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Fetal Heart Abnormality Detection in Prior Stage Using LeNet 20 Deep Learning Architecture

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ABSTRACT

Heart abnormalities are significant in medical diagnosis, traditionally detected through CT, X-ray, CTA, and MRI scans. However, these methods often yield inconclusive or erroneous results, leading to ineffective clinical recommendations. This study focuses on using ultrasound heart data for fetal anomaly prediction and classification, aiming to overcome the limitations of existing diagnostic methods. The purpose of this investigation is to develop a more reliable method for detecting fetal heart anomalies using deep learning techniques, specifically leveraging the LeNet 20 architecture. The goal is to improve the accuracy and reliability of fetal anomaly detection compared to conventional methods. Real-time fetal ultrasound heart samples were collected from NIMS super specialty hospital, Hyderabad, and pre-processed using tools such as Otsu threshold separation. The LeNet 20 convolutional neural network, consisting of 165 layers with max pooling, dense, hidden, and ReLU layers, was implemented using Python with TensorFlow, Keras, and scikit-learn libraries. The dataset was loaded as test samples via CSV files, and the LeNet 20 CNN model was employed for classification. The proposed LeNet 20 CNN model achieved significant improvements over existing fetal heart diagnosis models. Key findings include a detection score of 98.32%, F1 score of 98.23%, recall of 97.89%, accuracy of 98.32%, and sensitivity of 97.29%. These results indicate superior detection accuracy and reliability compared to previous methods. results of this study demonstrate notable enhancements over prior fetal heart diagnosis technologies. Specifically, the LeNet 20 CNN model outperformed existing methods in terms of detection accuracy and reliability. This investigation successfully addresses the limitations of conventional fetal heart diagnosis methods by employing CNN deep learning technology. The LeNet 20 architecture serves as an effective classifier and feature extractor, enabling accurate detection of fetal heart anomalies in prior stage.

1. INTRODUCTION

This section analyses concerns related to fetal, adult, and elderly heart disease in short. Today, a wide range of businesses are using AI. Medical institutions are making strides to include technology that enable medical image diagnosis. Congenital cardiac disease affects one in every 100 newborns. Defects in the heart or vein connections serve as a defining characteristic of this illness. Significant congenital heart disorders are responsible for 20% of newborn deaths. Meanwhile, medical equipment is continually improving. The likelihood of an effective therapy improves, and prospective outcomes are improved, especially when the condition is identified before birth and proper steps are followed. Fetal cardiac ultrasonography screening, a test procedure used during prenatal exams, is essential to attaining this. The universities and research institutions collaborated to develop the novel fetal cardiac ultrasound screening technology. With high accuracy, artificial intelligence is utilized to identify cardiac issues in fetuses, and the results are presented in an understandable way. The AI developed and learnt training data on healthy fetus hearts, including the ideal positions for each component to appear in. The data is then compared with the real heart and great veins to look for any problems. The outcomes are shown in real-time list format [1].

Fetal heart abnormalities represent a significant concern in prenatal care, necessitating accurate and timely detection for appropriate intervention. Conventional diagnostic methods often lack the sensitivity and specificity required for early-stage detection, leading to potential complications and suboptimal treatment outcomes. This study addresses this gap by proposing a deep learning-based approach utilizing the LeNet 20 architecture for early detection of fetal heart abnormalities. This introduction presents the research problem, its importance, and how the current study fits into the larger body of research.

In collaboration with OB-GYN physicians, the Fetal Cardiac Ultrasound Screening Technology is being established. Many medical professionals firmly believe that early detection of congenital cardiac disease is essential. Setting up specific arrangements before birth is believed to boost the likelihood of success in treating congenital heart disease (for example, by making the necessary preparations during the fetal period in a hospital with medical professionals and giving birth under a scheduled delivery schedule). However, despite recent increases, the incidence of diagnosis using screening tests is still inadequate. A fetus's heart is tiny, intricately structured, and beats quickly. Ultrasound tests are needed to see it, which calls for sophisticated technology. The examination method heavily relies on expertise, which causes discrepancies dependent on the abilities of people administering the test. In addition, there are differences in the quality of medical treatment between areas as a result of a decline in the number of OB-GYN physicians and their concentration in big cities [2].

The capacity to reliably identify cardiac illness in foetuses and transmit this data to clinicians has become a critical concern in order to close these gaps. Form a study team including an OB/GYN physician, an investigator from the Cancer Translational study Team of the Centre for Advanced Intelligence Project, an expert in the diagnosis of deadly heart rate ultrasonography, and an associate professor from the Showa University School of Medicine. The Figure 1 clearly explains about fetal ultrasound image and its orientations.

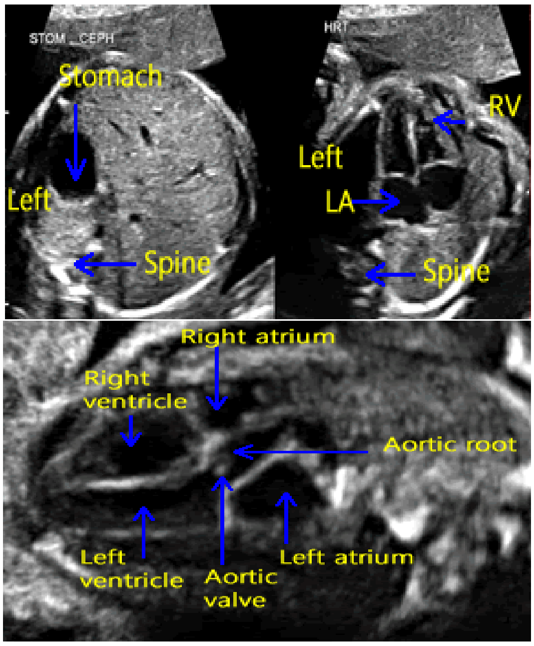

Figure 1. Fatal ultrasound heart image

1.1 Research problem

The inability to detect fetal heart abnormalities in the prior stage of development poses a critical challenge in prenatal healthcare. Early detection is essential for guiding interventions and improving patient outcomes. However, existing diagnostic modalities often fall short in providing accurate and reliable detection at this crucial stage.

