LETTER TO THE EDITOR

More Than Meets the AI

Electrocardiograms in Heart Failure Prognosis

We read with interest the paper by Schlesinger et $al¹$ $al¹$ $al¹$ on a deep learning model which predicts mean pulmonary capillary wedge pressure (mPCWP) using electrocardiogram (ECG) recordings, proving particularly accurate in patients with heart failure (HF). These findings may have implications for the future of the noninvasive assessment of mPCWP, enabling early detection and management of left ventricular failure, thereby improving HF prognosis.

Another fundamental monitored parameter for patients with HF in intensive care is central venous pressure (CVP), which in addition to mPCWP and arterial blood pressure determines volume therapy. Recently, Sadrawi et al^{[2](#page-0-1)} developed a deep convolutional autoencoder system able to predict CVP (Pearson's linear correlation: 0.916 \pm 0.001, root mean squared error: 2.220 \pm 0.039 mm Hg, mean absolute error: 1.329 \pm 0.036 mm Hg) and arterial blood pressure from ECG recordings. Moreover, pulmonary arterial pressure, an indicator of pulmonary hypertension (PH), is of prognostic value in HF and can also be deduced from ECG recordings.^{[2](#page-0-1)} Recent evidence suggests artificial intelligence (AI) algorithms can predict PH directly from ECG tracings. A cohort study by Kwon et al^{[3](#page-0-2)} developed an algorithm integrating deep and convolutional neural networks using 56,670 twelve-lead ECGs from 24,202 patients and tested its performance using 3,174 ECGs from 3,174 patients in 2 different hospitals. During the follow-up period, \sim 17% of patients developed PH; patients identified by AI as at high risk of developing PH at the initial echocardiogram had higher development rates of PH during follow-up than those identified as low risk (31.5% vs 5.9%, $P < 0.001$). As with mPCWP, measuring CVP and PH requires skill-dependent invasive procedures, so there remains the need to determine hemodynamic parameters using routine, noninvasive equipment. Thus, we would suggest integrating these data from ECGs together. The application of Schlesinger et al's deep learning model to biomedical data is further set in context by Toma et al.[4](#page-0-3)

Potter et al^{[5](#page-0-4)} showed improved accuracy of AI predictions by adding data from the signal processing method called continuous wavelet transform (CWT), which identifies ECG abnormalities in a timefrequency format. The AI model trained using CWT data was used to predict left ventricular dysfunction in patients at risk of HF. Model performance was tested in a group of 111 patients for which area under the curve (AUC) was 0.83 (95% CI: 0.74-0.92). This was markedly better than conventional prediction methods such as the ARIC (Atherosclerosis Risk In Communities) HF risk score (AUC: 0.72) and N-terminal pro–B-type natriuretic peptide (AUC: 0.53). Thus, it would be interesting to see the effect of CWT data on the accuracy of mPCWP predictions by Schlesinger et al. $¹$ $¹$ $¹$ </sup>

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The authors have reported that they have no relationships relevant to the contents of this paper to disclose.

The authors attest they are in compliance with human studies committees and animal welfare regulations of the authors' institutions and Food and Drug Administration guidelines, including patient consent where appropriate. For more information, visit the [Author Center.](https://www.jacc.org/author-center)

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