Deep Learning for Cardiovascular Disease Detection: A Review Based on Cardiac Magnetic Resonance Imaging Data

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Abstract—**Despite improvements, cardiovascular diseases (CVDs) remain the most significant killer globally, accounting for around 17.9 million lives annually. Advancement of cardiac imaging modalities has taken place with magnetic resonance imaging (MRI) along with artificial intelligence (AI) for changing scenarios of early diagnosis and management in CVDs. This work investigates the role and contribution of deep learning, especially Fully convolutional networks and convolutional neural networks, toward the improvement of accuracy and automation in cardiac MRI analysis. The integration of AI enables accurate segmentation, efficient clinical workflows, and scalable solutions for resource-limited environments. A review of publicly available datasets underlines challenges in data variability and generalizability and points to the need for standardized models and explainable AI approaches. This work, therefore, underlines the possibility of improved diagnostic efficiency and equity in healthcare delivery using AI-driven methodologies in cardiovascular diagnostics. Future directions will focus on refining model scalability, enhancing dataset diversity, and validating clinical applications to foster robust and adaptable solutions.**

Index Terms—**Cardiovascular diseases, Convolutional neural networks, Deep learning, Fully convolutional networks, Magnetic resonance imaging.**

I. Introduction

Cardiovascular diseases (CVDs) are currently the leading killer globally, with an estimated 17.9 million deaths annually and 32% of all global deaths (Rajiah, François and Leiner, 2023) (Doolub et al., 2024). The diseases vary from coronary artery disease and heart failure to structural heart defects that have a profound impact on quality of life and healthcare costs (Metan et al., 2021). Diagnosis and management are based on sophisticated imaging studies such as cardiac magnetic resonance imaging (MRI) and echocardiography that provide accurate structural and functional evaluation (Ahmadi-Hadad et al., 2024). Recent developments in imaging modalities combined with artificial intelligence (AI) have brought about a paradigm change that has enabled improved diagnostic accuracy and quicker workflow (Zhang et al., 2024). A few of the stressed developments in cardiac MRI have been high-field imaging and artificial intelligence, offering enhanced diagnostic parameters, i.e., myocardial perfusion with a precision greater than SPECT, though dependency on resources is a problem. Low-field MRI and adaptable AI models have been proposed as the path ahead to drive accessibility in low-resource settings (Chen et al., 2020) (Jafari et al., 2023). Artificial intelligence for cardiac diagnosis ranges from the segmentation-free 3D-convolutional neural network (CNN) for left ventricular ejection fraction (LVEF) estimation to CNN models for cardiac amyloidosis, with a very encouraging area under the curve (AUCs) of 0.99 and 0.96, respectively. Scalability issues and a lack of external validation are, however, concerns. Light models, transfer learning, and domain adaptation have been fundamental solutions to improvement in such cases (Oscanoa et al., 2023). Dataset variability, model bias, and lack of diversity in training data are issues that affect AI's generalizability in cardiovascular imaging (Khalifa and Albadawy, 2024) (Thoutireddy, 2021). Standardized datasets, explainable AI, and augmentation techniques have been suggested for improvement. The overview herein underscores the role of fully convolutional networks (FCNs) in cardiac MRI, their efficacy, segmentation precision, and the potential for clinical workflow automation. The way forward would be the creation of flexible and standardized models and improved validation processes to facilitate fair and efficient cardiovascular diagnosis. The rest of this paper is organized

ARO-The Scientific Journal of Koya University
Vol. XIII, No. 2 (2025), Article ID: ARO.11971. 17 pages
DOI: 10.14500/aro.11971
Received: 25 December 2024; Accepted: 27 May 2025
Regular review paper; Published: 09 July 2025
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 http://dx.doi.org/10.14500/aro.11971

as follows: Section 2 provides a background on CVDs, reviews FCNs in subsection 2.1, and MRI and publicly available datasets for cardiovascular imaging in 2.2. Section 3 discusses the techniques used in using FCNs for cardiac MRI analysis. Section 4 gives a detailed explanation of the results, their implications, and future expectations. Section 5 concludes the paper with key findings and recommendations for future research in this direction.

II. Cardiovascular

CVDs are a group of conditions that impact the heart and the blood vessels, e.g., stroke (restricted flow of blood to the brain), heart failure (ineffective pumping of the heart), and coronary heart disease (obstructed arteries) (Qiu, 2024). The key culprits are atherosclerosis, diabetes, elevated blood pressure, and lifestyle factors such as poor diet and smoking. CVDs include peripheral arterial disease (reduced blood flow to the limbs), arrhythmias (irregular heart rhythm), rheumatic heart disease (damage to valves due to infection), and congenital heart defects (heart defect at birth). Symptoms may range from as simple as chest pain and shortness of breath to pain in the limbs and stroke symptoms such as paralysis. Prevention is a healthy lifestyle, while treatments range from drugs and surgery to lifestyle changes (Amal et al., 2022). Visual aids in the form of cardiac anatomy, pathways of stroke, and circulation models are also required to comprehend the condition.

A. FNCs

Applications of deep learning models, specifically ConvNets, for image segmentation, with particular emphasis on medical imaging (Kako and Abdulazeez, 2022). Models such as AlexNet (Muhammad Hussain et al., 2022), VGG (Alghamdi et al., 2024), and GoogLeNet (Ohta et al., 2019) have advanced research into image segmentation, while their adaptation to medical studies, especially for identifying regions of interest, has become increasingly common. However, medical image segmentation has its own challenges, such as the irregular and nonuniform shapes and unclear boundaries of medical objects, which complicate the segmentation tasks (Yang et al., 2022).

A major breakthrough in image segmentation is the FCN, which was proposed in the year 2015. FCN processes images of any size and then generates output with class labels for each pixel, hence becoming very suitable for segmentation tasks (Daudé et al., 2022). The architecture of FCN comprises down-sampling layers (max-pooling and convolutional) to extract features and up-sampling layers (convolutional and transposed convolutional) to reconstruct high-resolution output. This model improves the accuracy of segmentation by incorporating semantic information from deeper layers and appearance information from shallow layers, leading to more precise and effective image segmentation (Amerini et al., 2021).

B. MRI and Public Dataset

MRI is a non-invasive diagnostic modality that employs powerful magnetic fields and radiofrequency waves to generate intricate images of the body's internal anatomy without the use of ionizing radiation (Campbell-Washburn et al., 2024). Cardiac MRI at low field strengths. Journal of MRI, 59(2), 412–430.', no date). It provides outstanding soft-tissue contrast, rendering it optimal for imaging the brain, spinal cord, joints, cardiovascular system, and abdominal organs (Schulz et al., 2024). Applications include diagnosing neurological conditions, heart diseases, joint injuries, tumors, and more. Specialized types, including functional MRI and cardiac MRI, further extend its usefulness (Cundari et al., 2024). Public datasets (Table I) facilitate reproducibility. The Automated Cardiac Diagnosis Challenge (ACDC) Dataset (Bernard et al., 2018), for instance, includes 1,902 annotated cardiac MRI scans of 100 patients with balanced demographics (age: 45–85 years; 52% male). Pre-processing includes noise removal through Gaussian filtering, intensity normalization, and data augmentation (rotation, flipping). Institutional access is required for proprietary datasets like the Cedars-Sinai Prospective Dataset (Lyu et al., 2021), but high-resolution three dimensional (3D) cine-MRI images along with expert annotations are available. MRI is safe and painless, with high-resolution images, but it may be costly, time-consuming, and unsuitable for some patients with implants or claustrophobia. Advances in AI integration and higher-field magnets continue to develop its capability (Catapano et al., 2024). Furthermore, this study introduces a new dataset (CADICA), specifically developed to facilitate the detection of coronary artery disease using invasive coronary angiography (Jiménez-Partinen et al., 2024).

III. Approaches

Mishra, Gupta, and Sharma (2024) presented a paper on the XGBoost algorithm for CVD prediction, showing high diagnostic accuracy and underlining its possible role in improving patient outcomes.

Chibueze et al. (2024): The study focused on using a CNN model to detect heart disease, highlighting caffeine as a risk factor. The model, trained on MRI data with extensive pre-processing, achieved 94.13% accuracy in classifying heart conditions (Fig. 1).

Recent research has used explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and SHAP to account for the black-box character of deep learning models. Grad-CAM, for example, was used by Iqbal, Khalid, and Ullah (2024) to display regions of interest that influence model judgments in the classification of coronary artery disease. High agreement was obtained when visualizations were compared to expert cardiologist ratings, confirming the model's clinical validity and legitimacy (Fig. 2).

Ogunpola et al. (2024) studied the machine learning model for the detection of CVD, which focused on methods such as XGBoost and CNN for high precision by balancing the data in pre-processing and fine-tuning (Fig. 3).

