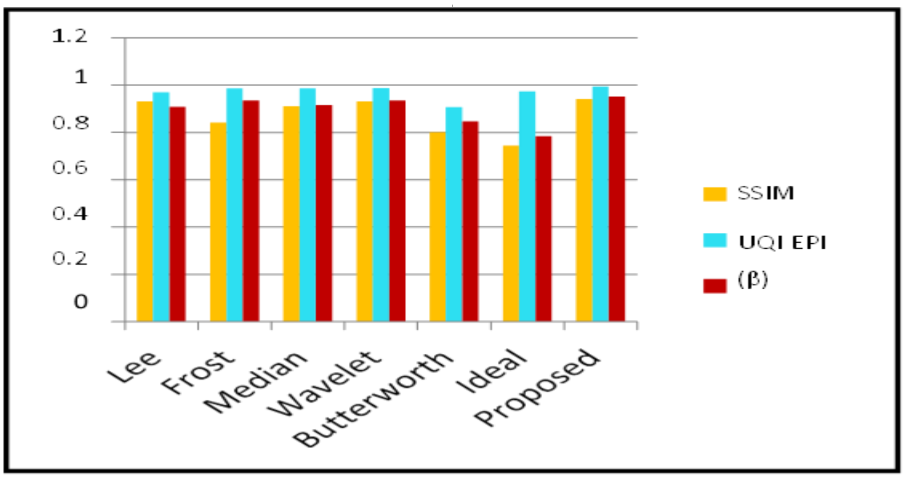

Figure. **4.** Comparative preprocessing performance

The experimental analysis of different segmentation methods with respect to DC, JI, and CC is shown in table 4. It shows that the K-means clustering proves higher when compared with the other algorithms.

Table.4 Quantitative analysis of segmentation methods

Method	DC	JI	CC
Otsu Thresholding	0.8611	0.7745	0.7456
Active contour	0.8574	0.7921	0.7259
Graph cut	0.7998	0.7153	0.7845
Level set	0.9375	0.8542	0.7848
K-means clustering	0.9887	0.8875	0.8645

The DC, JI, and CC of the proposed method give better performs than other techniques. The level set and proposed method are very close to each other, but when compared to the processing time proposed method proves better than the level set method. The active contour method performs better in processing time compared to other methods. Improvement in processing time can be achieved by changing the kernels, see to that better is the performance.

The experimental results show that the given dataset is trained and tested for a 16 layered VGG model and obtained a validation accuracy of 90%, as shown in figure 5. This validation accuracy can further be increased up to 95% by increasing the dataset. This method helps in diagnosing the prenatal disease well in advance.

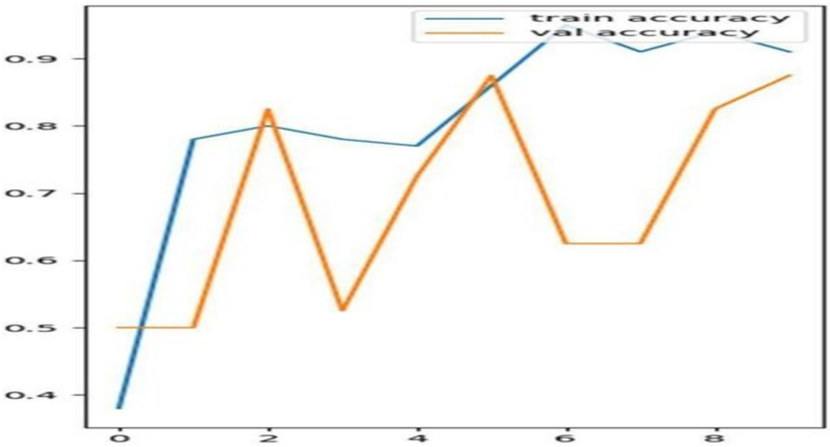

Figure .5. shows the real-time implementation of accuracy and loss graph after pre-processing and segmentation techniques.

VII. Conclusion

Even though we have many challenges in ultrasound to diagnose the disease, the radiologist prefers US modalities due to their non-ionization nature. Since prenatal screening requires lots of skills and experience, there exists a demand in developing computational intelligence methods for the automatic visual inception and classification of disease for the US images. This proposed system is the first framework for automatic diagnosing of PVSD quite at the early stages. This semiautomatic system will help the untrained sonographers and new trainers in diagnosing the disease accurately. Though this proposed system works with one particular type of CHD, the future work is to diagnosis the other critical CHD's in the near future.

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