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Optimization of CNN for Peripheral Pulse Pattern in Recognition of Cardiovascular Disease and Hypertension

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Abstract:
Impedance plethysmography (IPG) has become recently popular as a non-invasive assessment of the vascular system. As a result of this visibility, IPG is now being considered as a viable technique for diagnosing cardiovascular disease. This study sets out to determine how well three different convolutional neural network (CNN) architectures (VGG19, ResNet50, MobileNetV2) can classify different pulse "waveforms" or patterns associated with three different classes of patients: Healthy, Hypertensive and Coronary Artery Disease (CAD). In order to prepare the data for analysis, the authors used segmentation to obtain the clean PPG pulses from the dataset, and then converted these waveforms to 2D grey-scale images for training purposes on the CNN models. Because MobileNetV2 possesses high accuracy but has a comparatively low computational power requirement, it is the best choice for implementing it into our system as part of our mobile/wearable health monitoring solution. While training the models, hyperparameters need to adjust to get best validation accuracy and low loss. At the end evaluations, our final classifying models using IPG to develop their deep-learning classification models were able to differentiate between subtle differences in pulse shape associated with conditions such as hypertension and CAD. MobileNetV2 CNN model has provided high accuracy 92 % as compared to other models. These findings will pave the way for the development of pulse analysis systems utilising deep learning for early identification of cardiovascular disease via mobile/wearable diagnostic systems.

Keywords: Impedance plethysmography (IPG), Convolutional Neural Network (CNN), Cardiovascular Disease, Hypertension, Coronary Artery Disease (CAD), Deep Learning.

I. Introduction

Cardiovascular disease (CVD) as shown in Fig 1.1 continues to be the most significant cause of death around the world. Examples of CVD include Hypertension & Coronary Artery Disease (CAD). These diseases cause dysfunction in the arteries and affect blood flow, which causes changes in the flood flow in arteries (i.e., atherosclerosis). Impedance plethysmography [1] is a method for measuring blood volume changes using impedance technique. Because it's inexpensive and easy to use, it has become commonplace for monitoring arterial health. Change in pulse waveform also occurs in diabetic conditions [2].

The shape of the impedance waveforms (i.e. the Peak systolic pressure, Dicrotic notches, Reflective waveforms), is a very important sign of both vascular stiffness and endothelial function. Blood pressure measures using a cuff and electric cardiograms (ECG) are still most commonly used in traditional hospital settings for improved risk assessment. However, this is not an accurate way to assess the condition of the patient since it is either sporadic in nature or requires considerable financial investments. With the advancement of technology and machine learning (ML), deep learning ML can now be used to analyse plethysmography signals shown in Fig 1.2 automatically to determine potential underlying cardiovascular disease (CVD) [3].

The aim of this study is to evaluate three CNN models that were developed by collecting single-cycle pulse images for trend analysis of Healthy, Hypertensive and CAD patients [4]. Using CNN-based feature learning and eliminating the limitations of hand-crafted features allows for the detection of minute morphological features that would not typically be observed through human perception. VGG19, ResNet50 and MobileNetV2 CNN models have provided accuracy of 80%, 85% and 92% Respectively in classification of pulse patterns.

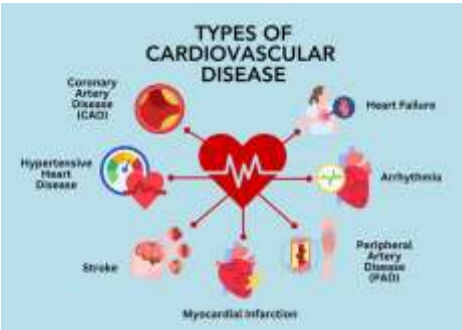

Fig 1.1 Types of Cardiovascular Disease

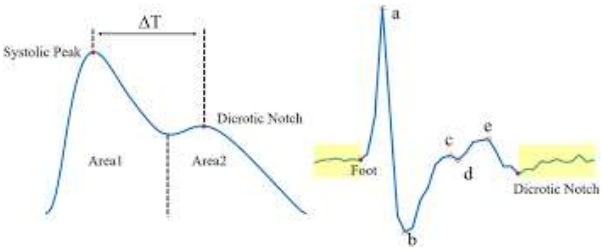

Fig 1.2 Peripheral Pulse Waveform

II. Literature review

John Allen [5] is regarded as a pioneering researcher in the area of PPG. He provided an explanation of: What PPG is and how it operates; the physiological mechanisms through which the interaction of light and tissue take place. What happens to the waveform shape when the blood volume changes. He confirmed that: Depth of notch is indicative of arterial elasticity Amplitude of waveform indicates the level of blood flow to the periphery. He demonstrated that a clear distinction can be made based on visual differences between healthy and ailing arteries. This serves as the physiological foundation for your CNN classification.