Vernikouskaya et al. (2024) developed a two-stage deep-learning method using YOLOv4 for region detection and U-Net for segmentation. Accurate segmentation with high

TABLE I
PROVIDES A SUMMARY OF THESE DATASETS FOR EASY COMPARISON AND SELECTION FOR SPECIFIC RESEARCH PURPOSES

Ref.	Dataset	Full name	Purpose	Number of images	Image resolution	Focus	Annotations provided	Source/Institution and link
Chibueze et al. (2024)	Enugu State University Teaching Hospital Dataset and Kaggle CAD Cardiac MRI Dataset	Heart disease MRI dataset	Classification of heart diseases using CNN, with a focus on caffeine intake as a risk factor.	90,500 MRI samples (20,500 from Enugu State, 70,000 from Kaggle)	224×256 px	T1-weighted MRI of cardiac structures	Labels for five heart disease types (e.g., coronary artery disease, myocardial infarction, arrhythmia)	Enugu State University Teaching Hospital (publicly provided for research) and Kaggle Link : (public)
Lalande et al. (2020)	EMIDEC	Assessment of myocardial infarction automatically from delayed cardiac MRI	Evaluation and quantification of myocardial infarction using DE-MRI and clinical data	150 exams	1.25–2.00 mm² pixel spacing; slice thickness: 8 mm; distance between slices: 10 mm	Short-axis LV DE-MRI.	Manual segmentation of myocardium, infarcted area, microvascular obstruction (MVO), and clinical parameters	University of Burgundy Franche-Comté, France Link (Public)
Girum et al. (2021)	EMIDEC	Automatic evaluation of myocardial infarction from delayed-enhancement cardiac MRI	To evaluate myocardial infarction using DE-MRI and clinical data via deep learning methods.	150 cases (100 training, 50 testing)	Resized–256×256	DE-MRI of the LV in short axis	Manual segmentation of myocardium, infarcted area, no-reflow area, and clinical characteristics	University of Burgundy, Dijon, France Link Public
Radau et al. (2022)	SCD	Cardiac Atlas project dataset	Localization of LV in MRI images	45 subjects (20 frames per subject)	256×256 pixels	LV localization and segmentation	Bounding boxes (labels around LV)	Public; Cardiac Atlas Project Dataset
Bernard et al. (2018)	ACDC dataset	Automated cardiac diagnosis challenge	Automated segmentation of cardiac MRI for disease classification.	1902 training images (100 patients)	1.37–1.68 mm²/pixel	Cine MRI of LV/RV and myocardium	Manual annotations for train set at two phases (ES and ED)	University Hospital of Dijon, France Restricted (MICCAI Challenge)
Han, 2023)	CVD dataset	CVD dataset	Predict CVD risks	70,000 records	N/A	Clinical and demographic features	11 features including age, cholesterol, BP	Kaggle User: Sulianova Kaggle Link (public)
Khozeimeh et al. (2022)	CAD cardiac MRI dataset	Cardiac MRI dataset	CAD classification	63,151	100×100 pixels	Healthy vs. CAD images	Labels for healthy and CAD conditions	Kaggle - CAD Cardiac MRI Dataset link (public)
Lupague et al. (2023)	Cardiovascular diseases risk prediction dataset	CVDs risk prediction dataset	Predict risk factors for CVDs	70,000 records	N/A	Medical and lifestyle features	Features like age, BP, cholesterol, gender	Kaggle User: Alphiree Kaggle Link (public)
Cervantes-Sanchez et al. (2019)	Coronary artery X-ray dataset	X-ray angiography dataset	Identify coronary heart disease	130 images	300×300 pixels	Coronary artery characteristics	Features: color, diameter, shape	Mexican Social Security Institute (Restricted)
Milosevic et al. (2024)	Heart disease dataset	Heart disease dataset	Heart disease classification with machine learning methods	4,238 records	Not applicable	Cardiology Diagnosis	16 patient characteristics (e.g., gender, age, blood pressure)	Kaggle: Public
Erdem et al. (2023)	Multimodal Imaging Dataset	Cardiac MRI and CT Dataset	Fusion and segmentation of heart images using different modalities	21 participants (CT+MRI)	Not specified	Multimodal Imaging	Segmentation labels for myocardium and epicardium	Northeastern University, Roux Institute : Public
Baskaran et al. (2020)	Segmentation of cardiovascur structures	Segmentation of multiple cardiovascular structures	Segment multiple cardiovascular structures for medical research and analysis	MRI images (specific count not mentio)	High resolution	Cardiovascular structure segmentation	Pixel-wise segmentation masks	Kaggle User: Saurabh Shahane Kaggle Link (public)
Lyu et al. (2021)	ACDC dataset	Automated cardiac diagnosis challenge	Synthesize motion-blurred images for cardiac motion artifact reduction.	150 MRI Scans	1.37–1.68 mm²/pixel	Cardiac MRI (5 subgroups)	Motion-blurred images created by a motion blurring process from motion-free data.	ACDC Challenge Public Link to Dataset.

(*Contd...*)

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TABLE I
(CONTINUED)

Ref.	Dataset	Full name	Purpose	Number of images	Image resolution	Focus	Annotations provided	Source/Institution and link
Lyu et al. (2021)	Cedars dataset	Cedars-Sinai prospective dataset	Acquiring prospective motion-blurred cine images for neural network training.	5 volunteers	Field of view: 225×300 mm	Cine cardiac MRI (5 slices per view)	Paired reference (motion-free) and motion-blurred images using 2D SSFP sequence.	Cedars-Sinai Medical Center Restricted (Informed Consent Required).
El-Taraboulsi et al. (2023)	ACDC	(ACDC) 2017	Evaluate cardiac function and segmentation	1,500 MRI time-series	Variable	Cardiac function and pathology	Segmentation labels for heart regions	MICCAI Challenge Kaggle Link (public)
Jiménez-Partinen et al. (2024)	CAD cardiac MRI dataset	CAD cardiac MRI dataset	Detection and analysis of coronary artery disease using cardiac MRI	1,200 MRI images	High resolution	Cardiac MRI segmentation	Labels for coronary artery regions	Kaggle User: Danial Sharifrazi Kaggle Link (public)
Tobon-Gomez et al. (2015)	Heart MRI image dataset: Left atrial segmentation	Heart MRI image dataset: Left atrial segmentation	Segment the left atrium from MRI images for deep learning research	30 datasets	3D MRI volumes	Left atrium segmentation in cardiac imaging	Labels for the left atrium's ground truth segmentation	King’s College London Kaggle Link (public)
Arshad et al. (2024)	Core-based CMR datasets	Compressive recovery with outlier rejection	Motion artifact reduction in cardiovascular MRI	3D cine: 7 datasets	1.3×1.3×1.0–2.1×2.3×2.0 mm	Cardiac and respiratory motion suppression	Yes (artifact correction results)	The Ohio State University Wexner Medical Center GitHub Repository (Public)
Schmidt et al. (2023)	UKB-CMR	UK Biobank cardiac MRI	To analyze biventricular function and morphology for cardiac disease research and therapy design	Up to 36,548	Not explicitly stated	Cardiac structure and function	Annotations on ventricular volumes, mass, ejection fraction, and other biventricular traits via deep learning	UK Biobank (Restricted Access)

MRI: Magnetic resonance imaging, SCD: Sunnybrook cardiac dataset, CNN: Convolutional neural network, DE-MRI: Delayed enhancement magnetic resonance imaging, ACDC: Automated cardiac diagnosis challenge, CAD: Coronary artery disease, CT: Computed tomography, CMR: Cardiovascular magnetic resonance, LV: Left ventricle, RV: Right ventricle, BP: Blood pressure, 3D: Three dimensional

TABLE II
Comparative Performance Metrics

Architecture	Task	Mean performance	95% CI	Standard deviation	Optimal use case
FCN	Segmentation	0.92 (Dice)	0.89–0.95	±0.03	LV/RV/Myocardium delineation
CNN	Classification	95.4% (Accuracy)	93.2–97.6%	±2.1%	Disease detection
U-Net	Segmentation	0.94 (Dice)	0.91–0.97	±0.02	Multi-structure segmentation
3D-CNN	Volume estimation	93.8% (Accuracy)	91.4–96.2%	±1.7%	LVEF/RVEF calculation

FCN: Fully convolutional network, CNN: Convolutional neural network, 3D-CNN: Three-dimensional convolutional neural network, CI: Confidence interval, LVEF: Left ventricular ejection fraction, RVEF: Right ventricular ejection fraction, LV: Left ventricle, RV: Right ventricle

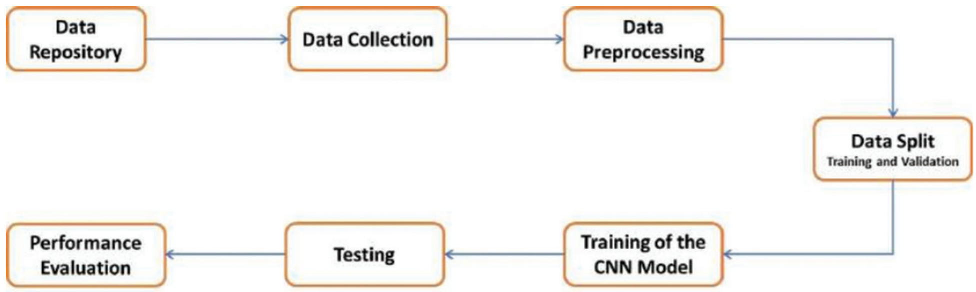

Fig. 1. Workflow for developing a convolutional neural network-based model (Chibueze et al., 2024).

