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Automated identification of left ventricular hypertrophy using cardiac ultrasound imaging: A systematic review of artificial intelligence driven approaches

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ABSTRACT

Left Ventricular Hypertrophy (LVH) is a significant cardiovascular risk marker that manifests in several clinical conditions, including Hypertension (HTN), Chronic Kidney Disease (CKD), and Hypertrophic Cardiomyopathy (HCM). This systematic review examines Artificial Intelligence (AI) approaches for the automated identification of these conditions using cardiac Ultrasound (US) imaging. Following the PRISMA guidelines, 37 relevant articles (7 reviews, 30 research papers) published between 2010 and 2025 were analysed. The analysis revealed three primary methodological approaches: feature learning pipelines, end-to-end Deep Learning (DL), and hybrid methods that combine both techniques. For CKD detection, only one study using cardiac US was identified, which achieved 99.09 % classification accuracy using Support Vector Machine (SVM) with steerable Gaussian filters and entropy features. HTN classification studies have demonstrated high performance across different approaches: traditional Machine Learning (ML) classifiers (decision trees with transform features: 99.11 %, weighted k-nearest neighbors: 98 %) and DL methods (Area Under Curve (AUC): 0.92–0.94). HCM studies ranged from binary classification (42.3 % of studies) to multi-class problems of increasing complexity (3-class: 38.4 %, 4-class: 11.5 %, 5-class: 7.6 %), with SVM achieving 95.2 % average sensitivity and DL models reaching an average AUC of 0.94. Current limitations include a predominant focus on binary classification problems, limited research on cardiac-based CKD detection, and a lack of standardized datasets. Future research directions include developing hybrid methodologies that combine traditional and DL approaches, creating standardized multimodal databases, implementing explainable AI techniques, and integrating Internet of Things technologies for continuous monitoring.

1. Introduction

Left Ventricular Hypertrophy (LVH) is a cardiac condition characterized by an abnormal increase in Left Ventricular (LV) wall thickness and mass, serving as an independent predictor of cardiovascular morbidity and mortality. The primary causes of LVH include Hyper-

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tension (HTN), Hypertrophic Cardiomyopathy (HCM), valvular disorders (e.g., aortic stenosis, mitral regurgitation), infiltrative myocardial diseases (e.g. Cardiac Amyloidosis (CA), Fabry disease), diabetes, and physiological LVH, as observed in athletes [1,2] (Fig. 1). The anatomic patterns of LVH vary depending on the aetiology and are typically categorized on the basis of LV remodelling as either concentric LVH or eccentric LVH. This classification is determined using the Relative Wall Thickness (RWT), which is evaluated as follows:

$$\text{RWT} = (2 \text{ x posterior wall thickness})/(\text{LV internal diameter at end-diastole}) \tag{1}$$

where RWT values ≥ 0.42 indicate concentric LVH, whereas values $<$ 0.42 represent eccentric LVH [3]. The geometry of LVH is influenced by multiple factors, including the type and severity of cardiac overload, age, neurohormonal effects, genetic predispositions, and other cardiac comorbidities [4].

Fig. 1 illustrates the various causes of LVH along with the available Artificial Intelligence (AI) methods that are applied to detect and analyse them using multiple modalities [6,7–35,36–40]. The literature indicates that limited work has been done on the applicability of AI in the auto-identification of LVH caused by excessive physical exercise. Thus, AI models distinguishing physiological LVH (hypertrophy caused by excessive physical exercise) are an underserved domain.

HTN remains the most common cause of LVH, affecting approximately 1.28 billion adults globally, with a prevalence that continues to increase, particularly in low and middle-income countries where cardiovascular monitoring may be limited [41]. HTN-induced LVH is associated with major adverse cardiac events, including death, stroke, heart failure, and peripheral vascular diseases. Typically, HTN leads to concentric LVH; however, in the presence of volume overload conditions such as Chronic Kidney Disease (CKD), eccentric LVH may develop. Nearly 50 % of CKD-related deaths are due to cardiovascular complications, emphasizing the importance of LVH in CKD prognosis [42]. HCM is a genetic disorder characterized by LVH in the absence of other cardiac or noncardiac conditions that could account for the observed hypertrophy. It is a leading cause of sudden cardiac death in young adults, with a high prevalence rate of approximately 1 in 500 individuals [43–45]. The various histopathological patterns of LVH include asymmetric septal hypertrophy, apical and concentric hypertrophy, reverse curvature, and sigmoid septum types [46]. Fig. 2 depicts the structural changes to the heart caused by various LVH aetiologies.

Early and accurate identification of LVH and its underlying etiologies has significant prognostic implications and impacts clinical management strategies. The differentiation between various etiologies of LVH is crucial for appropriate clinical management, as treatment strategies differ significantly across conditions such as HTN, HCM, and CKD. Traditional diagnosis relies heavily on expert interpretation of imaging studies, which are subject to inter-observer variability and require significant expertise [5]. Various diagnostic tests, such as echocardiography, Electrocardiogram (ECG), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) etc., have been employed for LVH detection [47–65].

Among these imaging modalities, echocardiography remains the most widely used modality because of its affordability and diagnostic sensitivity. However, distinguishing the specific cause of LVH from echocardiography images alone remains challenging, as conditions such as HCM, HTN, CKD and physiologic LVH in athletes may share similar echocardiographic features. This limitation created an opportunity for the application of AI techniques, which can detect patterns and features in echocardiographic images that may not be apparent to human observers.

Innovative AI-driven diagnostic tools leverage Deep Learning (DL) and advanced neural network architectures to automate and enhance cardiac image analysis. Several researchers have explored AI-based approaches for the automatic assessment and quantification of LVH [6, 66–71]. A groundbreaking vision foundation model such as EchoApex was designed for echocardiography, which is focused on improving the analysis and interpretation of cardiac Ultrasound (US) images using AI techniques [68]. It utilized self-supervised learning and trained on an extensive dataset of over 20 million echocardiographic images. The model categorizes various echo views, outlines and segments the cardiac structures using a prompt-based encoder-decoder and detects the LVH using a multiscale convolutional decoder [68]. Modern neural architectures such as Vision Transformer (ViT) and ResNet50 were applied for pretraining the model [68] to assess the performance of various neural network architectures. LV segmentation is also performed using a time-sensitive mixed attention mechanism [69] and a combination of a swin transformer and K-Net [70]. A recent vision language model, EchoCLIP, yielded remarkable results in the analysis of echocardiographic videos [71]. Studies have demonstrated that AI models using US heart images can effectively identify key causes of LVH, including CKD, HTN, and HCM [72].

1.1. Motivation

LVH consists of several etiologies that differ in the pattern and extent of LVH. Echocardiography is the most sensitive and widely used diagnostic modality in the evaluation of LVH. However, in a few circumstances, echocardiography may fail to identify the cause of LVH because of variable patterns and extent of LVH. This requires an experienced investigator with a clinical background, along with confirmatory testing. This imposes the need for an autodetection model using ultrasound heart images to establish an objective way of evaluating the cause

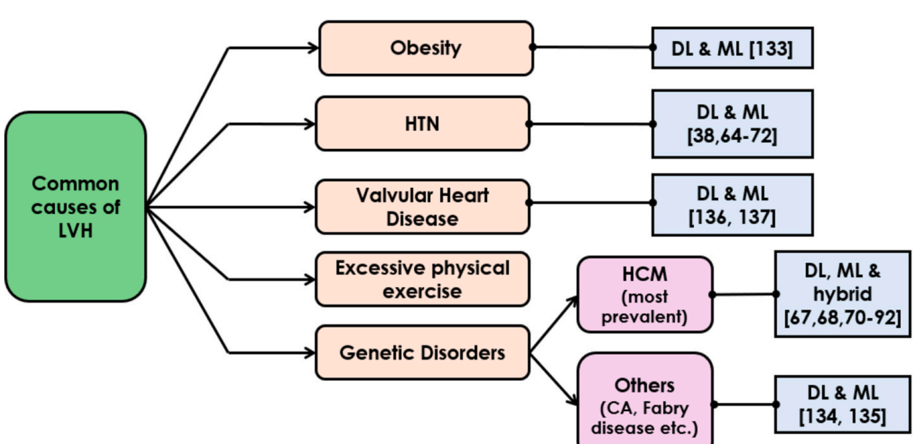


Fig. 1. Most common causes of LVH [5].

