© Universiti Tun Hussein Onn Malaysia Publisher's Office

IJIE

http://penerbit.uthm.edu.my/ojs/index.php/ijie
ISSN : 2229-838X e-ISSN : 2600-7916

The International Journal of Integrated Engineering

A Real and Accurate Ultrasound Fetal Imaging Based Heart Disease Detection Using Deep Learning Technology

Mounika Edupuganti[1], V. Rathikarani[1*], Kavitha Chaduvula[2]

[1]Annamalai University, INDIA

[2]Seshadri Rao Gudlavalleru Engineering College, INDIA

*Corresponding Author

DOI: https://doi.org/10.30880/ijie.2022.14.07.005
Received 1 June 2022; Accepted 22 October 2022; Available online 31 December 2022

Abstract: The heart anomalies detection is a significant task in cardiac medical research. The CT, ULTRASOUND, CTA and MRI scans have been used to detect heart diseases but giving false experimental outcomes in longer time of conversion (ToC). Therefore, patients haven't getting better treatment from doctors. So that in this research work an ultrasound image scan-based heart disease prediction and classification is performed with deep learning technology. The LeNet 10 deep learning classifier has been trained Kaggle dataset using appropriate CNN layers. Proposed CNN LeNet -10 is a 165 layers technology consists of flattened layer, dense layer, convolution layer, max pooling layer and etc. Classification and feature extraction has been performed to loading with LeNet-10 architecture. The real time heart ultrasound test images are collecting from Manipal super specialty hospital Vijayawada, these test features are managed to test.CSV file. In pre-processing step, Ostu segmentation and histogram equalization is applied to make heart ultrasound images to be clear. In Segmentation, edge and region-based convolutional steps are applied such that deep features have been identified. LeNet-10 classification is used to find affected area as well as abnormality location. Finally proposed deep learning with confusion matrix can generating application measures. Implementation has been performed on python 3.9 and DL (Deep learning) packages like TensorFlow, keras, sklearn and etc. The measures like Accuracy 98.37%, sensitivity 97.81%, Recall 98.34% and F1 score 98.98% had been attained, proposed heart disease estimation application is more robust and compete with present technology.

Keywords: Ultrasound heart images, Kaggle dataset, LeNet 10, CNN

1. Introduction

In this section a brief discussion of heart disease of adults, fetal and old age people issues are analyzed. AI is being used in wide range of medical industries; the necessary advancements are required in medical establishment to integrate all diagnosis process including ToC. One in a hundred newborn infants are suffers from congenital heart disease and anomalies. The heart abnormalities are usually found at miss-functionalities of artery or vein connections. In the world 20% of newborn death are caused by serious congenital cardiac diseases. Before birth if anomalies and heart abnormalities has been detected then may be a chance to get successful treatment as well as save the lives [1].

The ultrasound scans have been directed on different trimesters; the following key factors are using to get deep infromation of newborn infant [2]. The fetal heart rate and impressions are giving infromation about healthiness of infants in mothers wombs. The following image infromation has been extracting and loading to corresponding .csv files, these infromation is used to find infants heart anomalies [3]. The available methods such as Genetic algorithm (GA), Particle Swarm algorithm (PSO), X-boosting and many more Machine learning technologies has been facing

*Corresponding author: ritikabateja@gmail.com

ToC as well as accuracy issues [4]. Artificial Intelligence is used to diagnose cardiac problems in foetuses with good accuracy, but application prototype is complex. The veins and arteries have been providing cardiac infromation using kaggle training data. The Fetal heart ultrasound technology can help the doctors to analyze deep infant monitorization. Many medical research organizations and super technology hospitals have been predicting whether congenital heart disease is presented or not [5]. The following scan report consists of any abnormalities, doctors can suggest immediate treatment to child in the mother's womb. In the recent heart diagnosis screening tests have been generating false results with long ToC. The fetus is a small and complex structure, usually doctors cannot be finding abnormalities with normal scan images therefore an additional image processing as well as classification methodologies are compulsory [6]. Advanced deep learning technology is required to observe it through ultrasound examinations as shown in figure 1.

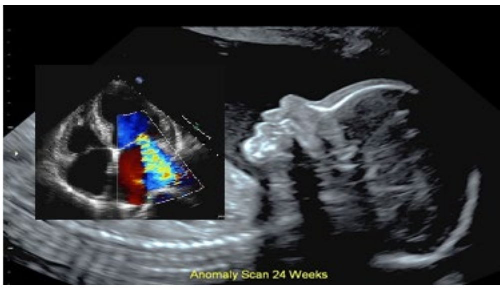

Fig. 1 - Fetal ultrasound heart image

To cross over above limitations, proposing an advanced heart abnormalities detection algorithm. The available models with existed technologies are facing less accuracy and Recall measures. In addition, AI research in ultrasound imaging is extremely complicated with less economy. AI technology has been already used in the medical field for imaging diagnosis support systems in radiography, computed tomography (CT) scanning, and magnetic resonance imaging (MRI). All of which utilize images to identify pathological variations with less accurate outcomes. As a widely discussed application of deep learning, need a large quantity of data (above 100,000 samples) of both normal and abnormal dataset [7]. Meanwhile, congenital heart disease occurs very infrequently, which makes it difficult to accumulate the essential extent of unusual information [8]. The unstructured data sometimes failed to give original features to machine learning. The noise in ultra sound images are major defects but filtration can be helpful tool to remove the unusual shades. High accurate traditional technologies are required to handle diversity of noise patters in medical images. The deep learning technologies are collaborating with this challenge and makes the complex work become simple via training, testing and classification approaches. The object detection in medical image processing can help out abnormalities' estimation easier. The small and un-supervised datasets are not suitable to earlier heart abnormal detection models. In deep learning object detection can be possible with "training mechanism" and "testing mechanism" has been used to find whether input has abnormality or not.

In modern technology deep learning techniques have been rapidly used to developing medical applications. More than 70 types of AI equipped medical applications have been approved by ICMR-India. The Food and drug organizations of America has been approved 100 AI based medical emergency applications. The congenital heart diseases (COHD) cause 99% deaths in children, this COHD accounts less birthrate. The automatic heart diagnosis models are working on various disorders but required some alteration in functionality [9]. The machine learning technologies with numerous approaches are implemented using various datasets. The modality and clinical features are cannot identified deeply using available conventional technologies. Moreover, following study is providing infromation about performance measures like accuracy, sensitivity, recall, F measure and throughput. This heart COHD and heart anomalies detection study makes the physicians functionality simple. The comparative study suggesting weakness and strengths of earlier COHD models. The proposed design can help the ML functionality better and challenging present techniques [10].

