Preliminary Evaluation of a Deep Learning Approach for Echocardiographic Screening for Rheumatic Heart Disease

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  - Screening
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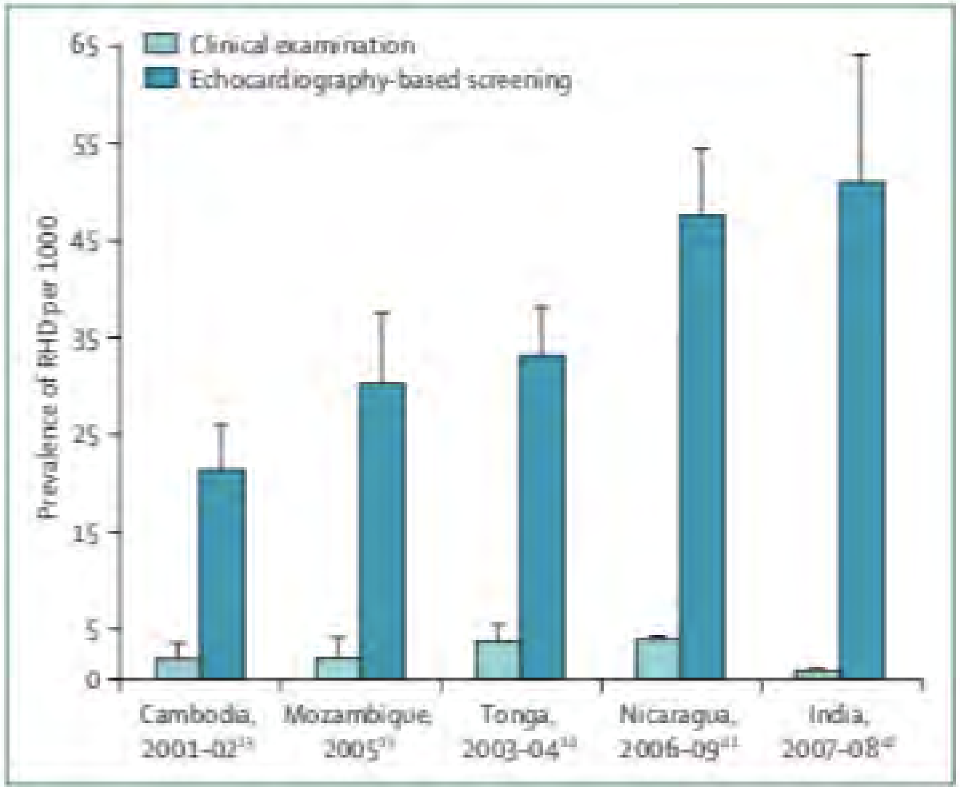
No disclosures

Echocardiographic Screening for RHD

- More sensitive and specific than clinical exam based screening
- 5-10 minute study, ~13 clips
- Barriers:
  - Shortage of specialized healthcare workers
  - Equipment
  - Electricity



Marijon 2012

Lu 2015

- Simplified criteria to detect RHD
    - Mitral regurgitation jet length ≥ 1.5 cm OR
    - Any aortic insufficiency

- Overall sensitivity 73.3% and specificity 82.4% for any RHD

- Sensitivity for definite RHD 97.9%

Single-View Handheld Echocardiogram Protocol

- Diamantino 2018
  - 587 studies including 76 definite, 122 borderline, and 389 on normal cases
  - Parasternal long axis color Doppler (PLAX-C) view only
  - Mitral regurgitation jet length $\geq$ 1.5 cm or any aortic insufficiency
  - Sensitivity of 81.1%, specificity of 75.5%