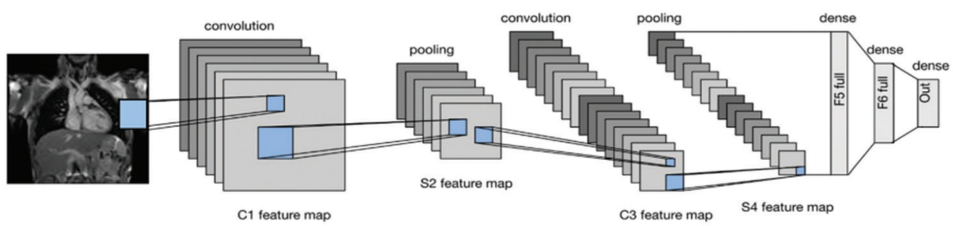

Fig. 2. Lightweight convolutional neural network with grad-class activation maps (Iqbal, Khalid, and Ullah, 2024).

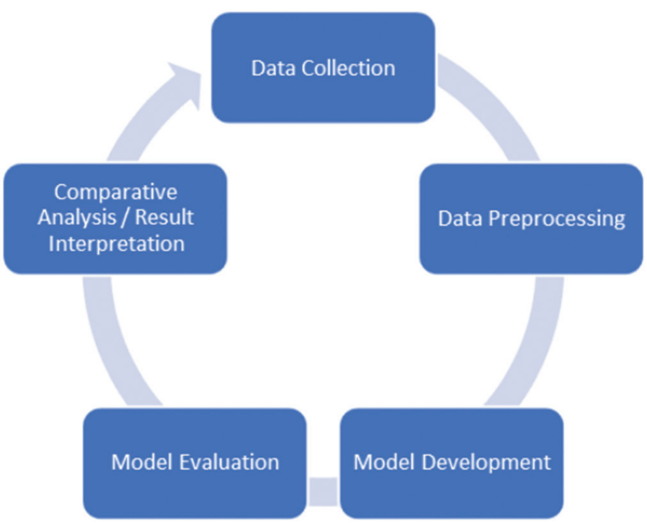

Fig. 3. Research method workflow (Ogunpola et al., 2024).

precision and efficiency; reduced memory consumption.

Bhan, Mangipudi, and Goyal, 2023 analyzed machine learning algorithms (Vanilla-CNN, fully convolutional neural network [FCNN], and ResNet) for RV segmentation in cardiac MRI, finding FCNN the most accurate for diagnosing CVDs (Fig. 4).

A. Comparison between CNN and FCNN

In Fig. 4 and Table II, FCNN and CNN performance have been evaluated on various segmentation and classification tasks. FCNN models have consistently performed better than CNNs on greater Dice scores for segmentation tasks, especially for left ventricle (LV) segmentation, where FCNN performed with a Dice coefficient of 0.93 compared to 0.86 for CNN. This is due to FCNN maintaining spatial hierarchies and end-to-end pixel-wise classification capability. While CNNs excel at image-level classification, FCNNs enhance diagnostic performance by enabling more precise segmentation of cardiac anatomy, which then feeds into classification models with higher-quality inputs.

Shaaf et al. (2023) utilized a faster region-based convolutional neural network (R-CNN) for efficient LV detection in cardiac MRI, which attained 91% accuracy with reduced computational cost by proposing and classifying advanced regions (Fig. 5).

Shaaf, Jamil, and Ambar (2023) addressed myocardial infarction detection using a CNN model for MRI segmentation, achieving robust performance across different evaluation metrics (Fig. 6).

Inomata et al. (2023) used a 3D-CNN model to estimate ventricular ejection fractions using cine-MRI data and attained highly accurate performance regarding the prediction of LVs (Fig. 7).

Shaaf et al. (2022) discussed a FCN for LV segmentation from cardiac MRI, achieving higher accuracy in LV

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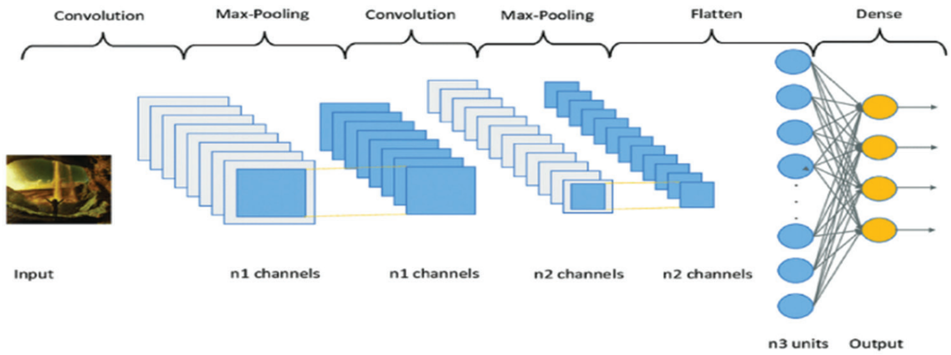

Fig. 4. Vanilla-convolutional neural network architecture for right ventricle segmentation (Bhan, Mangipudi, and Goyal, 2023).

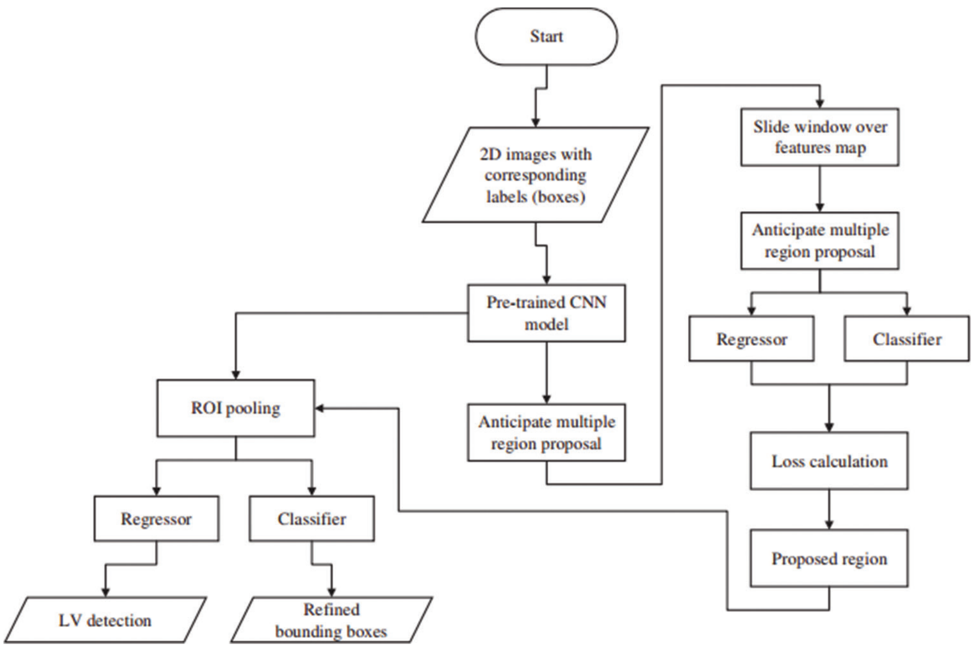

Fig. 5. Flowchart of the convolutional neural network-based region detection process (Shaaf et al., 2023).

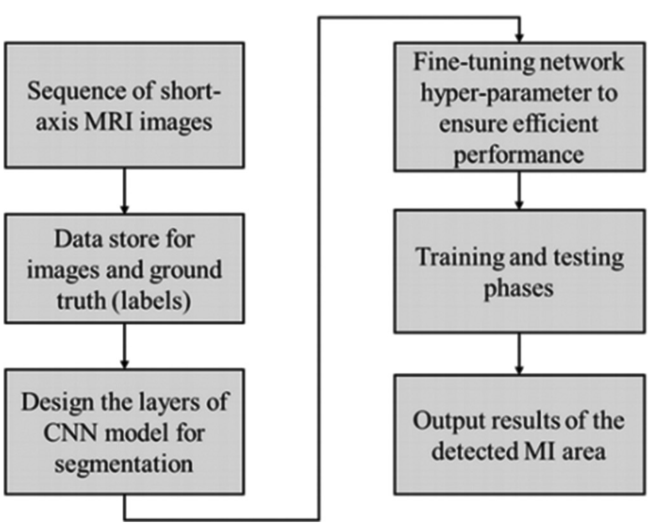

Fig. 6. Structure and workflow of the magnetic resonance imaging segmentation convolutional neural network system (Shaaf, Jamil, and Ambar, 2023).

segmentation compared to U-Net (Fig. 8).

Abualkishik, Almajed, and Almutairi (2022) proposed a fully deep convolutional network for CVD detection from MRI, achieving high accuracy with fast processing (Fig. 9).

Agibetov et al. (2021) investigated the application of CNNs in the fully automated diagnosis of cardiac amyloidosis using MRI and reached high diagnostics.

