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FETAL HEART DISEASE DETECTION VIA DEEP REG NETWORK BASED ON ULTRASOUND IMAGES

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ABSTRACT
Congenital heart disease (CHD) is the most prevalent congenital ailment. One in every four newborns born with serious coronary artery disease will require surgery or other early therapy. Early identification of CHD in the fetal heart, on the other hand, is more critical for diagnosis. Extracting information from ultrasound (US) images is a difficult and time-consuming job. Deep learning (Dl) CNNs have been frequently utilized in fetal echocardiography for CAD identification to overcome this difficulty. In this work, a DL based neural network is proposed for classifying the normal and abnormal fetal heart based on US images. A total of 363 pregnant women between the ages of 18 and 34 weeks who had coronary artery disease or fetal good hearts were included. These US images are pre-processed using SCRAB (scalable range based adaptive bilateral filter) for eliminating the noise artifacts. The relevant features are extracted from the US images and classify them into normal and CHD by using the deep Reg net network. The proposed model integrates the Reg net -module with the CNN architecture to diminish the computational complexity and, simultaneously, attains an effectual classification accuracy. proposed is evaluated using Matlab 2020b.The proposed network attains higher accuracy of 98.4% for the normal and 97.2% for CHD. To confirm the efficiency of the proposed Reg net is compared to the various deep learning networks.
Keywords: *Congenital heart disease (CHD), Deep learning, Ultrasound (US) images, Reg net -module, SCRAB (scalable range based adaptive bilateral filter).*

1. Introduction

In the general population, 0.8 percent of people suffer from congenital heart diseases (CHDs). CHD can be seen at birth and can actually affect a baby's heart structure and function (Lewis-Israeli et al., 2021). As a result, they have the potential to disrupt the circulation of blood in the heart and out of the body (Nurmaini et al., 2021). The severity of coronary heart disease varies from mild (a minor hole in the heart) to severe (mislaid or deformed heart parts) (Dakshina et al., 2023; Hamamoto et al., 2020). Approximately one in four infants born with heart defects have a perilous CHD (Komatsu et al. 2021). These are birth defects of the heart and blood vessels that can affect the heart's structure, function, and blood flow (Meng et al., 2019). Some common CHDs include atrial septal defect, ventricular septal defect, Patent ductus arteriosus, aortic stenosis, and transposition of the great arteries (Yamamoto et al., 2019; Yagel et al., 2018). The severity of CHDs can vary greatly and may require medical (Zafar et al., 2022; Hemamalini et al., 2022; Kumar et al., 2021a) intervention such as surgeries or medications. Early diagnosis and treatment can improve outcomes for individuals with CHDs (Pesapane et al., 2018; Lukhele et al. 2023).

CHD surgery fixes or treats a heart defect that a child is born with. A baby born with one or more heart defects has congenital heart disease (Lamture et al., 2023). Surgery is needed if the defect could harm the child's long-term health or well-being. Surgery or other practices are necessary in the initial stage of their life for babies with critical CHD. Others may cause some serious clinical signs in a baby that include blue-colored nails or lips, difficulty breathing, fatigue while feeding and sleepiness (Zhang et al., 2023a). To effectively enhance the infant's diagnosis, rapid recognition of CHDs is important because it can require anomalous fetal heart structures; thus, allowing clinical treatment as soon as possible (usually within a week after birth) is required (Xiao et al., 2023; Prayer et al., 2023). Some CHDs can be detected during pregnancy using a fetal echocardiogram, a type of ultrasound that creates ultrasound heart images of the fetus (Rana & Bhushan, 2023; Zhao et al., 2023).