1.2 Importance

Early detection of fetal heart abnormalities is paramount for facilitating timely interventions and optimizing patient care. By leveraging deep learning techniques, such as the LeNet 20 architecture, this study aims to improve the accuracy and efficiency of fetal anomaly detection, thereby enhancing prenatal care and reducing the risk of adverse outcomes. Establishing Within Existing Literature: The existing literature on fetal anomaly detection encompasses various methodologies, including traditional imaging techniques and machine learning-based approaches. Thematically organizing related work reveals the evolution of research in this area, highlighting advancements in diagnostic methodologies and the ongoing quest for improved accuracy and reliability. demonstrating promising results in enhancing diagnostic accuracy. However, gaps persist in achieving early-stage detection with sufficient reliability. This study aims to address these limitations by proposing a novel approach using the LeNet 20 architecture. Objectives: This study seeks to develop and evaluate a deep learning-based approach for the early detection of fetal heart abnormalities using the LeNet 20 architecture. The objectives include: Utilizing real-time fetal ultrasound data to train and validate the LeNet 20 CNN model for accurate classification of heart anomalies. Comparing the performance of the proposed method with existing diagnostic techniques, emphasizing metrics such as sensitivity, specificity, and overall accuracy. Assessing the clinical utility and potential impact of the developed tool in prenatal care settings, with a focus on facilitating early intervention and improving patient outcomes.

As previously said, ultrasound examination equipment is needed to diagnose foetuses. Additionally, ultrasonic imaging AI research is really challenging. The DL and ML based medical mage diagnosis can helps the patients using MRI, ultra sounds and CT scan radiology samples. Deep learning requires a significant amount of data (over 100,000 pieces) that includes both normal and abnormal data in order to learn, making it an extensively debated use of the technology. Congenital cardiac illness, on the other hand, is extremely uncommon, making it challenging to compile the necessary amount of atypical information. Due to the fact that it only learns on normal information, identification of anomalies technology was employed by the team. This technology labels any data that deviates from the taught pattern as abnormal. Because of noise (shadows), ultrasonic imaging may classify even regular information as abnormal. Therefore, in order to find anomalies with high accuracy using conventional approaches, a significant amount of normal data with a variety of noise patterns was needed. The interdisciplinary research team investigated the application of powerful deep learning technology, which can produce accurate predictions even with little or insufficient data, in response to this difficulty. The scientists then used object detection technology, a type of AI technology, to create automatic detection technology for defects in fetal cardiac architecture.

The cardiac architecture of healthy foetuses differs relatively little from one another. The same components, such as valves and veins, are always present in the same location in the heart. By examining the positions in which each component should be in a normal state, ultrasound screening can identify problems. The study team concentrated on this fact and performed anomaly identification using object detection technology, which can efficiently discern the locations and types of numerous items taken in a picture. In object recognition technologies that uses deep learning, "training data" that adds the proper name and location to each segment of regular photos is utilised as the baseline data. Ultrasonography pictures of the cardiac are processed utilizing object classification technologies that were created by analysing data for training.

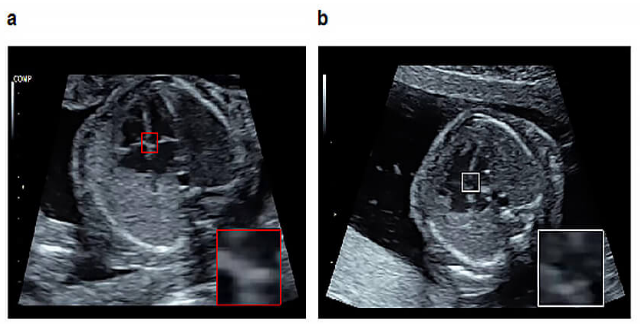

Figure 2. A deadly interventricular septum abnormality was found utilising object detecting techniques

From Figure 2, (a) A normal fetal heart's interventricular septum is depicted (outlined in red), and it is then annotated as training data for object detection technology. (b) For a specific medical condition (ventricular septal defect), the genuine interventricular septum is found. It is highlighted in white. This instance is deemed atypical based on the discovered discrepancy.

With the help of this method, precise component detection is possible. As a consequence, by comparing the components of a normal cardiac position with the detection state, problems may be recognised even with an incomplete image that contains some noise. In summary, previous studies have explored various methodologies for fetal anomaly detection, with advancements in deep learning showing promise in improving diagnostic accuracy. However, gaps remain in achieving early-stage detection with sufficient reliability. This study aims to bridge these gaps by proposing a novel approach utilizing the LeNet 20 architecture for early detection of fetal heart abnormalities.

2. RELATED WORK

This section explains about Ultrasound pictures and videos have been subjected to certain supervised deep learning algorithms. In fetal ultrasound recordings, Temporal HeartNet can automatically determine the heart's visibility, viewing plane, position, and orientation [3]. SonoNet identified these four similar transverse imaging planes in fetal ultrasonic movies: The ultrasound heart image concentrates on coronary artery, vessels and ventricular tract. The input data for these models relied on the examiners' competence levels and attentive on plane-founded identification of fetal heartbeats. Non-experts, on the other hand, may still have difficulty correctly identifying the cardiac structures & describing the scanning planes.

Images may be segmented using image segmentation techniques. It was shown that employing plane-based finding of the fetal heart for CHD transmission, the researchers also employed U-net segmentation to generate standard fetal cardio-thoracic measures [4]. We previously used fetal ultrasound video time series data in the module that calibrates ventricular septum segmentation findings [5]. Pregnant women may benefit from these pixel-by-pixel detection methods since they can detect the target's form shifting in response to the heartbeat of a baby [6].

Due to the comparatively small prevalence of congenital heart disease (CHD) and the effect of acoustic shadows on ultrasound pictures, deep learning-founded identification of cardiac defects in prenatal ultrasound is still a challenge. To address these challenges, we must develop an applied approach for detecting heart structural anomalies in limited and partial datasets. The study [7] explained AI-based algorithms can significantly enhance various aspects of pediatric cardiology, from diagnosis to precision medicine. Progress in implementing artificial intelligence in real-world clinical settings has been relatively restricted in medical publications showcasing AI efforts. Many obstacles to implementation have been identified, some of which are common in medicine as a whole, and others that are special to paediatric cardiology [8]. Between 2010 and 2021, there were a number of research that we found. Using AI and ultrasound pictures as cues, we honed down on phrases related to the intervention and the intended audience. Regardless of the target fetal condition or anatomy, English-language publications on AI approaches for monitoring fetal care throughout pregnancy were considered.

