Detection of elevated blood pressure based on machine learning and signal processing techniques

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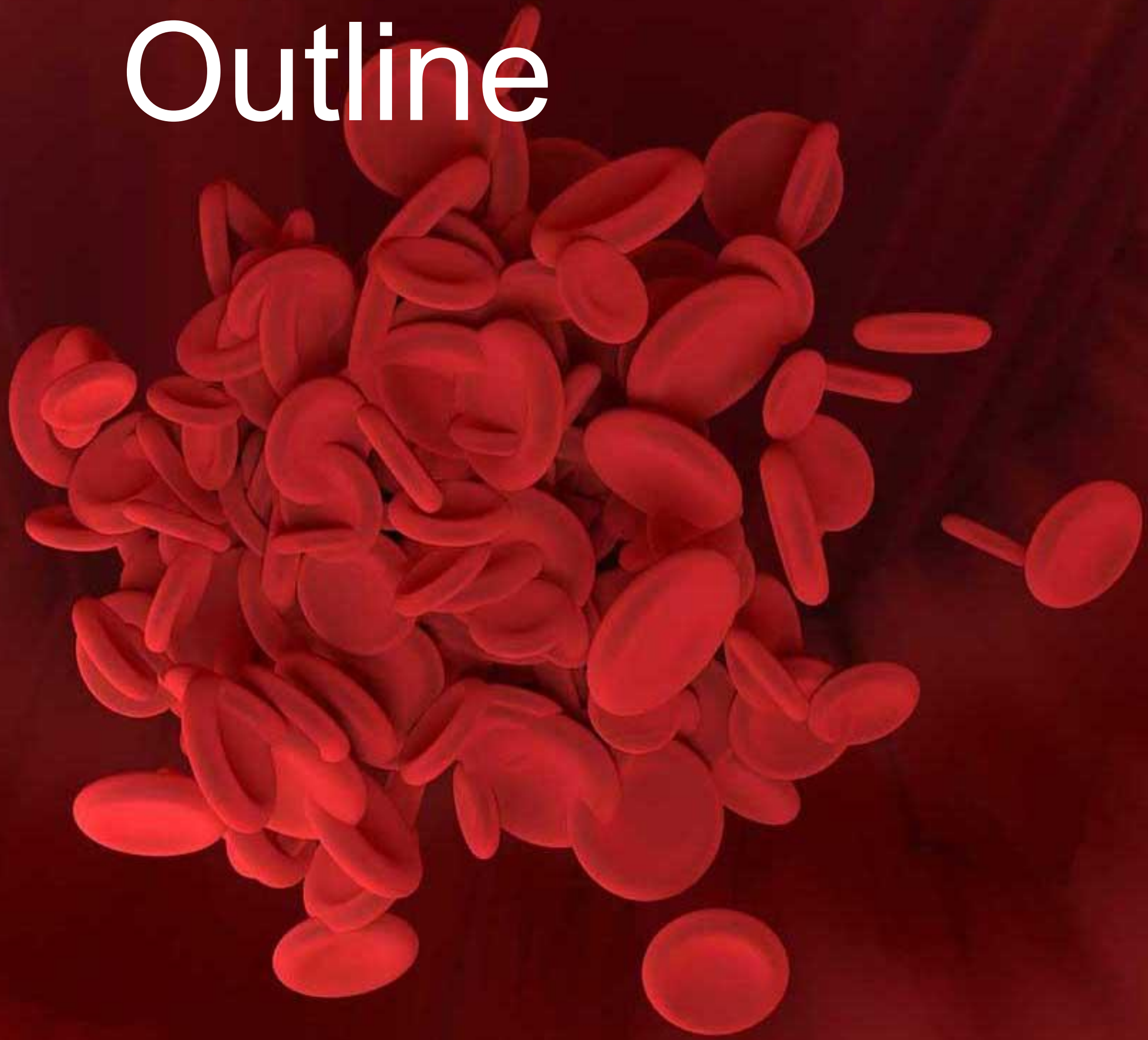
Outline



1 **Introduction**

Motivations and aim of the project are presented

2 **Literature Review**

The context of the current literature is provided

3 **Methodology**

Materials and Techniques are presented

4 **Results and Analysis**

Results are discussed

5 **Conclusions and Future Work**

High blood pressure

According to the **World Health Organization (WHO)**, high blood pressure or hypertension is a global public health issue. Primary diseases derived from this condition are [1]:

- **Heart attack**
- **Heart failure**
- **Kidney disease**
- **Diabetes, or**
- **Strokes**

- The WHO establishes that 1.1 billion individuals are affected by high blood pressure, with more than half living in low-income nations **[5]**.

- Hypertension is often referred to as the **"silent killer"** since it does not produce noticeable symptoms that could alert its presence [2].

Hypertension classification

Table 1. Blood Pressure Classification [5].

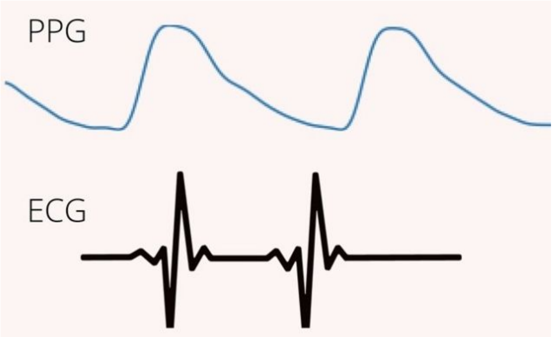
Blood Pressure Classification	Diastolic Blood Pressure (mmHg)	Systolic Blood Pressure (mmHg)
Normal (NT)	<80	<120
Prehypertension (PH)	80-89	120-139
Stage I Hypertension	90-99	140-159
Stage II hypertension	Equal or greater than 100	Equal or greater than 160

1. The recommended practice is to make consultation and ambulatory measurements [3,4, **5]**.

2. Cuff-based blood pressure devices **provide only a snapshot of blood pressure** and **require arterial compression, affecting users' quality of life** [4,**5**].

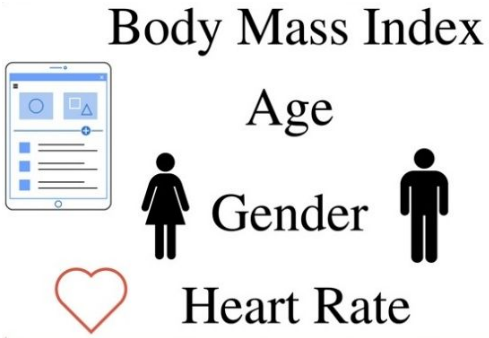
3. **Self-measurements** could provide wrong measurements and consequently a wrong classification **[5]**.

High Blood Pressure and Machine Learning



High Blood Pressure Detection using Statistical/Machine Learning [5]

- **Photoplethysmography (PPG) and Electrocardiography (ECG)**
  - **Deep Learning**
  - **Morphological Features (Pulse Arrival Time)**
- **Socio-demographic and clinical variables**
  - **Age**
  - **Gender**
  - **Body Mass Index**



Deep Learning and High Blood Pressure

Table 2. Results reported in the literature for the detection/classification of prehypertension through deep learning.

Author	Dataset	Features	Algorithm	Reported Metrics
Liang et al. [6]	Subset of MIMIC	Continuous **Wavelet Transform** (Morse Wavelet) From PPG	**Pre-trained GoogLeNet**	**F1 Score:80.52%**
Sun et al. [7]	Subset of MIMIC	PPG Derivatives and **Hilbert-Huang Transform** based Features	**Pre-trained AlexNet**	**F1-Score: 85.80%** Sensitivity: 95.26 % Specificity: 71.88%

Morphological Features and High Blood Pressure

Table 3. Results reported in the literature for the detection/classification of prehypertension through morphological features.

Author	Dataset	Features	Algorithm	Reported Metrics
Liang et al. [8]	Subset of MIMIC	ECG and PPG **Pulse Arrival Time** and 10 PPG Features	**K-Nearest Neighbors**	**F1 Score: 84.34%** Sensitivity:83.92% Specificity:84.76%
Liang et al. [9]	PPG-BP	10 PPG Features	**Weight K-Nearest Neighbor**	**F1 Score: 72.97%** Sensitivity: 65.85% Precision: 81.82%
Yao et al. [10]	PPG-BP	Physiological and **PPG Derivatives** Morphological Features	**Support Vector Machine**	**F1 Score:0.65** Precision: 0.67 Sensitivity:0.63 Specificity: 0.69
Sannino et al. [11]	Subset of MIMIC	PPG waveform no feature engineer specify	**Random Forest**	**F1 Score: 85.7%**

Clinical Data and High Blood Pressure

Table 4. Results reported in the literature for the detection/classification of hypertension through clinical variables.

Author	Dataset	Variables	Algorithm	Reported Metrics
Lopez et al. [12]	National Health Nutrition Examination Survey (NHANES)	**Sex, race, BMI, age, smoking status**	**Logistic Regression**	Sensitivity: 77%, Specificity: 68%
Lopez et al. [13]	(NHANES)	**Sex, race, BMI, age, smoking status**	**Multilayer Perceptron**	Sensitivity: 40%, Specificity: 87%

Disadvantages

Deep Learning approaches [5, 20]:

- Large sample sizes.
- High computational power and large training times.
- Its setting process is more like an art.
- Black-box approaches.

Feature extraction approaches [5, 20]:

- Which features do we pick?
- Which representation can be useful for classification?
- Morphological feature extraction requires a high quality waveform.

Variables such as age, gender, and body mass index have been associated with high blood pressure in several studies. Nevertheless, **they cannot provide a constant measurement [5]**.

Research Question, Hypothesis, and Objective

Research Question

What clinical variables and features from physiological signals could be used to generate a classification model that allows the detection of elevated blood pressure non-invasively?

Hypothesis

It is conjectured that the development of a model based on machine learning tools could detect elevated blood pressure non-invasively using a combination of clinical data and features from physiological signals such as photoplethysmography (PPG).

Aim

To develop a model that detects elevated blood pressure non-invalsively by using clinical data and physiological signals by training, and testing different types of **classical machine learning techniques.**

General Methodology

PPG signal classification	
Transfer Learning	**Wavelet Scattering Transform**

Clinical data classification	
Without Feature Selection	**Feature Selection**

Fusion	
Early Fusion	**Late Fusion**

Development Environment:

- Python - Google Colab
- 25.46 GB of RAM and Intel(R) Xeon(R) CPU 2.30GHz
- GPU for Transfer Learning

Libraries:

- PyWavelets
- Scikit-learn
- PyTorch
- Kymatio

Random Split. 75% of the data for training and 25 % for testing.

Hold-Out Method. Simplest form of cross-validation. Low computational cost [24].

The evaluation is of high variance [24].

Dataset (Guilin People Hospital [14])

Sample size: 219

Categorical Variables:

- Gender (48 % males and 52 % females)
- Hypertension Stage

Numeric variables:

- Age (21 to 19 years old)
- Height (cm)
- Weight (kg)
- Heart Rate (beats/minute)
- Body Mass Index (kg/m^2)

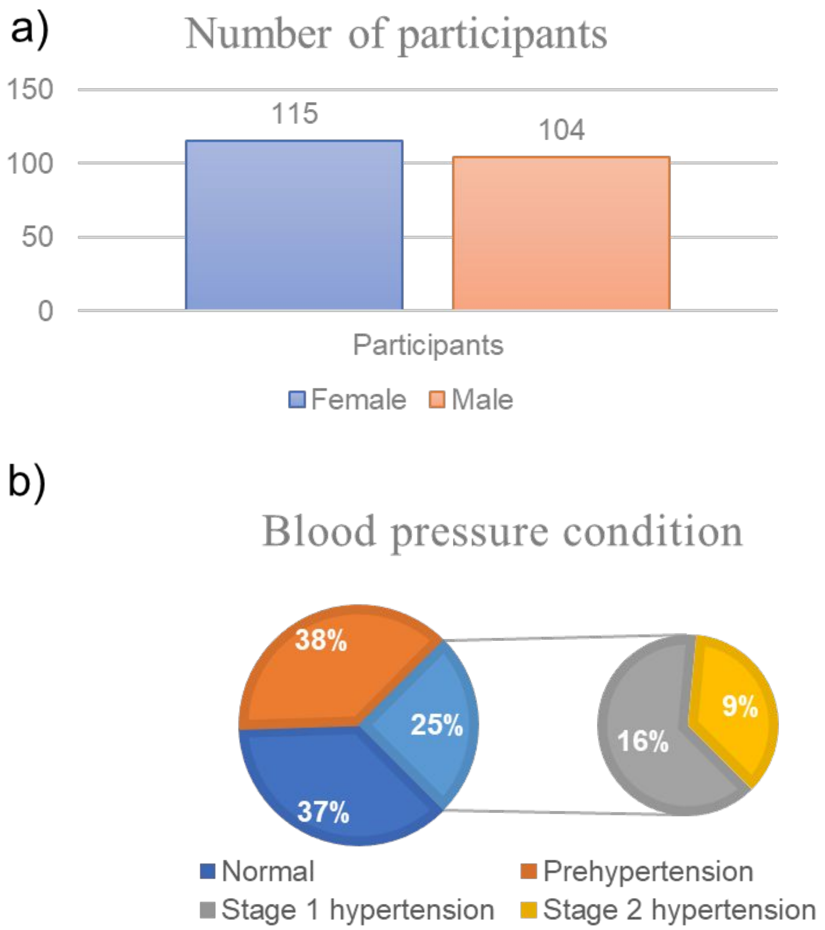


Figure 1. a) Number of participants according to their gender. b) Blood pressure classification stage in the group.

PPG Waveforms

Selection of the PPG segment based on the Skewness as Signal Quality Index [14].

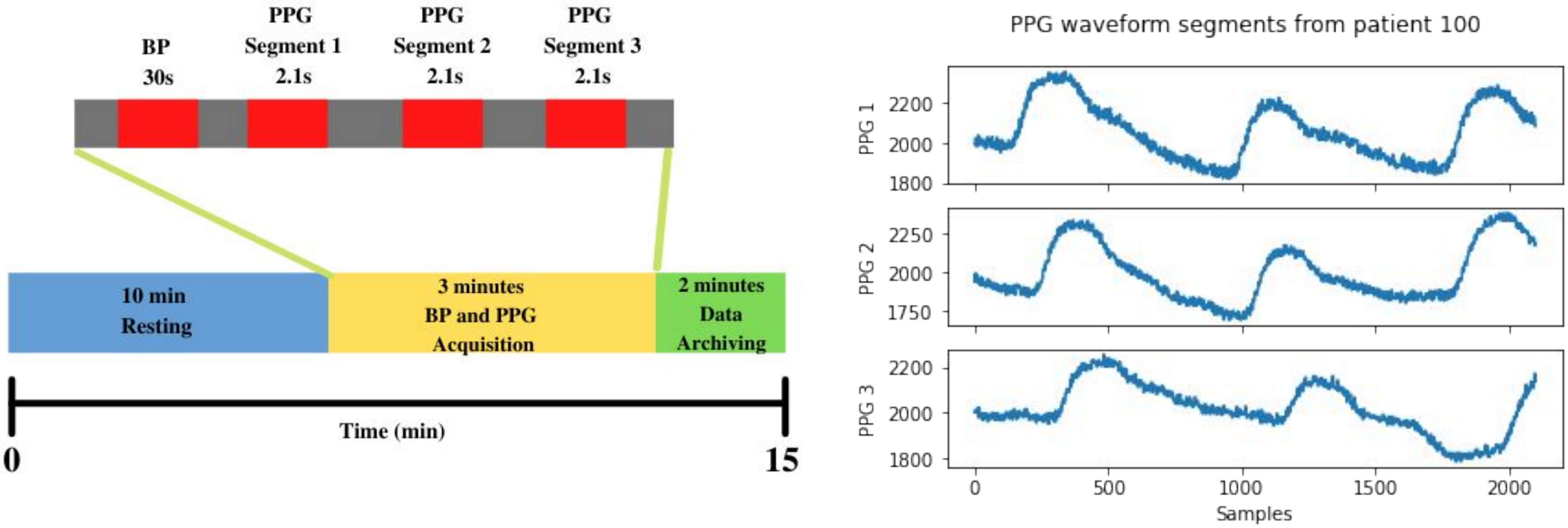
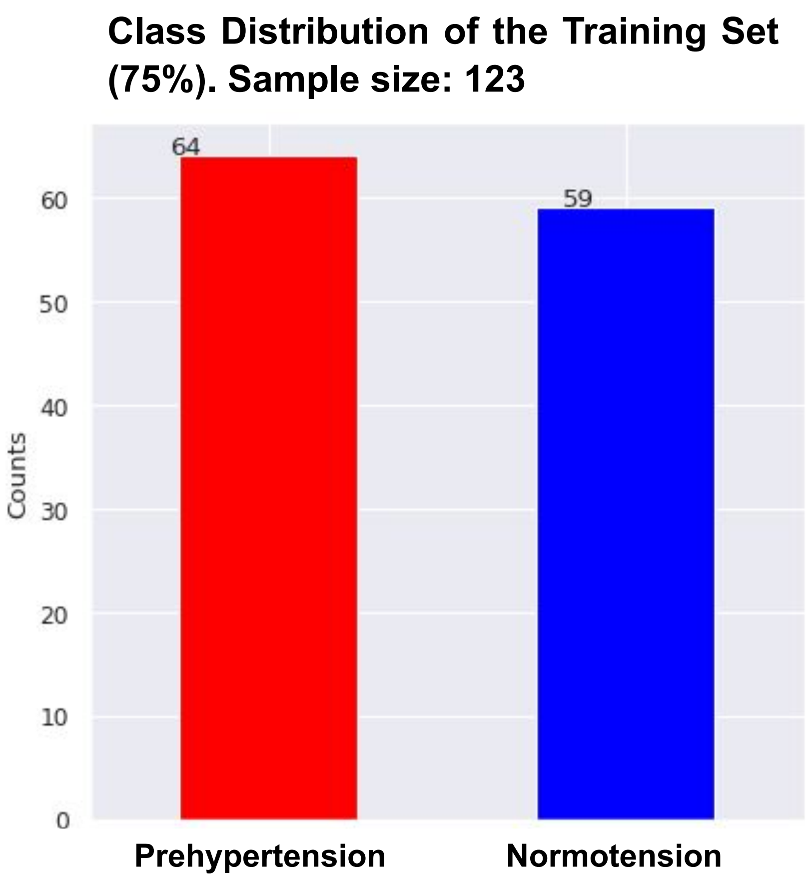


Figure 2. PPG signals collection process sampled at 1 kHz [14].

Training and Testing Splits Class Distribution



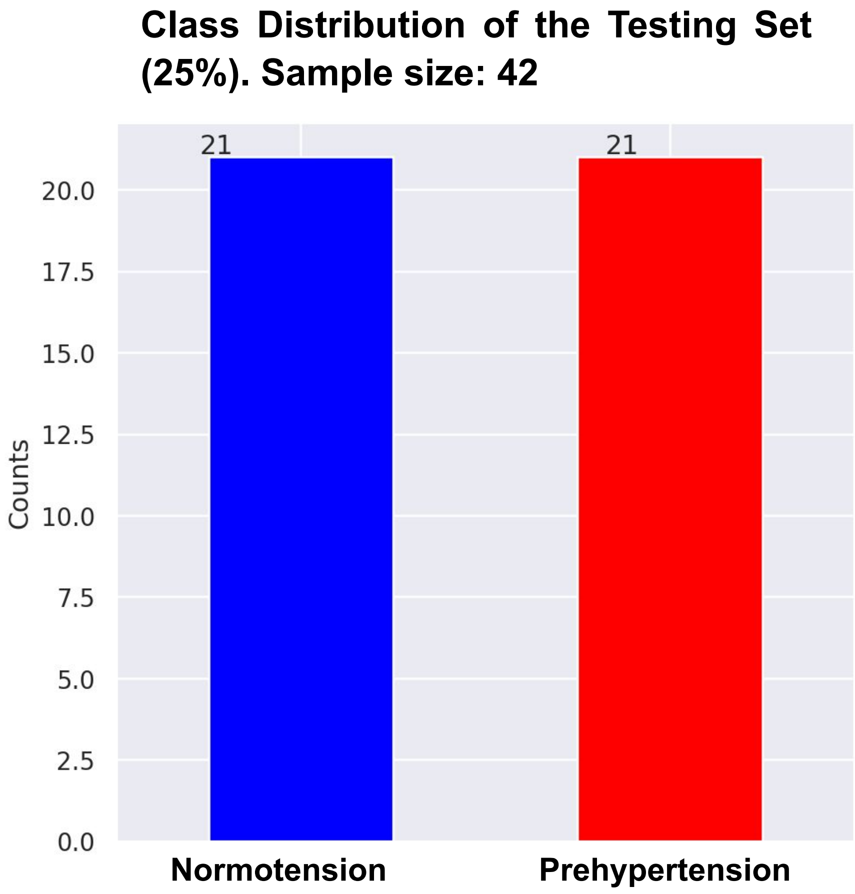


Figure 3. Class distribution of the training and testing sets.

