Heart Disease Diagnosis and Abnormality Detection Using Advanced Deep Learning on Echocardiograms

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Abstract: Cardiovascular disease is a leading cause of global mortality, necessitating precise diagnostic methods for early identification. Echocardiography functions as a non-invasive imaging technique to assess anatomical and functional anomalies of the heart. This study employed a publicly available EKG dataset of echocardiography pictures to construct a dual-branch deep learning system for classification and anomaly detection. Transfer learning models utilized for classification included VGG16, EfficientNetB, Proposed VGG16, Xception, and an Ensemble of VGG16 with Xception. The YOLO model family (YOLO v5, v8, v9, and v11) was employed for detection to identify aberrant locations using bounding box annotations. Experimental results indicated that the Ensemble model attained enhanced classification performance, with an accuracy of 93.3% and an F1-score of 93.4%. In contrast, YOLO v8 produced optimal detection outcomes, with a mean average precision (mAP) of 43.1%, providing a dependable method for localization. To improve interpretability, explainable AI methods like Grad-CAM were utilized to emphasize the discriminative areas influencing the model's judgments, hence providing transparency in medical analysis. Additionally, the trained models were incorporated into a Flask-based web framework to facilitate real-time inference, visualization of predictions, and smooth interaction between doctors and the automated system. The suggested system exhibits considerable potential in assisting clinicians with automated, precise, and interpretable diagnoses from echocardiography pictures, thus diminishing dependence on manual evaluation and enhancing diagnostic efficiency.

*“**Index Terms:** Deep Learning, Echocardiography, Heart Disease Classification, Convolutional Neural Networks (CNNs)”.*

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain a major worldwide health concern, resulting in high death and morbidity rates despite great progress in medical knowledge and healthcare delivery. The World Health Organization reports that cardiovascular diseases (CVDs), such as coronary artery disease (CAD), angina, and hypotension, constitute over 32% of global mortality, leading to around 17.9 million deaths per year [1]. These illnesses jointly impose significant social and economic burdens on individuals and healthcare systems globally. Timely and precise diagnosis of cardiac disease is essential to provide therapies that can mitigate disease progression and mortality risk. Clinical evaluations, electrocardiograms (ECGs), and imaging techniques like echocardiogram are essential for detecting cardiac problems, with echocardiography serving as a fundamental instrument for assessing structural and functional cardiac characteristics [3], [4].

Echocardiography offers significant insights into heart morphology and function; yet, interpreting echocardiographic pictures is intricate, labor-intensive, and reliant on professional assessment. This dependence on human skill constitutes a significant constraint, especially in areas with restricted access to qualified cardiologists [5], [6]. Furthermore, the manual interpretation of pictures is susceptible to intra-observer and inter-observer variability, resulting in conflicting diagnostic results. These challenges emphasize the necessity for automated and fast diagnostic techniques that can analyze echocardiographic data with exceptional precision and reliability. Recent breakthroughs in artificial intelligence (AI) and machine learning, especially in deep learning, present significant potential to improve cardiac imaging interpretation and facilitate more consistent and scalable diagnostic procedures.

The main aim of this project is to create and assess an automated method for classifying various heart disease states using echocardiographic pictures. This research aims to classify four primary cardiac conditions—angina, coronary artery disease, hypotension, and cardiovascular disease—utilizing a balanced collection of echocardiographic pictures [8]. The proposed paradigm seeks to enable objective, quick, and precise identification of various illnesses, thus alleviating the diagnostic burden on doctors and enhancing decision-making in clinical environments. This work aims to investigate the viability of incorporating computational techniques into standard echocardiography analysis to enhance the rigor and data-driven nature of cardiac evaluations [9].

This work is significant for its potential to improve diagnostic precision, accessibility, and efficiency in cardiovascular care. This research enhances the creation of intelligent healthcare systems by automating the processing of echocardiographic data, thereby aiding physicians in achieving fast and accurate diagnoses. The findings of this study may enhance patient management, especially in disadvantaged areas where specialized knowledge is limited. This study establishes a basis for future research in AI-assisted cardiac imaging, presenting prospects for the integration of multimodal data and longitudinal investigations to enhance automated cardiovascular diagnosis [10].

