Studie/Poster

«FULLY-AUTOMATED VENTRICULAR ECTOPIC BEAT CLASSIFICATION FOR USE WITH MOBILE CARDIAC TELEMETRY»

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FULLY-AUTOMATED VENTRICULAR ECTOPIC BEAT CLASSIFICATION FOR USE WITH MOBILE CARDIAC TELEMETRY

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INTRODUCTION

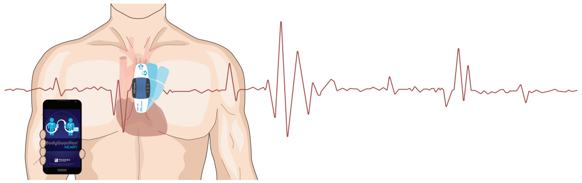
Ventricular ectopic beats (VEB) are a sub-category of abnormal heart contractions, which originate from the ventricles. For some patients, these beats signify a potentially life-threatening and treatable cardiac irregularity. Mobile cardiac telemetry (MCT) empowers physicians with valuable information regarding the occurrence and regularity of VEBs.

Interpreting and summarizing MCT study results is a time-consuming process. MCT is commonly prescribed for 10 to 30 days, generating large amounts of data. Generally, data is captured by service providers, annotated, and summarized into patient-specific reports for clinicians. Today, the growing popularity of MCT is driving the need for high-performance algorithms to assist with data annotation and summarization.

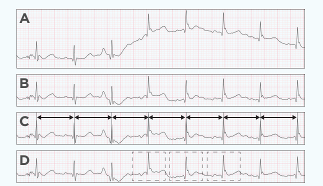
The proposed VEB classification algorithm, leverages big-data and deep learning to produce a classification model with sensitivity and specificity higher than any previously published fully-automated algorithm, and comparable to the state-of-the-art semi-automated algorithms, which require time-consuming patient-specific labeling of training data.

METHODOLOGY

ECG data used for training, tuning, and testing were collected using the BodyGuardian® Heart (BGH, Below) device. Data was collected from 3,493 unique patients and no patients were represented in any two of the datasets. The training, tuning, and testing datasets included 661,509, 76,021, and 614,250 beats, respectively.



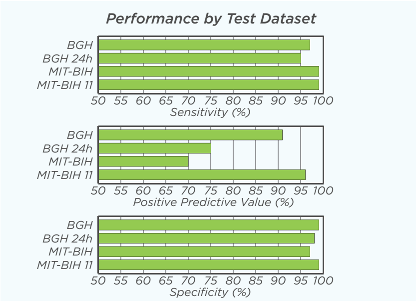
The training, tuning, and testing datasets were used for model training, hyperparameter tuning, and final model evaluation, respectively. Two BGH datasets were used for testing: 1) four, 24-hour records and 2) 971, 1-10 minute long records. Each BGH record was annotated and adjudicated by 3 certified ECG technicians, each with more than 5 years of experience.

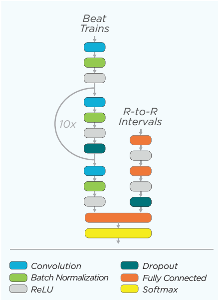


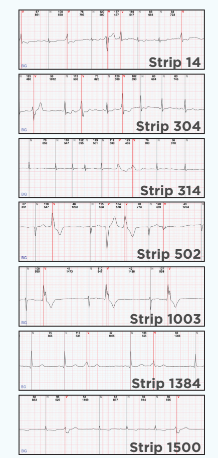
Data preprocessing. Raw data (A) was high-pass filtered (B), R-R intervals were calculated (C), and 1.5 second 3-beat trains were extracted.

Raw data was filtered and processed into R-R interval features and beat-trains, then processed by the deep learning model (Left). Filtering consisted of baseline wander removal using a DB-8 wavelet 0.5 Hz high pass filter. Individual beats were defined as 128 sample (0.5 second) segments. Beat trains were assembled from three consecutive beats. Four RR-interval measures were calculated for each beat: RR-previous, RR-next, RR-local mean, and RR-global mean. Only the center beat in each beat-train was associated with a label.

