

A novel automated junctional ectopic tachycardia detection tool for children with congenital heart disease



Jamie L.S. Waugh, MASC,* Raajen Patel, MS,* Yilong Ju, PhD,[†] Ankit B. Patel, PhD,^{‡§} Craig G. Rusin, PhD,^{||} Parag N. Jain, MD[¶]

From the *Division of Research, Medical Informatics Corp, Houston, Texas, [†]Department of Computer Science, Rice University, Houston, Texas, [‡]Department of Neuroscience, Baylor College of Medicine, Houston, Texas, [§]Department of Electrical and Computer Engineering, Rice University, Houston, Texas, ^{||}Division of Cardiology, Department of Pediatrics, Baylor College of Medicine, Texas Children's Hospital, Houston, Texas, and [¶]Division of Critical Care Medicine, Department of Pediatrics, Baylor College of Medicine, Texas Children's Hospital, Houston, Texas.

BACKGROUND Junctional ectopic tachycardia (JET) is a prevalent life-threatening arrhythmia in children with congenital heart disease (CHD), with marked resemblance to normal sinus rhythm (NSR) often leading to delay in diagnosis.

OBJECTIVE To develop a novel automated arrhythmia detection tool to identify JET.

METHODS A single-center retrospective cohort study of children with CHD was performed. Electrocardiographic (ECG) data produced by bedside monitors is captured automatically by the Sickbay platform. Based on the detection of R and P wave peaks, 2 interpretable ECG features are calculated: P prominence median and PR interval interquartile range (IQR). These features are used as input to a simple logistic regression classification model built to distinguish JET from NSR.

RESULTS This study analyzed a total of 64.5 physician-labeled hours consisting of 509,833 cardiac cycles (R-R intervals), from 40 patients with CHD. The extracted P prominence median feature

is much smaller in JET compared to NSR, whereas the PR interval IQR feature is larger in JET compared to NSR. The area under the receiver operating characteristic curve for the unseen patient test cohort was 93%. Selecting a threshold of 0.73 results in a true-positive rate of 90% and a false-positive rate of 17%.

CONCLUSION This novel arrhythmia detection tool identifies JET, using 2 distinctive features of JET in ECG—the loss of a normal P wave and PR relationship—allowing for early detection and timely intervention.

KEYWORDS Congenital heart disease; Junctional ectopic tachycardia; Arrhythmia; Time series analysis; Feature extraction; Signal processing; Machine learning

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Introduction

Arrhythmias are common during the early postoperative period, following cardiac surgery to repair congenital heart disease (CHD), with junctional ectopic tachycardia (JET) shown to be the most common arrhythmia.^{1,2} JET not only extends intensive care unit (ICU) stay; it also increases patient risk of morbidity and mortality.³

JET manifests as a narrow QRS complex tachyarrhythmia, usually with atrioventricular dissociation. The heart rate is usually higher than the 95th percentile value corresponding to the patient's age (heart rate >170–180 beats per minute [bpm] in infants) and the heart electrical activity

is found to begin in the autonomic tissue surrounding the atrioventricular node.⁴

One of JET's most distinctive features observed on an electrocardiogram (ECG) is the disappearance of the P wave or the appearance of retrograde P waves.⁵ Although the QRS complex is narrow, its morphology remains similar to that which occurs during normal sinus rhythm, resulting in a delay in diagnosis and subsequent interventions.

Early JET intervention has been shown to significantly improve patient outcomes.⁶ The need to recognize JET early places a large attentional burden on intensive care staff, especially nurses.⁷ This highlights the need for an automated framework that can rapidly and accurately recognize JET and alert clinicians and nurses, potentially saving patient lives.

Over the last decade, several computational frameworks for ECG-based arrhythmia detection have been proposed.

Address reprint requests and correspondence: Dr Parag N. Jain, Baylor College of Medicine, Texas Children's Hospital, MC E1420, 6651 Main St, Houston, TX 77030. E-mail address: pnjain@texaschildrens.org.

KEY FINDINGS

- The proposed P prominence median feature is smaller in junctional ectopic tachycardia (JET) compared to normal sinus rhythm.
- The proposed PR interval interquartile range feature is larger in JET compared to normal sinus rhythm.
- A simple logistic regression classifier using the above 2 interpretable features as inputs results in an area under the curve receiver operating characteristic curve of 93% for a test cohort consisting of 25 unseen patients.

These algorithms broadly fall into 2 categories: (1) purely handcrafted feature-based, that use statistical and signal processing techniques to extract simple but interpretable features; or (2) purely data-driven, that use lots of ECG data and complex machine learning architectures to extract powerful but clinically uninterpretable features.