2. LITERATURE REVIEW

Recent breakthroughs in deep learning have transformed medical image processing, facilitating automated and highly precise diagnostic systems. Harangi [11] introduced an ensemble-based deep convolutional neural network (CNN) methodology for skin lesion categorization, attaining notable enhancements in recognition accuracy via model diversity. Akram et al. [12] created a hybrid deep learning framework for skin lesion segmentation and classification in the context of the Internet of Medical Things (IoMT), highlighting its potential for real-time diagnostic applications. Although these research illustrate the efficacy of deep learning in dermatological imaging, they predominantly concentrate on external tissue classification, hence presenting potential to investigate analogous approaches in interior organ imaging, such as echocardiography.

Khan et al. [13] performed a systematic literature analysis on intelligent pneumonia identification from chest X-rays in respiratory imaging, emphasizing the superiority of deep learning over traditional machine learning models in managing extensive image data. The findings emphasize AI's efficacy in identifying pulmonary diseases; nevertheless, the research also highlights concerns with dataset imbalance and the restricted interpretability of model predictions. Zhou et al. [14] utilized machine learning for cardiac risk prediction in cancer patients, illustrating the potential of predictive models to evaluate therapy-induced cardiac dysfunction. Nonetheless, their research concentrated on longitudinal clinical data instead of imaging-based diagnostics, highlighting a deficiency in utilizing visual data from echocardiography for the classification of heart diseases.

Zhou et al. [15] conducted a thorough analysis of the expanding influence of deep learning in medical imaging, including significant trends, technological advancements, and prospective prospects across several imaging modalities. Their research highlighted the revolutionary capacity of deep learning in enhancing diagnostic precision, while also recognizing obstacles including processing requirements and the necessity for extensive annotated datasets. Nedadur et al. [16] further investigated the applications of artificial intelligence in the echocardiographic evaluation of valvular heart disease, demonstrating how AI tools may aid in both quantitative and qualitative cardiac assessments. Nevertheless, the study primarily concentrated on particular valve pathologies instead of a comprehensive classification of cardiovascular diseases, hence allowing for the development of models that can address many disease categories concurrently.

Additional research has shown the versatility of deep learning in diverse cardiac and non-cardiac imaging applications. Shabbir et al. [17] employed CNN architectures to classify heart murmurs using phonocardiogram representations, with significant accuracy while depending exclusively on audio data instead of echocardiographic images. Abdou [18] performed a literature assessment on efficient deep neural network designs for medical image interpretation, indicating that streamlined and optimized models can improve clinical applicability. Nevertheless, these models have not been thoroughly assessed on cardiac ultrasound imaging. Sun et al. [19] introduced a two-view attention-guided CNN for the categorization of mammographic images, enhancing diagnostic accuracy via contextual feature learning. Ahmad et al. [20] integrated a tailored AlexNet with a support vector machine for breast cancer diagnosis, demonstrating the potential of hybrid architectures to enhance diagnostic accuracy in medical fields.

3. MATERIALS AND METHODS

The proposed approach seeks to establish an automated deep learning framework for the classification of heart disease utilizing echocardiography pictures. A balanced dataset of echocardiographic pictures depicting various heart states was employed for model training and assessment. The workflow encompasses data preprocessing, model training, and validation utilizing advanced convolutional neural networks (CNNs) such as VGG16, EfficientNetB, Xception, and a modified VGG16 enhanced with Batch Normalization and Dropout layers, optimized through stochastic gradient descent with momentum to ensure stability and generalization. A combination of VGG16 and Xception was utilized to enhance classification accuracy, while YOLO models were applied for accurate localization of aberrant cardiac areas [28]. Explainable AI methodologies, such as Grad-CAM, offer interpretability by showing essential areas that affect predictions. A Flask-based web application was ultimately constructed for real-time image upload, categorization, and visualization, providing an accessible and dependable clinical decision-support tool.