Sadr et al. (2024) introduced a hybrid model that combined machine learning and deep learning to enhance the prediction of CVDs by using K-Nearest Neighbors (KNN), Extreme Gradient Boosting (XGB), CNN, and Long Short-Term Memory (LSTM) for improved results on public and local datasets (Fig. 10).

Ammar, Bouattane, and Youssfi (2021) proposed an automated UNet-based pipeline for cardiac segmentation and disease diagnosis, achieving high accuracy and efficiency (Fig. 11).

Wu, Fang, and Lai (2020) proposed a composite model combining CNN and U-Net in order to automate LV

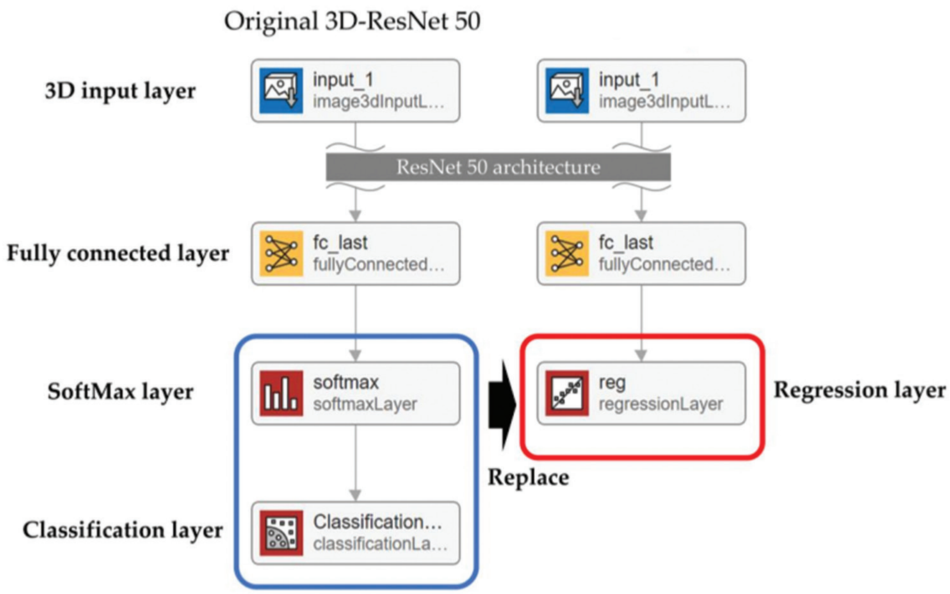

Fig. 7. Convolutional neural network for regression (Inomata et al., 2023).

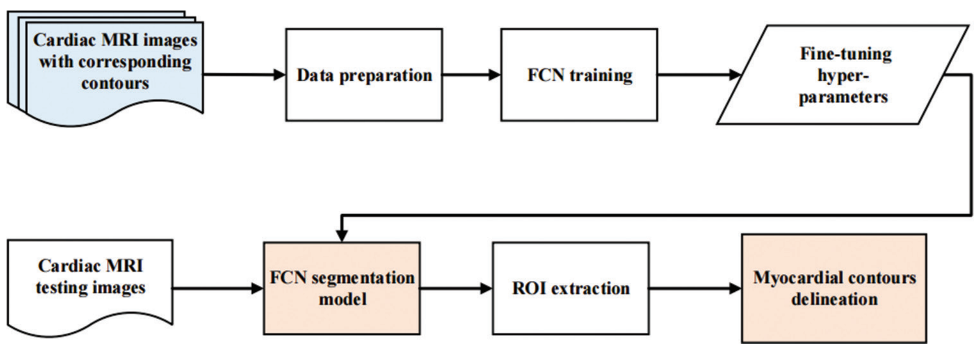

Fig. 8. Schematic of the cardiac magnetic resonance imaging segmentation and contour delineation pipeline (Shaaf et al., 2022).

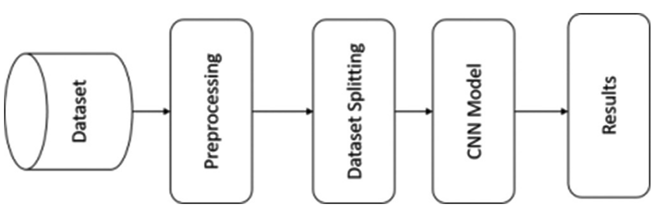

Fig. 9. Convolutional neural network model training pipeline from data preparation to results (Abualkishik, Almajed, and Almutairi, 2022).

segmentation in cardiac MRI with state-of-the-art accuracy and robustness (Fig. 12).

Liu et al. (2020) propose a CNN-based cardiac MRI segmentation method, filtering out non-heart regions and being robust to noise.

Simantiris and Tziritas (2020) discussed cardiac MRI segmentation with a dilated CNN, introducing domain-specific loss functions and novel augmentation methods to increase its accuracy and efficiency.

Penso et al. (2021) proposed a deep-learning method with dense skip connections for automated cardiac MRI segmentation, which achieved accurate ventricular delineation and demonstrated generalizability across datasets.

Liu et al. (2020) proposed a deep-learning framework that integrated residual CNNs and Bi-CLSTM for cardiac segmentation and disease diagnosis, achieving high accuracy on the ACDC dataset.

Zakariah and AlShalfan (2020) applied CNNs for left ventricular volume estimation. Reduced manual segmentation time; good accuracy in LV volume estimation (Fig. 13).

El-Rewaidy et al. (2021) proposed a multi-domain CNN approach for fast reconstruction of undersampled radial cardiac MRI and demonstrated significant improvements in image quality and reductions in acquisition times.

Baccouch et al. (2023) compared CNN and U-Net for the segmentation of cardiac MRI. U-Net was found to be more effective and efficient, and it performed better in all accuracy and similarity metrics (Fig. 14).

Qiao et al. (2020) compared various registration and CNN-based techniques to track cardiac motion. This was done using Groupwise MotionNet, which was seen to be more accurate with diverse training data.

Madan et al. (2022) discussed the role of AI in enhancing cardiovascular imaging in cardio-oncology, with an emphasis

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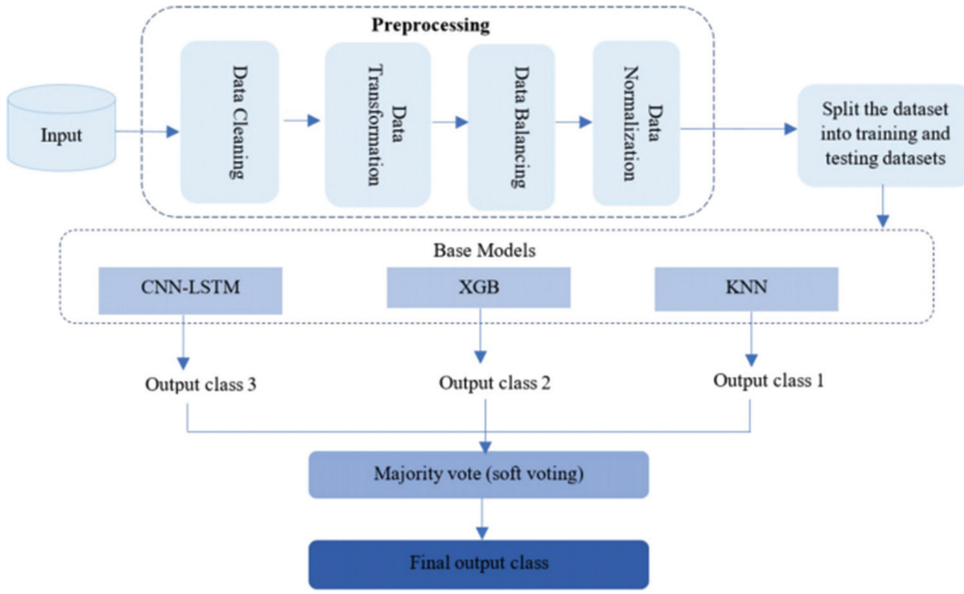

Fig. 10. Ensemble classification pipeline: Data preprocessing, XGB/KNN/Convolutional neural network base models, and soft voting integration (Sadr et al., 2024).