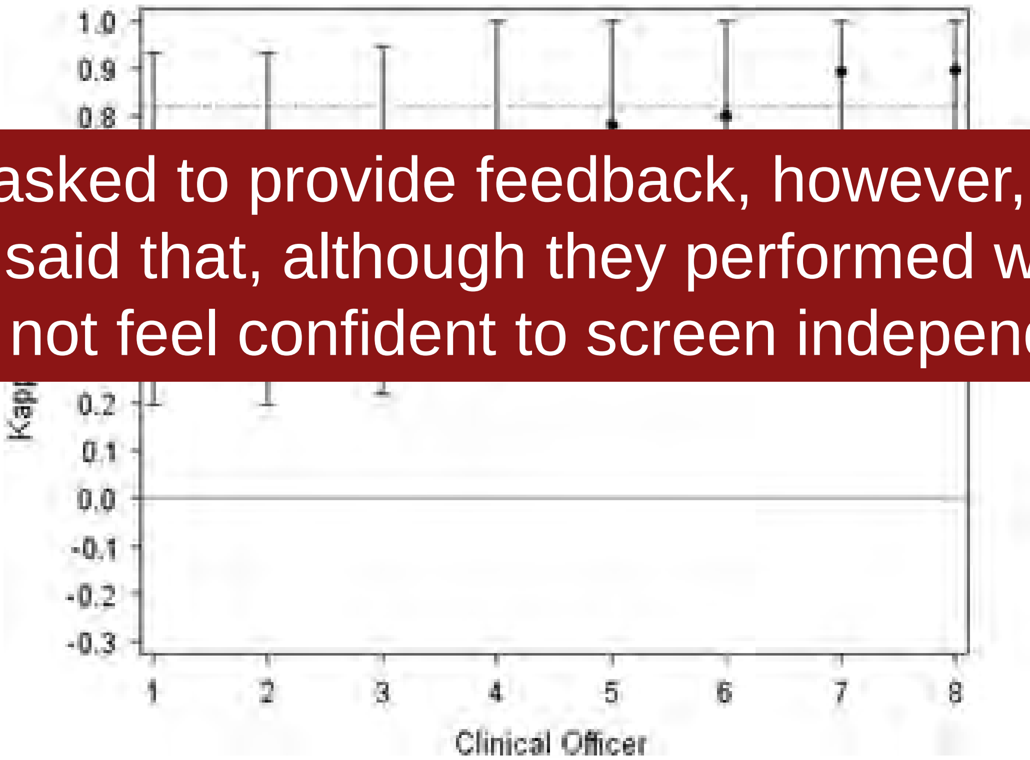
Sanyahumbi 2017

- 8 clinical officers in Malawi
  - 3 years clinical officer school
  - Subspecialty training pediatrics

- Study flow:
  - Training: 3 half-days of didactic cardiology lectures and computer RHD echo modules
  - Practical: 2 days of mentored echo screening (average 60 echos)
  - Evaluation: screened 20 children with & without RHD
    - Refer if mitral regurgitation jet more than 1.5 cm or any aortic regurgitation

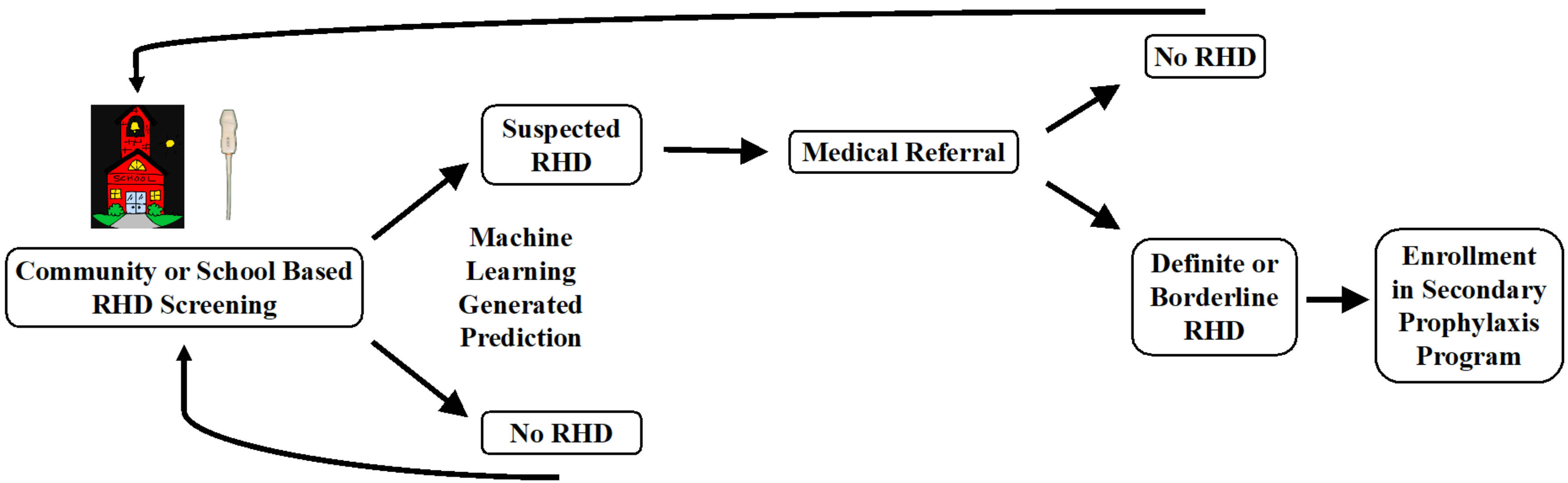
- Kappa statistics for agreement between clinical officer and cardiologist referral