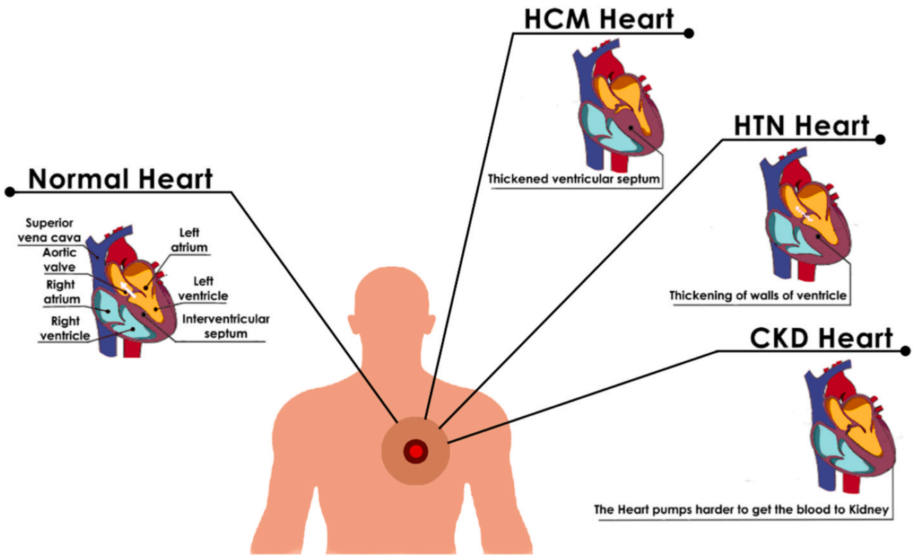


Fig. 2. Structural changes in the heart due to various forms of LVH with different causes.

of LVH. Furthermore, a few review articles (2020–2025) have explored the automated detection of HCM and HTN using DL and Machine Learning (ML) techniques, as summarized in Table 1.

As depicted in Table 1, AI techniques, such as ML, DL or a combination of these, are used to identify various causes of LVH with the help of heart US images. Siqueria et al. reviewed DL and ML methods that can segment and classify heart diseases, thereby enhancing the decision-making process [78,79]. In 2023, DL and ML techniques that are applicable for HCM detection from cardiac US images [77] as well as systems built using a ML methods that could support the community in increasing the ease of HTN using self-management strategies [76] were studied. Sanjeevi et al., in 2024 conducted a study of DL methods that aid in generating clinical decisions from automated transthoracic echocardiogram analysis [75]. A review conducted by Gudigar et al., in 2024 explored various DL and ML techniques that automatically detect HTN from images collected from various modalities, along with clinical and demographic data [74]. A recent study by Cirillo et al. assessed the performance of AI models that detect LVH along with its causes [73].

A critical analysis of these reviews has identified several gaps.

- ✓ **Systematic Review:** The literature reveals that the prior existing reviews (e.g., Refs. [76–79]) were partially aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [80], wherein the inclusion or exclusion criteria, assessment of quality, etc., were briefly addressed or not reported.
- ✓ **Cause:** There are multiple causes of LVH, but most reviews focus on a single cause, such as HTN [74,76] or HCM [77].
- ✓ **Modality:** Multiple modalities are collectively utilized for identifying the cause of LVH. Few studies have focused on the diseases characterized by LVH using a single modality.
- ✓ **Future work:** Elaborated discussions on future research directions are not visible in the existing reviews [73,76,79].

These gaps highlight the need for a comprehensive systematic review focused on the automated detection of CKD, HTN, and HCM using US imagery. This approach could aid researchers in developing a Computer-Aided Diagnostic (CAD) tool capable of detecting CKD, HTN, or HCM using a single imaging modality. Hence, this systematic review aims to address these gaps by compiling evidence on automated diagnostic tools to identify the causes of LVH, emphasizing the need for objective, AI-driven approaches using US heart images.

Table 1
Overview of the review articles for the automated detection of HCM and HTN.

Reference	Year	AI method	Comments
Cirillo et al. [73]	2025	DL and ML	Assess the diagnostic accuracy of AI models developed for detecting LVH and its common underlying causes
Gudigar et al. [74]	2024	DL and ML	Exploration of AI models developed for the identification of hypertension leveraging clinical data, physiological signals, and various imaging modalities
Sanjeevi et al. [75]	2024	DL	Examines cutting-edge research utilizing DL techniques to automate transthoracic echocardiogram analysis aiding the clinical decision- making
Stephen et al. [76]	2023	ML	Highlights ML and self-management strategies as key enablers for enhancing the effectiveness of mobile health systems for diabetes and hypertension
Muhamed et al. [77]	2023	DL and ML	Examines existing methods for HCM detection using echocardiography
Siqueira et al. [78]	2021	DL and ML	Analysis of AI applications supporting medical decision-making through the segmentation and classification of heart diseases using echocardiograms
Siqueira et al. [79]	2020	DL and ML	Discusses AI techniques employed to enhance medical decision-making and automate processes in transthoracic echocardiogram

1.2. Research questions

Primary research question: What are the current AI approaches for the automated identification of LVH using cardiac US imaging, specifically for detecting CKD, HTN, and HCM?

Secondary research questions.

- What are the performance characteristics of different AI methodologies (feature learning, DL, and hybrid approaches) for LVH characterization?
- What are the current limitations and research gaps in automated LVH detection using cardiac ultrasound?
- What future research directions are needed to advance automated LVH assessment?

1.3. Main contributions of our review

This review focuses on a systematic approach to analyse various ML and DL methods, which identify multiple causes, such as HCM, HTN and CKD, that are characterized by LVH using a single modality, i.e., 4-chamber apical heart images. These images are also analysed and interpreted using specific techniques, followed by an elaborate discussion of the future scope of the study.

Our major contributions are summarized as follows.

- ✓ **Systematic review**: A systematic review process was performed to select relevant articles according to the PRISMA guidelines.
- ✓ **Multiple pathology detection**: Included analysis of various ML and DL techniques that characterize LVH (i.e., CKD, HTN, and HCM) using heart US images.
- ✓ **Differentiating component:** This review includes LVH characterization using automated detection of CKD, HTN and HCM from US heart images compared with existing reviews.
- ✓ **Data Collection**: US images of the 4-chamber apical heart associated with CKD, HTN, and HCM were acquired and analysed.
- ✓ **Analysis of US images using Grad-CAM**: Apical 4-chamber heart US images of CKD, HTN, and HCM patients were analysed via the Gradient-weighted Class Activation Mapping (Grad-CAM) approach.
- ✓ **Challenges and future research perspectives**: A detailed discussion on challenges and future research directions using a single imaging modality is presented.

The paper is organized as follows: Section 2 describes the article selection process with the inclusion and exclusion criteria. Section 3 provides detailed descriptions of the CAD system for CKD, HTN, and HCM using US images. Sections 4 and 5 present our results and discuss future directions, respectively. Section 6 concludes the paper.

2. Search strategy and selection criteria

The literature utilized in this systematic review was compiled from five major research databases: Scopus, IEEE Xplore, Springer, Google Scholar, and PubMed. Publications from 2010–2025 were selected, and the search was restricted to English-language research articles, review papers, and conference papers within the Engineering and Computer Science domains, as this study focused on various disease detection using AI models. The primary imaging modality of interest was US.

The search strategy employed a combination of key terms related to imaging modality (e.g., "ultrasound," "echocardiogram," "cardiac ultrasound"), target conditions associated with LVH (e.g., "left ventricular hypertrophy," "chronic kidney disease," "hypertrophic cardiomyopathy," "hypertension"), and AI-based diagnostic approaches (e.g., "automated detection," "computer-aided diagnosis," "machine learning," "deep learning"). Specific query strings were formulated for each condition; for example, "cardiovascular AND ultrasound AND (chronic AND kidney AND disease OR ckd)" was used for CKD-related articles. (Appendix A).

The selection of relevant papers followed a three-stage approach. In the first stage, the decision on the document's relevancy was derived mainly from the abstract, title, and keywords obtained from the document. The following were considered part of the inclusion criteria during this stage.

1) The modality used should be US imagery.
2) The disease under consideration should be CKD, HTN, or HCM with LVH.
3) AI must be applied in the detection or identification of the considered disease.
4) The document should be within the 2010–2025 timeline.
5) Only English-language articles, reviews, and conference papers were considered.
6) The topic of interest is from the engineering and computer science domains.

From an initial pool of over 80,000 documents identified in the first stage, the selection was progressively narrowed through second-stage screening and third-stage verification. During the final verification stage, additional exclusion criteria were applied to eliminate studies that used non-US modalities, focused solely on clinical aspects without computational methods, involved non-human subjects, addressed cardiovascular diseases other than those of interest, lacked ML or DL components, or were not published in English (Appendix B).

This methodical approach yielded a final selection of 37 articles, comprising 7 review articles and 30 research articles, which form the core of this systematic review. Fig. 3 illustrates the complete article selection process following the PRISMA guidelines.

3. CAD tools for the characterization of LVH

The literature reveals various approaches to automatically characterize LVH using US images.

The key terms used in the review are as follows.

1. Data processing includes the preparation of the raw acquired data in a structured form, which can be utilized for further processing.
2. Data mining refers to the extraction of meaningful patterns from processed data.
3. AI is the broader perspective of computing technology and helps in building systems that require reasoning and problem-solving capabilities.
4. ML and DL are sub-components of the AI family and support the development of intelligent systems using various algorithmic approaches.

