ARTIFICIAL INTELLIGENCE

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Artificial Intelligence–Assisted Prediction of Late-Onset Cardiomyopathy Among Childhood Cancer Survivors

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abstract

PURPOSE Early identification of childhood cancer survivors at high risk for treatment-related cardiomyopathy may improve outcomes by enabling intervention before development of heart failure. We implemented artificial intelligence (AI) methods using the Children's Oncology Group guideline–recommended baseline ECG to predict cardiomyopathy.

MATERIAL AND METHODS Seven AI and signal processing methods were applied to 10-second 12-lead ECGs obtained on 1,217 adult survivors of childhood cancer prospectively followed in the St Jude Lifetime Cohort (SJLIFE) study. Clinical and echocardiographic assessment of cardiac function was performed at initial and follow-up SJLIFE visits. Cardiomyopathy was defined as an ejection fraction $< 50\%$ or an absolute drop from baseline $\geq 10\%$. Genetic algorithm was used for feature selection, and extreme gradient boosting was applied to predict cardiomyopathy during the follow-up period. Model performance was evaluated by five-fold stratified cross-validation.

RESULTS The median age at baseline SJLIFE evaluation was 31.7 years (range 18.4-66.4), and the time between baseline and follow-up evaluations was 5.2 years (0.5-9.5). Two thirds (67.1%) of patients were exposed to chest radiation, and 76.6% to anthracycline chemotherapy. One hundred seventeen (9.6%) patients developed cardiomyopathy during follow-up. In the model based solely on ECG features, the cross-validation area under the curve (AUC) was 0.87 (95% CI, 0.83 to 0.90), whereas the model based on clinical features had an AUC of 0.69 (95% CI, 0.64 to 0.74). In the model based on ECG and clinical features, the cross-validation AUC was 0.89 (95% CI, 0.86 to 0.91), with a sensitivity of 78% and a specificity of 81%.

CONCLUSION AI using ECG data may assist in the identification of childhood cancer survivors at increased risk for developing future cardiomyopathy.

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INTRODUCTION

Because of improved treatment and supportive care, 5-year survival rates for childhood cancer now exceed 85% with more than 500,000 childhood cancer survivors alive in the United States today.[1] Patients treated with anthracycline chemotherapy or cardiac-directed radiation are at increased risk for adverse cardiovascular sequelae,[2] including cardiomyopathy, coronary artery disease, and valvular heart disease.

Surveillance guidelines have been developed by a variety of oncology groups to guide long-term monitoring with the goal of identifying those who might benefit from early medical interventions.[3] While offering an opportunity for early detection of myocardial dysfunction, screening guidelines do not identify patients with preserved function who may yet develop cardiomyopathy.

We investigated whether childhood cancer survivors at risk of developing late-onset cardiomyopathy could be accurately identified before the development of echocardiographic evidence of dysfunction using machine learning algorithms directed at ECG waveforms.

MATERIALS AND METHODS

Study Population and Design

The St Jude Lifetime Study (SJLIFE) cohort is an ongoing study with prospective clinical follow-up of survivors of childhood cancer treated at St Jude Children's Research Hospital, Memphis, TN.[4,5] Participants in this analysis were at least 10 years from cancer diagnosis and ≥ 18 years of age at cohort entry and had completed at least two comprehensive clinical assessments on the St Jude Children's Research Hospital campus including physical examination, a

ASSOCIATED CONTENT

Data Supplement

Author affiliations and support information (if applicable) appear at the end of this article.

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CONTEXT

Key Objective

To investigate whether artificial intelligence (AI) applied to electrocardiograms can predict cardiomyopathy in adult survivors of childhood cancer exposed to cardiotoxic therapies.

Knowledge Generated

Clinical models predicted cardiomyopathy with a sensitivity of 62%, a specificity of 66%, and an area under the curve (AUC) of 0.69 (95% CI, 0.64 to 0.74). An AI model based on 86 signal processing–based ECG features was 76% and 79% sensitive and specific, with an AUC of 0.87 (95% CI, 0.83 to 0.90). Combining clinical and ECG features correctly predicted 78% of patients who developed cardiomyopathy and 81% who did not, with positive and negative predictive values of 30% and 97%, respectively, and an AUC of 0.89 (95% CI, 0.86 to 0.91).