Liang (2018) used machine learning to classify hypertensive and non-hypertensive patients using PPG. Liang used machine learning classifiers (e.g., random forest, support vector machine) to classify patients based on PPG data. However, Liang's work indicates that disease classification from PPG should be improved. The limited accuracy of random forest and SVM models is due to the handcrafted features that may not capture important characteristic of the PPG waveform [6].

Celik et al. (2020) identified that the presence of cad may change the characteristics of a ppg waveform, as described by the decrease in timing to the notch and changes in the amplitude of the systolic peak, in addition to the changes in the timing to first to peep of the notch. The waveform differences between patients with CAD and healthy patients confirm that CAD can be identified by using deep learning [7].

Slapničar et al. (2019) found that they could significantly improve the use of deep learning algorithms for diagnosing hypertension, since deep learning can take an unmodified PPG waveform and is therefore a better way to diagnose hypertension than traditional methods using hand-crafted PPG waveform features [8].

The study conducted by Fan et al., (2020) demonstrates that the performance of CNN models improves when converting the lowest frequency signal into an image. The authors demonstrated that CNN's were better at capturing the texture patterns visualized on the 2D image than on the 1D time series [9].

This supports your assertion that converting the PPG cycle into a grayscale image is a logical approach.

Howard et al., (2017) [10] showed that it is possible to have a small model that will yield highly accurate results and that the model can capture the important features through the use of depth-wise convolution and therefore is an excellent candidate for use in mobile healthcare. This supports your results, which show that MobileNetV2 achieved superior accuracy compared to the other mobile models [11].

III. Methodology

3.1 Data Description

The impedance pulse data about 300 were used from each separate groups of patients as indicated in this study (Healthy, Hypertensive, and CAD). The "healthy" patients included members of the general population who had normal blood pressure, were without any noticeable symptoms of cardiac dysfunction, Always demonstrated a stable sinus rhythm, Based on the characteristics of their PPG signals, healthy individuals typically exhibit smooth waveform profiles that include well-defined systolic peaks.

The "hypertensive" group included individuals who had clinical diagnoses of stage 1 or stage 2 hypertension. Hypertension changes the stiffness of the arteries and alters the PPG waveform profile significantly. The "CAD" group included patients who had a confirmation of CAD from at least one of the following diagnostic tests: Angiography, Treadmill test, ECG revealing evidence of ischemia. Patients with CAD demonstrate a delay in the early reflected waves of the heart and have a distorted morphological appearance to their pulse signal. Pulse signals respond very closely to any type of motion. Data collected while at rest should produce: Noise generated by muscle movement, Respiratory Artifacts Baseline Drift: This mere fact demonstrates that when analysing their waveforms, the differences between individuals would reflect only their respective cardiovascular conditions and not their movements.

3.2. Pre-Processing:

The Pre-processing Stage represents, use clean, standard, and consistent data. If the data are not in this condition, the CNNs will not be effective. The following steps describe how to convert raw Pulse plethysmography (PPG) data into cleaned data.