As illustrated in Fig. 4, these methodologies can be categorized into

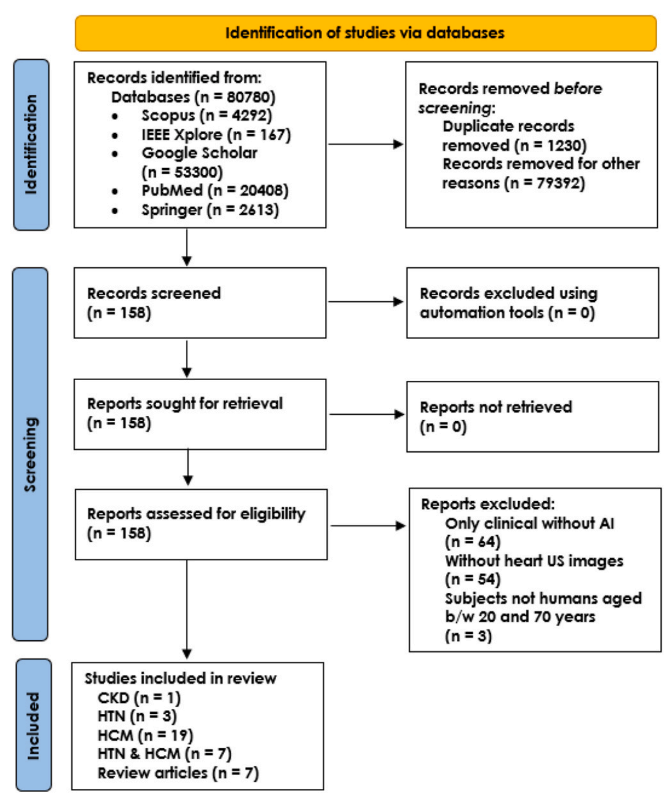


Fig. 3. Organization of the article selection and inclusion strategy using PRISMA guidelines.

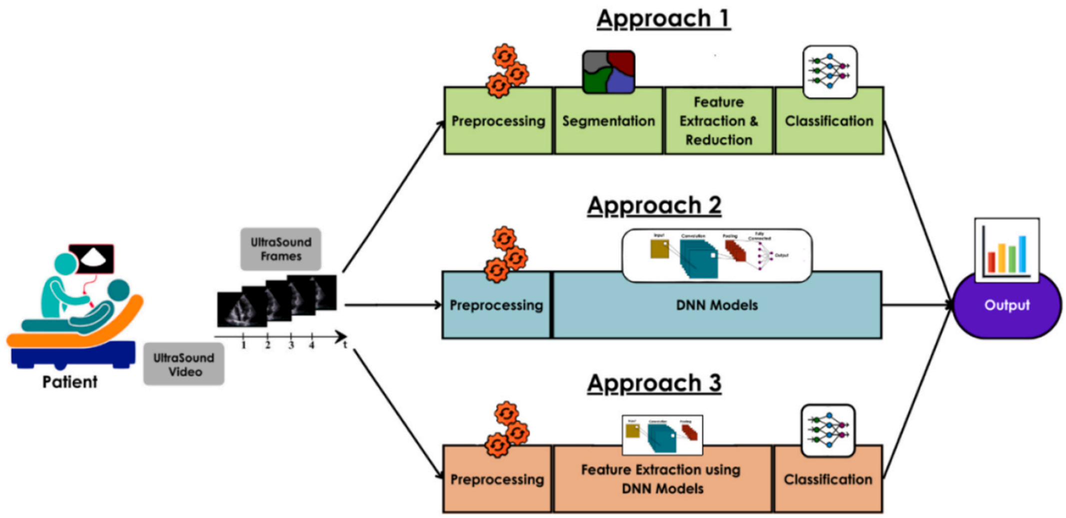


Fig. 4. Illustration of different approaches for CAD tools.

three distinct approaches: feature learning (traditional feature extraction methods), Deep Neural Network (DNN), and hybrid methods.

***Approach I* (Feature learning):** This traditional approach follows a sequential pipeline structure beginning with preprocessing of US images, followed by segmentation of the Region of Interest (RoI), extraction of relevant features, feature dimensionality reduction, and finally classification or prediction.

***Approach II* (Deep Neural Network):** In this approach, feature representation and classification are integrated into a unified structure. DL models such as Convolutional Neural Networks (CNNs) and ResNet variants autonomously learn hierarchical features directly from raw or minimally processed images.

***Approach III* (Hybrid methods):** This combines the elements of both approaches, where feature extraction is performed using DNN models and classification is performed using various ML algorithms.

The following subsections discuss the various methodologies available in the literature for the analysis or prediction of CKD, HTN, and HCM, which are the primary causes of LVH.

3.1. An automated model for the identification of CKD using heart US images

The kidneys function as the body's natural filtration system, and their impairment leads to CKD. The progressive nature of CKD from early to advanced stages is associated with various cardiovascular complications, making early diagnosis crucial. While numerous studies address automated CKD identification, they primarily follow one of three approaches: feature learning with traditional ML classifiers [66,81–90], end-to-end DL [91–95], or hybrid methods where DL-extracted features are fed into ML classifiers [96–98].

Notably, only one study [66] employed cardiac US images for CKD detection, while the majority utilized kidney US images [81–98]—a significant gap in the literature considering the strong association between CKD and cardiac structural changes. In the cardiac US-based approach [66], preprocessing involves image cropping using empirically determined coordinates, RoI mask generation, and noise reduction using a 5 $\times$ 5 median filter. Feature extraction uses steerable Gaussian filters to enhance cardiac structures, followed by image fusion techniques and entropy feature extraction from non-overlapping blocks to represent image saliency. Supervised Neighborhood Preserving Embedding (SNPE) [66] effectively reduces feature dimensionality while preserving underlying data relationships.

This methodology addresses a 4-class classification problem, distinguishing between advanced CKD stages (3, 4, and 5) and normal subjects using Support Vector Machine (SVM), which has proven particularly effective for medical image classification [66].

3.2. Automatic detection of HTN using heart US images

Hypertensive heart disease is referred to as secondary or pathological LVH and remodels the heart structure. Studies utilizing US images for automated HTN detection generally employ either feature learning approaches [6,7–12] or DL methods [9,10,13,14].

3.2.1. Preprocessing

Preprocessing techniques address outliers and unwanted image components, primarily focusing on image enhancement [6,7–10]. Common methods include Contrast Limited Adaptive Histogram Equalization (CLAHE) [8], the removal of labels and device-related information using specialized masks [6,8–10], standardization through image resizing [99], [6,7,8,10], and noise reduction via median filtering [6]. Some studies employ morphological operators to enhance images and isolate the RoI [7].

3.2.2. Feature extraction

The feature extraction methodologies used vary significantly across the reviewed studies. Some methods incorporate segmentation before feature extraction, such as using residual UNet (ResUNet) to segment the Interventricular Septum (IVS) before extracting static radiomic features alongside time and frequency domain characteristics [7]. Other approaches calculate longitudinal strain and strain rates from echocardiograms [11], employ transformation techniques such as Contourlet (CTLet) and dual-tree complex wavelets [8], or utilize 3D CNNs for video snippet feature extraction [12].

Recent innovations include microlevel feature extraction using Directional Guided Motion Sensitive (DGMS) descriptors with entropy-based feature ranking [6] and sophisticated temporal modelling with Bi-directional Long Short-Term Memory (LSTM) networks combined with multiple instance learning [12]. Dimensionality reduction employs techniques such as Fisher's Discrimination Ratio (FDR), Information Gain (IG), Relief-F weights [11], Pointwise Gated Boltzmann Machine (PGBM) for feature fusion [7], and Locality-Sensitive Discriminant Analysis (LSDA) [8].

3.2.3. Classification

Classification approaches address both binary (hypertensive/normal) [6,8,9,12] and multi-class problems [7,10,11,13–15]. Commonly used classifiers include K-Nearest Neighbors (KNN) [6,8], discriminant linear and quadratic models [8], and SVMs with various kernels, including radial basis functions and polynomial variants [7,8, 11], Decision Trees (DT) [8], and Logistic Regression (LR) [15]. The combination of CTLet and Shearlet (SHLet) transform features with DT classifiers has proven particularly effective for HTN classification [8].

DL approaches include multimodal frameworks such as LVH fusion, which integrates temporal, electrical, and echocardiographic data [9], and architectures such as InceptionResNetV2 [10], ResNet [13], and CNN aggregate networks [14]. Table 2 summarizes these approaches and their performance in HTN identification.

