Improve Computer-Aided Arrhythmia Diagnosis with Deep Learning Techniques Using Undiagnosed Electrocardiography Samples

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***Abstract*—**

***Index Terms*—ECG Classification, Deep Learning, Arrythmia Analysis**

I. Introduction

The research of the electrocardiogram (ECG) signal provides important insights for cardiac function and condition understandings. Heart function analysis is of special concern in the diagnosis of cardiovascular disease. The ECG computer-aided diagnosis (CAD) systems provides indispensable assist in long-term clinical monitoring, and a large number of approaches have been proposed for the task, easing the diagnosis of arrhythmic changes as well as further inspection, e.g., heart rate variability or heart turbulence analysis. As the wearable techniques promoted the accumulation of ECG data from personal and mobile healthcare applications, the automated ECG signal analysis techniques featured CAD systems tend to be more important.

Machine learning techniques had been widely used in data analysis and applied in ECG-CAD systems. These methods learn representations from the diagnosed samples collected from medical examinations, in order to assist the decision making of medical experts.

A large amount of samples with diagnosis can be used to improve the CAD systems' performance. These ECG signal samples can be easily acquired from routine medical examinations or Holter monitoring applications. However, making annotations one by one for the massive ECG signal samples could be time-consuming and inefficient, which would bring heavy burden for medical experts. Especially in the mobile healthcare or e-healthcare applications, the medical experts-based ECG analysis method would be impossible.

The possible solution for massive ECG automated analysis is to learn hypothesis from a small amount of samples annotated by medical experts (the labeled data) and then utilize the massive undiagnosed samples (the unlabeled data) to enhance the performance of the learned hypothesis.

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In machine learning, this technique is called learning with labeled (supervised learning) and unlabeled data (unsupervised learning). Enhance the performance of the learned hypothesis by using the labeled and unlabeled data together is known as semi-supervised learning, where an initial hypothesis is usually learned from labeled data and then refined with the information derived from the unlabeled ones. Deep learning refers to a rather wide class of machine learning techniques and architectures, with the hallmark of using many layers of non-linear information processing that are hierarchical in nature. As [] described the deep learning methods can be categorized as three categories: deep networks for unsupervised learning, deep networks for supervised learning, and hybrid deep networks.

Deep learning methods had been widely used in other domains like computer vision and acoustic signal analysis. In this paper, the deep learning methods are applied in ECG analysis. A deep feature based hybrid systems are proposed for ECG arrhythmia diagnosis.

The rest of the paper is organized as follows: Section II briefly reviews the arrhythmia diagnosis methods. Section III presents the datasets description. Section IV reports the experimental methods of deep learning techniques. Section V describes the results and performance assessment. Finally, Section VI concludes the paper.

II. Background

III. Dataset and Pre-processing

IV. Representations Learning with Deep Learning Methods

A. Sparse Autoencoder

B. Restricted Boltzmann Machine

V. Experiments

VI. Conclusions

Appendix A
Proof of the First Zonklar Equation

Appendix one text goes here.

Appendix B

Appendix two text goes here.

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