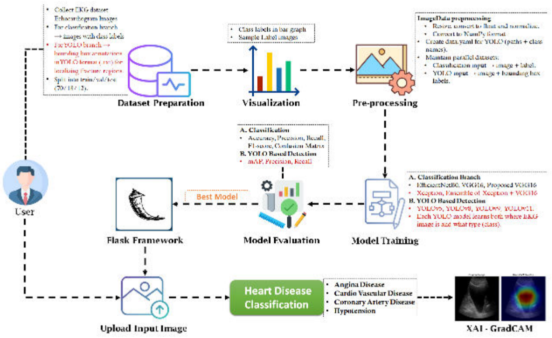


Fig.1 Proposed Architecture

The system architecture consists of several integrated modules intended for the automatic classification of heart disease using echocardiography pictures. The technique encompasses data preparation and augmentation layers, succeeded by deep learning models including VGG16, EfficientNetB, and Xception for feature extraction and classification [29]. The combination of VGG16 and Xception improves prediction accuracy, whilst YOLO models identify and localize aberrant cardiac areas. Grad-CAM offers visual interpretability, while a Flask-based web interface facilitates real-time picture submission, prediction, and visualization for clinical application [30].

a) Dataset Collection:

The research utilized a publicly accessible Echocardiogram (EKG) picture collection obtained from an open medical imaging repository. The collection comprises echocardiography images depicting various cardiac diseases, including angina, cardiovascular disease, coronary artery disease, and hypotension. Each echocardiography image in the classification branch is linked to a specific class label that indicates the identified cardiac disease. A detection-oriented dataset was concurrently produced by annotating aberrant cardiac regions with bounding boxes, encoded in the standard YOLO annotation format (.txt), facilitating accurate localization of problematic locations within the images. The dataset demonstrates heterogeneity in image resolution and acquisition settings, facilitating strong learning and generalization for both classification and anomaly detection tasks.

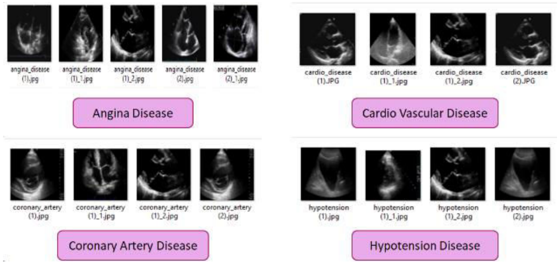


Fig.2 EKG Dataset

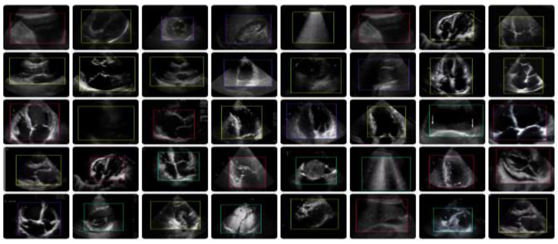


Fig.3

b) Visualization:

Data visualization was conducted to acquire a preliminary comprehension of the dataset's distribution and attributes. Class labels were depicted as bar graphs to assess class distribution across several heart disease categories, hence promoting equitable learning behavior during model training. Furthermore, representative sample photos from each category were analyzed to discern visual patterns, anatomical discrepancies, and possible noise in echocardiography images. This stage is crucial for detecting data anomalies, validating label accuracy, and developing a comprehensive understanding of the imaging attributes prior to subsequent processing.

c) Pre-processing:

Preprocessing was implemented to standardize echocardiography pictures and facilitate successful learning for classification and detection tasks. Images were scaled and standardized to guarantee consistent input dimensions and numerical stability during training. Data were systematically arranged into standardized numerical formats to facilitate efficient calculation. Distinct yet coordinated datasets were preserved for classification and detection, maintaining class labels for disease forecasting and bounding box annotations for anomaly localization. This step is essential for enhancing model convergence, minimizing bias, and guaranteeing consistency across parallel learning processes.

d) Algorithms:

VGG16: VGG16 is a deep convolutional neural network with 16 layers, engineered to extract hierarchical spatial characteristics from images using sequential convolutional and pooling processes. It improves classification precision by discerning intricate spatial patterns and structural links among visual data. The homogeneous layer arrangement promotes effective feature representation while ensuring computational simplicity. Due to its pre-trained weights and adaptability for fine-tuning, VGG16 [21] offers dependable feature extraction and strong performance, establishing it as a fundamental model for visual identification and medical image analysis tasks.

$$O_{i,j,k} = \sum_{m} \sum_{n} \sum_{c} X_{i+m,j+n,c} \; W_{m,n,c,k+} \, b_k \qquad (1)$$

EfficientNetB: EfficientNetB is a convolutional neural network architecture designed to attain enhanced accuracy while utilizing fewer parameters by employing compound scaling of depth, width, and resolution. It effectively equilibrates performance and computational expense, facilitating high precision despite constrained resources. By methodically enlarging model dimensions, it effectively captures intricate visual aspects while reducing the risk of overfitting. The architecture guarantees durability and flexibility to diverse image resolutions, providing a scalable solution for intricate categorization challenges that necessitate both accuracy and efficiency.

Proposed VGG16: The Proposed VGG16 is an augmented iteration of the traditional VGG16 design, incorporating Batch Normalization, Dropout layers, and stochastic gradient descent optimization with momentum. These adjustments enhance training stability, augment generalization, and reduce overfitting. Batch Normalization expedites convergence by the normalization of activations, whereas Dropout mitigates co-adaptation among neurons. The optimizer improves learning efficiency using momentum-based updates. This enhanced architecture fortifies feature extraction, attains superior predictive accuracy, and offers a more dependable foundation for deep image classification applications [23].

Xception: Xception is a deep convolutional architecture utilizing depthwise separable convolutions, aimed at effectively capturing spatial and channel-wise information in images. By disentangling cross-channel and spatial correlations, it dramatically improves feature extraction while diminishing computational complexity. The hierarchical structure enables the model to discern complex visual patterns and subtle distinctions with enhanced accuracy [24]. The architecture's capacity to harmonize efficiency and performance renders it appropriate for high-precision picture categorization and intricate visual recognition tasks.

$$O_{i,j,k} = \sum_{m,n} X_{i+m,j+n,c} \, W_{m,n,k} \quad (2)$$

Ensemble (VGG16 + Xception): The Ensemble model amalgamates the predictions of VGG16 and Xception architectures to enhance classification accuracy and robustness. Ensemble learning integrates many models to diminish variation and mitigate individual biases, hence improving generalization. Utilizing VGG16’s hierarchical feature extraction alongside Xception’s effective feature separation, the ensemble generates more consistent and dependable predictions. This integrative method promotes system stability, reduces overfitting, and elevates overall performance in intricate image-based decision-making procedures.

YOLO v5: YOLO v5 is a single-stage object detection method that concurrently forecasts object borders and class probabilities in real time. It utilizes an effective detection pipeline proficient at processing photos rapidly and accurately. By emphasizing end-to-end learning, it minimizes computing latency while preserving high localization accuracy. YOLO v5’s capacity to swiftly and precisely identify regions of interest improves automated visual analysis, facilitating practical applications in time-sensitive and data-intensive contexts.

YOLO v8: YOLO v8 is a sophisticated object identification model aimed at improving accuracy, speed, and robustness via enhanced architectural elements and refined training methodologies. It incorporates sophisticated loss algorithms and feature extraction methods to attain superior localization accuracy. The model proficiently recognizes objects of diverse dimensions in images, guaranteeing uniform detection efficacy. Its optimized architecture facilitates expedited inference without sacrificing accuracy, rendering it appropriate for extensive or real-time visual detection systems necessitating efficiency and dependability.