Modern cardiology refers to the current state of the field of cardiology, which is the scientific study of the heart and blood vessels (Mishra & Tiwari, 2023). Modern cardiology frequently uses ultrasound devices to screen for cardiovascular diseases because they are non-invasive, low-cost, radiation-free, and easy to use (Okafor et al., 2023). An ultrasound examination of the fetus is essential for a thorough diagnosis and for clinical mentoring (Zhan et al., 2022). The prognosis of a CHD is difficult using fetal ultrasound (US), since US imaging has the potential to create blurry boundaries (shadows), which affect the image quality and its accuracy (Brady et al., 2023; Jiang et al., 2023). As the healthcare practitioner acquires images, the process of echocardiography is dependent not only on the ability to capture images, but also on the ability to analyze those images using a highly developed pattern recognition technique (Picano et al., 2023; Nayak et al., 2022). Extracting information from ultrasound (US) images is more complicated and computationally demanding challenge (Ricci et al., 2020). By employing advanced deep learning models such as medical image and so on contribute to detecting different types of diseases (Kumar et al., 2021b; Sundarasekar & Appathurai, 2021).

To overwhelm this issue, deep neural networks have been usually used detecting CHD in fetal cardiac ultrasound images. Deep learning (DL) was employed for finite echocardiographic analyses to recognize the structural heart disease (Zhang et al., 2023b; Summerlin et al., 2022). The major contribution of the proposed work has been followed by,

- The intention of this work is to design a computational efficient classification technique for detecting CHDs in the fetal heart based on ultrasound images.
- These US images are pre-processed using SCRAB for eliminating the noise artifacts.
- The relevant features are extracted from the US images and classify them into normal and CHD by using the deep Reg net network.
- The proposed classification technique is evaluated based on its precision, F1 score, sensitivity, specificity, and accuracy.
- To confirm the efficiency of the proposed network, the Reg net was evaluated against various deep learning networks.

2. Literature Review

Cardiovascular diseases (CVDs) remain a significant global health concern, necessitating continuous advancements in diagnostic methodologies. In recent years, Deep Learning (DL) techniques have emerged as powerful tools in the domain of medical imaging, particularly in the detection and classification of Congenital Heart Diseases (CHDs). This literature review aims to provide a comprehensive analysis of state-of-the-art DL methods employed by researchers to enhance accuracy in identifying CHDs, primarily focusing on fetal hearts through the use of ultrasound (US) images.

Kusunose *et al.,* (2020) introduced a DL convolutional neural network (CNN) to identify regional wall motion anomalies (RWMAs) in cardiac images. Their model outperformed traditional diagnostic methods, showcasing the potential of DL in improving accuracy.

Toba *et al.,* (2020) suggested a DL approach for detecting the pulmonary to systemic flow ratio from chest radiographs, which was analyzed by employing intra-class correlation coefficients and Bl and Altman evaluation. The diagnostic accuracy of a high pulmonary to systematic flow rate of 2.0 or greater was assessed by a statistical tabulation and ROC curve.

Arnaout *et al.,* (2020) recommended a deep learning approach method for predicting double standard clinical performance on an urgent and global diagnostic challenge. They trained a combination of deep networks to classify the cardiac views and differentiate between healthy and complicated CHD employing 107,823 images from 1,326 retrospective echocardiograms and reviews from 18-24-weeks. Their approach, utilizing a vast dataset of echocardiograms, stands as a testament to the potential of DL as a stand-alone tool for retrospective image analysis.

Dozen *et al.,* (2020) introduced a new segmentation approach called Cropping-Segmentation-Calibration (CSC) that is unique to the ventricular septum in ultrasound films. CSC calibrates the output of U-net using time-series information from movies and particular section information. In 615 frames from 421 normal fetal cardiac US videos of 211 pregnant women were screened. The results demonstrate CSC's outstanding performance.

Barinov *et al.,* (2019) developed a Decision Support (DS) system based on AI used for US image analysis, which could aid in improving US detection accuracy. Although the DS system appears to be capable, its efficiency in terms of effect must also be assessed once incorporated into traditional medical frameworks. This system assesses the impact of workflow frameworks for DS incorporation on clinical diagnosis.