Relevance

AI may help classify adult survivors of childhood cancer before clinical recognition. Enhanced characterization of this at-risk population may help separate those in need of greater surveillance from those for whom a lower degree of monitoring may suffice.

core laboratory battery, 12-lead ECG (GE MAC 1200 machine), and two-dimensional Doppler ultrasound echocardiography (GE Medical Systems, Milwaukee, WI) with three-dimensional imaging for left ventricular volumes. Medical record abstraction was performed to determine cumulative anthracycline and cardiac radiation exposures. For survivors treated with radiation, cumulative dose, orientation, beam energy, field size, weighting, blocking, and anatomical position were abstracted. For each individual, all radiation therapy (RT) fields were reconstructed on computational phantoms scaled to their age at RT. To be eligible for our study, participants had to have an ejection fraction $\geq$ 50% at the time of their baseline SJLIFE assessment.

As of December 31, 2018, 1,326 participants had $>$ 1 on-campus clinical assessment including ECHO and ECG screening. Our final study cohort included 1,217 of 1,326 with no cardiomyopathy at their first visit with ECHO screening (Data Supplement).

Outcome. Cardiomyopathy was defined as an ejection fraction $<$ 50% or an absolute drop from the baseline $\geq$ 10% obtained by echocardiogram during any of the follow-up visits.

Treatment exposures. Four treatment exposures were included in the analysis. Cumulative anthracycline dose (milligram per square meter) was calculated by summing adriamycin, daunorubicin, epirubicin, idarubicin, and mitoxantrone in adriamycin equivalent doses.[6] Radiation to the chest was used in two different forms as a yes or no variable and maximum total dose. Mean heart doses (stray dose from leakage and scatter radiation from nonchest-directed radiation) were calculated by radiation physicists at MD Anderson Cancer Center, Houston, TX.[7]

Additional covariates. A total of 12 demographic and clinical variables were used in the analysis: age at diagnosis and at time of echocardiography (years), race, sex, body surface area (per square meter), primary cancer diagnosis, heart rate (beats/min), respiratory rate (respirations/min), systolic and diastolic blood pressures (mm Hg), smoking (yes or no), and the presence of clinically assessed cardiovascular risk factors (diabetes [treated by diet and/or medication], hypertriglyceridemia [fasting triglycerides $\geq$ 150 mg/dL and/or on a lipid lowering agent], hypertension [systolic blood pressure $>$ 140 mm Hg and/or diastolic blood pressure $>$ 90 mm Hg and/or on antihypertensive agents], or hypercholesterolemia [fasting total cholesterol $>$ 200 mg/dL and/or on a lipid lowering agent]). We also included respiratory rate (respiration/min) as subtle changes in respiratory rate may reflect underlying heart disease even in the early stages of disease. In addition to these, we extracted features (described in detail below) from 12-lead ECGs for use in the models.

Statistical Methods

Overview. The study was approved by the Institutional Review Board, and all survivors provided informed consent before participation. Characteristics of the survivors at baseline assessment were expressed as median and range for continuous variables and as count and percentage for categorical variables. They were compared between those who developed cardiomyopathy and those who did not. Categorical variables were compared using Pearson chi-square test and Fisher's exact test, and numerical variables were compared using Student's *t*-test. The results of statistical tests were considered to be significant if the two-sided *P* value was $<$ .05.

We used waveform data from 12-lead ECG recordings sampled at 500 Hz. Features were extracted using both signal processing and deep learning methods, and those features most discriminating for cardiomyopathy (diagnosed during follow-up) were selected using a stochastic optimization method, genetic algorithm (GA).[8] Features

