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Original Article

CNN Based Multi-Feature Fusion with Metaheuristic Algorithms for Effective Feature Extraction and Classification OF 2D Echo Cardiovascular Diseases

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Abstract - *Deep learning offers enormous potential to improve ultrasound quality through real-time heart anatomy and function analysis for clinical echocardiography and point-of-care diagnostics. Machine learning makes automating processes like echocardiography analysis, quality rating, view categorization, heart area segmentation, and diagnostic index computation easier. By extracting characteristics through data augmentation, existing approaches effectively categorize 2D echo data using high-performance deep neural networks. Using the Multi-Feature-Fusion (MFF) model, which combines wavelet packet energy, fuzzy entropy, and optimization algorithms for feature extraction, our system presents an innovative and efficient approach for analyzing and quantifying echocardiogram in real time. Using learned representations to improve target echo task learning, a Convolution Neural Network (CNN) has been trained on a large public dataset. The CNN integrates optimization techniques such as squirrel and crow meta-heuristics for efficient 2D echocardiography feature extraction, boundary identification, and image classification. A module locates regions of interest, and three thin routes extract high-level attributes and low-level texture. The model demonstrates its strong performance in reaching an accuracy of 98.2% for anomaly recognition, as evidenced by evaluation measures such as accuracy, specificity, sensitivity, precision, and AUC. This highlights the efficiency of our deep learning method, Multi-Feature Fusion, for the interpretation and quantification of Echocardiography in real-time.*

Keywords - *Echocardiography, Deep Learning, Multi-feature-fusion model, Real-time analysis, Abnormality recognition.*

1. Introduction

To implement feature extraction using the Multi-Feature Fusion MFF model by combining wavelet packet energy, fuzzy entropy, and optimization methods. Apply optimization methods such as squirrel and crow meta-heuristic algorithms for effective feature extraction in 2D Echocardiography by identifying the boundaries and classifying the images. Bedside echocardiography is becoming more common in emergency departments to expedite the triage of patients suffering from chest discomfort. In contrast with conventional equipment, poor image quality using equipment for bedside use could result in an incorrect diagnosis. To circumvent these constraints, we created a model with the convolution neural network CNN to train publicly available large-scale datasets with optimization methods such as squirrel and crow meta-heuristic algorithms. We collected data from Stanford University School of Medicine, which provides the internal test and training dataset, along with 2,811 tests from other hospitals, to form an external test collection. We utilized a DL model to detect three apical pictures and to segment the ventricle anterior during the preprocessing of data. A 3D Convolution Neural Network (CNN) was used for detection. In the end, the DL model computed the dimensions of the chambers in the heart and the left ventricular ejection by itself. Overall, with an accuracy of 96.2 percent, the view-choosing model chose the three apical perspectives. The model for segmentation was in good agreement regarding hand segmentation, with the average Dice being 0.89. In the internal assessment study, the model identified bedside and standard ultrasonography as having AUCs of 0.91 and 0.88, respectively. The AUCs on the outside test data ranged from 0.90 in both cases to 0.85. The assessments of cardiac function by computers were in agreement with the echocardiography report values (for instance, the average error for the left ventricular ejection was 4%). We've created an automated echocardiography process for bedside and conventional ultrasonography. It handles tasks like view selection, quality assessment, segmentation, wall motion abnormality identification, and heart function measurement. Quickly diagnosis is crucial for individuals with chest discomfort in emergency cases, aiding acute coronary syndrome detection. Echocardiography is cost-effective for assessing heart shape and function, although manual assessment is subjective and time-consuming. Our Multi-Feature Fusion (MFF) model integrates wavelet packet energy, fuzzy entropy, and optimization for feature extraction. Our deep learning model excels in image analysis, outperforming expert-based classification, segmentation, and quantification methods. Demonstrated with Stanford University echo datasets, our framework holds promise for clinical applications.

