Research Square

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AI-Enabled Digital Stethoscope for Early Detection of Congenital Heart Disease: Prospective Study

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Abstract

Background:

Early detection of congenital heart disease (CHD) is critical, particularly in low- and middle-income countries where access to pediatric cardiology services is limited. While auscultation remains a first-line screening tool, its accuracy is operator dependent. Advances in digital stethoscopes and artificial intelligence (AI) may enhance diagnostic performance.

Objective:

To evaluate the accuracy of an AI-based algorithm integrated with a digital stethoscope for detecting CHD in children, using echocardiography as the reference standard.

Methods:

In this prospective study, heart sounds were recorded from 721 subjects (382 with CHD, 339 controls) using the digital stethoscope at four standard auscultatory sites. Of these, 301 recordings were used for algorithm training and 420 for blinded forward testing. Recordings were denoised, transformed into mel-spectrograms, and analyzed using a convolutional neural network (CovNN) to classify CHD probability. A threshold probability of > 0.5 across > 2 sites was used to predict CHD. Performance was compared against echocardiography.

Results:

In forward testing, the AI algorithm correctly identified 222 of 233 CHD cases and 171 of 187 controls, yielding a sensitivity of 95.2% and specificity of 91.4%. The algorithm remained effective in noisy environments and in uncooperative children, where conventional auscultation is challenging.

Conclusion:

An AI algorithm integrated with a digital stethoscope demonstrated high sensitivity and specificity for CHD detection in children. By leveraging mel-spectrogram features, it overcomes key limitations of isolated time-domain or frequency domain analysis and shows promise as a scalable, non-invasive screening tool for early CHD detection, particularly in resource-limited settings.

Introduction

Congenital heart disease (CHD) is one of the most common birth defects, with a prevalence of 19.5 per 1,000 live births, accounting for over 25% of all congenital anomalies.[1] In India alone, more than 250,000 children are born each year with CHD.[2] While advances in diagnosis and treatment have significantly improved survival and quality of life in high-income countries, outcomes in low- and middle-income countries (LMICs) remain constrained by late detection, limited awareness, financial barriers, and unequal distribution of specialized cardiac centres.[2] Early identification of CHD is therefore crucial to improving access to timely care.

Although echocardiography is the gold standard for CHD diagnosis, cardiac auscultation remains a vital first-line screening tool. However, its accuracy depends heavily on the examiner's expertise, with considerable variability across training levels. Integrating artificial intelligence (AI) with digital stethoscopes offers a promising, low-cost, non-invasive strategy to enhance screening accuracy and bridge gaps in early CHD detection.

This pilot study aimed to evaluate the accuracy and feasibility of an AI algorithm integrated with a digital stethoscope for detecting CHD in children, and to compare it with a trained paediatric cardiologist as well as echocardiography as the reference standard.

Materials and Methods

Device

The stethoscope used in this study is a Class B, internally powered digital stethoscope that records, filters, and transmits heart and lung sounds via Bluetooth to a mobile application. It records frequencies from 20–20,000 Hz, supports switching between diaphragm and bell modes, and employs built-in noise-reduction algorithms to minimise ambient interference.

Patient recruitment and recording

Following institutional ethics approval, patients with CHD and healthy controls referred to the pediatric cardiology unit of a quaternary care hospital in India were prospectively recruited between October 2024 and August 2025. Exclusion criteria were prior cardiac surgery or intervention, inability to cooperate, refusal of consent, or significant respiratory disease. After clinical examination and echocardiography, heart sounds were recorded at the four standard auscultatory sites – aortic (right upper sternal border), pulmonary (left upper sternal border), tricuspid (left lower sternal border), and mitral (apex) - each for 20 seconds, using a digital stethoscope. Data was transmitted to the Android application for storage and further analysis.

Algorithm development

We used 301 subjects from our database (152 normal and 149 CHD) for training the algorithm, and the rest were used for forward testing.

Raw signals were denoised using a proprietary filtering algorithm to enhance the signal-to-noise ratio. Features were extracted by computing mel spectrograms.spectrogram is a visual representation of sound that applies the mel scale (a scale that transforms physical frequency (Hertz) into a perceptual unit of pitch). This aligns the frequency bands with human auditory perception. These spectrograms were used as input to a convolutional neural network (CovNN). Early layers captured low-level acoustic features, while deeper layers extracted higher-order representations, leading to classification of each recording as CHD or control based on probability scores (Fig. 1).

Forward testing

After training, the algorithm was prospectively tested in a blinded manner on newly collected recordings (Fig. 2). For each subject, site-level probabilities were computed from the corresponding Mel spectrograms. The ROC curve from the training data showed that an operating threshold of 0.518 provided a favourable trade-off between sensitivity and specificity (Fig. 3). A classification threshold of > 0.5 at > 2 sites defined CHD, while < 0.5 at > 2 sites defined control. If no majority was present, the average probability across all four sites was used. Predictions were compared with echocardiographic findings.

Statistical analysis

Analyses were conducted using IBM SPSS v20. Continuous variables were expressed as mean ± 2SD (parametric) or as median with interquartile range (non-parametric). Categorical variables were expressed as frequencies and percentages. Sensitivity, specificity, and predictive values of the algorithm were calculated, and categorical comparisons were performed using Chi-square tests. Receiver operating characteristic (ROC) curves were plotted to assess classification performance.

Results

721 subjects were recruited for the study, of whom 382 had CHD. The demographic characteristics are presented in Table 1. Heart sounds from 420 subjects (187 controls and 233 with CHD) were forward-tested by the AI algorithm.