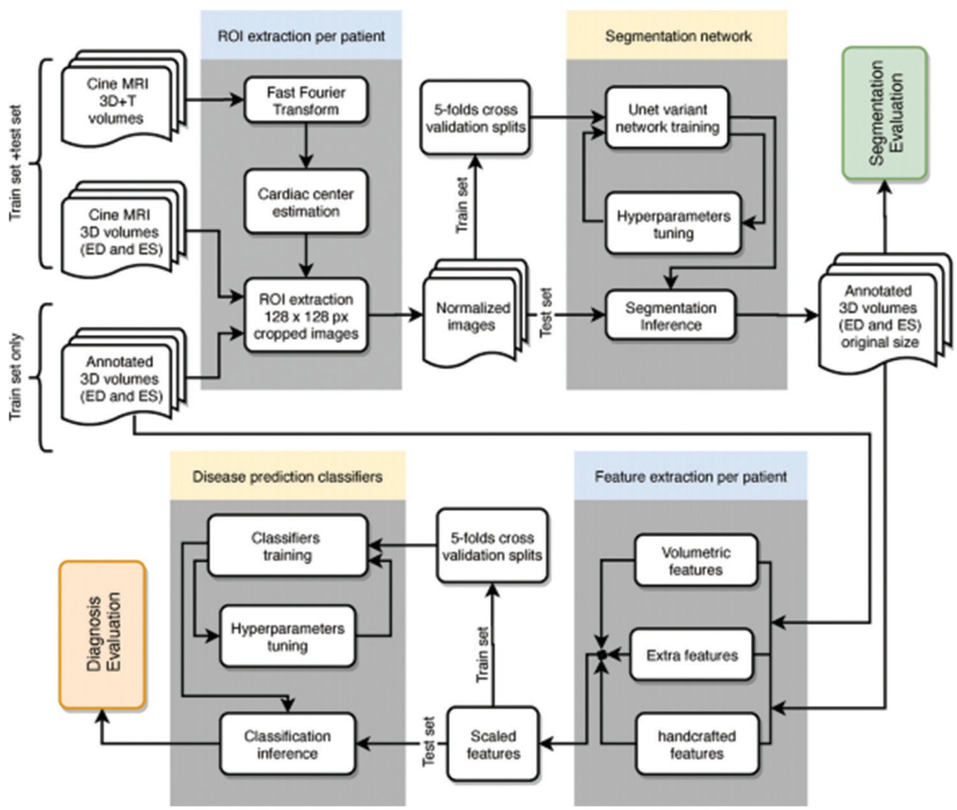

Fig. 11. Segmentation (top row) and diagnosis (bottom row) workflows (Ammar, Bouattane, and Youssfi, 2021).

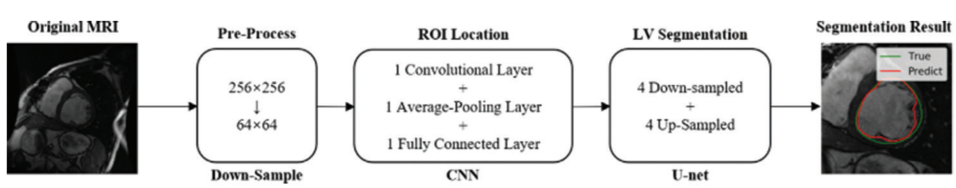

Fig. 12. Convolutional neural network-U-net structure for cardiac magnetic resonance imaging.

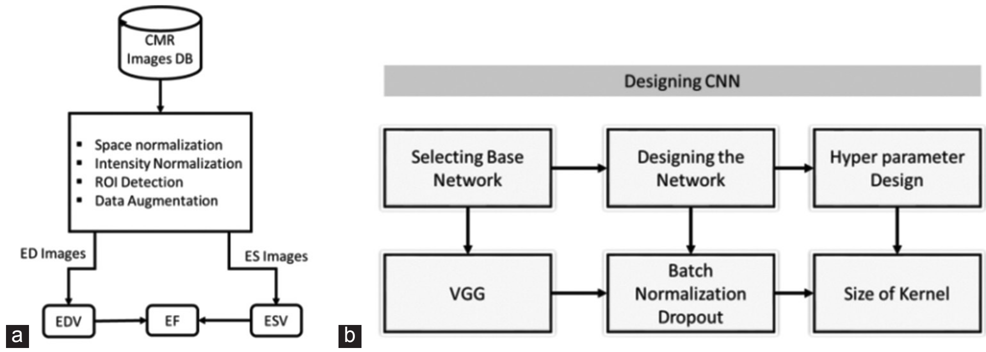

Fig. 13. (a) Proposed frameworks of left ventricle volumes prediction. (b) Design architecture of convolutional neural network (Zakariah and AlShalfan, 2020).

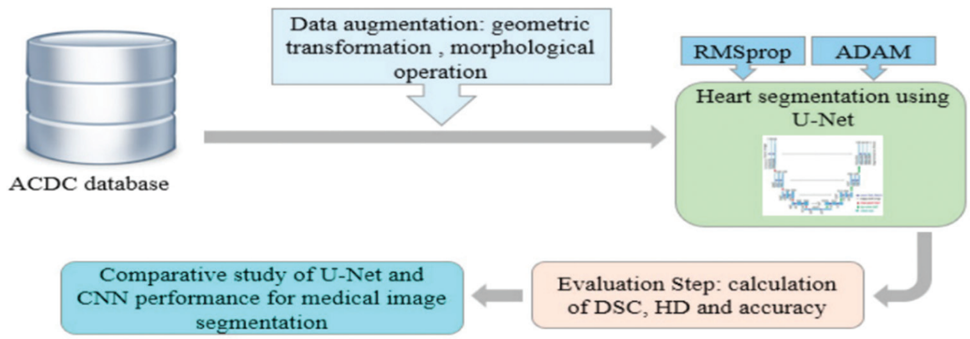

Fig. 14. Comprehensive framework for cardiac image segmentation and assessment method (Baccouch et al., 2023).

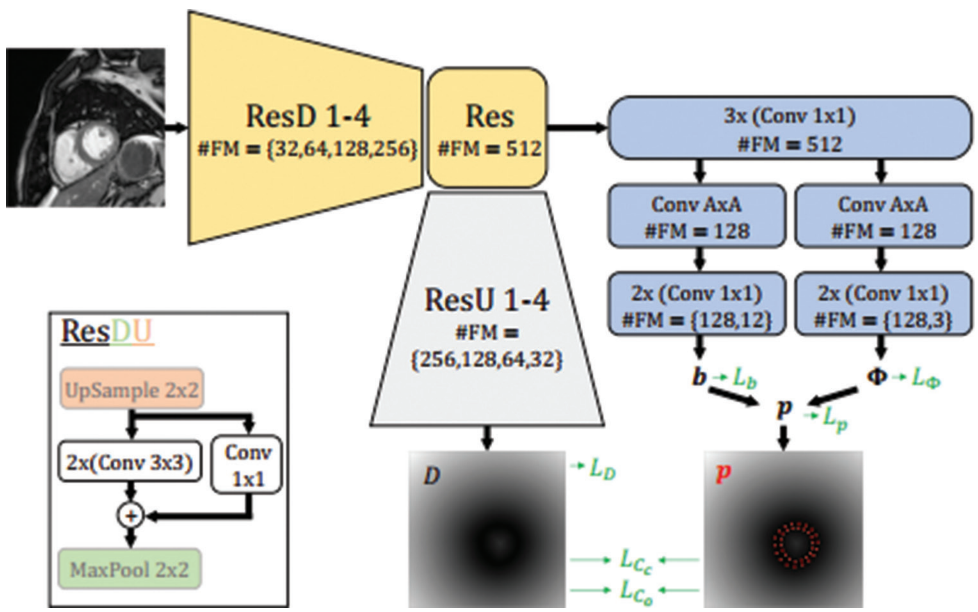

Fig. 15. A convolutional neural network architecture with three outputs: shape, pose, consistency (Tilborghs, Bogaert, and Maes, 2022).

on improving detection, precision, and personalization in treating cardiotoxicity in cancer patients.

Toledo et al. (2021) investigated CNN performance for LVS in cardiac MRI; efficient segmentation that can easily adapt to data size.

Germain et al. (2024) utilized 3D CNNs for non-segmentation-based estimation of LEVF and reported improved performance by the fusion of multiple cardiac MRI orientations.

Tilborghs, Bogaert, and Maes (2022) designed a shape-constrained CNN for cardiac MRI to improve the accuracy of myocardial shape and pose estimation (Fig. 15).

Huang et al. (2024) proposed a semi-supervised model for the segmentation of cardiac MRI and diagnosis of its diseases. Reduces dependency on annotated data with high segmentation accuracy (Fig. 16).

Bengio et al., 2019 explored machine learning and deep learning techniques for the detection of CVDs, tending to

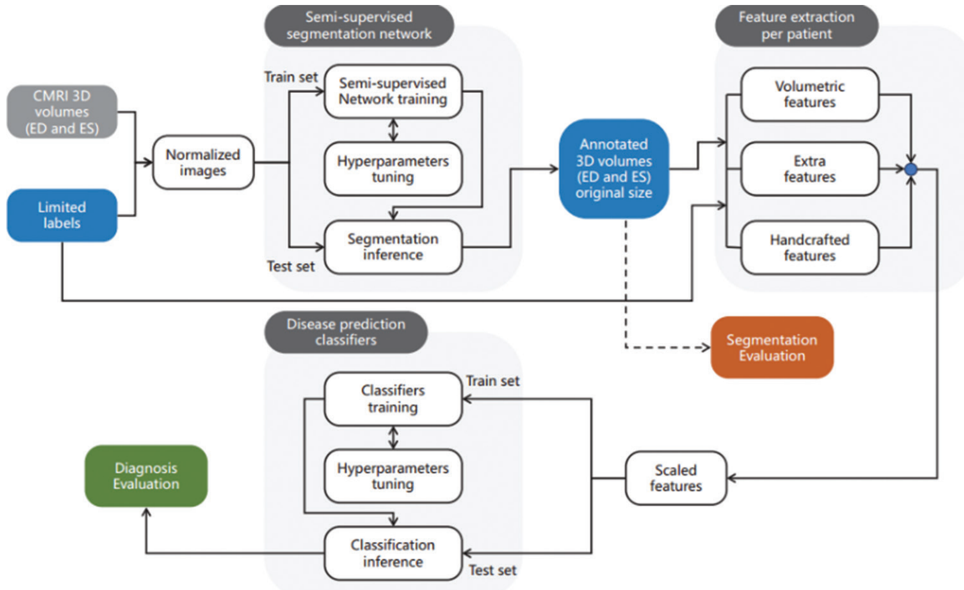

Fig. 16. A semi-supervised process uses cardiovascular magnetic resonance 3D images and partial labels for segmentation, feature extraction, and disease prediction (Huang et al., 2024).