RESULTS







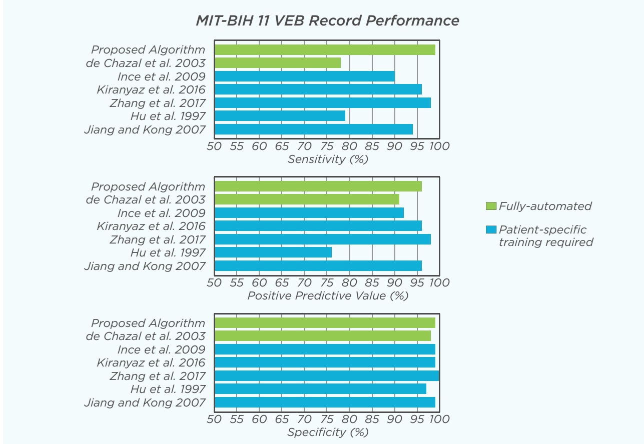
The optimized network (Above Right) incorporated a small two-layer network, which processed R-R intervals, and a deep convolutional network, which processed the beat trains. The convolutional network consisted of a repeating series of layers: 1-D convolution, batch norm, ReLU, and dropout. Dropout was excluded from the first and last series'. Classification was performed by a final fully-connected layer using the flattened output of the two networks.

Model performance was consistently high across the testing datasets (Above Left). The model achieved at least 94% VEB sensitivity on the BGH datasets and achieved 99% sensitivity on the MIT-BIH dataset. In all test cases 97% specificity or greater was achieved. Positive predictive value was lowest for the full MIT-BIH dataset, 75%, and highest for the 11 VEB records from the MIT-BIH dataset, 95%. Positive predictive value was highest for datasets with greater VEB prevalence.

VEB classification results from a random selection of ECG strips (Left). High amplitude multiform VEBs and a VEB/normal fusion beat correctly classified during normal sinus rhythm (Strip 14). Multiform VEBs correctly distinguished from lower and equal amplitude normal beats during sinus arrhythmia (strip 304). Low amplitude multiform VEBs correctly distinguished from low amplitude normal beats during atrial fibrillation/flutter (Strip 314). Both low and high amplitude multiform VEBs correctly classified during normal sinus rhythm (Strip 502). VEBs correctly classified during ventricular bigeminy in the presence of inverted normal beats (Strip 1003). Low amplitude VEBs correctly classified in the presence of high amplitude normal beats during sinus rhythm (Strip 1384). Low amplitude VEBs correctly classified in the presence of low amplitude normal beats during sinus rhythm (Strip 1500).

DISCUSSION

Model performance was evaluated with the commonly used 11 VEB records from the publicly available MIT-BIH arrhythmia database so that it could be easily compared with previously published work. The proposed model out-performed previously published fully-automated algorithms and either performed better or comparable to algorithms, which require time-consuming annotation of patient-specific data and subsequent patient specific training.



CONCLUSIONS

- The proposed model has the potential to improve patient care by efficiently providing clinicians with accurate VEB statistics in MCT reports.
- The proposed model achieved best-in-class performance due to the introduction of a novel deep learning architecture combined with the largest ever training data set applied to beat classification.
- Real-world performance was validated using MCT data captured from nearly 1,000 patients, demonstrating the model to be robust when presented with new data from unique patients.