3.3. Automated model for identification of HCM using heart US images

Research on automated HCM detection using US imagery follows three distinct methodological approaches. The feature learning approach [11,15–24] employs a sequential pipeline of preprocessing, segmentation, feature extraction, and classification. The DL approach [10,13,14,25–31]. integrates feature extraction and classification into a unified structure. Finally, the hybrid approach [32,33] extracts features using DL algorithms but employs traditional ML for the final classification.

3.3.1. Preprocessing

Preprocessing is essential for reducing model bias and enhancing performance by eliminating unhelpful features and artifacts from input images. This crucial stage involves three primary operations.

- ***Image enhancement and resizing*** [14,16–18,26,27,31,33]: Techniques include contrast adjustment, standardization of image dimensions, and structural improvement.
- ***Artifact removal*** [17,18,22]: Methods such as boundary anomaly correction, which involves setting edge pixels to black (typically at widths $\leq$80 pixels) [17,18].
- ***Denoising*** [11,16–18,20,22,33]: Various filters are employed, including a median filter [16,20,33], Speckle Reducing Anisotropic Diffusion (SRAD) [11,16–18], a Gaussian filter [22], a Fourier ideal and Butterworth filter [20], and a wavelet homomorphic filter [20].

Additional enhancement techniques include Gaussian smoothing [16], CLAHE [17,18,31], and specific resizing methods such as bicubic [33] and bilinear interpolation [14]. Some researchers also perform statistical preprocessing for null value removal and data cleaning [7,19, 21,23].

3.3.2. Feature extraction

After preprocessing, researchers extract discriminative features for classification. Segmentation techniques are implemented to select the RoI, and the most utilized algorithm is the Fuzzy C Means (FCM) clustering [17,18,20,22], which is computationally lighter than regular clustering techniques such as k-means. The labelling of the connected components in the segmented image is performed using the connected component labelling technique [17,18]. Moreover, Darwinian Particle Swarm Optimization (DPSO) is used over FCM to optimize the centroids and generate optimum clusters [22]. In Ref. [16], edge detection techniques, such as the Canny edge detector, are used to replace each pixel with a gradient value. DL models—ResUNet [7] and UNet++ [13]—are also used for IVS segmentation.

The RoI is employed to extract texture analysis features using the Gray-Level Co-occurrence Matrix (GLCM) [15,22] and Gabor filters [19]. Radiomic features, along with time and frequency domain features, are combined to form a feature map using the PGBM [7]. The Discrete Cosine Transform (DCT) is utilized in Refs. [18,22], which enables efficient storage by compressing the image pixels. In Ref. [33], local descriptors with Local Directional Pattern (LDP) are combined with features from pretrained ResNet50 and ranked using Student's *t*-test to create an integrated HCM index.

Statistical measures have also been applied by certain authors for

Table 2
Overview of the latest methods for automated identification of HTN using cardiac US images.

Year	Dataset	No of classes	Segmentation	Feature extraction	Feature ranking/ Dimensionality reduction	Classifier	Result
2022 [8]	112 subjects	2 (HTN/ normal)	Various transformation techniques		LSDA	DT	Acc. = 99.11 %
2023 [12]	297 subjects	2 (HTN/ normal)	Simpson's biplane + Bidirectional LSTM + Feature ensemble model+ 3D CNN				Acc. = 92 % AUC = 0.90 Sens. = 97 % Spec. = 84 %
2024 [6]	140 subjects	2 (HTN/ normal)		DGMS	Entropy- based technique	Weighted KNN	Acc. = 98 % Spec. = 98.4 % Sens. = 97.5 % AUC = 1
Work- related to HHD & HCM							
2021 [11]	30 subjects ECG + echocardiography	3 (HHD/HCM/ normal)	Longitudinal strain + Strain rate (echo) & amplitude + Temporal features (ECG)		FDR + IG + Relief - F weights	SVM	Prec. = 97.62 % Sens. = 93.33 % Spec. = 98.04 % F-measure = 95.43 % (best result)
2022 [7]	299 subjects	3 (HHD/HCM/ UCM)	ResUNet	Static radiomics features + Time and frequency features	PGBM	SVM	Sens. = 92.3 % Spec. = 77.1 % Acc. = 84.3 % AUC = 0.838 ± 0.049 (for HHD v/s HCM)
2022 [9]	2728 subjects ECG + echocardiography	2 (HTN/HCM)		Multi-modal DL framework			Prec. = 73 % Spec. = 96 % Sens. = 73 % F1- score = 73 % AUC = 0.92 (overall)
2022 [13]	724 subjects	4(normal/ HCM/HHD/ CA)	U-Net++		ResNet		AUC = 0.90 (for HCM)
2022 [14]	930 subjects	3 (HHD/HCM/ light chain CA)		Hybrid CNN - LSTM + Aggregate Network			AUC = 0.982 (for HCM) Acc. = 92.3 % (overall)
2023 [10]	586 subjects	3 (HTN/HCM/ CA)		InceptionResNetV2 model			Prec. = 80 % Rec. = 75 % F1- score = 77 % AUC = 0.92 (for HCM)
2023 [15]	289 subjects	4(CA/HCM/ UCM/HHD)	3D slicer software	Texture features using gray-level dependence matrix	Statistical techniques	LR	AUC >0.92 (for HHD) AUC = 0.88 (for HCM)

*Accuracy (Acc.), Area Under Curve (AUC), Precision (Prec.), Recall (Rec.), Sensitivity (Sens.), Specificity (Spec.).

feature analysis [17,20,21]. Dimensionality reduction techniques, particularly Principal Component Analysis (PCA) [18,19], are commonly applied to select the most relevant features while reducing computational complexity.

3.3.3. Classification

The classification stage reveals two prominent approaches in the literature.

- ***Binary classification***: Many studies [16,23–27,29,30,33,34] have focused on two-class problems (HCM present/absent or HCM versus other cardiomyopathy variants).
- ***Multiclass classification***: More complex studies [7,10,11,13–15,17–20,22,28,31,32] have attempted to differentiate between multiple cardiomyopathy variations.

Popular ML algorithms include Back Propagation Neural Network (BPNN) [17,18] with Levenberg–Marquardt optimization [20], SVM [7,11,22,33], Random Forest (RF) [23], XGBoost [24], linear decomposition analysis [19], and LR [15]. Ensemble approaches combining Artificial Neural Network (ANN), SVM, and RF have shown effectiveness in distinguishing pathological HCM from physiological hypertrophy in athletes [34].

DL implementations [10,13,14,25,27–31] include standard CNNs for binary classification [26,35]; specialized architectures such as the DL algorithm based on UNet (DPS-Net) [28]; and sophisticated models such as hybrid CNN-LSTM networks [14], SlowFast video recognition models [29], and InceptionResNetV2 [10]. The AIEchoDx framework [31] employs InceptionV3 for feature extraction, followed by 1D-CNN for classification, representing an advanced integrated approach.

Table 3 provides comprehensive details of the HCM detection methodologies, while Table 2 includes studies addressing both Hypertensive Heart Disease (HHD) and the HCM classification [7,9–11,13–15].

4. Results

In this section, the techniques from the literature that are utilized to automatically detect the presence of CKD, HTN, and HCM are analysed. In the subsequent sections, a discussion of the approach is included, which presents the dataset details, and further, the results obtained from the DL models are assessed and analysed.

CAD tools for medical image classification generally apply certain evaluation measures for analysing performance [100]. A literature review revealed that a set of evaluation parameters, such as Acc., Prec. (positive predictive value) and Rec. (sensitivity), composite metrics such as the F1-score, and summary metrics such as the AUC are utilized [91,92,101–104]. The authors use these metrics to highlight model performance. Visualization of the predictions made by the model across the ground truth labels is performed with the confusion matrix [102,103,105], which signifies an evaluation factor by its four components—true and false positives and true and false negatives. These four components are used to estimate various metrics, as mentioned previously, to evaluate model performance. The performance is determined to be better with higher values of these evaluation measures.

The automated detection of CKD using ML appears in the literature as a 4-class categorization model discriminating between patients with stages 3–5 CKD and normal subjects, as categorized by the National Kidney Foundation [66]. Using the feature learning approach, the SVM achieved the highest average accuracy of 99.09 % for this multiclass problem.

The classification model for hypertensive subjects is a 2-class problem categorizing the subject as either hypertensive or normal [6,8,12], a 3-class problem discriminating the subject as HHD/HCM/normal or other ailments [7,10,11,14] and a classification model with 4 classes: HHD/HCM/normal/some other ailment [13,15]. Heart US images are utilized in all the research articles considered in this review for the HTN classification model.

Across HTN classification studies, several ML approaches have demonstrated strong performance: SVM has 98.04 % specificity and 93.3 % sensitivity [11], whereas a DT classifier with CTLet and SHLet features has achieved 99.11 % accuracy for binary HTN classification [8]. Weighted KNN (98 % accuracy, 97.5 % sensitivity, 98.4 % specificity) [6] and bidirectional LSTM models (92 % accuracy, 97 % sensitivity) [12] also performed well. The DL approaches achieved comparable results, with InceptionResNetV2 reaching an AUC of 0.92 [10] and other DL models averaging an AUC of 0.941 [13,14].