To address this pressing need, we propose an ECG-based JET detection algorithm that combines clinically interpretable feature extraction and sophisticated data-driven learning. The proposed algorithm uses just 2 features that each capture P-wave displacement: P prominence median and PR interval interquartile range (IQR). We demonstrate that a simple logistic regression model using just these two features, distinguishes between JET and sinus rhythms with high accuracy on a test subset of patients.

Methods

Patient cohort

A single-center retrospective cohort study was performed at Texas Children's Hospital. The study was approved by the Institutional Review Board of Baylor College of Medicine. Informed consent was waived, as this was an observational study performed on aggregate de-identified patient information. The research reported in this paper adhered to the Helsinki Declaration guidelines.

All postoperative patients admitted to the cardiac intensive care unit (CICU) with CHD met inclusion criteria. Patients were randomly selected based on JET ICD-10 codes that occurred between January 2015 and May 2020 that were then confirmed by independent chart review.

Data collection

All patients admitted to the CICU at Texas Children's Hospital are continuously monitored using standard monitoring equipment. The physiologic data produced by these monitors are captured automatically using the Sickbay platform (Medical Informatics Corp, Houston, TX). Data captured by Sickbay includes both vital signs and high-resolution waveforms. Vital signs are generally collected once every 2 seconds and include time series such as heart rate, respiratory rate, oxygen saturation (SpO₂), all blood pressure measurements (mean, systolic,

diastolic), all ST-segment measurements, and temperatures. Waveform data are generally collected at 60–240 Hz, depending on the signal, and include time series such as ECG lead and pressure measurements, chest impedance, and the SpO₂ waveform. All data are time-synchronized. All signals and events measured from all devices and patients are passively recorded while they are in the CICU, resulting in a large, rich dataset that can be subdivided based on project.

ECG signal processing

The proposed method focuses on features based only on ECG data, since ECG is almost always measured. For consistency, only ECG lead II data are analyzed. Segments of data that include movement artifacts or are nonphysiological are discarded. The remaining ECG segments are filtered to remove frequencies outside of the range of 0.5–50 Hz.

Two interpretable ECG-only features based on the detection of R and P wave peaks are calculated: P prominence median and PR interval IQR. The detection of R and P wave peaks is implemented as follows.

After applying a 5 Hz third-order high-pass Butterworth filter and normalizing by the segment median and IQR, R wave peaks are detected using MATLAB's *findpeaks* function (MathWorks, Natick, MA). Thresholds for the minimum peak prominence, maximum peak width, and minimum peak distance are initialized and then adjusted based on the corresponding identified peak values. These were chosen heuristically as follows: the minimum peak prominence is initialized to 0.3, then set to one-third of the 75th percentile identified peak prominence; the maximum peak width is initialized to 0.2, then set to 3 times the 25th percentile identified peak width; and the minimum peak distance is initialized to 0.2, then set to half the 75th percentile identified peak distance. For the minimum peak distance initialization, 1 beat every 0.2 seconds corresponds to 300 bpm.^{8,9} For the maximum peak width initialization, assuming the QRS complex spans approximately 10% of the R-R interval period, an R peak width of 0.2 seconds corresponds to approximately 30 bpm.^{8,9} Inverted R waves are accounted for by finding peaks for both the original and inverted signals and then taking the set of identified peaks that has the higher median peak height.

The largest peak that occurs between 0.2 seconds and 0.07 seconds⁹ before each of the identified R wave peaks is determined using *findpeaks*. This peak is identified as the P wave unless it appears to be a pacing spike. If the second-largest peak occurs after the first-largest, has a larger width, and has a height (normalized by the minimum search period value) greater than 30% of that of the largest peak, the second-largest peak is taken as the P wave. The first is assumed to be a pacing spike.

All P prominence values are returned by *findpeaks* when the P waves are identified; P prominence is based on the vertical distance between the identified P peaks and the signal's nearby minima. The median P peak prominence over the past 130 seconds was found to be an important feature for the