1.1. Motivation

Two-dimensional echocardiography, often known as 2D echo, produces intricate pictures that provide vital insights into the anatomy and functioning of the heart. The photos possess several dimensions and exhibit diverse textures, forms, and patterns, necessitating advanced analysis. Echo pictures may exhibit substantial variations in terms of quality, patient location, and imaging parameters. Convolution Neural Networks (CNNs) have the capacity to acquire resilience to variations by identifying features that are unaffected by certain transformations or amounts of noise. Utilizing Convolution Neural Networks (CNNs) for multi-feature categorization enables incorporating varied information from several areas of interest in echo pictures, possibly enhancing diagnostic precision. Utilizing CNNs for 2D echo pictures provides opportunities for investigating new image-based biomarkers, prediction models, and personalized medicine techniques in the field of cardiology. The rationale for using CNN-based multi-feature categorization of 2D echo cardiovascular disorders arises from the need to use sophisticated machine learning approaches to boost diagnostic precision, automate image processing, and improve clinical decision support in the field of cardiology. These techniques have the dual purpose of optimizing healthcare processes and enhancing our comprehension and treatment of cardiovascular illnesses.

1.2. Research Gaps

The study of categorizing cardiovascular disorders in 2D echo using machine learning, specifically Convolution Neural Networks (CNNs), encounters many significant gaps and problems that provide potential for future exploration and enhancement. These are the primary areas where the study is lacking in this field: The issue lies in obtaining extensive, varied, and well-annotated datasets that may be used to train classification models with strong reliability. The quality of echo pictures might vary owing to variables such as imaging parameters, patient characteristics, and variations in operator performance. Research is necessary to create techniques that can effectively handle such unpredictability. The issue lies in obtaining extensive, varied, and well-annotated datasets that may be used to train classification models with strong performance. The quality of echo pictures might vary owing to variables such as imaging parameters, patient characteristics, and variations in operator performance. Research is necessary to create techniques that can effectively handle such unpredictability. Although deep learning models, such as CNNs, are very efficient, they are typically seen as opaque, which poses difficulties in understanding the decision-making process. Although 2D echo is informative, including data from other modalities like 3D echo, MRI, or clinical data (such as patient history and biomarkers) can improve classification accuracy and increase diagnostic confidence. It is essential to ensure that CNN-based models have good generalization capabilities across various patient demographics, imaging techniques, and healthcare environments to effectively deploy them in real-world scenarios. Establishing standardized processes for data gathering, preprocessing, and model assessment has the potential to enhance the reproducibility and comparability of research outputs. Investigation investigates integrating AI models into current clinical processes to assist decision-making without compromising workflow efficiency or increasing the cognitive load on healthcare practitioners. By addressing these research gaps, we may not only make progress in the area of AI-driven categorization of 2D echo cardiovascular disorders but also open up opportunities for more precise, understandable, and clinically significant uses of machine learning in cardiology.

1.3. Contributions

- This work introduces a technique for predicting the probability of plaque rupture by combining many features.
- The approach used a combination of global characteristics extracted from carotid ultrasound pictures, echo features from the Region of Interest (ROI), and expert information derived from ultrasound reports. This self-supervised technique enhanced the learning process for the target echo tasks by generating echo-specific representations.
- The importance of detecting high-risk plaque was highlighted, focusing on essential aspects. A comprehensive collection of features was developed to properly and fully assess the risk of carotid plaque.
- Our experimental findings demonstrate the performance of echo tasks when computing insufficiency is improved, indicating a potential for application in clinical practice.

2. Literature Review

A multi-stream structure with regression models was suggested for cardiac view recognition, outperforming conventional techniques with 85% accuracy. A deep learning algorithm involves three networks: an initial network for rough view recognition, an advanced CNN for refinement, and a final aggregated retinal block for anatomical identification. However, prior methods often neglected model speed and complexity. Anisotropic diffused filters and alternative de-speckling filters were evaluated for automated image processing. A personalized multi-head model with echo-specific representation achieved greater accuracy and real-time processing. Algorithms for computer vision. The LV segmentation challenge is seen as a problem of smoothing. Therefore, the researchers introduced a front mitral leaflet into segments.

The suggested method involves sampling echo cardiographic movies over time using a partially automated assessment of a scanning line. Nevertheless, the suggested approach was limited by segmentation oversizing, mostly due to inadequate scanning techniques.