Table 1
Information of patients recruited in study: Baseline demographic and diagnostic characteristics of the 721 subjects enrolled in the study, showing the distribution between training and testing cohorts and classification of congenital heart disease (CHD) by pulmonary blood flow (PBF) physiology

CHARACTERISTICS		TOTAL SUBJECTS (721)	SUBJECTS USED FOR TRAINING (301)	SUBJECTS USED FOR TESTING (420)
GENDER	Male	343 (48%)	139 (46%)	204 (48%)
	Female	378 (52%)	162 (54%)	216 (43%)
AGE	Less than one year	190 (26%)	63 (21%)	127 (30%)
	One year to 5 years	142 (20%)	51 (17%)	91 (22%)
	6 years to 18 years	176 (24%)	68 (22.5%)	108 (26%)
	More than 18 years	213 (30%)	119 (39.5%)	94 (22%)
CHD/NO CHD	No CHD (Structurally normal heart)	339 (47%)	152 (50.5%)	187 (45%)
	CHD present	382 (53%)	149 (49.5%)	233 (55%)
	Increased PBF	332 (87%)	92 (62%)	133 (57%)
	Decreased PBF	113 (29.5%)	34 (23%)	44 (19%)
	Normal PBF	124 (32.5%)	23 (15%)	56 (24%)

Heart sound recordings were transformed into mel spectrograms to generate time-frequency representations for AI analysis. Mel spectrograms were plotted for each physiology, namely normal heart sounds (Fig. 5), CHD with

increased pulmonary blood flow (PBF) (Fig. 6a-b), CHD with decreased PBF (Fig. 6c), and CHD with normal PBF (Fig. 6d).

Mel spectrogram with normal heart sounds shows low frequency energy bursts representing S1 and S2 sound with lack of high frequency components which would suggest pathology. (Fig. 5)

In contrast to the normal heart sound mel-spectrogram, patients with CHD demonstrated distinct acoustic signatures across different hemodynamic states. Patients with decreased PBF showed sparse striations with low spectral density. Post-tricuspid shunts exhibited dense, continuous high-frequency bands, while those with pre-tricuspid shunts showed intermittent diastolic high-frequency activity of lower intensity. In patients with normal pulmonary blood flow (aortic or pulmonary stenosis), rhythmic S1 and S2 components were preserved, with an additional mid-frequency systolic burst corresponding to an ejection murmur (Figs. 6a-d).

Of the 420 subjects who were forward tested, the classification threshold was satisfied in 396 (94.3%) and not satisfied in 24 (5.7%). Among the patients who did not satisfy the classification threshold, 10 had CHD, whereas 14 were normal (Fig. 4).

Comparison of AI algorithm with trained pediatric cardiologist:

Based on the reference standard established by cardiologist evaluation, 233 participants had CHD and 187 had no CHD. The AI algorithm correctly identified 226 of the 233 CHD cases and classified 175 of the 187 non-CHD cases, yielding 7 false negatives and 12 false positives. The AI algorithm achieved a sensitivity of 97.0% (226/233) and a specificity of 93.6% (175/187). The positive predictive value was 95.0% (226/238), and the negative predictive value was 96.2% (175/182). The overall diagnostic accuracy was 95.5% (401/420), indicating strong agreement with the cardiologist's diagnosis (Table 2).

Table 2
Performance of AI algorithm when compared to clinicians: This table presents the classification outcomes of the AI-enabled digital stethoscope relative to the cardiologist auscultation findings in the forward-testing cohort (n = 420). Sensitivity, specificity, and predictive values were calculated based on true-positive, true-negative, false-positive, and false-negative results. Abbreviations: AI = artificial intelligence; CHD = congenital heart disease

Cardiologist findings	**AI detected as normal**	**AI detected as abnormal**	
No CHD	True negative = 175	False positive = 12	Specificity = 93.5%
CHD	False negative = 7	True positive = 226	Sensitivity = 97%
	Negative predictive value = 0.96	Positive predictive Value = 0.95	

Comparison of AI algorithm with echocardiogram:

Based on the echocardiographic reference standard, 233 participants had CHD and 187 had no CHD. The AI algorithm correctly identified 222 of the 233 CHD cases and classified 171 of the 187 participants without CHD, resulting in 11 false negatives and 16 false positives. The AI algorithm achieved a sensitivity of 95.2% and a specificity of 91.4%. The positive predictive value was 93.3%, and the negative predictive value was 94.0%. The

overall diagnostic accuracy was 93.6%, indicating robust agreement between the AI algorithm and echocardiographic diagnoses in detecting CHD. (Table 3)

Table 3
Performance of AI algorithm: This table presents the classification outcomes of the AI-enabled digital stethoscope relative to the echocardiographic reference standard in the forward-testing cohort (n = 420). Sensitivity, specificity, and predictive values were calculated based on true-positive, true-negative, false-positive, and false-negative results. Abbreviations: AI = artificial intelligence; CHD = congenital heart disease

Echocardiographic diagnosis	AI detected as normal	AI detected as abnormal	
No CHD	True negative = 171	False positive = 16	Specificity = 91.4%
CHD	False negative = 11	True positive = 222	Sensitivity = 95.2%
	Negative predictive value = 0.94	Positive predictive Value = 0.93	

Subgroup analysis according to the type of CHD:

Among lesions with increased pulmonary blood flow (PBF), the AI algorithm correctly identified 130 of 133 pre-tricuspid shunt lesions, 70 of 70 post-tricuspid shunt lesions, and 8 of 9 admixture lesions, yielding an overall detection rate of 98% for this subgroup. Among lesions with decreased PBF, the AI algorithm correctly identified 9 of 10 patients with pulmonary atresia, 24 of 25 with pulmonary stenosis, and 8 of 9 with Eisenmenger physiology, yielding an overall detection rate of 93%. For CHD lesions with normal pulmonary blood flow, the AI algorithm correctly identified 51 of 56 cases, with 5 false negatives, yielding a detection rate of 91%. (Table 4)

Table 4
Performance of AI algorithm in patients with congenital heart disease in different hemodynamics. Positive predictive valve was calculated based on true positives and false positives. Abbreviations: CHD = congenital heart disease; PBF = pulmonary blood flow

Type of CHD		True positive	False negative	Detection rate
Increased PBF	Pre tricuspid	52	2	0.98
	Post tricuspid	70	0	
	Admixture	8	1	
Decreased PBF	Pulmonary atresia	9	1	0.93
	Pulmonary stenosis	24	1	
	Eisenmenger	8	1	
Normal PBF		51	5	0.91

Subgroup analysis according to age:

Diagnostic performance remained robust across all age groups, with sensitivity consistently exceeding 93% and positive predictive value exceeding 89%. The highest sensitivity was observed in infants (< 1 year), whereas specificity was highest in adults (> 18 years) (Table 5).

Table 5

Performance of AI algorithm in different age groups: This table presents the classification outcomes of the AI-enabled digital stethoscope in different age subsets. Sensitivity, specificity, and predictive values were calculated based on true-positive, true-negative, false-positive, and false-negative results in each age group.

Age Group	Sensitivity (CI)	Specificity (CI)	Positive predictive value (CI)	Negative predictive value
Less than 1 year	97.1% (92% – 99.4%)	77.3% (55% – 92%)	95.4% (90.5% – 97.8%)	85% (65% – 94.7%)
1 year to 5 years	93.3% (83.8% – 98%)	83.9% (66.3% – 94.5%)	91.8% (83.4% – 96%)	86.7% (71.3% – 94.4%)
6 years to 18 years	93.3% (81.7% – 98.6%)	92% (82.4% – 97.4%)	89.4% (78.3% – 95%)	95% (86.6% – 98.3%)
> 18 years	95.6% (78% – 99.8%)	98.6% (92.4% – 99.9%)	95.6% (75.8% – 99.4%)	98.6% (91% – 99.8%)

Analysis of false-negative cases

Among the 11 false-negative cases, most had absent, soft, or atypical auscultatory findings (Table 6). Four patients had no audible murmur on cardiologist examination, one had only a loud second heart sound, and the remaining lesions were associated with soft or atypical murmurs. This pattern suggests that most false negatives occurred in lesions with subtle acoustic signatures.

Table 6

Characteristics of patients labelled as false negative: This table summarizes the diagnostic category, demographic profile, AI-predicted CHD probability values across the four standard auscultation sites (mitral, tricuspid, aortic, pulmonary), and corresponding cardiologist auscultation assessments for the 11 subjects incorrectly classified as normal by the AI algorithm. Physical examination findings include documentation of heart murmurs or abnormal second heart sound, where present.

DIAGNOSIS	AGE/ GENDER	HEIGHT/ WEIGHT	AI PROBABILITY				AVERAGE (if averaged)	AUSCULTATION (By Cardiologist)
			Mitral	Tricuspid	Aortic	Pulm		
TOF with pulmonary atresia	5 year/ Female	112cm, 16.5kg	0.35	0.39	0.66	0.58	0.49	Continuous murmur at back
Sinus venosus ASD with PAPVC	1 year/ Male	85cm, 10.3kg	0.45	0.35	0.96	0.42		ESM
Tetralogy of Fallot very tiny antegrade flow	5 mo/ Male	63cm, 4.7kg	0.59	0.38	0.41	0.31		Soft ESM
Supracardiac TAPVC	2 mo/ Female	55cm, 2.8kg	0.49	0.19	0.18	1.0		ESM
Tiny PDA	3 year/ Male	101cm, 17.3kg	0.59	0.19	0.27	0.77	0.47	No murmur
CCTGA with IVS with mild AVVR	17 year/ Male	190cm, 52.2kg	0.65	0.23	0.65	0.30	0.47	No murmur
VSD with Eisenmenger syndrome	17 year/ Female	165cm, 46.3kg	0.07	0.51	0.32	0.99	0.48	Loud P2, No murmur
Bicupsid aortic valve (No AS/AR)	19 days/ Male	51cm, 3.1kg	0.16	0.51	0.40	0.71	0.46	No murmur
Tiny PMVSD	11 year/ Male	155cm, 49.7kg	0.20	0.22	0.28	0.35		No murmur
Small VSD	42 year/ Male	174cm, 89kg	0.12	0.27	0.27	0.54		PSM
Ostium secundum ASD	3 year/ Male	101cm, 13kg	0.23	0.42	0.42	1.0		S2 wide fixed split, ESM

Abbreviations: AI = artificial intelligence; ASD = atrial septal defect; AVVR = atrioventricular valve regurgitation; BAV = bicuspid aortic valve; CCTGA = congenitally corrected transposition of great arteries; CHD = congenital heart disease; ESM = ejection systolic murmur; IVS = intact ventricular septum; PAPVC = partial anomalous pulmonary venous connection; PDA = patent ductus arteriosus; PMVSD = perimembranous ventricular septal defect; PSM = pansystolic murmur; PBF = pulmonary blood flow; S2 = second heart sound; TAPVC = total anomalous pulmonary venous connection; TOF = tetralogy of Fallot; VSD = ventricular septal defect; yr = years; mo = months