ACKNOWLEDGMENTS

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Fully-automated ventricular ectopic beat classification for use with mobile cardiac telemetry

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Abstract— **We have developed a robust fully-automated model for classifying ventricular ectopic beats. The classifier relies on a 12-layer convolutional neural network that was trained using over 5,000 expertly-annotated ECG recordings from the BodyGuardian® Heart (BGH) monitor. The proposed model was evaluated using data from over 950 patients and achieved classification sensitivity of 97% and specificity of 99% when evaluated using real-world ambulatory ECG recordings collected by the BGH monitor. On the MIT-BIH arrhythmia database, the classifier achieved 99% sensitivity and 99% specificity, performing equal to or better than previously published work.**

I. Introduction

Ventricular ectopic beats (VEB) are a sub-category of abnormal heart contractions where the cardiac electric impulse originates from the ventricles. In the general population, VEBs are common and of little clinical consequence, but for some patients these beats signify a potentially life-threatening and treatable cardiac irregularity. Understanding the occurrence and regularity of ventricular ectopic beats empowers physicians with valuable information that is used to diagnose and develop treatment protocols for patients with cardiac disease [1].

Small untethered ECGs are commonly used to monitor patients for irregular heartbeats and rhythms over several weeks. Long-term monitoring increases the likelihood of capturing rare ventricular arrhythmias and helps to generate a patient-specific profile that accurately reflects the occurrence and persistence of VEBs. Detailed patient profiles that provide daily and hourly VEB burden support clinical decision making with regard to diagnosis and treatment planning.

In practice, evaluating long-term cardiac monitoring data is an extremely time-consuming process. Monitoring is commonly prescribed for 10 to 30 days generating huge amounts of data that must be annotated and summarized into patient-specific reports for clinicians. ECG annotation and report building is commonly provided by companies that employ a combination trained technicians and supporting algorithms. Growing clinical use resulting from increased incidence of cardiac disease, reduced cost of monitoring, and a rising aging population forces a greater reliance on algorithms in order to complete reporting in a timely manner while maintaining high-quality annotations. These factors are amplified in the case of mobile cardiac telemetry (MCT), where ECG is streamed directly to data processing centers, annotated, and may be used to quickly alert clinicians of potentially life-threating cardiac events. This functionality combined with evidence that diagnostic information from MCT is superior to that gained from conventional Holter and event based monitors [2], [3] has led to continued growth in the MCT market. For MCT to be most effective, data annotation must be performed quickly and with the highest possible accuracy.

Historically, ECG beat classification algorithms have relied on conventional machine learning models such as k-nearest neighbors and decision trees that construct decision-boundaries based on engineered features [4]–[11]. In the past 5-10 years, deep learning models outperformed conventional machine learning models on a variety of tasks including image classification [12]–[14], speech recognition [15], and ECG beat [16]–[21] and rhythm classification [22], [23]. Deep learning models rely on simple computational units with trainable parameters that can be stacked and connected in a manner that enables modeling of complex non-linear relationships. The large number of trainable parameters in deep learning networks make these models extremely sensitive to overfitting. They must be carefully designed and trained in order to produce a classifier that will generalize to new data. Many previously published deep learning beat classification algorithms have relied on the MIT-BIH database [24], [25], which consists of 30-minute ECG records from only 47 patients for both training and testing [16], [17], [19]–[21]. The small number of patients within this database significantly limits the ability of these algorithms to establish generalizability, particularly in cases where training and testing is performed using data from non-unique patients. The large amount of data required to train deep networks makes these issues very difficult to avoid when using the currently available public databases.

Semi-automated deep learning beat classification algorithms leverage the ability of deep neural networks to overfit by creating patient-specific beat classifiers [17]–[19], [21]. This is usually performed by training a general model using data from several patients and then leveraging inference learning to quickly retrain the general network using 5-minutes of data from a single patient. This process produces high-performance classifiers, but the time and computational resources required for implementation scale linearly with number of patients. Therefore, this process is currently impractical for servicing large patient populations. Additionally, it remains unclear how model performance is affected by 1) patient-specific training data that contains a limited representation of different beat classes, 2) small mistakes and inconsistencies in the labeling of patient-specific training data, and 3) long-term application i.e. how does

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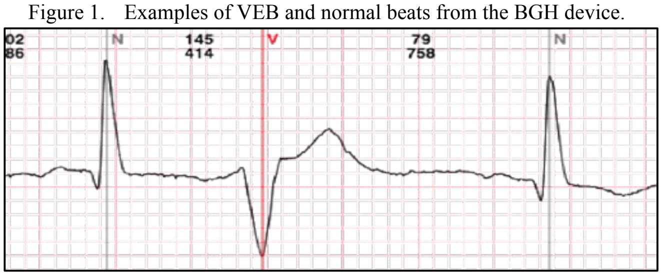
performance change day-to-day and with routine changes in signal integrity and lead placement.