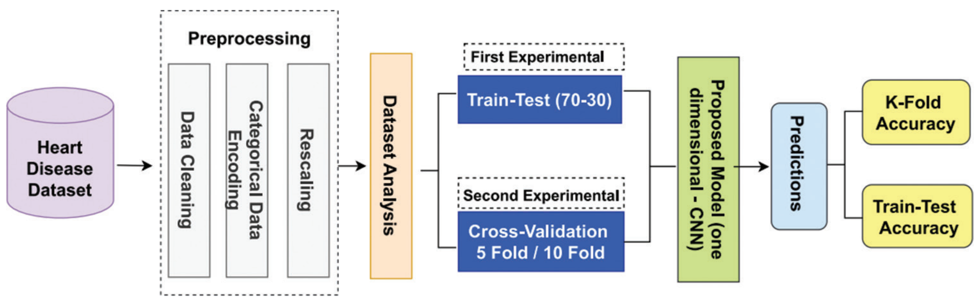

Fig. 17. Heart disease classification for process workflow data preprocessing, training 1D- convolutional neural network model, and cross-validation accuracy assessment (Honi and Szathmary, 2024).

models such as CNN, Naive Bayes, and decision trees for better predictions that could allow personalized healthcare.

Yong et al. (2020) proposed a layered Mask R-CNN model for the segmentation of ventricular MRI with high accuracy and for automatic detection of systolic dysfunction in CVD.

Honi and Szathmary (2024) presented a 1D-CNN model for the prediction of CVD with a high degree of accuracy that outperformed existing methods (Fig. 17).

Reza-Soltani et al. (2024) reviewed the role of AI and ML in enhancing cardiovascular imaging and diagnosis, emphasizing improved diagnostic accuracy, efficiency, and potential clinical integration.

Xu et al. (2023) enhanced the U-Net for cardiac MRI segmentation, providing an accurate ventricular and myocardial detection to support heart disease diagnosis.

Jeyachandra et al. (2024) (R. et al., 2023) developed a CNN-based deep-learning model with K-means clustering and particle swarm optimization for efficient prediction of heart disease (Fig. 18).

Li et al. (2024) proposed a deep-learning model that uses myocardial perfusion imaging to predict the time of cardiovascular incidents and to stratify patients according to risk (Fig. 19).

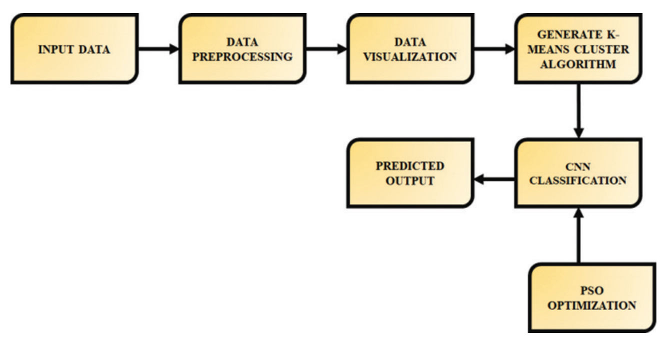

Fig. 18. Convolutional neural network classification system architecture with K-means and particle swarm optimization components (Jeyachandra. et al., 2023).

B. Data Preparation and Considerations

Pre-processing and data handling

All studies reviewed highlight the critical role of pre-processing in deep learning model performance optimization. Common steps include noise reduction through Gaussian filters, data normalization to align pixel intensity distributions, and data augmentation techniques such as rotation, flipping, and intensity scaling to enhance dataset diversity and avoid overfitting. For instance, Iqbal, Khalid, and Ullah (2024) used

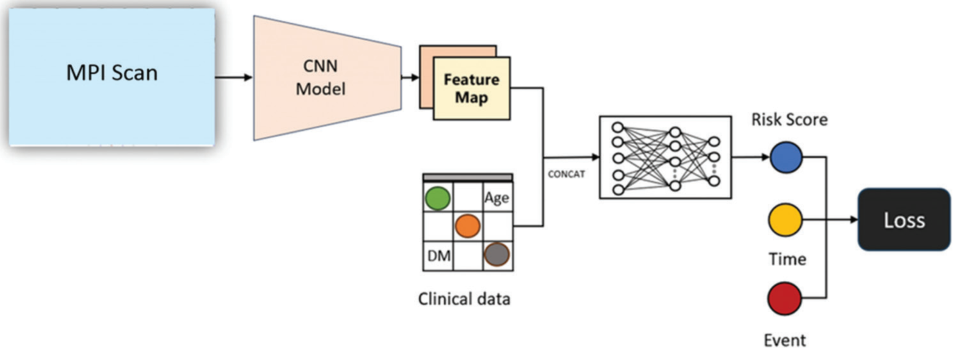

Fig. 19. The schematic diagram integrates inputs from myocardial perfusion imaging, clinical variables, or both for analysis (Li et al., 2024).

pre-processing and Grad-CAM to derive visual explanations of model predictions, enabling interpretability.

Dataset characteristics

The majority of the datasets used, e.g., ACDC and EMIDEC, are public and have manually segmented annotations, enabling reproducible benchmarking. However, the paper also refers to proprietary datasets (e.g., Enugu State University Hospital MRI data), where only very limited information regarding patient demographics and acquisition protocols prevents reproducibility. Proper documentation of dataset size, image resolution, and population diversity is needed for equitable model evaluation.

IV. Discussion And Limitation

I. The studies reviewed here have shown how deep learning models can transform the diagnosis of CVD using imaging like MRI. They are able to automate ventricular segmentation, myocardial analysis, and cardiac motion tracking tasks, specifically by CNNs and FCNs. FCNNs performed better than CNNs in segmentation across the board (e.g., Dice score: 0.93 vs. 0.85 for LV segmentation), whereas CNNs performed better in classification accuracy (94% vs. 89%) due to hierarchical feature extraction. However, FCNs' computational overhead and reliance on very large datasets are its disadvantages. The articles considered employed CNNs/FCNNs over transformers because of their proven performance in medical imaging, although federated learning would address the issue of data privacy in multi-center studies.

II. Key limitations are data heterogeneity (e.g., EMIDEC's one-center data collection) and small sample sizes (e.g., 150 participants in Lalande et al., 2020), which undermine generalizability. These can be mitigated with data augmentation and synthetic data generation (e.g., GANs). Upcoming research has to concentrate on hybrid models (i.e., CNN-Transformers) and federated systems to achieve a balance among accuracy, scalability, and privacy. This automatization offers access to a high-level examination of structural and functional pathologies and increases diagnostic precision, efficacy, and individualization. These advances facilitate early diagnosis and effective management of disease, reconfiguring CVD diagnosis and treatment.

Interpretability and Clinical Validation. As a response to the black-box nature of DL models and for the sake of facilitating clinical trust, more recent studies featured explainable AI (XAI) methods such as Grad-CAM and Layer-wise Relevance Propagation. For instance, Iqbal, Khalid, and Ullah (2024) employed Grad-CAM for visualizing image regions influencing model predictions in the classification of coronary artery disease. These regions of interest had high concordance with cardiologist readings, confirming model outputs' clinical utility and diagnostic accuracy. Explainability methods like these are necessary for model decision validation, guiding clinical processes, and ensuring the responsible use of AI in cardiovascular medicine.

The main drawbacks, according to Mishra, Gupta, and Sharma (2024), are data heterogeneity and limited generalizability. Overcoming such limitations involves the capacity to deploy solutions using diverse datasets, developing more sophisticated algorithms, and enhancing interactions between disciplines for accurate and improved results.

