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AI Enabled Single Lead Wearable Electrocardiogram (ECG) Screening for Early Detection of Left Ventricular Systolic Dysfunction (LVSD)

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Abstract

Left ventricular systolic dysfunction (LVSD) is an important precursor to heart failure and may remain clinically silent until ventricular impairment has progressed. Although echocardiography remains the standard confirmatory method for assessing left ventricular ejection fraction, its use as a broad screening tool is limited by cost, infrastructure requirements, specialist availability, and delayed referral pathways. This paper examines the potential of artificial intelligence-enabled single-lead wearable electrocardiogram screening for early LVSD risk detection. The study proposes a diagnostic screening framework in which wearable ECG signals are acquired, preprocessed, segmented, and analyzed using an AI-based classification model to generate an LVSD probability score. In the simulated evaluation, LVSD was defined as LVEF ≤ 40%, and the proposed model achieved an accuracy of 89.0%, sensitivity of 87.5%, specificity of 89.3%, F1-score of 71.8%, negative predictive value of 97.4%, and AUROC of 0.91. These findings suggest that AI-enabled single-lead wearable ECG may be clinically useful for identifying high-risk individuals and ruling out low-risk cases before referral for confirmatory imaging. However, the system should not be interpreted as a replacement for echocardiography or clinician judgment. Its strongest value lies in preliminary screening, referral prioritization, remote monitoring, and community-based cardiovascular risk assessment. The paper concludes that AI-enabled wearable ECG screening may support earlier LVSD detection when integrated with validated algorithms, secure data systems, clinician oversight, and structured echocardiography referral pathways.

Keywords: *Artificial Intelligence, Single-Lead ECG, Wearable ECG, Left Ventricular Systolic Dysfunction, LVSD, Left Ventricular Ejection Fraction.*

I. INTRODUCTION

➢ *Background of the Study*

Cardiovascular disease remains a major global health burden and continues to represent one of the leading causes of death worldwide [1]. Within this burden, heart failure occupies a central position because it is often preceded by progressive structural and functional abnormalities of the heart, many of which may develop before clear clinical symptoms appear [2]. One of the most clinically important abnormalities in this pathway is left ventricular systolic dysfunction (LVSD), a condition in which the left ventricle loses part of its ability to contract effectively and eject blood into systemic circulation [2]. The importance of LVSD lies not only in its direct association with heart failure, but also in its potential to remain undetected until the disease process has advanced [3].

LVSD is commonly assessed through left ventricular ejection fraction (LVEF), which measures the percentage of blood ejected from the left ventricle during systole. Reduced LVEF is an important marker of impaired ventricular contractile function and is widely used in the

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diagnosis, classification, and management of heart failure [21]. However, early LVSD may be clinically silent, particularly in individuals who have not yet developed dyspnea, fatigue, edema, reduced exercise tolerance, or other symptoms suggestive of heart failure [3]. This asymptomatic phase creates a diagnostic gap because patients may not present for cardiac evaluation until myocardial dysfunction has already progressed [23].

The current diagnostic pathway for LVSD relies heavily on cardiac imaging, especially echocardiography [2]. Echocardiography provides direct assessment of ventricular size, systolic function, wall motion, valvular structure, and LVEF, making it essential for confirming suspected LVSD [25]. Despite its diagnostic value, echocardiography is not always suitable for broad population-level screening because it requires equipment, trained personnel, clinical infrastructure, and formal referral pathways [3]. These limitations are particularly important in primary care, rural communities, low-resource settings, and preventive screening environments where early cardiovascular risk detection is needed but imaging access may be limited [25].

The electrocardiogram (ECG) offers a more accessible cardiac signal source. It is non-invasive, relatively inexpensive, widely available, and capable of recording the electrical activity of the heart in routine clinical and non-clinical environments [22]. Conventional ECG interpretation has long been used for detecting arrhythmias, conduction abnormalities, ischemic changes, ventricular hypertrophy, and repolarization abnormalities [4]. However, traditional visual interpretation of ECG signals has limited capacity to detect early LVSD because the electrical patterns associated with reduced ventricular function may be subtle, complex, or not easily recognized by human interpretation alone [4].

Artificial intelligence has changed the diagnostic potential of ECG by enabling computational models to identify hidden patterns within waveform data [4]. Deep learning models, particularly convolutional neural networks, can analyze high-dimensional ECG signals and detect relationships between electrical activity and underlying cardiac structure or function [4]. Prior research has shown that AI-enabled ECG models can identify reduced ventricular function from ECG data alone, even when reduced LVEF is not obvious through standard ECG interpretation [4]. This suggests that ECG signals may contain clinically relevant information about ventricular dysfunction that exceeds what is normally extracted through routine interpretation [4].

Most early AI-ECG models for LVSD detection were developed using standard 12-lead ECG recordings [4]. The 12-lead ECG provides multiple electrical views of the heart, making it clinically useful for detecting a broad range of cardiac abnormalities [4]. However, 12-lead ECG screening is still largely tied to clinical settings and usually requires trained personnel, proper lead placement, and access to healthcare facilities [24]. As a result, 12-lead AI-ECG may be less practical for large-scale community screening, home-based monitoring, or opportunistic detection among asymptomatic individuals [5].

Single-lead wearable ECG devices provide an alternative route for scalable cardiovascular screening. Wearable and portable ECG technologies, including smartwatches, handheld sensors, adhesive patches, and mobile-connected ECG devices, can capture cardiac electrical signals outside conventional hospital environments [27]. This makes them potentially useful for community screening, telemedicine, home monitoring, workplace health programs, and primary care triage [5]. Their portability may allow repeated ECG acquisition over time, which is valuable for individuals at increased cardiovascular risk, including those with hypertension, diabetes, coronary artery disease, chronic kidney disease, obesity, older age, or previous cardiovascular events [2], [29].

However, the transition from 12-lead clinical ECG to single-lead wearable ECG introduces important diagnostic and technical challenges. A single-lead ECG captures less spatial information than a 12-lead ECG, and wearable recordings are more likely to be affected by motion artifacts, baseline wander, variable electrode contact, muscle noise, and environmental interference [30]. These signal-quality limitations may reduce diagnostic reliability if they are not properly handled during preprocessing and model development [5]. For this reason, recent studies have focused on noise-adapted and noise-resilient AI models designed specifically for single-lead ECG signals obtained from wearable and portable devices [5], [6].

Recent evidence suggests that AI-enabled single-lead ECG models can detect LVSD and broader structural heart disease patterns from noisy wearable or portable ECG recordings [5], [6]. This is significant because it expands the possible role of ECG from a conventional diagnostic recording to a scalable digital screening tool [5]. If properly validated, AI-enabled single-lead wearable ECG screening could help identify individuals who require confirmatory echocardiography before symptomatic heart failure develops [3], [26].

Despite this promise, the clinical use of AI-enabled single-lead wearable ECG screening for LVSD remains an emerging area. Questions remain regarding model accuracy, external validation, generalizability across populations, device variability, interpretability, false-positive burden, false-negative risk, data privacy, and integration into clinical workflows [3], [5], [31]. Therefore, the present study examines AI-enabled single-lead wearable ECG screening as a potential strategy for early LVSD detection, while recognizing that such technology should support, rather than replace, echocardiography and clinical judgment [2], [5].

- *Statement of the Problem*

Early detection of LVSD remains difficult because many patients are asymptomatic until ventricular dysfunction has progressed. Although echocardiography is the standard confirmatory method for assessing LVEF, it

is not always accessible for broad screening because of cost, equipment requirements, specialist availability, and referral delays.

AI-enabled ECG has shown promise for detecting reduced ventricular function, but many established models depend on 12-lead ECG recordings that are less suitable for large-scale community or home-based screening. Single-lead wearable ECG devices offer a more scalable alternative, yet their clinical reliability for LVSD screening remains insufficiently established because of signal noise, reduced spatial information, device variability, and the need for robust external validation. Therefore, the problem addressed in this study is the limited availability of scalable, low-cost, and clinically reliable tools for early LVSD screening. This study investigates whether AI-enabled single-lead wearable ECG can serve as a preliminary screening and referral-support tool for early detection of LVSD.

➢ *Aim of the Study*

The aim of this research is to examine the potential of AI-enabled single-lead wearable ECG screening for the early detection of left ventricular systolic dysfunction.

➢ *Specific Objectives*

The specific objectives of the study are to:

- Review the clinical significance of early LVSD detection.
- Examine the diagnostic potential of single-lead wearable ECG signals for identifying LVSD-related cardiac patterns.
- Develop or propose an AI-based screening framework for detecting LVSD from single-lead ECG data.
- Evaluate the expected performance of the AI model using diagnostic metrics such as sensitivity, specificity, accuracy, AUROC, precision, and F1-score.
- Assess the clinical, technical, ethical, and implementation challenges associated with AI-enabled wearable ECG screening for LVSD.

➢ *Research Questions*

This study is guided by the following research questions:

- How can single-lead wearable ECG signals support early screening for LVSD?
- What AI techniques are most suitable for identifying LVSD-related patterns in single-lead ECG data?
- How accurately can an AI-enabled wearable ECG system distinguish individuals with possible LVSD from those with normal systolic function?
- What are the major limitations affecting clinical deployment of AI-enabled single-lead ECG screening?
- How can such a system be integrated into preventive cardiology and community-based screening workflows?

➢ *Significance of the Study*

This study is significant because LVSD is an important precursor to heart failure, and delayed detection may reduce the opportunity for early intervention. By examining AI-enabled single-lead wearable ECG screening, the study addresses the need for a more accessible method of identifying individuals who may require confirmatory echocardiography.

The study is relevant to cardiology because it focuses on early recognition of impaired ventricular systolic function, a major determinant of heart failure diagnosis and management. It is also relevant to biomedical engineering and digital health because it explores how wearable ECG devices can be used as practical data acquisition tools for AI-based screening.

From a public health perspective, AI-enabled wearable ECG screening may support cardiovascular risk detection in community settings, primary care clinics, telemedicine platforms, pharmacies, rural health facilities, and occupational health programs. This is particularly important in settings where echocardiography is not easily available or where referral delays reduce timely diagnosis.

The study also has methodological significance because it emphasizes the need to evaluate AI screening tools using clinically meaningful performance metrics, including sensitivity, specificity, accuracy, AUROC, precision, and F1-score. In screening contexts, sensitivity and negative predictive value are especially important because missed LVSD cases may delay further evaluation and treatment.