2.1. Traditional Machine Learning Algorithms

This study proposes a system that combines to identify the posterior wall of the Left Ventricle (LV) from echocardiogram pictures, specifically focusing on the Parasternal Long-Axis (PLAX) view. They attained a sensitivity of 67% and a specificity of 98%. Li et al. (2016) introduced a technique for accurately segmenting the myocardium in echocardiography. This approach used a combination of border detection. It was designed to apply to nonmedical pictures that exhibit significant changes in intensity.

3. Materials and Methods

3.1. Dataset

The dataset for Echo Net-Dynamic originates from Stanford University School of Medicine's echo net-dynamic study, featuring 10,030 deidentified echocardiography images. OpenCV and Pydicom preprocess the data by de-identification and format conversion. Echocardiography is a widely used imaging technique for assessing heart function. Echo Net-Dynamic provides a substantial echocardiogram video dataset for computer vision research, including expert annotations for cardiac motion and chamber sizes.

3.2. Wavelet Packet Energy

Wavelet analysis of packets is an innovative method based on the analysis of wavelets [15] to precisely split the signal's high-frequency and low-frequency components and provide a more thorough analysis of signals [16]. Every wavelet decomposition creates two sub-bands with high and low frequencies. Three-layer wavelet decomposition. 2n sub-bands are produced for the process of decomposing a signal using an n-layer wavelet packet. Here is the calculation for decomposition. Wavelet analysis of packets is an innovative method based on the analysis of wavelets [15] to precisely split the signal's high-frequency and low-frequency components and provide a more thorough analysis of signals [16].

$$d_{i,j,2m} = \sum_k h(k-2i) d_{k,j+1,m}$$
$$d_{i,j,2m+1} = \sum_k g(k-2i) d_{k,j+1,m} \tag{1}$$

The wavelet packet reconstruction calculation formula is:

$$d_{i,j+1,m} = \sum_k h(i-2k) d_{i,j,2m} + \sum_k g(i-2k) d_{i,j,2m+1} \tag{2}$$

