An Ensemble Deep Learning Algorithm for Structural Heart Disease Screening Using Electrocardiographic Images: PRESENT SHD

Online Supplement

Supplementary Table 24. Cumulative hazard across for new-onset structural heart disease or heart failure over median follow-up time across the cohort. --- 41

Supplementary Table 25. Age- and sex-adjusted Cox proportional hazard models for the prediction of new-onset structural heart disease or heart failure across model output probabilities in individuals at risk in the Yale New Haven Hospital and external validation sites.----------------------- 42

SUPPLEMENTARY METHODS

Data Sources

The electronic health records (EHR) data was acquired during patient care at the hospital sites in the Yale New Haven Health System using Epic and was extracted from the Clarity database.1,2 The YNHHS EHR data are linked to the CT death index to capture out-of-hospital mortality.

The Brazilian Longitudinal Study of Adult Health (ELSA-Brasil) study, a large multicenter prospective cohort study conducted in Brazil, enrolled,105 communitydwelling adults aged 35-74 years at their baseline visit during 2008-2010.^{3,4} These participants represent active and retired civil servants from six higher education and research institutions in Brazilian state capitals in three geographical regions of the country: Southeast (Belo Horizonte, Rio de Janeiro, São Paulo and Vitória), South (Porto Alegre) and Northeast (Salvador).5 The ELSA-Brasil study aimed to investigate the development and progression of chronic diseases and their determinants in the Brazilian adult population. Baseline data were collected using validated instruments, physical examinations, laboratory assessments, and imaging modalities.3 Additionally, all participants underwent protocolized 12-lead ECG and echocardiogram.3,4 To ascertain exposure status and to identify changes in baseline, ELSA-Brasil participants present for in-person follow-up visits every three to four years. Moreover, telephone interviews occur annually to obtain information on new diagnoses, hospitalization, and death with adjudicated clinical events based on expert medical record review.3

UK Biobank (UKB) is a prospective cohort of 502,468 community-dwelling adults aged 40-69 years recruited during 2006-2010.3 A group of these participants accepted to participate in the third or fourth UKB study visit during which the participants underwent 12-lead electrocardiograms (ECGs) in 2014-2021. The UKB dataset is linked with the national EHR from the UK National Health Service predating UKB enrollment, enabling access to EHR diagnosis and procedure codes.^{7,8} It is also linked to the national death index for complete capture of mortality data. We used data from UKB under research application #71033.

Signal Preprocessing

We used a standard preprocessing strategy to extract the signal waveform data from 12-lead ECGs, predominantly acquired using Philips PageWriter and GE MAC machines. We used linear interpolation to resample the ECGs that were obtained at 250Hz to align with a majority that were recorded at a sampling frequency of 500Hz as 10-second ECGs. Median pass filtering was done by subtracting a one-second median filter from the acquired signals to eliminate baseline drift. ECG signals were divided by a factor of 1000 and scaled to millivolts.

Model Evaluation on Novel ECG Formats

As a sensitivity analysis, we also evaluated the model on ECG images plotted in 4 novel formats that were not encountered by the model during training, including (a) Black-on-Red Standard: black ECG trace on red background grid plotted in standard clinical format, (b) Blue-on-Black Standard: blue ECG trace on black background grid plotted in standard clinical format, and (c) Black-on-black rhythm-on-top: black ECG trace plotted on black background with a single 10-second rhythm strip (lead I) above the 12 limb and precordial leads, and (d) Blue-on-red rhythm-on-top: blue

ECG trace plotted on red background in the rhythm-on-top layout (**Supplementary Figure 3.5**)."

