Electrocardiogram Monitoring and Interpretation: From Traditional Machine Learning to Deep Learning, and Their Combination

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Abstract

Cardiac arrhythmia can lead to morbidity and mortality and is a substantial economic burden. Electrocardiogram (ECG) monitoring is widely used to detect arrhythmia. The number of ECG recordings is increasing due to aging populations and availability of easy-to-use wearable devices. Manual interpretation of the high volume of recorded ECGs might not be a feasible and scalable solution. Therefore, machine learning algorithms are widely used for automatic ECG interpretation. In this paper, the challenges and differences between machine learning techniques for ECG monitoring and interpretation are reviewed, from traditional machine learning classifiers to deep learning and their combination.

1. Introduction

Cardiac arrhythmia, also known as heart arrhythmia, refers to an abnormal heart rhythm (e.g. irregular, too slow, or too fast heartbeats) [1]. Arrhythmia can lead to morbidity and mortality and is a substantial economic burden, the total direct annual healthcare cost of cardiac arrhythmias sums to $67.4 billion US dollars [2]. The prevalence of cardiac arrhythmia is age dependent and changes by arrhythmia type [2]. Atrial fibrillation (AF) is the most common cardiac arrhythmia that is associated with increased risk of stroke [3].

Electrocardiogram (ECG) monitoring is widely used for diagnosis of arrhythmia. The number of ECG recordings is increasing due to aging populations and availability of easy-to-use wearable devices. Due to the volume of recorded ECGs, manual interpretation for all people under monitoring might not be a feasible and scalable solution. Therefore, machine learning algorithms are widely used for automatic ECG interpretation. ECG monitoring using machine learning algorithms is advancing as automatic diagnosis of arrhythmia is challenging due to factors such as inter-subject variability and poor signal to noise quality. In this paper, the challenges and differences between machine learning techniques from traditional machine learning classifiers to deep learning and their combination for ECG monitoring and interpretations are reviewed.

2. ECG Recording

ECG is the most widely available and most frequently performed cardiac diagnostic test. It has been estimated that 300 million ECGs are recorded every year [4], although this number is likely to be greater today. Considering monitoring duration, ECG monitoring could be categorized as short-term and long-term monitoring. Recording ECG in an ICU using bedside monitors is an example of long-term recording in which ECG will be recorded continuously for the period that patient is in the ICU. Another example of long-term recording is the monitoring of patient by a Holter monitor. Recording of ECG during medical checkup by a medical-grade ECG recorder or ECG monitoring using a hand-held wearable device at home are examples of short-term ECG monitoring. Considering the number of ECG leads that are recorded simultaneously, ECG recording can be categorized as single or multi leads.

3. ECG Interpretation

An ECG can be interpreted by a trained health professional or by a specialized software. However, usually software-analysed ECGs require over-reading by an expert such as experienced cardiologist [5].

3.1. Automated ECG Interpretation

Automated ECG interpretation is the use of machine learning and rule-based expert systems for automatic analysis and diagnosis of ECG [6] to improve the correct interpretation of ECG [7]. With the availability of newer ECG monitoring equipment including wearable sensors, there is a shift toward real-time and remote cardiac monitoring that relies on automated ECG interpretation [8]. Extensive research by companies and by research labs is in progress to improve the performance of algorithms developed for automated ECG interpretation.

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3.1.1. Challenges in Automated ECG Interpretation

Some of challenges in automated ECG interpretation, especially using machine learning techniques, are listed below and should be considered in algorithm development:

- Recorded ECG often has noise/interferences such as baseline wander, EMG interference, and disconnection.
- ECG limb lead misplacement such as limb lead reversal may happen.
- Multi-lead ECG is not always available.
- The requirement for all supervised machine learning methods is the availability of annotated data that is typically provided by a domain expert such as cardiologists. Access to high-quality annotated ECG is limited.

3.1.2. Applicability of Research Studies for Automated ECG Interpretation

Having at least one of the following conditions limits applicability of research studies for automated ECG interpretation [9]:

- Presence of noise/interference in real ECG recordings was not considered in the algorithm development and only clean ECG was used.
- The algorithm was developed for classification between normal sinus rhythm (NSR) and only one or limited number of arrhythmias.
- A limited dataset with small sample size was used for algorithm development.
- The algorithm was developed for a specific setting such as short multi lead ECG recording.

3.1.3. Traditional Machine Learning for Automated ECG Interpretation

In traditional machine learning, handcrafted features that are often representative of cardiac arrhythmia will be used with classifiers such as support vector machine (SVM). Meaningful features are usually identified through:

a) *Interaction with experts and literature review:* For example, absence of p-wave and irregularity in RR intervals are cardinal features of AF that were reflected in features extracted from the top scores in the PhysioNet/Computing in Cardiology Challenge 2017 [10-12].

b) *Exploration of data for discovery of strong features:* As an example, extracted features from reconstructed phase space of ECG were proposed to capture changes in morphology of ECG due to AF through comparison of features between AF and NSR [13, 14].