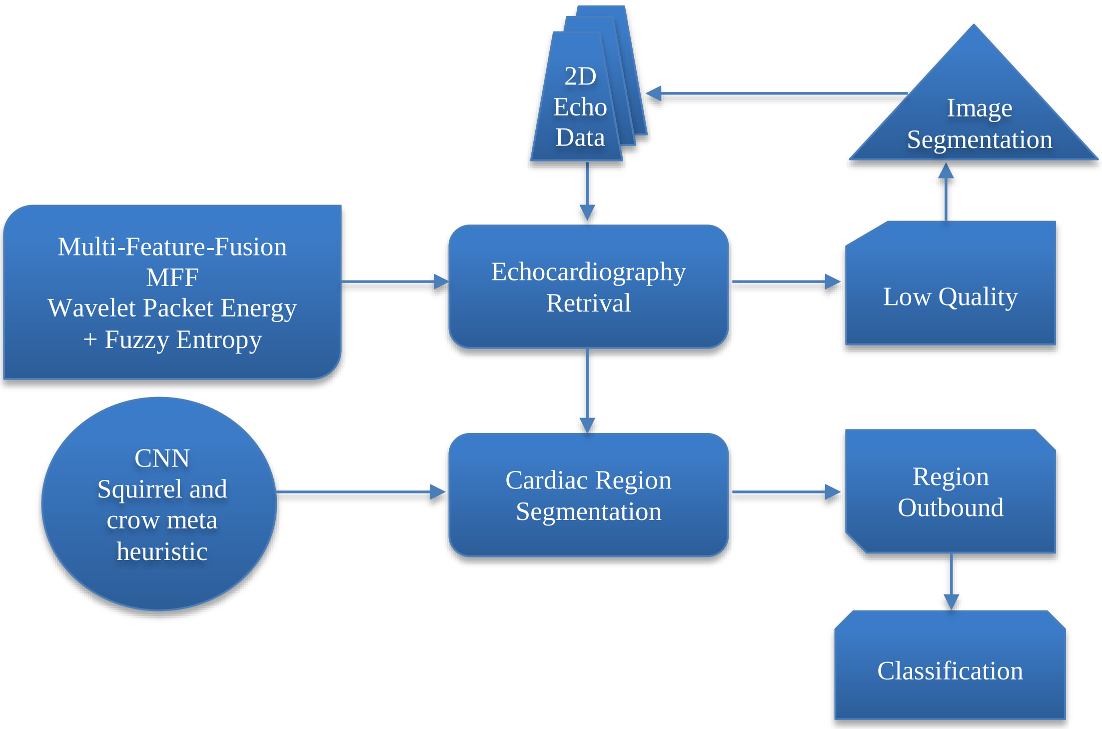

Fig. 1 Proposed workflow

The approach to wavelet packet energy seeks to determine the energy of signals on different scales of decomposition and then organize the energy levels into eigenvectors based on the scale ordering for recognizing [6, 18]. Wavelet packets have a wealth of characteristics, and the final result from the decomposition of a wavelet packet is called Ei,j(k), the energy within diverse frequency bands. Calculating formulas are according to:

$$E_{i,j} = \sum_{k=1}^{N} \left| d_{i,j}(k) \right|^2, \ j = 0,1...2^i - 1 \tag{3}$$

N denotes the initial signal length.

The wavelet packet power spectrum is made up of all Ei,j. The calculation formula for the fraction of wavelet packet energy Pi,j is as follows:

$$Pi,\ j = \frac{E_{i,j}}{\sum_{j=0}^{2^i-1} E_{i,j}} \tag{4}$$

3.3. Fuzzy Entropy

Both our minds and objects are prone to fuzzy thinking. It is possible to characterize fuzzy set theory as an effective technique for researching and understanding fuzzy real-world occurrences. Because fuzzy sets can precisely identify fuzzy items and are increasingly relevant in modelling systems and creating systems, this indicates that one of the main problems is analyzing the fuzziness that is quantitatively produced from the fuzzy set's context [6].

In Shannon's information, entropy is a crucial concept. It's a metric for determining how much freedom stochastic vectors have. The entropy is used to quantify the degree of fuzziness in a collection metric according to fuzzy set theory.

Fuzzy theories of entropy are the name given to this [18]. The degree of fuzziness within an unstructured collection is measured by fuzzy entropy. It is a crucial component of fuzzy systems that use algorithms to find patterns in fuzzy systems.

The entropy of a system, according to information theory, is a measure of the quantity of information in the system.

xi, i= (1......N) represent the potential outputs of source A with the probability p(xi).

$$H_{nonfuzzy}(A,P) = -\sum_{i=1}^{N} P(x_i) \log P(x_i) \tag{5}$$

Where $\sum_{i=1}^{N} P(x_i) = 1$ (6)

To differentiate from fuzzy entropy, the subscript "no fuzzy" is utilized. Higher entropy indicates a greater quantity of information.

$$F(A) = -\sum_{i=1}^{N} P(x_i) \log P(x_i) + \lambda \left(\sum_{i=1}^{N} P(x_i) - 1\right)$$

$$\frac{\partial F(A)}{\partial P(x_i)} = -\log P(x_i) - 1 + \lambda = 0 \tag{7}$$

The probability P(xi) of the histogram distribution represents the quantity of information for a set within a fuzzy domain.

3.4. Metaheuristic Algorithm

Metaheuristic algorithms are search methods designed to find good solutions for complex optimization problems. This project aims to create an efficient algorithm that produces high-quality results consistently. Meta heuristics balance local search and global exploration, often using randomization to transition between them. They're effective for modelling nonlinear systems and global optimization. By employing trial and error, Metaheuristics offer quick solutions to intricate problems when finding a perfect solution is challenging. Intensification and diversification are vital aspects, focusing on targeted search and exploring solution diversity, respectively.

3.5. Crow Search Algorithm CSA

Crows hide food, remember its location, and alter hiding spots if followed by others to prevent theft.

Step : 1 Provide the specific parameters for the CSA algorithm: the size of the population (n), the maximum number of iterations (Max), the step size of the flight (fl), and the probability of awareness (AP).

Step : 2 Create each crow and memory matrix in d-dimensional space. Each crow xi (Xi,1 to Xi,d) represents a solution. Initialize memory matrix.

Step : 3 Evaluate fitness using the fitness function for each crow.

Step : 4 Generate fresh locations for every crow located in a space with d dimensions. If crow i is tracking crow j, update i's position based on food location hidden by crow j, considering different scenarios.