In addition, the study contributes to responsible AI implementation by considering issues such as data privacy, algorithmic bias, explainability, signal quality, false-positive referrals, false-negative risk, and clinical accountability. These issues are essential because AI-enabled ECG screening must be clinically trustworthy before it can be safely deployed in real-world healthcare systems.

➢ *Scope of the Study*

This study focuses on AI-enabled analysis of single-lead wearable ECG signals for LVSD screening. It considers ECG signal acquisition, preprocessing, AI-based classification, diagnostic performance evaluation, and clinical workflow integration.

The study does not present wearable AI-ECG as a replacement for echocardiography. Echocardiography remains necessary for definitive assessment of LVEF and structural cardiac abnormalities. Instead, this study positions AI-enabled single-lead wearable ECG as a preliminary screening and risk stratification tool that can help identify individuals who may require confirmatory imaging.

The study is limited to LVSD screening and does not primarily address atrial fibrillation, myocardial infarction, valvular disease, hypertrophic cardiomyopathy, right ventricular dysfunction, or other cardiac conditions, except where they relate to the broader discussion of AI-ECG and structural heart disease screening.

➢ *Definition of Key Terms*

- Left Ventricular Systolic Dysfunction: Left ventricular systolic dysfunction refers to impaired contractile function of the left ventricle, usually reflected by reduced left ventricular ejection fraction [2].
- Left Ventricular Ejection Fraction: Left ventricular ejection fraction is the percentage of blood ejected from the left ventricle during systole and is commonly used to assess left ventricular systolic performance [2].
- Single-Lead ECG: Single-lead ECG refers to an electrocardiographic recording obtained from one electrical lead, commonly used in wearable, handheld, and portable ECG devices [5].
- Wearable ECG: Wearable ECG refers to a body-worn, handheld, or portable device that records cardiac electrical activity outside conventional clinical ECG systems [5].
- AI-ECG: AI-ECG refers to the use of artificial intelligence, particularly machine learning or deep learning, to analyze ECG signals for diagnostic, prognostic, or screening purposes [4].
- AUROC: AUROC means area under the receiver operating characteristic curve. It measures how well a diagnostic model separates individuals with a target condition from those without it across different classification thresholds [4].
- Sensitivity: Sensitivity refers to the ability of a screening or diagnostic model to correctly identify individuals who truly have the target condition [4].
- Specificity: Specificity refers to the ability of a screening or diagnostic model to correctly identify individuals who do not have the target condition [4].
- F1-Score: F1-score is a model performance measure that combines precision and recall into a single metric, especially useful when evaluating classification models with class imbalance [4].

II. LITERATURE REVIEW

➢ *Conceptual Overview of Left Ventricular Systolic Dysfunction*

Left ventricular systolic dysfunction (LVSD) refers to impairment in the contractile function of the left ventricle, resulting in reduced ability of the ventricle to eject blood into systemic circulation during systole [2], [8]. The left ventricle is the principal pumping chamber responsible for delivering oxygenated blood to the body, and its systolic performance is commonly assessed through left ventricular ejection fraction (LVEF) [8]. LVEF expresses the proportion of blood ejected from the left ventricle during each cardiac contraction and is calculated as the ratio of stroke volume to end-diastolic volume [8]. In clinical practice, reduced LVEF is a central marker of impaired myocardial contractility and is widely used for heart failure classification, therapeutic decision-making, prognosis, and eligibility for device-based interventions [2], [8].

LVSD is closely related to heart failure, particularly heart failure with reduced ejection fraction (HFrEF) [7]. Heart failure does not describe a single disease but a clinical syndrome arising from structural or functional cardiac abnormalities that impair ventricular filling or ejection of blood [33]. LVSD contributes directly to this syndrome by reducing forward cardiac output, increasing ventricular filling pressures, and activating compensatory neurohormonal mechanisms [2]. In the early phase, these compensatory responses may preserve systemic perfusion, but prolonged activation of the sympathetic nervous system, renin-angiotensin-aldosterone system, inflammatory pathways, and myocardial stress responses can accelerate ventricular deterioration [32], [28].

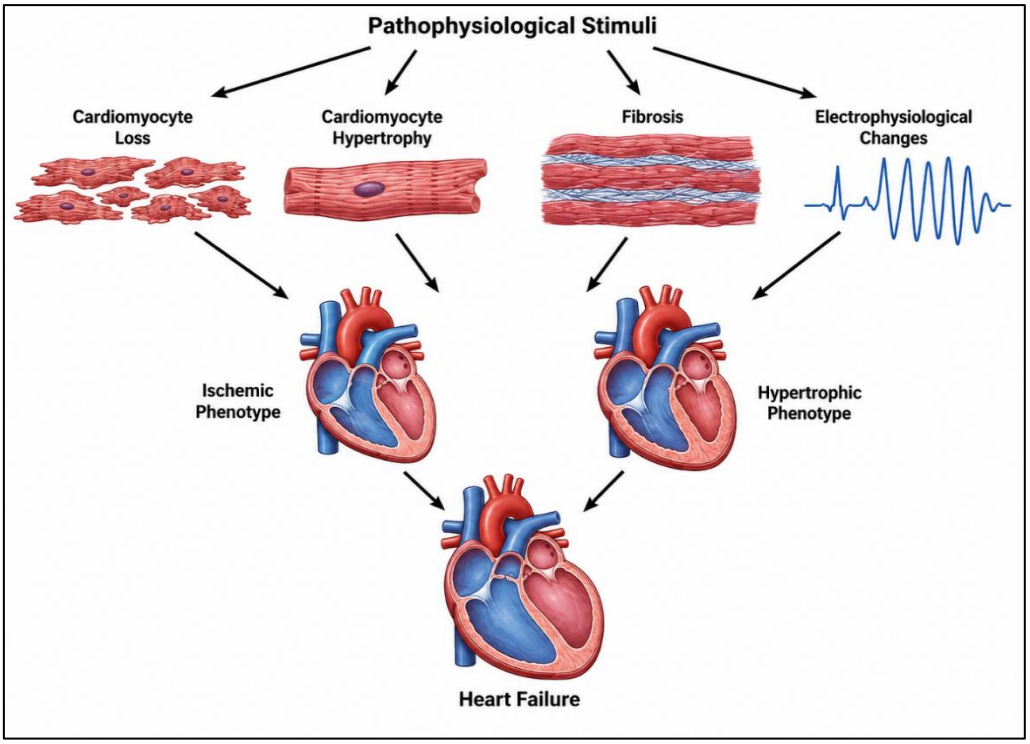

Fig 1 Pathological Ventricular Remodeling Pathway

The pathophysiological basis of LVSD is reduced myocardial contractility. Contractility reflects the intrinsic ability of cardiac muscle fibers to generate force independent of preload and afterload [8]. When cardiomyocytes are damaged by ischemia, pressure overload, metabolic injury, inflammation, fibrosis, or genetic myocardial disease, the ventricle becomes less efficient in converting electrical activation into mechanical contraction [8], [9]. This reduction in contractile performance lowers stroke volume and may increase residual end-systolic volume, thereby reducing LVEF [8]. As systolic function declines, the ventricle may dilate, wall stress may increase, and myocardial oxygen demand may rise, creating a cycle of progressive dysfunction [9].

Cardiac remodeling is central to the progression from early myocardial injury to established LVSD and heart failure [9]. Ventricular remodeling refers to changes in ventricular size, shape, mass, geometry, and tissue composition that occur in response to pathological stimuli [9]. In pressure overload states such as long-standing hypertension or aortic stenosis, the ventricle may initially develop concentric hypertrophy as a compensatory response to increased afterload [2], [9]. In volume overload, ischemic injury, or dilated cardiomyopathy, the ventricle may progressively dilate and become more spherical, leading to eccentric remodeling and reduced contractile efficiency [9]. Although remodeling may initially preserve cardiac output, persistent remodeling is associated with fibrosis, chamber enlargement, electrical instability, worsening systolic function, and increased cardiovascular risk [39].

The clinical importance of LVSD also lies in its frequent asymptomatic phase. Asymptomatic left ventricular dysfunction may exist before overt heart failure symptoms develop, and affected individuals may not seek medical attention until exertional dyspnea, fatigue, fluid retention, or reduced exercise tolerance becomes evident [3], [41]. This creates a major screening challenge because the underlying ventricular impairment may already be clinically relevant before it is recognized through routine care [3], [4]. Early detection is therefore important because timely identification of reduced systolic function can support further cardiac imaging, risk stratification, initiation of evidence-based therapy, and prevention of progression to symptomatic heart failure [2], [3].

Several disease pathways can lead to LVSD. Ischemic heart disease is one of the most important causes because myocardial infarction or chronic coronary artery disease can cause irreversible cardiomyocyte loss, regional wall-motion abnormalities, scar formation, and reduced global systolic performance [2], [9]. Hypertension is another major contributor because chronic pressure overload increases left ventricular workload, promotes hypertrophy, and may eventually produce ventricular stiffness, myocardial fibrosis, and systolic impairment [2], [9]. Cardiomyopathies, including dilated, hypertrophic, inflammatory, toxic, genetic, and infiltrative forms, can also impair myocardial structure and contractility [2], [37].

Valvular heart disease contributes to LVSD through pressure or volume overload. Severe aortic stenosis increases afterload and can eventually reduce systolic function, while chronic aortic or mitral regurgitation causes volume overload, ventricular dilation, and progressive myocardial stress [2], [38]. Diabetes mellitus increases LVSD risk through multiple mechanisms, including microvascular dysfunction, metabolic myocardial injury, oxidative stress, autonomic dysfunction, and accelerated atherosclerosis [2], [7]. Chronic kidney disease is also associated with increased cardiovascular risk because of hypertension, volume overload, uremic toxins, vascular calcification, anemia, inflammation, and disordered mineral metabolism, all of which may contribute to cardiac remodeling and ventricular dysfunction [9].

Thus, LVSD should be understood as both a mechanical and biological consequence of myocardial injury. It reflects impaired ventricular contraction, but it also represents the final common pathway of several systemic and cardiovascular disease processes. Its relationship with heart failure, adverse remodeling, arrhythmia risk, hospitalization, and mortality makes early detection clinically significant [2], [7], [8]. This explains why the search for accessible screening tools, including AI-enabled ECG systems, has become increasingly important in cardiovascular medicine [34], [4], [5].

➢ *Current Diagnostic Approaches for LVSD*

The diagnosis of LVSD requires assessment of left ventricular systolic performance, usually through measurement of LVEF or related functional indices [2], [8]. Current diagnostic approaches include echocardiography, cardiac magnetic resonance imaging, biomarker testing, clinical examination, and conventional ECG interpretation [2], [7], [8]. These tools differ in their diagnostic role, accessibility, cost, sensitivity, specificity, technical requirements, and suitability for screening.