Sanyahumbi 2017



"When asked to provide feedback, however, the clinical officers said that, although they performed well, that they do not feel confident to screen independently."

Machine Learning for Echo Based RHD Screening



Human Subjects Research

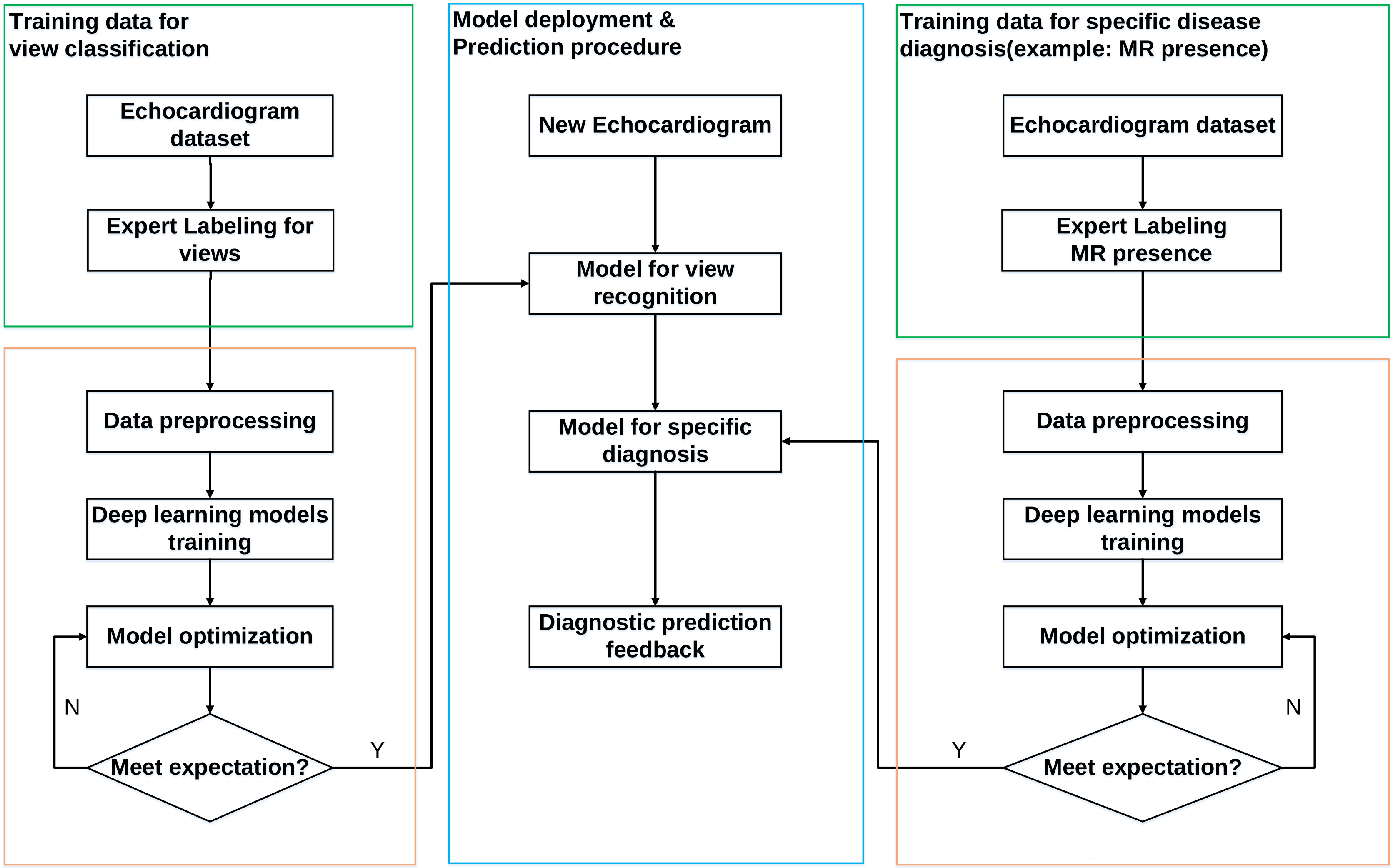
- Waiver of approval was obtained from the Stanford University Institutional Review Board.