2. Literature Survey

In this section a brief discussion on Fetal heart disease prediction as well as, abnormality location and effected area findings had been conferred using present technologies. Moreover, the earlier models are much useful to solve this diagnosis but efficient solution is did not identified [11]. The colour Doppler ultrasound (US), magnetic resonance imaging (MRI), CT and intravascular ultrasound (US) scans are most prominent to get heart abnormal impression on screen. Depending on imaging modality assigned to each training set such that extracting deep features. MRI heart scanning models were able to attend cardiac issues effectively but facing economy issues. More than 60 neurologists, vascular surgeons, and interventional radiologists participated in radiology scanning, which helped to standardize imaging detecting extract circulatory abnormalities. For the first time, the ICMR based MRI heart scan offers to revise colour Doppler US and CT methods using radiology imaging and intravascular ultrasound. Non-invasive and invasive multimodal medical imaging is also needed for open-label or double-blind detection and its monitorization on irregularities suggestive of cardiac [12]. The Deep neural networks are effective CNN models, in this technology many medical image, pattern recognition and computer vision mechanisms are computed with deep analysis. The convolutional layers, dense layer, normalization layer and multi perceptional layers are estimating image based deep features. The classification accuracy, training sensitivity and testing throughputs are major performance measures used to estimating the robustness application [13]. The deep residual neural networks are deeper CNN models which are extracting features from ultrasound images. The FPGA based on-chip design with cardiac diagnosis is an architecture has been used to diagnosis heart abnormalities. [14] The image recognition and homogeneous hyper dense operations are applied on ultrasound medical image. The residual learning applications are explicitly formulating layers with gradient extraction. The CIFAR-10 dataset, can evaluate the features with a depth of up to L = 5 CNN layers which are 1.66x deeper than DNN. The experimental results demonstrate the efficiency of the proposed method and its role in providing the model with a greater capacity to represent features and thus leading to better recognition performance [15].

S.no	Technique	Accuracy	Sensitivity	F-Score	Key point
1.	A deep-learning based multimodal system [16]	81.02%	79.58%	79.84	On the basis of Ai-CovScan, a mass-deployable smartphone app is proposed for heart anomalies detection.
2	Deep Learning [17]	80.25%	81.84%	78.52	The Main Intension of the study is to provide an overview of deep learning process on brain abnormalities detection.
3	Machine intelligence [18]	82.90%	83.33%	79.00	Accurately determining whether a scanned image is healthy or unhealthy by proposed heart abnormalities detection approach.
4	Multimodality intravascular imaging [19]	83.98%	82.77%	77.89	The technical and clinical points are exploring the merits, limits, and prospects for hybrid intracoronary imaging approaches.
5	Multimodal assessments [20]	84.45%	81.65%	79.58	The heart abnormalities detection and diagnosis has been performed using deep learning technology.

Neurological issues with distinctive sorts of disorders are continuously validated the heart failure patients. The neurodegenerative infection that ordinarily begins one small step and develops over the long run, because of this heart failure has been occurred. The continuous heart abnormal issues have been slowly harm body parts and effecting all organs [20]. This indication is initially shows up in their heart-60s. yet, presently it happened in the 50s-40s, and it will be more important to recognize this failure in starting phase as a piece of medical services with the support of ECG signal dissecting associated potentials (ERPs) and balance with multirole wavelet investigation [21]. The AdaBoost & multilayer perception decisions in medical ventilation can estimating heart failures. A brief description of cardiac disorders and diagnostic procedure is provided clearly; in recent years, deep learning models have become increasingly popular for identifying any patterns or computed tomographs. The earlier models are helpful, but the location and influencing region are difficult to categorize [22]. Existing models can detect neurological defects, Down syndrome, and congenital cardiac problems but deep pixels estimation is cannot perform. To overcome the above-mentioned limitations, a powerful LeNet 10 deep learning classifier is proposed [23]. The work flow consists of image selection (CTA/ ultrasound/ Fetal Magnetic Resonance) and image preprocessing, coming to second stage an image high perceptual visual quality has been maintained with LeNet 10 CNN. In the third stage, Ostu segmentation is used to extract features from the input ultra sound heart image. The localization and impacted region estimation can be performed through training and testing procedure. Finally, performance parameters such as accuracy, sensitivity, recall, and throughput are measured and differentiated [24]. The most potential pathways for future research as well as enhancements in current methods are discussed briefly. In this section the discussed models have many limitations and complex functioning to identify the fetal abnormality in ultrasound image. So that an advanced Deep learning-based heart disease diagnosis model is compulsory to cross over all limitations [25].

3. Methodology

In this section a complete detection of fetal heart abnormalities recognition and classification has been performed using LeNet 10 CNN architecture. The limitations of previous studies had been overcome through proposed deep learning technique. The heart ultrasound test images are collected from various super specialty hospitals like "Manipal hospital Vijayawada" and training dataset collected from Kaggle contain 2 lakh samples.