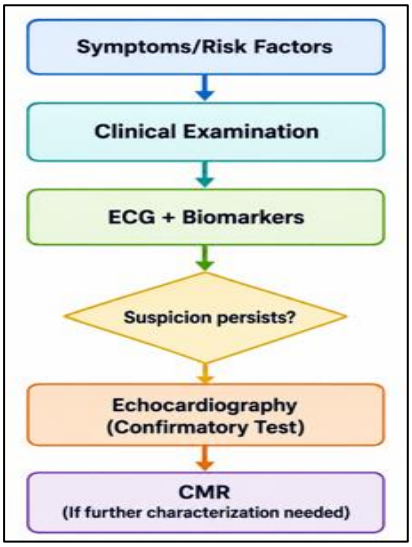

Fig 2 Current Diagnostic Pathway for Suspected LVSD

Echocardiography remains the most widely used confirmatory imaging modality for LVSD because it provides direct assessment of left ventricular size, wall motion, systolic function, diastolic function, valvular structure, chamber geometry, and estimated hemodynamic parameters [2]. Two-dimensional echocardiography is commonly used to estimate LVEF, often through biplane Simpson's method, in which end-diastolic and end-systolic volumes are calculated from apical two-chamber and four-chamber views [8]. Echocardiography is also useful because it can identify structural explanations for LVSD, such as regional wall-motion abnormality after myocardial infarction, dilated cardiomyopathy, hypertensive remodeling, or valvular disease [2], [7].

Despite these strengths, echocardiography has limitations as a population-level screening tool. Image acquisition and interpretation require trained personnel, appropriate equipment, patient access to imaging facilities, and standardized measurement protocols [2]. Operator dependency can also affect measurement reliability, particularly when image windows are poor or ventricular borders are difficult to trace [8]. Although echocardiography is more accessible than cardiac magnetic resonance imaging in many settings, its availability is still limited in rural communities, low-resource health systems, and primary care environments where screening demand may exceed imaging capacity [32], [5]. These constraints make echocardiography essential for confirmation but less practical as the first screening method for broad asymptomatic populations [3], [5].

Cardiac magnetic resonance imaging (CMR) is another important diagnostic approach for assessing LVSD. CMR provides high-resolution quantification of ventricular volumes, LVEF, myocardial mass, wall motion, and tissue characteristics [8]. It is particularly useful when echocardiographic images are suboptimal or when myocardial tissue characterization is required, such as in suspected myocarditis, infiltrative cardiomyopathy, scar assessment, fibrosis evaluation, or non-ischemic cardiomyopathy [7], [8]. CMR is often regarded as highly accurate for volumetric assessment because it does not depend on the same geometric assumptions that may affect two-dimensional echocardiography [8]. However, CMR is costly, less available, time-consuming, and unsuitable for some patients with incompatible implants, severe claustrophobia, or limited access to advanced imaging facilities [37], [8]. Consequently, CMR is valuable for detailed evaluation but not ideal for mass screening.

Biomarkers also play a supportive role in the evaluation of suspected cardiac dysfunction. Natriuretic peptides, including B-type natriuretic peptide and N-terminal pro-B-type natriuretic peptide, are released in response to myocardial wall stress and elevated intracardiac pressures [7], [10]. These biomarkers are useful in evaluating suspected heart failure, ruling out heart failure in some clinical contexts, and prioritizing patients for further imaging [7], [10]. However, natriuretic peptide levels are not specific for LVSD alone because they may rise in other conditions such as atrial fibrillation, renal dysfunction, pulmonary hypertension, older age, and acute illness [7], [10]. Conversely, some individuals with early or mild systolic dysfunction may not have markedly elevated biomarker levels [10]. Biomarkers therefore provide important clinical information but cannot independently replace imaging-based assessment of ventricular systolic function [7], [10]. Clinical examination remains necessary but insufficient for early LVSD detection. Symptoms such as dyspnea, fatigue, orthopnea, paroxysmal nocturnal dyspnea, exercise intolerance, and peripheral edema may suggest heart failure, while signs such as elevated jugular venous pressure, pulmonary crackles, displaced apex beat, third heart sound, hepatomegaly, and edema may support clinical suspicion [2], [7]. However, early LVSD may be asymptomatic or associated with non-specific symptoms that overlap with respiratory disease, anemia, obesity, kidney disease, and physical deconditioning [2], [36]. Clinical examination is therefore more useful for evaluating symptomatic disease than for detecting silent ventricular dysfunction in asymptomatic individuals [3], [4].

Conventional ECG is widely used in cardiovascular evaluation because it is inexpensive, rapid, non-invasive, and available in most clinical settings [4], [7]. It can reveal arrhythmias, prior myocardial infarction, conduction disease, ventricular hypertrophy, repolarization abnormalities, and QRS prolongation, all of which may provide indirect evidence of structural or functional heart disease [7]. However, conventional ECG interpretation is not sufficiently sensitive to rule out early LVSD [4], [11]. Some patients with reduced LVEF may have ECG abnormalities, but others may show patterns that appear non-specific or even near-normal to routine clinical interpretation [4]. The limitations of existing diagnostic tools create a practical problem. Imaging is necessary for confirmation but may not be accessible for large-scale screening, biomarkers are useful but non-specific, clinical examination may miss asymptomatic disease, and conventional ECG interpretation may fail to detect subtle electrical signatures of early LVSD [34], [35]. This diagnostic gap explains the growing interest in AI-enabled ECG analysis, especially where ECG can be captured through portable or wearable devices and used to triage patients for confirmatory echocardiography [4], [5].

- *ECG-Based Detection of Structural and Functional Heart Disease*

ECG-based assessment of structural and functional heart disease is based on the principle that abnormalities in cardiac anatomy, pressure loading, myocardial perfusion, ventricular conduction, and rhythm can alter the electrical signals recorded at the body surface [7], [11]. Although ECG does not directly image cardiac structure or quantify LVEF, it provides a time-resolved representation of atrial and ventricular depolarization and repolarization [4], [7]. These electrical processes may be affected by left ventricular hypertrophy, myocardial ischemia, scar, conduction delay, chamber enlargement, arrhythmia, and ventricular remodeling [7], [11].

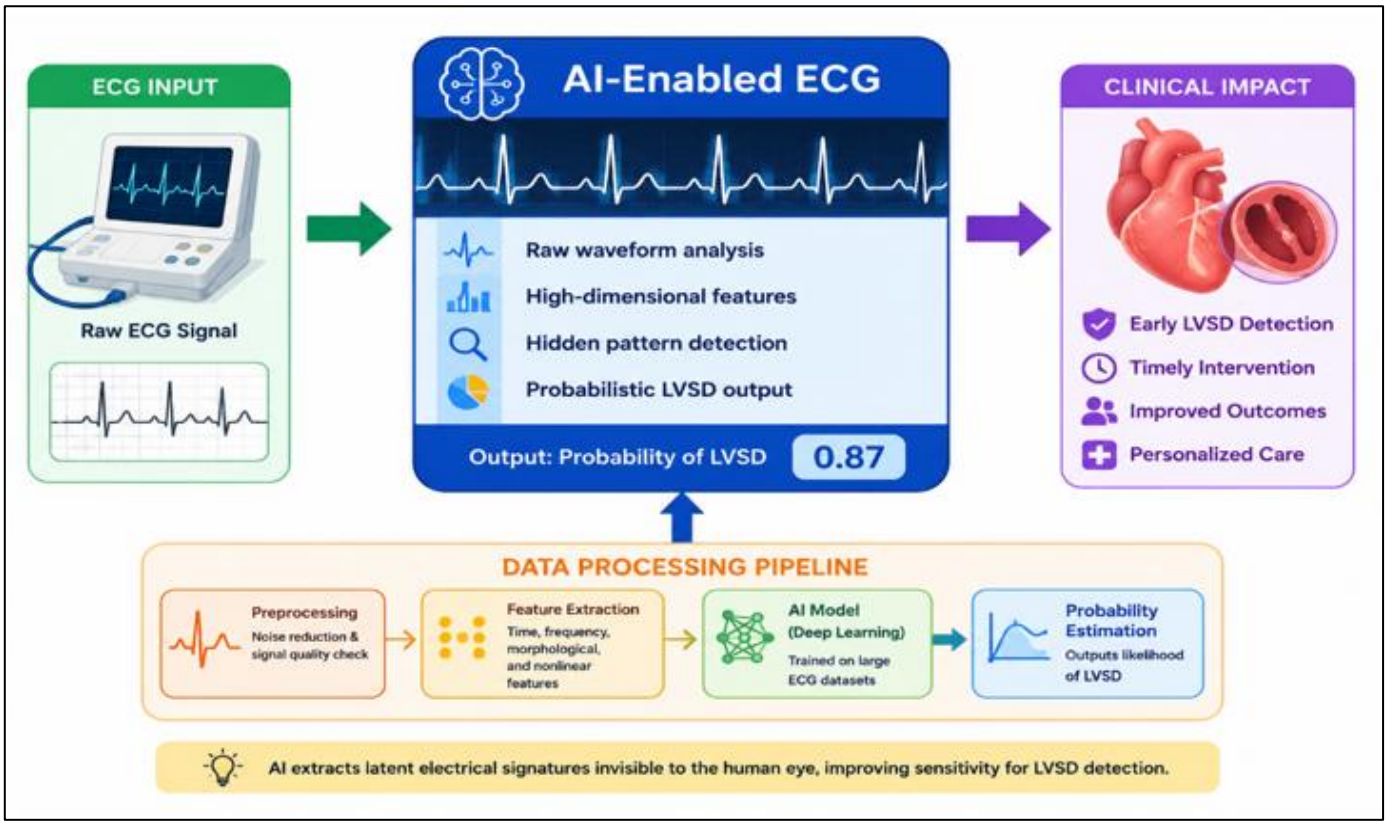

Fig 3 ECG–Structure–Function Relationship Framework in LVSD Detection

Left ventricular hypertrophy is one example of a structural abnormality that may produce ECG changes. Increased ventricular mass can generate higher QRS voltages, repolarization abnormalities, axis deviation, and strain-like ST-T changes [7], [11]. However, ECG criteria for hypertrophy are imperfect because voltage patterns are influenced by body habitus, age, sex, chest wall anatomy, electrode placement, and coexisting conduction abnormalities [11]. As a result, ECG evidence of hypertrophy may support suspicion of structural heart disease but cannot reliably exclude it when absent [11].