- Approved by the Malawi National Health Sciences Research Committee.

Echocardiograms

- 224 echos performed in Malawi, Africa, as part of a screening program to detect latent RHD.
- Philips CX50 portable echocardiography machine with an S5-1 transducer probe.
- Abbreviated RHD screening protocol.
- Machine settings were consistent with World Heart Federation recommendations for echocardiographic diagnosis of RHD.

System Construction Pipeline

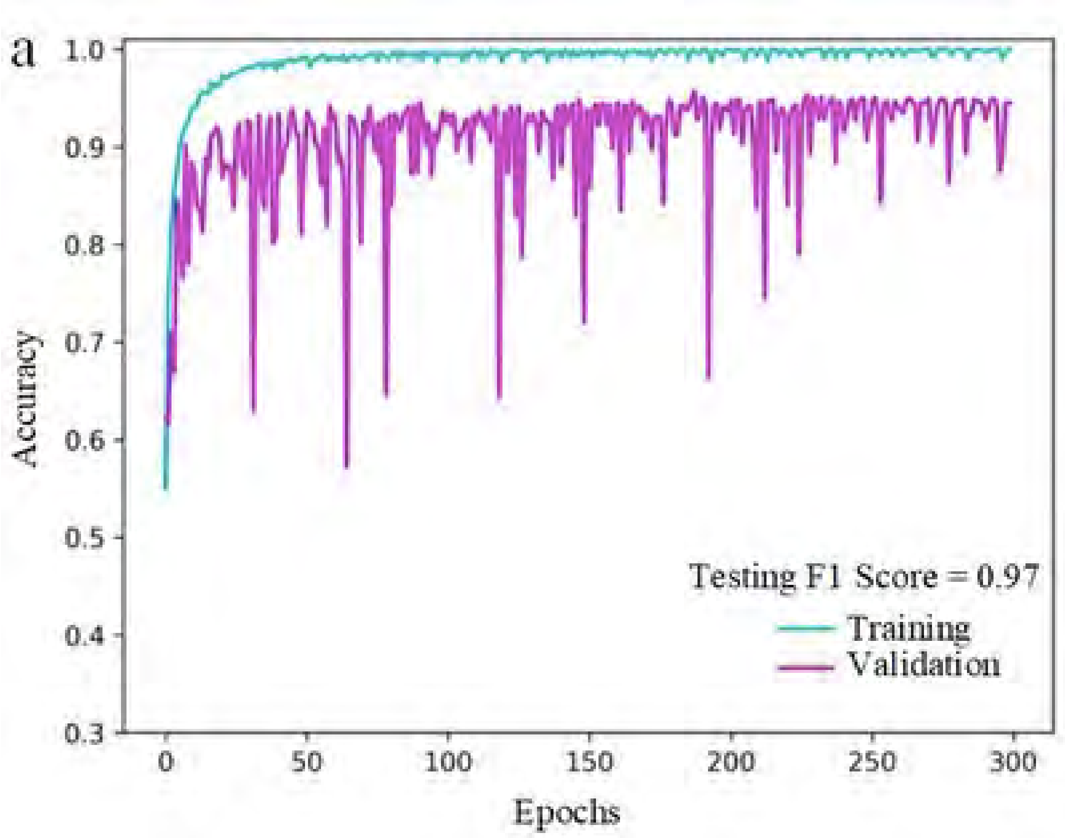


Echocardiographic Data Distribution

View	Total Clips	Training	Validation	Testing
PLAX	1538	1138	200	200
PLAX-C	1104	704	200	200
PSAX-AV	122	69	25	28
PSAX-AV-C	72	48	2	22
PSAX-MV	232	139	30	63
PSAX-MV-C	54	27	6	21
A4C	1227	827	200	200
A4C-C	612	365	122	125
A5C	1094	694	200	200
A5C-C	578	359	105	114