Iqbal, Khalid, and Ullah (2024) is one such major problem this model faces in identifying the region of interest of MRI frames that can be addressed with better pre-processing techniques and uses of XAI methods such as GradCAM. Ogunpola et al. (2024) identified the two major issues as data imbalance and low generalizability that can be overcome by some of the preprocessing techniques like oversampling and normalization. Vernikouskaya et al. (2024) state that there is a restricted size of the dataset without external validation. Future studies can use 3D architecture to avoid such limitations. Bhan, Mangipudi, and Goyal, (2023) limitations are the generalization across models and the greater diversity of datasets. Limitations can be reduced by employing more diverse and larger datasets, enhancing the overall segmentation accuracy. Shaaf et al. (2023) state that the datasets used are small and limited and can be handled using transfer learning and data augmentation, enhancing the model's performance and the power of analysis. Shaaf et al. (2023), the model also has some disadvantages, such as it cannot detect myocardial infarction in some of the apical slices. This can be overcome by the application of a hybrid model that combines the classification model and the segmentation model. In Inomata et al. (2023), among the disadvantages of the model is that the right ventricle is not very accurate. In order to reduce the limitations of the model, the following points have to be kept

http://dx.doi.org/10.14500/aro.11971

TABLE III
COMPARATIVE PERFORMANCE METRICS OF DL MODELS

Ref.	Year	Application	Dataset name	Methodology	Feature type	Classifier	Train samples	Test samples	Performance	Outputs
Mishra, Gupta and Sharma (2024)	2024	CVDs	Heart disease dataset (Kaggle)	XGBoost algorithm	Cardiac features such as age, gender, blood pressure, cholesterol, and other health indicators from patients	Random Forest	~70–80% (estimated)	~20–30% (estimated)	Accuracy: 97.56%.	CVDs
Chibueze et al.	2024	Heart disease detection	MRI dataset from Enugu State University Teaching Hospital, CAD Cardiac MRI	CNN	Image-based features	CNN	14,350	6,150	Accuracy: 94.13%	CVDs
Iqbal, Khalid and Ullah (2024)	2024	Real-time CAD classification	CAD Cardiac MRI	Lightweight CNN model adapted from LeNet-5	Image-based features	Lightweight CNN	51,331	323	Accuracy: 99.35% (Balanced Accuracy: 99.13%)	Binary classification: Healthy vs. CAD images
Ogunpola et al. (2024)	2024	Heart disease prediction via ML.	Cardiovascular Heart Disease Dataset	XGBoost, CNN, SVM, KNN, RF, Gradient Boost, LR	Patient health metrics focusing on CVD risk factors (e.g., blood pressure, cholesterol, age).	XGBoost	700	300	Accuracy: 98.5%,	Predicts the likelihood of heart disease presence or absence.
Vernikouskaya et al. (2024)	2024	Cardiac MRI segmentation for LAA.	Cardiac MRI dataset was collected from 29 patients	Two-stage CNN: YOLOv4 for localization, U-Net for segmentation	ROI Localization (e.g., left atrium, right atrium, aortic arch)	CNN-based (YOLOv4 and U-Net)	For YOLOv4: 567 images, for U-Net 1,817 images	For yolov4: 2643 images, for U-Net 455 images	Accuracy: 97% for YOLOv4. And for U-Net is 99.8%	Segmented cardiac structures
Bhan, Mangipudi and Goyal (2023)	2023	CVD diagnosis via right ventricle segmentation	Cardiac MRI	Vanilla CNN, FCNN, ResNet	Segmentation from RV MRI Images	FCNN	70–80%	20–30%	FCNN: highest accuracy is 89%	Segmentation maps of the right ventricle
Shaaf et al. (2023)	2023	Left ventricular cavity detection	SCD	Faster R-CNN with RPN	Short-axis cardiac MRI images	Faster R-CNN-based	80%	20%	Accuracy: 91%,	Detected LV area in cardiac MRI images
Shaaf, Jamil and Ambar, (2023)	2023	Detection of myocardial infarction	EMIDEC	CNN for automatic segmentation of LV and myocardium from short-axis MRI images	Pixel-level features	CNN	Not specified	Not specified	Accuracy: 0.86, Dice Score Coefficient (DSC) : 0.81, Intersection over Union (IOU): 0.8	Segmentation of LV, myocardium, and MI areas
Inomata et al. (2023)	2023	Estimation of left and right ventricular ejection fractions (EFs)	ACDC	3D-CNN based on ResNet50	3D motion features	3D-CNN	80% (5-fold CV)	20% (5-fold CV)	LVEF: Mean Absolute Error (MAE) 9.41, RMSE 12.26, RVEF: MAE 11.35, RMSE 14.95	Estimation of LVEF and RVEF
Shaaf et al. (2022)	2022	LV segmentation from short-axis cardiac MRI for cardiac function	EMIDEC	FCN for automatic segmentation of the LV	Pixel-level features	FCN	100 patients	50 patients	Dice: 0.93, Jaccard: 0.87, Sensitivity: 0.98, Specificity: 0.94	LV segmentation for the heart
Abualkishik, Almajed and Almutairi, (2022)	2022	CVD detection	Kaggle cardiovascular illness dataset	Fully DNN, image analysis	MRI Images	DNN	40,000	20,000	Accuracy 88%	ECG signal analysis, MRI feature extraction
Agibetov et al. (2021)	2021	Diagnosis of Cardiac Amyloidosis	CMR dataset (502 cases)	CNN	Image features from MRI	CNN	80% (10 -fold)	20% (10 -fold)	ROC AUC: 0.96 (LGE protocol), Sensitivity: 94%, Specificity: 90%	Automated diagnosis of cardiac amyloidosis

(*Contd...*)

TABLE III
(Continued)

Ref.	Year	Application	Dataset name	Methodology	Feature type	Classifier	Train samples	Test samples	Performance	Outputs
Sadr et al. (2024)	2024	CVD diagnosis	Dataset I (62,267 records), Dataset II (918 records), Dataset III (577 records)	Combination of CNN, LSTM, KNN, XGB+Majority Voting Ensemble	Nominal and numeric features	CNN-LSTM+ KNN+ XGB	80%	20%	Dataset I :80.25% Dataset II: 95.85% Dataset III : 90.87%	Prediction of CVD presence/absence
Ammar, Bouattane and Youssfi, (2021)	2021	Heart disease classification and cardiac MRI segmentation	ACDC	A modified U-Net CNN for segmentation of the LV, RV, and MYO.	Volumetric features of heart structures (Primary Features, Handcrafted Features)	MLP, RF, SVM	100	50	Dice=0.92, Validation accuracy=0.98, test accuracy=0.92	- Segmentation masks for LV, RV, and MYO structures. - Disease class prediction for heart conditions.
Wu, Fang and Lai (2020)	2020	LV segmentation in cardiac MRI	MICCAI 2009	Combined CNN and U-Net	Image Features (ROI Binary Masks and Down-sampled Images)	Combines CNN and U-net	30	15	Dice=0.951, VOE=0.053, HD=3.641	LV segmented images
Liu et al. (2020)	2020	Cardiac MRI segmentation	Custom (85 patients)	CNN+Image Saliency	ROI-based saliency maps	CNN	2100 Images	600 Images	Accuracy 93.14%	Segmented ventricles, septum, and apex
Simantiris and Tziritas, (2020)	2020	Cardiac MRI Segmentation	ACDC	DCNN with domain-specific constraints.	Image intensities	DCNN	1,902 original MRI images+2,876 augmented images (4,778 total)	c	Average Dice coefficient of 0.916 on test data	Segmented images for Right Ventricle, LV, and Myocardium
Penso et al. (2021)	2021	Cardiac segmentation in CMR images	DB1, DB2	Dense FCN (U-Net based)	Dense skip blocks	FCNN	DB1=180, DB2=N/A , external validation	DB1=30, DB2=12	Dice: 0.944 (LV), 0.908 (RV), 0.851 (Myo) (DB1); Dice: 0.940 (LV), 0.880 (RV), 0.856 (Myo) (DB2)	LV and RV segmentation maps
Liu et al. (2020)	2020	Cardiac image segmentation and heart disease diagnosis.	ACDC	Residual CNN and Bi-CLSTM combination	CMR images	Residual CNN+Bi-CLSTM segmentation.	100 patients	50 patients	Achieved a 94% overall accuracy	Cardiac segmentation and disease classification
Zakariah and AlShalfan, (2020)	2020	CVD Detection	SCD and CAP	CNN with ADAM optimizer	LV EF		100	40	RMSE±AESD in EDV, ESV, EF: High accuracy	LV volume and ejection fraction predictions
El-Rewaidy et al. (2021)	2021	Cardiac MRI radial reconstruction	108 subject dataset	MD-CNN	Complex-valued	Multi-domain CNN	87	21	Improved MSE and SSIM compared to kt-RASPS; sharp LV borders	Faster and higher-quality cine images
Baccouch et al. (2023)	2023	Cardiac MRI segmentation	ACDC	U-Net vs. CNN comparison for medical image segmentation	Pixel-level	Medical Image Analysis and Segmentation	100 patients	50 patients	Dice Similarity of 97.9%, HD of 5.318 mm	Segmentation masks of cardiac structures
Qiao et al. (2020)	2020	Cardiac motion tracking from cine MRI	MICCAI 2011 STACOM, others	Registration-based and CNN-based (Groupwise MotionNet)	Motion fields	Cardiac Motion Tracking Methods	2,900	Not specified	CNN method: Average EPE 0.94 mm; Registration: Average EPE 2.89 mm; CNN is faster with real-time performance	Quantitative motion fields
Madan et al. (2022)	2022	Cardio-oncology imaging	Various imaging sources in cardio-oncology	AI-guided imaging in echocardiography, CMR, CT, etc.	Cardiac strain, LV function	AI	Not specified	255 patients	Improved detection accuracy	LVEF, GLS predictions

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TABLE III
(*Continued*)

