Introduction: Forecasting arrhythmic time-series data for cardiac action potentials (APs) is challenging, primarily because cardiac cells and tissue exhibit complex dynamics during arrhythmias. Previous work has shown that high-quality predictions can be found using an autoencoder network combined with a traditional echo state network (AE-ESN). We assessed the relation between the training data length and quality of predictions for an AE-ESN-based machine-learning approach to time-series forecasting for cardiac voltage data.

Methods: We used an AE-ESN to train and predict cardiac APs. The AE consists of a layered long short-term memory neural network that encodes the input in a feature-rich representation, then reconstructs the input from this latent space. The ESN has a randomly constructed reservoir with random weights between connected nodes and a fully connected linear read-out layer. Only the weights of the readout layer are updated during training, making the ESN approach computationally efficient. Our dataset was a 20.6-second microelectrode recording from a zebrafish heart under a constant diastolic interval pacing protocol, which led to complex irregular alternans dynamics.

Results: We analyzed training requirements for the AE-ESN by considering AP duration (APD) error for predictions using 125, 17, and 6 training APs (TAPs); see figure. With 125 TAPs, mean APD$_{50}$ error across 33 APs was $2.9 \pm 1.4$ms, which increased marginally to $3.3 \pm 2.8$ms when only 17 TAPs were used. With 6 TAPs, however, APD$_{50}$ error increased to $6.9 \pm 7.5$ms, consistent with poorer AP shape predictions. When APD$_{80}$ was chosen to reflect more of repolarization, 125 TAPs produced $4.9 \pm 2.6$ms mean error, with increases to $6.1 \pm 4.2$ms and $9.9 \pm 6.9$ms with 17 and 6 TAPs, respectively.

Conclusions: The AE-ESN approach can be used to forecast complex AP recordings with low mean APD$_{50}$ error ($<5$ms) using as few as 17 TAPs, but more TAPs are needed to achieve similar mean error in APD$_{80}$.