$$\mathcal{L} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} \quad (3)$$

YOLO v9: YOLO v9 is a real-time object detection system enhanced for greater recall and superior identification of nuanced or diminutive features. It improves upon earlier iterations by employing advanced attention mechanisms and effective feature fusion techniques [26]. It achieves high inference speed and enhanced detection coverage by predicting object classes and bounding boxes in a single pass. YOLO v9's sophisticated design guarantees enhanced resilience to fluctuations in image circumstances, delivering precise and thorough detection performance in dynamic or intricate contexts.

$$\mathcal{L}_{YOLOv9} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{dfl} + \mathcal{L}_{dfl} \quad (4)$$

YOLO v11: YOLO v11 exemplifies a cutting-edge real-time object identification approach, featuring improved accuracy, recall, and computing efficiency. It enhances previous architectures by utilizing superior feature pyramids and enhanced detecting heads, facilitating accurate multi-object localization. The model adeptly reconciles detection velocity with dependability, facilitating the concurrent identification of several targets. Its sophisticated processing pipeline guarantees uniform, high-quality detection outcomes, rendering it appropriate for practical applications that necessitate swift, precise, and scalable object recognition across varied imaging conditions.

e) Integration of XAI & Flask Framework:

Techniques of explainable artificial intelligence were integrated to enhance the transparency and interpretability of deep learning models. Grad-CAM was utilized to produce heatmaps highlighting the most significant areas within echocardiography pictures that contribute to the model's predictions. This module graphically emphasizes distinct cardiac regions, allowing clinicians to comprehend the reasoning behind automated conclusions, thus enhancing trust, aiding clinical validation, and promoting educated medical interpretation of categorization results.

A Flask-based framework was created to offer an interactive and user-friendly interface for model deployment. The infrastructure enables users to input echocardiography pictures and obtain real-time predictions produced by trained models. It blends categorization, detection, and visualization outputs, facilitating effective user engagement with the analytical system and enhancing practical usefulness in clinical settings.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test refers to its capacity to correctly distinguish between patient and healthy cases. To assess the accuracy of a test, one must compute the ratio of true positives and true negatives across all assessed cases. This can be expressed mathematically as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (5)$$

Precision: Precision assesses the proportion of accurately classified cases among those identified as positive. Consequently, the formula for calculating precision is expressed as:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (6)$$

Recall: Recall is a metric in machine learning that assesses a model's capacity to recognize all pertinent instances of a specific class. It is the proportion of accurately predicted positive observations to the total actual positives, offering insights into a model's efficacy in identifying occurrences of a specific class.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} (7)$$

F1-Score: The F1 score is a metric for evaluating the accuracy of a machine learning model. It amalgamates the precision and recall metrics of a model. The accuracy metric quantifies the frequency of true predictions generated by a model throughout the entire dataset.

$$F1\, Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (8)$$

mAP: Mean Average Precision (MAP) is a statistic for evaluating ranking quality. It evaluates the quantity of pertinent recommendations and their placement within the list. MAP at K is determined as the arithmetic mean of the Average Precision (AP) at K for all users or queries.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k \quad (9)$$

Table.1 Performance Evaluation – Classification

ML Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
VGG16	**0.933**	**0.941**	**0.933**	**0.934**
EfficientNetB	0.896	0.902	0.896	0.897
Proposed VGG16	0.291	0.325	0.291	0.290

Xception	0.928	0.935	0.928	0.929
Ensemble (Xception+VGG16)	**0.933**	**0.941**	**0.933**	**0.934**

Table 1 illustrates a performance comparison utilizing Accuracy, Precision, Recall, and F1-Score measures, indicating that the Ensemble (Xception + VGG16) model surpasses all other models with the highest evaluation scores.

Table.2 Performance Evaluation – Detection

ML Model	**Precision**	**Recall**	**mAP**
Yolo v5	0.237	0.925	0.422
Yolo v8	0.438	0.625	0.431
Yolo v9	0.188	0.750	0.401
Yolo v11	0.391	0.719	0.409

Table 2 juxtaposes detection models utilizing Precision, Recall, and mean Average Precision (mAP), indicating that YOLO v8 surpasses other YOLO iterations with a peak mAP value of 0.431.

