

ECG BEAT CLASSIFICATION USING CAPSULE NETWORKS

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208565C

Dissertation submitted in partial fulfillment of the requirements for the degree
Master of Science in Artificial Intelligence

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DECLARATION

Candidate:

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Supervisor:

The above candidate has carried out research for the Masters' thesis under my supervision.

Signature of the supervisor:

Date:

DEDICATION

I dedicate this research to the whole world.

ACKNOWLEDGEMENTS

I was fortunate to have an attentive and knowledgeable supervisor who helped me in many ways to carry out this research and achieve the outcomes. Therefore, I would like to convey my gratitude to my supervisor Dr. Thushari Silva for the support.

I would also like to mention the help and guidance given by Dr. Asoka Karunananda in preparing research process and the thesis document which helped me immensely to complete it.

ABSTRACT

Electrocardiogram is a low cost non-invasive technology used to detect cardiac activity which leads to detection of diseases related to cardio vascular system. Because of the high prevalence of cardiovascular disease among people all over the world, electrocardiogram is used frequently to diagnose these diseases which has reduced the mortality rate significantly. Due to recent developments of telemetry devices and popularity of outpatient monitoring, long term ECG monitoring has become a norm in most clinical practices to detect underlying cardiac conditions. However, due to extreme amount of data generated, the automatic ECG classification systems has become an essential requirement. These automated systems can detect and report anomalies in ECG signal without requiring a cardiologist or technician to manual check the whole ECG signal. Although these systems provide significant assistance to healthcare workers, the accuracy and explainability of these systems are still not addressed completely.

In this thesis, I have presented an ECG beat classification system using Capsule networks. The goal here is to address the aforementioned issues of existing ECG beat classification methods and technologies. Therefore, for this purpose, the approach I have taken is first and foremost based on the hypothesis that the ECG beat classification can be modelled using the capsule network approach. According to this approach, once the raw ECG signal is given as the input, the accurately classified ECG beats should be obtained as the output. For this, the design of the system was drafted to contain several key sections which work together to produce the expected outcome. These sections include, ECG signal acquisition, preprocessing and classification. The signal acquisition was included to acquire ECG raw signal from sources with different standards. Then the preprocessing stage was introduced to remove noise, baseline wander like artifacts and also to detect QRS complexes which is essential for beat classification. Then the deep learning model training was carried out using capsule network as the base technology. Finally, in addition to the aforementioned sections, the evaluation was carried out to ensure the performance and the explainability of the trained model. Unlike many existing researches on ECG classifications, we have implemented a model that can both perform better and provide feature-wise explanations for the classification. Sensitivity, Specificity, Positive predictivity like performance parameters are used to evaluate the model in terms of classification performance. The accuracy values obtained for this model was 98.89%, 99.44%, 99.56%, 98.83% and 99.17% for N, L, R, A and V beat classification and 97.94% for overall classification accuracy. As the conclusion, we identified that this ECG classification model based on Capsule networks has comparable performance to the other existing beat classification systems. In addition to that, the feature-wise explainability given by the capsule network model shows the superiority of this method in terms of reliability and practical usability.

Keywords: ECG, Beat Classification, Capsule Networks, Explainability

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LIST OF ABBREVIATIONS

Abbreviation	Description
AAMI	Association for the Advancement of Medical Instrumentation
ACC	Accuracy
AHA	American Heart Association
AI	Artificial Intelligence
APB	Atrial Premature Beat
CAD	Computer Assisted Diagnosis
CapsNet	Capsule Network
CNN	Convolutional Neural Network
CVD	Cardio Vascular Disease
DBN	Deep Belief Network
DL	Deep Learning
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
F1	F1 Score
FDA	Food and Drug Administration (USA)
FN	False Negative
FP	False Positive
FPGA	Field Programmable Gate Arrays
KNN	K-Nearest Neighbor
LBBC	Left Bundle Branch Block
LSTM	Long Short Term Memory
MIT-BIH	Massachusetts Institute of Technology – Beth Israel Hospital
ML	Machine Learning
PCA	Principle Component Analysis

PP	Positive Predictivity
PVC	Premature Ventricular Contraction
RBBB	Right Bundle Branch Block
SE	Sensitivity
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
VFib	Ventricular Fibrillation