Narasimhan (2018) introduced a dynamic anomaly identification and localization model based on deep learning to extract the important features instantly. Each video is signified as a cluster of cubic patch in this method for detecting global and regional discrepancies. They employed a sparse denoising autoencoder, which reduces processing time and the specificity in frame-level disease recognition by more than 2.5 %. based on the UMN and the UCSD Pedestrian dataset.

Bhushan *et al.,* (2023) presented a novel method for detecting CHF in PCG recordings. Their method combines traditional ML with full stack DL. DL learns from time-domain (i.e., the raw PCG signal) and spectral representations of the signal, whereas classical ML relies on a large set of features defined by experts. They used both our personal dataset for CHF detection and six public PhysioNet datasets from the recent PhysioNet Cardiology Challenge to evaluate the method's efficacy. They identified 15 expert features that enable ML models to differentiate between CHF phases (decompensated during hospitalisation and recompensated afterwards) with 93.2% accuracy.

Ji & Ke (2023) presented as the red blood cell volume coefficient of variation. Their research sought to evaluate the possible link between RDW levels and all-cause mortality in CHF patients after controlling for other covariates. The findings recorded from the fully adjusted Cox proportional hazard model showed that higher RDW was associated with a greater risk of 30-day, 90-day, 365-day, and 4-year all-cause death; the HRs and 95% confidence intervals were 1.11 (1.05, 1.16), 1.09 (1.04, 1.13), 1.10 (1.06, 1.14), and 1.10 (1.06, 1.13), respectively. The results were stable and reliable using subgroup analysis. Smooth curve fitting and the K-M survival curve method further validated their results.

Nurmaini *et al.,* (2022) proposed a novel, multiple-CHD classification method based on DenseNet201. Their experiments showed that DenseNet201, is superior to state-of-the-art approaches. The proposed model successfully predicts CHDs with good performance, validated with inter-patient data and three expert fetal cardiologists. While CHD is the most common congenital disability, CHD is still relatively rare. The sensitivity, specificity, and accuracy of the DenseNet201 model were 100%, 100%, and 100%, respectively, for the intra-patient scenario and 99%, 97%, and 98%, respectively.

Sarra *et al.,* (2022) proposed two DL-based frameworks, GAN-1D-CNN, and GAN-Bi-LSTM. These frameworks contain: (1) a generative adversarial network (GAN) and (2) a one-dimensional convolutional neural network (1D-CNN) or bi-directional long short-term memory (Bi-LSTM). The GAN model is utilized to augment the small and imbalanced dataset, which is the Cleveland dataset. The 1D-CNN and Bi-LSTM models are then trained using the enlarged dataset to diagnose HD. The proposed frameworks increased the dataset first to avoid the prediction bias caused by the limited data. The GAN-1D-CNN achieved 99.1% accuracy, specificity, sensitivity, F1-score, and 100% area under the curve (AUC). Similarly, the GAN-Bi-LSTM obtained 99.3% accuracy, 99.2% specificity, 99.3% sensitivity, 99.2% F1-score, and 100% AUC. respectively. These results show that it is reliable to use our frameworks for augmenting limited data and predicting heart disease.

Kumar & Ramana (2021) developed a brand-new method for categorizing CVD MRI images and doing severity analysis. They established the Cat Fuzzy Neural Model for identifying CVD disorders like heart attacks, angina, strokes, arrhythmias, and coronary heart diseases. A method for analyzing the severity and segmenting the damaged area from the MRI is called HAC-ABO. With a 0.18% lower error rate than previous methods, this model achieved a prediction accuracy of 99.3%.

Van Velzen *et al.,* (2019) proposed a method for predicting cardiovascular mortality based on lung screening chest CT scans. The results of the trials demonstrate that structures including the coronary arteries, the aorta, and the fat surrounding the heart are likely to contain crucial information for predicting CVD mortality when CAE is performed using FPL. AUC = 0.71, which describes how well the proposed technique performs in describing CVD event prediction.