Nearly 42.3 % of the literature works discuss the HCM classification model as a 2-class problem [9,16,23–27,29,30,33,34] 38.4 % of the multiclass problem is a 3-class problem [7,10,11,14,17,18,20,22,32,35] 11.5 % is a 4-class problem [13,15,28], and 7.6 % is a 5-class problem [19,31]. The 2-class model tries to classify the incoming data as an HCM or normal subject, as in Refs. [16,23,27,33], and an HCM or some variation of cardiomyopathy, as seen in Refs. [24,26,30]. Variations in different forms are categorized into different types of cardiomyopathies, as mentioned in Ref. [106]. Gene mutations lead to the most common type of inherited cardiomyopathy, i.e., HCM.

In HCM studies, model complexity varies from binary classification (HCM vs. normal [16,23,27,33] or HCM vs. other cardiomyopathies [24,26,30]) to sophisticated multi-class models. These include 3-class models distinguishing HCM from DCM and normal subjects [17,18,20,22] or combining HCM with HTN against normal subjects [11], UCM [7], or CA [10,14]; 4-class models [13,15,28]; and more complex 5-class approaches [19,31] incorporating multiple cardiac conditions.

All the research articles considered utilized the same modality of heart US images as input sources. Many ML algorithms are utilized for classification, and SVM yields 95.2 % sensitivity on average [7,11,33] 91.36 % accuracy [22]. The BPNN is yet another commonly used ML algorithm for the classification of HCM [17,18,20] and results in a 90.76 % average accuracy. The use of DL models yielded an AUC of 0.94 (average) [9,10,13,14,25,28,30,31], and the DL algorithms classified the HCM with an average sensitivity of 93.5 % [26,29]. The use of CNNs was observed in 16.6 % of the studies cited in the review [14,25,26,31]. The variants of the ResNet model are also approximately 16.6 % as part of the DL technique used for HCM classification [10,13,30,33].

An overview of the performance of various classifiers for the classification of CKD, HTN and HCM is shown in Fig. 5.

Across all three conditions, the SVM emerged as a consistently strong performer, achieving 100 % accuracy for binary classification of CKD and HCM and 90 % average accuracy for HTN. The DL approaches perform competitively, with only a 1.8 % lower accuracy than the SVM for HCM classification. The effectiveness of these classifiers depends significantly on feature extraction techniques: steerable filters for CKD [66]; transformation techniques with LSDA for HTN [8]; and more complex approaches for HCM, including LDP with pretrained ResNet50 features [33] and combinations of FDR, IG, and Relief-F algorithms [11]. SVMs are generally the best classifiers for CKD, HTN and HCM classification [66,7,11,22].

It is evident from the literature that the scope of the research work spans countries, as depicted in Fig. 6, and that researchers are exploring various ML, DL and hybrid techniques for the detection and analysis of HCM, HTN and CKD (Fig. 7).

5. Discussion

In the literature, different diagnostic tools have been created to detect LVH caused by CKD, HTN and HCM in the past decade. Fig. 6 quantifies the country-wise research work applied for the detection of LVH due to CKD, HTN, HCM and both HTN and HCM using heart US images. ML algorithms, DL models and hybrid paradigms (a combination of ML and DL algorithms) are used for the diagnosis of causes of LVH, such as CKD, HTN and HCM.

Table 3
Details of the recent techniques for the automated identification of HCM using heart US images.

Year	Dataset	No of classes	Segmentation	Feature extraction	Feature ranking/ Dimensionality reduction	Classifier	Result
2014 [16]	24 M mode images	2 (presence/absence of HCM)	Canny edge detector + Anisotropic diffusion filtering + Gaussian smoothing				Success rate = 83 %
2015 [17]	70 echo videos	3(normal/DCM/HCM)	FCM, connected component labelling	Statistical features extracted from Zernike moments		BPNN	Sens. = 88.5 % Spec. = 93.94 % Acc. = 92.08 %
2016 [18]	60 echo videos	3(normal/DCM/HCM)	FCM thresholding and clustering, morphological closing - connected component labelling	PCA + DCT		BPNN	Sens. = 85.7 % Spec. = 92.54 % Acc. = 90.2 %
2016 [19]	59 subjects	5 (3 types of CA, HCM and normal)		Gabor filters- the first and second-order texture analysis features	PCA	LDA	Promising results for distinction of 5 classes
2016 [34]	139 subjects	2(ATH/HCM)		Information gain method		Ensemble model with majority voting	Model exhibits the best diagnostic performance at end- systole and LV volume is the best predictor for discriminating the classes
2018 [20]		3 (Normal/DCM/HCM)	FCM clustering	Statistical features extracted (gray level difference statistical features)		BPNN with Levenberg–Marquardt classifier	Acc. = 90 %
2018 [22]	90 echo videos	3 (Normal/DCM/HCM)	FCM clustering + DPSO	GLCM + DCT features		SVM	Acc. = 91.36 %
2018 [35]	14035 echocardiograms	3 (HCM/CA/PAH)	CNN				AUC = 0.93 (HCM) AUC = 0.87 (CA) AUC = 0.85 (PAH)
2021 [25]	99 subjects	2 (positive genotype/ negative genotype)	Reference model (Mayo/Toronto HCM Genotype Predictor score) + DCNN				AUC = 0.86 (for Mayo + DCNN) AUC = 0.84 (for Toronto + DCNN)
2021 [26]	3632 images	2 (DCM/HCM)	Manual selection of RoI & features + CNN				Sens. = 95.7 % Spec. = 100 % F1-score = 97.8 % Acc. = 98.2 %
2021 [23]	3548 subjects	2 (HCM yes/No)				RF	Acc. = 95 % Rec. = 99 % Prec. = 97 % F1-score = 98 %
2021 [28]	340 subjects	4(normal/diseased phenotypes - HCM, DCM, atrial fibrillation)	DPS-Net				AUC = 0.968 (for HCM)
2022 [33]	163 subjects	2 (HCM/healthy)		LDP + Pretrained ResNet50	Student's *t*-test	SVM	Acc. = 100 %
2023 [27]	173 images	2 (HCM/normal)	UNet				Acc. = 85 %
2023 [24]	138 subjects	2(CA/HCM)		Clinical + Echocardiographic data		XGBoost	AUC = 0.98 (for HCM)
2023 [29]	11583 echo videos	2 (HCM/normal)	SlowFast: deep video action recognition model + Transfer learning				Acc. = 93.13 % F1-score = 92.98 % Sens. = 91.3 % Spec. = 93.97 %
2023 [30]	158 subjects	2 (HCM with/without arrhythmia)	SE - ResNet-50				AUC = 0.974 (for HCM complicated by arrhythmia) Sens. = 86.7 % Spec. = 100 %
2023 [31]	1276 subjects	5 (atrial septal defect, DCM/ HCM/prior myocardial infarction/normal)	AIEchoDx - feature extraction network Inception V3 to extract feature vectors - classification by multiple layer 1 D - CNN				AUC = 0.9957 (for HCM)
2024 [32]	442 subjects	3 (HCM/CA/normal)		Customized ResNet		Linear classifier	Prec. = 90.6 % Rec. = 90 % Micro F1-score = 89.9 %

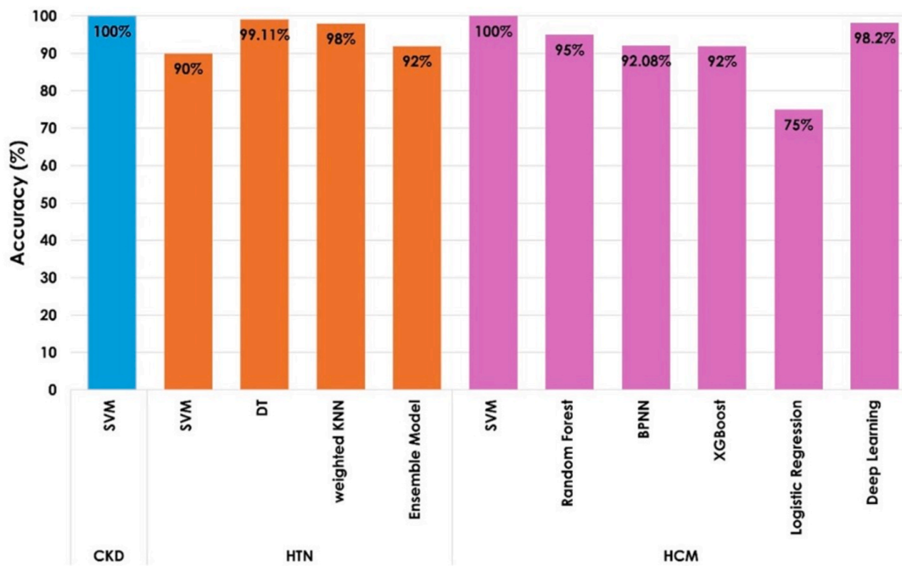


Fig. 5. Maximum accuracy obtained by the classification approaches used for CKD, HTN, and HCM identification.

