Real-time prediction of cardiovascular diseases using reservoir-computing and fusion with electronic medical record

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2022 IEEE 4th International Conference on Artificial Intelligence Circuits and Systems (AICAS) | 978-1-6654-0996-4/22/$31.00 ©2022 IEEE | DOI: 10.1109/AICAS54282.2022.9869980

***Abstract*—Cardiovascular diseases (CVDs) are a leading cause of death in USA and globally, but many people suffering from CVDs are asymptomatic in the early stages leading to reduced awareness, and less chances of managing the disease. This work presents a potential solution for at-home monitoring by leveraging predictive power of artificial intelligence (AI) for developing a fusion framework that combines patient electrocardiogram (ECG) and electronic medical record (EMR) for predicting risk of CVDs at an early stage. To improve energy-efficiency of wearable ECG sensor, in-sensor analog reservoir-computing is proposed that precludes need for front-end digitization and transmission of raw sensor data. The fusion framework predicts ischemic heart disease (I20-I25 ICD codes) with area under the receiver operating characteristic (AUROC) of 0.91, and other heart diseases (130-I52 ICD codes) with AUROC of 0.95 which is better than state-of-the-art while not requiring laboratory test results.**

***Index Terms*—cardiovascular disease, artificial intelligence, in-memory computing, data fusion, artificial neural network, reservoir-computer**

I. Introduction

Ambulatory monitoring is becoming increasingly important for medical specialties, and particularly cardiovascular care, but continuous monitoring is difficult at patient home since current CVD risk prediction models generally require laboratory test results. Automating CVD risk prediction at patient home reduces burden on healthcare system and can potentially improve patient outcomes. We propose an AI framework that uses only ECG and EMR data, and can be used by clinically untrained users to self-monitor risk of CVDs. As shown in Fig. 1, the proposed framework has the following components – a. wearable sensor for collecting patient ECG data continuously over long periods of time b. AI models that predict CVD risk from ECG and EMR c. a meta-classifier that performs fusion of prediction scores from ECG and EMR models to provide accurate, personalized inference for each user. The proposed framework is simple, non-invasive and requires only a wearable sensor and a smart-phone for data collection and natively running AI models while ensuring security of patient data.

To improve energy efficiency of wearable sensor, we propose in-sensor AI model for analyzing ECG signal (ECG model) that significantly reduces transmission volume by transmitting only prediction scores for each segment than raw

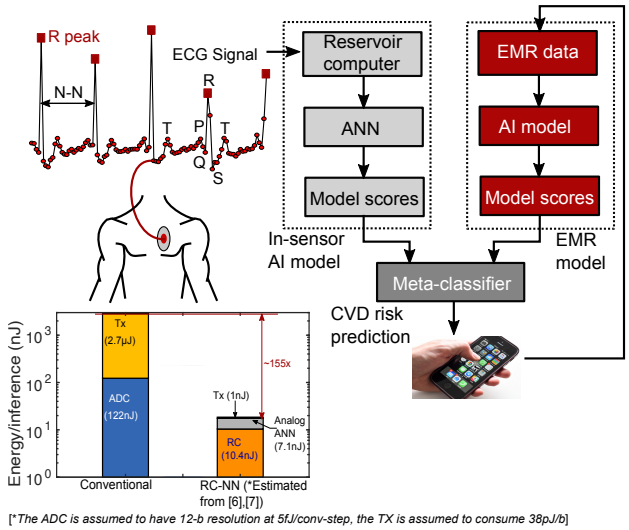

Fig. 1: Overview of the proposed AI framework for fusion of sensor and EMR data for CVD risk prediction

data. Reducing transmission energy is critical for wearables with small energy budget since wireless transmission is typically the largest consumer of energy. However, integrating AI classifier into a resource constrained wearable is challenging since AI algorithms can be computationally intensive. The majority of attempts [1]–[5] to reduce energy consumption of AI circuits use a) in-memory/near-memory computing b) reduced precision computations to reduce communication costs of movement of input activations (IAs)/output activations (OAs)/weights between memory and compute units. With reduced transmission energy and optimized AI computations, front-end analog-to-digital conversion (ADC) and digital feature extraction becomes a major energy bottleneck for bio-medical sensors. Digitization of ECG signals before AI computations is particularly energy-inefficient since ECG signal is sparse and only carries meaningful information in small portions of the entire segment - the QRS complex, and P and T waves (see Fig. 1). To address energy bottleneck due to front-end digitization, we propose an analog signal processing reservoir-computing neural network (RC-NN) that directly processes analog ECG samples. For 6 second ECG segments sampled at 1kHz, the proposed technique can reduce