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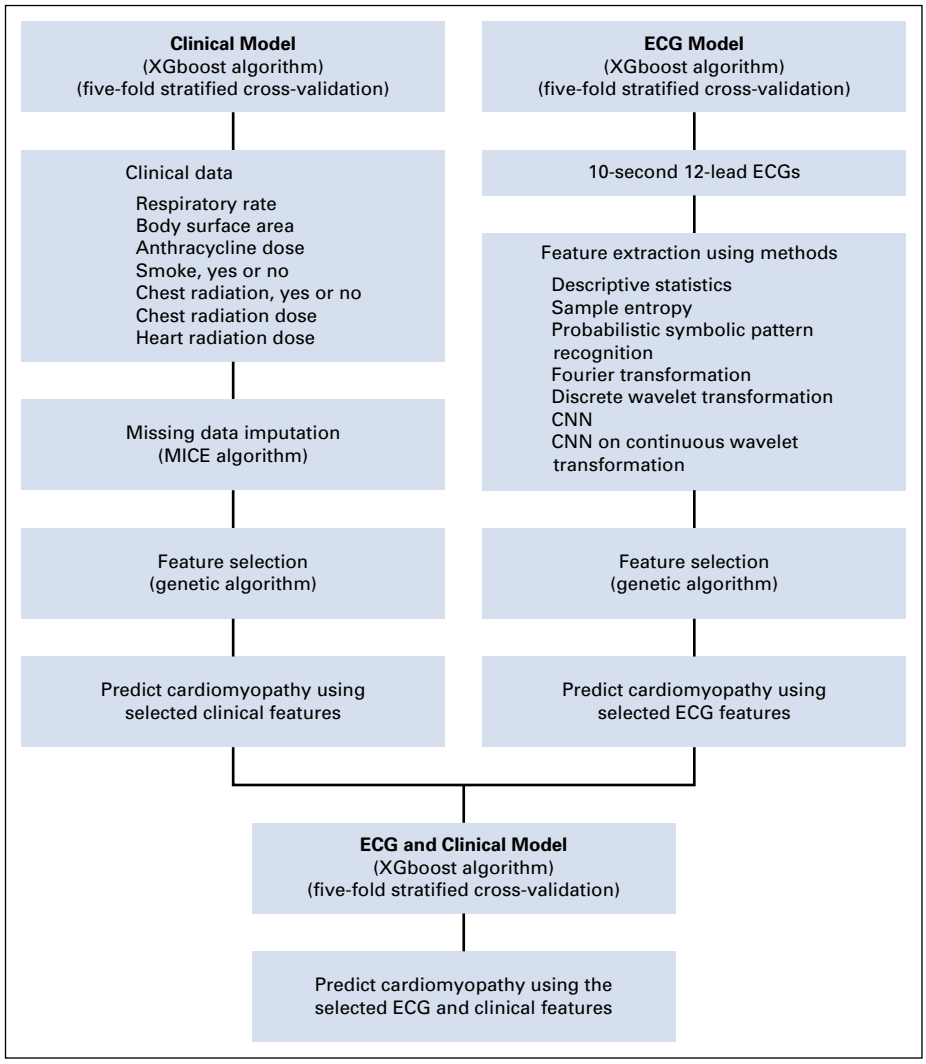

FIG 1. First column shows the analytic flow for developments of the clinical model (light blue), including the missing data imputation, determination of important clinical features, and clinical model building. The second column shows the analytic flow for development of the ECG model (light blue), including the feature extraction through signal processing and deep learning methods, determination of important extracted ECG features of each method, and ECG model building. The bottom row shows the combination of selected ECG and clinical features and final model building (dark blue). CNN, convolutional neural network; XGboost, extreme gradient boosting.

were also selected from clinical data using GA (Fig 1). Extreme Gradient Boosting (XGboost)[9] method was applied to the selected features of ECG from each method separately and then combined with clinical data to predict cardiomyopathy.

Feature extraction. Using baseline ECG data, we generated measures from each lead, including mean, median, kurtosis, skewness, variance, and other general features including root mean square and mean crossing rate of observed amplitude values. Sample entropy was calculated for each ECG lead as a measure of signal regularity of the signal. We segmented each ECG recording to 1 second epochs and computed sample entropy for each epoch sequentially. For probabilistic symbolic pattern recognition features, dissimilarities were calculated with reference to 1,100 healthy ECG recordings.[10] We decomposed ECG signals using a Fourier transform into basic sinusoidal waves at different frequencies and used amplitudes and phases of the waves as a feature. Both continuous and discrete wavelet transformations were used to extract features from the frequency spectrum. The discrete wavelet transformation was implemented by calculating descriptive statistics from a five-level wavelet decomposition. The continuous wavelet transformation was completed by calculating the similarity between signal and wavelets at each frequency and time points by shifting wavelets through signals to obtain a two-dimensional scaleogram. We then trained a convolutional neural network to extract features from the scaleograms. Finally, features were extracted using waveform data from 12-lead ECG recordings. Each 12-lead ECG signal was overlaid on top of each other to form one signal with 12 channels. Residual neural networks were used to extract features. We designed our neural network architectures in Python using the Keras library with TensorFlow backend (see the Data Supplement for full listing of all feature extraction approaches).