Ref.	Year	Application	Dataset name	Methodology	Feature type	Classifier	Train samples	Test samples	Performance	Outputs
Toledo et al. (2021)	2021	LV segmentation in MRI	LVSC	CNN (U-Net variations, VGG, ResNet, EfficientNet)	Cardiac MRI pixels	CNN	80% 8,000 samples	20% 2,000 samples	High DICE score (80% - 90%)	LV segmentation masks
Germain et al. (2024)	2024	Segmentation of the LV in cardiac MRI images using (CNNs).	Cine-MRI dataset	Segmentation-free 3D-CNN predicts LVEF using combined imaging planes.	Cardiac features for LVEF estimation.	3D-CNN	933 (5-fold CV)	149 per fold	AUC: 0.99 (LVEF < 40%), 0.97 (LVEF>60%).	The estimated left ventricular ejection fraction (LVEF).
Tilborghs, Bogaert and Maes (2022)	2021	Prediction of myocardial shape	ACDC	Combines CNNs with a statistical shape model "to guide segmentation.	Cardiac MRI landmarks and distance maps	Shape-constrained CNN	80% 1,226 images	20% 307 images	Segmentation accuracy: 99%.	Myocardial segmentation
Huang et al., (2024)	2024	Cardiac MRI segmentation and disease prediction	ACDC	Semi-supervised deep learning with CNN and Transformer	Clinical indices, voxel features.	Two-layer ensemble classifier	70	50	Dice: 87.83%, Accuracy: 100%	Disease classification and clinical index calculation
Bengio et al., (2019)	2024	CVD detection and prediction	Clinical data, MRI, ECG, Echo	Various ML and DL algorithms (e.g., KNN, Decision Trees, Naive Bayes)	Clinical imaging data	Naive Bayes. Logistic Regression Decision Trees KNN - CNN	Not specified	Not specified	Accuracy improvements with ensemble models	Prediction of CVD risk
Yong et al. (2021)	2020	Automatic NMR segmentation for CVD	Hospital NMR images	Deep learning, Mask R-CNN segmentation	Ventricular regions	Mask R-CNN	13,000 images	32,000 images	Dice metric: 0.92 (LV), 0.89 (RV)	Segmentation of left and right ventricles
Honi and Szathmary (2024)	2024	CVD early prediction	UCI Heart Disease dataset	1D CNN with feature selection	Heart health indicators	1D-CNN	70% 717 samples	30% 308 samples	Accuracy: 99.95%	CVD risk prediction
Reza-Soltani et al. (2024)	2024	cardiovascular imaging and diagnosis	Various imaging datasets	Supervised ML (CNNs, logistic regression), unsupervised ML (clustering)	Imaging features	AI and ML in cardiovascular imaging	Not specified	Not specified	CNN models achieved 93% sensitivity and 95% specificity in CT plaque	Segmentation, lesion detection
Xu et al. (2023)	2023	Cardiac MRI segmentation	275 MRI scans	Improved U-Net deep learning model with batch normalization, and weighted loss functions	MRI imaging features	Softmax	80% 220	20% 55	Dice index: LV (0.965), RV (0.938), Myocardium (0.895); Hausdorff index: LV (5.4), RV (11.7), Myocardium (8.3)	Segmentations of LV, RV, and myocardium
Jeyachandra et al. (2023)	2024	Heart disease prediction	SDN dataset	CNN integrated with PSO optimization and K-Means clustering	Clinical and medical image data	LSTM and CNN	Not specified	Not specified	Accuracy: 97.7%, Recall: 94.17%	Accurate heart disease prediction and identification
Li et al. (2024)	2024	Cardiovascular event risk assessment	1928 MPI scans	End-to-end survival training with ResNet50, leveraging Cox regression-based survival analysis	MPI imaging and clinical data	Risk scoring model	80% 1540	20% 388	The MPI-AI risk score outperformed traditional clinical predictors with AUCs of 0.747 (all events) and 0.727 (MACE).	Risk stratification and time-to-event prediction

CT: Computed tomography, CVD: Cardiovascular disease, MRI: Magnetic resonance imaging, EF: Ejection fraction, FCN: Fully convolutional network, RPN: Region proposal network MRI: Magnetic resonance imaging, SCD: Sunnybrook cardiac dataset, CAD: Coronary artery disease, CNN: Convolutional neural network, DNN: Deep convolutional network, MYO: Myocardium, DCNN: Dilated convolutional neural network, CAP: Cardiac atlas project, MD-CNN: Multi-domain CNN, LVSC: LV segmentation challenge, PSO: Particle swarm optimization, AI: Artificial intelligence, ML: Machine learning, DL: Deep learning, LV: Left ventricle, RV: Right ventricle, LVEF: Left ventricular ejection fraction, AUC: Area under the curve, CMR: Cardiovascular magnetic resonance, FCNN: Fully convolutional neural network, R-CNN: Region-based convolutional neural network, RMSE: Root mean square error, AESD: Absolute Difference of Squared Errors, EDV: End-Diastolic Volume, ESV: End-Systolic Volume, EF: Ejection Fraction, MSE: Mean Squared Error, SSIM: Structural Similarity Index Measure, kt-RASPS: k-t Radial Sparse-Sense, HD: Hausdorff Distance, EPE: End-Point Error, GLS: Global Longitudinal Strain, MACE: Major Adverse Cardiovascular Events.

in mind: improving the prediction of RVEF, expanding the data set, and integrating different forms of images. Shaaf et al. (2022) The dataset size and data diversity are limitations of this model. In order to rise above these limitations, the dataset size can be improved, and data balancing can be improved. Abu Al-Kashik et al. (2022) Bias and noise in the input images and data bias are some of the drawbacks of the research. Such drawbacks can be removed by applying pre-processing filters and using multi-class AUC to choose features. Drawbacks of Agibetov et al. (2021) include data imbalance, a single-center study, and poor performance at the beginning phase. To mitigate these limitations, use bigger datasets an1d use additional imaging markers. These research limitations, Liu et al. (2021), are dependence on specific datasets and suboptimal phase image processing. To remedy these limitations, optimize the dataset for improved generalization and take into account phase field approaches. Ammar et al. (2021) The difficulty of this paper will be in segmenting the heart muscle. These issues can be resolved by increasing the dataset size and experimenting with various architecture designs. Wu et al. (2020) limit boundary precision and dataset capacity; these issues can be alleviated through the use of data augmentation and boundary-fitting algorithms. Wu et al. (2020) acquired that the data set size and precision of boundaries are the best shortcomings of this study, and they asserted that adding more data and fitting the boundaries are the best solutions. Liu et al. (2020) state that the shortcomings of this study are excessive computational burdens and over-segmentation resulting from weak boundaries. To overcome such drawbacks, larger datasets need testing, and segmentation on various MRI data is boosted. Penso et al. (2021) state that the drawbacks of the study are that RV and apical slices are difficult to manipulate. These can be overcome by using stronger geometric contrast methods. Liu et al. (2020) Disadvantages of this research are the absence of continuity among slices and computational burden, which can be addressed using temporal context and extended convolution for improving accuracy. Zakariah and AlShalfan (2020) state that among the drawbacks of paper is that initially obtained results are not optimized to the optimal; therefore, there's always a possibility to improve accuracy or use better optimization techniques. El-Rewaidy et al. (2021) observe that the main problem of this study is that it fails to evaluate irregular rhythms and receive one slice; hence, the expanded data needs to be generalized as a solution in the future.

In summary, these pieces of work represent the position of DL in transforming the segmentation, abnormality diagnosis, and treatment personalization of CVD by presenting data augmentation, transfer learning, explain ability of AI, and deep architecture as techniques that will guarantee scalability and adaptability. This calls for a convergence of disparate data, hybrid models such as the combination of CNNs and LSTMs, and strong clinical validation to achieve computational and data-based barriers that would improve diagnostic accuracy, efficiency, and equity in health care delivery.

The main contribution of "Early Detection of CVDs Using Deep Learning on Medical Imaging Data" lies in the application of FCNs and CNNs to enhance the accuracy and automation of cardiac MRI analysis to diagnose CVDs such as hypertrophic cardiomyopathy and dilated cardiomyopathy efficiently.

V. Conclusion

This study demonstrates the immense potential of deep learning technologies, particularly FCNs and CNNs, in transforming the early diagnosis and treatment of CVDs. AI-driven cardiac MRI analysis holds promise for enhanced diagnostic accuracy, reduced manual intervention, and enhanced clinical workflow efficiency. While advances have been realized, constraints in dataset heterogeneity, model generalizability, and computational needs demand continued innovation in AI models. The utilization of explainable AI, strict validation protocols, and heterogeneous datasets is also important in overcoming current limitations and ensuring equitable implementation across varied healthcare settings. Methodological preference for FCNs over CNNs for segmentation was guided by the former's ability to maintain spatial information, whereas CNNs were preferred for classification owing to the latter's specialty in hierarchical feature learning. More complex approaches like transformers were not studied extensively in the literature covered but represent an encouraging avenue for modeling global relations in cardiac MRI. Future priorities will involve interdisciplinary working, scalable infrastructure, and real-world clinical integration to harness fully the potential of AI for cardiovascular medicine.

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