Class	Total samples	Training	Validation	Testing
No-MR	1302	812	224	266
MR	717	458	125	134

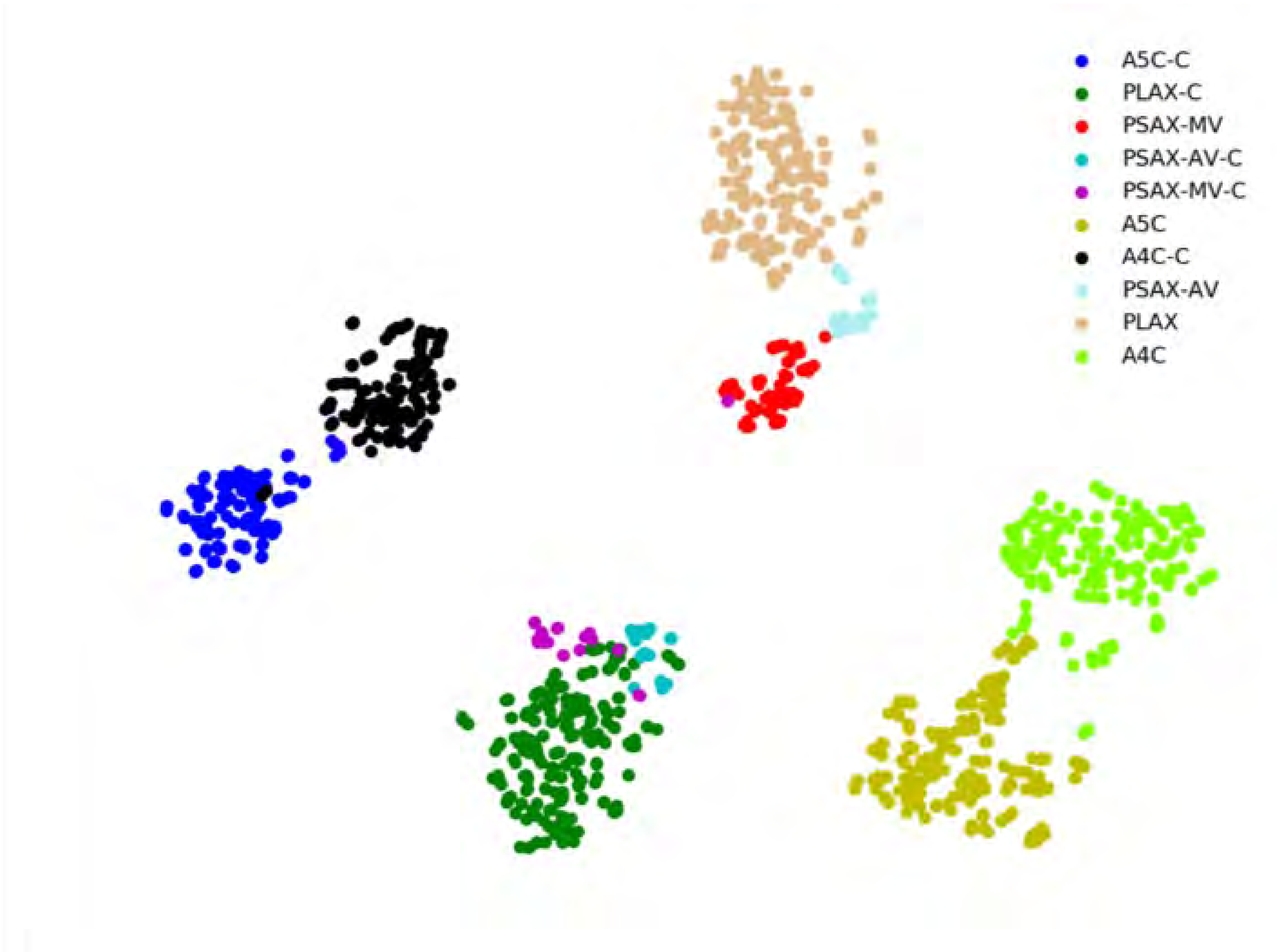
Performance of View Classification Model: F1 Score



