

THESIS

**SCALOGRAM DRIVEN HYPERTENSION CLASSIFICATION USING
PHOTOPLETHYSMOGRAPHY (PPG) SIGNAL: A DEEP LEARNING
APPROACH**



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Abstract:

Blood pressure is a basic physiological parameter in the cardiovascular circulatory system. Long-term abnormal blood pressure will lead to various cardiovascular diseases, making the early detection and assessment of hypertension profoundly significant for the prevention and treatment of cardiovascular diseases. In this study, we investigate whether or not deep learning can provide better results for hypertension assessment when compared to the classical signal processing and feature extraction methods. We tested a deep learning method for the classification and evaluation of hypertension using photoplethysmography (PPG) signals based on the continuous wavelet transform (using Morse) and convolutional neural network. We collected 163 data recording, with 74 healthy subjects (38 male and 36 female) and 89 subjects were detected as hypertension people (20 male and 69 female). According to the seventh report of the Joint National Committee, blood pressure levels are categorized as normotension (NT), prehypertension (PHT), and hypertension (HT). In order to assess the hypertensin by using PPG signals, twelve classification experiments were conducted. The classification experiments were including: (1) Normotension vs Prehypertension; (2) Normotension vs Stage-1 Hypertension; (3) Prehypertension vs Stage-1 Hypertension; (4) Normotension vs Prehypertension vs Stage-1 Hypertension; (5) Classification based on Pulse Pressure; (6) Classification based on systolic blood pressure; (7) Classification based on diastolic blood pressure; (8) Classification based on brachial systolic blood pressure; (9) Classification based on brachial diastolic blood pressure; (10) Classification based on aortic systolic blood pressure; (11) Classification based on aortic diastolic blood pressure; (12) Classification based on Pulse Wave Velocity.

The validation accuracy of these twelve classification trials were 91%, 92%, 97%, 91%, 92%, 82%, 88%, 84%, 86%, 88%, 89% and 93%, respectively. The tested deep method achieved higher accuracy for hypertension assessment when compared to the classical signal processing and feature extraction method. Additionally, the method achieved comparable results to another approach that requires electrocardiogram and PPG signals.

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Abbreviations

PPG: Photoplethysmography

CVD: Cardiovascular diseases

BPV: Blood pressure variability

BP: Blood Pressure

PHT: Prehypertension

HPT: Hypertension

NT: Normotension

ECG: Electrocardiogram

PAT: Pulse arrival time

ML: Machine learning

DL: Deep learning

CNN: Convolutional neural networks

ANN: Artificial neural networks

DBN: Deep belief networks

SAE: Stacked autoencoders

PAT: Pulse arrival time

LVH: Left ventricular hypertrophy

CAD: Coronary Artery Disease

DASH: Dietary Approaches to Stop Hypertension

TIA: Transient ischemic attack

PRV: Pulse Rate Variability

LED: Light emitting diode

PD: Photodiode

SNR: Signal to noise ratio

AC/DC: Alternative current/ Direct current

CT: Crest time

CWT: Continuous wavelet transform

STFT: Short-time Fourier transform

MLR: Multivariate linear regression

NB: Naive Bayes

SVM: Support vector machines

RF: Random forest

MLP: Multilayer perceptron

AUC: Area under the curve

KNN: K-nearest neighbor

RNN: Re- current Neural Network

DBN: Deep Belief Network

RBM: Boltzmann Ma- chine

LSTM: Long Short-Term Memory

MIMIC: Multi-parameter Intelligent Monitoring in Intensive Care

Aix: Augmentation index

bSBP: brachial systolic blood pressure

bDBP: brachial diastolic blood pressure

GPU: Graphical Processing Unit