Discussion

Cardiac auscultation remains the cornerstone of CHD screening: it is inexpensive, non-invasive, and universally available. However, its diagnostic accuracy is inherently operator-dependent and varies substantially with the examiner's training and experience. Previous studies have reported sensitivities of 82% and specificities of 56% among medical students and pediatric residents. These figures improve modestly with pediatricians (sensitivity 93%, specificity 59%) and are highest with pediatric cardiologists (sensitivity 81%, specificity 91%).[3–5] With the widespread availability of advanced cardiac imaging, reliance on bedside cardiac examination has progressively declined, contributing to reduced proficiency in auscultation among healthcare providers. These limitations underscore the need for technologies that can standardize cardiac auscultation and improve early detection of CHD, particularly in settings where pediatric cardiology expertise is limited.

To our knowledge, this is the first prospective study from India evaluating an artificial intelligence (AI)-enabled digital stethoscope for detecting CHD in children, with echocardiography as the reference standard. The AI algorithm demonstrated strong diagnostic performance, with high sensitivity and specificity for detecting structural heart disease. These findings compare favourably with previously published AI-assisted auscultation systems, which have reported sensitivities ranging from 83% to 94% and specificities between 89% and 97%. [6–8] Importantly, unlike many earlier algorithms that required recordings to be obtained in quiet environments or during breath-holding, our algorithm incorporates robust denoising techniques that enable reliable analysis despite background noise and patient movement [7]. This capability is particularly relevant in pediatric practice, where crying, restlessness, and ambient clinical noise frequently limit the quality of auscultatory recordings.

The robust performance observed in this study is likely attributable, in part, to the use of mel-spectrogram-based feature extraction with a convolutional neural network (ConvNN). Conventional time-domain phonocardiographic analyses primarily characterize the timing of cardiac events but often have limited frequency resolution and are susceptible to environmental noise and overlapping heart sounds. [9,10] In contrast, mel-spectrograms preserve both temporal and frequency-domain information while approximating human auditory perception, enabling the network to identify subtle acoustic signatures, including low-intensity murmurs, pitch variations, and dynamic frequency patterns such as crescendo–decrescendo murmurs. These complementary temporal–spectral features likely enhanced discrimination between normal and pathological heart sounds and are consistent with observations from previous AI-based auscultation studies. [11,12].

An important finding of this study was the close agreement between the AI algorithm and expert cardiologist assessment. Compared with cardiologist auscultation, the algorithm achieved strong sensitivity and specificity, demonstrating diagnostic performance comparable to expert clinical examination. Similar findings have been reported for recent AI-assisted auscultation platforms, including systems that achieved sensitivities approaching 97% for detecting abnormal heart sounds when compared with pediatric cardiologists.[13] While pediatric cardiologists maintain high diagnostic accuracy, such expertise is unavailable in many primary and secondary healthcare facilities, particularly in low- and middle-income countries. Consequently, screening is often performed by healthcare providers with limited experience in cardiac auscultation, and reported sensitivities may fall below 40% in neonatal practice.[14] The close agreement between the AI algorithm and pediatric cardiologist assessment suggests that AI-assisted auscultation has the potential to reduce operator dependence, standardize screening, and facilitate timely referral to specialized cardiac centers.

Although echocardiography remains the definitive diagnostic modality for CHD, its use as a population-level screening tool is constrained by the need for specialized equipment, trained personnel, and substantial healthcare resources. When validated against echocardiography, the AI algorithm demonstrated favourable diagnostic accuracy, with performance comparable to that reported in previous pediatric AI auscultation studies.[15] These findings support the role of AI-enabled digital stethoscopes as an effective first-line screening or triage tool rather than a replacement for echocardiography. Early identification of children requiring comprehensive cardiac evaluation has the potential to reduce diagnostic delays, improve referral pathways, and optimise the utilisation of limited echocardiographic services, particularly in resource-constrained healthcare systems.

The diagnostic performance of the AI algorithm remained consistently high across all pediatric age groups, supporting its applicability from infancy through adolescence. Notably, the highest sensitivity was observed among infants younger than one year of age, a population in whom conventional auscultation is often challenging because of higher heart rates, shorter cardiac cycles, crying, and patient movement. The algorithm's ability to maintain high diagnostic performance under these conditions highlights its potential utility in newborn and infant screening programmes. Likewise, the preservation of high sensitivity and specificity in older children suggests that the algorithm performs robustly across a broad spectrum of pediatric clinical settings.

Subgroup analysis showed consistently high detection rates across diverse hemodynamic categories of CHD. Diagnostic performance was highest for lesions with increased pulmonary blood flow, likely reflecting prominent turbulent flow patterns and characteristic systolic or continuous murmurs generated by these defects. In contrast, lesions with decreased or normal pulmonary blood flow often produce softer, shorter, or less distinctive murmurs, making automated acoustic detection inherently more challenging. Nevertheless, the algorithm maintained high diagnostic performance across all major hemodynamic groups, suggesting that the extracted acoustic features generalized well across a wide spectrum of congenital cardiac lesions.

The pattern of false-negative cases suggests that the algorithm predominantly missed lesions with limited acoustic expression rather than those with prominent pathological murmurs. Notably, several patients had no audible murmur even on expert cardiologist examination, indicating that these lesions are inherently difficult to detect by auscultation alone. This finding suggests that the algorithm's limitations largely parallel those of conventional clinical auscultation rather than a failure to recognize obvious cardiac abnormalities.