Techniques and Metrics

- Techniques
  - Transfer Learning
    - Inception Net
    - ResNets
    - DenseNets
  - Machine Learning
    - Support Vector Machine (SVM)
    - Logistic Regression (LR)
    - Linear Discriminant Analysis (LDA)
    - K-Nearest Neighbor (KNN)
    - Decision Tree

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Recall = \frac{TP}{TP + FN} \qquad Sensitivity = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP} \qquad Specificity = \frac{TN}{TN + FP}$$

$$F1 - Score = 2\frac{(Precision)(Recall)}{Precision + Recall}$$

Detection of normotension and prehypertension based on PPG signals

Pre-Processing

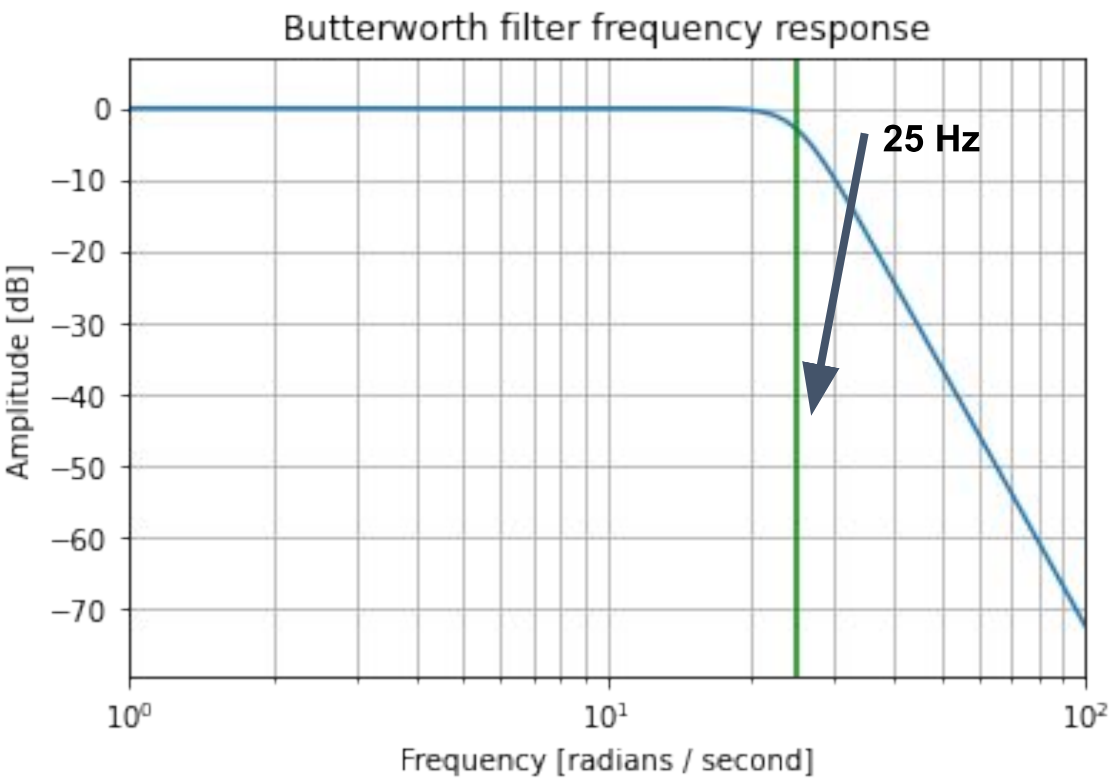


Figure 4. Butterworth low-pass filter with cut-off Frequency 25Hz of 6^{th} order [15].

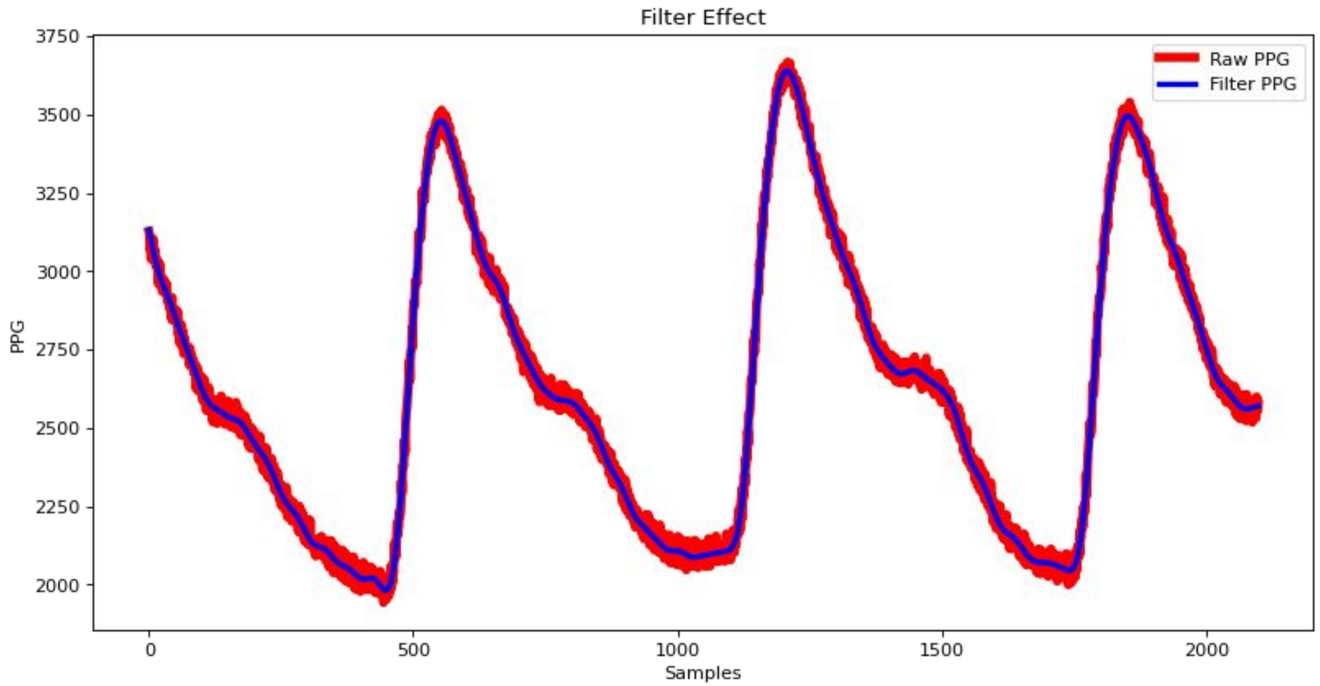


Figure 5. Comparison of a filtered PPG signal with the Raw PPG.

Transfer Learning Approach

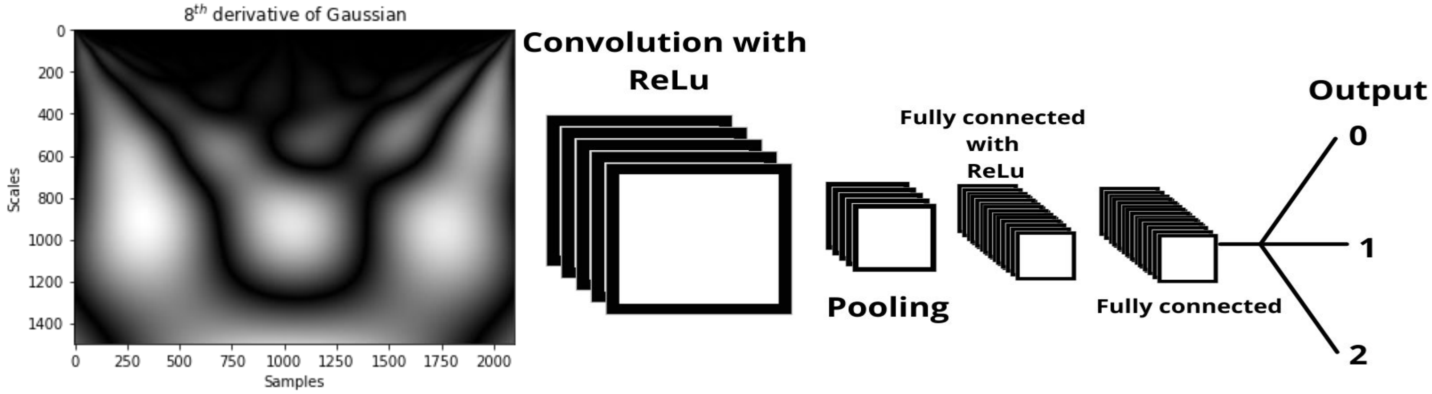
Scalogram Representation through Wavelet Transform

8^{th} Derivative of Gaussian [21]

→

Fine-tuning Convolutional Neural Network (CNN)

Pre-trained CNN [22]	Top-5 Accuracy %
ResNet-18	89.07
DenseNet-121	91.97
ResNet-50	91.42
ResNet-32	92.86
Inception v3	93.45



Frequency Resolution from 0.4 Hz to 300 Hz.

Figure 6. CNN General Structure.

Results

Table 5. Results of applying the transfer learning for Normotension (NT) and prehypertension (PHT) and detection.

ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %	Best Epoch
ResNet-18	LR:0.01	NT	73.81	60.00	61.11	55.00	57.89	24
		PHT			59.09	65.00	61.90	
DenseNet-121		NT	73.55	62.50	60.00	**75.00**	66.67	24
		PHT			66.67	**50.00**	57.14	
ResNet-50		**NT**	**65.08**	**57.50**	**66.67**	**30.00**	**41.38**	12
		PHT			**54.84**	**85.00**	**66.67**	
ResNet-32		NT	73.02	60.00	66.67	40.00	50.00	23
		PHT			57.14	80.00	66.67	
Inception v3 (48 layers)		NT	75.40	60.00	60.00	60.00	60.00	23
		PHT			60.00	60.00	60.00	

Wavelet Scattering Transform (WST)

Stéphane Mallat [16].

- How signals should be represented for classification?
- **Creates a representation that is invariant to translations and stable to small time-warping deformations** [16]**.**
- Reduce the within-class variance.
- The **magnitude** of the **Fourier Transform** is **translation invariant** but not stable to small time-warping deformations [16].
- The **Wavelet Transform** is **translation covariant** [16].

Properties [16]:

- Contracting Operator
- Preserves the Energy
- Stable to small time-warping deformations
- Fast Computation *O(Nlog(N))*

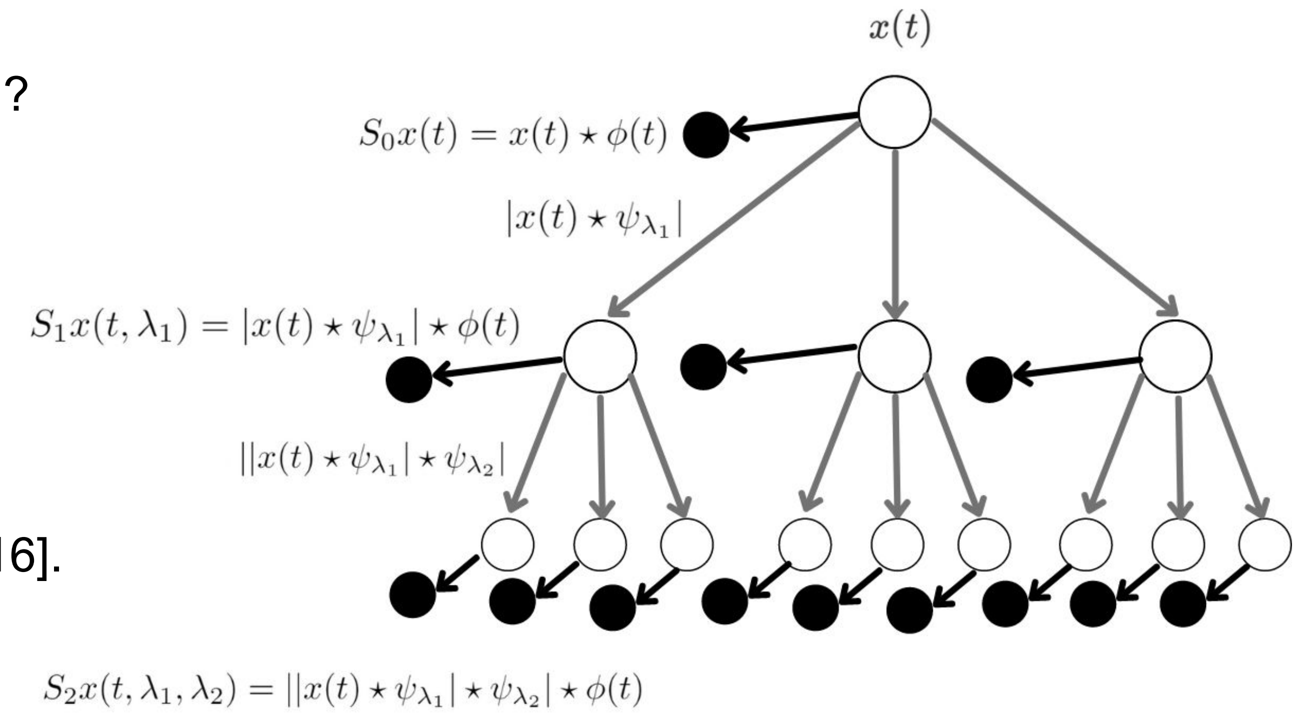


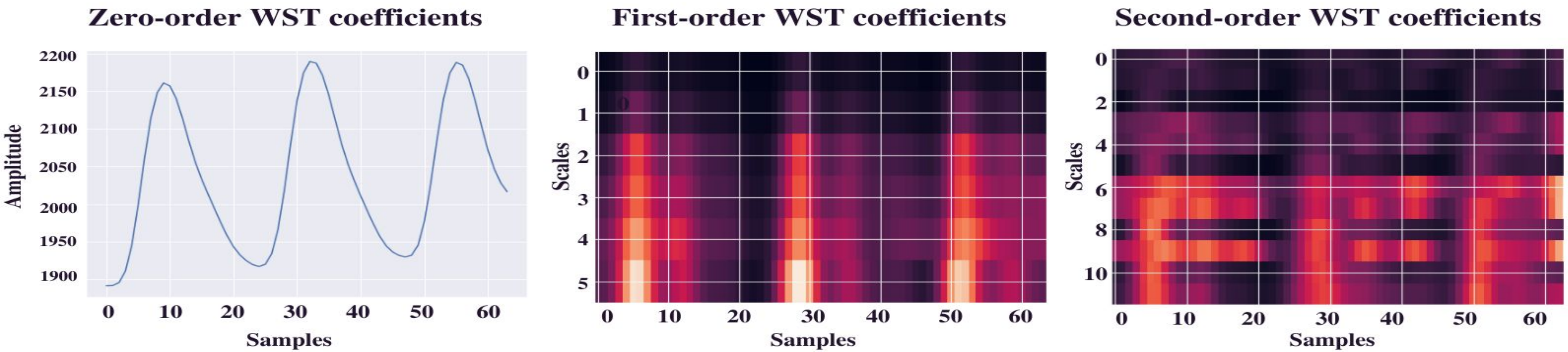
Figure 7. WST schematic representation [20].

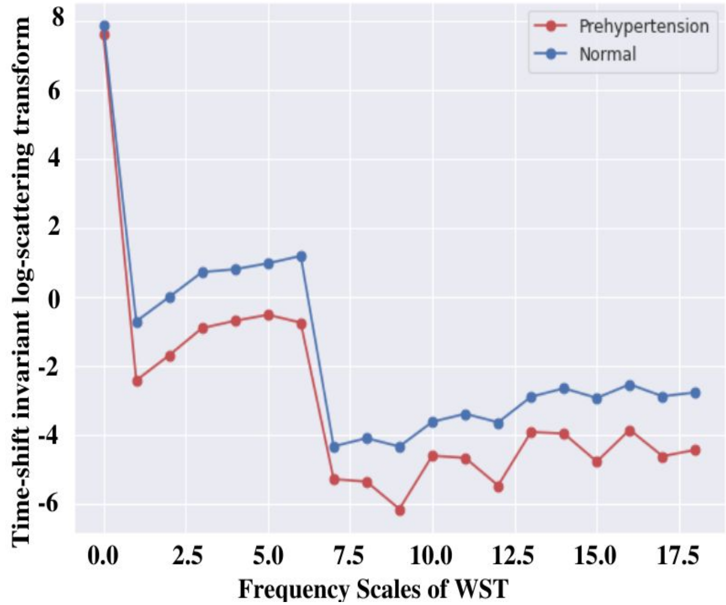
WST computation example

Parameters

Wavelets per Octave
Q = 1

Size of the Invariant
J = 5





Z-score Standardization

Figure 8. WST computation considering a **quality factor of 1** and feature representation (19 features) **[20].**

Results

Table 6. Results of applying the WST and ML for NT and PHT detection **[20].**

ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM	**C:100, Kernel: RBF, Gamma:0.01**	**NT**	**72.35**	**71.42**	**84.61**	**52.38**	**64.70**
		PHT			**65.51**	***90.47***	***76.00***
LR	C: 10 Penalty: L2	NT	66.66	64.29	65.00	61.90	63.41
		PHT			63.64	66.67	65.12
LDA	Not Applicable	NT	70.73	59.52	58.33	66.67	62.22
		PHT			61.11	52.38	56.41
KNN	K: 6	NT	65.85	64.29	62.50	**71.43**	66.67
		PHT			66.67	57.14	61.54
Decision Tree	Criterion: Gini Impurity Max depth: 6	NT	82.92	57.14	55.56	**71.43**	62.50
		PHT			60.00	42.86	50.00

Clinical Data Classification

Detection of normotesion and prehypertension based on Clinical Data

Clinical data and machine learning

Without feature selection

- Age
- Heart Rate
- Body Mass Index
- Gender
- Weight
- Height

Feature Selection

- Age
- Heart Rate
- Body Mass Index

The selected variables are in accordance with the variables commonly used for high blood pressure risk stratification reported in [5].

ML and clinical data

Table 7. Results of training only with the clinical variable without feature selection for NT and PHT detection **[20]**.

ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM	**C:1000, Kernel: RBF, Gamma: 0.00001**	**NT**	**64.22**	**64.29**	**68.75**	**52.38**	**59.46**
		PHT			**61.54**	***76.19***	***68.09***
LR	C: 10 Penalty: L2	NT	63.41	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
LDA	Not Applicable	NT	65.04	57.14	57.14	57.14	57.14
		PHT			57.14	57.14	57.14
KNN	K: 5	NT	73.98	61.90	63.16	57.14	60.00
		PHT			60.87	66.67	63.64
Decision Tree	Criterion: Gini Impurity Max depth: 1	NTT	65.04	54.76	53.57	**71.43**	61.22
		PHT			57.14	**38.10**	45.71

Feature Selection

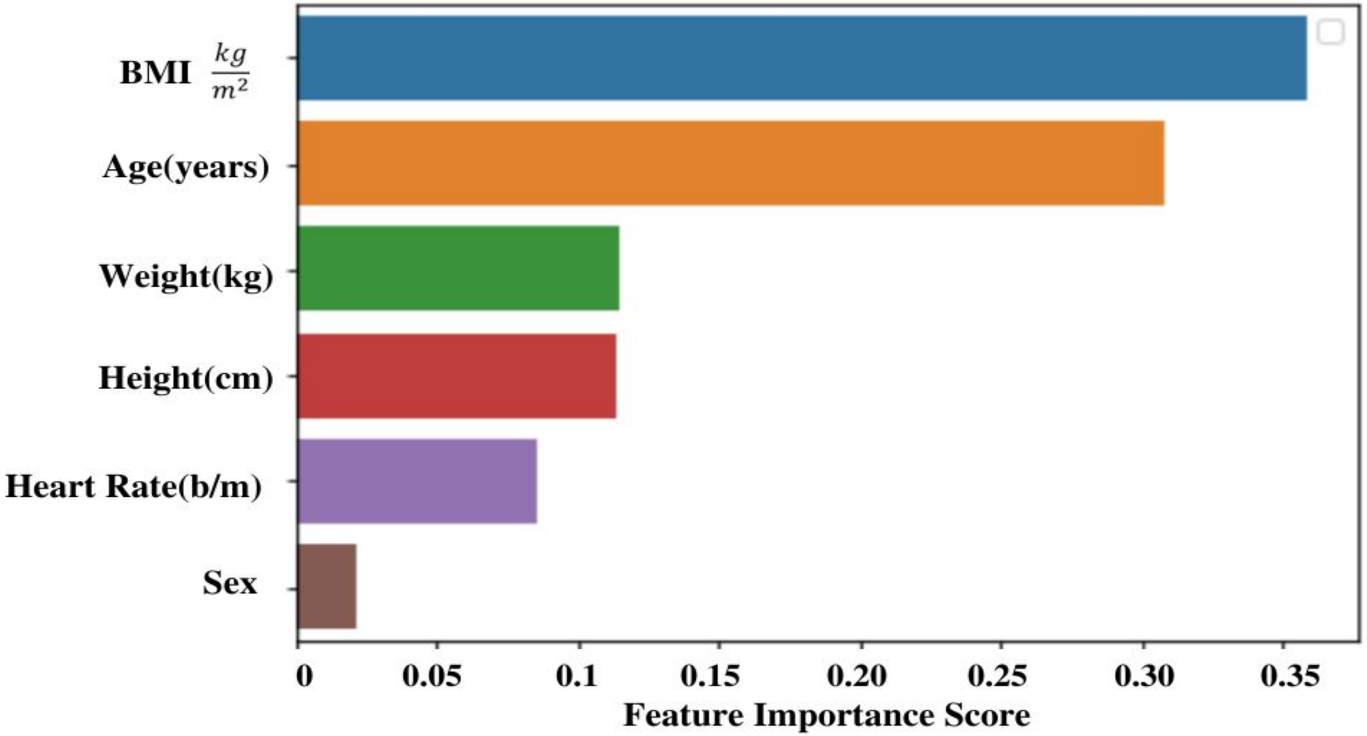


Figure 9. Relative feature importance of clinical data computed through **Gini Impurity [20]**.

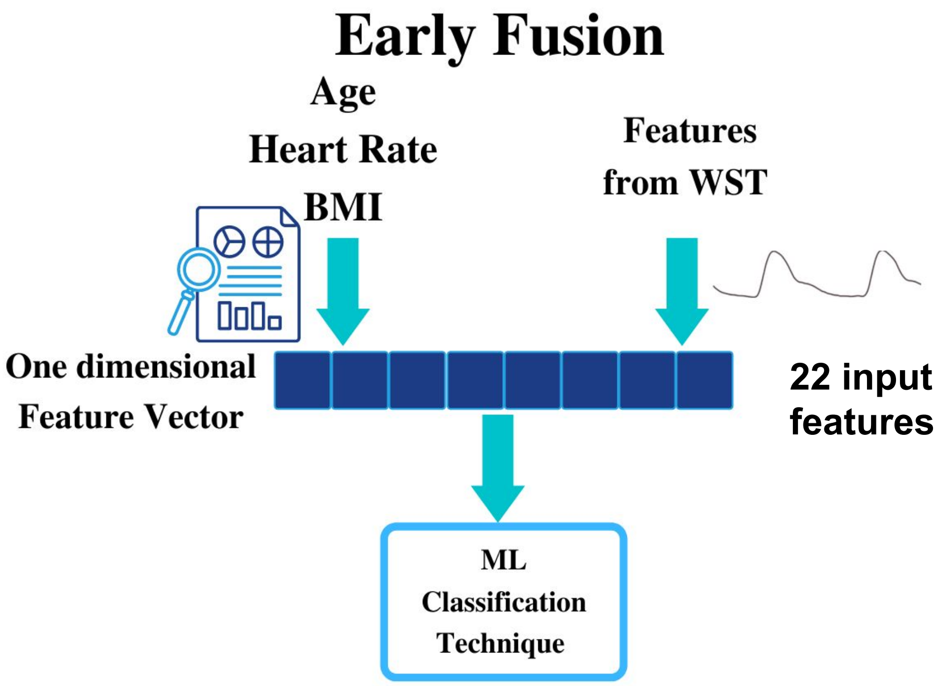
Results

Table 8. Results of training only with the clinical variable with feature selection for NT and PHT detection **[20]**.

ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM	**C:1000, Kernel: RBF, Gamma: 0.001**	**NT**	**69.10**	**66.67**	**70.59**	**57.14**	**63.16**
		PHT			**64.00**	***76.19***	***69.57***
LR	C: 1 Penalty: L2	NT	63.41	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
LDA	Not Applicable	NT	63.41	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
KNN	K: 9	NT	72.35	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
Decision Tree	Criterion: Gini Impurity Max depth: 7	NT	65.04	54.76	53.57	**71.43**	61.22
		PHT			57.14	**38.10**	45.71

Detection of normotension and prehypertension based on PPG and Clinical Data

Early Fusion



22 input variables (19 WST features + 3 clinical variables)

Figure 10. Schematic representation of early fusion [18,19,**20**].

Results Early Fusion

Table 9. Results of the Early Fusion approach for NT and PHT detection **[20]**.

ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM	C:100, Kernel: RBF, Gamma: 0.01	NT	82.11	61.90	63.16	57.14	60.00
		PHT			60.87	66.67	63.64
LR	C: 0.001 Penalty: L2	NT	73.17	64.29	66.67	57.14	61.54
		PHT			62.50	71.43	66.67
LDA	Not Applicable	NT	73.17	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
KNN	**K: 5**	**NT**	**72.35**	**69.05**	**70.00**	**66.67**	**68.29**
		PHT			**68.18**	***71.43***	***69.77***
Decision Tree	Criterion: Gini Impurity Max depth: 3	NT	73.17	52.38	57.89	52.38	55.00
		PHT			56.52	61.90	59.09

Late Fusion

Model 1: Machine Learning Techniques trained with Age, Heart Rate, and BMI.

Model 2: SVM trained with WST.

Model 3: LR trained with WST.

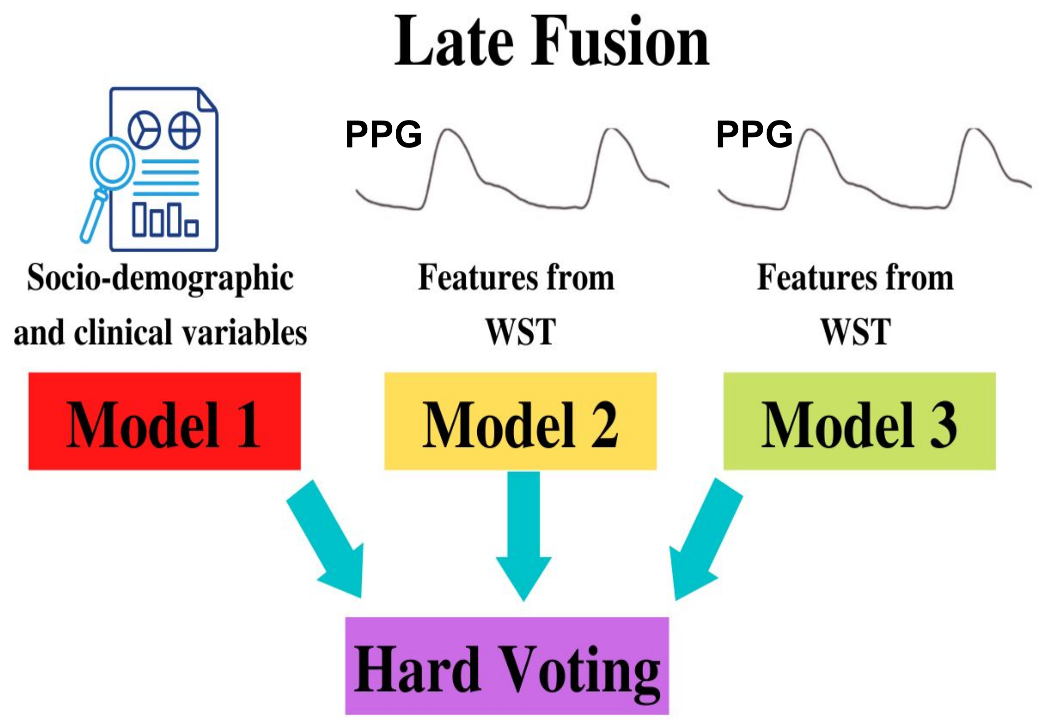


Figure 11. Schematic representation of late fusion [18,19, **20**].

Results Late fusion

Table 10. Results of the late fusion approach for NT and PHT detection **[20]**.

PPG models based on WST	Clinical data models	Class	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM+LR	**SVM**	**NT**	**69.05**	**75.00**	**57.14**	**64.86**
		PHT		**65.38**	***80.95***	***72.34***
	LR	NT	66.67	70.59	57.14	63.16
		PHT		64.00	76.19	69.57
	LDA	NT	66.67	70.59	57.14	63.16
		PHT		64.00	76.16	69.57
	KNN	NT	66.67	73.33	52.38	61.11
		PHT		62.96	**80.95**	70.83
	Decision Tree	NT	61.90	72.22	**61.90**	66.67
		PHT		66.67	**76.19**	71.11

Selected Models for each experiment

Table 11. Results obtained in each experiment presented in this work.

Experiment	Features	Algorithm	Metrics %
NT and PHT detection based on PPG	19 WST Features	Support Vector Machine	F1-score: 76.00 Sensitivity: 90.47 Specificity: 52.38
NT and PHT detection based on Clinical Data	Age, BMI, and Heart Rate	Support Vector Machine	F1-score: 68.09 Sensitivity: 76.19 Specificity: 52.38
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	Early Fusion KNN	F1-score: 69.77 Sensitivity: 71.43 Specificity: 66.67
		Early Fusion LR	F1-score: 66.67 Sensitivity: 71.43 Specificity: 57.14
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	Late Fusion (SVM + SVM + LR)	F1-score: 72.34 Sensitivity: 80.95 Specificity: 57.14

Comparison with the Literature

Table 12. Comparison with the literature reported metrics refer to PHT class **[20]**.

Author	Dataset	Features	Algorithm	Reported Metrics %
Liang et al. [6]	Subset of MIMIC	Continuous Wavelet Transform (Morse Wavelet) From PPG	Pre-trained GoogLeNet	F1-Score:80.52
Liang et al. [8]	Subset of MIMIC	ECG and PPG Pulse Arrival Time and 10 PPG Features	K-Nearest Neighbors	F1-Score:84.34 Sensitivity:83.92 Specificity:84.76
Sannino et al [11].	Subset of MIMIC	PPG waveform no feature engineer specify	Random Forest	F1-Score: 85.7
Yao et al. [10]	**PPG-BP**	**Physiological and PPG Derivatives Morphological Features**	**Support Vector Machine**	***F1-Score: 65*** ***Sensitivity: 63*** **Specificity: 69**
Sun et al. [7]	**Subset of MIMIC**	**PPG Derivatives and Hilbert-Huang Transform**	**Pre-trained AlexNet**	***F1-Score: 85.80*** ***Sensitivity: 95.26*** **Specificity: 71.88**

Author	Dataset	Features	Algorithm	Reported Metrics %
Liang et al.[9]	PPG-BP	PPG morphological features	Weight KNN	F1-score: 72.97 Sensitivity:65.85 Precision: 81.82
NT and PHT detection based on PPG	PPG-BP	19 WST Features	Support Vector Machine	F1-score: 76.00 Sensitivity: 90.47 Specificity: 52.38
NT and PHT detection based on Clinical Data	PPG-BP	Age, BMI, and Heart Rate	Support Vector Machine	F1-score: 68.09 Sensitivity: 76.19 Specificity: 52.38
NT and PHT detection based on PPG and Clinical Data	PPG-BP	Age, BMI , Heart Rate, plus 19 WST Features	Early Fusion KNN	F1-score: 69.77 Sensitivity: 71.43 Specificity: 66.67
NT and PHT detection based on PPG and Clinical Data	PPG-BP	Age, BMI , Heart Rate, plus 19 WST Features	Late Fusion (SVM + SVM + LR)	F1-score: 72.34 Sensitivity: 80.95 Specificity: 57.14

5-Fold Cross-Validation Results

Table 13. 5-Fold Cross-Validation Results of each of the selected models.

Experiment	Features	Algorithm	5-Fold Cross-Validation Mean ± Standard Deviation %		Hold - Out Method
NT and PHT detection based on PPG	19 WST Features	**Support Vector Machine**	**F1-score:** 70.32 ± 19.80 **Sensitivity:** 81.50 ± 19.20 **Specificity**: 46.67 ± 16.09		F1-score: 76.00 Sensitivity: 90.47 Specificity: 52.38
NT and PHT detection based on Clinical Data	Age, BMI, and Heart Rate	**Support Vector Machine**	**F1-score:** 70.57 ± 12.37 **Sensitivity:** 88.61 ± 6.11 **Specificity:** 35.87 ± 14.61		F1-score: 68.09 Sensitivity: 76.19 Specificity: 52.38
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Early Fusion KNN and LR**	**KNN**	**F1-score**: 57.56 ± 0.097 **Sensitivity**: 56.66 ± 14.33 **Specificity:** 58.70 ± 9.78	F1-score: 69.77 Sensitivity: 71.43 Specificity: 66.67
			LR	**F1-score:** 69.36 ± 12.35 **Sensitivity**: 79.66 ± 8.05 **Specificity:** 46.12 ± 20.07	F1-score: 66.67 Sensitivity: 71.43 Specificity: 57.14
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Late Fusion (SVM + SVM + LR)**	**LR 19 WST**	**F1-score**: 69.91 ± 17.39 **Sensitivity:** 77.72 ± 0.1446 **Specificity:** 49.21 ± 21.75	F1-score: 72.34 Sensitivity: 80.95 Specificity: 57.14
			SVM Age, BMI Heart Rate	**F1-score:** 70.57 ± 12.37 **Sensitivity**: 88.61 ± 6.11 **Specificity**: 35.87 ± 14.61	
			SVM 19 WST	**F1-score:** 70.32 ± 19.80 **Sensitivity:** 81.50 ± 19.20 **Specificity:** 46.67 ± 16.09	

Conclusions

- This work proposed to use the WST as a feature extraction technique on PPG waveforms for elevated BP detection.

- The use of the **PPG and the WST** for elevated BP detection showed a *similar* performance to other works in the literature **in terms of F1-score for the PHT class and sensitivity** without relaying in deep learning approaches and morphological feature extraction.

- **Late Fusion showed** a better performance than Early Fusion in terms of **sensitivity and F1-score**.

- Nevertheless, considering the effect of clinical data in the fitted models does not provide better performance in terms of **F1-score** than employing only the PPG data.

Future Work

- It can be explored to analyze the clinical data by employing a multi-level model by stratifying based on age or BMI values similar to the work of Xing et al. [17].
- Explore methods to deal with the unbalanced proportion of the dataset.
- It can be explored to test the proposed methodology with different distributions.

Contributions

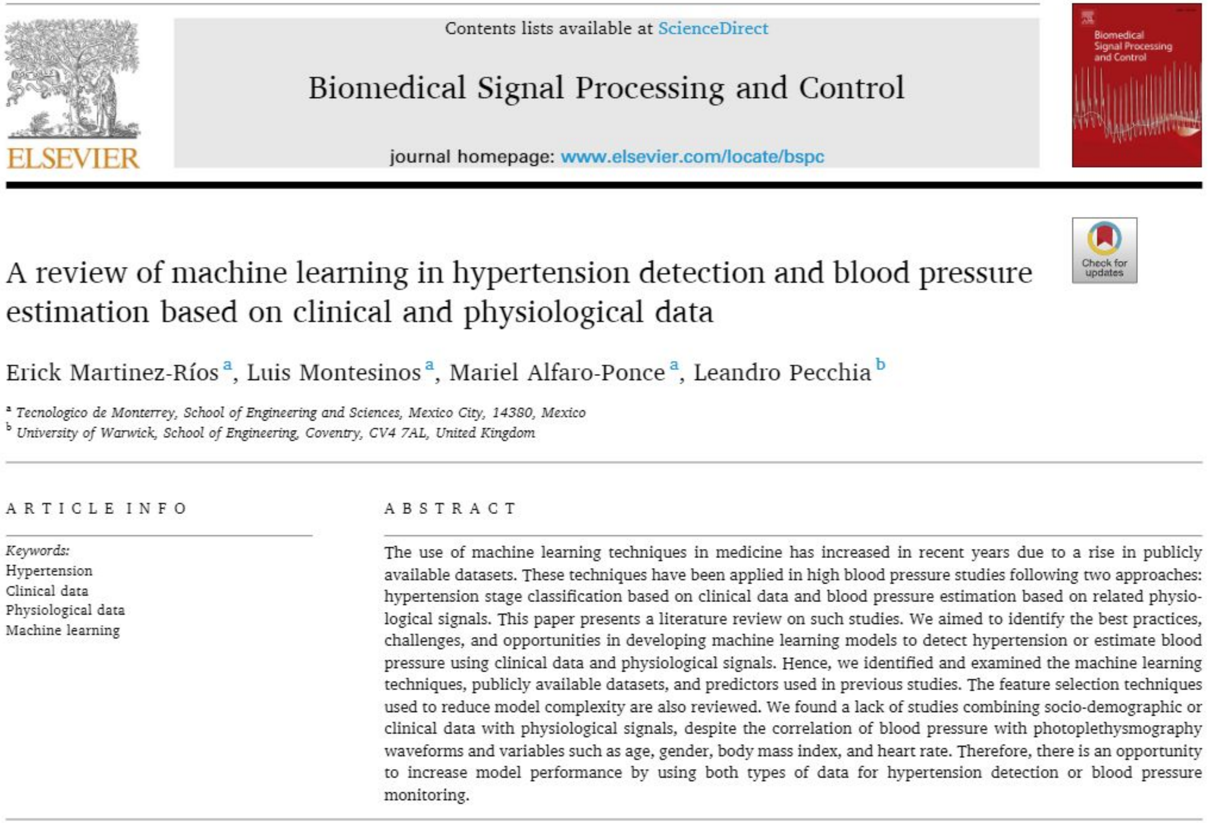
- Machine Learning based detection of normotension and prehypertension using the **wavelet scattering transform** and PPG signals.

- An assessment of **multimodal approaches** for the detection of prehypertension using clinical data and PPG features acquired from the **wavelet scattering transform**.

- A comparison between **unimodal and multimodal classifiers** for normotension and prehypertension detection.

Overall Results

Martinez-Ríos, Erick, et al. "A review of machine learning in hypertension detection and blood pressure estimation based on clinical and physiological data." *Biomedical Signal Processing and Control* 68 (2021): 102813.