3.6. Squirrel Search Algorithm (SSA)

Flying squirrels begin foraging in warm seasons, gliding between trees for food. In the fall, they gather acorns for quick energy and then seek nutritious winter food like hickory nuts. Storing nuts helps them survive extreme weather by reducing the need for energy-expensive hunting. With fewer leaves, predation risk increases, slowing forest activity without full hibernation. Flying squirrels resume activity after winter. This constant lifecycle process forms the basis of the Seasonal Squirrel Algorithm (SSA). These factors guide a mathematically simplified model.

- Flying squirrels are abundant in the deciduous forest, with each squirrel often occupying its own tree.
- Every squirrel actively searches for food and efficiently utilizes the available food resources by engaging in energetic foraging behaviours.
- There are three kinds of trees that can be found in the forests that are: normal trees the oak tree (acorn nuts source of food) as well as hickory trees (hickory nuts are a food source).
- It is thought that the forest area being examined contains three oak trees and one hickory.

3.7. Segmentation

Segmentation involves three pathways: Spatial (SP), Handcrafted (HP), and Context (CP). SP has 3 convolution layers with high channel capacity, extracting rich, low-level data at low computation. HP uses custom kernels based on geometry, stats, or textures. CP focuses on receptive field size; the lightweight model (Exception) rapidly down samples for suitable fields while maintaining context. It's enhanced with global mean pooling for extensive receptive fields and global context information.

3.8. Analyze and Identify Overarching Characteristics of Ultrasound Pictures on a Global Scale

The ultrasound scans of the tissues may vary depending on the specific medical equipment, imaging settings, operator, and patients. Therefore, normalization and cropping of images are required before feature extraction. Three picture cropping techniques that we use in our system. In Figure 2, in the beginning, unnecessary details such as dates, machine type, and marks should be removed when cutting photographs. The second thing to remember is that all photos cropped should have the same size. In order to limit the loss of information and minimize information loss, the image cropped must be maintained at top quality. Following cropping, linear normalization can be used to normalize the image using the following method (1) [16]. IN is for the normalized value of a pixel, and I refer to the initial gray value. The phrases "Max" and "Min" are associated with the maximum and minimum gray levels of a picture.

$$IN = (I - Min)(newMax - newMin/Max - Min) + newMin \quad (8)$$

The original images were cropped, normalized, and then scaled down until they reached a particular size. To determine the characteristics of global carotid ultrasound images, A classic CNN model called AlexNet 18 uses model complexity and the results of an experimental study [8]. Then, the Alex Net model is developed in the manner that is the standard method. The parameters are adjusted until the learning and validation results are adjusted. In addition, in line with one of the global features, the second layer in the model is completely connected, will be duplicated, and reduced to d dimensions. In the course of our test and adjusting the d at 10. Then, we compared AlexNet's linked layers. The results showed that the first fully linked layer did the best.