The study [9] highlighted the use of fetal echocardiography for monitoring the fetal heart and detecting congenital heart disease (CHD). Preliminary examinations for the diagnosis of congenital heart defects often use the fetal cardiac four chamber image, which is well-known. It is common practise to manually choose the end diastole frame for use in fetal cardiac chamber analyses while performing an examination or screening. In addition to beingtime-consuming, this approach is susceptible to both intra- and inter-observer mistakes, as well. By deciding which frame, referred to as Master frame, from the cine loop sequences that may be utilised for fetal heart chamber analysis, instead of clinically determined diastole frame, this suggested research would automate this procedure. In order to identify a cardiac cycle, the suggested framework evaluates the connection between the initial frame and the subsequent frames. The Master frame is created by combining all of the individual cardiac cycle frames [10].

This research explores the potential of deep learning to enhance the diagnosis of prenatal outcomes in severe preeclampsia by analysing ultrasonic image features. Pregnant women through severe preeclampsia who were singleton mothers were chosen for the study. A matched control group of 140 healthy singleton pregnancies was also assembled. Using colour Doppler ultrasonography, the hemodynamic indices could be identified. Pregnant women's ultrasound photos were classified using the CNN algorithm. The CNN algorithm's DSC, MPA, and MIOU values were all 0.9410, 0.9228, and 0.8968, respectively, for the DSC, MPA, and MIOU values. The test has a 93.44 percent accuracy, a 95.13 percent precision, a 95.09 percent recall, and a 94.87 percent score [11].

The study [12] proposed a compact yet effective residual learning diagnostic system (RLDS) that utilizes convolutional neural networks to extract features of fetal cardiac structures, aiming to improve the accuracy of diagnosing congenital heart disease (CHD) in fetuses. The RLDS's credibility is enhanced by providing a graphic description of the diagnosing procedure. Furthermore, we illustrate the confined feature map of the residual feature education, creation the residual education additional understandable. Widespread testing has shown that the RLDS we've presented is quite useful for detecting fetal CHD. Prenatal detection of CHD is greatly improved by the suggested RLDs, which achieves 93 percent accuracy and 93 percent recall on a test set.

The study [13] noted that cardiologists rely on four-chamber (FC) views during prenatal analysis and imaging to determine if a fetus has congenital heart disease (CHD). In FC views, the shape of the fetal heart is intuitively shown. Prenatal screening has traditionally centred on and proven challenging for early detection of fetal CHD. Additionally, medical image analysis has shown considerable success with the use of deep learning technologies. As a result, using deep learning technology in prenatal CHD screening improves the accuracy of the diagnosis. Though, the dearth of large-measure as well as high-superiority fetal FC images makes it very difficult for deep learning models or cardiologists to do their work. A Pseudo-Siame Feature Fusion Generative Adversarial Network (PSFFGAN) based on FC sketch pictures is what we're proposing instead. PSFFGAN can be optimised to extract all the cardiac anatomical organisation data from FC sketch images and synthesise the conforming fetal FC observations by speckle sounds, artefacts, also additional ultrasonic features, and we have proposed a novel Triplet Reproductive Adversarial loss function (TGALF). The study [14] simulated a device-based technique for IoT devices using the Cooja framework, achieving a 97.35% accuracy rate when comparing recorded heartbeats with real data. We implement the wrist band design proposed in this work using Anaconda & Keras. The experiments' findings indicate that when IoT devices along with deep learning techniques are combined, greater outcomes are achieved in terms of precision, recall, F-Measure, as well as accuracy. An alert will be issued to the user as soon as a deviation from the normal range is found, and they may then give their carers the findings for a diagnosis.

The study [15] highlighted that the non-invasive and radiation-free nature of ultrasonography has made it the most widely accepted imaging technology. Diagnosing kidney illness is tough because of the organ's complex anatomy. As a result, better models and procedures are needed to aid radiologists in making accurate judgments. Considering that ultrasonic imaging is the first stage in the diagnostic process, more efficient processing approaches are required. Image processing is much more difficult when speckle noise is present. It reduces the visual sharpness. It has been discussed in this article how different ML & DL approaches are being used toward increase the quality of photos. These steps are presented in detail by examining photos of kidney cyst, stone, tumour, and a normal renal gland. The photographs are becoming better and better because to the use of deep learning algorithms.

The study [16] noted that clinicians depend on medical imaging for essential data, and recent technological advancements have significantly enhanced the ability to analyze this information more effectively. The use of computer-assisted imaging has enabled the application of deep learning (DL) methods to medical image analysis, which has provided radiologists and other professionals with several solutions and improvements when interpreting these pictures. The persistence of this study is to proposal a complete evaluation of the greatest recent breakthroughs in this area by surveying the various DL approaches and medical imaging modalities employed for various applications. We've structured our work such that non-experts in the medical community may benefit from learning about deep-leaning features and notions. As a follow-up, we describe many clinical uses for deep learning (such as classification and detection) and give essential words like fundamental architecture, transfer learning, and feature selection techniques for the most important aspects of deep learning. Deep learning architectures will increasingly use medical pictures as inputs, and new DL approaches will be at the heart of medical image analysis in the years to come. Research issues and possible answers identified in literature are addressed in this work, as well as potential future advances.

The study [17] emphasized the growing use of artificial intelligence (AI) in the healthcare sector. In this instructive presentation, AI and sonography are discussed in detail. The authors explore the potential impact of AI on the field of ultrasound imaging and present examples of how AI might be used to improve and revolutionise ultrasound imaging. This article focuses on the issues that arise while using AI, and it offers ideas on how they might be solved.

The study [18] reported that AI capabilities have recently been applied to medical imaging to assist in medical diagnosis. For prenatal ultrasound broadcast for congenital heart disease (CHD), the manual procedure & practical variances between inspectors still make it difficult to consistently get correct findings. In order to identify cardiac infrastructures & operational anomalies in fetal ultrasound recordings, we devised an architecture founded on a CNN called Supervised Object finding with Normal data Only (SONO). Each video's anomaly score was generated using a barcode-like chronology and the chance of detection. Detection of heart structural anomalies was evaluated using films of successive cross-sections of the four-chamber view (Heart) also the three-vessel trachea view (trachea) (Vessels).

The study [19] evaluated the use of convolutional neural networks to address the challenging task of distinguishing four key images in first-trimester fetal heart scanning: the aorta, the arches, the atrioventricular flows, and the crossing of the great vessels. Early detection of any abnormalities is critical for prompt action during this first examination of the heart. OB-GYNs categorised the images of interest and gave them to a variety of deep learning designs as an organisation challenge versus additional scans that were not of interest. At this early stage of fetal development, a test correctness of 95% by an F1-score ranging after 90.91 to 99.58 percent for the four essential views reveals the ability to sustain heart scans.