Feature selection. We implemented a GA algorithm to select the best subset of all ECG features and clinical variables for the predictive model, which provided the minimum classification error. The GA was started with a

random subset of features (different variable combinations) and iteratively mixed subsets (to obtain different feature combinations) based on their performance (area under the curve [AUC] value in predicting cardiomyopathy) to obtain feature combinations yielding better performance. XGboost was used as a fitness function on the iterated GA processes from 40 generations, with a crossover probability of .5 and a mutation probability of .05. We implemented GA separately on features extracted from each feature extraction method and then combined selected features for the final prediction models.

Missing data imputation. Of the 20 clinical variables, all except two had < 1% missingness. Dose to the heart from RT had the highest missing rate (2.8%), followed by chest radiation dose (0.9%), and chest radiation (yes or no) (0.8%). We imputed missing clinical data using the multivariate imputation by chained equation method in the MICE package in R.[11]

Predictive modeling. Although there are many machine learning algorithms for classification tasks, XGBoost has shown superior performance in several complex problems and data science competitions such as Kaggle challenges.[9,12] For the computationally intensive classification at multiple stages (classification models based on features from individual feature extraction methods, ECG features selected from feature extraction methods and clinical data, and a combination of ECG features and clinical data), we used the XGboost algorithm for all classification tasks. We used Bayesian hyperparameter optimization for tuning hyperparameters in the XGBoost model. For the XGBoost model (Data Supplement), optimization occurred when the learning rate was 0.16 and the total number of trees was 1,869. Following five-fold stratified cross-validation, model performance was assessed using metrics including sensitivity, specificity, and AUC.

RESULTS

Study Population Characteristics

Among 1,217 eligible survivors (51% male and 86% White), the median time between baseline and subsequent visits was 5.2 (range 0.5-9.2) years. The median age at cancer diagnosis was 8.4 (0.0-22.7) years and 31.7 (18.4-66.4) years at baseline SJLIFE assessment. Eight hundred seventeen (67.1%) were exposed to chest radiation (median dose 2,600 cGy, 150-6,200), and 932 (76.6%) to anthracycline therapy (median cumulative dose 168.7 mg/m^2, 35.1-734.2). Half (n = 609) had at least one cardiovascular risk factor, including 92 (7.6%) with diabetes, 249 (20.5%) with hypertriglyceridemia, 247 (20.3%) with hypertension, and 383 (31.5%) with hypercholesterolemia. Demographic and clinical characteristics of the study participants at the time of baseline visit are shown in Table 1.

One hundred seventeen (9.6%) survivors developed cardiomyopathy between the baseline and subsequent follow-up visit. Survivors who developed cardiomyopathy were significantly older at cancer diagnosis (10.2 *v* 8.2; $P < .04$) and baseline SJLIFE assessment (33.9 *v* 31.4; $P < .01$). Those with cardiomyopathy had a higher median anthracycline (206.3 mg/m^2 *v* 157.2 mg/m^2; $P < .001$) and heart radiation (2,320 cGy *v* 2,025 cGy; $P < .001$) dose.

Cardiomyopathy Prediction

Feature extraction. A total of 168 ECG features (such as mean, median, skewness, etc) were extracted from 12 leads (14 features per lead). Among these features, eight were selected by GA and found by XGBoost to predict cardiomyopathy with a sensitivity of 65%, a specificity of 67%, and a five-fold cross-validated AUC of 0.74. In a similar manner, 72 features reflecting sample entropy were extracted and, of these, 10 variables were selected by GA. With XGboost, these 10 features predicted cardiomyopathy with a sensitivity of 63%, a specificity of 65%, and a five-fold cross-validated AUC of 0.67. The list of all feature extraction methods considered and their associated five-fold cross-validated model performance metrics are shown in Table 2. Detailed information about the predictors is presented in the Data Supplement.

Model performance of ECG data. Overall model performance was calculated using the 86 selected ECG features extracted from the combination of methods listed in the Data Supplement and applying XGBoost. Cardiomyopathy was predicted with a five-fold cross-validated sensitivity of 76%, a specificity of 79%, and an AUC of 0.87 (95% CI, 0.83 to 0.90) using these 86 ECG features.