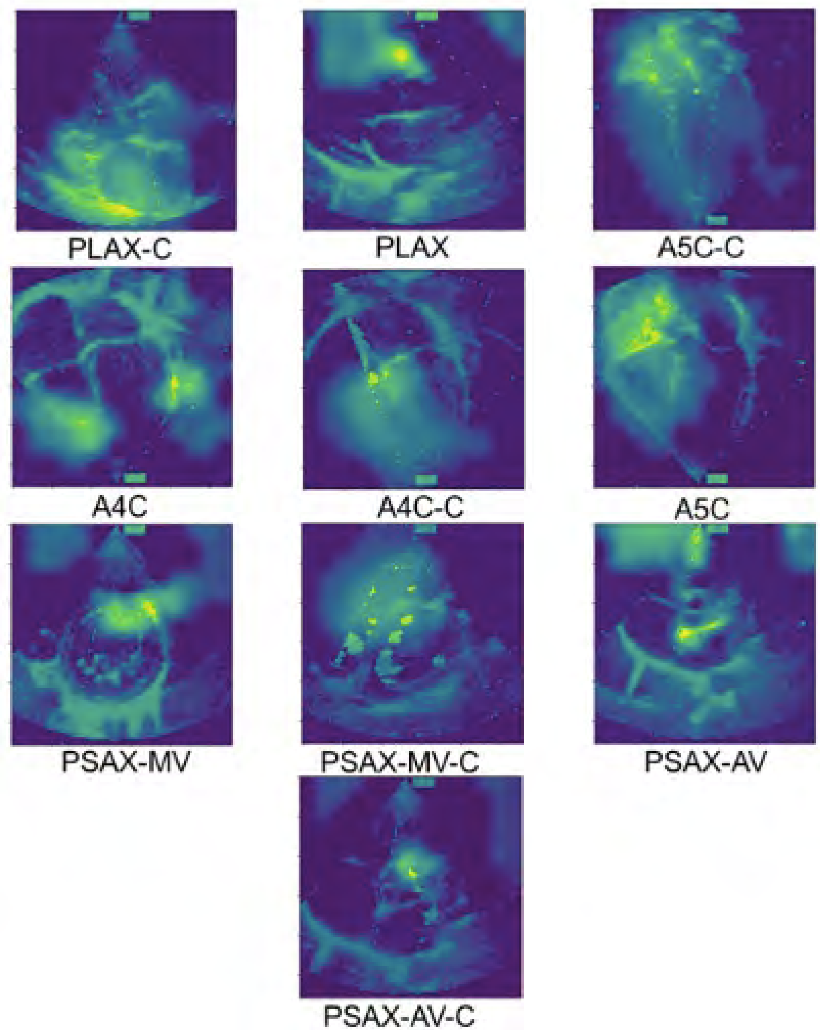
Performance of View Classification Model: F1 Score

View	Precision	Recall	F1-score	Testing sample
PLAX	1.00	1.00	1.00	200
PLAX-C	0.98	0.97	0.97	200
PSAX-AV	0.96	0.96	0.96	28
PSAX-AV-C	0.72	0.95	0.82	22
PSAX-MV	0.94	0.98	0.96	63
PSAX-MV-C	1.00	0.71	0.83	21
A4C	0.97	0.99	0.98	200
A4C-C	0.96	0.98	0.97	125
A5C	0.99	0.96	0.98	200
A5C-C	0.97	0.96	0.96	114