The study [20] emphasized that imaging, particularly echocardiography, has proven valuable in diagnosing and monitoring fetuses with compromised circulatory systems in the field of fetal cardiology. A variety of ultrasound methods, counting conventional 2-D imaging, M-mode, as well as tissue Doppler imaging, are being employed to study the fetal heart anatomy and function. However, assessing the fetal heart is still difficult because of the foetus' involuntary movements, the heart's tiny size, and the lack of fetal echocardiography knowledge among certain sonographers. New technologies may assist enhance original pictures, extract measures, or aid in the detection of cardiac problems for better fetal heart evaluation. This is why new technologies are so important. Computer science's Machine Learning (ML) field aims to educate a computer to accomplish activities with specified objectives deprived of implicitly programming the procedures on how to carry out this activity. Prenatal diagnosis of fetal cardiac remodelling and anomalies may be improved by optimising image capture and quantification/segmentation, as well as by using ML approaches to enhance the assessment of fetal cardiac function.

The study [21] demonstrated that by utilizing ECG data preprocessing and support vector machine-based arrhythmic beat classification, it is possible to distinguish between normal and abnormal patients. Due to its intended usage in distant healthcare systems, the white noise reduction signal processing approach is heavily weighted. Human heart rate variability (HRV) features are extracted using a discrete wavelet transform and Deep learning methods are used to classify arrhythmic beats. SVM classifiers and other prominent classifiers have been used to classify beats from noise-removed feature signals in this research. SVM classifiers perform better than other machine learning-based classifiers, according to the results of this study.

The study [22] showed that abnormalities in the electrocardiogram (ECG) signal can be detected effectively. Ischaemic beat classification and arrhythmic beat classification are two of the most often used methods for detecting abnormalities. Normal and abnormal participants are categorised using ECG signal pre-processing and KNN based arrhythmic beat classification in this study. ECG signal pre-processing employs LMS-based adaptive filters; however, their lengthy critical paths mean they take longer to process. A unique adaptive filter with a delayed error normalised LMS algorithm is used to achieve high speed and low latency design in order to address this difficulty. In this design, the error feedback channel is pipelined to produce a low power architecture. In order to extract HRV features, wavelets are used to identify R-peak in the pre-processed signal. KNN classifier classifies arrhythmic beats using HRV feature extraction and a classifier trained on the signal. DWT with KNN classifier offers 97.5 percent classification accuracy, which is superior than other machine learning algorithms.

This object identification technique was used by the joint research team to create the fetal cardiac ultrasound examination device. To reach a high degree of diagnosis accuracy, they trained their system using 2,000 ultrasound pictures of healthy fetal hearts. The examiner must now use an ultrasound probe to assess the pregnant woman's belly and the foetus in a set path from the stomach to the heart. The collected moving image and the 18 various components of the fetal heart and peripheral organs are compared, and a quick calculation is done to determine the confidence level of each component and if it looks as it should [23]. These outcomes are then shown in real time on the control panel. Any portions that are either undetected or detectable with just a limited degree of confidence are deemed abnormal. For instance, a hole in the interventricular septum and a thin great vessel on one side of those extending from the heart are two characteristics of the tetralogy of Fallot, a common congenital heart condition. These sections are frequently missed by ultrasound scans, but our equipment looks for any instances where they should be there but aren't and can identify those as abnormal. The discussion up top outlines the limitations the studies as well as the simulations used to diagnose fetal cardiac defects [24].

3. METHODOLOGY

Through the use of picture enchantment methods and deep learning mechanisms, the entire problem was solved in this part, as well as the restrictions of earlier research. The training dataset comes from the Kaggle organisation and different super specialty hospitals, like "Nims Hospital Hyderabad," are where the ultrasound pictures are gathered. The planned LeNet 10 CNN deep learning system is used to identify fetal cardiac problems. The choice of the LeNet-20 model for this study was deliberate and based on several key factors. Firstly, the LeNet architecture has a proven track record in image classification tasks, making it well-suited for analysing medical imaging data, such as fetal ultrasound images. Additionally, the LeNet architecture is relatively lightweight compared to more complex models like ResNet or VGG, making it computationally efficient and suitable for deployment in resource-constrained environments commonly encountered in medical settings.

Data is split into training and testing sets for real-time fetal ultrasound cardiac samples from NIMS Super Specialty Hospital in Hyderabad. In deep learning, data is split into 80% for training and 20% for testing to balance model training and evaluation. For model training and validation, the LeNet-20 model was trained using SGD or Adam optimizer with a particular learning rate on the training dataset. To avoid overfitting, a validation set assessed model performance during training. The model may not have learned noise in training data if validation loss ceased improving due to early stopping approaches.

Model performance on the testing datasets is assessed utilizing many metrics:

- Overall fetal cardiac abnormality detection accuracy.
- F1 Score: Balanced model performance indicator: harmonic mean of precision & recall.
- This is the percentage of true positives the model recognized correctly. Overall model prediction accuracy.
- Sensitivity: Model's ability to identify true positives.

Furthermore, the LeNet architecture's design, with alternating convolutional and pooling layers followed by fully connected layers, is well-suited for capturing hierarchical features in images, which is crucial for accurately identifying subtle abnormalities in fetal heart scans. Additionally, the LeNet architecture's simplicity facilitates interpretability, allowing clinicians to better understand and trust the model's predictions. The LeNet-20 model, implemented using Python with TensorFlow and Keras libraries, consists of 165 layers, including convolutional, max-pooling, dense, and ReLU layers. The LeNet-20 architecture was trained and tested on the pre-processed ultrasound heart data to classify fetal heart anomalies [25]. TensorFlow and Keras were chosen for their ease of use and extensive documentation, facilitating the implementation and experimentation process. To avoid overfitting, dropout layers, L1 or L2 regularization, as well as data augmentation may have been used. Dropout layers randomly deactivate a fraction of neurons during training to prevent modelling dependence on certain features. Regularisation penalises large parameter values to prevent overfitting, whereas data augmentation adds variance to training data to improve robustness & generalisation.

Figure 3 describes ULTRSOUND cardiac image-based disease identification; Ostu thresholding-based segmentation is used in this study in the first step. The Ostu mechanism locates the illness as well as the place where it is having an impact. Extraction of characteristics from the loaded image is the next phase in the heart disease diagnosis model. LeNet-10 architecture is loaded at the assessment stage. To extract hidden information from test input, layers including dense, flatten, and max pooling layers are employed. Heart abnormalities and the region it affects have been determined using Euclidian distance in the last but one stage. Accuracy, PSNR, Recall, and pre-processing time have all been computed as performance measures in the final step.