Model performance of clinical data. Of the 20 clinical features that were evaluated, seven were selected for the clinical data model: respiratory rate, body surface area, cumulative anthracycline dose, smoking, chest radiation (both as a dichotomous variable [yes or no] and cumulative dose), and mean heart dose from RT. The model constructed with these variables had a five-fold cross-validated sensitivity of 62%, a specificity of 66%, and an AUC of 0.69 (95% CI, 0.64 to 0.74).

Model performance of ECG plus clinical data. The 86 selected ECG features were combined with the seven clinical features to build a final model. The confusion matrix for prediction of cardiomyopathy is provided in Table 3. The model correctly predicted 78% of patients who developed cardiomyopathy, with a positive predictive value of 30%. The model correctly predicted 81% of patients who did not develop cardiomyopathy, with a negative predictive value of 97%. Overall, 81% of the model predictions were correct, with an AUC of 0.89 (95% CI, 0.86 to 0.91). Receiver operating characteristic curves of these models are shown in Figure 2.

Subgroup analysis. A subgroup analysis was conducted to assess model performance for predicting cardiomyopathy at 0.5-5 years and 5-9 years following the baseline SJLIFE assessment. At 0.5-5 years, the sensitivity was 79%, specificity 81%, and AUC 0.89 (95% CI, 0.85 to 0.93), and

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TABLE 1. Characteristics of the Study Population at Baseline SJLIFE Assessment

	Total (N = 1,217)		Cardiomyopathy (n = 117)		No Cardiomyopathy (n = 1,100)		
Risk Factors	**No.**	**%**	**No.**	**%**	**No.**	**%**	***P***
Sex							.10
Female	602	49.5	49	41.9	553	50.3	
Male	615	50.5	68	58.1	547	49.7	
Race							.06
Black	156	12.8	22	18.8	134	12.2	
White	1,041	85.6	94	80.3	947	86.1	
Others	20	1.6	1	0.9	19	1.7	
Diagnosis							< .01
Leukemia	501	41.2	30	25.6	471	42.8	
Sarcoma	150	12.3	23	19.7	127	11.5	
Hodgkin lymphoma	206	16.9	31	26.5	175	15.9	
Non-Hodgkin lymphoma	88	7.2	15	12.8	73	6.6	
CNS	85	7.0	5	4.3	80	7.3	
Neuroblastoma	59	4.9	4	3.4	55	5	
Wilms tumor	99	8.1	6	5.1	93	8.5	
Others	29	2.4	3	2.6	26	2.4	
Cardiovascular risk factors							.29
Hypertriglyceridemia	249	20.5	29	24.8	220	20	
Hypertension	247	20.3	19	16.2	228	20.7	
Hypercholesterolemia	383	31.5	42	35.9	341	31	
Diabetes	92	7.6	16	13.7	76	6.9	
Any of the above	609	50	65	55.6	544	49.5	
Smoking[a]							.93
Yes	479	39.4	47	40.2	432	39.3	
No	738	60.6	70	59.8	668	60.7	
Chest radiation							< .01
Yes	415	34.1	55	47.0	360	32.7	
No	802	65.9	62	53.0	740	67.3	

(Continued on following page)

TABLE 1. Characteristics of the Study Population at Baseline SJLIFE Assessment (Continued)

	Total (N = 1,217)		Cardiomyopathy (n = 117)		No Cardiomyopathy (n = 1,100)		
Risk Factors	**Median**	**Range**	**Median**	**Range**	**Median**	**Range**	***P***
Age at diagnosis, years	8.4	0.0-22.8	10.2	0.4-21.2	8.2	0.0-22.8	.04
Age at baseline SJLIFE evaluation, years	31.7	18.4-66.4	33.9	19.7-54.7	31.4	18.4-66.4	.01
Survival time, years	22.7	10.4-49.8	23.6	11.4-45.3	22.6	10.4-49.8	.36
Time from baseline assessment, years	5.2	0.5-9.2	5.3	0.9-9.5	5.2	0.5-9.2	.15
Heart rate, beats/min	76.0	41-138	78.0	46-115	76.0	41-138	.56
Respiratory rate, breaths/min	18.0	12-28	18.0	14-24	18.0	12-28	.04
Systolic blood pressure, mm Hg	123.0	84-224	124.0	93-200	122.0	84-224	.27
Diastolic blood pressure, mm Hg	76.0	49-118	77.0	55-111	76.0	49-118	.11
Body surface area	1.86	1.1-3.0	1.9	1.3-2.8	1.9	1.1-3.0	.02
Anthracycline, mg/m^2[b]	168.7	35.1-734.2	206.3	49.2-693.3	157.2	35.1-734.2	< .01
Chest radiation dose, cGy	2,600.0	150-6,200	2,600.0	450-4,500	2,600.0	150-6,200	< .01
Mean heart radiation dose, cGy[c]	2,070.0	50-4,920	2,320.0	170-4,920	2,025.0	50-4,520	< .01