Several limitations should be acknowledged. First, this was a single-center study, and external validation across geographically diverse populations is necessary before widespread implementation. Second, patients with previously operated CHD were excluded to optimize algorithm development, which may limit generalizability to postoperative populations. Third, the algorithm was designed to identify abnormal heart sounds rather than classify individual cardiac lesions or quantify murmur severity. Future iterations incorporating lesion classification and murmur grading may further enhance its clinical utility. Fourth, auscultation recordings were limited to the four standard precordial sites and did not include additional areas such as the axillae, back, or right parasternal border, potentially limiting performance in patients with atypical cardiac anatomy or dextrocardia. Finally, critical congenital heart defects were relatively under-represented in our cohort, and additional evaluation in larger multicentre studies with greater representation of complex lesions will be important to establish diagnostic performance across the full spectrum of CHD.

In conclusion, this study demonstrates that an AI-enabled digital stethoscope can detect congenital heart disease in children with excellent diagnostic accuracy and robust performance across age groups and diverse

hemodynamic lesion profiles. By reducing operator dependence and enabling reliable cardiac auscultation in routine clinical settings, this technology has the potential to strengthen frontline CHD screening, improve referral pathways, and expand access to early diagnosis, particularly in resource-limited settings where pediatric cardiology expertise and echocardiography are not readily available. Widespread adoption of such AI-assisted auscultation could meaningfully reduce delays in CHD diagnosis and improve equity and cardiovascular outcomes across low- and middle-income regions..

Abbreviations

CHD – Congenital heart disease, AI – Artificial intelligence, CovNN – Convolutional neural network, LMIC – Low and middle income countries, ROC - Receiver operating characteristic, PBF – Pulmonary blood flow

Declarations

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Conflict of Interest Disclosure The authors have no conflicts of interest relevant to this article to disclose.

Ethical Approval This study was approved by the Institutional Ethics Committee at Kokilaben Dhirubhai Ambani Hospital & Medical Research Institute, Mumbai, India
IEC – A Code: 048/2024

Data Availability Data are available from the corresponding author upon reasonable request.

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Figures

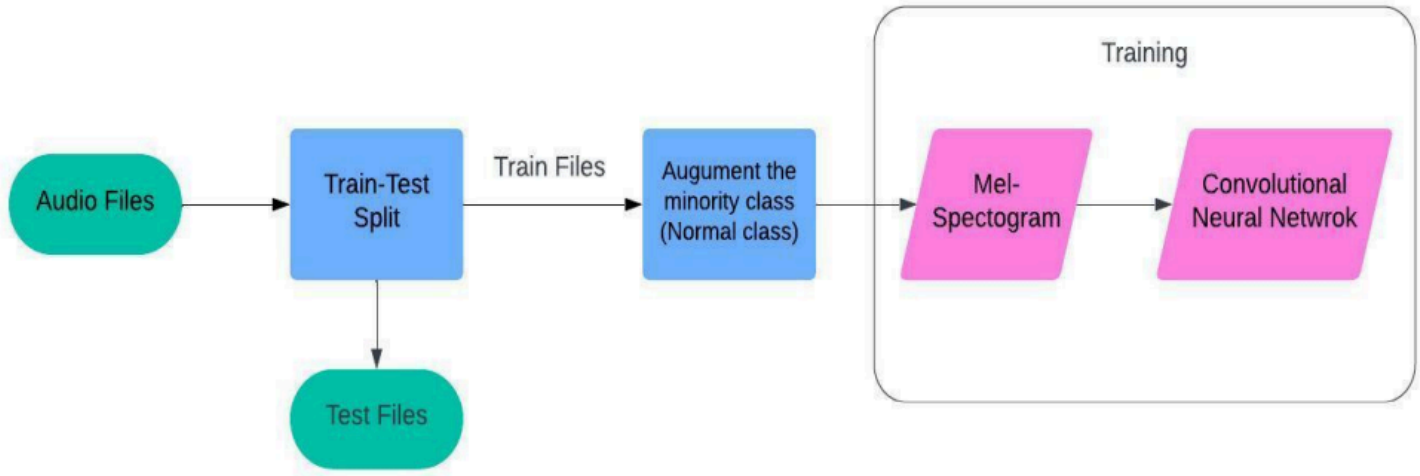


Figure 1

Training process of AI algorithm: Raw signals were denoised using a proprietary filtering algorithm to enhance the signal-to-noise ratio. Features were extracted by computing mel spectrograms, which emphasize frequency bands aligned with human auditory perception. The mel spectrogram prepared in the previous step is used as input to the CovNN model. It learns frequency modulations or rhythmic structures relevant to murmur detection. Early layers captured low-level acoustic features, while deeper layers extracted higher-order representations, leading to classification of each recording as CHD or control based on probability scores.