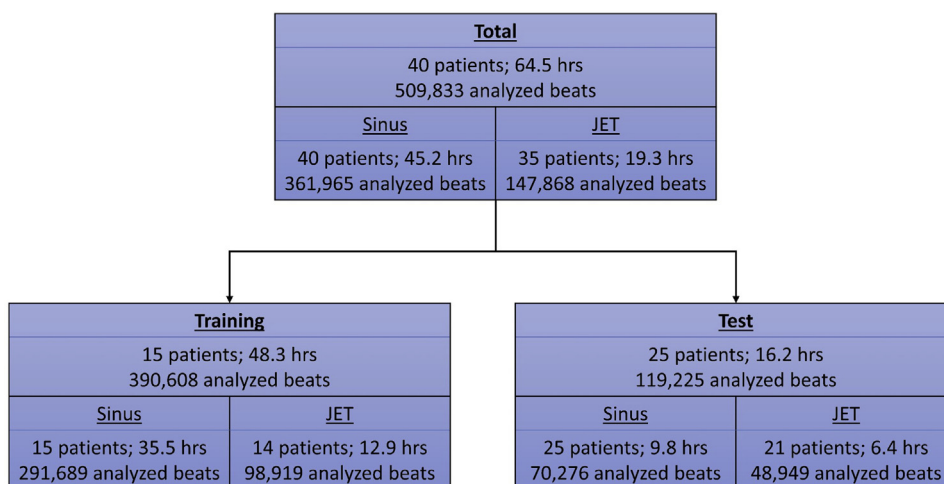


Figure 1 Cohort breakdown in terms of expert-labeled hours and the corresponding number of patients they span as well as analyzed beats, for both sinus and junctional ectopic tachycardia (JET) labels, as well as Training and Test cohorts.

classification of ECG data as JET or sinus, as is commonly described by physicians experienced with JET patients.

The PR interval is taken to be the time between the identified P and R peaks. The IQR of the PR interval over the past 10 seconds was also found to be useful in the classification of ECG data as JET or sinus. This is because when P waves disappear in JET, the peak detector still chooses the largest peak, but it is an arbitrary peak and thus inconsistent with time.

Classification model

The proposed method uses a simple logistic regression model with the features described above passed in as input. Training and testing were done using Spark through Sickbay's MATLAB research interface, RapidResearch. The regularization parameter was chosen in training based on leave-1-patient-out cross-validation. No data from test patients were used in training. Once the model is trained, classification can be made for each new set of features, which are calculated on a per-beat basis.

Results

Patient cohort

The cohort and label breakdown are shown in [Figure 1](#). The complete cohort for this study consists of 40 patients with CHD, who had a median age of 1.8 (IQR spanning 0.15–6.4) years in which the male-to-female ratio was 18:22. [Supplemental Table 1](#) lists the fundamental cardiac diagnoses at times of admission for additional CHD context. A total of 64.5 hours of data was labeled by a senior pediatric cardiac critical care physician (of which 509,833 cardiac cycles [R-R intervals] were analyzed): 19.3 hours (147,868 analyzed beats) spanning 35 patients were labeled as JET and 45.2 hours (361,965 analyzed beats) spanning all 40 patients were labeled as sinus. The training cohort consists of 15 patients and a total of 48.3 physician-labeled hours (of which 390,608 R-R intervals were analyzed): 12.9 hours (98,919 analyzed beats) spanning 14 patients were labeled

as JET and 35.5 hours (291,689 analyzed beats) spanning all 15 patients were labeled as sinus. The test cohort consists of 25 patients and a total of 16.2 physician-labeled hours (of which 119,225 R-R intervals were analyzed): 6.4 hours (48,949 analyzed beats) spanning 21 patients were labeled as JET and 9.8 hours (70,276 analyzed beats) spanning all 25 patients were labeled as sinus.

Feature extraction

[Figure 2](#) demonstrates the differences between expert-labeled sinus and JET data on a per-patient basis. Each plot shows approximately 30 beats of raw ECG data starting near the beginning of an expert-labeled event. The identified R wave peak is centered for each beat (using the R peak detection described above). A period of data equal to half the average R-R interval (across the 2 R-R intervals that include the centered R wave) is plotted on either side of the centered R wave. Each row contains data from a unique patient. Though the overall ECG morphology changes significantly from patient to patient, each of these examples clearly shows the disappearance of the P wave in JET compared to sinus.

An example of expert-labeled sinus and JET for a patient is shown in [Figure 3](#), along with the beat-by-beat P prominence and PR interval features (shown by the red vertical lines and black horizontal lines, respectively). The P peak prominence values are larger, and the PR interval values are more consistent in data labeled as sinus compared to the same features in data labeled as JET. All time values in this paper are normalized to remove patient protected health information.

An example of the P prominence median and PR interval IQR features is shown in [Figure 4](#) (top and bottom, respectively) for a couple of patients. Features derived from expert-labeled sinus data are shown in the left column and features derived from expert-labeled JET data are shown in the right column. The P prominence median is much smaller in JET compared to sinus, whereas the PR interval IQR is larger in JET compared to sinus.