Signal Model Development

For each image-based CNN, a corresponding signal-based CNN model was trained using the same disease labels and in the same training population as the image models. We evaluated multiple CNN architectures, experimenting with the number and size of convolutional layers as well as dropout and learning rates. The architecture with the highest AUROC for LVSD detection in the validation set was selected as the final architecture for training the individual disease detection models.9,10 This architecture comprised an input layer with dimensions of (5000, 12, 1), representing a 10-second, 500 Hz, 12-lead ECG. The input layer was followed by 7 2-dimensional convolutional layers, progressively increasing the number of filters from 16 to 64 while incorporating varying kernel sizes (7x1, 5x1, and 3x1) to capture different levels of feature abstraction. A batch normalization layer, a ReLU activation layer, and a 2-dimensional max-pooling layer with different pool sizes (2x1 and 4x1) followed each convolutional layer. Next, the output of the $7th$ convolutional layer was used as the input for a fully connected network that included two dense layers. Each dense layer was followed by a batch normalization layer, a ReLU activation layer, and a dropout layer with a rate of 0.5. Finally, the model output was a dense layer with a single class and a sigmoid activation to generate the output probability of the label. The loss function was adjusted by calculating model weights using the effective number of samples class re-weighting approach to ensure that the learning is not impacted by the differential prevalence of positive and negative labels. The LVSD model was trained first and the weights from the optimal epoch were transferred to initialize the training for the models for sLVH and valve disease labels.

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SUPPLEMENTARY FIGURES

Supplementary Figure 1. Flow Diagram of study population and analysis. Abbreviations: ECG, electrocardiogram; TTE, transthoracic echocardiogram; YNHHS, Yale New Haven Health System.

Supplementary Figure 2. Examples of 12 variations in the electrocardiographic images used for convolutional neural network training.

Supplementary Figure 3. Example of 4 electrocardiographic images plotted in the standard layout and used for model evaluation.

Supplementary Figure 4. Novel electrocardiogram formats used for model evaluation.

Abbreviations: ECG, electrocardiogram

(A) Standard ECG format (presented here for reference)

(B) Black-on-Red colors in standard ECG layout

(C) Blue-on-Black colors in standard ECG layout

(D) Black-on-Black colors in rhythm-on-top layout

(E) Blue-on-Red colors in rhythm-on-top layout

Supplementary Figure 5. Overview of methodology to identify individuals at risk of new-onset disease in the hospitalbased validation sites.

Abbreviations: ECG, electrocardiograms; HF, heart failure; SHD, structural heart disease; TTE, transthoracic echocardiograms.

Supplementary Figure 6. PRESENT-SHD performance metrics across probability thresholds in the held-out test set.

Abbreviations: NPV, negative predictive value; PPV, positive predictive value.

Supplementary Figure 7. PRESENT-SHD performance for detection of structural heart disease including left ventricular systolic dysfunction, severe left-sided valve diseases, and severe left ventricular hypertrophy across study cohorts.

Supplementary Figure 8. Receiver operating characteristic curves for detecting individual structural heart disease across study cohorts.

Abbreviations: AR, aortic regurgitation; AS, aortic stenosis; AUROC, area under the receiver operating characteristic curve; sLVH, severe left ventricular hypertrophy; IVSd, interventricular septal diameter at end-diastole; LVDD, left ventricular diastolic dysfunction; LVEF, left ventricular ejection fraction; MR, mitral regurgitation; NPV, negative predictive value; PPV, positive predictive value.

SUPPLEMENTARY TABLES

Supplementary Table 1. Diagnosis and procedure codes used to identify longitudinal outcomes.

Supplementary Table 2. Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis + Artificial Intelligence (TRIPOD + AI) checklist.

¹ D=items relevant only to the development of a prediction model; E=items relating solely to the evaluation of a prediction model; D;E=items applicable

Thems reteam only to the development of a prediction model; E=tems retating solety to the evaluation of a prediction model; D ; E=tems applicable to both the development and evaluation of a prediction model

² Separate

TRAPOD+*X*I

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 $\frac{4}{3}$ This relates to the analysis code, for example, any data cleaning, feature engineering, model building, evaluation. $\frac{5}{3}$ This relates to the code to implement the model to get estimates of risk for a new in

Supplementary Table 3. Demographic and clinical characteristics of the model development population (including training and validation sets).

Abbreviations: AR, aortic regurgitation; AS, aortic stenosis; ECG, electrocardiogram; IQR, interquartile range; LVSD, left ventricular systolic dysfunction; SHD, structural heart disease; sLVH, severe left ventricular hypertrophy; MR, mitral regurgitation

Footnote: Missing values were considered 'indeterminate' for individual SHD components. For composite SHD, the label was considered positive if any of the SHD components was flagged positive, negative is all SHD components were flagged negative, and 'indeterminate' otherwise.