Fig4 Comparison Graph– Classification

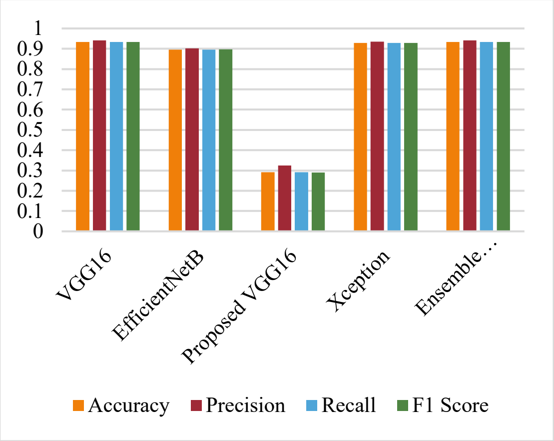


Figure 4 presents a comparative graph of Accuracy, Precision, Recall, and F1-Score, demonstrating that the Ensemble (Xception + VGG16) model attains superior performance across all evaluation measures.

Fig.5 Comparison Graph – Detection

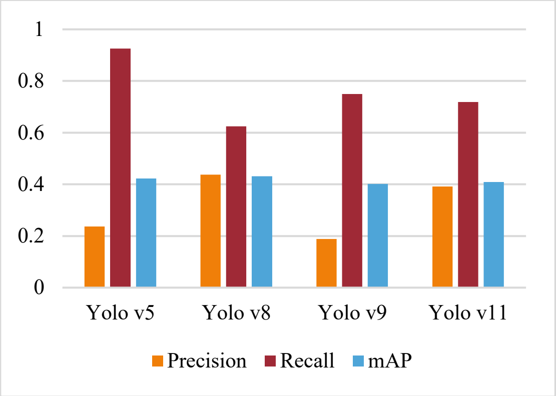
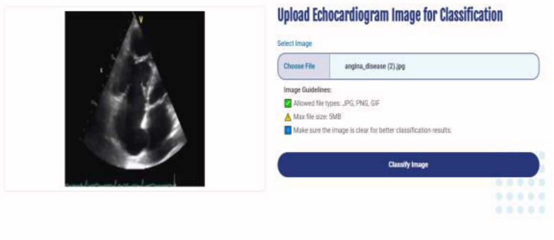


Figure 5 presents a comparative graph of Precision, Recall, and mAP metrics, demonstrating that YOLO v8 has enhanced detection performance relative to other YOLO versions across all evaluative parameters.


Upload Echocardiogram Image for Classification

Select Image

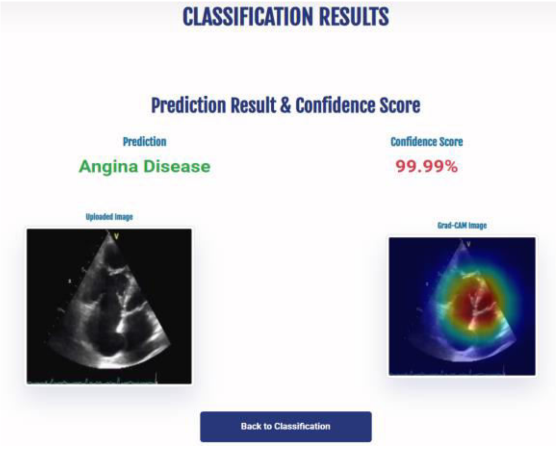
angina_disease (2).jpg

Image Guidelines:

- ✓ Allowed file types: JPG, PNG, GIF
- ⚠ Max file size: 5MB
- Make sure the image is clear for better classification results.

Fig.6 Upload the Image

The interface (fig.6) permits users to submit echocardiography pictures, facilitating effortless input submission for automated heart disease classification and anomaly identification.