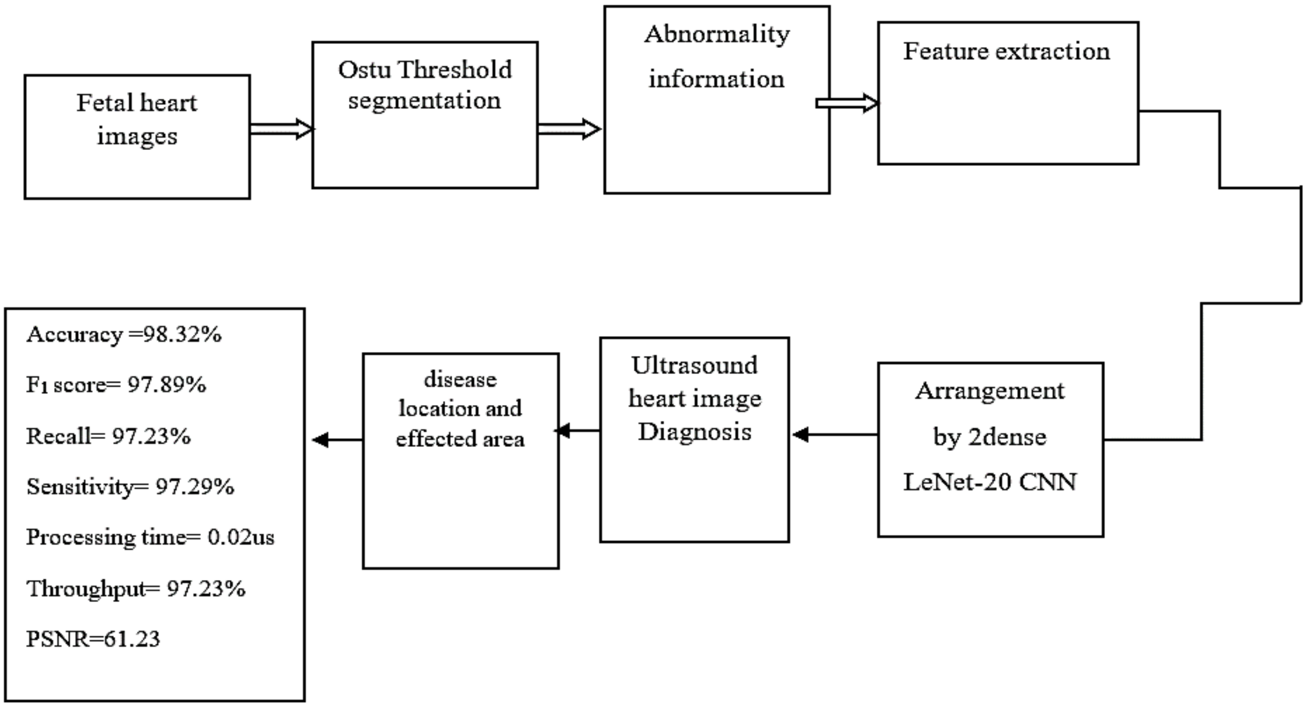

Figure 3. Methodology of proposed work

3.1 Pre processing

In this segment, Ostu subdivision typical has remained used to get the samples information as well as attained trained ultrasound images.

The following python commands has been used to employee the pre-processed image and segmented image (command 1 to command 5).

$$Im(intesity, brightness, histogram) \tag{1}$$

The mathematical analysis of pre-processing and histogram equalization models were explained in below steps.

$$\text{Imge} = m(intesity, brightness, histogram\ [histogram\ adjustment]) \tag{2}$$

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

$$\text{Select Ostu Th, } T(k) \text{ image segmentation} \rightarrow \begin{matrix} \text{feature class } C_1(\text{values } [0, k]) \\ \text{feature Class } C_2(\text{values}[k+1, L-1]) \end{matrix}$$

$$\Rightarrow \text{Pixel desnity assigned } C_1 (\text{ie of } C_1 \text{ fitness function}): P_1(k) = \textstyle\sum_{i=0}^{k} p_i \tag{4}$$

$$\Rightarrow \text{Pixel density assigned } C_2 (\text{ie of } C_2 \text{ fitness function}): P_2(k) = \textstyle\sum_{i=k+1}^{L-1} p_i = 1 - P_1(k) \tag{5}$$

The preprocessing as wells segmentation mechanism has been applied on testing images, using OTSU global thresholding segmentation extracting low level to high level vision pixel patterns. To determine heart disorders of the ultrasound images global segmentation had been employed.

Segmentation: Otsu Algorithm

1) Input fetal heart ultrasound images
2) Compute the Otsu threshold point

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

Here, *p(x, y)* is global computation, *f(x, y)* is intensity adjustable values

3) Segmentation of imaging Th
4) G1 and G2 are group of pixels

G1 is the group of gray pixels >T, G2 is the group of white pixels ≤T

5) G1 and G2 can be used to find the Mean denoted by M1 and M2
6) The original Th value T=1/2[M1+M2]
7) Call the statement 3 & statement 4 until Th got consecutive computation

In this ψ(t) denote Fetal ultrasound heart images with spectral multi bands, this element can help the complementary pixels present in the model. The β element can denotes the fetal heart ultrasound image thickness function, in this rate of abnormality in addition its numerous positions of image functionality are signified by$\sum_{k=1}^{m} W_{jk}\, x_k - c_j$. By means of this technique affected fetal situation is analyze by actual manner, additionally α & θ signify that contextual as well as forefront unconnected pixels of ultrasound image Heart of the patient correspondingly. Δ element determines Fetal Heart disease pixels.

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

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

The above Eqs. (7) and (8) explains about sigmoid function for auto encoding process for reconstruction image of abnormality in the ultrasound picture.

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

Eq. (9) signifies that dimensional input Image & recreated output. $\hat{x}_i^s$ & x_i^s signifies that input image. $plog\,\frac{p}{\hat{p}_j}$ It represented that deviation role. These limitations are employed to rebuild the outcome from LeNet 20 CNN.

