PPG Signal-Based Classification of Blood Pressure Stages Using Wavelet Transformation and Pre-Trained Deep Learning Models

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Abstract

This article proposes a new method for identifying photoplethysmography (PPG) data, a non-invasive blood pressure (BP) measurement. Individual characteristic inconsistencies hinder PPG signal feature extraction. An innovative method for extracting PPG characteristics using continuous wavelet transform (CWT) and transfer learning is presented in this research. Pre-trained deep learning models like InceptionV3, VGG-16, and ResNet101 use robust characteristics to assess BP severity. The major purpose of this approach is to classify blood pressure values into average, pre-hypertension, and hypertension stages 1 and 2. The proposed method was trained on 219 individuals' PPG datasets. At the same time, InceptionV3, VGG-16, and ResNet101 had 99.5%, 22.5%, and 92.5% accuracy. Despite that, the study's findings reveal classifier behavior and how to improve the model's assessment metrics by utilizing category variances and modifying deep-learning network parameters. The proposed method for noninvasive blood pressure assessment utilizing PPG signals appears promising. Based on these findings, non-invasive blood pressure monitoring systems can be improved.

1. Introduction

Worldwide, cardiovascular diseases (CVDs) kill 17.9 million persons. CVDs include coronary artery disease, cerebrovascular disease, and rheumatic heart disease. One-third of CVD-related deaths occur before age 70, with heart attacks and strokes accounting for more than eight in ten [1]. Prehypertension and hypertension are responsible for up to 8.5 million annual fatalities. These deaths are predominantly attributable to ischaemic heart disease, stroke, vascular disease, and renal disease [2]. PPG is a simple and low-cost optical method for detecting changes in blood volume in microvascular tissue substrate. It was utilized for non-invasive epidermis protection measures [3]. Deep learning (DL) has succeeded in biomedical signal processing, particularly in classifying PPG and ECG waveforms [4]. DL algorithms can leverage CNNs, RNNs, and pre-trained DL models for intelligent processing. In Islam et al., segmentation, filtering, denoising, and sequential Z-Score normalization were performed sequentially on input data to classify arrhythmia signals. CNN-GoogleNet was utilized in [6], and CWT categories and segment lengths of 2.1 seconds were used for data processing. Wu et al. divided PPG into three classes (Normal blood pressure, hypertension in stages I and II). Both models have an accuracy of 75%-87% for 2.1 seconds. Using the GoogLeNet pre-trained model and CWT, Liang et al. [7] classified PPG into three classes (Normal, prehypertension, and hypertension) with an F1-score of 82.95 %. Frederick and others employed AvgPool_VGG-16. A moving average filter divided the PPG signal into four categories: normal, prehypertension, stage 1, and stage 2 hypertension. The model had an average accuracy of 39%, 42%, and 71% compared to Alexnet, ResNet -50, and VGG-16, respectively, while AvgPool_VGG-16 was 80%.

The main limitation of earlier studies was that they utilized pre-trained models without enhancing the accuracy or data size of the networks for DL. This article uses a transferred Inception-V3 pre-trained model to classify the PPG signal into four classes with five-fold cross-validation in training and then test the classifier algorithms' performance.

2. Methodology

The approach used in this study can be centered on the design and execution of the steps in the process that will reach the overall approach. The first step was to collect PPG records of different types, then prepare PPG data by using A zero-phase second-order Butterworth filter, then the third step was to make Continuous Wavelets Transform (CWT) for data to convert the PPG signal into different images for hypertension classes. After that, the data was entered into a transferred pre-trained model in order to acquire the best model specifications and achieve classification between four classes. The three primary steps of the PPG signal categorization implementation approach are as shown in Figure 1.

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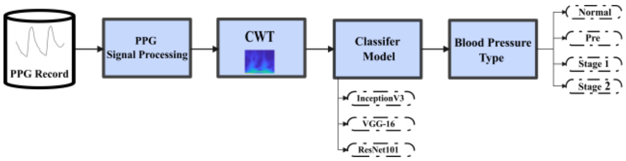

Figure 1. Overall basic flowchart of Study.

2.1. Dataset Description

A public PPG signal dataset from Liang et al. [9] was used. Signals came from 219 subjects (104 males and 115 women, ages 57 to 15; heights 161 to 8 cm; weights 60 to 11 kg). A probe sampling at 1 kHz gathered the left index finger PPG signal. An Omron 7201 electronic sphygmomanometer monitored the right forearm blood pressure. Based on recording descriptions, PPG signals were classified as Normal, Prehypertension, Stage 1 hypertension, and Stage 2 hypertension.

2.2. Dataset Preprocessing

Accurate physiological indicator detection and health monitoring, screening, and diagnosis require high-quality, low-noise PPG signals [10]-[11]. A zero-phase second-order Butterworth filter with a 0.5 to 15 Hz band pass range eliminated baseline drift and non-wave frequencies [12]. Figure 2 shows the PPG signal output filter.