CLASSIFICATION RESULTS

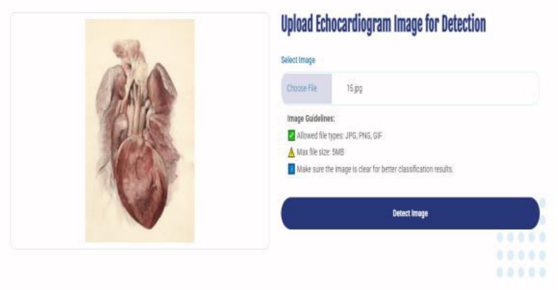
Prediction Result & Confidence Score

Prediction: Angina Disease

Confidence Score: 99.99%

Fig.7 Predicted Result

Figure 7 illustrates the prediction of angina disease with a confidence score of 99.99%, accompanied by a Grad-CAM representation that emphasizes key areas affecting the classification decision.


Upload Echocardiogram Image for Detection

Select Image: 15.jpg

Image Guidelines:

✓ Allowed file types: JPG, PNG, GIF

⚠ Max file size: 5MB

ℹ Make sure the image is clear for better classification results.

Fig.8 Upload the Image

The interface (fig.8) allows users to upload an echocardiography image for the detection of abnormalities, facilitating the identification of regions affected by cardiac illness.

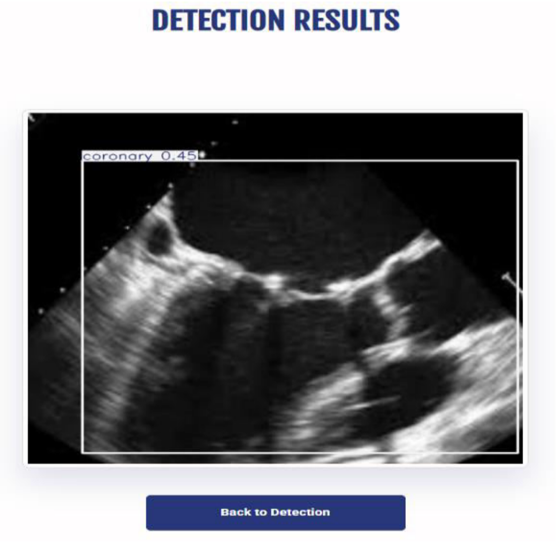

DETECTION RESULTS

Fig9 Predicted Result

The system displays detection results (fig.9) indicating coronary artery disease with a confidence value of 0.45, emphasizing the isolated aberrant area within the echocardiography image.

5. CONCLUSION

The established framework illustrates the efficacy of deep learning in the categorization and diagnosis of heart disease from echocardiography pictures. The ensemble of VGG16 and Xception outperformed other classification models, achieving an accuracy of 93.3% and an F1-score of 93.4%, demonstrating its proficiency in capturing intricate spatial representations and enhancing prediction reliability through model integration. YOLO v8 had the best balanced performance in detection, attaining a mean average precision (mAP) of 43.1% with enhanced precision and recall, facilitating more accurate localization of aberrant cardiac areas. The results validate that the combined use of classification and detection methods offers a thorough evaluation of both disease presence and geographical anomaly data. The integration of Grad-CAM images improved interpretability by emphasizing key areas that affect predictions, hence augmenting clinician confidence. The incorporation of the trained models into a Flask-based web framework facilitates real-time inference, visualization, and user interaction, hence facilitating practical clinical implementation. The study introduces a comprehensive, interpretable, and implementable deep learning framework that aids cardiologists in effective decision-making, diminishes dependence on manual assessment, and possesses considerable promise for enhancing early diagnosis and patient outcomes.

Future research may concentrate on augmenting the dataset's size and variety by integrating multi-center echocardiography image libraries to improve generalizability across various patient populations. Exploration of supplementary deep learning architectures, including DenseNet, Inception, and Vision Transformers, may enhance classification accuracy and robustness. Strategies for optimization, such as hyperparameter tweaking, learning rate scheduling, and the implementation of advanced optimizers, may be explored to enhance training efficiency. Integrating multimodal data, including patient demographics, clinical history, and ECG signals with echocardiography pictures, may yield a more comprehensive diagnostic paradigm. Moreover, employing cross-validation with extensive annotated datasets and comparing results with clinical expert evaluations would enhance the system's dependability and therapeutic relevance.

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