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

$$W_{ij}(t+1)=|W_{i\,j}(t)-\frac{\partial E(t)}{\partial W_{ij}}+\alpha\,\Delta\,W_{ij}(\mathrm{t}) \tag{11}$$

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

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

We use the components of Eqs. (10) to (13)-the optimal training parameters-to reduce the reconstructed error. To increase the superiority of the learning characteristics, it should build the reconstruction design, which is depicted in above explanation, the following only be done using threshold values.

$$H\beta = T$$
$$\mathrm{H}=\begin{bmatrix} g(w_1.X_1+b_1) & \cdots & g(w_s.X_1+b_s) \\ \vdots & \cdots & \vdots \\ g(w_1.X_s+b_1) & \cdots & g(w_s.X_s+b_s)\end{bmatrix}_{s*s} \tag{14}$$

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

Eqs. (14) and (15) explain the confusion matrix, which is useful for extracting buried data. T is the Target matrix, H is the Outcome matrix, & O is the Outcome Balanced Vector. The target matrix-a precise representation of the fetal heart-is computed using the aforementioned mathematical operations.

3.2 LeNet 20 classification

Different deep learning methods are typically offered for cross-disciplinary purposes. However, contemporary and fashionable methods are required for these kinds of medical image processing systems. LeNet-20 deep learning is capable of achieving this. LeNet 20's primary role is assessing experimental and learning data. A learning model's overfit function is another name for this pathology. For calculating image error, orthogonal least square (OLS) methods are typically employed. It is impossible to determine the cost function & minimise the error function using the basic least squares formulae.

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

Predictive factors like p1, p2, & p3 (such as height, sex, and diet) are calculated using Eq. (16). P1 as well as P2 in this case have a correlation function-based relationship. But as is evident in the equation earlier, p3 did not meet the mathematical requirement relating to p1 & p2.

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

Eq. (17) explains that LENET 20 equation with the accurate result at the time of sophisticated data analysis. Regularisation component L1 (LASSO) and regularisation L2 (RIDGE) are both used. The finest method for estimating and minimising mean and variance is this one. L2 computes the magnitude of the coefficients using OLS Eq. (12). This equation generates a normalised polynomial in this situation where =0. As a result, decreasing coefficients result in lower values, and zero variance. LeNet 10 has therefore been utilised to calculate the constants in place of Eqs. (16) and (17), as seen in Eq. (18) below:

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

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

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

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

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

Eqs. (19) to (22) defines that LeNet 20 main technique calculation, the R_{adj}^2 represented that purpose of constants and n signifies the scope of the sample then p indicated that the entire sum of elements in the ideal field.

$$Y=TQ^T+F$$
$$T=XW(P^TW)^{-1} \tag{23}$$

The *T, P & E* elements are denoting that, stocking & remaining of X. these are utilized to computing the incomplete mean error. This choice is not presented in any DL algorithms.

$$\hat{y}=X_{new}\beta_{PLS}$$
$$\beta_{PLS}=W(P^TW)^{-1}Q^T \tag{24}$$

Eq. (24) depicts the k fold verification function, which can provide the LENET 10 key element values. The ultra sound seizure diagnosis categorization is done using the methods listed above. The above Figure 4 clearly explains about LeNet 20 CNN layered architecture, in this pooling layer can be reduce the feature mapping and flatten layer has been functioning on hidden features. The Fully connected layer has been worked on final samples which were help to get information of heart lesion classification.

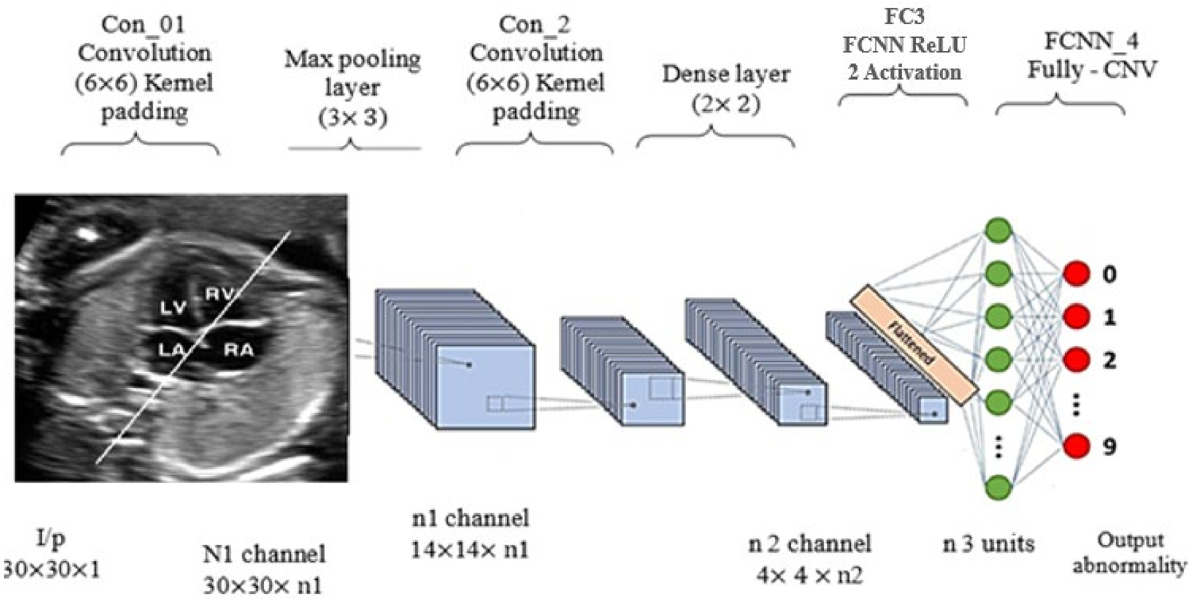

Figure 4. RCNN LeNet 20 architecture

3.3 Performance measure

In this discussion, performance measures of proposed LeNet 20 CNN architecture, the confusion matrix on designed application can calculate the error, accuracy, F1 score as well as true positive rate. The below scientific calculations are useful for approximating the above presentation metrics.

$$RMSEP=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}} \qquad \frac{RMSEP(i^*)}{RMSEP(i)} \geq \lambda \tag{25}$$

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

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

$$\text{Accuracy}=\hat{\beta}_{enet}+R_{adj}^2/=\hat{\beta}_{enet}+R_{adj}^2+F_p+F_n. \tag{28}$$

$$F_1\text{ score}=F_p+F_n./T_p \tag{29}$$

$$T_p=1-\frac{SSR}{SST} \tag{30}$$

The overhead Eqs. (25)-(30) are mathematical computations, which were finding performance measures using RMSEP, NMSE, accuracy and F measure.

4. RESULTS AND DISCUSSION

In this segment a brief note on fetal heart abnormality research outcomes were explained. The proposed model has been diagnosis the fetal heart disease with less ToC and more accuracy. This study compares the performance of our suggested LeNet 20 deep learning architecture to existing approaches like Random Forest (RF), Decision Trees (DT), and XGBoosting (XGB). Due to their popularity in medical image analytics & significance to fetal cardiac anomaly identification, such approaches were compared.