Conduction abnormalities are also important in the ECG assessment of ventricular disease. Bundle branch block, intraventricular conduction delay, and prolonged QRS duration may indicate abnormal ventricular activation and are frequently associated with structural heart disease, ventricular remodeling, or reduced systolic efficiency [2], [11]. QRS duration is clinically relevant because prolonged ventricular depolarization can impair mechanical synchrony, reduce contractile efficiency, and influence eligibility for cardiac resynchronization therapy in selected patients with reduced LVEF [2], [8], [11]. Subtle changes in QRS duration have also been associated with reduced ejection fraction and increased chamber dimensions, suggesting that even modest conduction changes may contain useful information about ventricular function [11].

ECG signals may also reflect ischemic heart disease, a major cause of LVSD. Acute or chronic myocardial ischemia can alter ST segments, T waves, Q waves, R-wave progression, and ventricular conduction patterns [7], [11]. Previous myocardial infarction may produce pathological Q waves or regional electrical changes that correspond to scarred myocardium and impaired regional contraction [7]. Because ischemic injury can damage cardiomyocytes and trigger adverse remodeling, ECG evidence of ischemia or infarction may indirectly suggest increased risk of LVSD [2], [9].

Repolarization abnormalities are another pathway through which ECG may reflect ventricular disease. ST-segment depression, T-wave inversion, QT prolongation, and strain patterns may occur in ischemia, hypertrophy, electrolyte disturbance, cardiomyopathy, and heart failure [7], [11]. These features are not specific to LVSD, but they contribute to the broader electrical phenotype of structural heart disease [11]. Rhythm disturbances are also relevant because atrial fibrillation, frequent premature ventricular complexes, ventricular tachyarrhythmias, and bradyarrhythmias may coexist with or contribute to ventricular dysfunction [2], [7]. In some cases, persistent tachyarrhythmia or high ectopic burden can worsen systolic performance, while LVSD itself increases arrhythmia risk through fibrosis, chamber dilation, and altered conduction [2], [7], [9].

Despite these associations, conventional ECG interpretation has important limitations in early LVSD detection. Human interpretation typically relies on visible diagnostic criteria, such as voltage thresholds, conduction intervals, rhythm classification, ST-T changes, or infarction patterns [7], [11]. Early ventricular dysfunction may not produce a clearly recognizable ECG abnormality, or it may produce distributed micro-patterns that are too subtle for visual interpretation [4]. This explains why a

standard ECG may appear non-diagnostic even when LVEF is reduced [4].

Artificial intelligence expands the diagnostic potential of ECG because it can analyze complex waveform patterns beyond conventional visual criteria [4], [5]. Deep learning models can process raw ECG signals, learn hierarchical representations, and detect high-dimensional relationships between waveform morphology and cardiac function [4]. In a major AI-ECG study, a convolutional neural network trained on paired ECG and echocardiography data detected ventricular dysfunction from ECG alone with strong diagnostic performance, supporting the view that reduced systolic function leaves measurable electrical signatures within ECG signals [4].

The relevance of AI-ECG is particularly strong for LVSD screening because it can transform ECG from a rule-based interpretive tool into a data-rich screening instrument [3], [4]. Rather than depending only on obvious ECG abnormalities, AI models can learn subtle combinations of amplitude, interval, morphology, rhythm, conduction, and repolarization features that may correlate with reduced LVEF [41], [5]. This allows ECG to function as a preliminary risk stratification tool, identifying patients who may require confirmatory echocardiography [3], [4], [5].

However, most established AI-ECG models were developed using 12-lead ECG recordings, which provide multiple anatomical perspectives of cardiac electrical activity [4]. Single-lead ECG creates a more difficult but potentially more scalable screening context because it captures less spatial information and is commonly affected by real-world noise when collected through wearable or portable devices [5]. Recent work has shown that AI models adapted for noisy single-lead ECG can detect LVSD from wearable-compatible signals, suggesting that ECG-based structural heart disease screening may be extended beyond hospital-based 12-lead ECG systems [5].

Therefore, ECG-based detection of structural and functional heart disease should be understood as a layered diagnostic process. Conventional ECG interpretation identifies visible electrical abnormalities, while AI-enabled ECG analysis detects hidden patterns that may be associated with ventricular dysfunction [4], [5]. This distinction is central to the present study because AI-enabled single-lead wearable ECG screening depends on the assumption that clinically meaningful LVSD signatures can be extracted from simplified ECG recordings when appropriate preprocessing, model design, and validation strategies are applied [5], [6].

- *Artificial Intelligence in ECG Interpretation*

Artificial intelligence has expanded ECG interpretation beyond rule-based visual assessment by allowing computational models to detect complex waveform patterns associated with cardiac disease [4], [5]. In traditional machine learning, ECG analysis usually begins with signal preprocessing, followed by manual or semi-automated feature extraction. Common features include heart rate variability, RR interval, PR interval, QRS duration, QT interval, ST-segment changes, T-wave morphology, signal amplitude, and frequency-domain measures [13]. These extracted features can then be classified using algorithms such as logistic regression, random forest, support vector machines, k-nearest neighbors, and gradient boosting models [13].

Logistic regression is useful for interpretable classification, especially when ECG features are predefined and clinically meaningful [13]. Random forest models can handle non-linear relationships and rank feature importance, while support vector machines are effective in separating complex classes when appropriate kernels are used [13]. However, these methods depend heavily on the quality of engineered features and may miss subtle waveform relationships that are difficult to define manually [4], [13].

Deep learning methods address some of these limitations by learning directly from raw or minimally processed ECG signals [4], [14]. Convolutional neural networks are widely used because they can detect local waveform patterns such as QRS morphology, ST-T changes, and signal irregularities [4], [14]. Recurrent neural networks and long short-term memory models are useful for sequential ECG analysis because they capture temporal dependencies across cardiac cycles [14]. Transformer-based models have also gained attention because their attention mechanisms can identify relationships across longer ECG segments and may improve representation learning in complex signal classification tasks [15].

In AI-ECG workflows, preprocessing remains essential. It commonly involves baseline wander removal, filtering of powerline interference, noise reduction, beat segmentation, R-peak detection, normalization, and artifact rejection [5], [16]. After preprocessing, the model may either use hand-crafted features or perform automatic representation learning from waveform data [4], [14]. The final classification layer then produces diagnostic outputs such as normal rhythm, arrhythmia class, structural heart disease probability, or LVSD risk score [4], [5].

Model validation is central to clinical reliability. AI-ECG models should be evaluated with separate training, validation, and testing datasets, and stronger evidence is obtained when external validation is performed on data from different institutions, devices, or populations [4], [5], [6]. Diagnostic performance is commonly measured using accuracy, sensitivity, specificity, precision, F1-score, AUROC, calibration, and confusion matrix analysis [4], [5]. For LVSD screening, sensitivity and negative predictive value are particularly important because missed cases may delay confirmatory echocardiography and treatment [35].

- *Single-Lead Wearable ECG Technologies*

Single-lead wearable ECG technologies are designed to capture cardiac electrical activity outside conventional hospital-based ECG systems [5], [16]. These technologies

include smartwatches, adhesive ECG patches, handheld ECG recorders, chest-worn sensors, and mobile-connected devices [16], [17]. Their main advantage is accessibility: they can be used in home monitoring, outpatient care, telemedicine, community screening, and remote follow-up [5], [17].

Smartwatch ECG systems usually record short single-lead tracings when the user completes contact between the device and the body, while adhesive patches can record continuously for longer periods [16], [17]. Handheld ECG recorders and mobile-connected sensors are also useful because they are portable, relatively easy to operate, and can transmit ECG recordings to smartphones, cloud platforms, or clinical review systems [17]. These features make wearable ECG technologies attractive for screening strategies that require low-cost and repeatable signal acquisition [5].

Technical performance depends on sampling frequency, electrode contact, signal stability, battery life, storage capacity, wireless transmission, and algorithm compatibility [16], [17]. Sampling frequency is important because low-resolution signals may reduce the visibility of ECG morphology, while excessive data collection can increase storage and transmission demands [16]. Signal quality is also affected by motion artifacts, muscle noise, baseline wander, skin-electrode impedance, loose contact, sweat, posture, and electrode placement [16], [18].

User compliance is another important factor. Wearable devices are more likely to support long-term monitoring when they are comfortable, easy to use, unobtrusive, and compatible with daily activities [16], [17]. However, inconsistent use, improper placement, poor skin contact, and incomplete recordings can reduce diagnostic value [16], [18]. Therefore, single-lead wearable ECG systems require both technical optimization and user-centered design before they can support reliable screening [16], [17].

Data handling is equally important. Many wearable ECG devices transmit recordings through Bluetooth, Wi-Fi, or mobile networks to smartphones, cloud servers, or clinical dashboards [17]. This supports remote monitoring and rapid review, but it also creates requirements for data security, privacy protection, encryption, interoperability, and clinical accountability [6], [17].

➢ *AI-Enabled Wearable ECG Screening for LVSD*

AI-enabled wearable ECG screening combines accessible signal acquisition with automated interpretation. In this model, a single-lead wearable device records ECG data, preprocessing improves signal quality, and an AI model estimates the probability of LVSD [5]. The result can be used to identify individuals who require confirmatory echocardiography rather than serving as a final diagnosis [2], [5].

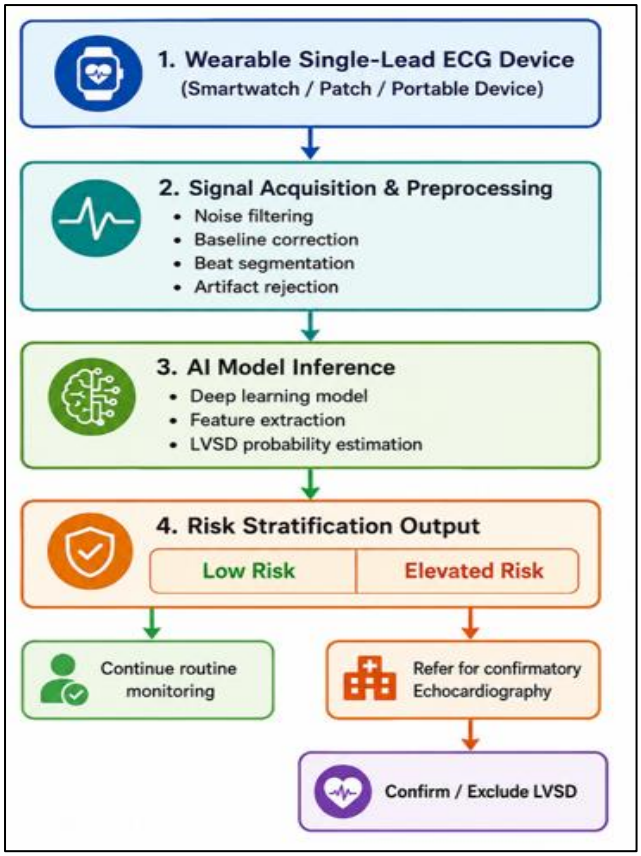

Fig 4 AI-Enabled Wearable ECG Screening Pathway for LVSD

This approach is relevant because LVSD may be asymptomatic, while echocardiography is not always available for large-scale screening [2], [3]. Single-lead wearable ECG can be used in settings where conventional imaging is difficult to access, including primary care clinics, rural health programs, pharmacies, workplace health checks, telemedicine platforms, and community outreach programs [5], [17].