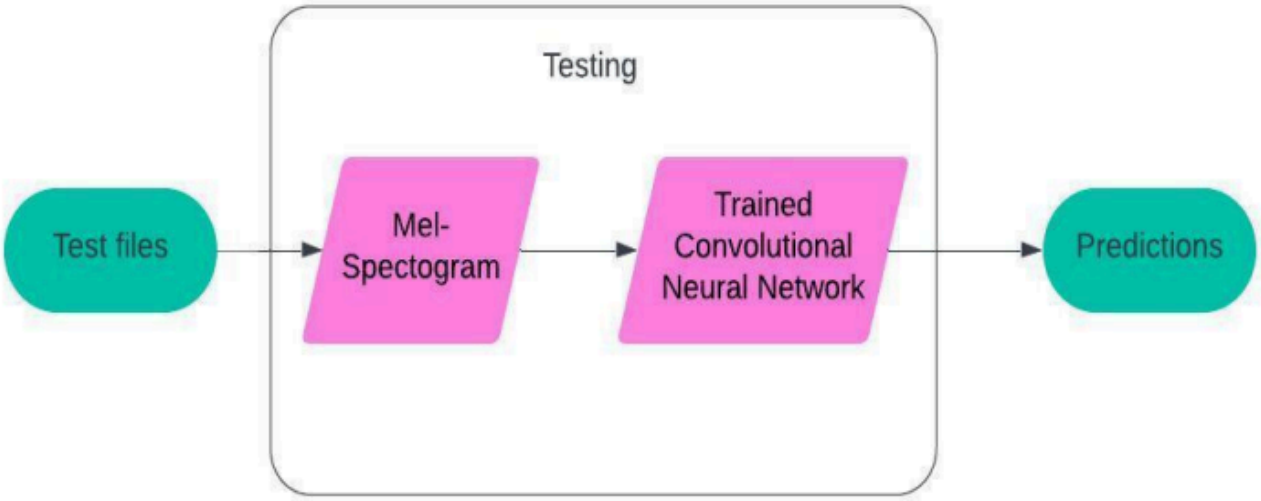


Figure 2

Testing process of AI algorithm: Forward testing was performed on the trained algorithm and based on the probability score classification was done as CHD or no CHD.

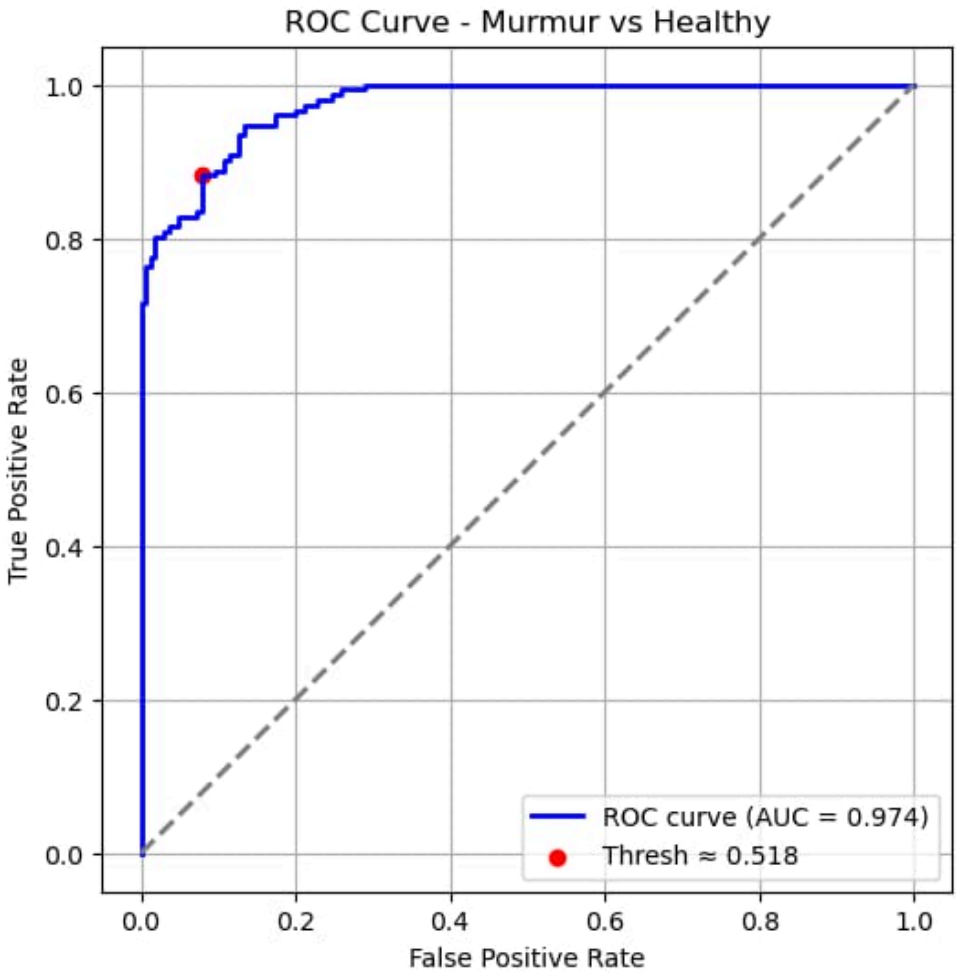


Figure 3

The ROC curve illustrates the performance of a classification model in distinguishing between congenital heart disease (CHD) and healthy controls using heart sound recordings. It shows a high discriminative ability with an area under the curve (AUC) of 0.974, indicating excellent classification performance. The red dot highlights the operating threshold (≈0.518), which corresponds to a favourable trade-off between sensitivity and specificity