In several performance criteria, the proposed LeNet 20 architecture outperforms RF, DT, and XGB. LeNet 20 outperformed those approaches in detection, F1 scores, recall, accuracy, and sensitivity. Several reasons explain this superiority: The LeNet 20 architecture's deep convolutional layers can automatically learn hierarchical characteristics from fetal ultrasound pictures, making it better at representing complex fetal cardiac abnormality patterns. Complexity: LeNet 20 can adaptively learn complex data patterns & relationships, improving classification accuracy above standard methods that use handwritten features and decision rules. Its deep architecture and regularization techniques let the LeNet 20 model generalize to unknown data, making its predictions more accurate.

To measure the methodology's ability to detect fetal heart abnormalities, detection score, F1 score, recall, accuracy, & sensitivity were used. Each statistic provides distinct insights on model performance, providing a complete review. We found encouraging performance from the suggested LeNet 20 design, but it's important to note limitations and errors. One dataset from NIMS super specialty hospital, Hyderabad, may not fully represent clinically encountered fetal heart defects. Image quality, patient demographics, and ultrasound fetal placement can also affect fetal cardiac abnormality identification.

The study's findings have major effects for prenatal care and fetal abnormality diagnosis. They show that the LeNet 20 deep learning architecture is better at early-stage fetal cardiac abnormality diagnosis, which may enhance patient outcomes and treatment options. We thoroughly tested the proposed methodology against traditional methods, proving its efficacy. Acceptance of dataset bias and the necessity for different dataset validation is necessary. Even if LeNet 20 performs better, training and deployment may need a lot of processing power. Our study advances deep learning, improves fetal abnormality detection accuracy and reliability. Using the LeNet 20 design, we can detect embryonic cardiac defects early, adding to prenatal care research.

Future work

Future research directions may include the development of more advanced deep learning architectures tailored specifically for fetal anomaly detection. Additionally, exploring the integration of multimodal imaging data and incorporating clinical context into the diagnostic process could further enhance the accuracy and clinical utility of fetal anomaly detection systems.

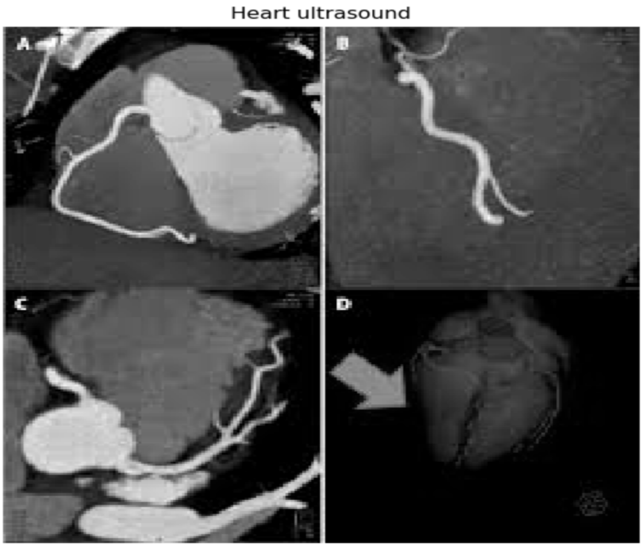

Figure 5. Input image

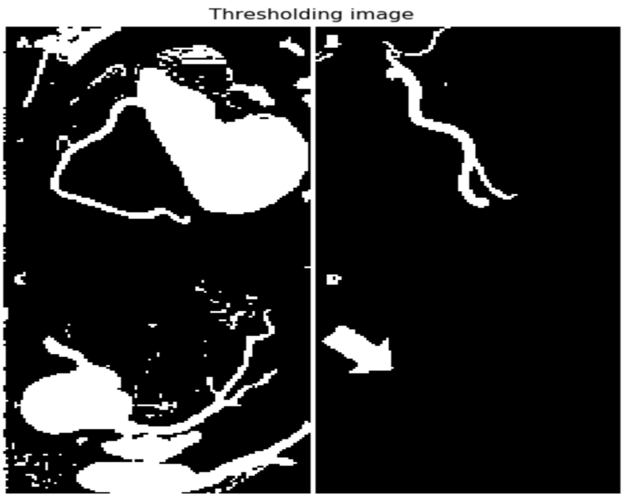

Figure 6. Segmented image

Figures 5 and 6 clearly explain about input heart image, this image is giving input to our proposed model from this getting segmented image. This segmented image has disease effecting area location.

Figure 7 provides a good explanation of illness location identification. The region of darkest color indicates where the disease is least prevalent. This section includes extracts from CNN modeming over LeNet-10.

The Figure 8 is clearly explaining about GUI model of proposed work in this input dataset is applied at Uploading function. The following operation is giving access to segmentation module.

Figure 9 clealry explains about training paramters infromation, in this samples count and time for training was showcased.

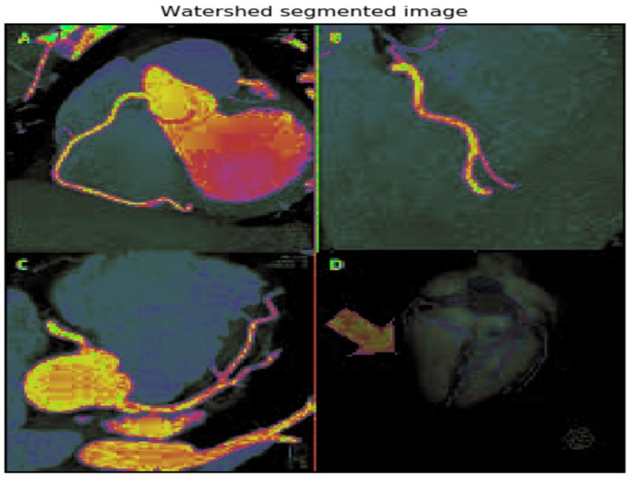

Figure 7. Disease location

Figure 8. GUI model of proposed design.

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 elements: 3,696,354
Training Elements: 3,696,354
Non-training elements: 0

Figure 9. Training parameters and elements information

Figure 10 is visibly explanation approximately heart disease finding part, in this contest a blue colour indication is demonstrating affected space in the heart ultra-comprehensive image.