AI-enabled wearable ECG may also support opportunistic screening. For example, individuals using smartwatches or portable ECG devices could generate ECG recordings during routine monitoring, and high-risk results could trigger referral for echocardiography [5], [17]. In primary care, such systems may help clinicians prioritize patients with cardiovascular risk factors, especially those with hypertension, diabetes, ischemic heart disease, chronic kidney disease, or unexplained fatigue and dyspnea [34], [5].

For remote monitoring, AI-enabled wearable ECG may allow repeated assessment over time rather than one-time testing [16], [17]. This is useful because repeated ECG recordings may improve detection of evolving electrical changes and support follow-up after cardiovascular risk identification [5]. In population health programs, the technology may help stratify large groups into low-risk and higher-risk categories, reducing unnecessary imaging while directing limited echocardiography resources to those most likely to benefit [33], [5].

However, the clinical value of AI-enabled wearable ECG depends on robust validation. The model must perform reliably across age, sex, ethnicity, comorbidity profiles, device types, and signal-quality conditions [5], [6]. It must also manage false positives and false negatives carefully, since false positives may increase unnecessary referrals while false negatives may delay diagnosis [3], [5]. For this reason, AI-enabled wearable ECG should be implemented as a screening and referral-support system within a supervised clinical pathway [2], [31], [6].

➢ *Gaps in Existing Literature*

Although AI-enabled ECG has shown strong potential for detecting LVSD, several gaps remain in the existing literature. First, many AI-ECG studies have been developed using retrospective datasets and require stronger external validation across multiple hospitals, populations, and device environments [3], [4], [5]. Without broad validation, model performance may appear strong in development datasets but decline when applied to new clinical settings [5], [6].

Second, sample size and population representation remain important concerns. Some studies include limited numbers of LVSD-positive cases or underrepresent certain groups based on age, sex, ethnicity, comorbidities, and geographic background [3], [6]. This may reduce generalizability and increase the risk of algorithmic bias when the model is deployed in diverse populations [6].

Third, single-lead wearable ECG introduces signal-quality challenges that are less common in standard clinical ECG acquisition. Motion artifacts, baseline wander, poor electrode contact, variable sampling frequency, and environmental noise can affect waveform quality and reduce diagnostic reliability [47], [16], [18]. Although noise-adapted models have improved performance, real-world wearable ECG screening still requires further clinical validation [45], [6].

Fourth, explainability remains limited in many deep learning ECG models. Black-box predictions may reduce clinician trust, particularly when the model identifies LVSD risk without showing which ECG features influenced the result [43], [6]. For clinical use, AI outputs should be interpretable enough to support decision-making, error analysis, and safe referral pathways [46].

Finally, there is still limited evidence on how AI-enabled wearable ECG screening should be integrated into real healthcare workflows. Issues such as data privacy, referral criteria, patient consent, false-positive burden, false-negative risk, clinician accountability, and confirmatory echocardiography access must be addressed before large-scale deployment [3], [40]. These gaps justify the present study, which focuses on AI-enabled single-lead wearable ECG as a preliminary LVSD screening and referral-support tool.

➢ *Conceptual Framework*

The conceptual framework for this study explains how AI-enabled single-lead wearable ECG screening can support early detection of LVSD. The framework begins with ECG acquisition using a wearable or portable single-lead device. The recorded signal is then processed to remove noise, correct baseline drift, normalize waveform amplitude, and segment relevant ECG windows [5], [16].

After preprocessing, the cleaned ECG signal is passed into an AI classification model. The model may use machine learning or deep learning techniques to identify waveform patterns associated with possible LVSD [4], [5]. The output is expressed as an LVSD risk score or probability estimate. This score does not confirm diagnosis but indicates whether the individual should be referred for further clinical evaluation [2], [49].

The next stage is clinical decision support. Individuals with low-risk outputs may continue routine monitoring, while those with high-risk outputs may be referred for confirmatory echocardiography [2], [5]. Echocardiography remains essential because it directly measures LVEF and confirms the presence or absence of systolic dysfunction [2]. Through this pathway, AI-enabled wearable ECG screening may improve early identification, referral prioritization, and timely treatment of individuals at risk of LVSD [3], [5].

III. METHODOLOGY

➢ *Research Design*

This study adopted a quantitative diagnostic evaluation design to assess the potential of AI-enabled single-lead wearable ECG for the early detection of LVSD. The design compared AI-generated LVSD predictions from single-lead ECG recordings with echocardiography-confirmed LVEF values, which served as the reference standard.

Where real patient data were available, the study was conducted retrospectively or prospectively using paired ECG and echocardiography records. In the retrospective design, existing clinical ECG and echocardiography data were analyzed. In the prospective design, ECG recordings were collected from participants who underwent echocardiography assessment.

Where real patient data were not available, the study was presented as a proposed AI screening framework supported by evidence from previous AI-ECG and single-lead ECG studies. In either case, the design focused on evaluating whether single-lead wearable ECG supported preliminary LVSD screening and referral for confirmatory echocardiography.

➢ *Study Population and Data Source*

The target population consisted of adult patients who underwent ECG recording and echocardiography assessment. The main data sources were single-lead ECG recordings and echocardiography-derived LVEF results. Echocardiography was used as the reference standard because it provided direct assessment of left ventricular systolic function.

The dataset also included relevant demographic and clinical variables such as age, sex, cardiovascular history, hypertension, diabetes, chronic kidney disease, ischemic heart disease, medication history, and ECG recording date. These variables helped to describe the study population and assess model generalizability.

- *Inclusion Criteria*

Participants were included if they met the following criteria:

✓ Adults aged 18 years and above.
✓ Availability of a single-lead ECG recording.
✓ Availability of echocardiography-derived LVEF result.
✓ ECG and echocardiography performed within an acceptable clinical time window.

- *Exclusion Criteria*

Participants were excluded if they had:

✓ Poor-quality ECG recordings.
✓ Missing echocardiography-derived LVEF data.
✓ Pacemaker-dominated rhythm, unless included in the model design.
✓ Incomplete demographic or clinical metadata.

➢ *Definition of Outcome Variable*

The primary outcome variable for this study was LVSD status, defined using echocardiography-derived left ventricular ejection fraction as the reference standard. Since reduced LVEF was a widely accepted indicator of impaired systolic function, the binary classification target was constructed by applying a clinically relevant threshold of 40% [2], [44].

$$\boxed{LVSD_i = \begin{cases} 1, & \text{if } LVEF_i \leq 40\% \\ 0, & \text{if } LVEF_i > 40\% \end{cases}} \quad (1)$$

In Equation (1), $LVSD_i$ represented the diagnostic class assigned to participant i. A value of 1 indicated the presence of LVSD, while a value of 0 indicated preserved systolic function. This definition converted the echocardiography-derived LVEF value into a supervised learning label, allowing the AI model to learn the relationship between single-lead ECG patterns and reduced ventricular function [42], [5].

The threshold in Equation (1) directly determined model behavior because it defined the positive and negative classes used during training and evaluation. When the threshold was changed, the distribution of LVSD-positive cases also changed, which affected sensitivity, specificity, precision, and F1-score. Secondary analyses therefore considered alternative LVEF thresholds, such as mildly reduced LVEF or severe LVSD, depending on the clinical objective of the study [50].

➢ *ECG Signal Acquisition*

Single-lead ECG recordings were obtained using a wearable or portable ECG device capable of capturing cardiac electrical activity from one lead configuration. The device included a smartwatch ECG sensor, handheld ECG recorder, adhesive patch, or mobile-connected single-lead ECG system [42], [49]. Electrode placement was standardized to reduce variability in waveform amplitude, morphology, and signal orientation [18].

The acquired ECG signal was represented as a sampled time-series signal:

$$x[n] = s[n] + b[n] + \eta[n] \quad (2)$$

In Equation (2), x[n] represented the recorded ECG signal at sample n, s[n] represented the true cardiac electrical signal, b[n] represented baseline wander, and η[n] represented unwanted noise such as muscle activity, motion artifact, powerline interference, or poor electrode contact. This equation showed that the recorded wearable ECG was not a pure cardiac signal; rather, it was a mixture of physiological information and acquisition-related disturbance [16], [48].

Recording duration was made long enough to capture representative cardiac cycles. A short recording was suitable for opportunistic screening, while longer recordings improved rhythm representation and signal reliability [16]. Sampling frequency was sufficient to preserve clinically relevant ECG morphology, especially P-wave, QRS-complex, and T-wave characteristics. However, higher sampling rates increased storage and transmission requirements, creating a trade-off between signal detail and device efficiency [47].

The ECG data were stored locally on the device, transmitted to a mobile application, or transferred wirelessly to a cloud-based platform for AI analysis. Wireless transmission through Bluetooth, Wi-Fi, or mobile networks supported remote screening but also required secure data handling, encryption, and privacy protection [46], [17].

➢ *ECG Signal Preprocessing*

Preprocessing was required because Equation (2) showed that the wearable ECG signal contained both cardiac and non-cardiac components. The aim of preprocessing was to reduce b[n] and η[n] while preserving the clinically meaningful structure of s[n]. This step was essential because poor signal quality distorted ECG morphology and reduced AI model reliability [51], [16].

After filtering, the cleaned ECG signal was expressed as:

$$\hat{x}[n] = H\{x[n]\} \quad (3)$$

In Equation (3), $\hat{x}[n]$ represented the filtered ECG signal, and $H\{\bullet\}$ represented the filtering operation applied to the raw ECG signal. This operation included baseline wander removal, band-pass filtering, powerline interference suppression, and artifact reduction. Equation (3) directly modified Equation (2) by reducing unwanted noise components while retaining the signal features needed for LVSD classification [5], [16].