Liu *et al.,* (2020) suggested a greyscale image segmentation methodology in the PET picture, which is a low-resolution greyscale image, has been improved with an improved Itti method, and an enhance GrabCut image segmentation method. The positioning of the heart in the image is made possible by the convolutional neural network. The placement result crops the original cardiac CT image and removes several non-target areas.

Neyja *et al.,* (2017) presented an e-Health implementation plan for an IoT-based healthcare system that makes use of an HMM chain and ECG sensors. The program aims to improve patient care for those with cardiovascular diseases (CVD) by facilitating better monitoring and prompt intervention. In order to facilitate localization and prompt intervention for the treatment of CVD patients, this implementation makes use of patient route estimators, patient tables, and alert management schemes inside the hospital because real-time patient monitoring from various locations continues to be a significant challenge for IoT-based healthcare systems.

In summation, this literature review not only consolidates the achievements of DL in cardiovascular image analysis but also emphasizes its potential for reshaping the landscape of CHD diagnostics. The closing focus on the RegNet, a lightweight CNN architecture, signals a promising direction for future research in classifying CHDs from normal fetal hearts based on US images.

In the proposed work, a deep neural network named Reg net, a type of lightweight CNN architecture was used for classifying CHD from normal fetal based on US images.

2.2 Research Gap

By analyzing the literature in detail, the following research gaps were identified related to the proposed research problem. Although, several advancements are made in classification of the fetal heart, however it faces a number of challenges like congenital heart defects, to functional problems, such as arrhythmias.

3. Research Methods

In this section, we introduce a novel Reg net for detecting the congenital heart disease (CHD) from ultrasound images. Ultrasound images contains Speckle noise so we used Scrab filter is used to remove Noises. The proposed Reg net for automatic diagnosis of CHD framework includes pre-processing of US images, feature extraction phase, and detection of CHD Reg net noise free images to most relevant features extracted from advanced DL network that used for efficient classification of abnormal and normal the overall workflow of the proposed approach is illustrated in Figure.1.

3.1 Data pre-processing

A total of 363 pregnant women with fetal normal heart or coronary artery disease were enrolled between 18 and 34 weeks. I had a fetal echocardiogram at week. An ultrasound of the foetus was performed on me. Four Showa University hospitals in Japan conducted patient examinations. These ladies all took part in research that had been authorised by institutional review boards at RIKEN, Fujitsu Limited, Showa University, and the National Cancer Centre. The chest grew to fill at least half to two thirds of the screen with the right heart setting. Each video primarily showed a cross-section of the body taken from the stomach level and seen from the apex down through the heart to the vascular arch. The characteristics of CHD are detailed in.

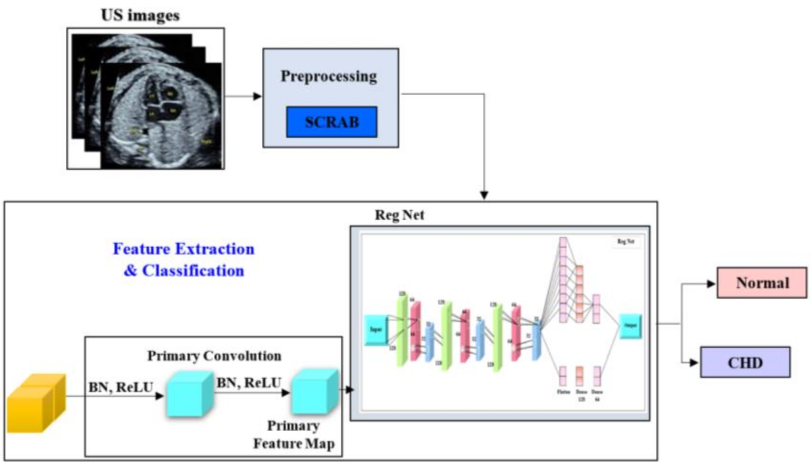

Fig. 1. Architecture of the proposed methodology

3.2 Data pre-processing

Preprocessing is a crucial step in improving small changes in medical imaging by reducing noise. Bilateral filters include noise reduction, nonlinear, levelling, and edge preservation ones. The weighted average intensity of each neighboring pixel is generated using a Gaussian distribution function once the intensity pixel value has been determined. Following that, weights were determined using the Euclidean distance and the radiometric discrepancy. At these parameters, noise in the input image is minimized but image pixel edges are kept. Images with noise record less complete edge variation values. This is seen as a serious weakness of bilateral filters.