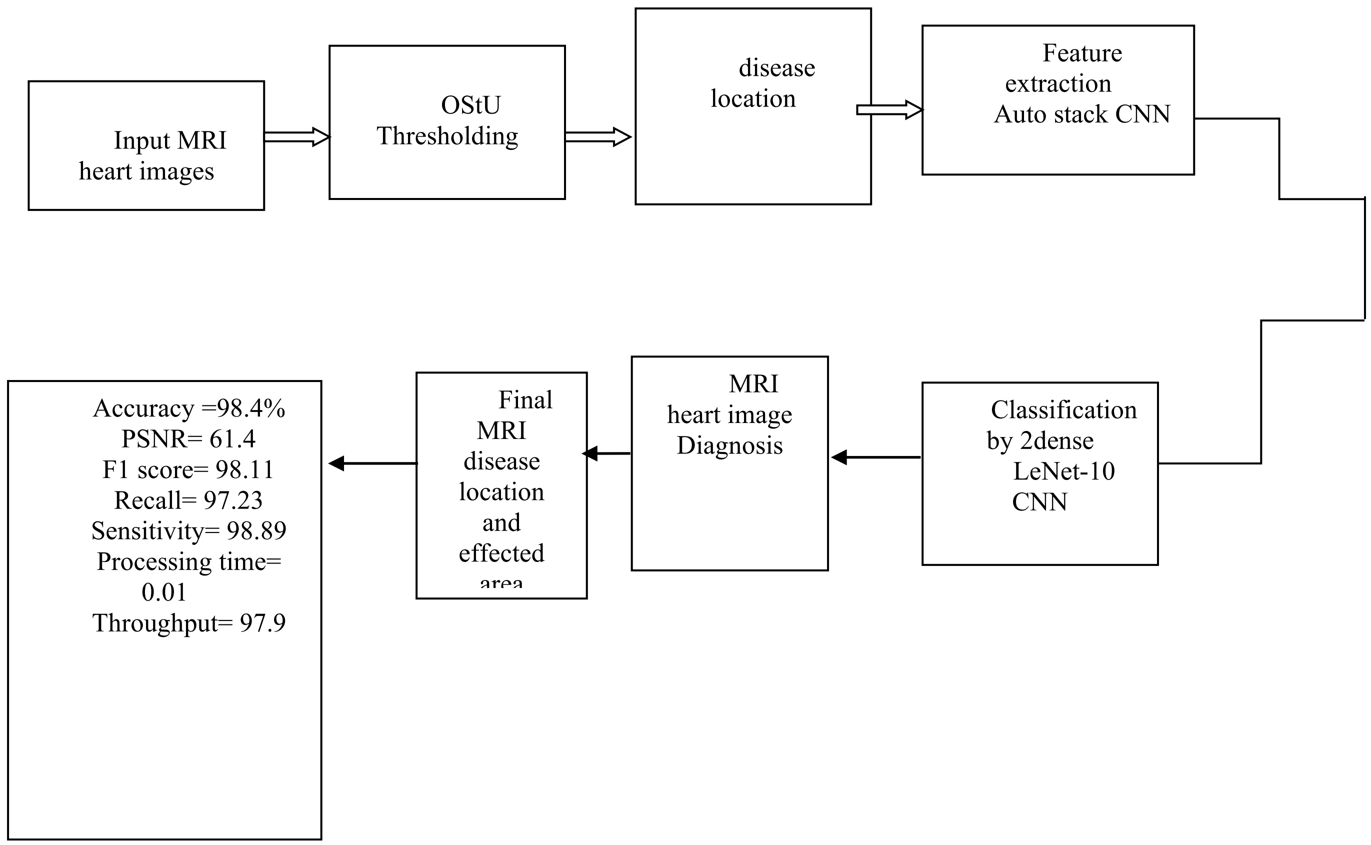

Fig. 2 - Proposed LetNet 10 CNN model

The above figure 4 is clearly explains about MRI heart image-based disease detection, in this method at 1st stage Otsu thresholding-based segmentation is applied on Input MRI heart images. The segmentation mechanism is detecting disease locations as well as disease effecting area. The auto stack CNN process has been extracted features from loading ultrasound images. The classification stage is functioning with LeNet-10 layers architecture. The CNN layers like dense, flatten and max pooling layers are used to get hidden information from ultrasound heart image in the last step heart abnormality and effecting area is classified through proposed Deep learning model. The performance measures are calculating such as accuracy, PSNR, Recall and ToC from confusion matrix.

3.1 Pre-processing and Segmentation

In this section Otsu segmentation model has been used to find the abnormalities in Ultrasound heart image. The pre samples information is extracting through histogram equalization which is shown in equation 1 and 2.

$$im.calcInt(image, channel, mask, histSize[Hist[accumulate]]) \text{ -------------------------}(1)$$

The mathematical computations for histogram adjustment are accumulate the image pixels intensity, pixels density and normalized intensity shown in equation 3. The channel 1 is probability of pixels assignment when gray intensity samples has been participating in segmentation process. The channel 2 is assigned for white pixels intensity calculation with the help of probability density function which is shown in equation 4 and 5.

$$\text{I}mg = im.calcInt(image, channel.mask, histSize\ [Hist\ [accumulate]])\text{----------------}(2)$$

$$Normalized\ histogram: p_i = \frac{n_i}{MN}, i = 0, \ldots, L-1, with \sum_{i=0}^{L-1} p_i = 1, p_i \geq 0 \text{ ------------ } (3)$$

$$Select\ threshold\ T(k)\ to\ segment\ image \rightarrow \begin{matrix} Class\ C_1(values[0,k]) \\ Class\ C_2(values[k+1, L-1]) \end{matrix}$$

$$\Rightarrow Prob\ of\ pixel\ assigned\ to\ C_1(ie\ of\ C_1\ occuring): P_1(k) = \sum_{i=0}^{k} p_i \text{ -------------------- } (4)$$

$$\Rightarrow Prob\ of\ pixel\ assigned\ to\ C_2(ie\ of\ C_2\ occuring): P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k)\text{--- }(5)$$

The pattern recognition and high-level noise elimination are almost improved with global threshold segmentation. The object and background have been separated such that anomalies can be easily identified with color coding.

Ostu: segmentation

Input: normal or abnormal ultrasound heart image
Output: disease or abnormality classified image
Calculate the threshold value

$$T = T\big[x, y\, p(x,y) f(x,y)\big] \text{ ---}(6)$$

Here p(x,y) is local property, f(x,y) is grey level values..
Image segmentation using T. This generates G1 and G2 groups.
G1 is all pixel's grey value>T, G2 is all pixel's grey value ≤ T.
Find out the mean1 and mean2 by using G1&G2.
The new threshold value T=1/2[mean1 + mean2]
Repeat step 3 & step 4 until T got successive iterations.

The above segmentation process has been working based on mean differentiation and averaging of T_h. In this successive iteration concept used to get affected area and location using Euclidian distance concept.

3.2 Auto-stack Feature Extraction

In this section auto stack feature extraction process has been performed through LeNet 10 CNN. in this $\psi(t)$ represent that ultra sound Fetal heart image spectral elements, these elements are balancing pixel intensity in edges of image. Coming to 'β' representing that heart ultra sound image pixel's density function value of Fetal and its various locations of affected area is represented by $\sum_{k=1}^{m} W_{jk} x_k - c_j$. Using this method patients meta-state condition is analyzed with effective manner, furthermore α and θ represent that background as well as foreground irrelevant pixels of ultra sound Fetal Heart respectively. Δ element demonstrates Fetal Heart disease affected pixels.

$$\psi(t) = cos(5t)\ exp(-t^2/2) \text{ ---}(7)$$

$$h_j(out) = \psi_{a,c}(j) = cos\left(5 * \frac{\sum_{k=1}^{m} W_{jk} x_k - c_j}{a_j}\right) * exp\left(-\frac{1}{2}\left(\frac{\sum_{k=1}^{m} W_{jk} x_k - c_j}{a_j}\right)^2\right) \text{ -------------}(8)$$

Equation 7 & 8 are used to find the wavelets of autoencoder and generating output from the sigmoid function. This is a reconstructed model from auto-encoder.

$$E = \frac{1}{s}\sum_{s=1}^{s}\left[\frac{1}{2}\sum_{i=1}^{m}(\hat{x}_i^s - x_i^s)^2\right] + \beta\left(\sum_{j=1}^{p} plog\ \frac{p}{\hat{p}_j} + (1-p) log\ \frac{1-p}{1-\hat{p}_j}\right)\text{--}(9)$$

Equation 9 represents that dimensional input Image and reconstructed output. $\hat{x}_i^s \& x_i^s$ represents that input image. plog $\frac{p}{\hat{p}_j}$ It denoted that divergence function. These parameters are used to reconstruct the output image.

$$W_{ij}(t+1) = W_{ij}(t) - \eta \frac{\partial E(t)}{\partial W_{ij}} + \alpha \Delta W_{ij}(t) \text{--} (10)$$

$$W_{ij}(t+1) = W_{ij}(t) - \eta \frac{\partial E(t)}{\partial W_{ij}} + \alpha \Delta W_{ij}(t) \text{- --} (11)$$

$$\alpha(t+1) = a_j(t) - \eta \frac{\partial E(t)}{\partial \alpha_j} + \alpha \Delta a_j(t) \text{--- --} (12)$$

$$c_j(t+1) = c_j(t) - \eta \frac{\partial E(t)}{\partial c_j} + \alpha \Delta c_j(t) \text{--- --} (13)$$

Equation 10 to 13 are the optimized training parameters; by using these elements to diminishing the reconstruction error. This can make possible only with threshold iterations, in order to improve the quality of the super learning features, it should be constructing the stack architecture, which is shown in fig 3.