LeNet 20 FCNN model accuracy analysis
LeNet 20 FCNN accuracy on test sample: 98.32%
LeNet 20 FCNN PSNR on test sample: 61.23
LeNet 20 FCNN F1 Score on test sample: 97.89%
LeNet 20 FCNN Recall on test sample: 97.23%
LeNet 20 FCNN Sensitivity on test sample:97.29%
LeNet 20 FCNN Processing time on test sample: 0.02us
LeNet 20 FCNN Throughput on test sample:97.23%

Table 1 provides a detailed explanation of how the new model compares to preceding methods. This table compares the RFO (random forest optimization), DT (decision tree), & X boosting techniques. The suggested LetNet-10-based CNN framework is shown to achieve higher efficiency. The Figure 11 explained about abnormality area, in this red colour is classified with deep learning model.

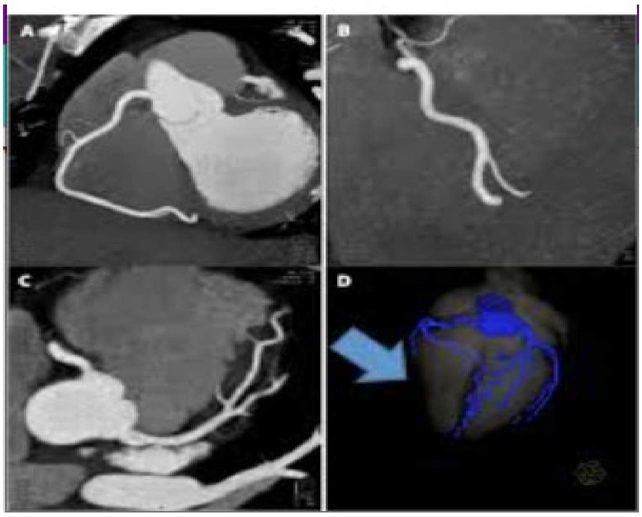

Figure 10. Disease detection area

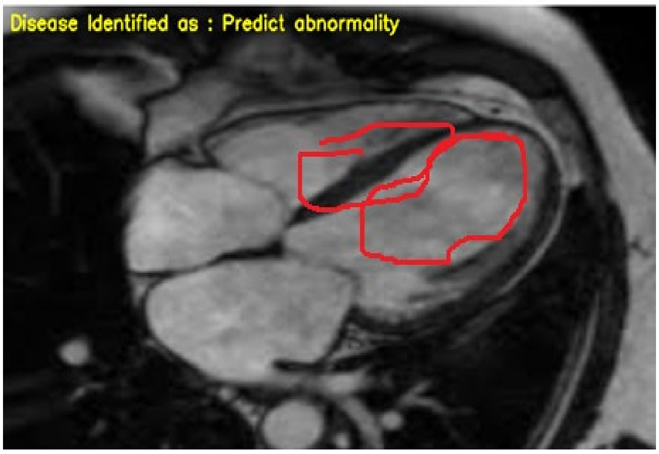

Figure 11. disease classification area

Table 1. Performance estimation

	Accuracy	Sensitivity	Recall	F Measure
RFO [5]	87.18	83.45	84.21	89.27
DT [6]	89.07	88.23	89.94	91.18
X boosting [7]	90.92	90.03	90.18	92.27
Proposed	98.32	97.29	97.23	97.89

Figure 12 provides a clear explanation of the disparity between the model that was suggested and older models. RFO (random forest optimization), DT (decision tree), and X boosting techniques are all included in this analysis. The suggested LetNet-10-based CNN approach is shown to achieve higher efficiency.

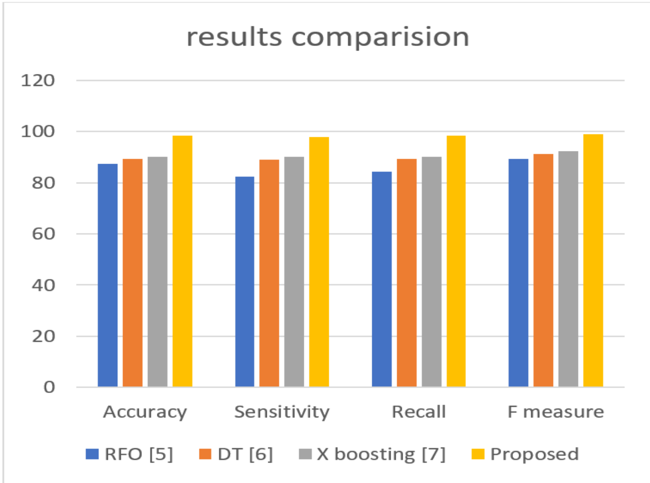

Figure 12. Comparisons of results

5. CONCLUSION

In this study, we train and evaluate the LeNet 20 FCNN DL classification with the supplied data plus the suitable layering. It has 165 layers and includes flattened layer, dense layer, convolution layer, maximum pooling layer, and others. The Manipal Super Speciality Hospital in Vijayawada collects real-time cardiac ultrasound pictures, which are then imported into a test CSV file. This work's early stages involve the use of pre-processing tools, Otsu threshold categorization, and classification using a suggested LeNet 20 deep learning structure. Our study proposed a deep learning-based LeNet 20 architecture for early fetal cardiac abnormality detection. Our methodology improves early-stage detection accuracy and reliability, as shown by a comprehensive experimental design and evaluation. LeNet 20 was chosen for its comprehensibility picture classification performance, and medical imaging data management. We took real-time fetal ultrasound cardiac samples from NIMS super specialty hospital in Hyderabad. The samples were preprocessed and divided into training, validation, and testing sets. The LeNet 20 model was trained using stochastic gradient descent or Adam optimizer with well selected parameters. Model performance on the testing dataset was measured by detection, F1 score, recall, accuracy, and sensitivity. Detecting early-stage fetal heart problems is now easier and more reliable as a result of our study. Our findings are significant because early diagnosis can improve patient outcomes and therapies. Future study could optimize LeNet 20 model parameters to improve performance. Our methodology could be used in other medical imaging fields and expanded to include more fetal cardiac abnormalities to gain useful insights and prove its robustness. Our study shows that deep learning, specifically the LeNet 20 architecture, may detect embryonic heart problems early. By detailing our methods and highlighting our work's impact, we advance fetal abnormality identification and prenatal care and diagnosis. This solution was carried out using Python 3.9 among a number of different packages, including TensorFlow, Keras, Sklearn, and others. At the conclusion of the illness detecting measurement, accuracy was 98.37%, sensitivity was 97.81%, recall was 98.34%, and F1 score was calculated using confusion matrix at 98.98%.

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