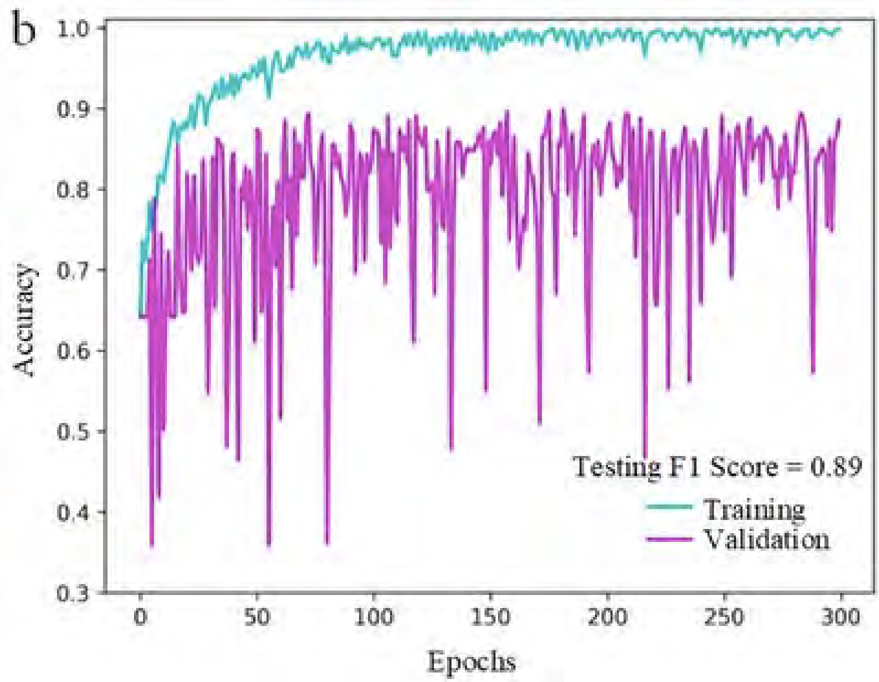
Performance of View Classification Model: t-distributed Stochastic Neighbor Embedding