TABLE I: Demographic distribution of the cohort used

Characteristics (N=no CVD, D = CVD)		Ischemic heart diseases						Other heart diseases					
		6 months		1 year		2 years		6 months		1 year		2 years	
		N	D	N	D	N	D	N	D	N	D	N	D
		1394	133	1387	140	1384	143	1393	134	1385	142	1381	146
Gender	Male	710	59	708	61	707	62	710	59	703	66	706	63
	Female	684	74	679	79	677	81	683	75	682	76	675	83
Ethnic group	Hispanic	42	5	42	5	42	5	42	5	42	5	42	5
	Non-hispanic	1249	118	1242	125	1239	128	1248	119	1239	128	1235	132
	Unreported	103	10	103	10	103	10	103	10	104	9	104	9
Age bins (years)	<30	123	9	123	9	123	9	123	9	123	9	123	9
	30-50	307	22	306	23	303	26	307	22	303	26	301	28
	50-70	639	72	637	74	636	75	639	72	635	76	636	75
	70-89	325	30	321	34	322	33	324	31	323	32	321	34

energy consumption by $155\times$ compared to naively transmitting all digitized ECG samples. The energy consumption of the proposed RC-NN is based on prior prototypes fabricated by our group [6], [7]. The rest of this paper is organized as follows: Section II introduces the dataset and the AI models used for CVD prediction, Section III presents the CVD risk prediction results with the proposed fusion AI framework, and Section IV brings up the conclusion.

II. Fusion AI framework

A. Dataset

Dataset of de-identified CVDs was obtained from Emory University Hospital (EUH) with the approval from Emory Institutional Review Board (IRB) for our informatics study. The cohort consists of 1527 patients admitted to the Intensive Care Units (ICUs) within the Emory Healthcare system in Atlanta, Georgia from 2001 to 2019, and consists of patients with ischemic heart diseases (I20-I25 ICD codes), patients with other heart diseases (I30-I52 ICD codes) and the rest without CVDs. Table I presents the overall patient demographics used in this work. The cohort is partitioned into 1222 training samples and 305 test samples randomly. The proposed AI framework analyzes 6s ECG segments and predicts CVD at 6 months, 1 year and 2 years before event.

B. Reservoir-computing neural network

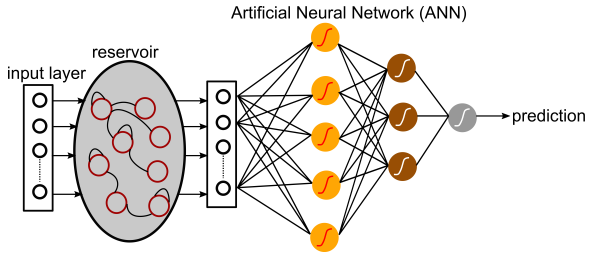

Fig. 2: Schematic of the reservoir-computing neural network used for prediction from ECG

Fig. 2 shows schematic of the RC-NN used for in-sensor analysis of ECG signal. Reservoir-computing (RC) is a well-known computing paradigm that uses static nonlinearity to project the input signal to high-dimensional space, thus allowing easier separation of different input classes. No training is performed in the input or reservoir layers, and the weights are drawn from random distribution. While reservoir computing was invented almost two decades earlier [8] and has been extensively used in the machine-learning literature, hardware implementation of reservoir computing have been mostly on optics/photonics platform [9], [10], with few analog implementations [11]–[14]. In contrast to prior analog RC, the RC-NN in this work is based on the architecture in our prior work [6] and does not require large capacitors to realize biological time-constants which is energy-inefficient, and does not require background calibration for analog delay elements or nonlinearity element. A 3-layer artificial neural network (ANN) is used as read-out layer for the RC-NN and performs classification on the states of neurons in the reservoir layer.