Abbreviation: SJLIFE, St Jude Lifetime Cohort.

[a]Current and past smoking.

[b]Adriamycin equivalent dose.

[c]Among participants with chest-directed radiation therapy only.

TABLE 2. Model Performance Results of Each ECG Feature Extraction Method

Method	No. Features Extracted	No. Features Selected	AUC	Sensitivity (%)	Specificity (%)
Descriptive statistics	168	8	0.74	65	67
Sample entropy	84	10	0.67	63	65
PSPR	72	10	0.80	68	72
Fourier transformation	528	14	0.72	63	66
Discrete wavelet transformation	384	14	0.73	65	67
Continuous wavelet transformation	372	15	0.73	66	69
CNN	448	15	0.76	71	71

Abbreviations: AUC, area under the curve; CNN, convolutional neural network; PSPR, probabilistic symbolic pattern recognition.

78%, 81%, and 0.88 (95% CI, 0.84 to 0.92), respectively, 5-9 years after the baseline visit (Data Supplement).

DISCUSSION

Machine learning techniques applied to ECG data collected among a large clinically assessed cohort of adult survivors of childhood cancer (22 years from cancer diagnosis) were able to accurately classify the risk for late-onset cardiomyopathy (AUC 0.89 for the model incorporating ECG and clinical data). A model using only ECG features was similar (AUC 0.87, sensitivity 76%, and specificity 79%), and both outperformed the clinical model (AUC 0.69 sensitivity 62%, and specificity 66%). Our model performance predicting cardiomyopathy in 0.5-5 years or 5-9.2 years was similar, suggesting time invariant cardiomyopathy risk up to 9.2 from the baseline ECG. Artificial intelligence (AI) may help classify high-risk cancer survivors before clinical detection could occur and in doing so identify survivors in need of enhanced surveillance and/or early intervention to ameliorate long-term morbidity. If these findings hold, AI may also help limit subsequent costly evaluations and procedures in patients who are less likely to develop events such as cardiomyopathy.

Predictive models for heart disease are increasingly common. Our model performance exceeded that reported among survivors participating in the well-characterized Childhood Cancer Survivor Study. Using self-reported data from more than 13,000 five-year cancer survivors (median age at follow-up 32 years and range 6-59 years; median survival time 19 years and range 0-34 years) in a model focused primarily on chemotherapy and radiation exposures yielded an AUC ranging from 0.68-0.82 for predicting heart failure at age 40 years[13] Using similar models, the same investigators reported AUCs ranging from 0.66-0.67 for ischemic heart disease and 0.68-0.72 for stroke by age 50 years in this population.[14] Chen et al[15] incorporated traditional cardiovascular risk factors (hypertension, dyslipidemia, and diabetes) reported by Childhood Cancer Survivor Study participants to predict risk for heart failure at 50 years and obtained AUCs between 0.69 and 0.77 across age categories 20-35 years. Additionally, applying convolutional neural networks in a large (n = 180,922) noncancer population evaluated over 24 years, Attia et al[16] recently reported an AUC of 0.87 for identifying atrial fibrillation based on a single ECG. Our model, which applies AI to ECG data, predicts cardiomyopathy as well as, or better than, these previous studies.

AI has also shown promise for the early detection of cardiac dysfunction in other populations. Cardiac sympathetic denervation has been recognized as an early feature in Parkinson's Disease (PD),[17-20] and reduced heart rate variability has been associated with increased risk of PD.[21] Work from our group has shown that classification of PD is possible using ECGs collected in the presymptomatic state.[22] Attia et al[23] have also used neural networks on 12-lead ECGs to identify asymptomatic left ventricular dysfunction, suggesting that early disease might subtly affect cardiac conduction.