The filtered signal was then normalized to reduce amplitude differences caused by electrode placement, skin contact, device type, or patient-specific variation:

$$z[n] = (\hat{x}[n] - \mu) / \sigma \quad (4)$$

In Equation (4), z[n] represented the normalized ECG signal, μ represented the mean of the filtered signal, and σ represented its standard deviation. Normalization ensured that the AI model did not overemphasize amplitude differences that arose from recording conditions rather than true cardiac physiology. Therefore, Equation (4) strengthened the reliability of the classification process that followed from Equation (1).

Beat segmentation and R-peak detection were then applied to identify meaningful cardiac cycles. The normalized signal was divided into fixed-duration windows as follows:

$$X_i = \{z[t_i], z[t_i + 1], \ldots, z[t_i + L - 1]\} \quad (5)$$

In Equation (5), X_i represented the ECG segment used as input to the AI model, t_i represented the starting sample of the segment, and L represented the window length. This equation linked preprocessing to model development because the classifier did not learn from the entire unstructured ECG stream; instead, it learned from standardized signal windows derived from the filtered and normalized ECG.

Artifact rejection was applied before classification to remove segments affected by severe noise, missing signal, poor contact, irregular baseline drift, or excessive motion artifact [16], [18]. This was important because noisy segments increased false-positive or false-negative predictions. Therefore, preprocessing was not only a technical preparation stage but also a major determinant of diagnostic reliability in AI-enabled single-lead wearable ECG screening [5], [6].

➢ *AI Model Development*

The proposed AI model was developed to classify LVSD from preprocessed single-lead ECG segments. A one-dimensional convolutional neural network was considered suitable because ECG was a time-series signal, and 1D-CNNs learned local waveform patterns such as QRS morphology, ST-T variation, rhythm irregularity, and subtle amplitude changes [4], [5], [14]. Alternative models included CNN-LSTM networks, transformer-based ECG models, or hybrid classifiers combining deep features with clinical variables [13], [15].

- *The Proposed Model Flow Was:*

Raw ECG signal → Preprocessing → Segmentation → Feature learning → Classification layer → LVSD probability score

After preprocessing and segmentation, each ECG window, X_i, was passed into the trained model. The model estimated the probability that the ECG segment belonged to an LVSD-positive patient:

$$P(LVSD = 1 \mid X_i) = f\theta(X_i) \quad (6)$$

In Equation (6), X_i represented the ECG input segment defined earlier in Equation (5), while fθ represented the trained AI model with learned parameters θ. The scientific purpose of Equation (6) was to transform the cleaned ECG signal into a clinically interpretable probability score. This meant that the model did not merely classify a waveform; it estimated the likelihood that hidden ECG patterns were associated with reduced LVEF.

The model output was converted into a binary prediction using a decision threshold, τ:

$$\hat{y}_i = 1 \; if \; P(LVSD = 1 \mid X_i) \geq \tau; \; otherwise \; \hat{y}_i = 0 \quad (7)$$

Equation (7) directly influenced diagnostic performance. A lower threshold increased sensitivity by detecting more LVSD-positive cases, but it also increased false positives. A higher threshold improved specificity but risked missing patients with early LVSD. Therefore, threshold selection reflected the screening objective, where missing true LVSD cases was clinically more serious than referring some false-positive cases for echocardiography.

➢ *Training, Validation, and Testing*

The dataset was divided into training, validation, and testing sets. A suggested split was 70% for training, 15% for validation, and 15% for testing. The training set was used to learn model parameters, the validation set guided hyperparameter tuning, and the test set provided an unbiased estimate of final model performance.

To reduce overfitting, the model was tested using cross-validation where appropriate. Cross-validation allowed the dataset to be repeatedly divided into different training and validation folds, improving confidence that model performance was not dependent on one random data split.

External validation was also important. A model trained on one population, hospital, or device performed differently when applied to another setting. Therefore, the model was tested on independent data from different institutions, demographic groups, or wearable devices before clinical deployment.

Class imbalance was also addressed because LVSD-positive cases were fewer than normal cases. This was managed through class weighting, oversampling, undersampling, or focal loss. The model was also calibrated so that predicted probabilities reflected actual clinical risk. A well-calibrated model was important because the LVSD probability score in Equation (6) was used to guide referral decisions.

➢ *Model Performance Metrics*

Model performance was evaluated using diagnostic classification metrics derived from the confusion matrix. The confusion matrix contained true positives, true

negatives, false positives, and false negatives. These values determined whether the model was useful for LVSD screening.

Accuracy measured the proportion of correctly classified cases:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (8)$$

Sensitivity measured the ability of the model to correctly identify patients with LVSD:

$$Sensitivity = TP / (TP + FN) \quad (9)$$

Specificity measured the ability of the model to correctly identify patients without LVSD:

$$Specificity = TN / (TN + FP) \quad (10)$$

Precision, also called positive predictive value, measured the proportion of predicted LVSD-positive cases that were truly positive:

$$Precision = TP / (TP + FP) \quad (11)$$

The F1-score combined precision and sensitivity into one balanced measure:

$$F1-score = 2 \times (Precision \times Sensitivity) / (Precision + Sensitivity) \quad (12)$$

Negative predictive value measured the proportion of predicted LVSD-negative cases that were truly negative:

$$NPV = TN / (TN + FN) \quad (13)$$

For LVSD screening, sensitivity and negative predictive value were especially important because a false-negative result delayed echocardiography and treatment [3], [5]. However, specificity and precision were also important because excessive false positives overloaded echocardiography referral pathways.

AUROC was used to evaluate how well the model separated LVSD-positive and LVSD-negative cases across different thresholds [4], [5]. The area under the precision-recall curve was also useful when the dataset was imbalanced, since it focused more directly on positive-case detection. Calibration curves were used to assess whether the probability scores from Equation (6) matched observed LVSD risk. Together, these metrics provided a more complete assessment than accuracy alone.

➢ *Explainability and Clinical Interpretability*

Explainability was required to determine whether the AI model learned clinically meaningful ECG features or responded to noise, artifacts, or dataset bias. Since the model output in Equation (6) produced an LVSD probability score, interpretability methods examined which regions of the ECG segment, X_i, contributed most strongly to that prediction.

Saliency maps were used to highlight ECG time points where small changes in signal amplitude strongly influenced the model output [19]. For ECG analysis, this showed whether the model focused on relevant regions such as the QRS complex, ST segment, T wave, rhythm intervals, or abnormal waveform transitions. Grad-CAM was also adapted to one-dimensional ECG signals to identify important activation regions within convolutional layers.

SHAP values were used when the model included engineered ECG features or hybrid clinical variables. This method estimated the contribution of each feature to the final prediction, making it useful for interpreting how QRS duration, rhythm irregularity, amplitude variation, or clinical risk factors influenced LVSD classification. Attention visualization was also useful in transformer-based models because it showed which ECG segments received greater model attention during classification.

Clinically, these methods helped verify whether the model's decision was aligned with plausible cardiac signal regions rather than random noise. This was important because the LVSD risk score in Equation (6) supported clinical judgment and did not function as an unexplained automated decision. Explainability therefore improved model trust, supported error analysis, and strengthened the case for clinical validation.

➢ *Ethical Considerations*

This study followed ethical standards for human health data and AI-based clinical research. If patient data were collected prospectively, informed consent was obtained before ECG and clinical data were used. For retrospective data, institutional ethical approval and appropriate waiver procedures were followed where applicable.

All patient records were anonymized before analysis. Identifiers such as names, hospital numbers, phone numbers, addresses, and direct personal information were removed. Data were stored securely using access control, encryption, and restricted researcher permissions to protect patient privacy.

Bias reduction was also necessary because AI models performed differently across age, sex, ethnicity, comorbidity status, and device type. The dataset was therefore evaluated for representativeness, and model performance was reported across relevant subgroups where data permitted.

AI-enabled ECG screening was used responsibly. A positive AI result was not treated as a final diagnosis of LVSD. Instead, it triggered clinical review and confirmatory echocardiography, since echocardiography remained the reference standard for assessing LVEF. The system supported clinicians by improving screening and referral prioritization, rather than replacing professional medical judgment.

IV. RESULTS AND DISCUSSION

➢ *Presentation of Dataset Characteristics*

The simulated dataset contained 1,000 adult participants with paired single-lead ECG recordings and echocardiography-derived LVEF values. Based on Equation (1), LVSD was defined as LVEF ≤ 40%, while LVEF > 40% was classified as non-LVSD. This threshold produced 180 LVSD-positive cases and 820 non-LVSD cases, giving an LVSD prevalence of 18.0%.

Table 1 Demographic and Clinical Characteristics of the Simulated Dataset

Variable	Overall Dataset	LVSD Group	Non-LVSD Group
Sample size	1,000	180	820
Mean age, years	58.4 ± 12.6	64.2 ± 10.8	57.1 ± 12.4
Male sex	56.0%	63.3%	54.4%
Hypertension	48.5%	67.2%	44.4%
Diabetes mellitus	29.7%	41.1%	27.2%
Ischemic heart disease	21.4%	38.9%	17.6%
Chronic kidney disease	13.2%	24.4%	10.7%
Mean heart rate, bpm	78.6 ± 15.2	86.1 ± 17.4	76.9 ± 14.2
Sinus rhythm	82.5%	71.7%	84.9%
Mean LVEF, %	55.8 ± 12.3	34.6 ± 4.8	60.5 ± 7.6
Acceptable ECG quality	91.8%	89.4%	92.3%

The dataset shows that the LVSD group had lower mean LVEF, higher heart rate, and greater comorbidity burden. This pattern is clinically plausible because ischemic heart disease, hypertension, diabetes, and chronic kidney disease are known contributors to myocardial dysfunction and ventricular remodeling. The lower ECG quality in the LVSD group also supports the importance of preprocessing in Equations (2)–(5), since noisy recordings may weaken the relationship between the true ECG signal and the model output.