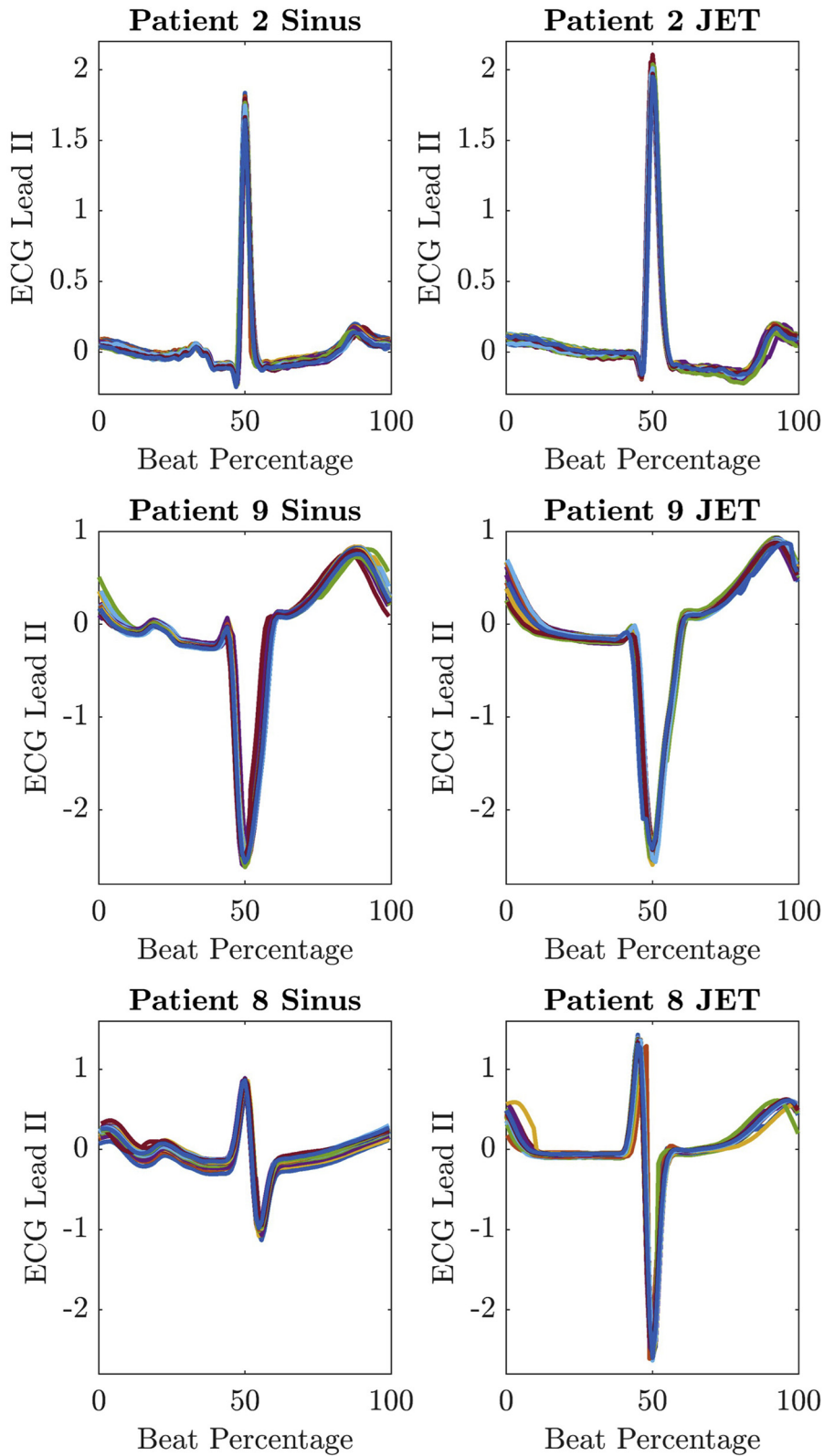


Figure 2 Comparison of intra and inter-patient sinus and junctional ectopic tachycardia (JET) beats. ECG = electrocardiogram.

Performance

The likelihood calculated for 4 test cohort patients across expert-labeled events is shown in Figure 5. The algorithm labels (green background color for sinus and red

background color for JET) align closely to the expert labels (left column plots contain expert-labeled sinus data and right column plots contain expert-labeled JET data).