The use of a relatively inexpensive and widely available test such as an ECG to generate risk stratification for childhood cancer survivors holds appeal. Currently recommended as a baseline assessment by the Children's Oncology Group's Long-Term Follow-up Guidelines for Survivors of Childhood, Adolescent, and Young Adult Cancers, the focus has largely been to monitor QT intervals (25). Our study suggests additional value from ECGs obtained on cancer survivors. The addition of seven clinical variables to the ECG data yielded only a marginal improvement in AUC, from

TABLE 3. The Confusion Matrix for Prediction of Cardiomyopathy

		Predicted		
		No Cardiomyopathy	Cardiomyopathy	
Actual	No cardiomyopathy	True negatives: 892	False positives: 208	Specificity: 81%
	Cardiomyopathy	False negatives: 26	True positives: 91	Sensitivity: 78%
		Negative predictive value: 97%	Positive predictive value: 30%	Accuracy: 81%

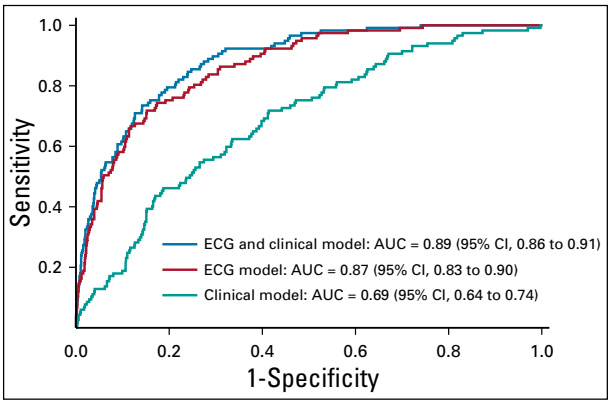

FIG 2. Receiver operating characteristic curves of the models based on ECG features, clinical features and ECG, and clinical features. AUC, area under the curve.

0.87 to 0.89, highlighting the informative value of the digital ECG data. The performance of such predictive models suggests the possibility for remote monitoring via mobile or wearable devices with ECG recording functionality. With such an approach, at-risk patients can potentially be identified for heightened surveillance that could potentially be facilitated by remote applications.

Understandably, the features identified in our models are not immediately interpretable and bear little relationship to classical ECG characteristics such as p-waves, QRS complexes, and t-waves typically used for diagnosis of chamber dysfunction. Clinical use of our model will require its execution on the digital data underlying standard 12-lead ECGs—a computationally simple task—to generate a risk score for future cardiomyopathy. The development of such predictive models might assist clinicians by identifying those who could benefit from early initiation of preventive therapeutics to reduce or minimize the risk of future cardiomyopathy and associated heart failure.

Despite the large volume of clinically assessed data available in the SJLIFE cohort, there are a number of limitations to acknowledge. Cohort participants comprised childhood cancer survivors evaluated at a single institution, and although we performed five-fold cross-validation for model training and testing, external validation is warranted in other cancer cohort data sets where clinically assessed long-term follow-up is available. However, it should be noted that there is no other comparable childhood cancer survivor cohort to SJLIFE in the United States with similarly clinically assessed data for external validation. Therefore, future effort for external validation will require international collaboration with cohorts with sufficient long-term follow-up ECHO and ECG screening of childhood cancer survivors cohorts. Second, although the cohort size was relatively large (1,217 patients), the small number of patients who developed cardiomyopathy precluded our ability to test whether the model performed differently by sex, age, race, or other characteristics. Additional follow-up as the SJLIFE cohort ages may permit theses analyses. Finally, we did not evaluate whether deep learning applied to other tools, such as echocardiograms, could also predict cardiomyopathy, add to, or outperform the predictions made from the ECG. Future work on these topics is needed.

In conclusion, we developed an AI-assisted model based on ECG features predictive of cardiomyopathy with a sensitivity of 76%, a specificity of 79%, and an AUC of 0.87, suggesting that machine learning may play a role in the identification of childhood cancer survivors at risk for developing cardiomyopathy. Future investigation will focus on validation in other cancer survivor populations and the application of remote monitoring techniques to screen and monitor long-term survivors of childhood cancer.

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AUTHORS' DISCLOSURES OF POTENTIAL CONFLICTS OF INTEREST

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Consulting or Advisory Role: GENERAL DYNAMICS Information Technology Peer Review and Science Management

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