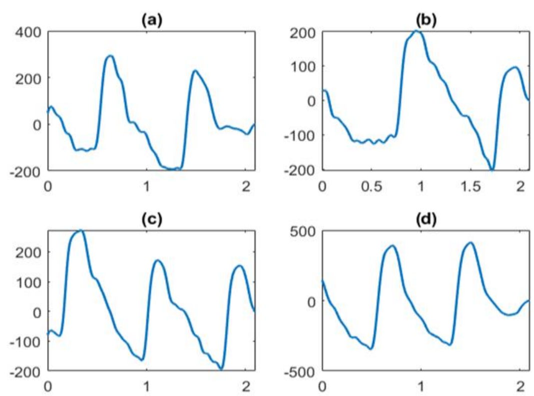

Figure 2. Samples of the preprocessed PPG types: (a) Normal case; (b) Prehypertension case; (c) Stage 1 of hypertension case; (d) Stage 2 of hypertension case.

2.3. CWT

The continuous wavelet transform (CWT) reveals signal fluctuations and hidden information. With a basis wavelet, CWT is possible [13]. The CWT is the result of adding the signal $\boldsymbol{x(t)}$ and scaled and shifted forms from a mother wavelet $\boldsymbol{\varphi(t)}$ together as illustrated in equation 1[14].

$$\mathbf{CWT(scale, position)} = \int_{-\infty}^{+\infty} \mathbf{x(t)} * \boldsymbol{\varphi}\mathbf{(scale, position, t)dt} \tag{1}$$

For implementing the CWT, Morlet Wavelet is frequently utilized. According to Grossmann and Morlet (1984; Teolis 1998), the Morlet wavelet is:

$$\boldsymbol{\psi M(t)} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{\pi f_b}}} \boldsymbol{e^{j2\pi f_c t}}\, \boldsymbol{e^{-\frac{t^2}{f_b}}} \tag{2}$$

In this paper we use the Continuous wavelet transform filter bank built in MATLAB® to select CWT parameters; analytic Morlet (Gabor) Wavelet, sampling frequency (1000 Hz), and frequency range (0.5 -15 Hz). The CWT representation has been generated for all types of PPG signals, and the final images are saved alongside their appropriate classes, as seen in Figure 3. The stored photos will next be subjected to the deep learning models, as will be demonstrated next.

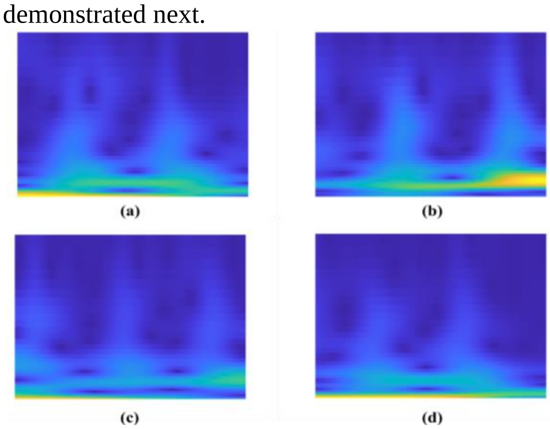

Figure 3. Samples of the CWT representation of PPG types: (a) Normal; (b) Prehypertension; (c) Stage 1 hypertension; (d) Stage 2 hypertension.

2.4. Data Oversampling

Data sampling alters training cases to balance class distribution, allowing classifiers to work like traditional classification. Data oversampling is an advanced supervised learning approach where the classification target attribute has a robust data distribution. This issue emerges when the class of interest has fewer samples than the other classes [15]. Oversampling in this research addresses skewed data—the amount of data on each class before and after over-sampling is shown in Table 1.

2.5. Deep Learning Models

Based on the dataset previously discussed, several transfer pre-trained deep learning models were suggested for the classification of the four stages of hypertension. InceptionV3, VGG-16, and ResNet101 were the categorization algorithms that were modified in this study. The size and variety of the dataset were taken into

consideration when applying these methods. The next sections contain a detailed explanation of the procedures employed. The third version of CNN from the Inception family of architecture, Inception v3 adds several enhancements. Among these enhancements are factorized convulsions, which lower the parameters without lowering network effectiveness. As a regularized, it employs label smoothing. It also makes use of an additional classifier to spread label information throughout the network and support regularization. Due to its structure, the work that uses Inception-v3 as an example makes certain enhancements. The structure of the model is such that the final 15 layers are removed, and the results of the bottleneck layer are used as the feature results, making it more appropriate for the experiment [16].

Table 1. Raw data classification.