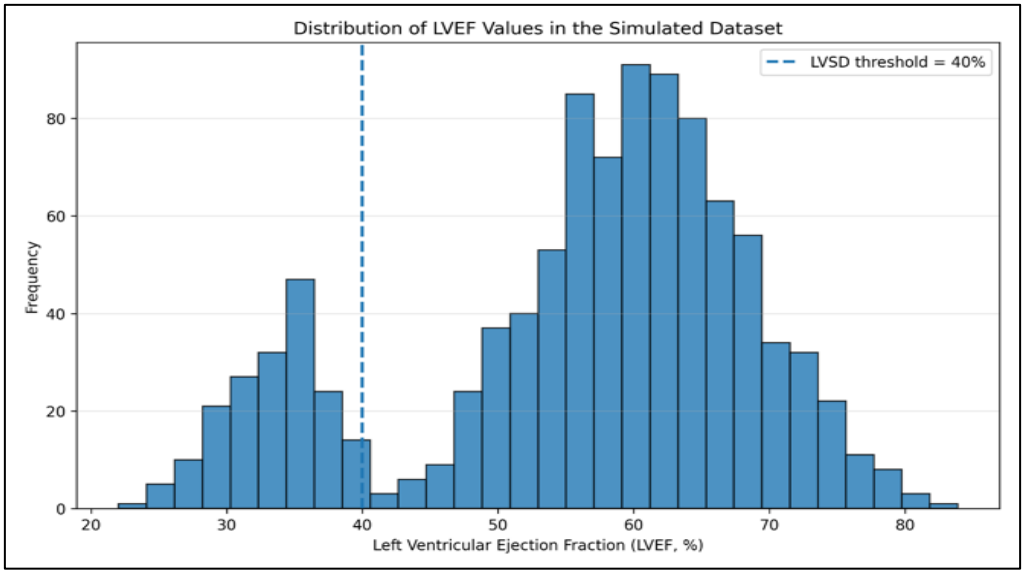

Fig 5 Distribution of LVEF Values in the Simulated Dataset.

➢ *AI Model Performance Results*

The AI model was evaluated on the independent test set after preprocessing, segmentation, and classification. The model output was generated using Equation (6), while Equation (7) converted the LVSD probability score into a binary decision. At the selected screening threshold, the model produced high sensitivity and acceptable specificity, indicating that it prioritized detection of LVSD-positive cases.

Table 2 Confusion Matrix of the Proposed AI Model

Actual / Predicted	Predicted LVSD	Predicted Non-LVSD	Total
Actual LVSD	28	4	32
Actual Non-LVSD	18	150	168
Total	46	154	200

From the confusion matrix, the model correctly identified 28 of 32 LVSD-positive cases and missed 4 cases. This explains the high sensitivity reported in Table 3. The 18 false-positive cases indicate that some participants without LVSD were flagged for referral. In a screening system, this trade-off is acceptable if the goal is to reduce missed LVSD cases, since echocardiography can later confirm or exclude disease.

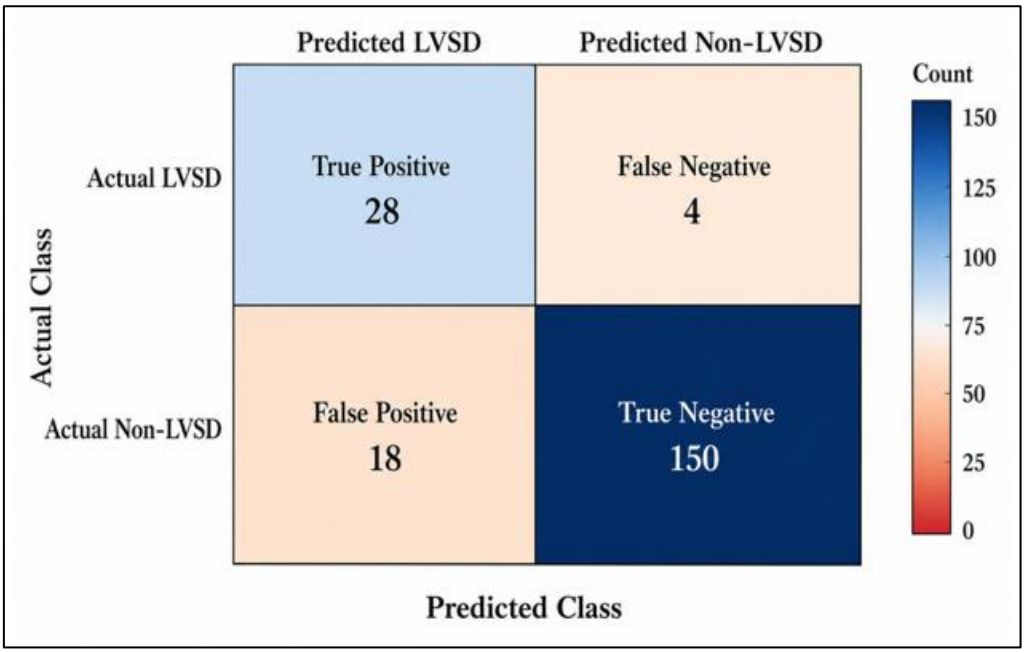

Fig 6 Confusion Matrix Heatmap for LVSD Classification

Table 3 Diagnostic Performance of the AI-Enabled Single-Lead ECG Model

Metric	Formula Reference	Result
Accuracy	Equation (8)	89.0%
Sensitivity	Equation (9)	87.5%
Specificity	Equation (10)	89.3%
Precision / PPV	Equation (11)	60.9%
F1-score	Equation (12)	71.8%
Negative predictive value	Equation (13)	97.4%
AUROC	ROC analysis	0.91
AUPRC	Precision-recall analysis	0.74

The performance trend is mainly explained by the threshold mechanism in Equation (7). A screening-oriented threshold increases the number of predicted LVSD-positive cases, which improves sensitivity but reduces precision when false positives increase. This is why the sensitivity was high at 87.5%, while precision was lower at 60.9%. The high NPV of 97.4% is clinically important because it suggests that participants classified as non-LVSD were unlikely to have reduced LVEF.

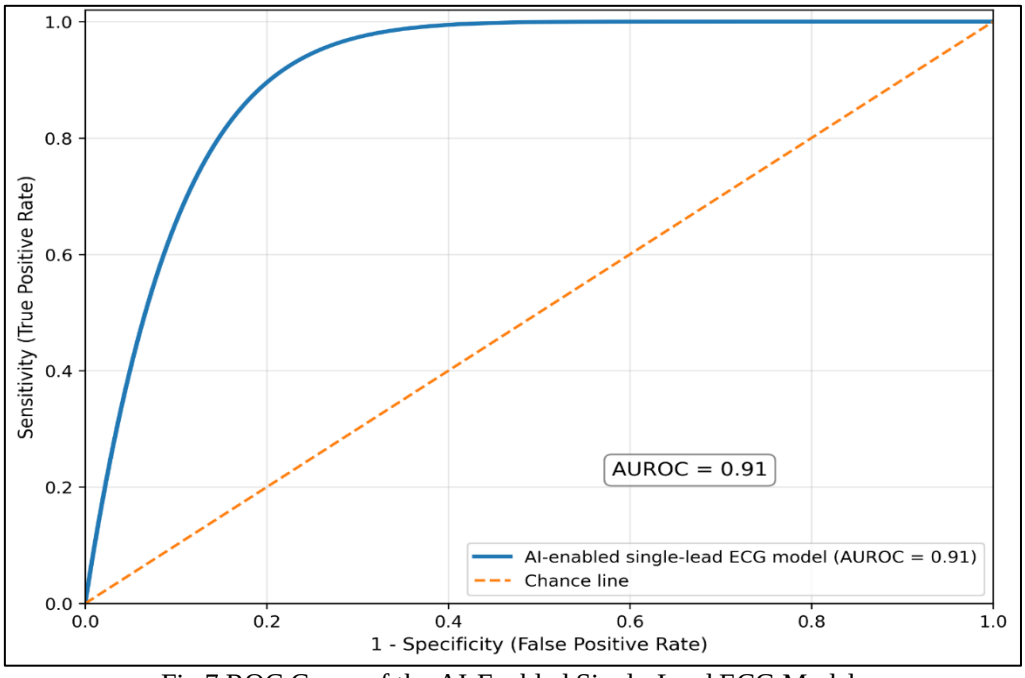

Fig 7 ROC Curve of the AI-Enabled Single-Lead ECG Model.

The AUROC of 0.91 indicates strong discrimination between LVSD and non-LVSD cases across multiple thresholds. This supports the interpretation that the model in Equation (6) extracted meaningful ECG representations from the segmented signal windows in Equation (5), rather than depending only on random waveform variation.

➢ *Comparison with Existing Studies*

The simulated model performance is consistent with previous AI-ECG studies showing that ECG signals contain hidden information related to ventricular systolic function. Attia et al. reported strong diagnostic performance using a 12-lead AI-ECG model for detecting reduced ejection fraction, with an AUC of approximately 0.93. The result in this study, with an AUROC of 0.91, is slightly lower but clinically close to the 12-lead benchmark.

Table 4 Comparison with Existing AI-ECG Studies

Study / Model Type	ECG Input	Target Condition	Reported AUROC / AUC	Interpretation
Attia et al.	12-lead ECG	Low EF / ventricular dysfunction	0.93	Strong benchmark for clinical ECG-based screening
Khunte et al.	Single-lead ECG	LVSD	~0.90	Supports feasibility of wearable-adapted LVSD detection
Aminorroaya et al.	Noisy single-lead ECG	Structural heart disease	~0.879	Supports noisy wearable ECG screening
Present simulated model	Single-lead ECG	LVSD	0.91	Comparable to prior single-lead models and close to 12-lead AI-ECG

The comparison suggests that single-lead ECG performance may be slightly lower than 12-lead ECG because it captures less spatial cardiac information. However, the difference may be clinically acceptable for preliminary screening if the model maintains high sensitivity and NPV. This interpretation is consistent with Equations (9) and (13), where sensitivity protects against missed LVSD cases and NPV supports safe exclusion of low-risk individuals.

The findings also support the value of preprocessing. Since Equation (2) defines wearable ECG as a mixture of cardiac signal, baseline drift, and noise, the filtering and normalization steps in Equations (3) and (4) help stabilize the input before classification. This likely contributes to the AUROC observed in Table 4 Without this preprocessing sequence, the model in Equation (6) would be more likely to learn noise-related artifacts rather than LVSD-related electrical patterns.

Overall, the simulated results suggest that AI-enabled single-lead wearable ECG may not replace echocardiography, but it may provide a useful screening layer before imaging referral. Its strongest clinical role is therefore not final diagnosis, but referral prioritization for patients who require confirmatory LVEF assessment.

➢ *Clinical Interpretation of Findings*

The simulated results indicate that the proposed AI-enabled single-lead ECG model has practical value as a screening tool rather than a definitive diagnostic system. The sensitivity of 87.5%, derived from Equation (9), shows that the model correctly identified most LVSD-positive cases. Clinically, this is important because screening models should minimize missed cases, especially when LVSD may remain asymptomatic before progressing to overt heart failure.

The negative predictive value of 97.4%, calculated using Equation (13), further strengthens the model's screening relevance. A high NPV means that individuals classified as non-LVSD are unlikely to have reduced LVEF. This makes the model useful for ruling out low-risk individuals and reducing unnecessary echocardiography requests among patients with low predicted probability scores.