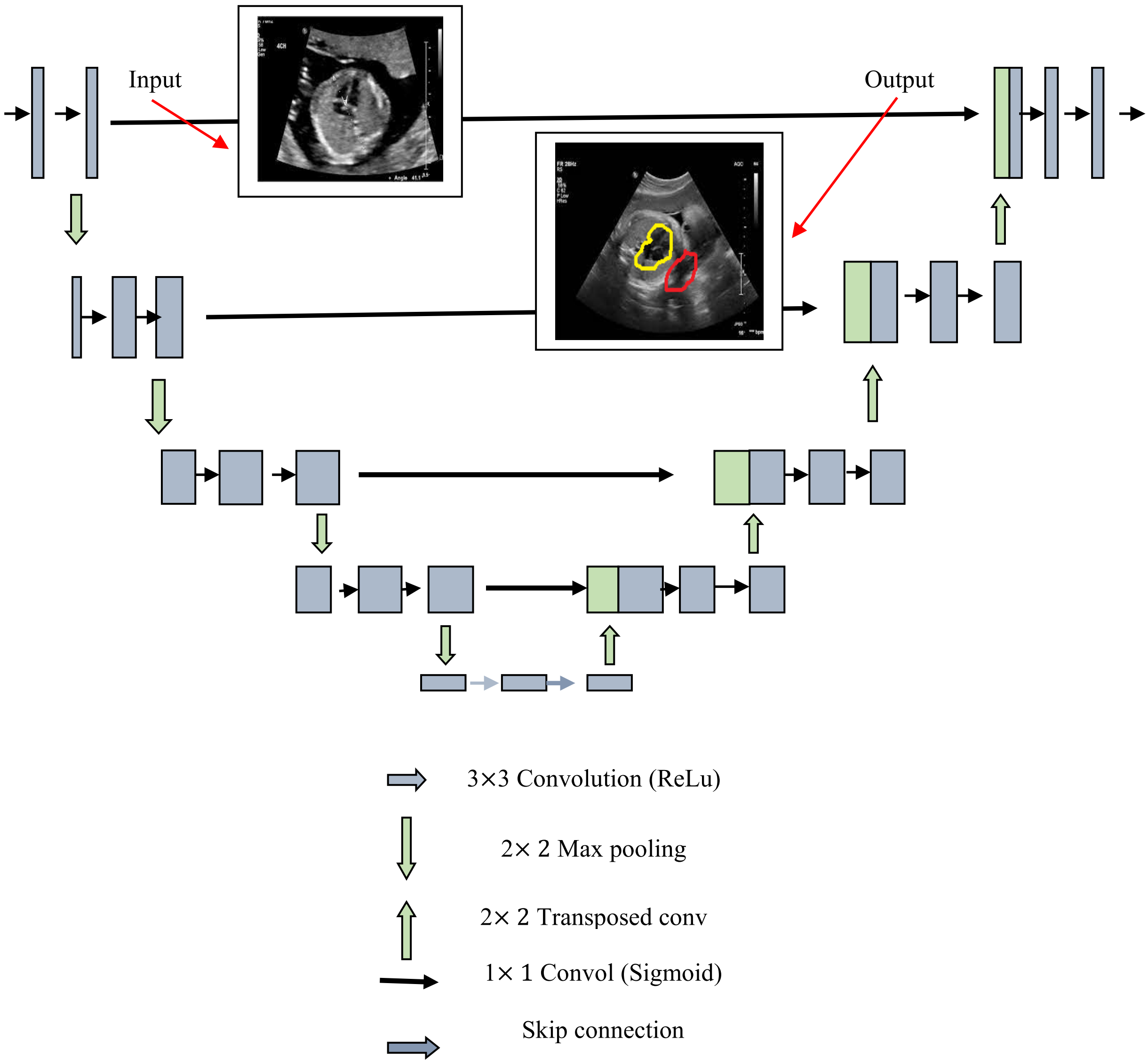

Fig. 3 - CNN auto stack architecture

$$H\beta = T$$

$$H = \begin{bmatrix} g(w_1.X_1 + b_1) & \cdots & g(w_s.X_1 + b_s) \\ \vdots & \dots & \vdots \\ g(w_1.X_s + b_1) & \cdots & g(w_s.X_s + b_s) \end{bmatrix}_{s*s} \text{--(14)}$$

$$\beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_{\hat{s}} \end{bmatrix}_{\bar{s}*1} \text{ and } T = \begin{bmatrix} t_1 \\ \vdots \\ t \end{bmatrix}_{s*1} \text{---(15)}$$

Equation 14 & 15 explains that confused matrix, this can be helpful for hidden information extraction. H is the output matrix, β output weighted vector and T is the Target matrix. The above mathematical computations are used to calculate the target matrix, which is an accurate Fetal Heart image feature extractor.

3.3 LeNet 10 Classification

LeNet 10 architecture is used to categorized the extracted features, such that getting abnormalities and hidden infromation. The layers like as dense, flatten, and max pooling layers has been used to classify the fetal heart affected area.