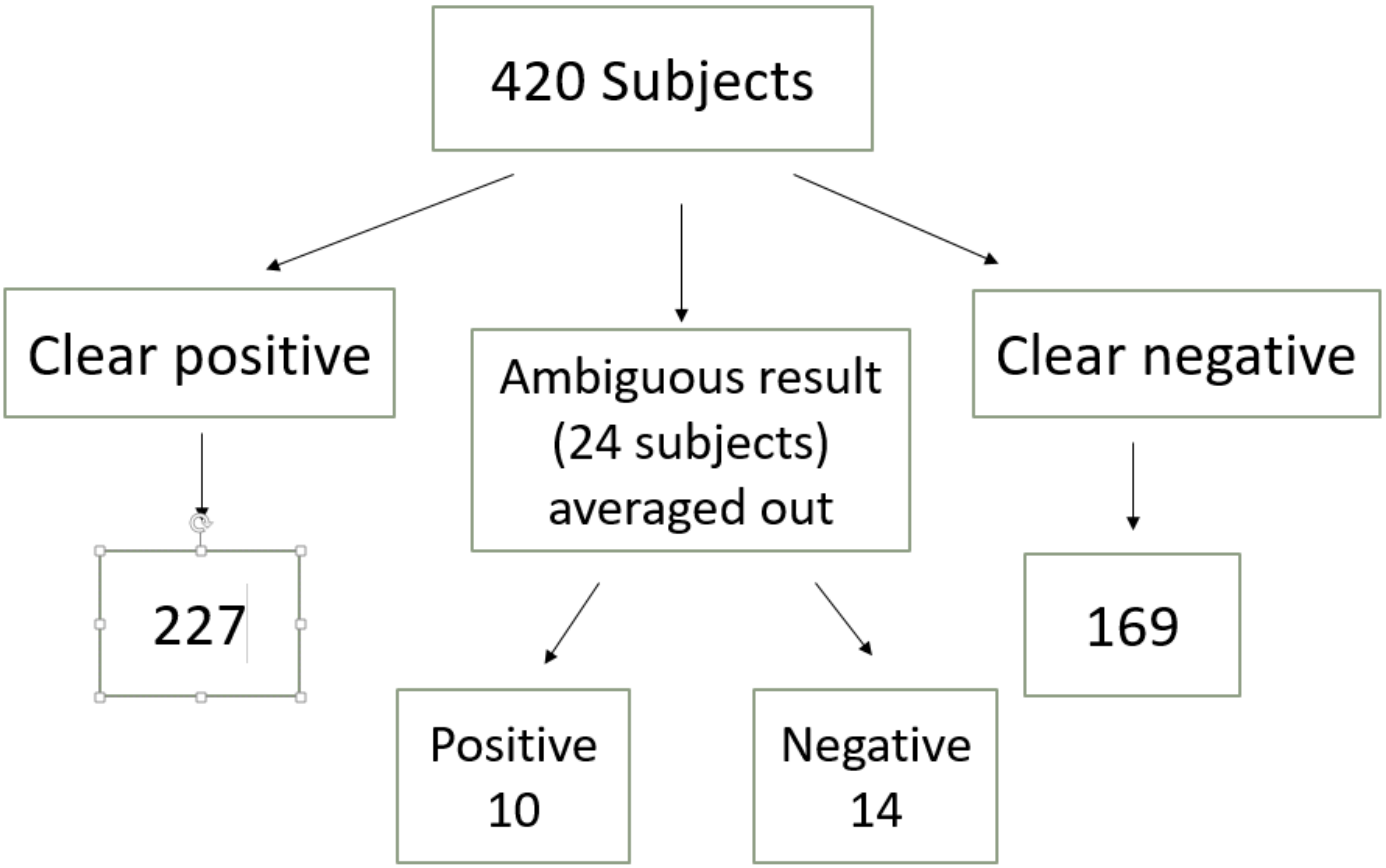


Figure 4

No majority was found in 24 subjects. The average probability across all four sites was calculated for these subjects, and 10 were found to be positive for CHD whereas 14 were found to be negative. Rest subjects were clear positive or negative for CHD.

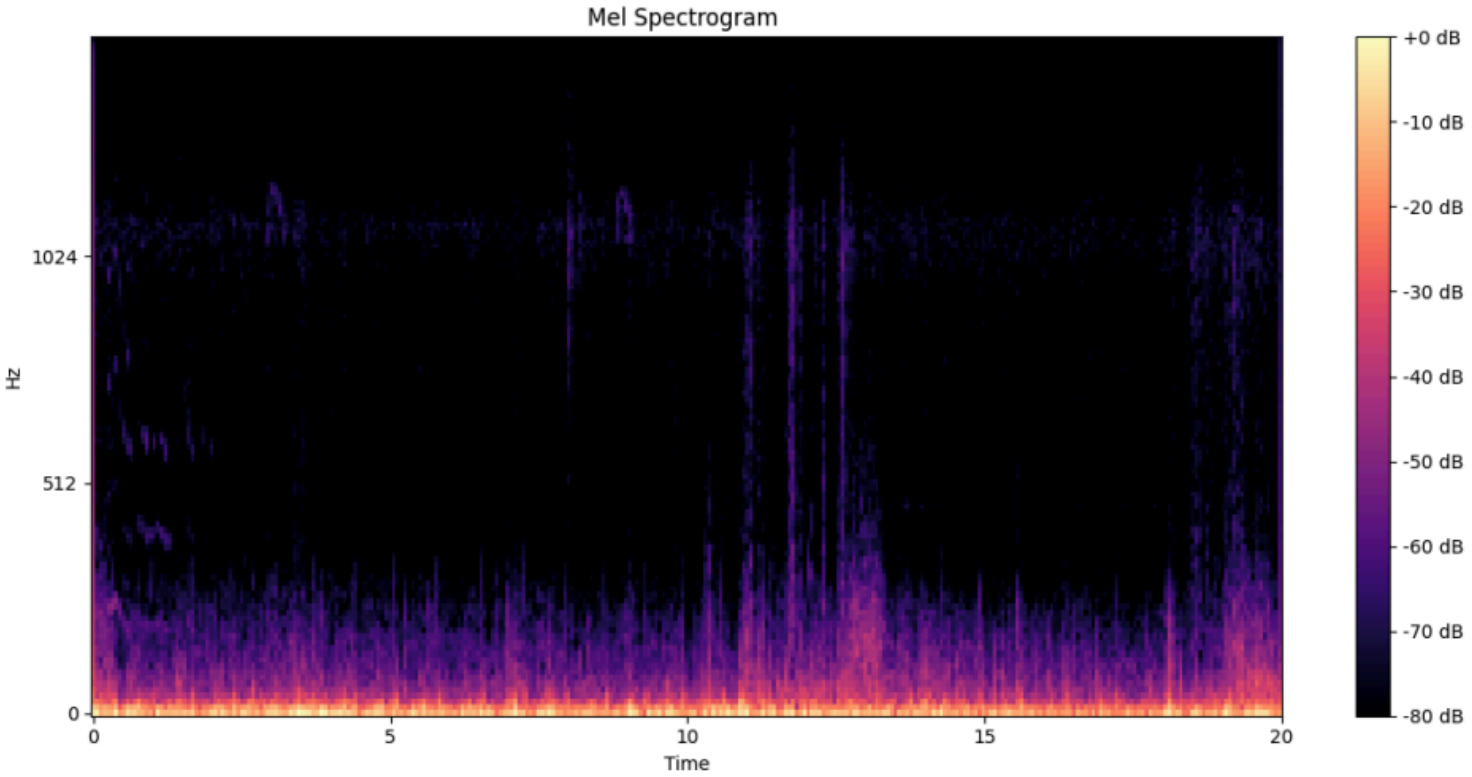
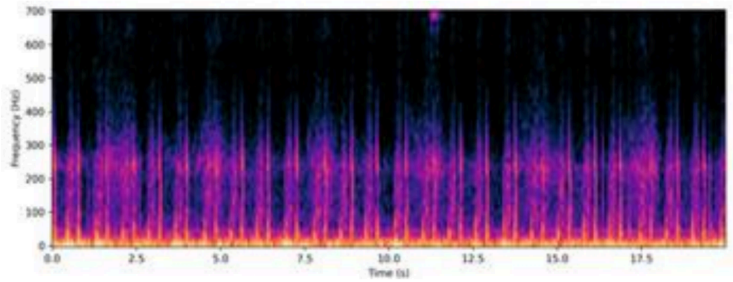