The majority of the cited beat classification algorithms classify beats according to the ANSI/AAMI EC57 standard [26], which recognizes five main classes: normal (N), supraventricular ectopic (SVEB), ventricular ectopic (VEB), ventricular-normal fusion (F), and paced/unclassifiable beat (Q). This work focuses on only the classification of VEBs verses non-VEBs (Figure 1) as these beats serve a particularly important role in the diagnosis and treatment of cardiac disease. Rhythm classification algorithms currently implemented on the BGH platform provide rhythm burden information, which in the case of atrial fibrillation, supplants the need for SVEB detection and burden calculation.

Figure 1. Examples of VEB and normal beats from the BGH device.



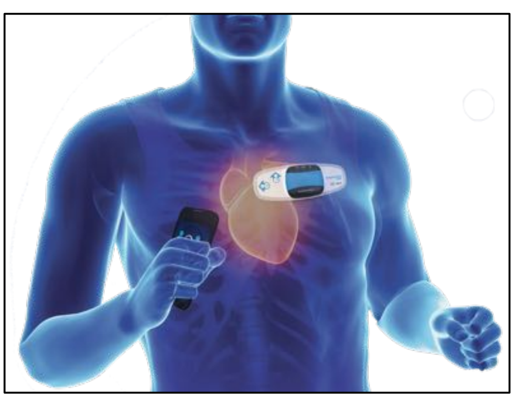
In this study, we present results from a fully-automated deep learning VEB classification model that was trained using real-world, expertly annotated ambulatory ECG data from over 3,000 unique patients. The resulting model classification sensitivity and specificity is comparable to or higher than previously published work, generalizes to new patients, and remains robust when operating on long-term data captured from different patients throughout a 24-hour period.

II. Methodology

A. Data

ECG data used for model training, tuning, and testing were collected using the single-lead MCT BodyGuardian® Heart (BGH) device (Preventice Solutions, Rochester, MN) (Figure 2). Records within the BGH dataset were collected from a pool of 3,493 unique patients and no patients were represented in any two of the training, tuning, and testing datasets. In all, 661,509 beats were included in the training dataset, 76,021 beats were included in the tuning dataset, and 614,250 beats were included in the testing dataset (Table 1).

Figure 2. BodyGuardian Heart device and placement.



The training dataset was used for model training, the tuning dataset was evaluated using multiple versions of the trained model in order to guide hyperparameter selection, and the test datasets were used for the final model evaluation. Two datasets from the BGH monitor were used for testing: one consisted of four, 24-hour records from four patients and the other included 971, 1 to 10 minute long records from 957 patients. Each BGH record was annotated and adjudicated by 3 certified ECG technicians, each with more than 5 years of experience evaluating ECG signals in clinical and lab environments. Five-class beat labeling was performed in accordance with EC57: 2012 [26]. For training, VEB and F were mapped into the VEB class and N, SVEB, and paced beats were mapped into the non-VEB class. Unclassifiable beats were removed from the training data as they do not provide useful information during the training process. These beats, however, were included in testing dataset. Approximately half of the BGH records were selected for their high prevalence of ventricular ectopy and the remaining were selected to represent a variety of cardiac rhythms.