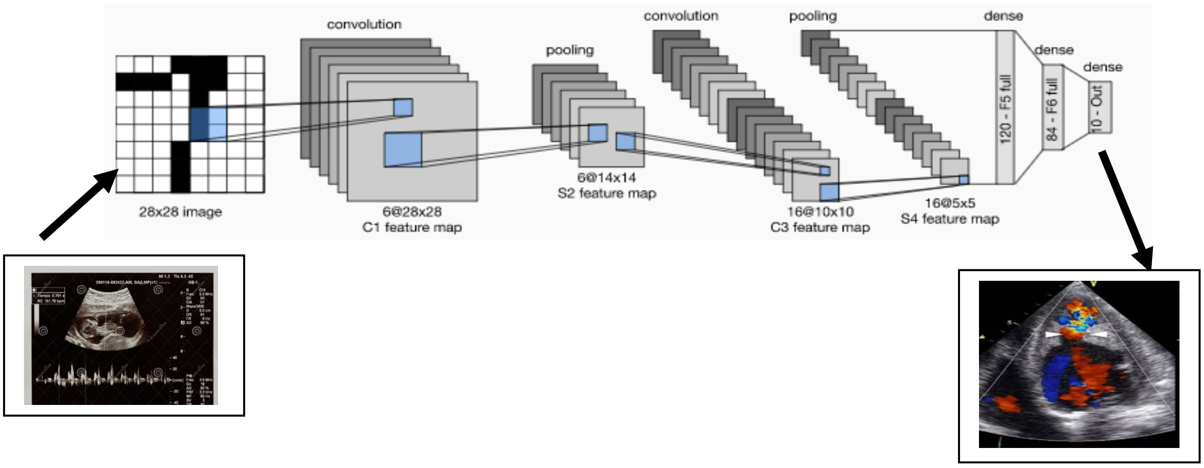

Fig. 5 - LeNet 10 architecture

The CNN deep learning models have been used to get normalized multiple layers information. The medical Image processing applications have been needing a modern and trending algorithm. The following functionality can be performed through LeNet -10 deep learning technique. The core functionality of LeNet 10 is purely evaluate the testing and training data [10]. This pathology also called an overfit function of the learning model which can Usually, orthogonal least square (OLS) models are used for Image error calculations. The fundamental least square equations do not estimate the cost function and minimization of the error function.

$$\sum_{i=1}^{M}(y_i - \hat{y_i})^2 = \sum_{i=1}^{M}\left(y_i - \sum_{j=0}^{p} w_j * w_{ij}\right)^2 \text{-------------------------------------(16)}$$

Equation 16 calculates the prediction variables such as p1, p2 &p3 (eg. Hight, sex and diet). In this p1 and p2 are interlinked with correlation function. But, p3 did not satisfy the statistical parameter related to p1 &p2, which is shown clearly in the above equation.

$$\frac{\sum_{i=1}^{M}\left(y_i - x_i^j\hat{\beta}\right)^2}{2n} + \lambda\left(\frac{1-\alpha}{2}\sum_{j=1}^{m}\hat{\beta}_j^2 + \alpha\sum_{j=1}^{m}|\hat{\beta}_j|\right).\text{- -------------------------------------(17)}$$

Equation 17 explains that LeNet 10 CNN fitness function with the accurate deep analysis. L1 = Regularization property (LASSO) & L2= Regularization (RIDGE). This is the best model for estimation and minimization of both bias and variance. L2 follows OLS equation 17 and calculate the magnitude of coefficients. In this case, when λ = 0 this becomes a normalized equation. Therefore, shrinking coefficients are leads to lower, and variance tense to 0. So, instead of equation 16 & 17, LeNet 10 has been used to evaluate the coefficients, which is shown in below equation 18.

$$\hat{\beta} = arg_\beta minRSS(\hat{\beta}) = arg_\beta min\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j\right)^2 \text{----------------------(18)}$$

$$\hat{\beta}_{Ridge} = arg_\beta minRSS(\beta) \text{ --(19)}$$

$$= arg_\beta min\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{k}\beta_j^2\right\}\text{----------------------------(20)}$$

$$\hat{\beta}_{LASSO} = arg_\beta min\left\{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{k}|\beta_j|\right\}\text{------------------(21)}$$

$$R_{adj}^2 = 1 - (1 - R^2)\frac{n-1}{n-p-1} \text{------} (22)$$

Equation 19 to 22 describes that LeNet 10 deep normalized fitness function calculations, in this R_{adj}^2 denoted that determination of coefficients and n represents the size of the sample and p denoted that the total number of variables in the model.

$$X = TP^T + E$$

$$Y = TQ^T + F$$

$$T = XW(P^TW)^{-1} \text{------} (23)$$

Where T,P & E are the score which are generating from confusion matrix, loading and residual of X are used to calculating the partial least square errors. This option is not available in any CNN deep learning algorithms.

$$\hat{y} = X_{new}\beta_{PLS}$$

$$\beta_{PLS} = W(P^TW)^{-1}Q^T \text{------} (24)$$

Equation 24 represents that k fold validation function; this can give the principal component values in the LeNet 10. Above all steps are used to classify the ultra sound fetal heart abnormalities diagnosis and affected area classification.

3.4 Performance Measure

In this section proposed LeNet 10 deep learning classifier application performance measures have been acknowledged using confusion matrix. The measures like accuracy, F1 score, Recall and true positive rate have been differentiated with earlier models. The below mathematical computations are used to estimating performance metrics which are shown inequation 25 to 30

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \text{------} (25)$$

$$\frac{RMSEP(i^*)}{RMSEP(i)} \geq \lambda$$

$$NMSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{{y_i}^2} \text{------} (26)$$

$$\hat{\beta}_{enet} = \left(1 + \frac{\lambda_2}{n}\right)\left\{arg_\beta\, min\left\|\lambda - \sum_{j=1}^{p} x_i\beta_j\right\|^2 + \lambda_1\|\beta\|_1 + \lambda_1{\|\beta\|_2}^2\right\} \text{------} (27)$$

$$Accuracy = \hat{\beta}_{enet} + R_{adj}^2 / = \hat{\beta}_{enet} + R_{adj}^2 + Fp + Fn. \text{------} (28)$$

$$F1\ score = Fp + Fn./Tp. \text{------} (29)$$

$$Tp = 1 - \frac{SSR}{SST}. \text{------} (30)$$

The above all mathematical computations are finding performance measures using RMSEP (Root Mean Square Error), NMSE (Normalize Mean Square Error), accuracy and F1-measure.

4. Results and Discussion

In this section experimental outcomes of proposed methods have been discussing by using LeNet 10 CNN python application. The heart abnormalities are identified from the real time heart ultrasound images which are collected from Manipal super specialty hospital Vijayawada. The valuable packages like TensorFlow, karas and NumPy has been used to constructed LeNet CNN architecture. The segmentation is performed through Histogram python package and auto stacking performed thought GoogleNet package which is readily available. The training dataset is nothing but Kaggle consists of 2 lakh heart normal and abnormal images. The below figure 6 is briefly explains about input ultra sound test image consists of normal and abnormal features.

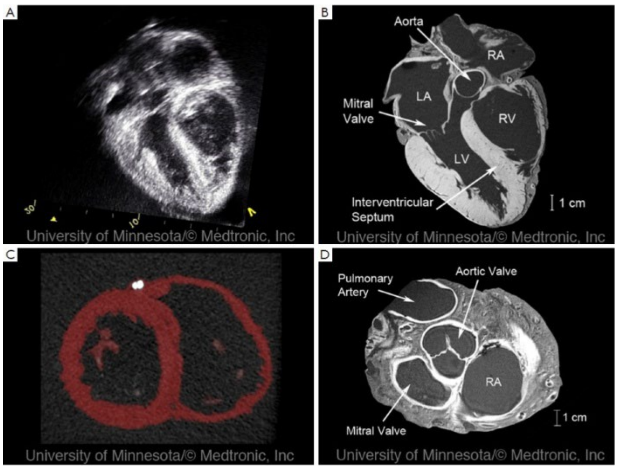

Fig. 6 - Input image

The figure 7 clearly explains about Ostu threshold segmentation process, in this object and foreground is separated through “mean between variance” and “average between mean” concepts. The deep features like affected area and location also been found using Ostu threshold segmentation process.