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A review of machine learning in hypertension detection and blood pressure estimation based on clinical and physiological data

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Keywords:
Hypertension
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Physiological data
Machine learning

ABSTRACT

The use of machine learning techniques in medicine has increased in recent years due to a rise in publicly available datasets. These techniques have been applied in high blood pressure studies following two approaches: hypertension stage classification based on clinical data and blood pressure estimation based on related physiological signals. This paper presents a literature review on such studies. We aimed to identify the best practices, challenges, and opportunities in developing machine learning models to detect hypertension or estimate blood pressure using clinical data and physiological signals. Hence, we identified and examined the machine learning techniques, publicly available datasets, and predictors used in previous studies. The feature selection techniques used to reduce model complexity are also reviewed. We found a lack of studies combining socio-demographic or clinical data with physiological signals, despite the correlation of blood pressure with photoplethysmography waveforms and variables such as age, gender, body mass index, and heart rate. Therefore, there is an opportunity to increase model performance by using both types of data for hypertension detection or blood pressure monitoring.

Overall Results

Martinez-Ríos, Erick, Luis Montesinos, and Mariel Alfaro-Ponce. "A machine learning approach for hypertension detection based on photoplethysmography and clinical data." *Computers in Biology and Medicine* (2022): 105479.

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A machine learning approach for hypertension detection based on photoplethysmography and clinical data

Erick Martinez-Ríos, Luis Montesinos, Mariel Alfaro-Ponce *

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A R T I C L E I N F O

Keywords:
Blood pressure
Classification
Machine learning
Risk stratification
Wavelet transform

A B S T R A C T

High blood pressure early screening remains a challenge due to the lack of symptoms associated with it. Accordingly, noninvasive methods based on photoplethysmography (PPG) or clinical data analysis and the training of machine learning techniques for hypertension detection have been proposed in the literature. Nevertheless, several challenges arise when analyzing PPG signals, such as the need for high-quality signals for morphological feature extraction from PPG related to high blood pressure. On the other hand, another popular approach is to use deep learning techniques to avoid the feature extraction process. Nonetheless, this method requires high computational power and behaves as a black-box approach, which impedes application in a medical context. In addition, considering only the socio-demographic and clinical data of the subject does not allow constant monitoring. This work proposes to use the wavelet scattering transform as a feature extraction technique to obtain features from PPG data and combine it with clinical data to detect early hypertension stages by applying Early and Late Fusion. This analysis showed that the PPG features derived from the wavelet scattering transform combined with a support vector machine can classify normotension and prehypertension with an accuracy of 71.42% and an F1-score of 76%. However, classifying normotension and prehypertension by considering both the features extracted from PPG signals through wavelet scattering transform and clinical variables such as age, body mass index, and heart rate by either Late Fusion or Early Fusion did not provide better performance than considering each data type separately in terms of accuracy and F1-score.

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https://www.gaceta.unam.mx/con-hipertension-31-millones-de-mexicanos/


For your attention and time,
THANK YOU

Sensitivity and Specificity

- Cross-sectional study of 551 participants of white British, South Asian and African Caribbean patients where the detection of **clinical Blood Pressure** Measurement had a **sensitivity** of between **75-97%** and a **specificity** of **33-65%. Home Blood Pressure** Measurement had a **sensitivity** of **68-88 %** and **specificity** of **64-80**% [24].

- **Pooled sensitivity** of clinic blood pressure measurement was **74%** (95 % CI: 65–82%), and the **pooled specificity** was of **79%** (95 % CI: 69-87%). Besides, the pooled sensitivity and specificity of **home monitoring blood pressure** were **71** % (95 % CI: 61-80%) and **82**% (95 % CI: 77-87%). This analysis was based on 58 studies [25].

- Meta-analysis of 8 studies **showed a pooled sensitivity** of **0.54** (95 % CI, 0.37-0.70) for **office-based blood pressure** screening, with a **specificity of 0.90** (95 % CI, 0.84-0.95). Meta-analysis of 4 **home high blood pressure** confirmation studies reported a **pooled sensitivity** of **0.84** (95 % CI, 0.76-0.90) and a **pooled specificity** of **0.60** (95 % CI, 0.48-0.71) [26].

- **Sensitivity of 31.1** % (95 % CI, 22.9-40.6) **for clinic diagnosis**, and **82.2** % (73.8-88.4) for **home diagnosis**, while the **specificities** were of **79.5** % (64.0-89.4) for **clinic**, and **53.3** % (38.9-67.2) for **home diagnosis**. Study carried-out to 510 participants from 12 care centers of Washington [27].

High blood pressure, Mexico

- According to the National Survey of Health and Nutrition of the Midway 2016, carried out by the National Institute of Public Health (INSP) and the Ministry of Health, **one in four adults in Mexico** suffers from **high blood pressure**, that is, **25.5 percent of the population**. In **men** the prevalence is **24.9%** and in **women** is **26.1%** [28].

- Approximately **30 million people** suffer from hypertension in Mexico [28].

- **40 percent are unaware** that they have this disease, and about 60 percent who know the diagnosis, **only half are controlled** [28].

5-Fold Cross-Validation Results

Table 13. 5-Fold Cross-Validation Results of each of the selected models.

Experiment	Features	Algorithm	5-Fold Cross-Validation Mean ± Standard Deviation %		Hold - Out Method
NT and PHT detection based on PPG	19 WST Features	**Support Vector Machine**	**F1-score:** 70.32 ± 19.80 **Sensitivity:** 81.50 ± 19.20 **Specificity**: 46.67 ± 16.09		F1-score: 76.00 Sensitivity: 90.47 Specificity: 52.38
NT and PHT detection based on Clinical Data	Age, BMI, and Heart Rate	**Support Vector Machine**	**F1-score:** 70.57 ± 12.37 **Sensitivity:** 88.61 ± 6.11 **Specificity:** 35.87 ± 14.61		F1-score: 68.09 Sensitivity: 76.19 Specificity: 52.38
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Early Fusion KNN and LR**	**KNN**	**F1-score**: 57.56 ± 0.097 **Sensitivity**: 56.66 ± 14.33 **Specificity:** 58.70 ± 9.78	F1-score: 69.77 Sensitivity: 71.43 Specificity: 66.67
			LR	**F1-score:** 69.36 ± 12.35 **Sensitivity**: 79.66 ± 8.05 **Specificity:** 46.12 ± 20.07	F1-score: 66.67 Sensitivity: 71.43 Specificity: 57.14
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Late Fusion (SVM + SVM + LR)**	**LR 19 WST**	**F1-score**: 69.91 ± 17.39 **Sensitivity:** 77.72 ± 0.1446 **Specificity:** 49.21 ± 21.75	F1-score: 72.34 Sensitivity: 80.95 Specificity: 57.14
			SVM Age, BMI Heart Rate	**F1-score:** 70.57 ± 12.37 **Sensitivity**: 88.61 ± 6.11 **Specificity**: 35.87 ± 14.61	
			SVM 19 WST	**F1-score:** 70.32 ± 19.80 **Sensitivity:** 81.50 ± 19.20 **Specificity:** 46.67 ± 16.09	

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NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Early Fusion KNN and LR**	**KNN**	**F1-score**: 57.56 **Sensitivity**: 56.66 **Specificity:** 58.70	F1-score: 69.77 Sensitivity: 71.43 Specificity: 66.67
			LR	**F1-score:** 69.36 **Sensitivity**: 79.66 **Specificity:** 46.12	F1-score: 66.67 Sensitivity: 71.43 Specificity: 57.14
NT and PHT detection based on PPG and Clinical Data	Age, BMI , Heart Rate, plus 19 WST Features	**Late Fusion (SVM + SVM + LR)**	**F1-score**: 70.22 **Sensitivity:** 82.62 **Specificity:** 43.92		F1-score: 72.34 Sensitivity: 80.95 Specificity: 57.14

Sensitivity and Specificity

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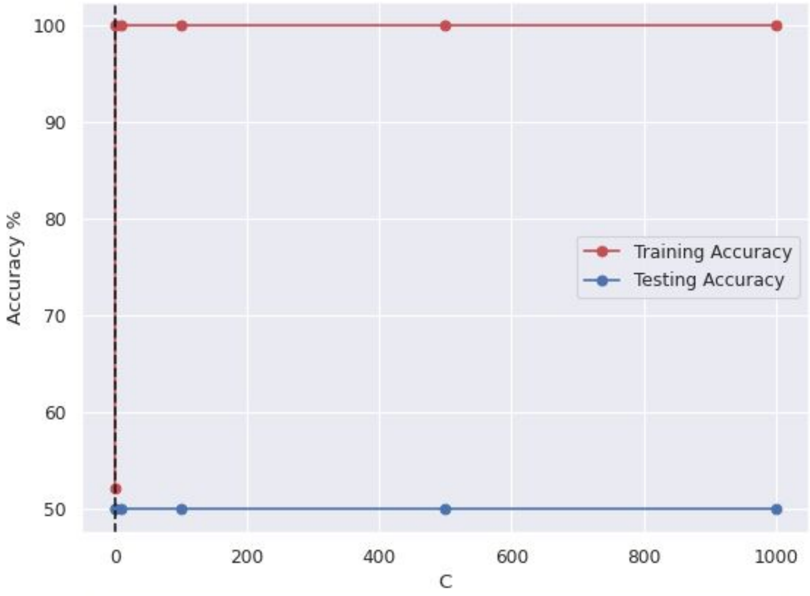
Results Proposed Experiment

Table A. Results of applying the WST and ML for NT and PHT detection (1152 inputs).

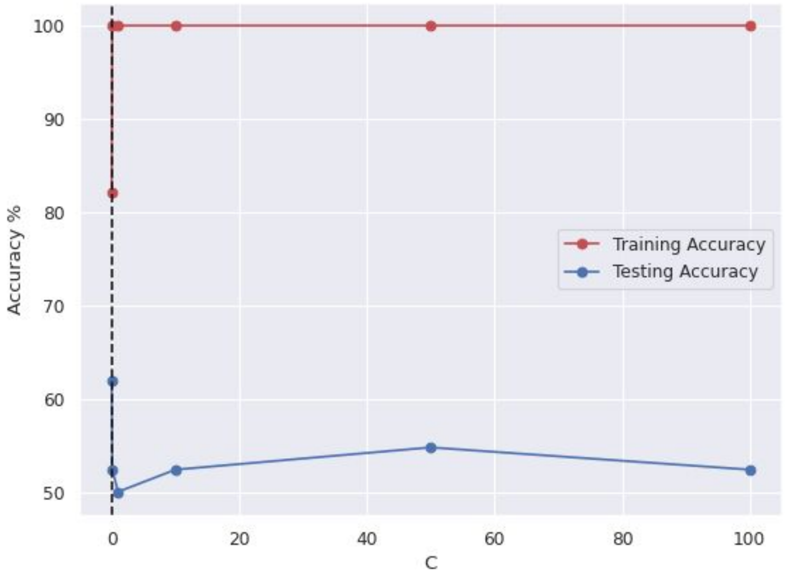
ML Method	Hyperparameters	Class	Training Accuracy %	Testing Accuracy %	Precision %	Recall %	F1-score %
SVM	**C:100, Kernel: RBF, Gamma:0.01**	**NT**	52.03	50.00	0.00	0.00	0.00
		PHT			50.00	100.00	66.67
LR	C: 10 Penalty: L2	NT	82.11	61.90	61.90	61.90	61.90
		PHT			61.90	61.90	61.90
LDA	SVD	NT	95.93	54.76	53.85	66.67	59.57
		PHT			56.25	42.86	48.65
KNN	K: 3	NT	77.72	69.05	68.18	71.43	69.77
		PHT			70.00	66.67	68.29
Decision Tree	Criterion: Gini Impurity Max depth: 2	NT	73.17	64.29	66.67	57.14	61.54
		PHT			62.50	71.43	66.67

Results - Proposed Experiment

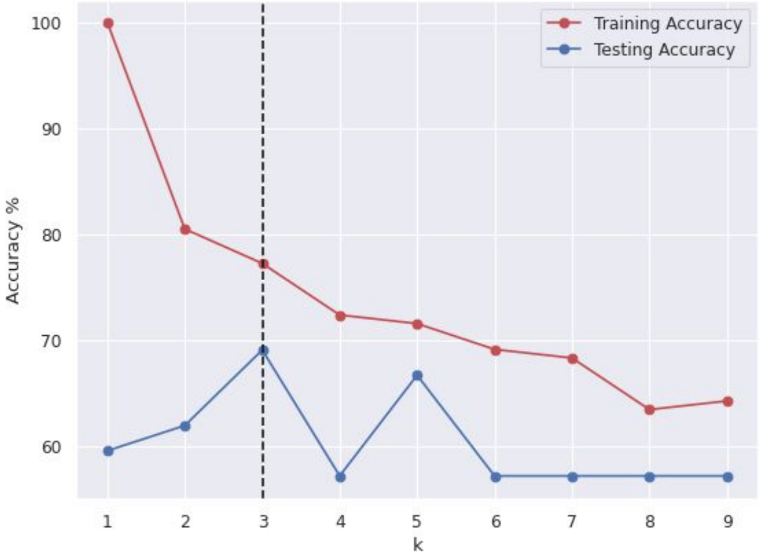
SVM



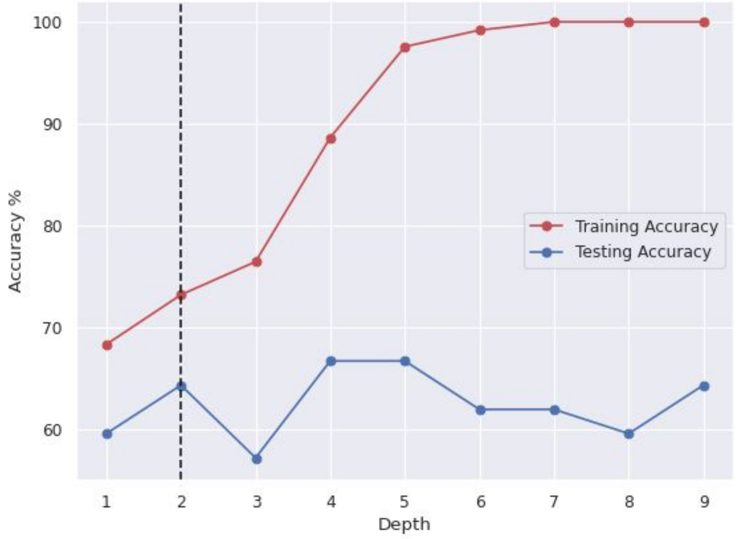
LR



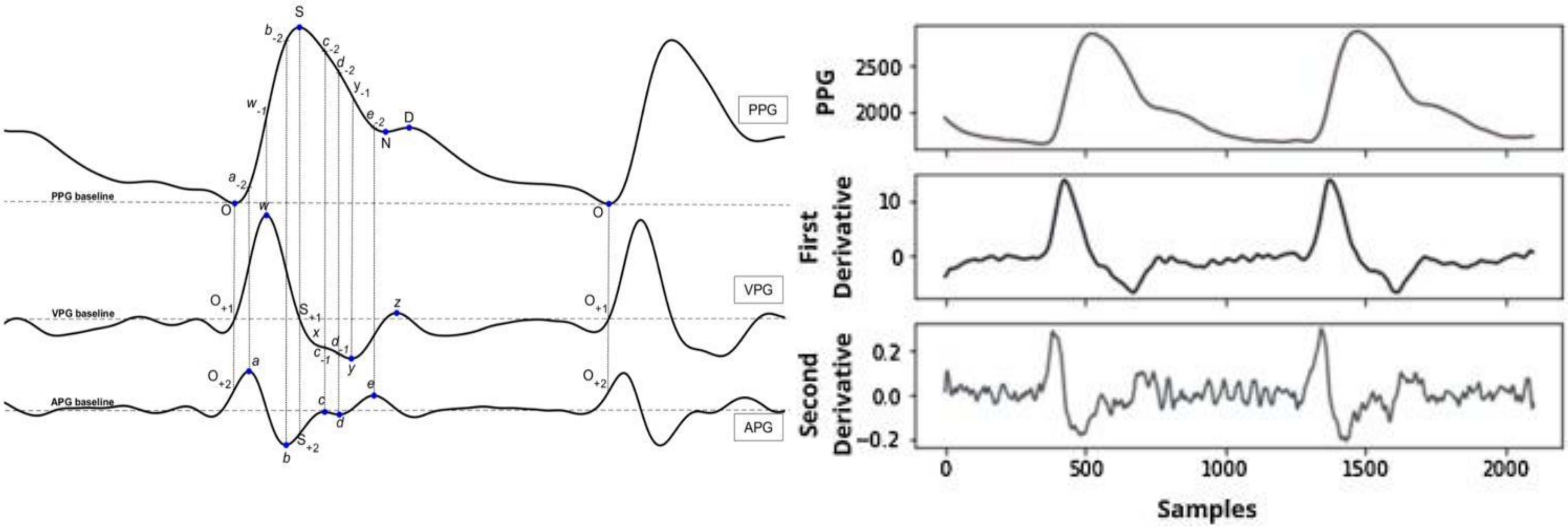
KNN



Decision Tree

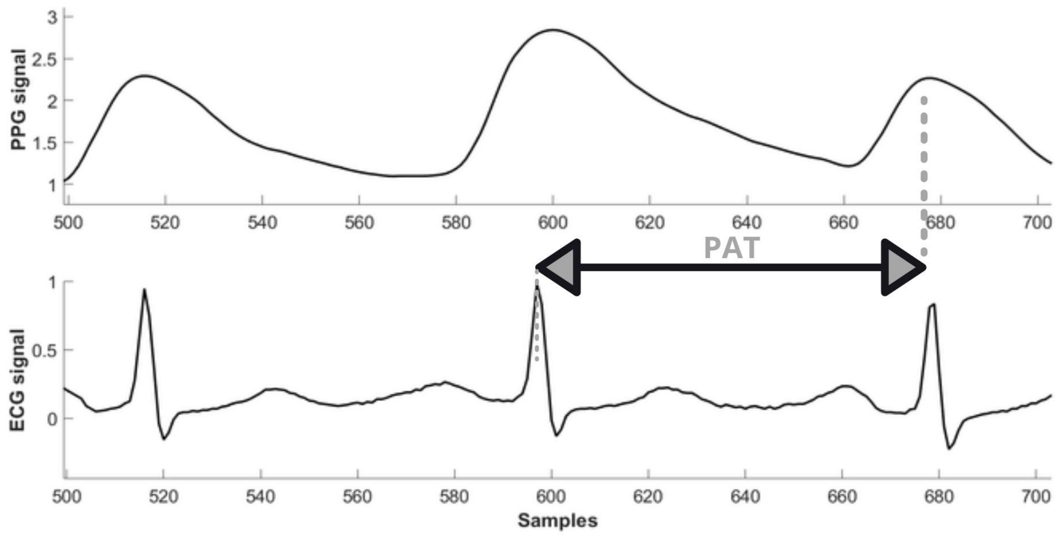


Signals used for high blood pressure detection

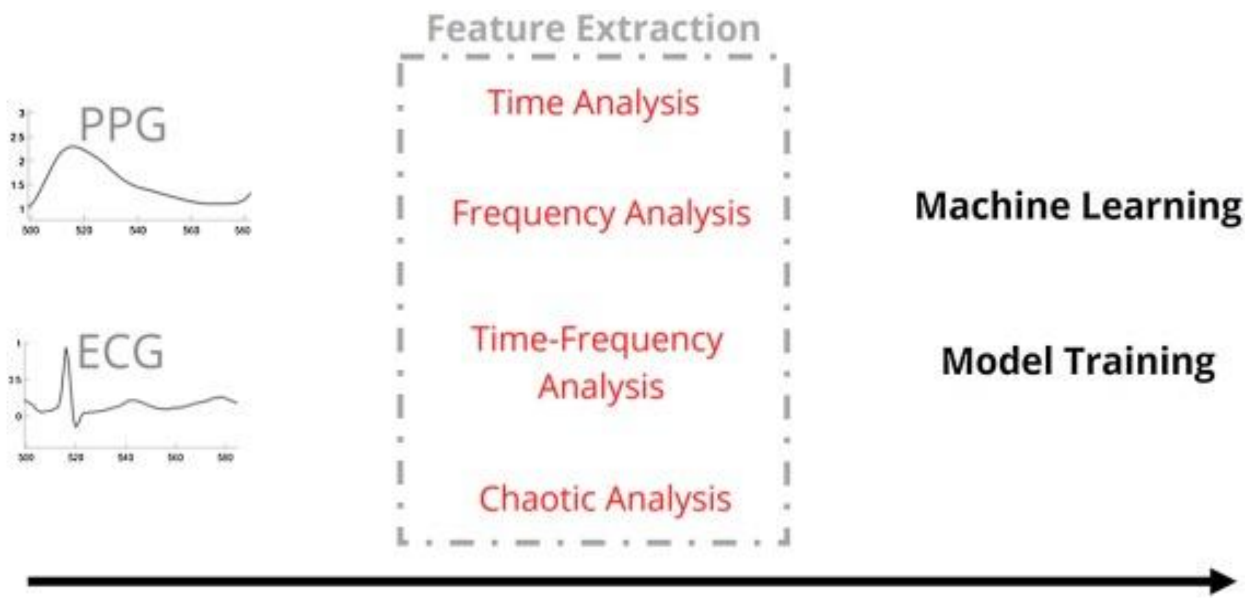


PPG Morphological Features based on PPG derivatives [5,8,9].