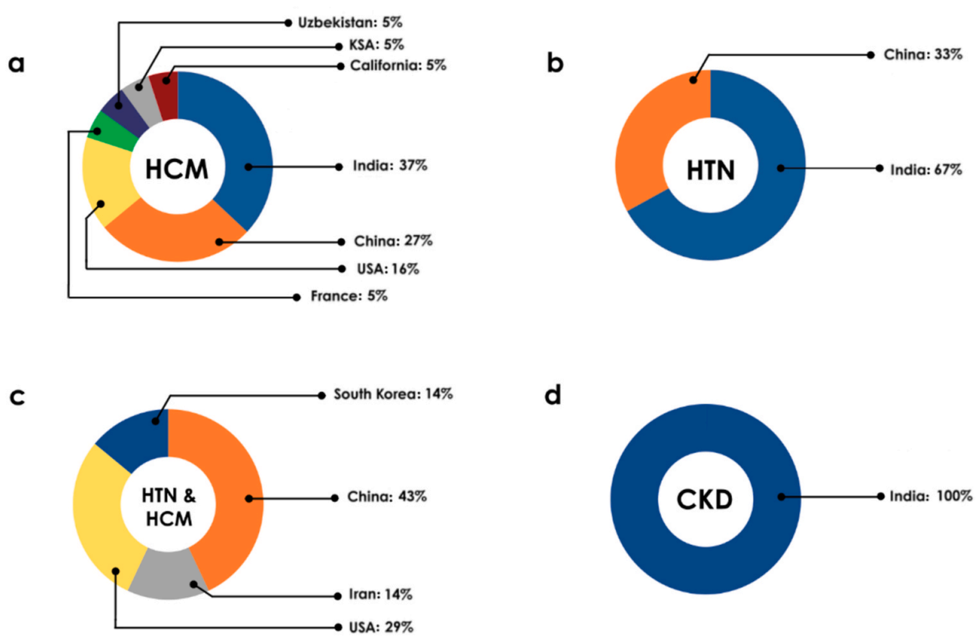


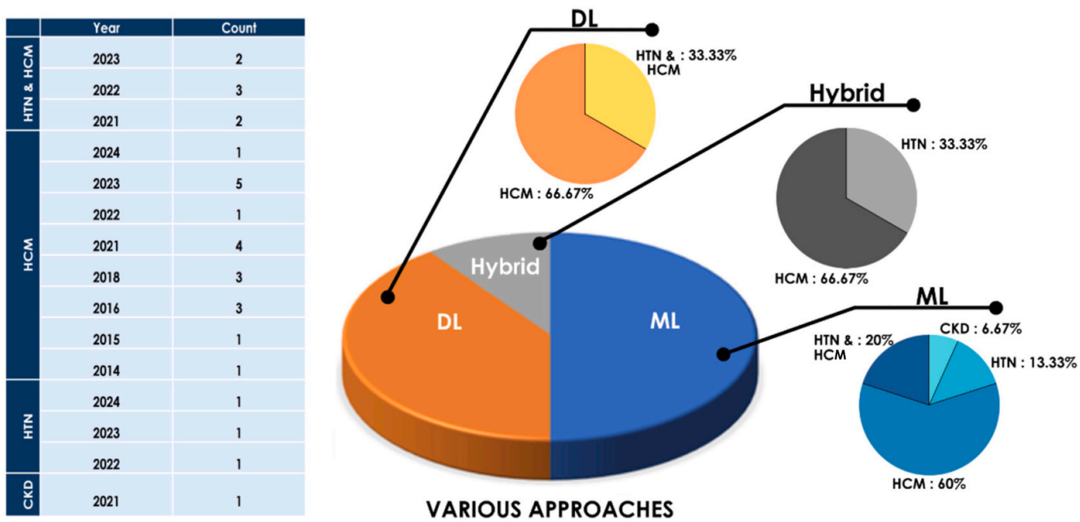
Fig. 6. Country wise distribution of the articles pertaining to a) HCM, b) HTN, c) HTN & HCM and d) CKD.

As evident from Fig. 7, ML algorithms remain the predominant approach for diagnosing these three conditions, despite the growing potential of DL methods. Seven key studies [7,9–11,13–15] have successfully utilized echocardiograms to simultaneously identify both HCM and HHD, demonstrating the feasibility of multi-condition detection using a single imaging modality.

Interestingly, various modalities are used in the literature for identifying/detecting CKD [107–109], HTN [110–114], and HCM [115–119]. Notably, CKD studies have focused on kidney images in the diagnosis of CKD [81–98], whereas studies on the automated evaluation of LVH induced by CKD are underreported.

Most of the research articles have used kidney US images [81–98] because of their relatively low cost for predicting the stages of CKD or its presence. However, the use of kidney US images requires expert radiologists to qualitatively analyse and assess CKD stages and is a time-consuming process. CKD is diagnosed when the Glomerular Filtration Rate (GFR) falls below 60 mL/min/1.73 m2 for at least 3 months [120]. In addition, the detection of different stages of CKD requires a thorough investigation of renal function, histologic abnormalities, structural abnormalities of the kidney as detected by imaging, and transplantation history. Cardiac imaging in CKD patients elucidates the effect of CKD on the heart and characteristically reveals that patients with LVH are mostly in the higher stages of CKD. In contrast, cardiac imaging cannot be used to diagnose CKD [121].

In the literature, there is only one research article that references heart US images for assessing CKD stages [66]. The presence of various cardiovascular diseases, hyperlipidaemia, metabolic bone disease, etc., is highly documented in CKD patients. According to clinical observations, higher stages of CKD often demonstrate dysfunction of the systolic and diastolic left ventricles, a mass increase in the left ventricle and other functional and structural changes in the heart that could further lead to heart failure. Cardiac mortality is also relatively high for CKD



	Year	Count
HTN & HCM	2023	2
	2022	3
	2021	2
HCM	2024	1
	2023	5
	2022	1
	2021	4
	2018	3
	2016	3
	2015	1
	2014	1
HTN	2024	1
	2023	1
	2022	1
CKD	2021	1

Fig. 7. Year wise paper distribution.

patients compared with normal subjects. Thus, continuous assessment of cardiac structure in CKD patients is essential to provide efficient medical treatment preemptively and reduce mortality. Echocardiography plays a vital role in evaluating the existence of cardiovascular diseases in CKD patients by detailing the structural modifications of the heart.

For HTN and HCM detection, various imaging modalities have been explored [110–114], with echocardiography emerging as particularly valuable because of its ability to visualize cardiac structural changes [6, 7–15] and its non-invasive nature [114]. Despite this potential, relatively few studies have focused on characterizing LVH or HCM using