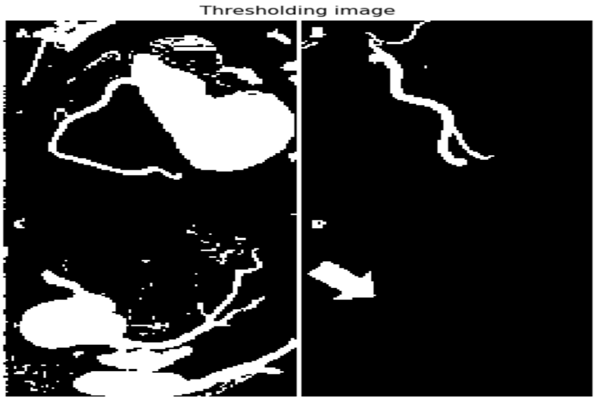

Fig. 7 - Segmented image

Figure 7 is clearly explaining about disease location and affected area, in this impression dark color region is most effected with disease. The following feature are extracting from LeNet-10 CNN modeming.

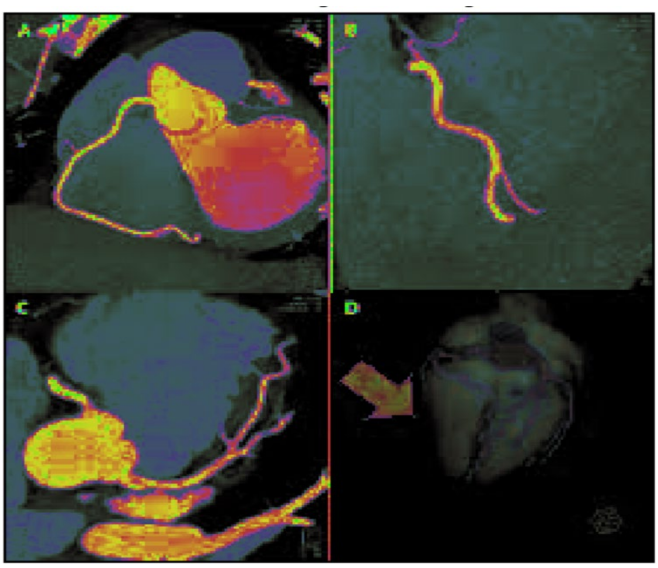

Fig. 8 - Disease location

The below figure 8 is describing that GUI of proposed application, which is implemented on python 3.7.0 software tool. This application consists of 6 buttons which are nothing but upload, train & test, Auto stack & LeNet 10, driveHq cloud and prediction. The upload button can call training sample from Kaggle dataset, which is available at local server. The train and test button can perform training as well as testing functionality such that extracting deep features. Auto-stack encoder block has been used to normalized the data and ready estimate heart disease on ultrasound image. The test images have been collected from DriveHq cloud which is freely available cloud platform. Finally, prediction block has been used to classify the test image whether the input consist of abnormality or not.

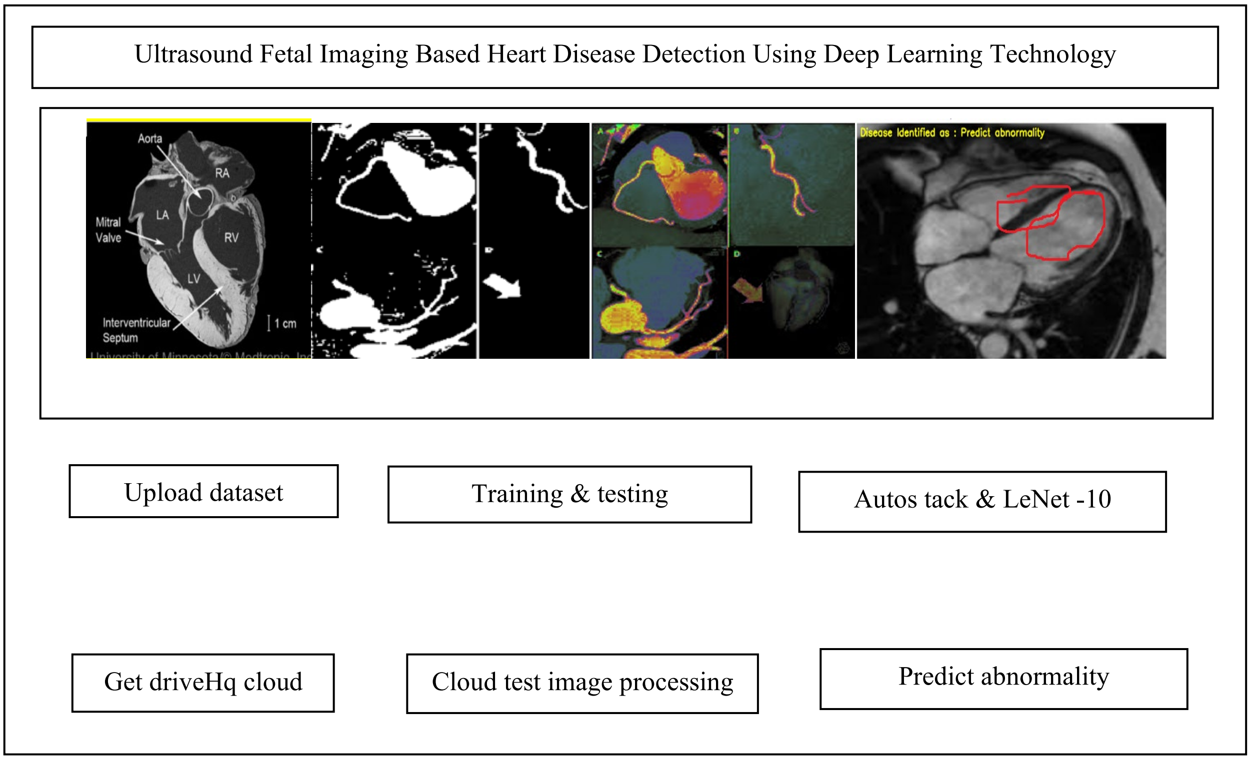

Fig. 9 - GUI LeNet 10 design

The below table 1 is explans about layers architecture and corresponding LetNet 10 CNN calling, in this convolutional layer, dense layer, pooling layer and ReLu layers have been came to picture. In these 3,696,354 samples are extracted and 10000 samples are testing.