Signal used for high blood pressure detection

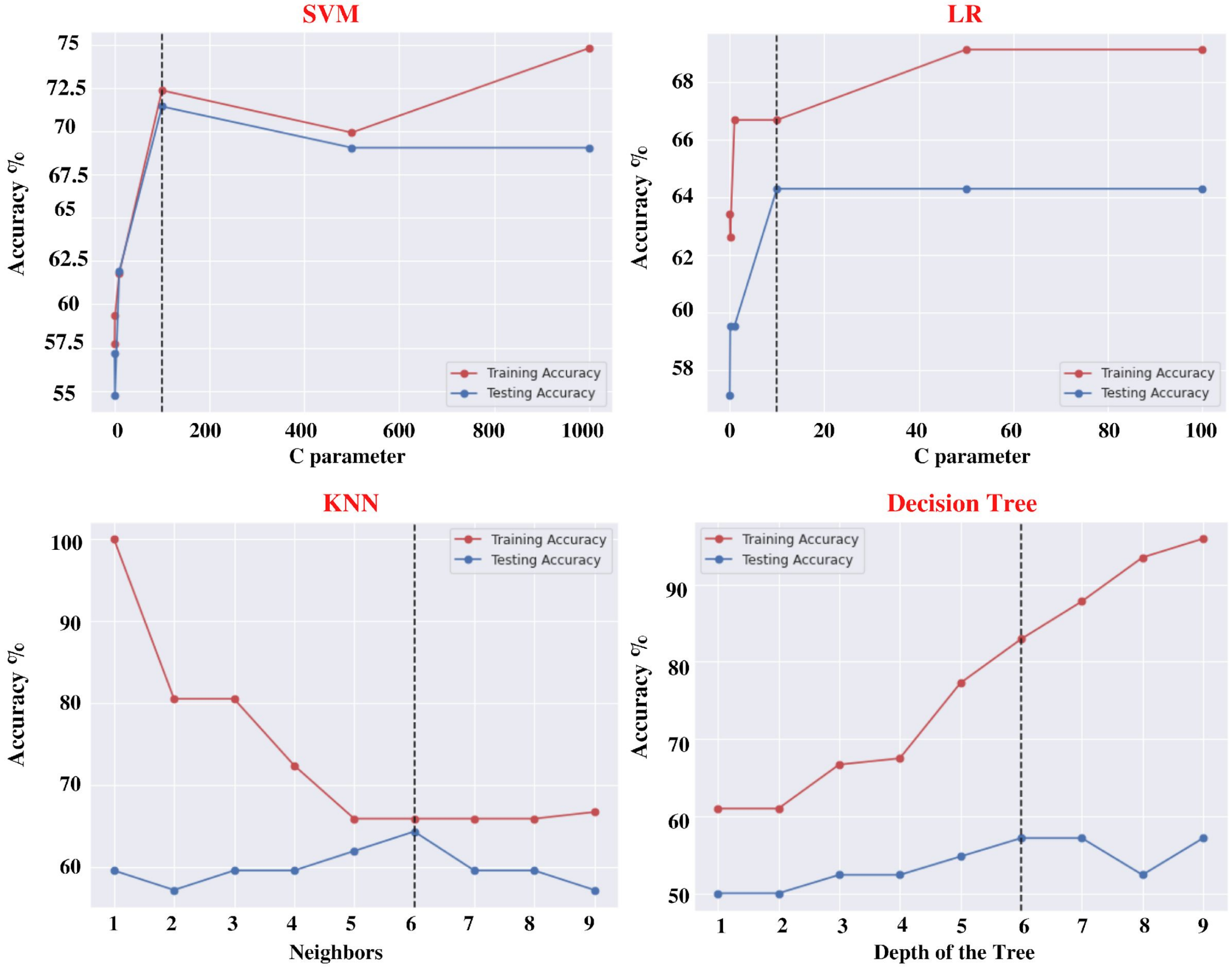


Pulse Arrival Time estimation based on the PPG and ECG waveforms [5].



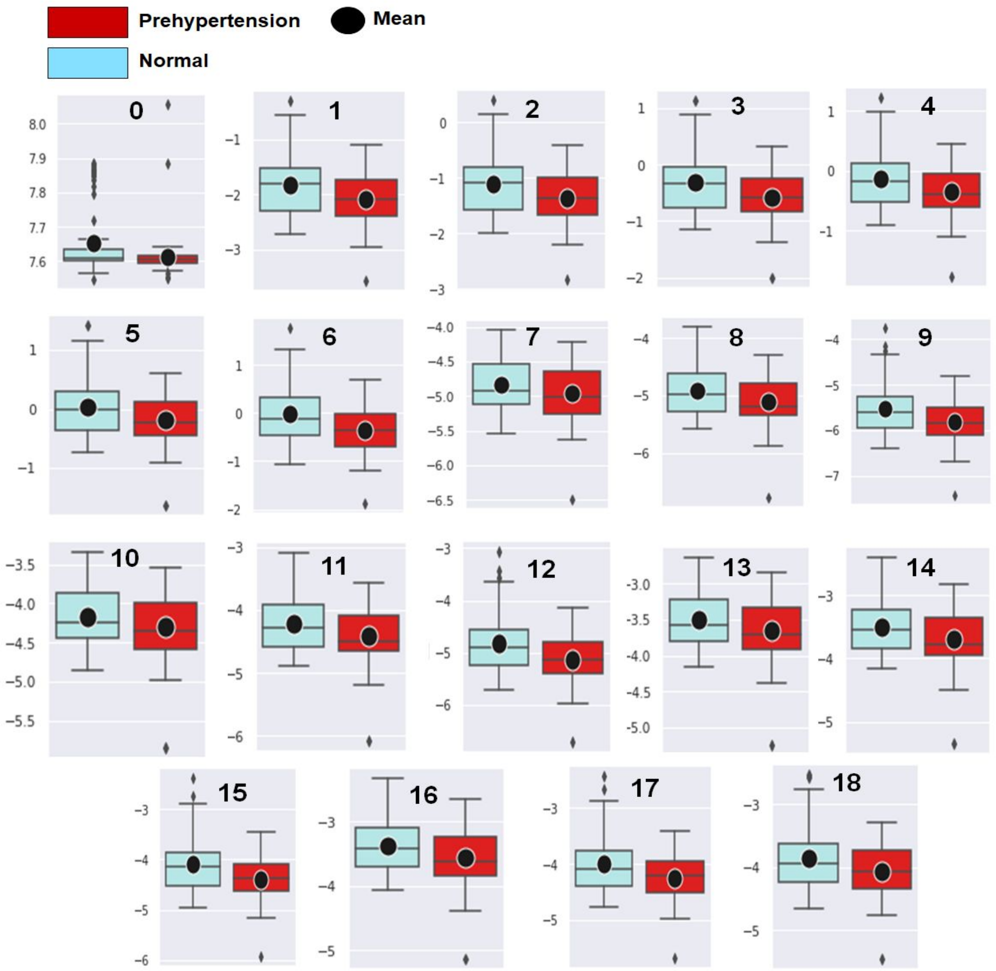
PPG feature extraction techniques [5].

PPG and WST



Training (red) and testing (blue) sets' accuracy while varying the ML techniques' hyperparameters trained with the age, sex, BMI, heart rate, height, and weight for NT and PHT detection. The vertical dash line shows the hyperparameter value that produces the best trade-off between the training and testing set accuracies. The top graphs show the results of the SVM and LR; the bottom graphs show the results of KNN and the decision tree [20].

Results



Two-sided Welch's T-Test

$\alpha = 0.05$

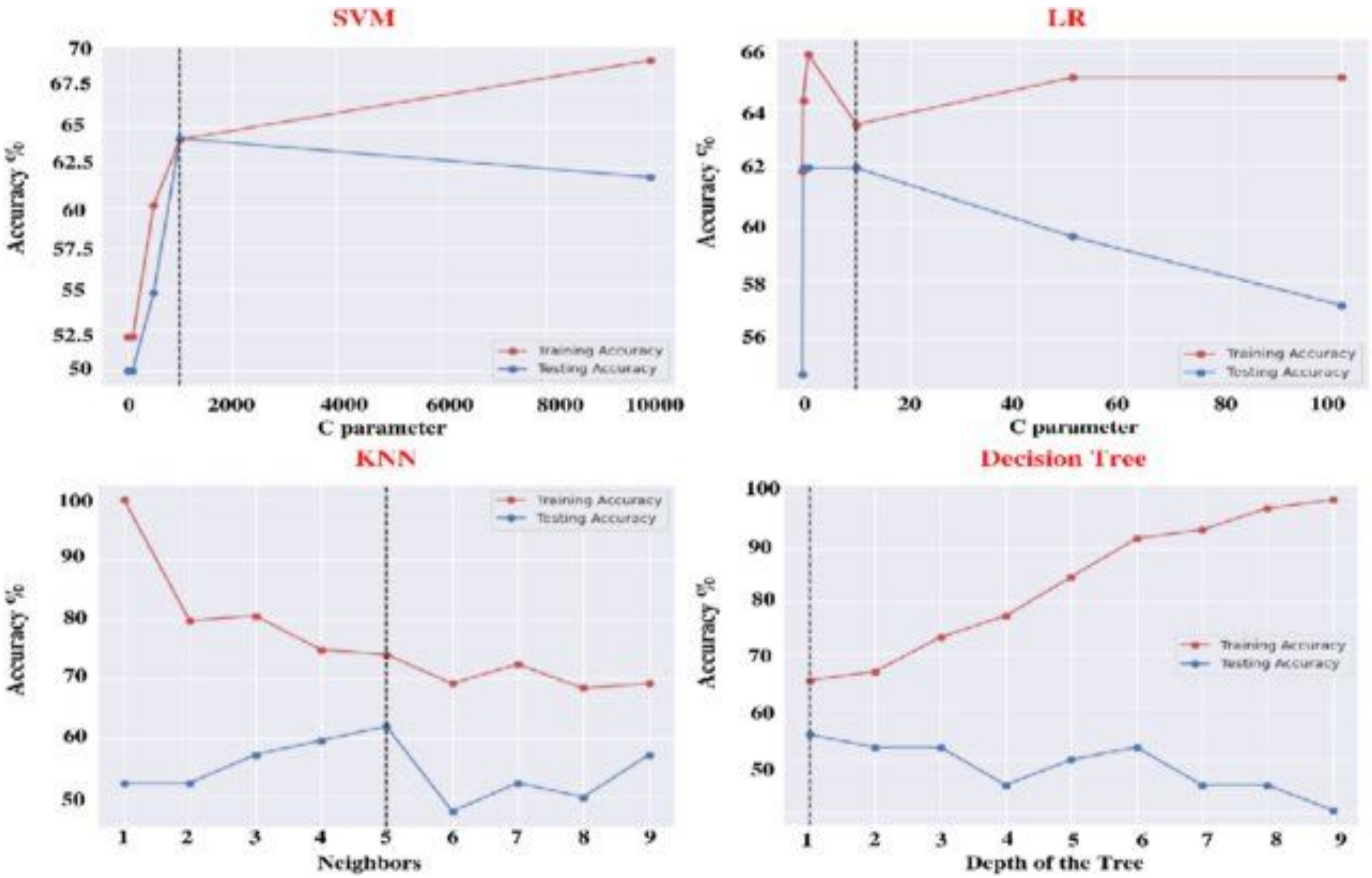
$n_{NT} = 80, n_{PHT} = 85$

WST Scales	NT Mean ± SD	PHT Mean ± SD	Test Statistic	p-value
0	7.6542 ± 0.0995	7.6116 ± 0.0596	3.2559	0.0013
1	-1.8228 ± 0.5722	-2.1005 ± 0.4567	3.4111	0.0008
2	-1.0980 ± 0.5627	-1.3696 ± 0.4494	3.3923	0.0008
3	-0.3184 ± 0.5391	-0.5748 ± 0.4321	3.3363	0.0010
4	-0.1273 ± 0.4995	-0.3566 ± 0.4067	3.2032	0.0016
5	0.0452 ± 0.4987	-0.1862 ± 0.3993	3.2581	0.0013
6	-0.0223 ± 0.6284	-0.3510 ± 0.4711	3.7605	0.0002
7	**-4.8378 ± 0.3803**	**-4.9621 ± 0.3938**	**2.0491**	**0.0420**
8	-4.9219 ± 0.4455	-5.1063 ± 0.4193	2.7173	0.0073
9	-5.5236 ± 0.5983	-5.8293 ± 0.4610	3.6378	0.0003
10	**-4.1657 ± 0.3842**	**-4.2970 ± 0.3950**	**2.1506**	**0.0329**
11	-4.2257 ± 0.4481	-4.4118 ± 0.4224	2.7236	0.0071
12	-4.8252 ± 0.5952	-5.1264 ± 0.4574	3.6062	0.0004
13	-3.5027 ± 0.3945	-3.6482 ± 0.4041	2.3257	0.0212
14	-3.5008 ± 0.4495	-3.6876 ± 0.4290	2.7092	0.0074
15	-4.1057 ± 0.5812	-4.3906 ± 0.4450	3.4976	0.0006
16	-3.3778 ± 0.4428	-3.5606 ± 0.4362	2.6529	0.0087
17	-3.9986 ± 0.5384	-4.2433 ± 0.4186	3.2257	0.0015
18	-3.8503 ± 0.5082	-4.0556 ± 0.4066	2.8376	0.0051

The association between PPG and blood pressure may not have been observed due to the finger size, lousy blood circulation, cold temperature, or elevated blood viscosity [17].

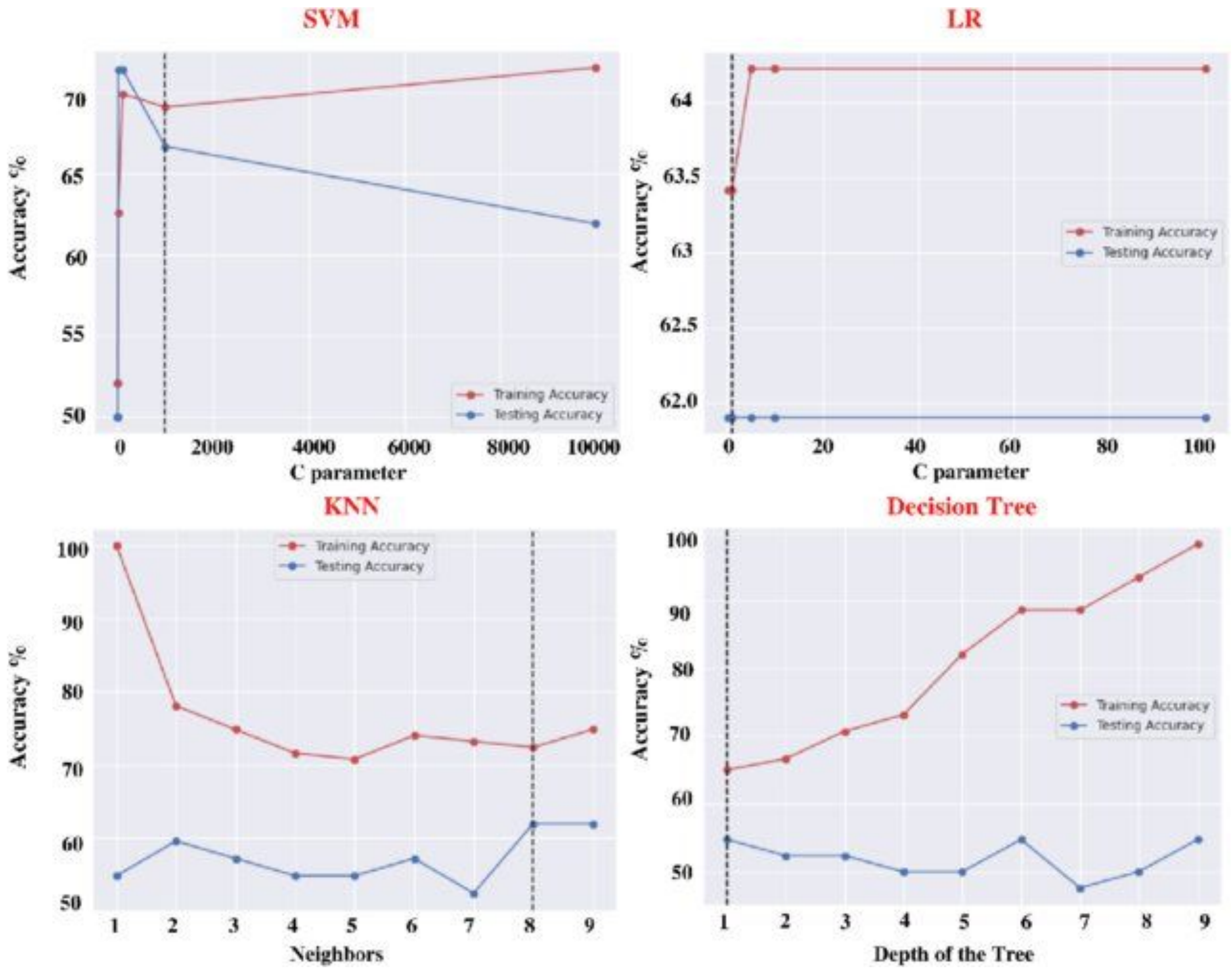
Comparison of the features obtained through the WST between normotension versus prehypertension and difference of means test [20].