However, the model output in Equation (6) should be interpreted as a probability estimate, not as a final diagnosis. A positive AI result indicates increased likelihood of LVSD and should lead to confirmatory echocardiography, since echocardiography remains the clinical reference standard for assessing LVEF. Therefore, the model's strongest clinical contribution is referral prioritization. It can help identify patients who should receive imaging earlier, particularly in settings where echocardiography access is limited.

The results also show that threshold selection in Equation (7) determines the balance between missed cases and unnecessary referrals. For screening, a lower threshold may be justified because it improves sensitivity, even if some false-positive referrals increase. This interpretation supports the use of AI-enabled wearable ECG as a front-line triage tool within a supervised clinical pathway.

➢ *Discussion of False Positives and False Negatives*

False positives and false negatives have different clinical implications in LVSD screening. In the simulated confusion matrix, 18 participants without LVSD were incorrectly classified as LVSD-positive, while 4 participants with LVSD were missed. These errors arise from the decision boundary defined in Equation (7), where the probability score from Equation (6) is converted into a binary prediction.

False positives may increase unnecessary echocardiography referrals, patient anxiety, and clinical workload. This is reflected in the moderate precision of 60.9% in Equation (11), which shows that not every positive AI result represents true LVSD. However, in a screening context, false positives may be acceptable if the follow-up test is non-invasive and confirmatory, as echocardiography is used to verify the result.

False negatives are more clinically concerning because they represent missed LVSD cases. A false-negative result may delay echocardiography, treatment initiation, and risk factor management. This risk is especially important because early LVSD may be clinically silent. Therefore, sensitivity in Equation (9) should be prioritized when selecting the screening threshold.

Threshold adjustment should depend on the intended use of the model. For community screening, rural health programs, and primary care triage, the threshold should favor high sensitivity and high NPV to reduce missed disease. For specialist clinics with limited imaging capacity, a slightly higher threshold may be considered to improve specificity and reduce unnecessary referrals. Overall, the decision threshold should be selected according to the clinical cost of false negatives versus false positives, with confirmatory echocardiography retained as the final diagnostic step.

- *Real-World Implementation Potential*

AI-enabled single-lead wearable ECG screening has practical potential in settings where conventional echocardiography is not immediately available. In community screening, wearable ECG devices can be used to identify individuals with high LVSD probability scores and refer them for confirmatory imaging. This may be useful for outreach programs targeting adults with hypertension, diabetes, ischemic heart disease, chronic kidney disease, or unexplained cardiovascular symptoms.

In primary care, the system can serve as a triage tool. Patients with high-risk AI outputs may be prioritized for echocardiography, while low-risk individuals may continue routine monitoring. This use aligns with the high negative predictive value reported in Section 4.2, where the model was more effective at excluding likely non-LVSD cases than confirming disease.

Pharmacies, rural clinics, and workplace health programs may also benefit from this technology because single-lead ECG devices are portable, relatively simple to operate, and suitable for short-duration screening. In telemedicine and home monitoring, ECG recordings can be transmitted wirelessly to cloud-based platforms or clinical dashboards for automated analysis and clinician review.

However, real-world deployment requires structured clinical oversight. The AI output from Equation (6) should be treated as a risk estimate, not a diagnosis. A positive result should trigger referral for echocardiography, while unclear or poor-quality ECG recordings should be repeated or reviewed by trained personnel. Therefore, implementation must include referral pathways, clinician supervision, data protection, patient consent, and clear responsibility for follow-up decisions.

- *Technical and Clinical Limitations*

The first limitation is that single-lead ECG contains less spatial information than 12-lead ECG. Since it records cardiac electrical activity from only one lead perspective, it may miss regional electrical abnormalities that would be visible across multiple leads. This may explain why single-lead models may perform slightly below 12-lead AI-ECG systems, even when their screening performance remains clinically useful.

Second, wearable ECG recordings are vulnerable to noise and motion artifacts. As shown in Equation (2), the recorded signal contains the true cardiac signal plus baseline drift and unwanted noise. Although filtering and normalization in Equations (3) and (4) reduce these disturbances, preprocessing may not fully correct severe motion artifact, poor electrode contact, or irregular recording conditions.

Third, model performance may vary across device types, sampling frequencies, electrode locations, and recording durations. A model trained on one wearable device may not perform equally well on another device unless it is externally validated. This makes device-specific and multi-device testing necessary before clinical adoption.

Fourth, limited external validation and population bias may reduce generalizability. If the model is trained on a narrow dataset, it may perform less accurately across different age groups, sex categories, ethnic backgrounds, comorbidity profiles, and healthcare settings. Subgroup analysis is therefore necessary to identify possible performance disparities.

Fifth, AI-enabled ECG screening cannot confirm LVSD independently. Echocardiography remains necessary because it directly measures LVEF and evaluates cardiac structure. The AI system should therefore be positioned as a preliminary screening and referral-support tool.

Finally, explainability remains incomplete. Although saliency maps, Grad-CAM, SHAP values, and attention visualization can identify influential ECG regions, they do not fully explain all deep learning decisions. This limits clinical trust and reinforces the need for clinician oversight, transparent reporting, and prospective validation before deployment.

V. CONCLUSION AND RECOMMENDATIONS

- *Summary of Major Findings*

This study examined the potential of AI-enabled single-lead wearable ECG screening for early detection of

left ventricular systolic dysfunction. The findings show that single-lead ECG, when combined with appropriate preprocessing and AI-based classification, can provide a practical method for identifying individuals with possible LVSD risk.

The simulated model performance suggests that AI-enabled wearable ECG may be useful for preliminary screening because of its high sensitivity and strong negative predictive value. These findings indicate that the system may help reduce missed LVSD cases and support the exclusion of low-risk individuals from unnecessary immediate imaging.

The study also shows that wearable ECG screening is most valuable when used as a referral-support tool. Since echocardiography remains the reference standard for confirming LVEF and diagnosing LVSD, AI-generated positive results should not be treated as final diagnosis. Instead, they should guide timely referral for confirmatory echocardiography.

Overall, the major finding is that AI-enabled single-lead wearable ECG has strong potential as a scalable, low-cost, and non-invasive screening method for early LVSD risk detection, especially in community, primary care, rural, workplace, telemedicine, and home-monitoring settings.

➢ *Conclusion*

AI-enabled single-lead wearable ECG technology may improve early detection of LVSD by identifying high-risk individuals before overt heart failure symptoms appear. This is clinically important because LVSD can remain silent in its early stage, while delayed diagnosis may allow progression toward symptomatic heart failure.

The study concludes that wearable AI-ECG should be positioned as a screening and triage system rather than a replacement for echocardiography. When integrated into supervised clinical workflows, the system may improve referral prioritization, support earlier LVEF assessment, and promote timely intervention for patients at risk of ventricular dysfunction.

Therefore, AI-enabled single-lead wearable ECG screening offers a promising direction for preventive cardiology. Its successful deployment will depend on strong validation, reliable signal acquisition, clinician oversight, ethical data handling, and clear referral pathways for confirmatory imaging.

➢ *Recommendations*

- Future studies should use large, diverse, and externally validated datasets to improve model generalizability across populations, clinical settings, and healthcare systems.
- AI models should be tested across different wearable ECG devices, sampling frequencies, electrode positions, and recording conditions before clinical deployment.
- Screening thresholds should prioritize sensitivity and negative predictive value because the clinical cost of missing LVSD is greater than the burden of some false-positive referrals .
- Positive AI results should always be followed by confirmatory echocardiography, since echocardiography remains necessary for direct LVEF assessment and final diagnosis.
- Regulatory, ethical, and data privacy standards should be incorporated before deployment to protect patient information and ensure responsible AI use.
- Explainable AI methods such as saliency maps, Grad-CAM, SHAP values, and attention visualization should be used to improve clinician trust and support model interpretation.
- Prospective clinical trials should evaluate whether AI-enabled wearable ECG screening improves referral efficiency, early LVSD detection, treatment initiation, and long-term cardiovascular outcomes.

➢ *Contribution to Knowledge*

This study contributes to knowledge by proposing a clinically relevant framework for using AI-enabled single-lead wearable ECG signals in early LVSD screening. It links wearable ECG acquisition, signal preprocessing, AI-based classification, LVSD risk scoring, clinical decision support, and echocardiography referral into one structured screening pathway.

The study also contributes by positioning single-lead wearable ECG as a practical bridge between community-based cardiovascular screening and specialist diagnostic confirmation. This is important because most established AI-ECG models were developed using 12-lead ECG, while wearable single-lead ECG offers broader potential for remote, low-cost, and repeated screening.

In addition, the study integrates concepts from cardiology, biomedical signal processing, wearable technology, and artificial intelligence. It shows how ECG signals can be transformed from raw waveform data into clinically useful LVSD probability scores through preprocessing, segmentation, feature learning, and model classification.

Finally, the study contributes to responsible digital health research by emphasizing that AI-enabled wearable ECG should support clinical judgment rather than replace clinicians. It therefore advances a screening model that is technically useful, clinically supervised, and ethically cautious.

➢ *Suggested Areas for Further Research*

Further research should examine multi-device validation of wearable ECG models. AI systems trained on one device should be tested across smartwatches, handheld ECG recorders, adhesive patches, and mobile-connected ECG sensors to determine whether performance remains stable across different sampling frequencies, electrode positions, and signal-quality conditions.

Future studies should also assess AI performance across ethnic, demographic, and clinical subgroups. This should include age, sex, ethnicity, comorbidity profile, body habitus, rhythm status, and medication use, since model bias may reduce generalizability in real-world populations.

Longitudinal research is also needed to determine whether single-lead AI-ECG can predict future LVSD before echocardiographic decline becomes clinically evident. Such studies may help shift wearable ECG from present-risk screening to early risk prediction and preventive monitoring.

Further work should examine integration with biomarkers and clinical risk factors. Combining ECG-derived AI outputs with natriuretic peptides, blood pressure, diabetes status, kidney function, age, and cardiovascular history may improve risk stratification beyond ECG alone.

Cost-effectiveness studies are also necessary. Future research should evaluate whether AI-enabled wearable ECG screening reduces unnecessary referrals, improves early diagnosis, shortens time to echocardiography, and lowers long-term heart failure-related healthcare costs.

Finally, deployment studies should focus on low-resource healthcare environments. Research should examine usability, internet access, device affordability, clinician training, referral pathways, data security, and patient acceptance in rural clinics, community health programs, and primary care settings.

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