Performance of View Classification Model: Class Activation Mapping Technique

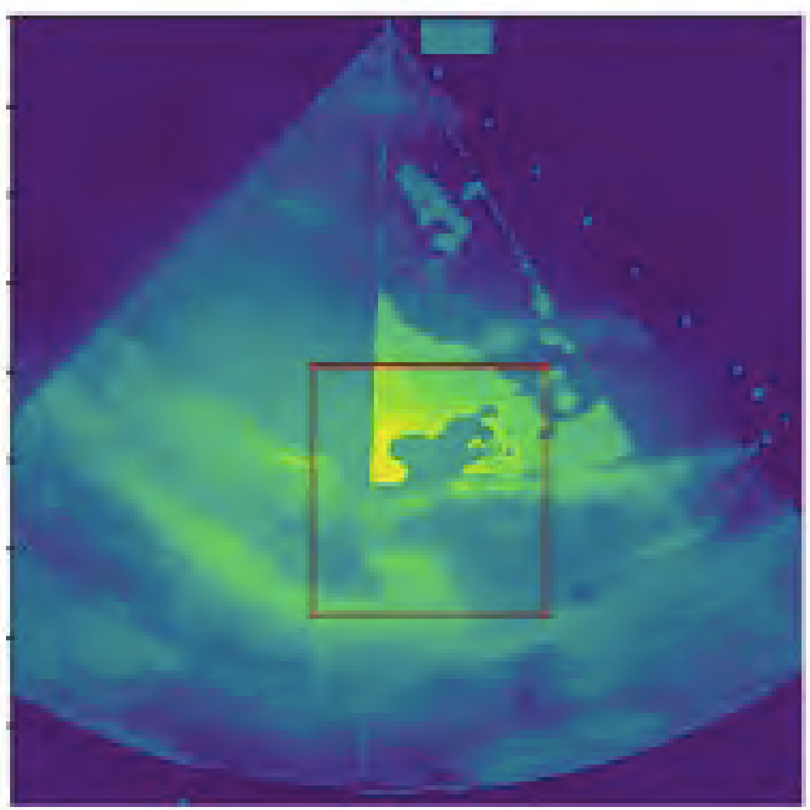


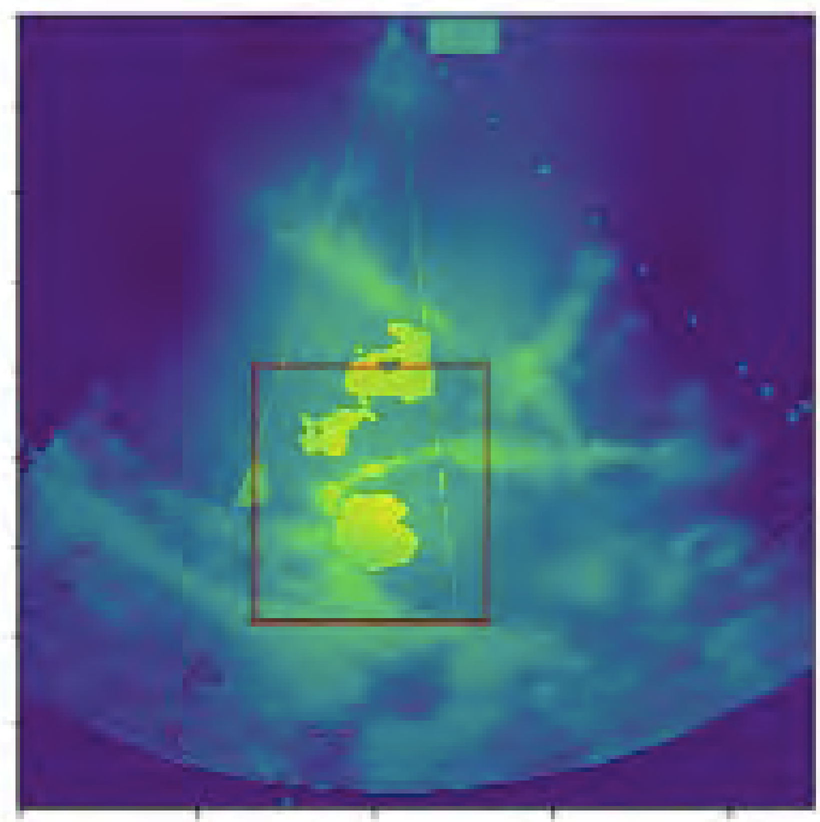
Performance of MR Detection Model: F1 Score



Class	Precision	Recall	F1-score	Testing sample
No-MR	0.93	0.86	0.90	95
MR	0.84	0.92	0.88	74

Performance of MR Detection Model: Class Activation Mapping Technique





Conclusions

- We present an automated pipeline for assessment of MR in the PLAX-C view with promising early results.
- This study further demonstrates the potential of machine learning in the echocardiographic diagnosis of cardiac disease.
- Our model is capable of achieving a high level of accuracy despite echocardiographic image variability.
- This pipeline is an encouraging first step and suggests the feasibility of building an automated RHD tool from this image set.

Limitations

- Doesn’t differentiate MR severity.
- Haven’t delved into aortic regurgitation yet.
- Limited training data size.
- All echocardiograms obtained in Malawi.

Next Steps

- We now have access to thousands of RHD screening echocardiograms to continue to improve our model.

- We have connected with researchers across the world interested in harnessing the potential of AI for RHD screening.

- We hope that this tool will reduce morbidity and mortality from RHD worldwide.

Thank You

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Definite: A, B, C, or D	
A. Pathologic MR and at least two morphologic features of RHD of the mitral valve	
B. Mitral stenosis with mean gradient ≥ 4 mm Hg	
C. Pathologic AI and at least two morphologic features of RHD of the aortic valve	
D. Borderline disease of both the aortic and mitral valves	
Borderline: A, B, or C	
A. At least two morphologic features of RHD of the mitral valve	
B. Pathologic MR	
C. Pathologic AI	
Pathologic MR (all criteria must be met)	Pathologic AR (all criteria must be met)
Seen in two views	Seen in two views
Jet length ≥ 2 cm (in at least one view)	Jet length ≥ 1 cm (in at least one view)
Velocity ≥ 3 m/sec for one complete envelope	Velocity ≥ 3 m/sec for one complete envelope
Pansystolic jet in at least one envelope	Pandiastolic jet in at least one envelope
Morphologic features of the mitral valve	Morphologic features of the aortic valve
Anterior leaflet thickening ≥ 3 mm	Irregular or focal thickening
Chordal thickening	Coaptation defect
Restricted leaflet motion	Restricted leaflet motion
Excessive leaflet tip motion during systole	Prolapse

Convolutional Neural Networks (CNN)