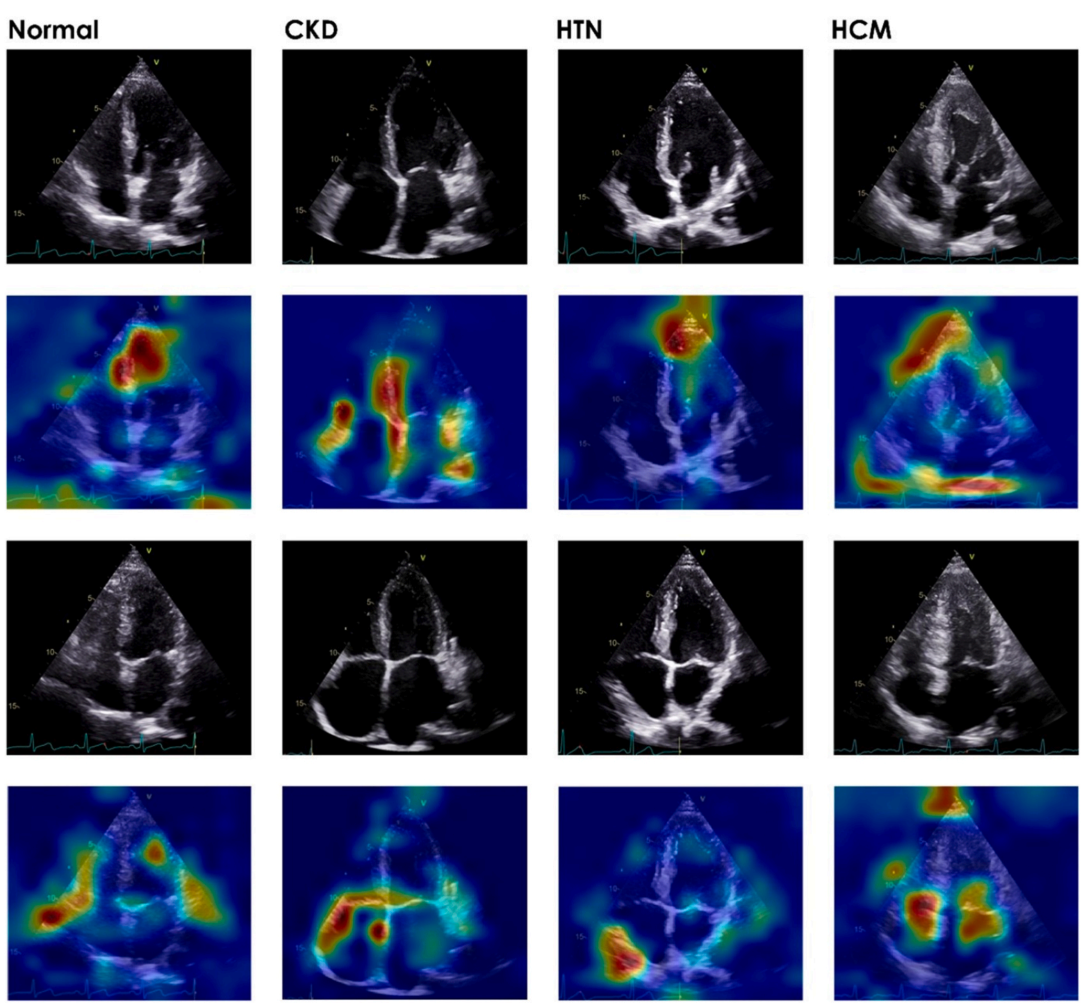


Fig. 8. End-diastole apical 4-chamber view (first row) and corresponding heatmaps (second row), end-systole apical 4-chamber view (third row) and corresponding heatmaps (fourth row).

echocardiograms, which represents a significant research gap. Further, different CNN variants [122–131] can be explored with various classifiers (such as SVM, KNN etc.) to identify HTN and HCM effectively in future. The integration of CAD tools with echocardiographic imaging offers promising opportunities for automated LVH characterization.

Furthermore, to understand the interpretability of CKD, HTN, and HCM, US images have been used. Echocardiographic examination of normal individuals revealed normal cardiac structure and function. LV wall thickness is ≤ 11 mm at end-diastole. LV chamber mass and volume remained normal, with an RWT of ≤ 0.42. In addition, the Left Atrial (LA) size also depicts a normal range. In the presence of HTN, during echocardiographic evaluation, the clinician focuses on the development of LVH, which is the cardiac remodelling that happens secondary to increased wall stress. Here, the LV wall thickness and mass increased more than the normal range did. Furthermore, HCM shows a hypertrophied LV and/or Right Ventricle (RV) with small LV cavities with concentric remodelling. These phenotypes generally exhibit either asymmetrical septal hypertrophy with at least a 15 mm thick LV wall or segmental hypertrophy, depending on the type of HCM. CKD patients display an increased LV mass and volume, as the pathology results in pressure and volume overload to the heart (first and third rows in Fig. 8). Here, overall heart size may increase proportionately with increased cardiac output. An increase in LV mass, along with a concomitant increase in LV volume, is denoted as eccentric hypertrophy in cardiac remodelling.

Each condition presents distinctive echocardiographic features: HTN typically causes increased LV wall thickness and mass due to increased wall stress; HCM manifests as a hypertrophied LV/RV with small LV cavities and concentric remodelling (often with asymmetrical septal hypertrophy ≥ 15 mm or segmental hypertrophy); and CKD patients present increased LV mass and volume due to pressure and volume overload, resulting in eccentric hypertrophy with proportionate heart enlargement. Advanced cases of all three conditions may exhibit LA enlargement due to diastolic dysfunction. While these patterns are distinguishable, echocardiography alone is insufficient for definitive differential diagnosis, which is why Grad-CAM analysis [132] provides valuable complementary insights through heatmaps visualizing discriminative regions. The Grad-CAM technique was used as a supporting element of this review (Fig. 8), indicating that, along with echocardiograms, CAD models could help in understanding the discriminable changes in the heart. Moreover, echocardiograms play a vital role in detailing the subtle structural definitions of the heart, and they are relatively inexpensive compared with other measurement modalities, especially other imaging modalities. Heart US images aligned with CAD tools can improve the early detection of HTN, which can lead to better management of these patients. In this context, the use of an AI-derived autodetection model may help clinicians evaluate LVH patients and objectively classify the cause of LVH.

In general, despite being a wide, easy, and commonly available modality, heart US imaging is not well utilized for the diagnosis and prognosis of CKD, HTN and HCM, which could then be used for the characterization of LVH. Heart US is a non-invasive approach. Moreover, LVH can be identified and characterized in a single attempt using echocardiograms, which is a time-saving and cost-effective approach. Multiple disorders can be characterized, and automating this process of LVH analysis would help reduce the dependency on US operators for interpretation. It would also yield efficiency for the medical treatment of the respective subjects, thus addressing the Sustainable Development Goal - 3, i.e. SDG-3 (Good Health and Well-Being).

5.1. Limitations of existing studies

Current research predominantly focuses on binary classification [6,8,9,12,16,23–27,29,30,33,34], which limits its clinical utility. More sophisticated approaches using multi-class models—such as the 5-class [19,31] and 4-class [28] models—have demonstrated the depth at which DL approaches can explore structural variations in echocardiograms to identify diverse disease states. Similarly, HTN identification predominantly focuses on 2-class problems, with limited research exploring 4-class classification. Thus, increasing the number and diversity of images may increase the generalizability and accuracy of these results. Additionally, research on CKD identification using US images is extremely limited, with only one article found in the literature review [66]. Hence, there is a need for extensive research in this area. Moreover, there is a lack of research on the quantification of uncertainty and explainability of CAD systems using heart US images. Explainability clarifies the decision-making process of a model, whereas uncertainty quantification identifies the regions of low confidence [133]. Furthermore, the combination of both provides deeper insight into model predictions, thus enabling safer and more effective clinical decision-making systems [133]. This is yet another possibility for researchers to address this issue and showcase the reliability and trustworthiness of the system in use.

5.2. Limitations of the current review

In the present study, an automated system to identify CKD, HTN, and HCM using heart US images with various ML and DL models is reviewed. Several researchers have worked on ML methods that identify ailments impacted by LVH, such as coronary artery disease [134]. However, this review focuses mainly on a few of those diseases that typically lead to LVH. There is no exploration of methods that can use only one type of imaging modality to assess CKD, HTN, or HCM. Hence, it is difficult to compare the studies, as they have been implemented using various private datasets. While reviewing, it is observed that the usage of DL models on US heart images could be explored further, as the work done in this domain is comparatively less common than that of generic ML models. Researchers could easily compare their developed models if standard measures were available to assess heart pathology due to LVH.

5.3. Challenges and future perspectives

5.3.1. Future research directions

From the derived studies, it is evident that there is limited work towards the identification and classification of multiple causes of LVH using a single modality. Thus, this review highlights the need for such CAD tools, which are reliable, robust and interpretable, along with Internet of Things (IoT) systems, for the assessment of diseases that could lead to LVH.

In this section, potential avenues for future research to identify causes for LVH using heart US images are discussed. Fig. 9 schematically represents future research directions for advancing automated tools designed to assess LVH.

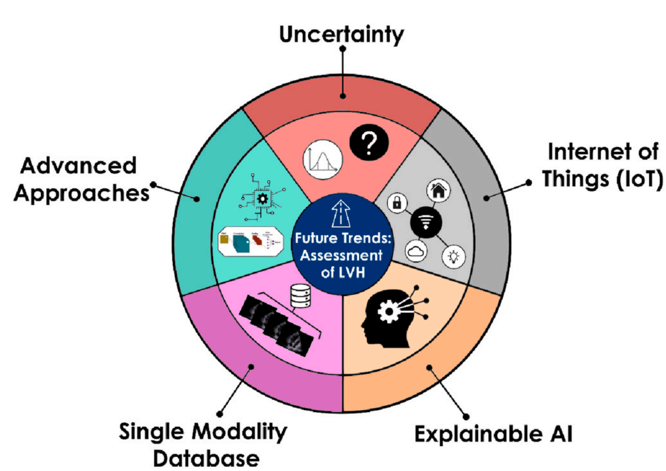


Fig. 9. Future research directions for automated assessment of LVH.

Advanced approaches: Future research pedagogies should leverage hybrid methodologies that combine the interpretability of traditional feature engineering with the representational power of DL. The integration of handcrafted traditional features with the automated features learned by the DL models yields generalizable approaches. Such enhanced feature extraction approaches, with appropriately weighted individual significant pixels in US images, lead to more interpretable, reliable and robust CAD tools.