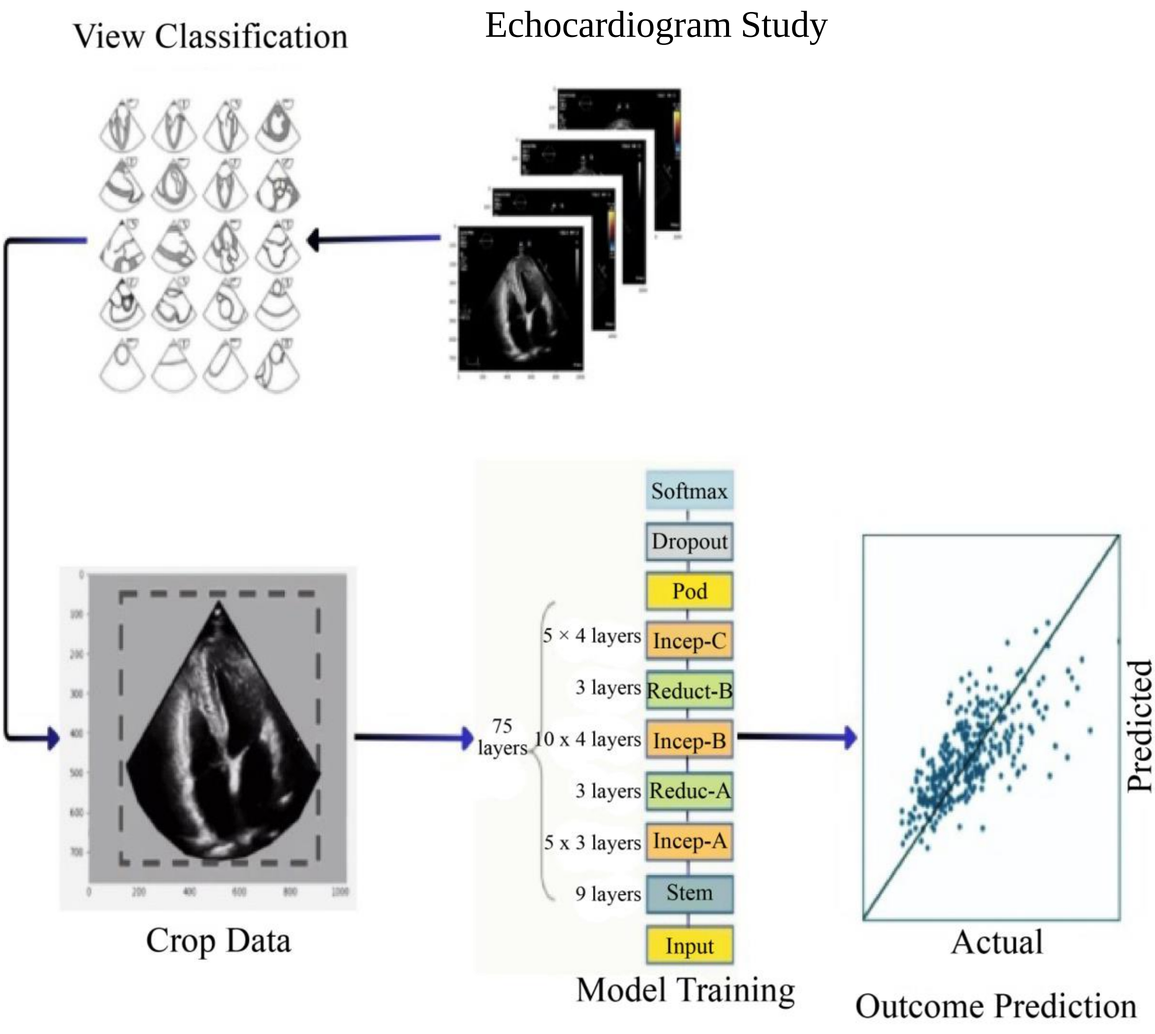

Fig. 2 EchoNet workflow for image selection, cleaning, and model training

4. Result and Discussion

The research assesses the effectiveness of a suggested method for retrieving echoes, segmenting the cardiac area, and improving measuring efficiency. Performance is assessed using metrics such as precision, accuracy, recall, F-score, and index quantification, which are calculated using the Pearson correlation coefficient, which is shown using the Bland-Altman graph. The computational complexity, along with frames per second of the system, is also evaluated. Experiments were conducted using Pytorch and NVIDIA GTX1080Ti graphics cards. The model's efficacy was evaluated using advanced models and view categorization head. The study created a CNN model using over 2.6 million images from 2850 patients' echocardiography. The model was trained using three categorization tests and an over 2.6 million image database. The model underwent training to execute precise medical categorization or prediction tasks.

Table 1. The baseline characteristics of the individuals in question were discovered by analyzing the data sets utilized for training and testing

Characteristics	Learning Set	Experimental Data
Number-of-Sufferer	2853	376
Plurality-of-Images	1,624,790	169,680
Sex-(%-Male)	51.4%	53.8%
Span-Mean-Years-(std)	62.3-(16.2)	63.8-(17.8)
Weight-Mean-Kg-(std)	77.8-(21.2)	79.9-(21.9)
Height Point-Mean,-m-(std)	1.70-(0.12)	1.71-(0.12)
BMI-Mean-(std)	28.3-(6.5)	29.5-(6.9)
Bellwether-or- Implantable Cardioverter-Defibrillator-Lead-(%-Present)	14.2	15.7
Highest-Left-Atrial-Enlargement-(%-Present)	18.2	21.3
Hypertrophic Cardiomyopathy-(%-Present)	34.3	39.0
Greater Distention -Volume-mL-Mean-(std)	95.3-(46.2)	96.9-(14.0)
Stroke-Capacity,-mL:-Mean-(std)--	46.7-(39.4)	48.3-(38.2)
Discharge-Fraction:-Mean-(std)	54.2-(11.3)	53.7-(12.0)