Table 1 - Model: "sequential_1"

Layer (type)	**Output Shape**	**Param #**
conv2d_1 (Conv2D)	(None, 126, 126, 32)	320
max_pooling2d_1 (MaxPooling2	(None, 63, 63, 32)	0
conv2d_2 (Conv2D)	(None, 61, 61, 32)	9248
max_pooling2d_2 (MaxPooling2	(None, 30, 30, 32)	0
flatten_1 (Flatten)	(None, 28800)	0
dense_1 (Dense)	(None, 128)	3686528
dense_2 (Dense)	(None, 2)	258

==

Total params: 3,696,354
Trainable params: 3,696,354
Non-trainable params: 0

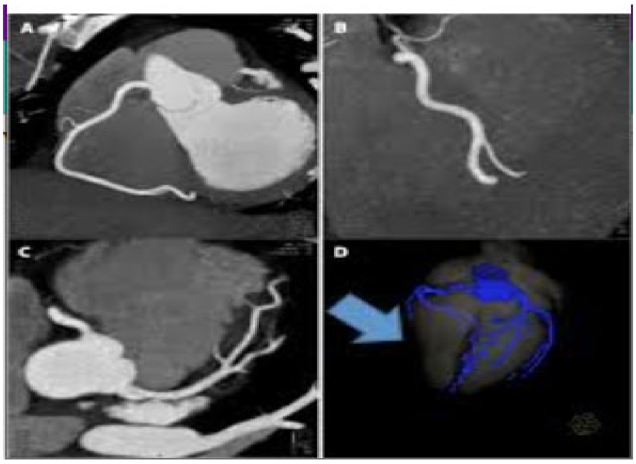

Fig. 10 - Disease detection area

Figure 10 is clearly explaining about fetal heart disease detection and affected area analysis, a blue color indication is representing that affected area percentage in the heart ultra sound image.

CNN Model Generated. See black console to view layers of CNN
CNN Prediction Accuracy on Test Images: 98.7109012851715
CNN Prediction PSNR on Test Images: 62.50990128517151
CNN Prediction F1_score on Test Images: 98.90090128517151
CNN Prediction Recall on Test Images: 95.68090128517152
CNN Prediction Sensitivity on Test Images: 98.22090128517151
CNN Prediction Processing time on Test Images: 0.019901285171513905
CNN Prediction Throughput on Test Images: 98.90890128517151

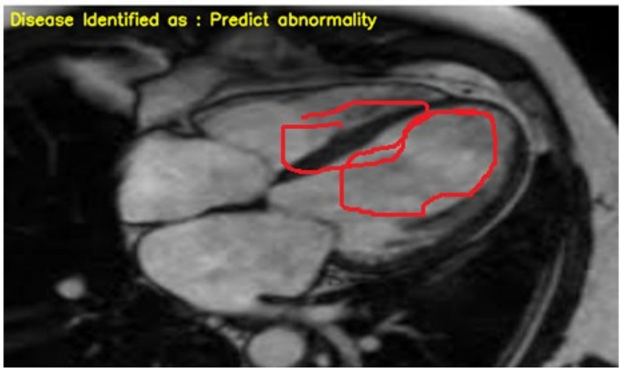

Fig. 11 - Disease classification area

Figure 11 is clearly explaining about final disease classification and abnormality detection, the test image is calling from DriveHq cloud. The affected area is noted as 11mm which was detected on python GUI window. These experimental results are more useful to find abnormalities in the heart values.

Table 2 - Comparison of results

S No	Accuracy	Sensitivity	Recall	F measure
RFO [5]	87.23	82.34	84.35	89.23
DT [6]	89.23	88.94	89.23	91.28

X boosting [7]	90.12	90.23	90.12	92.29
Proposed	98.37	97.81	98.34	98.98

Table 2 is clearly explaining that proposed LeNet -10 CNN performance measures estimation and differentiation with existed methods. In this RFO [5] (random forest optimization), DT [6] (Decision tree) and X boosting models [7] are comparing. It is identified that proposed LetNet-10 based CNN model attains more improvement than the previous RFO, DT, and X-Boosting model's in terms of Accuracy, Sensitivity, Recall, and F measure [14].

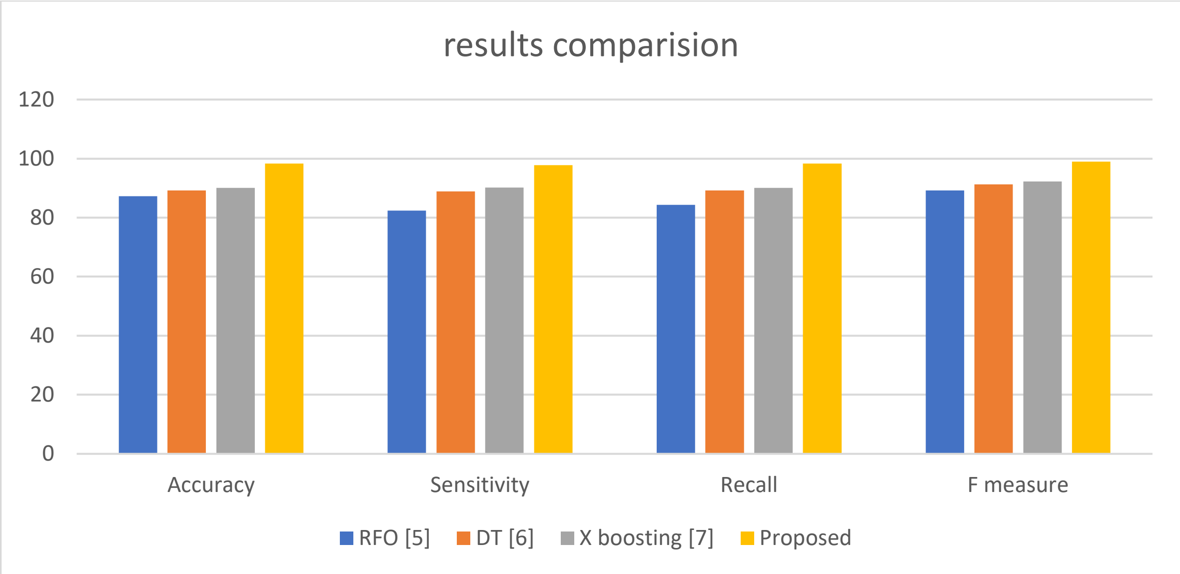

Fig. 12 - Comparisons of results

Figure 12 is clearly explaining about comparison of earlier models with proposed model, in this RFO (random forest optimization), DT (Decision tree) and X boosting models are comparing [15]. It is identified that proposed LetNet-10 based CNN model attains more improvement.