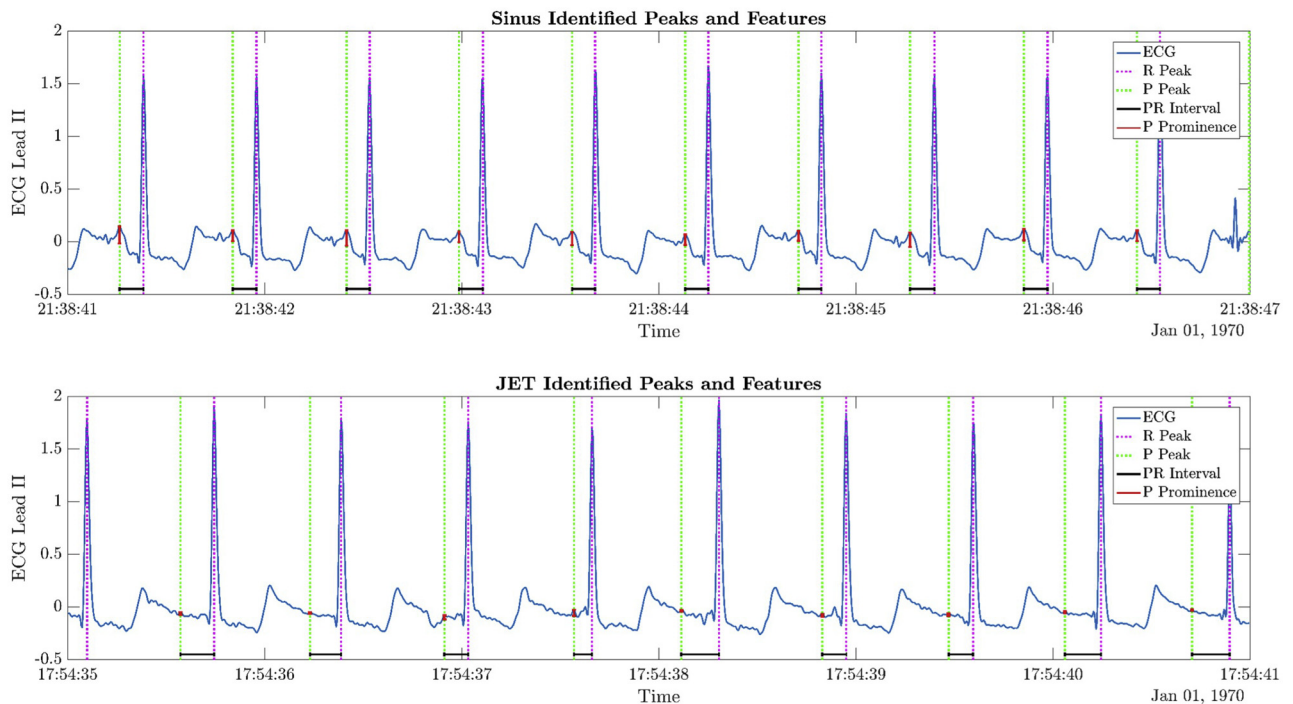


Figure 3 P prominence and PR interval features displayed relative to sinus (top) and junctional ectopic tachycardia (JET) (bottom) electrocardiogram (ECG) data on a per-beat basis.

Algorithm classification is performed per beat, each time a new set of features is available. JET likelihood is calculated as a linear combination of the 2 features (P prominence median and PR interval IQR), where a classification of JET is made when JET likelihood is above a selected threshold and a classification of sinus is made when JET likelihood is below that threshold. The visualizations in [Figure 5](#) show both JET and sinus algorithm-labeled events, where classification labels that are less than 5 seconds were discarded.

Similar to the comparison of JET and sinus features shown in [Figure 3](#), the trained model finds that JET likelihood increases as the P prominence median decreases and as the PR interval IQR increases. This means the model is most certain when both the P prominence median is large and the PR interval IQR is small (low JET likelihood) or when both the P prominence median is small and the PR interval IQR is large (high JET likelihood).

The test cohort was found to have a median heart rate of 124 bpm with an IQR of 34 bpm. Higher heart rate JET data were found to be misclassified more often than lower heart rate JET data. The median (IQR) heart rate of correctly classified JET data was 130 (32) bpm, whereas that of misclassified JET data was 154 (23) bpm.

Finally, the area under the curve (AUC) receiver operating characteristic (ROC) was calculated in Spark through Sickbay's MATLAB research interface, RapidResearch. This implementation had a 93% AUC. The AUC-ROC curve is plotted in [Figure 6](#) as well as the true- and false-positive rates relative to the choice of threshold. The threshold used for the above event identification plots was 0.73, resulting in a test