Class Name	Raw data	Over sampling
Normal	250	250
Prehypertension	250	250
Stage 1	97	250
Stage 2	55	250

2.6. Methods of Evaluation

The experimental findings in this work are validated using the five-fold cross-validation approach. Five-fold cross-validation involves splitting the data set into five equal parts, using one as the test set, the rest as the training set, and then testing the model using the testing part to estimate its metrics. Figure 4 shows the five-fold cross-validation process steps:

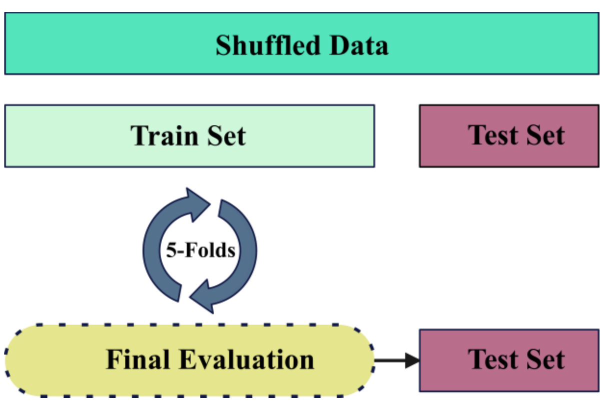

Figure 4. Illustration for model training /testing process.

Five measures assessed this paper's performance. Sensitivity, specificity, accuracy, precision, and F1-score. [17].

3. Results and Discussion

This section presents the proposed model's experimental results, emphasizing overall accuracy as the primary evaluation metric. A detailed evaluation of each class is also provided, including its accuracy, sensitivity, specificity, precision, and score. The proposed method uses continuous wavelet transform (CWT) to convert photoplethysmography (PPG) signals into distinct images for non-invasive blood pressure (BP) classification into four classes: normal (N), prehypertension (P), stage 1 hypertension (S1), and stage 2 hypertension (S2). We compared the efficacy of transfer learning based on the inception-v3 model to that of other methodologies.

Our results indicate that using transfer learning, notably with classifying CWT images derived from PPG signals, can significantly enhance accuracy. In addition, based on transfer learning, the neural network model classifies PPG signals with remarkable accuracy. In addition, oversampling techniques are used to address the challenge of class imbalance in the dataset, a common issue in supervised learning paradigms. In addition, the experimental results are validated using a five-fold cross-validation strategy. The model is evaluated using a distinct test set to estimate performance metrics not included in the training data. The experiment results are presented in Tables 2 and 3, with Table 2 displaying the results obtained with unbalanced data and Table 3 displaying the results obtained with the oversampling technique. Table 3 demonstrates that the deep learning model, specifically the inception-v3 transfer learning model, obtained high specificity and sensitivity values that were closely aligned.

The results demonstrate unequivocally that the inception-v3 model generates exceptional precision, sensitivity, specificity, and F1-score performance.

Table 2: The Evaluation test for pre-trained models for imbalanced data.

		IncepV3	ResNet 101	Vgg16
Acc.	N	0.9449	0.6142	0.4016
	P	0.9134	0.4488	0.6299
	S1	0.9685	0.8583	0.8504
	S2	0.937	0.8819	0.9213
Sen.	N	0.94	0.75	0.4
	P	0.83	0.36	0
	S1	0.89	0.5	0
	S2	1	0.36	0
Spe.	N	0.94	0.6	0
	P	1	0.82	0.63
	S1	0.97	0.86	0.85
	S2	0.93	0.93	0.92
Pre.	N	0.92	0.16	1
	P	1	0.88	0
	S1	0.73	0.056	0
	S2	0.47	0.33	0
F1-	N	0.93	0.27	0.57
	P	0.91	0.51	0
	S1	0.8	0.1	0
	S2	0.64	0.35	0
Overall, Acc.		0.8819	0.4016	0.4016

Table 3: The Evaluation test for pre-trained models for over sampling data.

		IncepV3	ResNet 101	Vgg16
Acc.	**N**	0.995	0.945	0.225
	P	0.995	0.935	0.76
	S1	1	0.985	0.725
	S2	1	0.985	0.74
Sen.	**N**	1	0.85	0.23
	P	0.98	0.92	0
	S1	1	0.98	0
	S2	1	0.95	0
Spe.	**N**	0.99	0.98	0
	P	1	0.94	0.76
	S1	1	0.99	0.73
	S2	1	1	0.74
Pre.	**N**	0.98	0.91	1
	P	1	0.84	0
	S1	1	0.96	0
	S2	1	1	0
F1	**N**	0.99	0.88	0.37
	P	0.99	0.88	0
	S1	1	0.97	0
	S2	1	0.97	0
Overall, Acc.		0.995	0.925	0.225

4. Conclusions

This study demonstrated that Pre-trained DL models, such as Inception-V3 and CWT, can enhance the classification of PPG signals. This method's applicability and efficacy are enhanced by addressing the limitations of previous research and utilizing five-fold cross-validation. Future studies might improve and expand this novel methodology by building on these findings.

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