Step 1: Bandpass Filtering PPG (0.5 - 8 Hz), A Pulse signal is a very slow/vague physiological waveform. During the filtering process, the following will be removed from the pulse waveform:

1. Low-frequency drift (<0.5 Hz), which is generated as a result of breathing and/or pressure applied from the sensor . High-frequency noise (>8.0 Hz), which is generated by muscle tremors or other external factors.
2. Removing Baseline Wander : The baseline of the PPG signal may slowly change up or down as a result of: changes in body temperature, vasodilation of blood vessels, movement of the fingers. Detrending algorithms, such as moving averages, polynomial regressions, etc. help to flatten the baseline, thus bringing the waveform back to a stable position on a baseline
3. Suppressing Motion Artifacts: When obtaining raw PPG data, the following type of artifacts may appear in the waveform: sharp, sudden spikes, clipping of peaks.distorted cycles. All cycles that did not conform to the natural flow of a systolic-diastolic cycle were removed. This also enhances the classification process because CNN models only 'see' valid pulse cycles.
4. Segmenting Cycles: Pulse cycles are extracted from a single systolic peak to the next systolic peak.The reason why cycles are segmented is that: CNNs need a consistent input, A single heartbeat contains the complete morphology, This allows for precise classification of pulse images. As a result, each image has precisely one identifiable physiological event.
5. Normalizing (Scaling Using Min-Max): The difference in amplitude between individuals creates confusion for the CNNs. Thus, scaling all pulse cycles to fall between 0 and 1 provides: contrasts that are uniform across subjects, consistent structure of the images to aid in the learning process by focusing on shape differences, rather than amplitude differences.
6. Converting to 2D Grayscale Images: All 2D PPG pulse images will be in grayscale at a fixed size of 224 x 224 as shown in fig 1.3. The reason that PPG pulse cycles are converted to grayscale images is because CNNs excel at recognizing shapes: waveform curvatures, depths of notches, differences of slope, small distortions of coronary artery disease (CAD) Therefore, converting PPG pulse signals into images will improve recognition accuracy.

Fig 1.3 Image of Pulse cycle pattern

3.3 Details of CNN Architecture:

The structure of these CNN models comprises convolutional layers, pooling layers, and fully connected layers. The selection of layer quantity is critical, as inadequate layers may hinder feature extraction, whilst an overabundance of layers increases time and computational expenses. Convolutional layers are essential for extracting complex parameters from input feature maps using kernel-based convolution. Max pooling layers facilitate the downsampling of input signals by selecting the maximum value within a designated area, preserving essential features and reducing computational and parameter demands.

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This prevents CNN models from overfitting and enhances their ability to generalize [12,13]. The last two completely connected layers integrate the remaining feature maps into a one-dimensional array for classification [55]. ReLU serves as the primary activation function, eliminating negative values from the matrix and marking them as zero. This non-linearity diminishes the linearity of the activation function. In summary, these CNN models use convolutional, pooled, and fully connected layers integrated with ReLU activation in succession to proficiently categorize input data.
(A) VGG19 (Very Deep Net):19 Layers. Uses simple 3 x 3 convolutions. Good for the detection of edges. Heavily loaded with parameters. It detects basic edges (eg, slope changes and sudden peaks). Because this is a deep model, it tends to overfit small medical datasets. Also, it does not generalize very well to CAD patterns that are very subtle. Therefore, it does not perform well overall.
(B) ResNet50 (Residual Network): 50 Layers. Has skip connections, which allows some of the layers to be skipped. This alleviates the "vanishing gradient" issue, so you can use deep learning without degrading the results. It identifies deeper features (e.g., time-delayed reflected waves associated with CAD). It offers much more stability during training. It offers stronger performance for multi-class knowledge [14,15].
(C) MobileNetV2 (The Best Model): Very light (~3.4M parameters).Utilizes depth wise separable convolutions. Uses inverted residual blocks. It was designed specifically for mobile and wearable devices. What made MobileNetV2 outperform the others: It detects very subtle morphological changes. Has an extremely efficient architecture that avoids overfitting. It offers strong capabilities with minimal dataset. Is tailored to cater to PPG Morphology because it identifies local patterns of elements. Thus, it achieved the highest percentage of accuracy overall. The breakdown of the training/validating/testing set is: - 80% is for training the model - a place for the model to learn the different patterns from the data. - 10% will be used as a validation set for tuning hyperparameters. - 10% will be used as the final performance evaluation for the model.