In summary, a challenge of traditional machine learning is the pre-processing and feature engineering that is required for quantification of arrhythmia. However, traditional machine learning methods typically allow interpretation of developed models based on physiology.

3.1.4. Deep Learning for Automated ECG Interpretation

Deep learning-based approaches for automated ECG interpretation have been used in the following ways:

1- *Creating ECG annotations:* methods in this group will create ECG annotations (e.g. P-wave, QRS, and T-wave onset and offset) and then will perform feature extraction using extracted annotations for traditional machine leaning. For example, Vollmer et al. used a convolutional neural network (CNN) for detection for creating ECG annotations [15].

2- *Feature learning:* algorithms in this group will use deep learning for extracting features to replace handcrafted features. The output of a deep neural network will be used as an input to traditional classifiers such as an SVM. For example, Pourbabaee et al. used a CNN with one fully connected layer for feature learning and applied features to other classifiers such as linear SVM for AF detection [16]. An automatic feature learning using deep learning is capable of creating features without having domain knowledge.

3- *Feature learning and classification:* algorithms in this group will use deep learning for both feature engineering and classification. For example, spectrograms of ECG were used with densely connected convolutional neural network for detection of NSR, AF, other rhythms, and noise [9, 17, 18]. The combination of CNNs and long short-term memory (LSTM) networks was used for cardiac arrhythmia detection in another study [19].

The reduced feature engineering efforts of deep learning-based approaches may allow novel feature discovery and learning hidden patterns that might not be clear using traditional machine learning methods. However, interpretation of deep learning models is challenging.

3.1.5. Hybrid Approach for Automated ECG Interpretation

In the hybrid approach, both traditional machine learning and deep learning will be utilized for automated ECG interpretation. Three schemas of hybrid approaches are shown in Figure 1. In the first schema, shown in Figure 1(a), traditional machine learning could be used for pre-processing or initial data analysis and the output of a classifier could be used as input into a deep learning-based algorithm such as an LSTM for automated ECG interpretation. As shown in Figure 1(b), traditional machine learning could be used for post-processing of classification that was done by a deep learning-based algorithm. As an example, when the probability of NSR and *other* rhythm was close to each other in the cardiac arrhythmia detection proposed by [9, 17], a traditional feature-based approach was performed to make the final decision.

In Figure 1(c), an ensemble of deep learning-based and traditional machine leaning can be created by using a final decision rule for cardiac arrhythmia classification. This approach improved the classification performance in another bio-signal task - classification of normal/abnormal heart sound recordings [20], and might lead to similar improvements in cardiac arrhythmia classification.

Combination of traditional machine learning and deep learning has been applied in recent research [9, 17, 20] and may allow the benefits of both approaches (better interpretability of traditional machine learning and the power of deep learning in the identification of hidden patterns in data) when applied to ECG monitoring and interpretation.

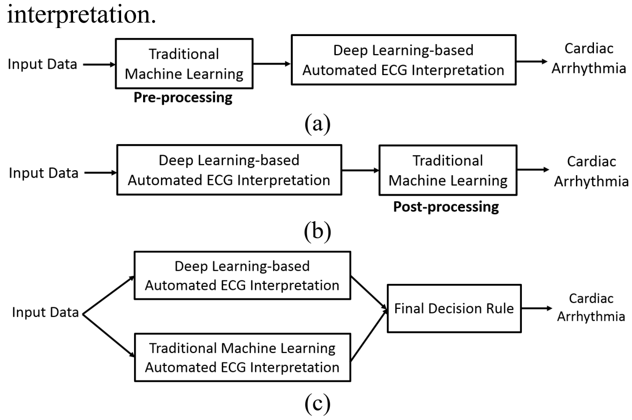

Figure 1. Combination of traditional machine learning and deep learning hybrid approach, for automated ECG interpretation.

4. Potential Future Opportunities

Below is a list of potential opportunities for improving the application of different machine learning techniques in automated ECG interpretation:

- Benchmarking performance of different algorithms on the same dataset (preferably a large dataset recorded in multiple locations with different equipment) similar to the task in the PhysioNet/Computing in Cardiology Challenge 2016.
- Consideration of computational efficiency/running time of algorithms during algorithm development in addition to algorithm performance.
- Consideration for integration of different algorithms in wearable devices with limited processing resources.

5. Conclusion

In this article, traditional machine learning, deep learning, and their combination for automated ECG interpretation were reviewed. In conclusion, it is not trivial to pick the best machine learning method for ECG monitoring and interpretation. Promising results achieved by combining traditional machine learning with novel deep learning approaches and improvement in interpretability of these combined models may increase the popularity to these techniques.

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