No Feature Selection (Clinical Data)



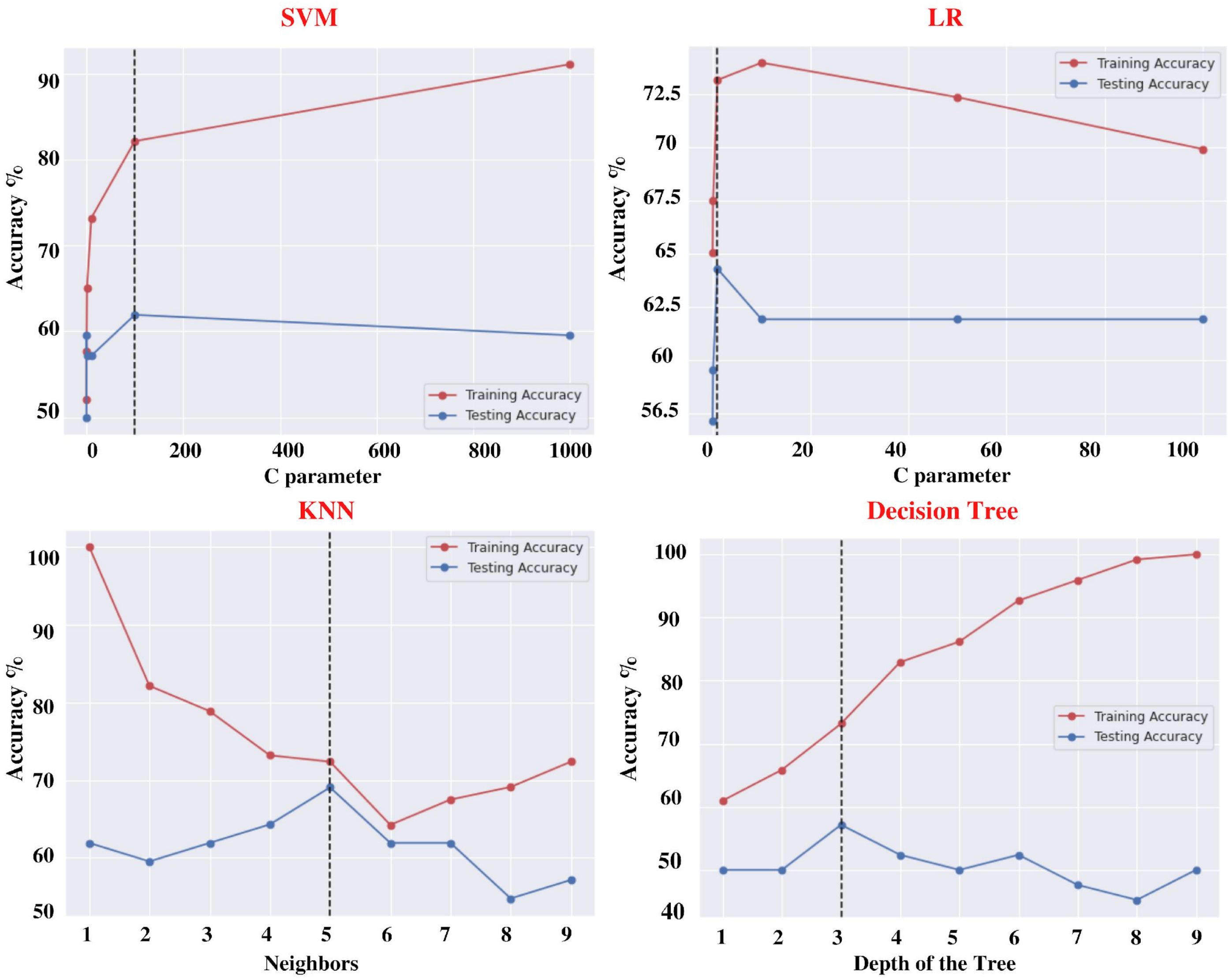
Training (red) and testing (blue) set accuracies while varying the hyperparameters of the respective ML techniques trained with the age, sex, BMI, heart rate, height, and weight for NT and PHT detection. The vertical dash line shows the hyperparameter value that produces the best trade-off between the training and testing sets. The top graphs show the results of the SVM and LR; the bottom graphs show the results of KNN and the decision tree [20].

Feature Selection (Clinical Data)



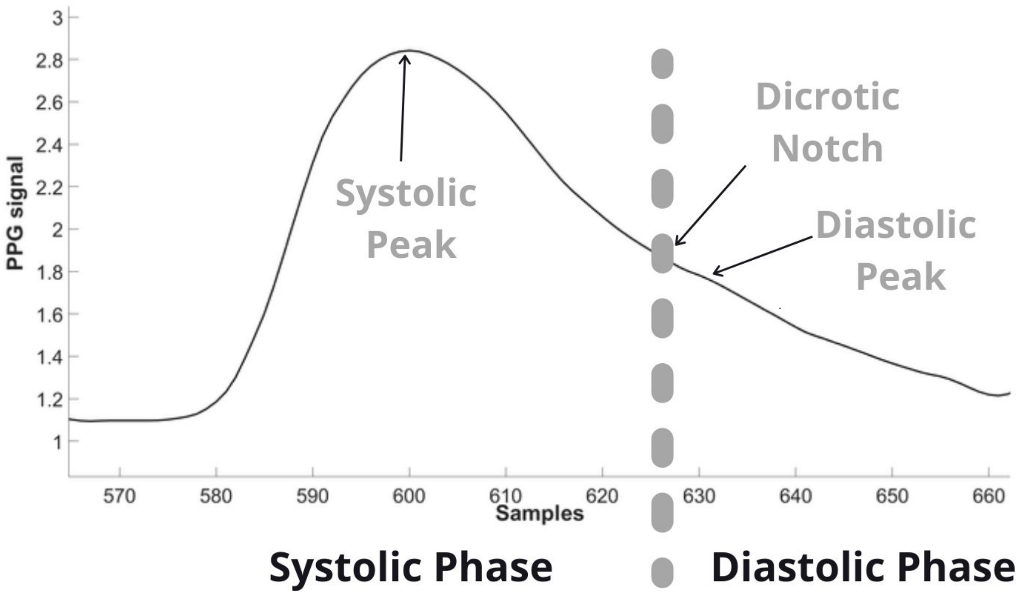
Training (red) and testing (blue) set accuracies while varying the hyperparameters of the respective ML techniques trained with the age, BMI, and heart rate selected through the Gini Importance for NT and PHT detection. The vertical dash line shows the hyperparameter value that produces the best trade-off between the training and testing sets' accuracies. The top graphs show the results of the SVM and LR; the bottom graphs show the results of KNN and the decision tree [20].

Early Fusion

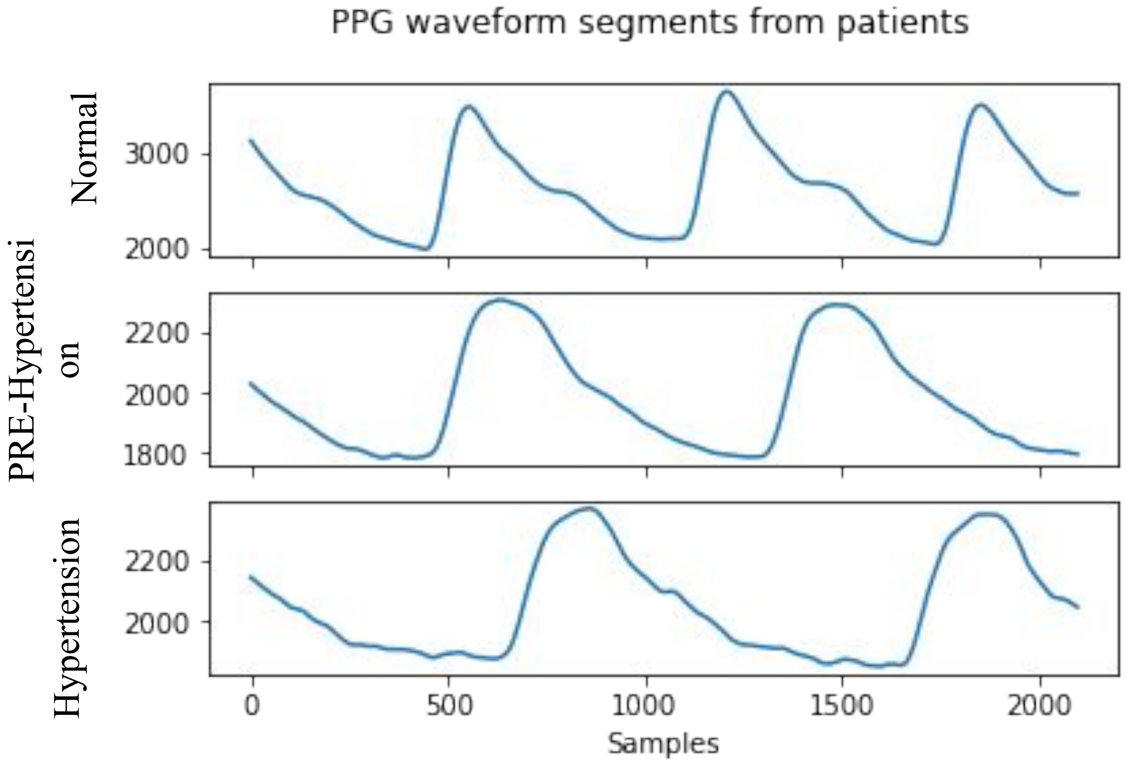


Training (red) and testing (blue) sets accuracies while varying the hyperparameters of the respective ML techniques trained through the concatenated feature vector generated from 19 features from the WST plus age, BMI, and heart rate for NT and PHT detection. The vertical dash line shows the hyperparameter value that produces the best trade-off between the training and testing set's accuracies [20].

Signal used for high blood pressure prediction [5]

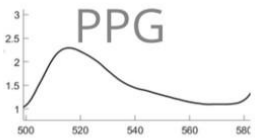


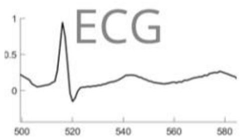
Morphology of the PPG waveforms [5].



Comparision of PPG segments of normal, prehypertension and hypertension subjects [5].

Feature Extraction from ECG and PPG





Feature Extraction

- Time Analysis
- Frequency Analysis
- Time-Frequency Analysis
- Chaotic Analysis

Machine Learning

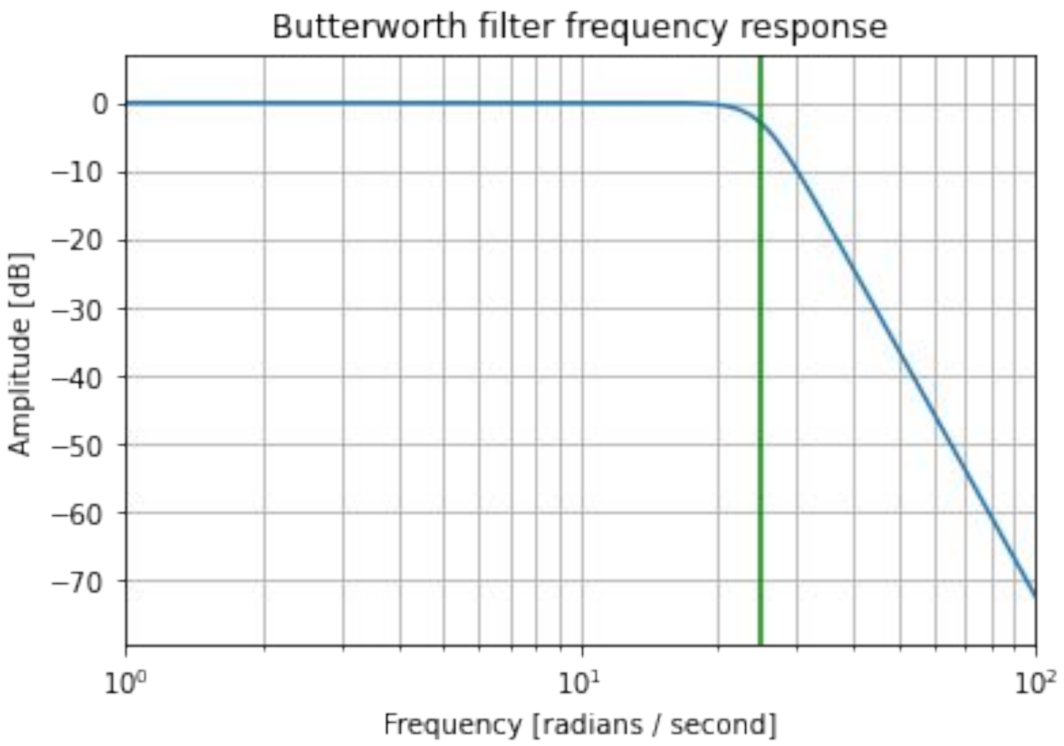
Model Training

- Peaks, period, average, standard deviation.
- Fourier Transform, Power Spectral Density, Gabor Transform
- Continuous and Discrete Wavelet Transforms.
- Entropy

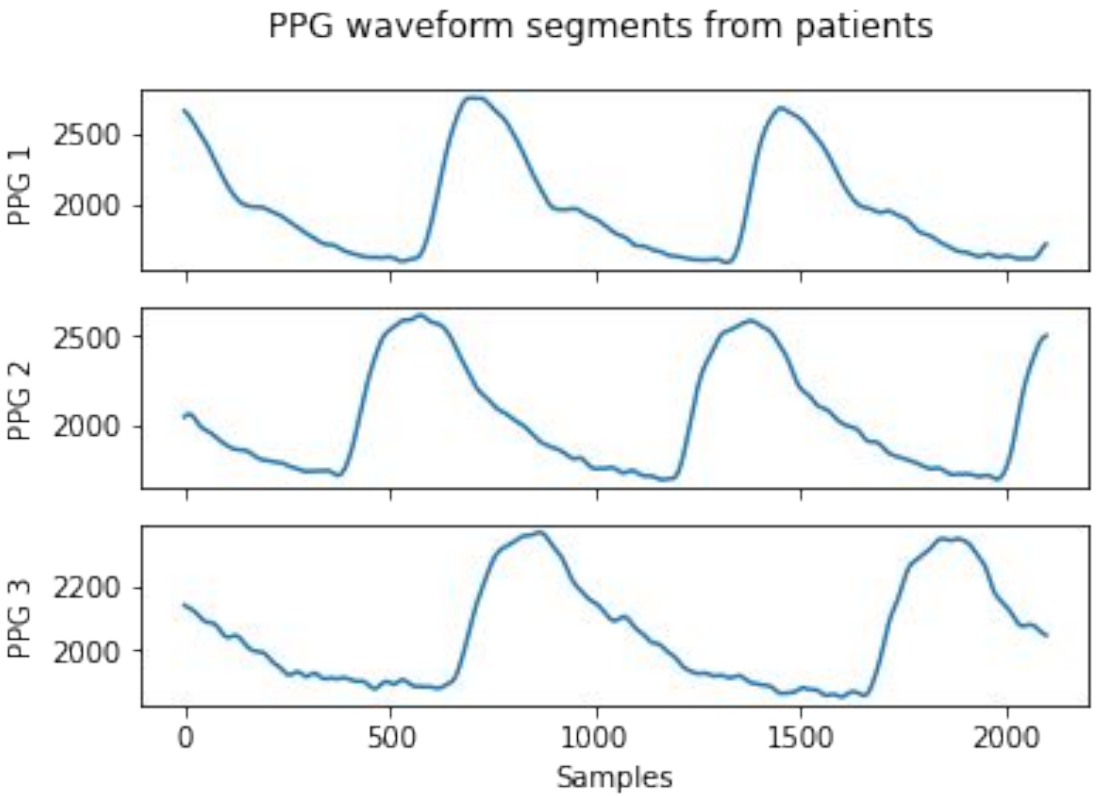
Dataset presentation

- The selected dataset consists of clinical data from patients admitted to the Guilin People's Hospital in China [3].
- This dataset aims to **find relationships between variables such as age, gender, weight, height with blood pressure and its stages.**
- The data was collected from **219 subjects** with ages between **21 to 89 years old**. Males conform 48% of the subjects while females correspond to 52%.

PPG Signal Filtering

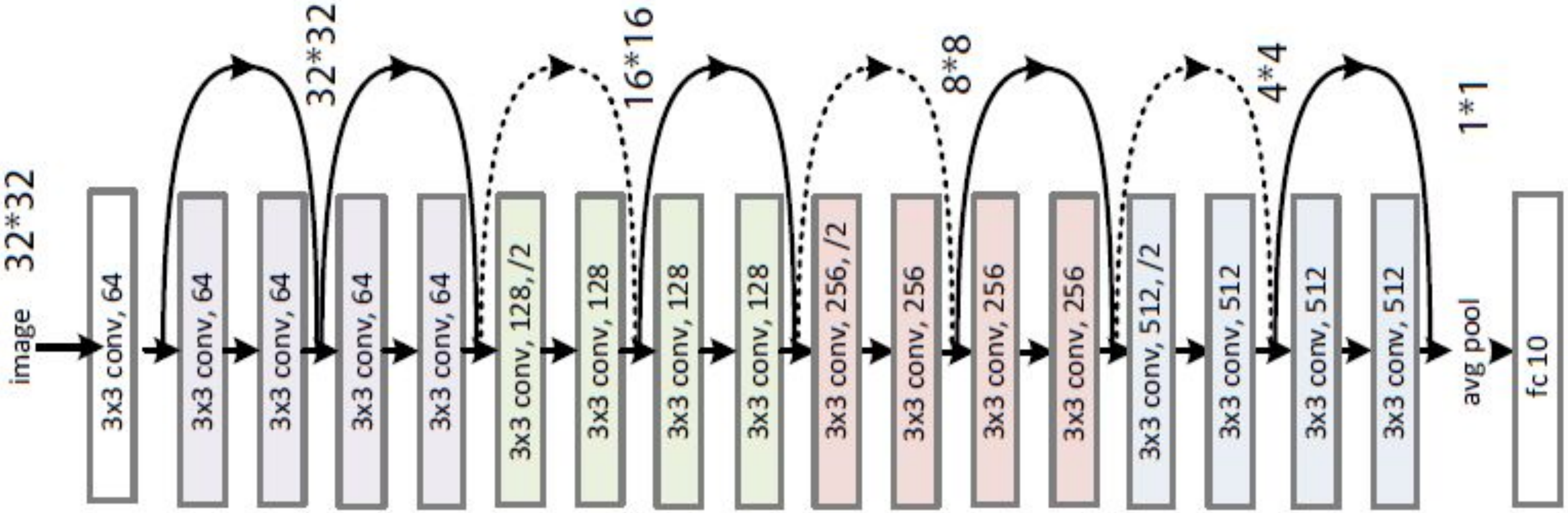


Butterworth IIR– Low Pass Filter with a cut-off Frequency of 25 Hz of order 6.



Signal after low pass filtering.