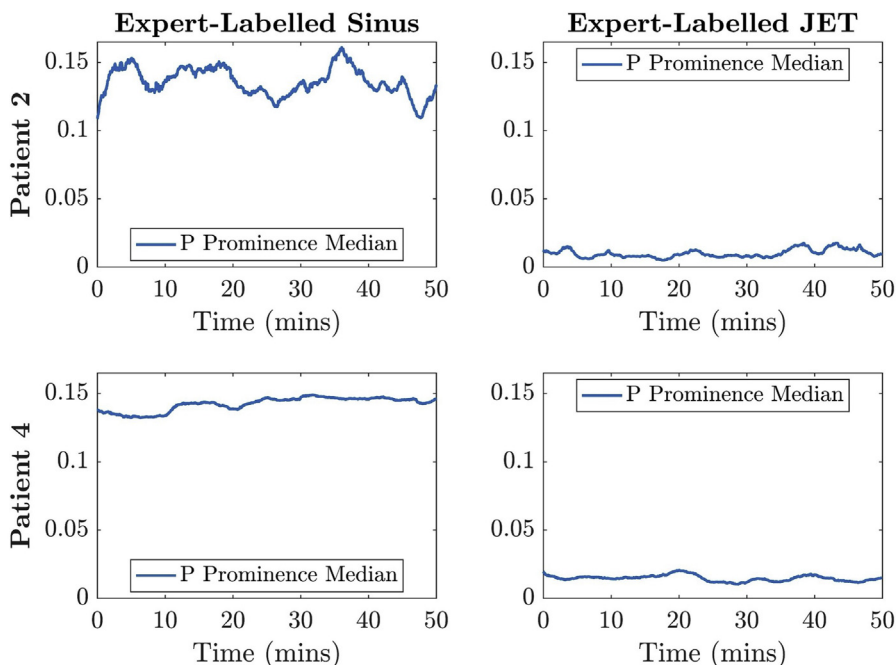
true-positive rate of 90% and a test false-positive rate of 17%. Note that the threshold (and thus the true- and false-positive rates) can be adjusted based on the user's preference and/or case at hand.

Discussion

JET is one of the most common postoperative arrhythmias observed in patients after surgery repairing congenital heart defects. Early intervention, which is critical to improving patient outcomes, is often delayed owing to the resemblance of ECG morphology during JET to that in sinus rhythm.¹⁰ To assist physicians and nurses with this enormous burden, we propose a computational framework for accurate and precise JET detection. Our framework distills the key morphologic features of an ECG waveform into just 2 parameters per cardiac cycle that are then summarized over larger intervals of time. These are fed into a logistic regression classifier, which we demonstrate achieves a high area under the ROC curve of 93%. Overall, this paper makes the following novel contributions: (1) a novel morphologic parameterization algorithm that is tailored toward efficient representation of ECG waveforms; and (2) an end-to-end computational framework that takes raw ECG data as input and predicts the likelihood of JET on a per-cardiac-cycle basis. Our framework achieves high sensitivity and specificity on a dataset of pediatric cardiac ICU patients.

There is an extensive body of literature that uses computational tools to extract meaningful information from ECG

P Prominence Median



PR Interval IQR

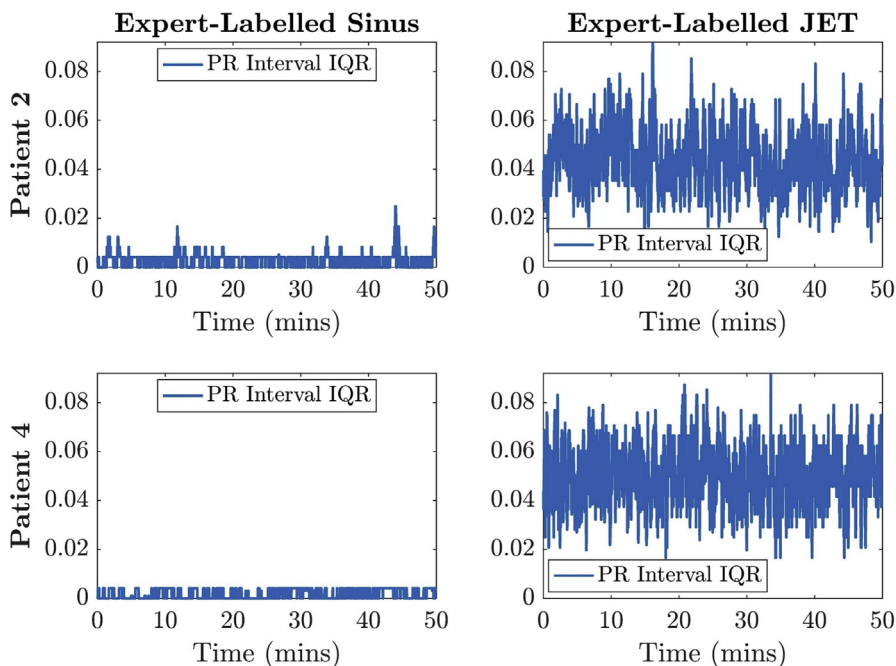


Figure 4 P prominence median (top) and PR interval interquartile range (IQR) (bottom) features shown for expert-labeled sinus (left column) and junctional ectopic tachycardia (JET) (right column) events for 2 training cohort patients.