Output of the RC with N reservoir neurons can be mathematically expressed as

$$\vec{R_k}[n] = h\left(G_i\vec{W} \times \vec{X}[n] + G_f\vec{W_r} \times \vec{R_k}[n-1]\right) \quad (1)$$

where $\vec{X}$ is analog ECG input with D samples, $\vec{W}$ is $N \times D$ input weight matrix, $\vec{W}$ ($D >> N$), $\vec{W_r}$ is $N \times N$ interconnection weight matrix for the reservoir layer, $H(\cdot)$ is nonlinear activation for RC, G_i is input scaling factor and G_f is feedback gain. As in [6], identity matrix is used for $\vec{W_r}$ which simplifies the hardware implementation. The restriction on $\vec{W_r}$ is consistent with [15] which has shown through systematic investigation that a simple reservoir architecture with sparse interconnections provides comparable accuracy as more complicated reservoir architectures. The RC-NN architecture is optimized on the prediction of ischemic heart diseases 6 months before the event through 10-fold cross-validation on the training data. Table II shows mean and standard deviation of F1 score on the diseases class for different values of G_i, G_f and N. $G_i = 0.7$, $G_f = 0.1$ and $N = 40$ are selected corresponding to the highest mean F1 score. Fig. 4 shows the results of optimization of the 3-layer ANN architecture by plotting the mean F1 score as a function of [number of neurons in the first hidden layer, number of neurons in the second hidden layer]. Based on the optimization results, the number of neurons in the first and second hidden layers are set to 20 and 6 respectively.

TABLE II: Parameter optimization for reservoir layer

		N=10		N=25		N=40		N=55	
		F1 score		F1 score		F1 score		F1 score	
Gf	Gi	Mean	Sigma	Mean	Sigma	Mean	Sigma	Mean	Sigma
0.1	0.1	0.7974	0.0217	0.7885	0.0195	0.8472	0.0063	0.8329	0.0188
0.1	0.4	0.8018	0.0058	0.8179	0.0107	0.8292	0.0103	0.8372	0.0063
0.1	0.7	0.8407	0.0072	0.8477	0.0091	0.8577	0.0022	0.8494	0.0058
0.1	1	0.8405	0.0145	0.8475	0.0106	0.8427	0.0104	0.8490	0.0035
0.4	0.1	0.8051	0.0163	0.8275	0.0151	0.8356	0.0134	0.8201	0.0163
0.4	0.4	0.8376	0.0039	0.8321	0.0070	0.8386	0.0082	0.8419	0.0100
0.4	0.7	0.7755	0.0164	0.8402	0.0088	0.8251	0.0103	0.8242	0.0174
0.4	1	0.7758	0.0131	0.7937	0.0090	0.8087	0.0064	0.8087	0.0102
0.7	0.1	0.7837	0.0070	0.8128	0.0112	0.8442	0.0041	0.8262	0.0107
0.7	0.4	0.7681	0.0134	0.7619	0.0065	0.7990	0.0132	0.7909	0.0213
0.7	0.7	0.6462	0.0146	0.7473	0.0102	0.7648	0.0057	0.7487	0.0067
0.7	1	0.7349	0.0187	0.7841	0.0099	0.7276	0.0160	0.7538	0.0108
1	0.1	0.5977	0.0173	0.7077	0.0320	0.6990	0.0176	0.6588	0.0426
1	0.4	0.6069	0.0257	0.6145	0.0143	0.6428	0.0183	0.6455	0.0152
1	0.7	0.6162	0.0145	0.6080	0.0228	0.6277	0.0313	0.6183	0.0089
1	1	0.6324	0.0091	0.7678	0.0059	0.8093	0.0112	0.8053	0.0138