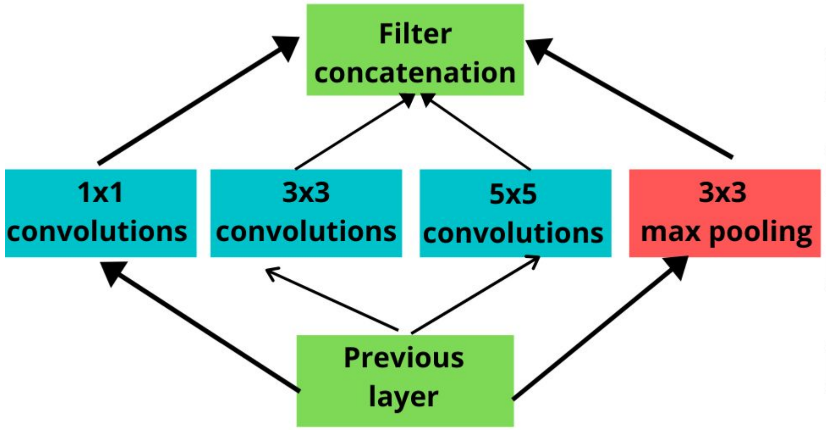
Res-Net



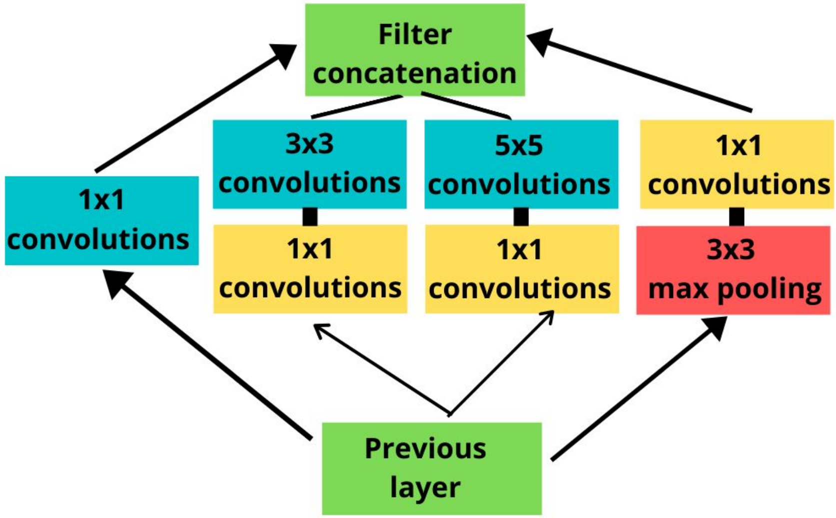
Residual Convolutional Neural Network Example

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

Inception



(a) Inception module, naive version

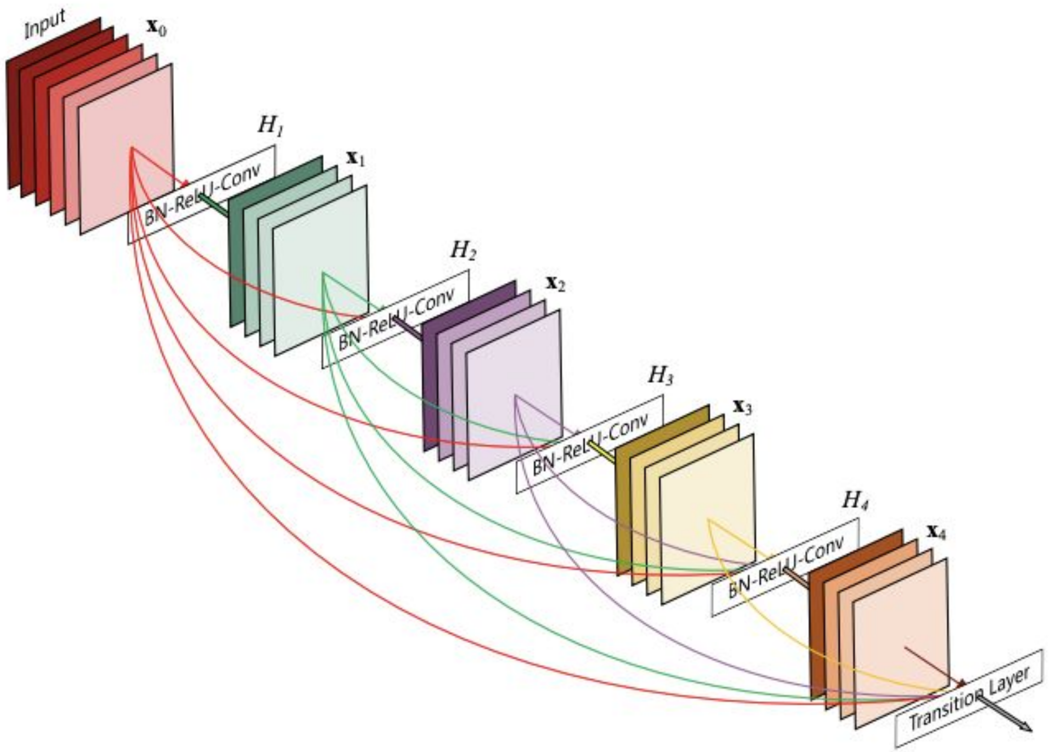


(b) Inception module with dimension reduction

Inception Module

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1–9, 2015

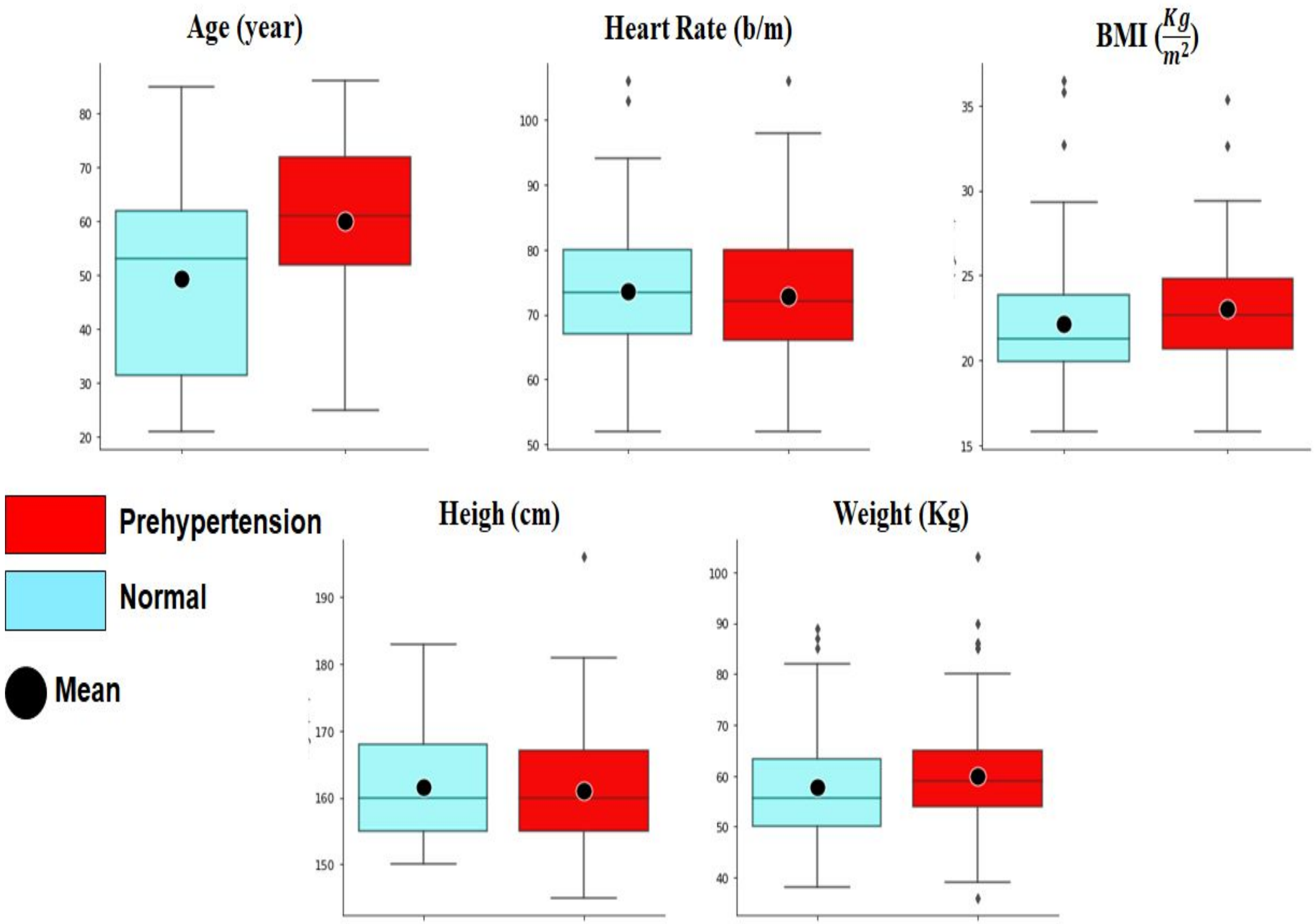
Dense-Net



Densely Connected Convolutional Networks

Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pagesn 4700–4708, 2017.

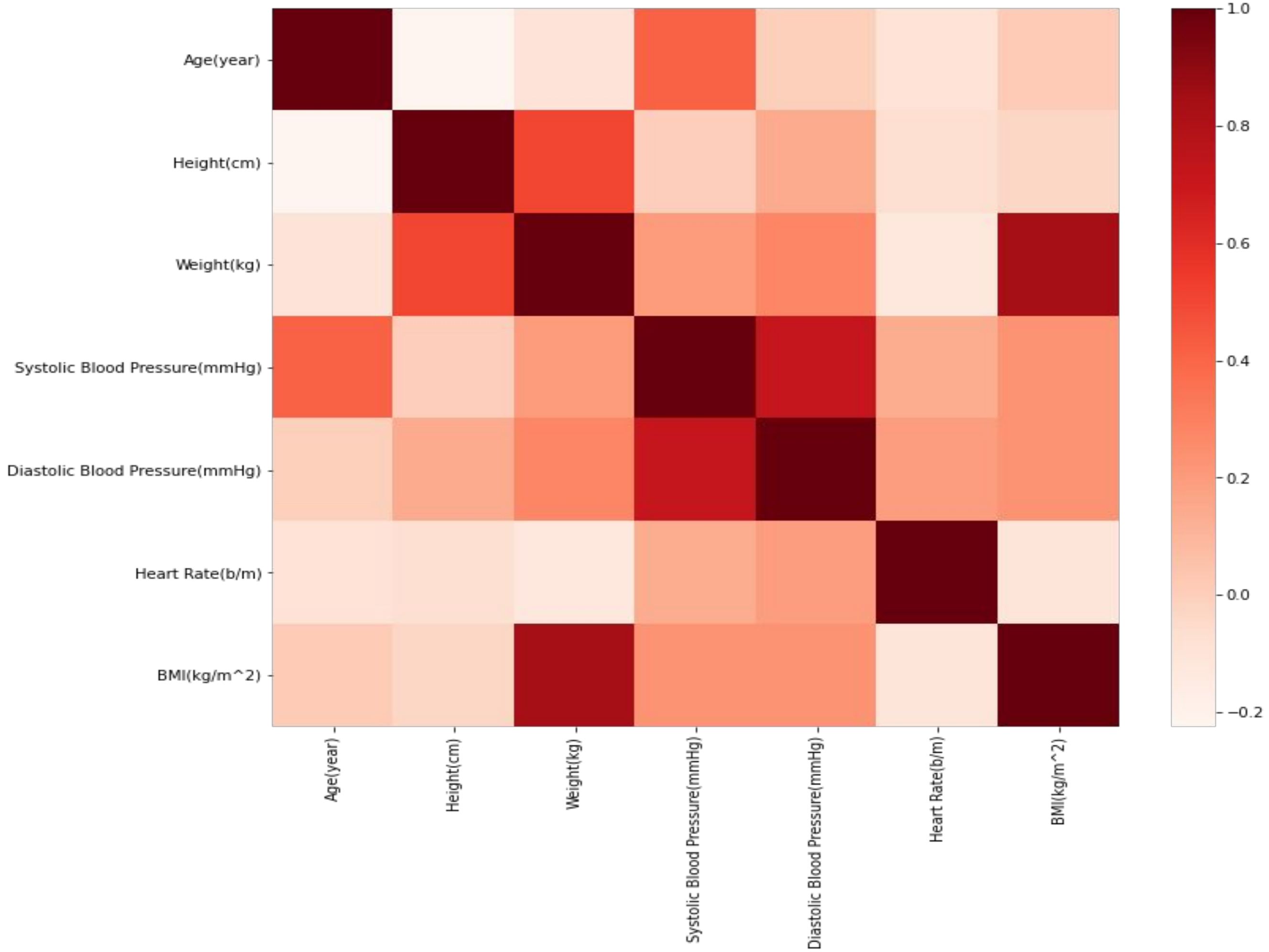
Results



Normotension vs Prehypertension	Classes	Welch's t-test (two-sided) $\alpha = 0.05$ $n_n = 80$, $n_p = 85$				Mann-Whitney U-test (two-sided) $\alpha = 0.05$ $n_n = 80$, $n_p = 85$			
Variables		Mean	Standard Deviation	Test-Statistic	P-Value	Median	U-Statistic	Z-score	P-Value
Age	Normotension	49.425	17.0066	-4.26049	3.5335e-05	53	2171	-3.9115	9.1733e-05
	Prehypertension	60.0	14.3294			61	4549		
BMI	Normotension	22.1436	3.8209	-1.6774	0.0954	21.27	2689	-2.2074	0.0273
	Prehypertension	23.0905	3.3335			22.665	4031		
Heart Rate	Normotension	73.6875	10.2354	0.5636	0.5737	73.5	3602	-0.7961	0.4259
	Prehypertension	72.7738	10.3927			72.0	3118		
Weight	Normotension	57.8250	10.8187	-1.3609	0.1754	55.5	2919.5	-1.4491	0.1470
	Prehypertension	60.2142	11.5254			59.5	3800.5		
Height	Normotension	161.5375	7.9874	0.2988	0.7654	160.0	3238	-0.4013	0.6888
	Prehypertension	161.1428	8.8171			160.0	3482		

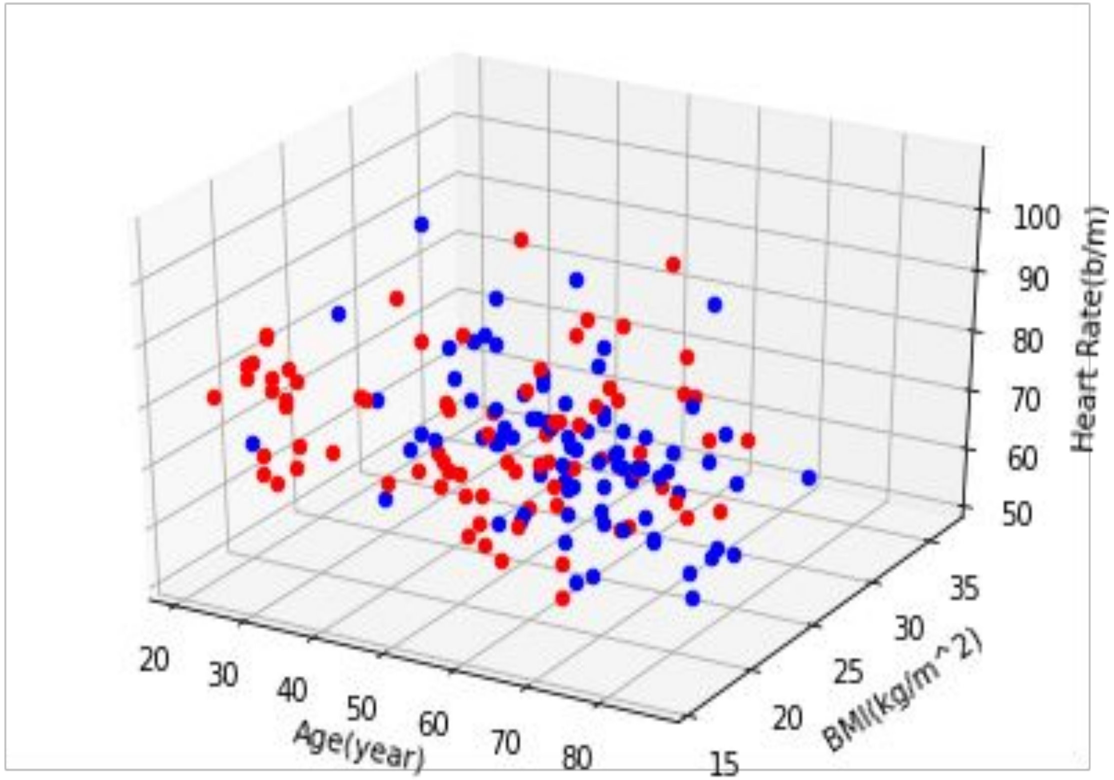
Box Plot of Numeric Variables and Statistical Tests.

Results



Correlation heatmap of numeric variables

Results



Scatter plot of the selected variables. The red dots are the patients label with prehypertension and blue dots patients label with normotension.

Wavelet Scattering and CNN

Convolutional Neural Network

Convolution (Learn Filters)

↓

Non-Linearity

↓

Pooling (Average Pooling)

Wavelet Scattering

Convolution with Wavelet

↓

Modulus

↓

Averaging (Scaling Function)

Wavelet Scattering

Fourier Transform Invariant to Translations

$$\widehat{x}(\omega) = \int x(u) e^{-i\omega u} du$$

$$x_c(t) = x(t-c)$$

$$\widehat{x}_c(\omega) = e^{-ic\omega}\, \widehat{x}(\omega).$$

$$|\widehat{x}_c(\omega)| = |\widehat{x}(\omega)|$$

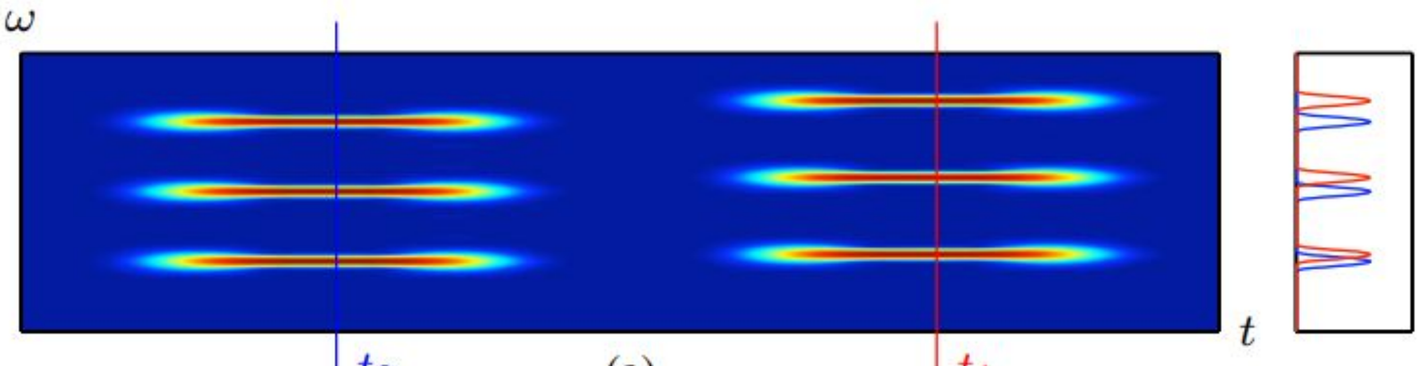
Andén, J., & Mallat, S. (2014). Deep scattering spectrum. *IEEE Transactions on Signal Processing*, *62*(16), 4114-4128.

Instability to Deformations of Fourier Transform

$$x_\tau(t) = x(t - \tau(t))$$

$$x_\tau(t) = x((1-\epsilon)t)$$

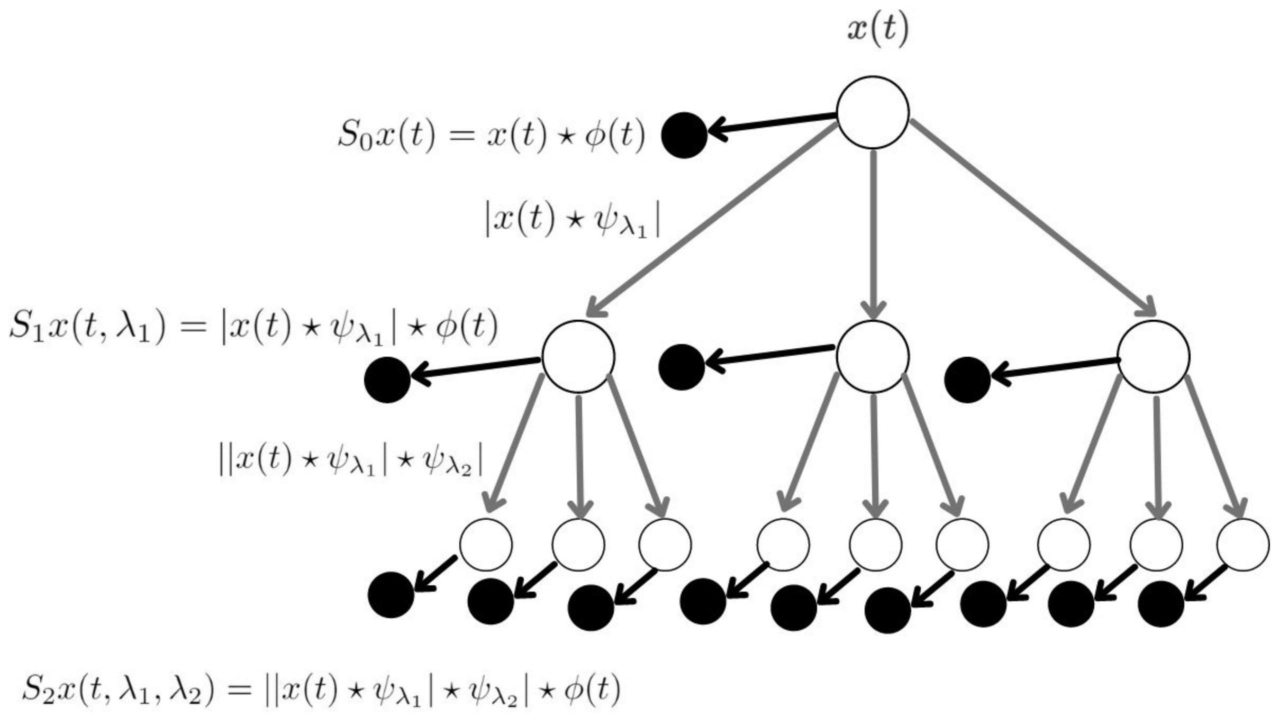
$$\widehat{x}_\tau(\omega) = (1-\epsilon)^{-1}\, \widehat{x}((1-\epsilon)^{-1}\omega)$$



