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Electrocardiogram (ECG) Augmentation and Classification Using Deep Learning Techniques

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Abstract

Electrocardiograms (ECGs) play a vital role in the clinical diagnosis of heart diseases. An ECG record can be used to detect the abnormalities of the heart and to discover numerous arrhythmias. The screening of cardiac arrhythmias requires a detailed study of the ECG records by the cardiologists, this process is time-consuming and too difficult. Hence, the automation process of arrhythmias identification and ECG analysis is crucial in the medical field.

Medical datasets like the MIT-BIH arrhythmia dataset are often very limited and strongly imbalanced, which makes training the models—especially deep learning models—technically challenging, and the models will tend to be biased in favor of classes that contain a large number of samples.

This thesis proposes a novel data-augmentation technique using generative adversarial networks (GANs) to restore the balance of the dataset and improve the classification of ECG heartbeats. Furthermore, two deep learning approaches—an end-to-end approach and a two-stage hierarchical approach—in addition to multiple deep convolutional neural networks (CNNs) and Recurrent Neural Networks (RNNs) are proposed to eliminate hand-engineering features by combining feature extraction, feature reduction, and classification into a single learning method.

Results show that augmenting the original imbalanced dataset with generated heartbeats by using the proposed techniques more effectively improves the performance of ECG classification than using the same techniques trained only with the original dataset. Furthermore, we

demonstrate that augmenting the heartbeats using GANs outperforms other common data augmentation techniques.

Our best results obtained with these techniques achieved overall accuracy above 98.0%, precision above 90.0%, specificity above 97.4%, and sensitivity above 97.7% after the dataset had been balanced using GANs, results that outperform several other ECG classification methods. The best results are achieved using inception-based deep CNN after solving the imbalance problem using GANs.

All experiments in this thesis are conducted on the MIT-BIH dataset, which is the most common arrhythmia dataset.

List of Publications

- 1) A. M. Shaker, M. Tantawi, H. A. Shedeed and M. F. Tolba, Generalization of Convolutional Neural Networks for ECG Classification Using Generative Adversarial Networks, in IEEE Access, vol. 8, pp. 35592-35605, 2020 (Impact Factor : 4.098).
- 2) A. M. Shaker, M. Tantawi, H. A. Shedeed and M. F. Tolba, Combination of Convolutional and Recurrent Neural Networks for Heartbeat Classification. Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020). AICV 2020. Advances in Intelligent Systems and Computing, vol 1153. pp 362-37, Springer, Cham, , 2020.
- 3) A. M. Shaker, M. Tantawi, H. A. Shedeed and M. F. Tolba, Heartbeat Classification Using 1D Convolutional Neural Networks. Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2019. AISI 2019. Advances in Intelligent Systems and Computing, vol 1058, pp 502-511, Springer, Cham, 2019.
- 4) A. M. Shaker, M. Tantawi, H. A. Shedeed and M. F. Tolba, Deep Convolutional Neural Networks for ECG Heartbeat Classification Using Two-stage Hierarchical Method. Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2020. AISI 2020. Advances in Intelligent Systems and Computing, 2020 (Accepted).

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List of Abbreviations

<u>Abbreviation</u>	<u>Stands for</u>
ADASYN	AD Aptive SYN thetic
AE	Atrial E scape
ANN	A rtificial N eural N etworks
AP	A berraed Atrial P remature
APC	Atrial P remature C ontraction
BAP	B locked Atrial P remature
CAD	C omputer A ided D esign
CNN	C onvolutional N eural N etworks
CVD	C ardiao V ascular D iseases
DCGAN	D eep C onvolutional G enerative Adversarial Networks
DWT	D iscrete W avelet T ransform
ECG	E lectro C ardio G ram
FN	F alse N egative
FP	F alse P ositive
FPN	F usion of P aced and N ormal
GAN	G enerative A dversarial N etworks
HOS	H igher O der S pectra
ICA	I ndependent C omponent A nalysis
LBBB	Left B undle B ranh B lock
LDA	L inear D iscriminant A nalysis
LSTM	L ong S hort- T erm M emory
NE	N odal (Junctional) E scape
NLP	N ature L anguage P rocessing

NOR	NOR mal
NP	Nodal (Junctional) P remature
PCA	P rincipal C omponent A nalysis
PNN	P robabilistic N eural N etwork
PVC	P remature V entricular C ontraction
RBBB	R ight B undle B ranch B lock
RNN	R ecurrent N eural N etwork
SMOTE	S ynthetic M inority O versampling T echnique
SNR	S ignal-to- N oise- R atio
SVM	S upport V ector M achine
TN	T rue N egative
UN	U Nclassifiable
VE	V entricular E scape
VF	V entricular F lutter Wave
VFN	F usion of V entricular and N ormal
WT	W avelet T ransform
WHO	W orld H ealth O rganization

Chapter 1

Introduction