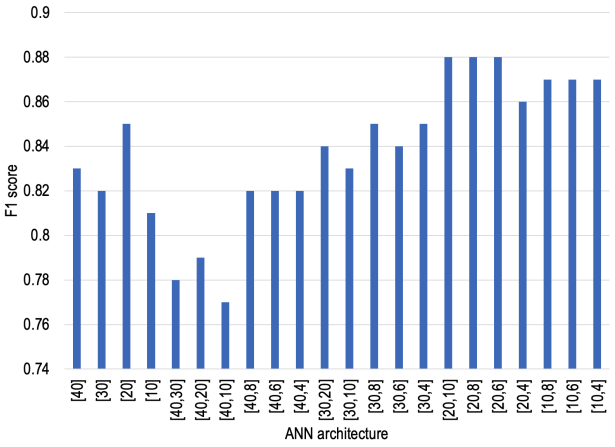

Fig. 3: Optimization of the ANN architecture

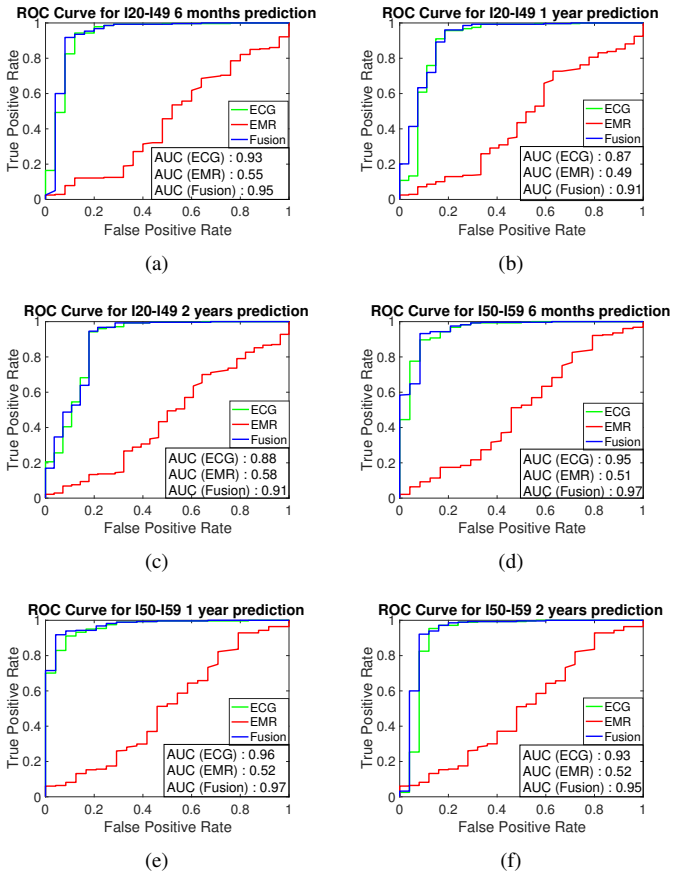

Fig. 4: AUROC plots for (a) 6 months (b) 1 year (c) 2 years before ischemic heart diseases (I20-I25) event; and (d) 6 months (e) 1 year (f) 2 years before other heart diseases (I30-I52) event

TABLE III: CVD prediction results with EMR models

	Ischemic heart disease			Other heart diseases		
	6 months	1 year	2 years	6 months	1 year	2 years
Random forest	0.53	0.53	0.53	0.53	0.51	0.51
Linear SVM	0.52	0.53	0.53	0.55	0.55	0.54
Logistic regression	0.48	0.48	0.48	0.48	0.48	0.48