Single-modality database: Creating standardized, multi-center databases to assess LVH (i.e., CKD, HTN, and HCM) using heart US images represents a significant challenge but is essential for algorithm validation and clinical implementation. Hence, there is an enormous demand to develop CAD tools to identify LVH using this dataset. Thus, the utilization of a single modality, such as an echocardiogram, for generating the dataset is quite significant. Further installation of such systems in rural hospitals would assist in improving patient health management systems by recognizing various conditions, such as CKD, HTN, and HCM.

Uncertainty quantification: With appropriate ML or DL techniques, the process from feature extraction to classification can be automatically handled, making the model highly reliable. The reliability of the results can be significantly improved by applying uncertainty quantification methods [135]. Addressing the uncertainty in the test and training data, the noise form in the data, and the knowledge estimated from the data will certainly impact the uncertainty obtained in the model-based predictions [135]. The DL model is trained using an input collection of datasets for which the performance goals and the architecture are designed. Different learning parameters are optimized during this training process, and all these stages involve uncertainty and should be quantified to optimize model performance. This quantification would support the model by incorporating appropriate optimization techniques to tune the parameters and hyperparameters that are involved in the feature extraction and classification process, which further generates more reliable results.

Explainable AI (XAI): The role of AI in healthcare applications has been appreciable in recent studies. AI models, during their initial development, focused mainly on specific tasks, particularly in generating clinical decisions. AI is in demand for applications that support the ease of management of health data and services, which can tremendously reduce health professionals' workload. The usage of AI models can be justified only by increasing the confidence in the model performance, i.e., an ML or DL model. This is possible by using specific XAI techniques that detail the process of prediction or classification by the respective model. More reliability and acceptance of AI in the healthcare sector can be obtained by adding XAI techniques [136]. Among several methods, perturbation-based methods such as SHapley Additive exPlanations (SHAP) [137], Local Interpretable Model Explainer (LIME) [138] and Randomized Input Sampling for Explanation (RISE) [139] are performed by applying modifications in pixel information to determine the model response. Gradient-based attribution methods such as Grad-CAM [132], Grad-CAM++ [140], SmoothGrad [141], and integrated gradients [142] highlight the image pixels that influence the model's classification or prediction. Apart from these other methods, concept-based explanations, attention maps [143], class activation and feature visualization methods [144], etc., deliver generalizable and interpretable responses towards the model's behaviour. These methods can be used widely, as they can elucidate hospital management application findings. It is also reliable for explaining high-dimensional imaging data. Furthermore, it can be explored in CAD systems to identify LVH using US images.

IoT (Internet of Things) integration: Future systems will likely integrate AI-based prediction models with IoT technologies to create comprehensive cardiac monitoring solutions. The era of smart homes and smart cities has demanded the need for systems that can support humankind with real-time and continuous monitoring of health, thereby enabling early detection and proactive care to be delivered in time. Researchers in recent years have explored the use of IoT systems in patient monitoring, wherein heart diseases can be predicted using DL models with data collected from various sensor data [145]. The COVID-19 pandemic has accelerated the acceptance of AI and smart healthcare technologies [146,147], creating opportunities for IoT-enabled devices that can detect early signs of CKD, HTN, and HCM through continuous monitoring of vital parameters via wireless sensor networks. Such integrated systems could significantly reduce morbidity and mortality by enabling earlier intervention and more personalized treatment approaches.

6. Conclusion

AI solutions significantly enhance CAD tools for the early diagnosis of CKD, HTN, and HCM. Non-invasive and cost-effective US heart imaging expedites diagnosis and potentially reduces mortality. An automated system using this single modality supports rapid LVH assessment by health professionals. This study reviewed state-of-the-art techniques for the automated identification of CKD, HTN, and HCM using heart US images. The experimental studies demonstrated the advantages of US imagery for characterizing LVH-related diseases. While ML approaches currently dominate the literature, DL models show significant potential for future exploration despite being comparatively underrepresented. Recommendations to enhance automated LVH detection systems include the following.

1) Hybrid feature extraction approaches using ViT and various attention mechanism models are implemented to capture the subtle variations in the left ventricle of the heart across the cardiac cycle.
2) Improving the transparency and reliability of the AI-assisted LVH diagnostic tool by quantifying XAI and uncertainties.

Finally, this research field offers several opportunities for researchers to better understand the signature of the heart structure using 4-chamber heart US images.

CRediT authorship contribution statement

Jimcymol James: Writing – original draft. **Anjan Gudigar:** Writing – review & editing, Visualization, Supervision, Methodology, Conceptualization. **U. Raghavendra:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Jyothi Samanth:** Writing – original draft. **M. Maithri:** Visualization. **Aryaman Kaprekar:** Visualization. **Mukund A. Prabhu:** Validation. **Massimo Salvi:** Writing – review & editing. **Filippo Molinari:** Writing – review & editing. **Edward J. Ciaccio:** Writing – review & editing. **U. Rajendra Acharya:** Writing – review & editing, Visualization, Conceptualization.

Data availability statement

All the data used in this systematic review are available in the cited publications. The Excel files with the search strategy, inclusion criteria, and data extraction are available from the corresponding author upon reasonable request. The data utilized in this study are registered under Mendeley data available at https://doi.org/10.17632/j6krmr75xd.1.

Ethical statement

The research study adheres to the highest standards of ethics. It does not involve the use of human participants and animals. All the analysis are made by the publicly available sources and scientific literature.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Summary of search queries used in the review.

HCM	• automatic AND (identification OR detection) AND hypertrophic AND cardiomyopathy AND (machine AND learning OR deep AND learning) AND PUBYEAR >2009 AND PUBYEAR <2024 AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "COMP")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE, "re") OR LIMIT-TO (DOCTYPE, "ar")) • automatic AND (identification OR detection) AND hypertrophic AND cardiomyopathy AND (machine AND learning OR deep AND learning)AND (LIMIT-TO (SUBJAREA,"COMP")OR LIMIT-TO(SUBJAREA,"ENGI"))AND(LIMIT-TO(DOCTYPE,"ar")OR LIMIT-TO(DOCTYPE,"re"))AND (LIMIT-TO(LANGUAGE,"English")) • automatic detection of hypertrophic cardiomyopathy using ultrasound image • hypertrophic cardiomyopathy detection using machine learning • Prediction of Hypertrophic Cardiomyopathy using echocardiography • Automated diagnosis and assessment of cardiac structural alteration in hypertrophic cardiomyopathy ultrasound images • detection of hypertrophic cardiomyopathy induced LVH from ultrasound images • echocardiography and hypertrophic cardiomyopathy • detection of hypertrophic cardiomyopathy from ultrasound images • automated identification/detection of Hypertrophic Cardiomyopathy using deep/machine learning • automatic detection of hypertrophic cardiomyopathy using ultrasound image • hypertrophic cardiomyopathy from ultrasound images
HTN	•automated AND diagnosis AND assessment AND of AND cardiac AND structural AND alteration AND in AND hypertension AND ultrasound AND images AND PUBYEAR > 2009 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "COMP")) AND (LIMIT-TO (LANGUAGE , "English")) •detection of hypertension induced LVH from ultra sound images AND PUBYEAR>2009 AND PUBYEAR <2025 AND (LIMIT-TO (SUBJAREA,"ENGI")) • detection of hypertension from heart ultrasound • detection of hypertension induced LVH from ultrasound images • Automated diagnosis and assessment of cardiac structural alteration in hypertension ultrasound images • echocardiography and hypertension • machine learning algorithms to detect hypertension from cardiac ultrasound • automated diagnosis of hypertension from ultrasound images • machine AND learning AND algorithms AND to AND detect AND hypertension AND PUBYEAR >2009 AND PUBYEAR <2025 AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (LANGUAGE, "English"))
CKD	• automated identification, Chronic kidney disease; (automated identification) AND (Chronic kidney disease) AND (Ultrasound OR Machine Learning OR Deep Learning); (Automated Identification OR Automated Detection) AND (Chronic kidney disease OR ckd) AND (Ultra sound images OR Machine Learning OR Deep Learning OR CAD); • Detection of chronic kidney disease OR ckd using ultrasound images • Automated detection of chronic kidney disease from ultrasound • Prediction of ckd from ultrasound images • CKD identification using trans-thoracic echocardiography • echocardiography and chronic kidney disease • Computer Aided Diagnostic tool for Chronic kidney disease

Appendix B. Detailed information about the exclusion criteria used in the review.

During the screening phase, records were systematically excluded based on predefined criteria.

- Studies used non-ultrasound modalities
- Focused on non-cardiac ultrasound imaging
- Articles not addressing CKD, HTN, or HCM
- Those lacked AI/ML components
- Manuscripts that were purely clinical without computational methods
- Those involved non-human subjects
- Articles that were not in English
- Timeline fell outside the 2010–2025 timeframe
- Articles that were not from Engineering or Computer Science domains.

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