To allow for comparison with previously published research, the model was evaluated on the commonly used 11 VEB records from the publicly available MIT-BIH arrhythmia database [24], [25] and also using the entire database. MIT-BIH contains 48 30-minute two-lead ECG records, from 47 patients. The 11 commonly used VEB records include: 200, 202, 210, 213, 214, 219, 221, 228, 231, 233, 234. In accordance with previous work, a single lead was used from these records, in 45 of the records the lead was a modified-lead II and in three records was lead V5 (Table 1).

TABLE I. Dataset Summary

Dataset name	*Number of unique patients*	*Number of records*	*Total hours*	*Beat counts*		
				non-VEB	*VEB*	*Total*
BGH train	3,493	5,729	138	617,119	44,390	661,509
BGH tune	957	971	16.1	71,203	4,818	76,021
BGH test 1	4	4	96.0	389,088	40,791	429,879
BGH test 2	957	971	16.1	71,577	4,282	75,859
MIT-BIH test 11	11	11	5.52	23,763	3,174	26,937
MIT-BIH test all	47	48	24.1	101,276	7,236	108,512

A. Data preprocessing

DC-offset and baseline wander were removed from raw signals using a DB-8 wavelet high pass filter. The filter was implemented by decomposing each signal using the discrete wavelet transform, zeroing coefficients in the lowest frequency band, and reconstructing the filtered signal using the inverse discrete wavelet transform. The filter cut-off frequency was set to 0.5 Hz by selecting a decomposition level such that the lowest frequency band was 0-0.5 Hz [27].

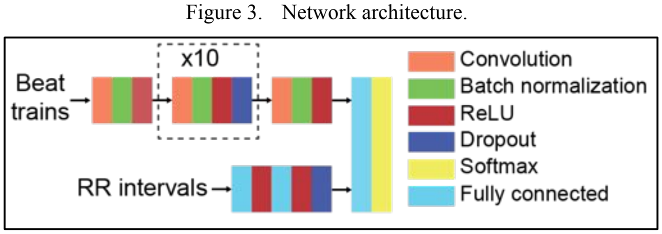
Beat detection was not performed in this study, only beat classification was performed. Many highly accurate (>99%) fully-automated beat detection algorithms have been previously described [28], [29] and are implemented as a matter of course in MCT analysis. Beat locations were defined using the true beat annotation locations, which were placed at the peak of each QRS-complex. Individual beats were defined as 128 sample segments, which were centered at QRS-complex peak. Data from the BGH device was captured at 256 Hz resulting in 0.5 second beat windows. To achieve consistent sample lengths (a requirement when using simple convolutional network architectures) MIT-BIH signals were downsampled from their native 360 Hz to 256 Hz then segmented. Because the relative rate between consecutive beats helps to inform beat labeling, four RR-interval measures were calculated for each beat: $RR_{previous}$, RR_{next}, RR_{local_mean}, and RR_{global_mean}. $RR_{previous}$ and RR_{next} were calculated as the intervals between a beat, and the previous and next beat, respectively. Zero padding was used at the beginning and end of each record where one of these intervals could not be calculated. RR_{local_mean} was calculated as the average RR-interval using the six nearest RR-intervals. RR_{global_mean} was calculated as the average RR-interval for the entire record regardless of record length.

For beat classification by humans, nearby beats provide useful context. Beat trains, three beats long, were assembled from consecutive beats in order to make this context available to the classifier. Only the center beat in each beat-train was associated with a label. Zero-padding was used before and after beats at the beginning and end of each record, respectively. These beat trains and set of four RR-intervals comprised our deep learning model input data.

B. *Deep learning model architecture*

The network architecture incorporated two paths, a small two-layer neural network, which operated on heart rate intervals, and a deep convolutional network, which operated on the beat trains. The two-layer network used 16 and 64 neurons in the first and second layers, respectively, and dropout was applied after the second layer. The deep convolutional network consisted of a repeating series of layers: 1-D convolution, batch normalization [30], ReLU activation, and dropout. Dropout was excluded from the first and last repeating layers in the network (Figure 3). All convolutional layers had a filter length of 8 and had 32*i* filters, where *i* was incremented by one every four convolutional layers. A stride of 2 was implemented on alternate convolutional layers. At the end of the network the two paths were joined by concatenating the output of the small network with the flattened output of the deep convolutional network. The resulting vector was passed through a single fully-connected layer and softmax activation to produce probability distributions for each beat class.