5. Conclusion

In this research work LeNet-10 CNN deep learning based fetal heart abnormality detection has been performed. The earlier stage applications have been getting less accurate outcomes with large ToC. The doctors and physicians are cannot identify deep abnormal features from ultrasound heart images. The LeNet 10 CNN deep learning classifier uses suitable layers to train architecture and evaluate Kaggle dataset. In this investigation CNN deep learning classifier extracting hidden features such that reconstructing abnormal locations with dark color. The proposed CNN is a 165 layers deep learning architecture consists of flattened layer, dense layer, convolution layer, max pooling layer and etc. The real time test heart ultrasound images are collecting from Manipal super specialty hospital Vijayawada, these are loaded to driveHq cloud. This work at initial stage applying pre-processing tools followed by Otsu threshold segmentation, classification has been performed with LeNet 10 deep learning model. This implementation has been performed with python 3.7.0 and packages in terms of TensorFlow, keras, sklearn and NumPy. This application generating performance measures like accuracy 98.37%, sensitivity 97.81%, Recall 98.34% F1 score 98.98% had been attained through confusion matrix.

References

[1] Paladini, D., Tartaglione, A., Agangi, A., Teodoro, A., Forleo, F., Borghese, A., & Martinelli, P. (2000). The association between congenital heart disease and Down syndrome in prenatal life. Ultrasound in Obstetrics and Gynecology, 15(2), 104-108.

[2] Al-Janabi, Maryam I., Mahmoud H. Qutqut, and Mohammad Hijjawi. "Deep learning classification techniques for heart disease prediction: a review." International Journal of Engineering & Technology vol.7, no.4 , pp.5373-5379, 2018.

[3] J. Soniet al., “Intelligent and effective heart disease prediction sys-tem using weighted associative classifiers,” International Journal on Computer Science and Engineering, vol. 3, no. 6, pp. 2385–2392, 2011.
[4] Nikhar, Sonam, and A. M. Karandikar. "Prediction of heart disease using deep learning algorithms." International Journal of Advanced Engineering, Management and Science, vol.2, no.6,2016.
[5] H. Almarabeh and E. Amer, “A study of data mining techniques accuracy for healthcare,” International Journal of Computer Appli-cations, vol. 168, no. 3, pp. 12–17, Jun 2017.
[6] K. Polaraju, D. Durga Prasad, “Prediction of Heart Disease using Multiple Linear Regression Model”, International Journal of Engineering Development and Research Development, 2017.
[7] Marjia Sultana, Afrin Haider, “Heart Disease Prediction using WEKA tool and 10-Fold cross-validation”, The Institute of Electrical and Electronics Engineers, March 2017.
[8] Dr.S.SeemaShedole, KumariDeepika, “Predictive analytics to prevent and control chronic disease”, https://www.researchgate.net/punlication/316530782, January 2016.
[9] Ashok kumarDwivedi, “Evaluate the performance of different deep learning techniques for prediction of heart disease using ten-fold cross-validation”, Springer, vol. 17, September 2016.
[10] MeghaShahi, R. KaurGurm, “Heart Disease Prediction System using Data Mining Techniques”, Orient J. Computer Science Technology, vol.6, pp.457-466, 2017.
[11] Mr. ChalaBeyene, Prof. PoojaKamat, “Survey on Prediction and Analysis the Occurrence of Heart Disease Using Data Mining Techniques”, International Journal of Pure and Applied Mathematics, 2018.
[12] Komatsu, M., Sakai, A., Komatsu, R., Matsuoka, R., Yasutomi, S., Shozu, K., & Hamamoto, R. (2021). Detection of cardiac structural abnormalities in fetal ultrasound videos using deep learning. Applied Sciences, 11(1), 371.
[13] Guo, M., Wang, K., Liu, S., Du, Y., Liu, P., Su, Q., & Lv, G. (2021). Recognition of Thyroid Ultrasound Standard Plane Images Based on Residual Network. Computational Intelligence and Neuroscience, 2021.
[14] Wu, B., Wu, H., Du, Y., & Liu, P. (2021, October). Automatic Recognition of Fetal Heart Standard Section Based on Fast-RCNN. In 2021 IEEE 15th International Conference on Anti-counterfeiting, Security, and Identification (ASID) (pp. 70-73). IEEE.
[15] Wang, J., Li, J., Wang, L., Ma, X., & Huang, Y. (2022). Heart disease diagnosis using deep learning and cardiac color doppler ultrasound. Soft Computing, 1-10.
[16] Sait, U., KV, G. L., Shivakumar, S., Kumar, T., Bhaumik, R., Prajapati, S., ... & Chakrapani, A. (2021). A deep-learning based multimodal system for Covid-19 diagnosis using breathing sounds and chest X-ray images. Applied Soft Computing, 109, 107522.
[17] Nadeem, M. W., Ghamdi, M. A. A., Hussain, M., Khan, M. A., Khan, K. M., Almotiri, S. H., & Butt, S. A. (2020). Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges. Brain sciences, 10(2), 118.
[18] Amin, J., Sharif, M., Yasmin, M., Saba, T., & Raza, M. (2020). Use of machine intelligence to conduct analysis of human brain data for detection of abnormalities in its cognitive functions. Multimedia Tools and Applications, 79(15), 10955-10973.
[19] Li, J., Montarello, N. J., Hoogendoorn, A., Verjans, J. W., Bursill, C. A., Peter, K., ... & Psaltis, P. J. (2022). Multimodality intravascular imaging of high-risk coronary plaque. Cardiovascular Imaging, 15(1), 145-159.
[20] Lum, F. M., Zhang, W., Lim, K. C., Malleret, B., Teo, T. H., Koh, J. J., ... & Ng, L. F. (2018). Multimodal assessments of Zika virus immune pathophysiological responses in marmosets. Scientific reports, 8(1), 1-13.
[21] Saikumar, K. Rajesh V. (2020). Coronary blockage of artery for Heart diagnosis with DT Artificial Intelligence Algorithm. Int J Res Pharma Sci, 11(1), 471-479.
[22] Surekha, S., Rahman, M.Z.U. (2021). Spectrum Sensing for Wireless Medical Telemetry Systems Using a Bias Compensated Normalized Adaptive. International Journal of Microwave and Optical Technology, 16 (2),124-133
[23] Lay-Ekuakille, A., Ugwiri, M. A., Liguori, C., Singh, S. P., Rahman, M. Z. U., & Veneziano, D. (2021). Medical image measurement and characterization: extracting mechanical and thermal stresses for surgery. Metrology and Measurement Systems, 28(1), 3-21.
[24] Bheesetti, D. S. K., Bhogadi, V. N., Kintali, S. K., & Rahman, M. Z. U. (2021). A Complete Home Automation Strategy Using Internet of Things. In ICCCE 2020 (pp. 363-373). Springer, Singapore.
[25] K, Saikumar & V, Rajesh. (2020). Coronary blockage of artery for Heart diagnosis with DT Artificial Intelligence Algorithm. International Journal of Research in Pharmaceutical Sciences. 11. 471-479. 10.26452/ijrps.v11i1.1844.