$$s_r(u,x,v) = A\,exp(-\frac{1}{2}\left(\frac{||f(u)-f(x)-v(x)||}{\sigma_r})^2\right) + B$$

$$v(x) = \{\left|f(x) - mean\left(\pi_y\right)\right| \; |u-v| \leq z \qquad 0 \quad otherwise$$

Where Ω_y refers to the pixel set of $(2n+1)*(2n+1)$pixel window where n=2.

3.3 Feature extraction and Classification

CNNs are created particularly for classifying and identifying images. Instead of completely linked layers, which would be too expensive for CNNs to use for huge input images, local receptive fields are created for each neuron in hidden layers. Reg net modules are induced in CNN networks, as illustrated in Fig. 2, to minimise network capacity, increase feature utility, and extract multi-scale features at the lowest level. Each neuron in a convolutional layer of neurons receives inputs from earlier layers in a condensed neighbourhood window.

RegNet is an approach for sequentially investigating and creating neural network structures that takes responsibility for the connections among normalization methods, structural selections, and framework performance. Every unit has a 1*1 conv2d, a 3*3 group conv2d, a last 1*1 conv2d, and a ReLU layer after every conv2d level. The pooling layer is the final layer after the layer of convolution. The pooling process is typically applied within the feature networks that have been produced to reduce the total quantity of characteristic visualizations and network configurations by using the appropriate computations. In this investigation, the maximum pooling using stride (s=1) was employed. There were accordingly 128, 64, and 32 units. The max size of input for the framework is 224x224 that is the standard data size for RegNet systems. Flatten level, dense layers, and 9 conv2d layers with filter diameters of 128* 64*32 is employed in the proposed framework. There are a total of 194*903*073 training variables for 224x224 illustrations.

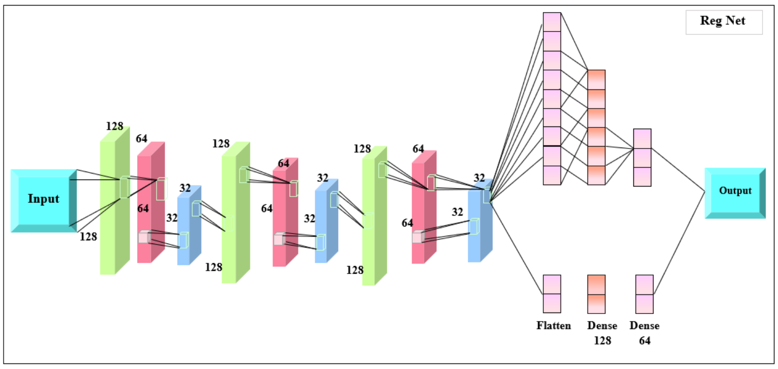

Fig. 2. Architecture of Reg-Net

The design of the RegNet framework was determined by a normalized linear process that was influenced by chosen parameters rather than fixed factors like width and length. After optimization, the following equation was used to determine the unit widths in equation.

$$S_k = \omega_0 + \omega_c . k \;\; for\; 0 \leq k \leq l$$

Each subsequent block extended the breadth of every one by a number of ω_a . The estimation then included an extra variable ω_0 and they estimated as S_k. One way to describe the RegNet module is as follows:

$$\omega_k = \omega_0 . \omega_n{}^{rk}$$

The normalized S_k after scaling rk and computing the encoded per-block dimensions are expressed in equation (4). The width of every phase j was effectively calculated by adding every unit of identical dimension combined to produce each phase. The variable at width W , ω_0 denotes the starting phase, ω_c expressed the gradient, ω_n denotes the variable dimension to establish a RegNet by expressing the RegNet area of design.