Figure 3. Network architecture.



The model was constructed, tuned, and deployed using TensorFlow. The Adam algorithm [31] was used to optimize trainable model parameters using a weighted cross-entropy objective function. Cross-entropy weighting was applied to compensate for highly imbalanced classes in the training data. The weights were calculated as the reciprocal of the number of beats for each class in the training dataset.

C. *Model performance evaluation*

Classifier performance was evaluated using the ANSI/AAMI EC57 guidelines for calculating VEB classification sensitivity (Se), positive-predictive value (+P), and specificity (Sp). These results rely on the five beat class labels referenced in the EC57 guidelines: N, SVEB, VEB, F, and Q, and differ from conventional scoring as they do not penalize specific types of beat misclassification. For example, a normal/ventricular fusion beat that is misclassified as ventricular ectopic beat is not counted as a true-positive, false-positive, false-negative, or a true negative, it is simply discarded from the performance evaluation calculations [26].

III. Results

Model performance was consistently high across the testing datasets (Table 2). The model achieved VEB sensitivity ≥0.94 on all datasets, reaching 0.99 on the MIT-BIH dataset. In all cases specificity was 0.97 or greater. Positive predictive value was lowest for the full MIT-BIH dataset, 0.75, and highest on the 11-record MIT-BIH dataset, 0.95. Positive predictive value was highest for datasets with greater VEB prevalence (Table 1), which is to be expected for an algorithm that is otherwise relatively consistent.

TABLE II. Model Performance by Dataset per EC57

	VEB Se	*VEB +P*	*VEB Sp*
BGH tuning	0.94	0.76	0.98
BGH testing 1	0.97	0.91	0.99
BGH testing 2	0.95	0.75	0.98
MIT-BIH testing 11	0.99	0.96	0.99
MIT-BIH testing all	0.99	0.70	0.97

IV. Discussion

Table 3 compares VEB classification performance with previously published algorithms. Our results demonstrate the proposed model to be better or comparable to the best performing algorithms currently published, the majority of which are not fully-automated and require pre-annotated patient data. Considering that our model was not trained using any beats from the MIT-BIH database, the proposed model demonstrates an excellent ability to generalize. The large number of training beats from a diverse patient population combined with a deep network architecture are credited for the observed performance and the model's ability to generalize. Deeper models allow for complex future representation and the large diverse dataset helps to prevent over-training. The proposed fully-automated algorithm has the potential to improve patient care by providing clinicians with accurate, efficient, and consistent VEB counts during MCT. Future work will expand on the proposed model to test more complex model architectures and further improve classification performance and provide VEB multi-form classification.

TABLE III. PERFORMANCE COMPARISON USING THE 11 COMMON MIT-BIH TESTING RECORDS

	VEB Se	*VEB +P*	*VEB Sp*
Hu et al. [19]	0.79	0.76	0.97
de Chazal et al.[a] [32]	0.78	0.91	0.98
Jiang and Kong [33]	0.94	0.96	0.99
Ince et al. [20]	0.90	0.92	0.99
Kiranyaz et al. [21]	0.96	0.96	0.99
Zhang et al. [17]	0.98	0.98	1.00
Proposed model [a]	**0.99**	**0.96**	**0.99**

a. Fully automated

V. CONCLUSION

We have presented a robust deep learning model capable of classifying ventricular ectopic beats recorded using a single-channel MCT device. This algorithm addresses one important aspect of reporting, VEB classification, helping to address the growing need for reliance on algorithms used to accurately analyze, annotate, and summarize long-term ECG monitoring studies.

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