(a)

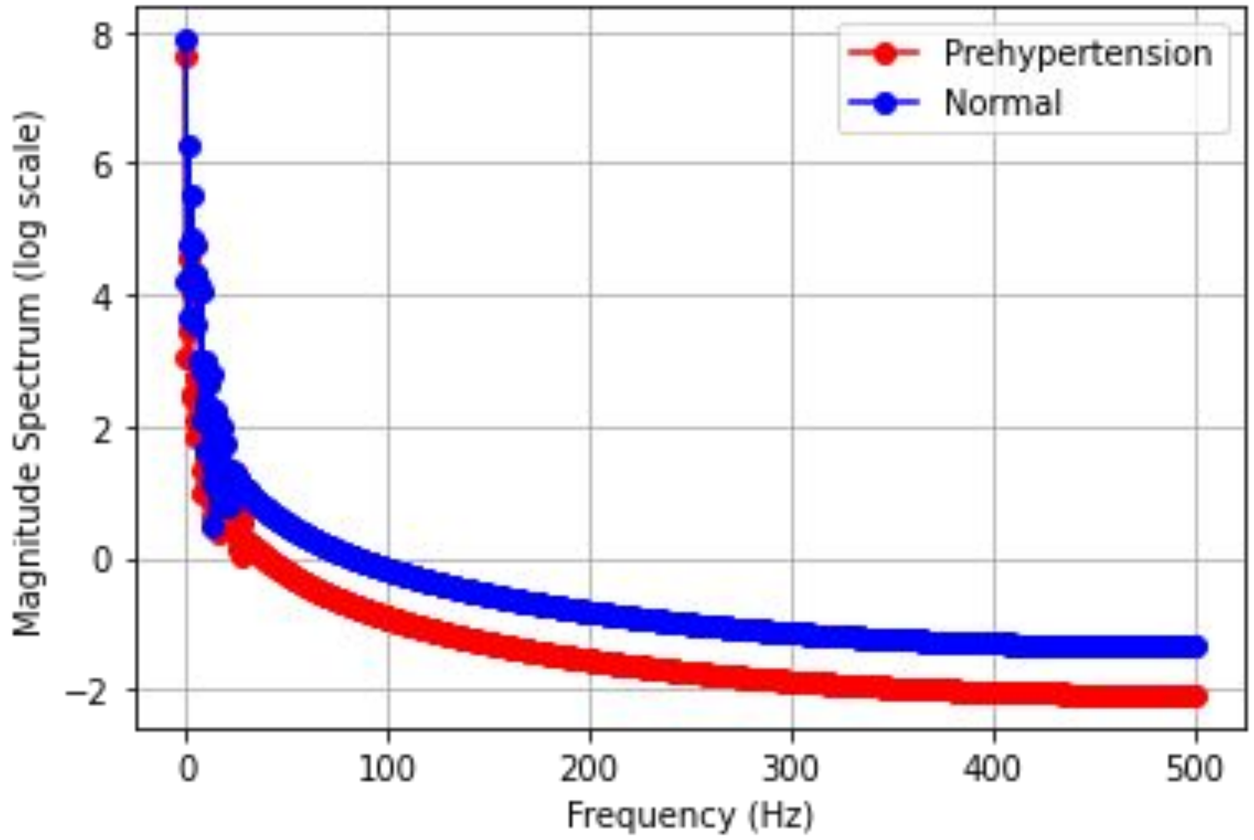
$$\|\Phi(x) - \Phi(x_\tau)\| \le C \sup_t |\tau'(t)|\, \|x\| \,.$$

Wavelet Scattering [20]



Andén, J., & Mallat, S. (2014). Deep scattering spectrum. *IEEE Transactions on Signal Processing*, *62*(16), 4114-4128.

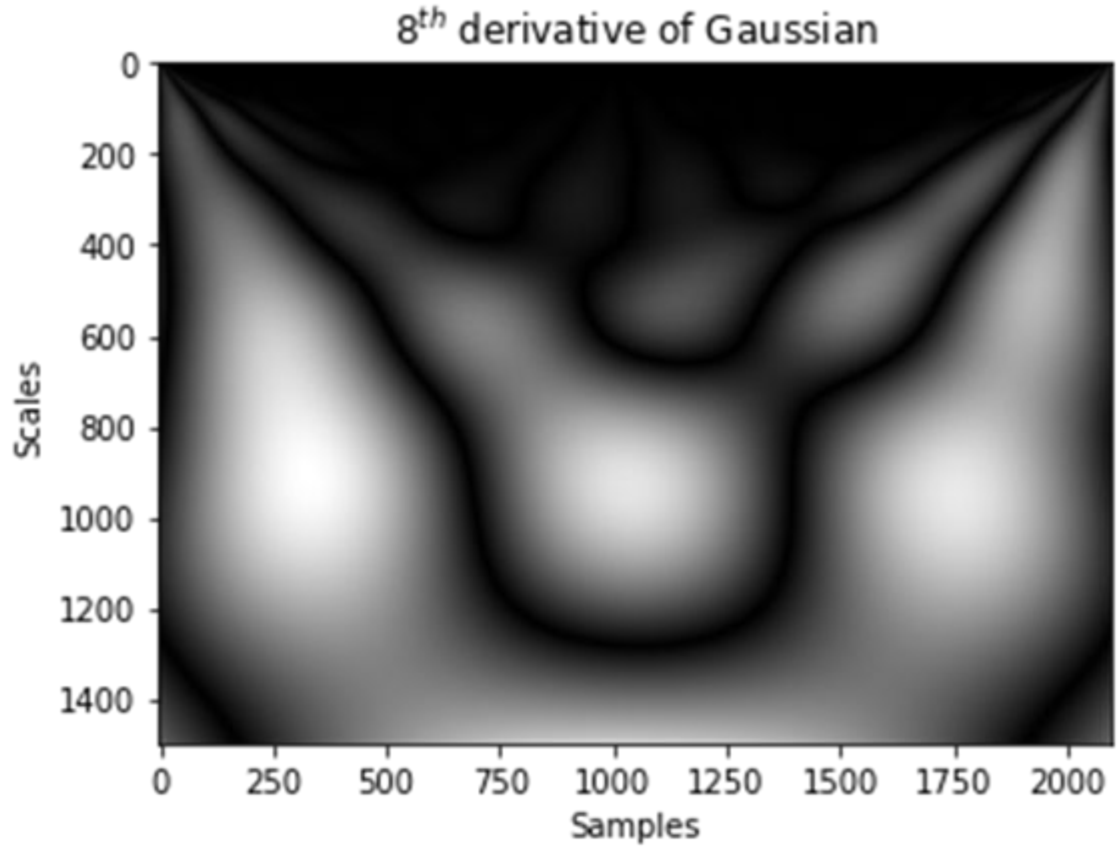
Results



Magnitude Spectrum of PPG waveforms of normotension and prehypertension subjects.

Wavelet Transform-Scalogram

0 Scale:
300Hz



$$\psi(t) = Ce^{-t^2}$$

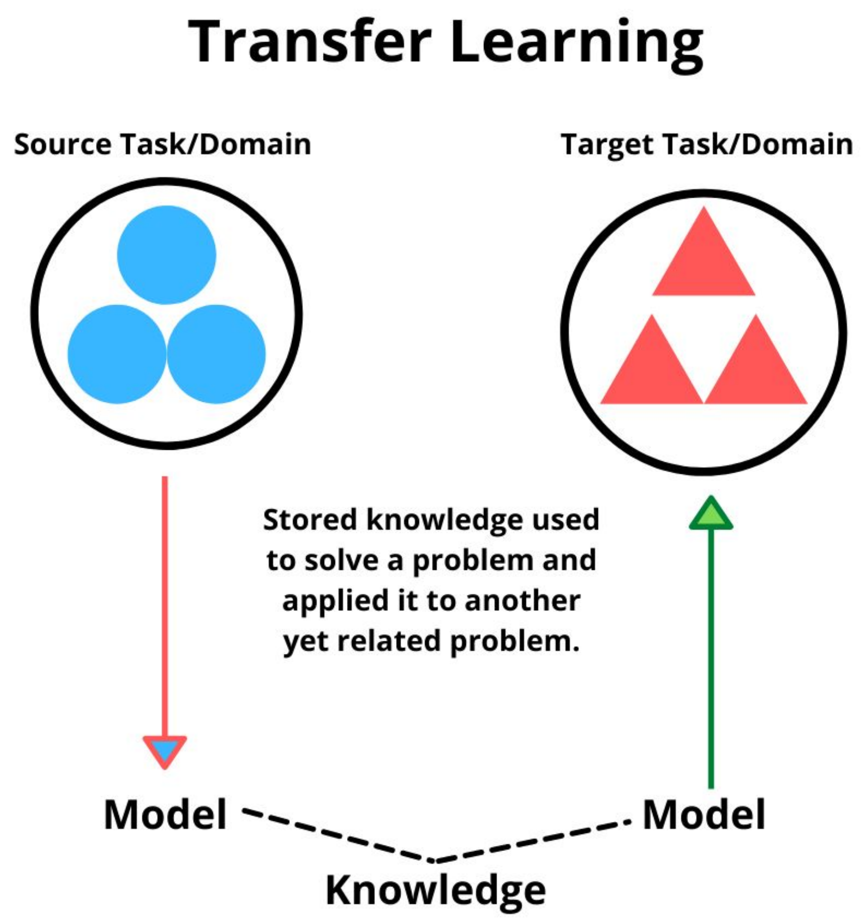
Derivative of Gaussian Wavelet.

C **is an order normalization constant.**

$$cwt(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right) dt$$

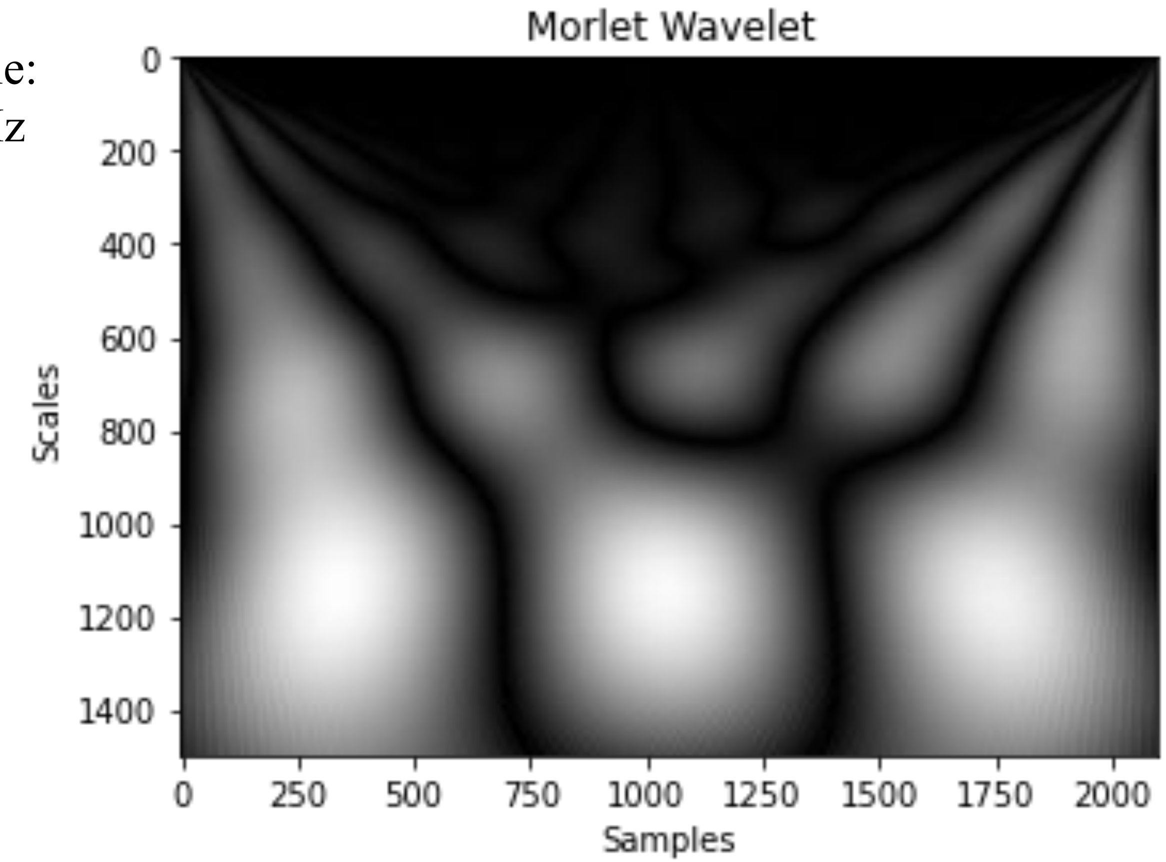
The scale of the CWT is ***a***, the time shift is defined by ***b***, f(t) is the input signal.

Transfer Learning Paradigm



Wavelet Transform-Scalogram

0 Scale:
300Hz



$$\psi(t) = e^{-\frac{t^2}{2}} cos(5t)$$

Morlet Wavelet

$$cwt(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right) dt$$

The scale of the CWT is ***a***, the time shift is defined by ***b***, f(t) is the input signal.

Trends

- **Electronic health records (EHRs)** have enabled machine learning techniques to detect and monitor different medical conditions or diseases, hypertension not being the exception.
- The ML used in the medical field goes from traditional logistic and linear regression methods to more complex techniques such as artificial neural networks (ANN) with diverse architectures and characteristics.
- **The resulting ML models are meant to provide medical experts with a tool to support clinical decision-making.**

References

•

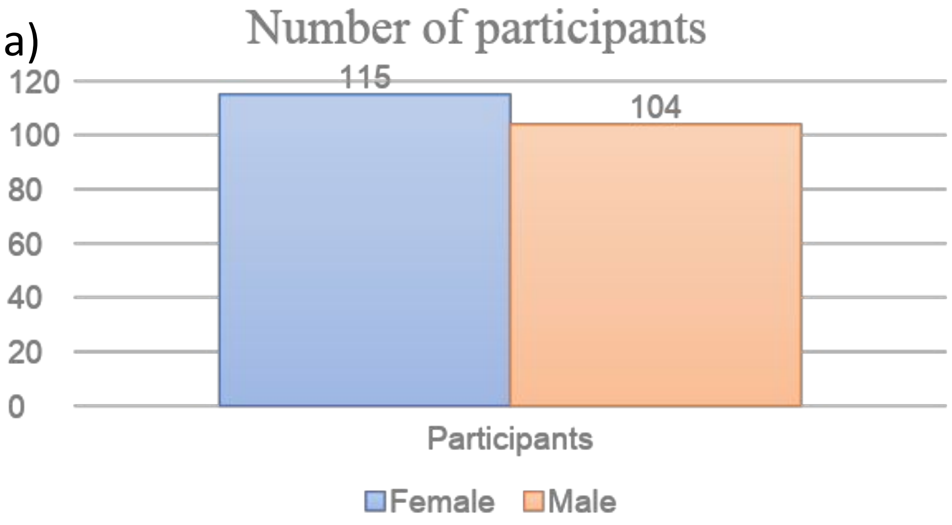
Errors

Accuracy of the pre-trained models [38].

Pre-trained CNN	Acc@1	Acc@5
Alex-Net	56.522	56.522
Dense-Net	69.758	89.078
Res-Net	74.434	91.972

Types of variables

a)



b)

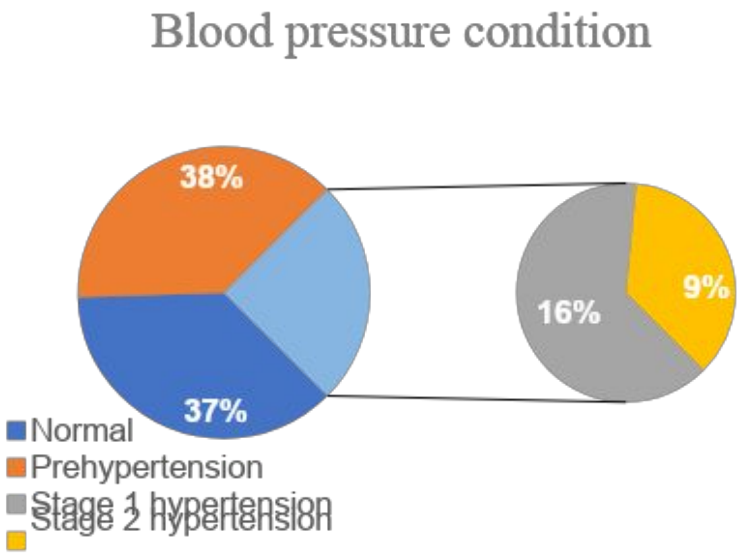


Figure 1. a) Number of participants according to their gender. b) Blood pressure classification stage in the group.

Description of Variables

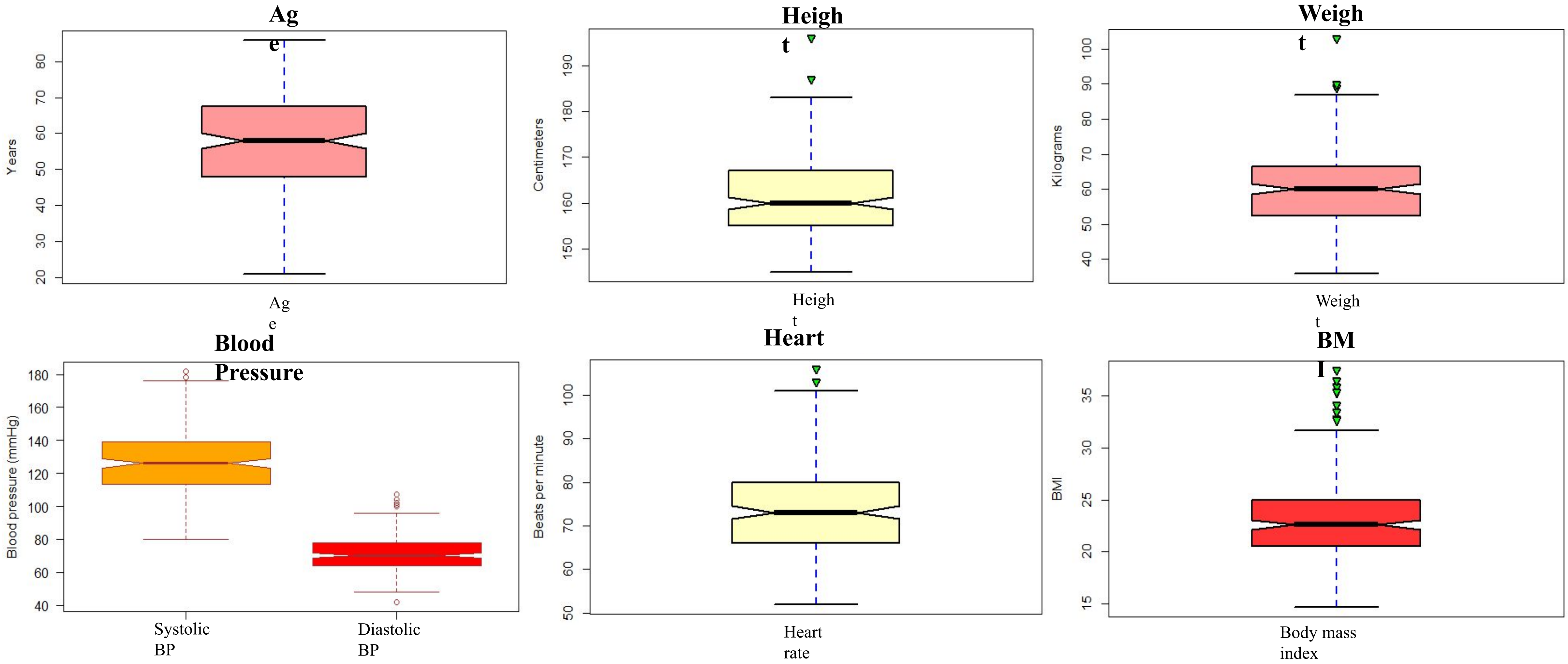


Figure 2. Box Plot of each variable

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