waveforms and use this information to detect arrhythmias. Most of the computational frameworks fall into 2 broad categories: those using handcrafted feature engineering where the features are interpretable, and those using more complex data-driven architectures where the features have limited clinical interpretability. Tools using handcrafted features

have been proposed using Generalized Discriminant Analysis,¹¹ wavelet analysis,^{12–14} and nonlinear Bayesian filters.¹⁵ Various data-driven neural network architectures have achieved high accuracy in detecting arrhythmias, such as convolutional neural networks,^{10,16,17} long short-term memory networks,^{18,19} and radial basis networks.²⁰ Most

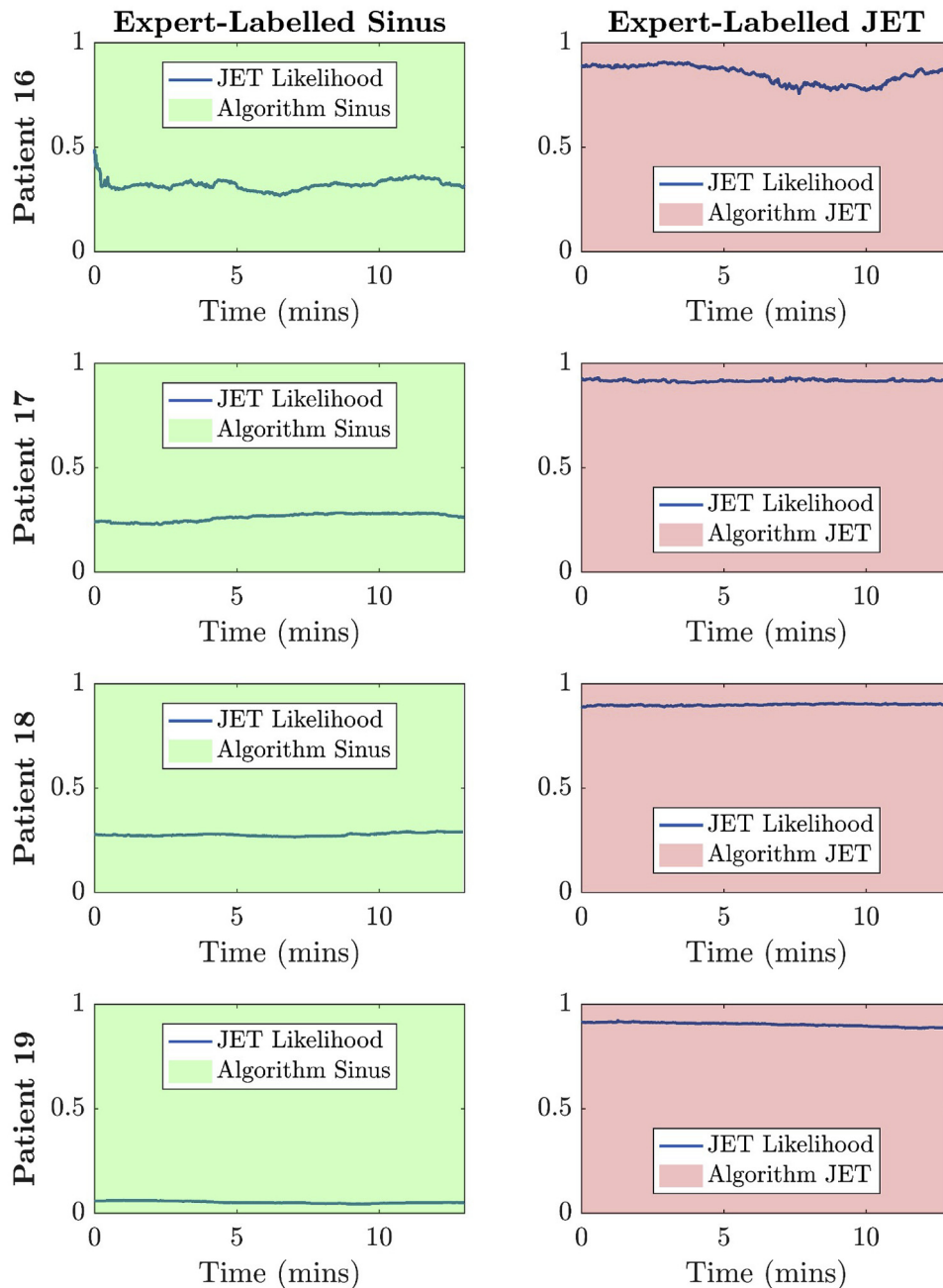


Figure 5 Algorithm likelihood and corresponding identified events (green background for sinus and red background for junctional ectopic tachycardia [JET]) displayed for expert-labelled sinus (left column) and JET (right column) events for 4 test cohort patients.

of these models detect sinus rhythm, premature ventricular contractions, atrial fibrillation, ventricular fibrillations, and heart blocks. However, no existing computational model has been used to detect junctional tachyarrhythmias.