4. Results and Discussions

The experimental setup of this research was implemented by utilized MATLAB 2019b, a DL toolbox. In this result analysis, the US images from [14] dataset, it was used for classifying the normal and CHD in the fetal heart. The performance of the proposed approach is calculated using the specific parameters. Furthermore, the calculation of the proposed Reg net is compared with classic DL methods is also provided.

4.1. Performance analysis

The performance calculation is calculated based on accuracy, specificity, sensitivity, precision and F1 score.

$$specficity = \frac{TN}{TN + FP}$$

$$sensitivity = \frac{TP}{TP + FN}$$

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

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

$$f1 = 2(\frac{precision*recall}{precision+recall})$$

To evaluate the performance of the whole segmentation procedure. For his two classes based on US images, the proposed classification model produced encouraging results.

Table 1 - Performance analysis of the proposed methodology

Classes	Accuracy	Specificity	Sensitivity	Precision	F1score
Normal	0.984	0.962	0.942	0.932	0.934

CHD	0.972	0.945	0.912	0.926	0.925

Table.1 illustrates the performance evaluation of the proposed technique based on the accuracy, specificity, sensitivity, F1 score and precision.

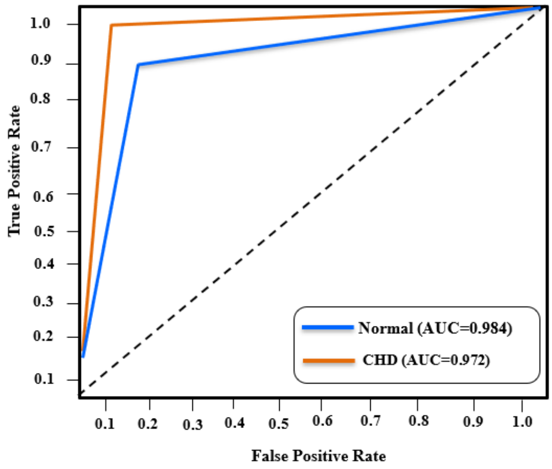

Fig. 3. ROC Curve of The Proposed Method

Based on this evaluation the ROC curve is generated for two classes (normal and CHD) as depicted in fig.3. The proposed classification method achieved high AUC of 0.984 for the normal and AUC of 0.972 for CHD (abnormal) that can be measured via TPR and FPR parameter.

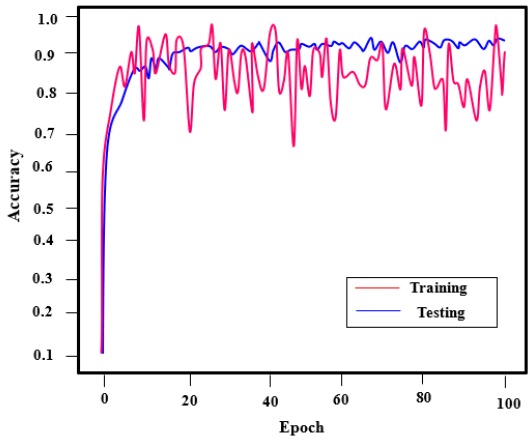

Fig. 4. Training And Testing Accuracy Of The Proposed Network

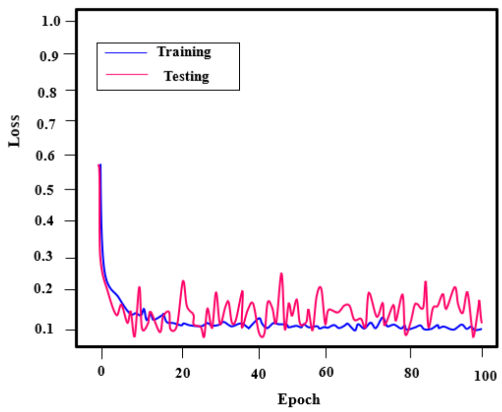

Fig. 5. Training And Testing Loss of The Proposed Network

The testing and training accuracy achieved by the proposed method based on the epochs is given in fig.4. The proposed technique attains the overall acc range of 97.08% Further, training and testing loss is also calculated to determine error rate of proposed model is shown in fig.5, since lower loss rate could lead to a high accuracy result.