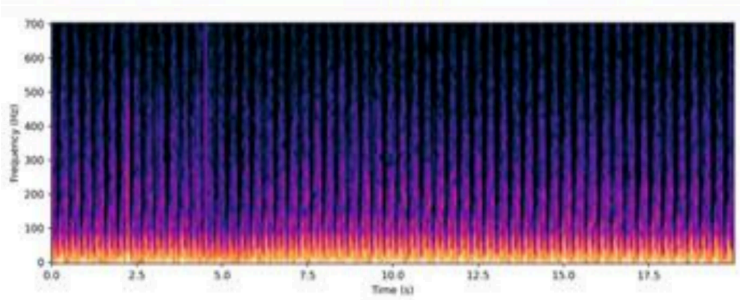
Figure 5

Mel spectrogram of normal heart sounds: This Mel spectrogram illustrates the time–frequency representation of a 20-second recording of normal heart sounds. Distinct, periodic bursts of low-frequency energy (below 150 Hz) correspond to the first (S1) and second (S2) heart sounds. These occur at regular intervals consistent with a normal heart rate and rhythm. The absence of sustained high-frequency components or irregular energy patterns suggests the lack of pathological murmurs or additional heart sounds, indicating normal cardiac acoustic activity.

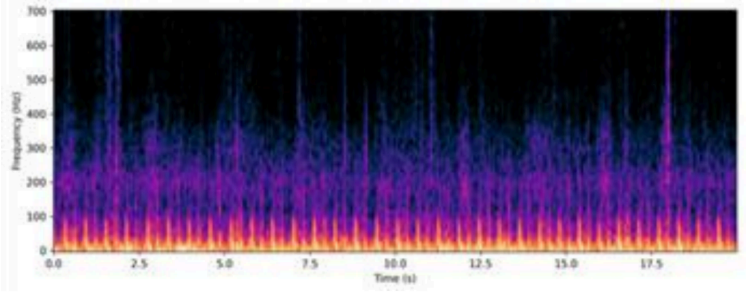
6a



6b



6c



6d

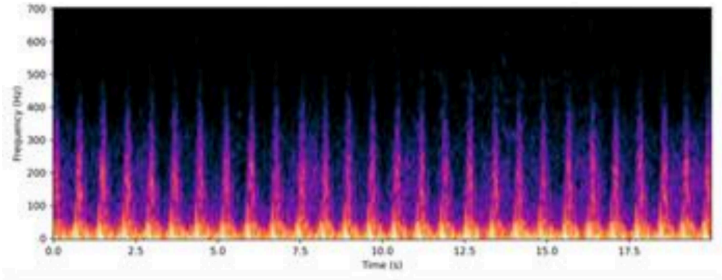


Figure 6

a-d: **Comparative melspectrograms of heart sounds across different hemodynamic states.**
(a) Increased pulmonary blood flow due to pre-tricuspid shunt (ASD) with intermittent diastolic high-frequency activity of lower intensity.
(b) Increased pulmonary blood flow due to post-tricuspid shunt (VSD/PDA) demonstrating dense, continuous high-frequency activity.
(c) Decreased pulmonary blood flow (TOF/severe PS) showing sparse striations with low spectral density.

(d) Normal pulmonary blood flow with aortic stenosis showing preserved S1 and S2 with additional mid-frequency systolic bursts corresponding to the ejection murmur.