Our JET detection model performs at a high sensitivity and specificity, with an AUC-ROC of 93%, using the P prominence median and the PR interval IQR as features. Note that the performance metric used to evaluate existing ECG arrhythmia detection implementations is the percentage of true arrhythmias that were correctly detected. In a clinical setting, however, too many false-positives cause alarm fatigue in ICU staff,^{21,22} which increases the

likelihood of an actual JET event going undetected. Our framework thus uses the area under the ROC curve as the performance metric, providing physicians a complete picture of the true detection vs false alarm performance of the classifier. This also equips physicians with the capability to set the detection threshold, depending on how sensitive they would like the classifier.

Limitations

Though the interpretability and simplicity of a straightforward logistic regression model are paramount in

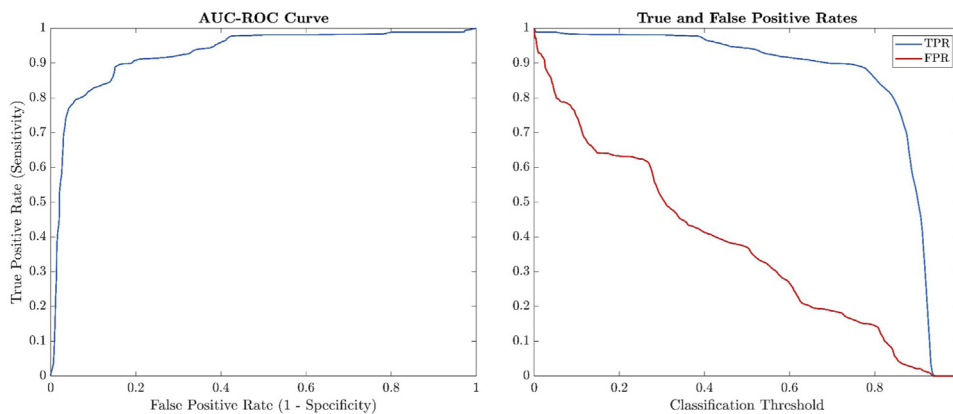


Figure 6 Area under the curve receiver operating characteristic (AUC-ROC) curve; true-positive rate (TPR) and false-positive rate (FPR) plotted as a function of the classification threshold.

physicians' understanding and trust of the classifier, such a model is restricted by its structure and therefore limited in its performance. The proposed method assumes that there is a linear relationship between the features and the likelihood of JET, which works as an approximation but does not capture all the subtleties of the underlying relationships.

Another limitation is the cohort size of 40 patients. Though a large amount of data was analyzed, a larger number of unique patients would better confirm the generalizability of the proposed algorithm. Note that the model did generalize well to the test cohort of 25 patients, from a training cohort of 15 patients.

Future directions

Going forward, the false-positive rate curve should be reduced so that clinicians are not overwhelmed from alarm fatigue. This can be addressed by exploring new models that are still interpretable but allow the data to be approximated more closely. We plan to evaluate other classification models, such as decision trees, that may allow for closer representations of the data. These models allow for nonlinear representations of multiple features in an interpretable structure. Further, we plan to evaluate the utility of features from central venous pressure waveform data, since these data are used by physicians, when available, to identify JET. Another potential data source we plan to evaluate is the oxygen saturation waveform.

Finally, we plan to validate the algorithm on a cohort of 100 or more patients, collected from multiple sites, while maintaining a large, diverse separate test set. This will allow us to account for more of the variability that exists across patients and device measuring modalities, leading to improvements in our feature extraction techniques, feature selection, and choice and tuning of the model, and thus the algorithm's overall performance. The cohort-representative diversification of the training and test sets will make for a more robust model and provide increased confidence in obtaining similar performance when applied to an arbitrary set of new patient data.

Conclusion

JET remains a life-threatening postoperative arrhythmia in children with CHD. Our novel arrhythmia detection tool identifies JET with high sensitivity and specificity, allowing for early detection and timely intervention.

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Authorship: All authors attest they meet the current ICMJE criteria for authorship.

Patient Consent: Informed consent was waived, as this was an observational study performed on aggregate de-identified patient information.

Ethics Statement: The study was approved by the Institutional Review Board of Baylor College of Medicine. The research reported in this paper adhered to the Helsinki Declaration guidelines.

Appendix Supplementary data

Supplementary data associated with this article can be found in the online version at <https://doi.org/10.1016/j.hroo.2022.02.014>.

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