4.2. Comparative analysis

In this section, we perform a comparative evaluation of the proposed method and existing DL models. We examined the performance of existing methods on the basis of specificity, sensitivity and accuracy, and illustrated that the results of the proposed method are more efficient. Table 2 illustrates the overall performance comparison between the DL model and the proposed method. From Table 2, deep neural networks such as AlexNet, ResNet, VGG-16, Dense, and MobileNet were compared with the proposed models.

Table 2 - Comparative Analysis of DL Networks With The Proposed Model

Network	Accuracy	Specificity	Sensitivity
AlexNet	91.24	89.04	86.23
ResNet-50	96.32	94.58	91.04
VGG-16	92.53	90.17	87.98
DenseNet	93.57	91.24	88.45
MobileNet	94.41	92.56	89.27
Reg net	97.08	95.35	92.07

The efficiency of the proposed method is evaluated based on the computational cost and the accuracy of the networks as shown in fig.6. The accuracy obtained by the Reg net is 97.08% and the computational cost drastically reduced compared to other networks. Approximately, ResNet-50 gives the accuracy as same as Reg net but it takes high computational cost. Similar to that MobileNet and AlexNet gives the satisfy accuracy but on the other hand they require high computational complexity as well DenseNet. From this analysis the proposed Reg net achieves high range of accuracy than the existing CNN models.

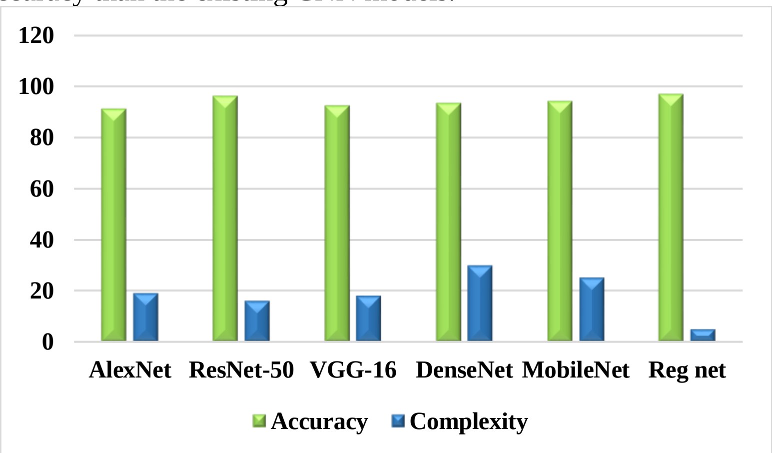

Fig. 6. Comparison Of Existing Deep Learning Networks with Reg Net

5. Conclusion

In this section proposed Reg net network for classifying the normal and abnormal fetal heart based on US images. A total of 363 pregnant women having a fetus with a normal heart or CHD underwent fetal cardiac ultrasound screening at 18–34 weeks. These US images are pre-processed using SCRAB (scalable range based adaptive bilateral filter) for eliminating the noise artifacts. The relevant features are extracted from the US images and classify them into normal and CHD by using the deep Reg net network. The proposed model integrates the Reg net -module with the CNN architecture to diminish the computational complexity and, simultaneously, attains an effectual classification accuracy. The proposed method achieves higher accuracy of 98.4% for the normal and 97.2% for CHD. However, these methods have the potential to be applied as useful surgical guidelines and clinical reports to aid examiners in fetal heart ultrasound imaging.

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