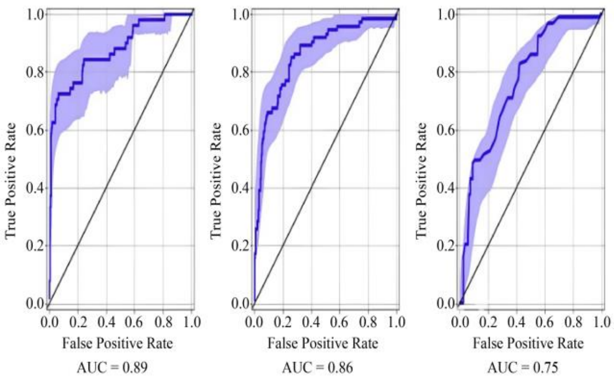

Fig. 3 AUC using MMF on 2D echo Data

Table 2. Experimental findings are compared between the CNN and CNN+MMF approaches and the enhanced method

Model	Accuracy (%)	Sensitivity (%)
CNN	95	91
CNN+MMF	98	98

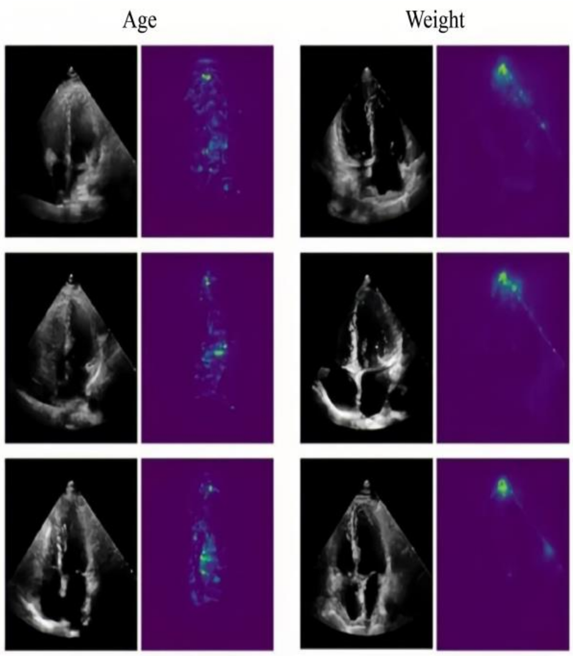

Fig. 4 Feature selection using MMF on 2D echo Data

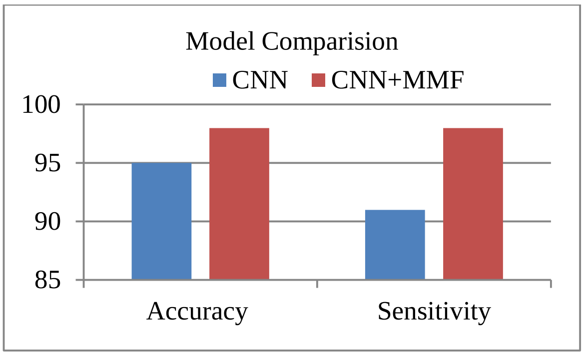

Fig. 5 The models compared with CNN and CNN MMF with feature extraction

The findings reveal that the CNN+MMF models performed better, having feature extraction along with using the metaheuristic approach to identify the area of the 2D echo pictures with some ambiguity in the data.

5. Conclusion

Deep CNNs, trained on conventional echocardiography images using MMF extraction or meta-heuristic methods, can detect local cardiac characteristics and interpretable indicators like age, gender, weight, and size. Our models achieve high precision for tasks interpreters handle, such as estimating ejection percentage, chamber volume and recognizing pacemaker leads. They excel at challenging tasks like predicting heart phenotypes from images.

We propose a strategy utilizing collected phenotypes and interpreters from medical records, enabling external validation and quicker application to larger datasets. However, while superior to prior work, our approach doesn't uniformly outperform human evaluation in tasks involving clinical data like ESV, EDV, and EF, requiring deeper clinical understanding and context integration.

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