Supplementary Table 4. Demographic and clinical characteristics of the held-out test set and the external validation cohorts.

Abbreviations: AR, aortic regurgitation; AS, aortic stenosis; ECG, electrocardiogram; IQR, interquartile range; LVSD, left ventricular systolic dysfunction; SHD, structural heart disease; sLVH, severe left ventricular hypertrophy; MR, mitral regurgitation

Footnote: Missing values were considered 'indeterminate' for individual SHD components. For composite SHD, the label was considered positive if any of the SHD components was flagged positive, negative is all SHD components were flagged negative, and 'indeterminate' otherwise.

Supplementary Table 5. Model performance on novel electrocardiogram formats not encountered during training.

Supplementary Table 6. Model discrimination in subsets of the held-out test set where transthoracic echocardiograms were performed before, after, or on the same day as the electrocardiogram.

Abbreviations: AUPRC, area under the precision-recall curve; AUROC, area under the receiver operating characteristic curve; ECG, electrocardiogram; TTE, transthoracic echocardiogram.

Supplementary Table 7. Performance for detection of structural heart diseases for convolutional neural network model for structural heart disease in the heldout test set.

Supplementary Table 8. Performance for detection of structural heart diseases for extreme gradient boosting model variations in the held-out test set.

Abbreviations: AUROC, area under the receiver operating characteristic curve; CNN, convolutional neural network; SHD, structural heart disease; XGBoost, extreme gradient boosting.

Supplementary Table 9. Model performance characteristics for signal-based ensemble model for detection of structural heart disease across the held-out test set and external validation cohorts.

Supplementary Table 10. Performance metrics for detecting structural heart disease across key demographic subgroups in Bridgeport Hospital.

Supplementary Table 11. Performance metrics for detecting structural heart disease across key demographic subgroups in Greenwich Hospital.

Supplementary Table 12. Performance metrics for detecting structural heart disease across key demographic subgroups in Lawrence + Memorial Hospital.

Supplementary Table 13. Performance metrics for detecting structural heart disease across key demographic subgroups in Westerly Hospital.

Supplementary Table 14. Performance metrics for detecting structural heart disease across key demographic subgroups in Brazilian Longitudinal Study of Adult Health.

Supplementary Table 15. Performance metrics for PRESENT-SHD for detecting structural heart disease in simulated screening cohorts with varying prevalence.

Abbreviations: AR, aortic regurgitation; AS, aortic stenosis; MR, mitral regurgitation; LVSD, left ventricular systolic dysfunction; sLVH, severe left ventricular hypertrophy; NPV, negative predictive value; PPV, positive predictive value; SHD, structural heart disease; SVD, severe valvular disease.

* Prevalence in the held-out test set

Supplementary Table 16. Performance metrics for convolutional neural network for detecting left ventricular systolic dysfunction in the held-out test set and across external validation cohorts.

Supplementary Table 17. Performance metrics for convolutional neural network for detecting moderate or severe leftsided valvular disease in the held-out test set and across external validation cohorts.

Supplementary Table 18. Performance metrics for convolutional neural network for detecting moderate or severe aortic regurgitation in the held-out test set and across external validation cohorts.

Supplementary Table 19. Performance metrics for convolutional neural network for detecting moderate or severe aortic stenosis in the held-out test set and across external validation cohorts.

Supplementary Table 20. Performance metrics for convolutional neural network for detecting moderate or severe mitral regurgitation in the held-out test set and across external validation cohorts.

Supplementary Table 21. Performance metrics for convolutional neural network for detecting severe left ventricular hypertrophy in the held-out test set and across external validation cohorts.

Supplementary Table 22. Baseline demographic and clinical characteristics of individuals without structural heart disease or heart failure included for the assessment of PRESENT-SHD for prediction of new-onset disease.

Supplementary Table 23. Performance metrics for risk stratification of new-onset structural heart disease or heart failure in individuals at risk in the Yale New Haven Hospital and external validation sites.

Supplementary Table 24. Cumulative hazard across for new-onset structural heart disease or heart failure over median follow-up time across the cohort.

Supplementary Table 25. Age- and sex-adjusted Cox proportional hazard models for the prediction of new-onset structural heart disease or heart failure across model output probabilities in individuals at risk in the Yale New Haven Hospital and external validation sites.