TABLE IV: CVD prediction performance

ECG model						
3-layer ANN	Ischemic heart diseases			Other heart diseases		
	6 months	1 year	2 years	6 months	1 year	2 years
Macro F1	0.92	0.84	0.88	0.88	0.85	0.86
Sensitivity	0.94	0.97	0.96	0.97	0.98	0.95
Specificity	0.86	0.86	0.9	0.94	0.81	0.85
EMR model						
Linear SVM	Ischemic heart diseases			Other heart diseases		
	6 months	1 year	2 years	6 months	1 year	2 years
Macro F1	0.53	0.53	0.53	0.55	0.55	0.54
Sensitivity	0.92	0.92	0.92	0.88	0.88	0.88
Specificity	0.09	0.11	0.11	0.21	0.21	0.2
Fusion model						
2-layer ANN	Ischemic heart diseases			Other heart diseases		
	6 months	1 year	2 years	6 months	1 year	2 years
Macro F1	0.94	0.9	0.94	0.94	0.88	0.93
Sensitivity	0.97	0.97	0.97	0.98	0.98	0.97
Specificity	0.89	0.91	0.91	0.9	0.81	0.89

C. EMR model

The EMR model uses 4 categorical (gender, age, race, ethnicity) and 3 textual data-types (reason for admission, diagnosis, admit order) for CVD risk prediction. As the first data pre-processing step, we applied standard data cleaning steps including removing empty cells and special characters. For conversion of categorical data to numerical features, we used label encoding technique. The vectorization of textual data was performed using term frequency-inverse document frequency (Tf-idf) algorithm. Typically, the Tf-idf weight is composed of two terms: the first term computes the normalized term Frequency (TF) which is given by TF(n) = (number of times term n appears in a document) / (total number of terms in the document). The second term in the TF-idf weight is the inverse document frequency which is computed as the logarithm of the number of documents in the corpus divided by the number of documents where the specific term appears. We trained the Tf-idf tokenizer using our training dataset. Finally, the numeric representation of the categorical data and Tf-idf representation of textual data are combined using linear concatenation. We standardized features by removing the mean and scaling to unit variance. Centering and scaling are performed independently on each feature by computing the relevant statistics on samples in the training set. The mean and standard deviation values are then used on holdout test data using the same transformation function. Given the static nature of EMR, we designed a single-point prediction model for distinguishing CVD versus non-CVD cases, and tried parametric (logistic regression) and non-parametric machine learning models (linear support vector machine - SVM, Random Forest). Hyper-parameter tuning is done through 10-fold cross validation on the training data. Table III shows the accuracy of different EMR models on the test set. Linear SVM achieves the highest accuracy and is used for fusion with predictions from sensor data.

TABLE V: Comparison with state-of-the-art CVD prediction works

	Data source	Model	Time-to-event	F1 score	AUC	Vitals	Lab tests	Demographics
[16]	New Zealand primary care cohort	Cox	2 years	–	0.73	2	4	3
[17]	Fuwai hospital	Random forest	3 years	0.56	0.79	2	9	1
[18]	Korean national health sample cohort	DNN	2 years	0.12	0.78	7	16	2
[19]	Shenzhen medical data	Logistic regression	3 years	–	0.84	2	6	3
[20]	ADVANCE cohort	Cox	4 years	–	0.7	5	18	4
[21]	Cardiff diabetes database	Cox	4 years	–	0.67	2	3	1
This work	Emory University hospital	Fusion	2 years	**0.93**	**0.91/0.95**	**1**	**0**	7

III. CVD PREDICTION RESULTS

A 2-layer ANN with 7 hidden neurons is used as the meta learner that combines prediction scores from the ECG and EMR model for the final CVD risk prediction. Table IV summarizes performance of the ECG, EMR and fusion models. Fusion of ECG and EMR improves F1, specificity and sensitivity compared to ECG and EMR models by themselves. Fig. 4 shows the AUROC plots for prediction of CVD events at different time-points. Table V compares this work with state-of-the-art CVD prediction works. The proposed technique achieves the highest F1 score and AUC without requiring laboratory tests and using a single physiological signal which is a prime enabler of the proposed solution for at-home monitoring and is the key differentiation from existing works.

IV. CONCLUSION

This work has demonstrated a late fusion AI framework for continuously monitoring user health at-home and predicting CVD risk at least two years before CVD event. The proposed work can potentially transform management of patients with CVDs and improve outcomes.

ACKNOWLEDGMENT

This work is supported in part by National Science Foundation grant CCF-1948331 and Air Force Research Laboratory under agreement number FA8650-18-2-5402.

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