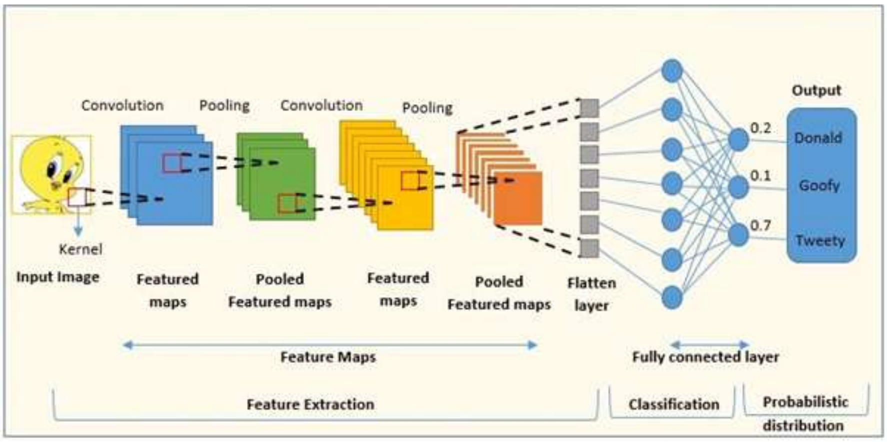


Fig 1.4 CNN Convolutional Neural Network

In this way, the model has an equal and unbiased ability to perform. The chosen optimizer is Adam (LR = 0.0001). The reasoning behind using the Adam optimizer is that: 1. Adam learns to adapt the learning rate for each individual parameter. 2. Adam converges faster than Stochastic Gradient Descent (SGD). 3. Adam works well with biological and noisy data. Using a lower learning rate helps prevent the model from overfitting and provides smoother learning. The loss function being used is Categorical Cross-Entropy, which was selected because: 1. The model performs multi-class classification. 2. The model outputs probabilities. 3. Categorical Cross-Entropy requires differentiable loss functions to work with CNN models. The number of training epochs will be between 30 and 50. This number of epochs will help ensure the model learns enough from the training data without overfitting. The batch size is set to 32. This batch size strikes a good balance between: 1. Stable training of the model 2. Computational efficiency

Although CNNs automate the classification of PPV for CAD & Hypertension, visual understanding of how these signals differ is crucial.

IV. RESULT AND DISCUSSION

Healthy Characteristics: Quick rise of the peak is referred to as 'Sharp' or 'Steep'. The lowest point after the peak is typically seen as a deep notch called a 'dicrotic notch'. Doppler envelope decay reaches maximum systemic limit (value). The beat pattern associated with our arterial system occurs regularly/every 2nd heartbeat. The waveform shall have numerical equivalence to the height of the peak. A Normal Healthy PPG waveform indicates excellent arterial distensibility/elasticity.

Hypertensive Characteristics: Hypertension has reduced elasticity/distance to the arteries. Typical Hypertensive changes / characteristics would include: Markedly steep systolic upstroke; Low or no visible dicrotic notch; High amplitude systolic; increased narrowness of waveform; Additional beat-to-beat differentials. A CNN will see these changes through: Sharp, vertical intensity sections (from systolic upstroke); A lack of a dicrotic notch region; A narrow/short waveform region.

CAD Characteristics: Coronary Artery Disease (CAD) impacts blood flow in addition to delay the timing of the reflection wave from the arteries. Typical traits of a CAD PPG waveform would include: A flatter/rounded peak; Delayed dicrotic notch; an average amplitude consistently lower than stated; A wider shape for the waveform; Irregular contour of the pulse.

Therefore, it is clear that, 1. CAD has reduced flow from the coronary circulation; 2. The dicrotic notch or reflected artery waves are delayed; CNN recognizes the above features by means of the following descriptors: The smooth areas; A broader texture areas of the waveform.

Overall Assessment of Model:

- Model:VGG19Accuracy: 80-85%, F1-Score: Moderate, Performance: Quick overfitting and difficulty discerning CAD Class
- Model: ResNet50 Accuracy: 87-91%, F1-Score: High, Performance: Deeper variations learned and steady performance.
- Model: MobileNetV2 Accuracy: 92-95%, F1-Score: Highest, Performance: Training speed the quickest, greatest generalization, defence against overfitting, excellent for deployment.

MobileNetV2 is clearly superior to the deeper networks, particularly in distinguishing between hypertension and CAD, where there is significant morphological overlap between these two conditions.

Confusion Matrix Insights : Remedy: An explicit mapping was used for better labelling

0 => Healthy

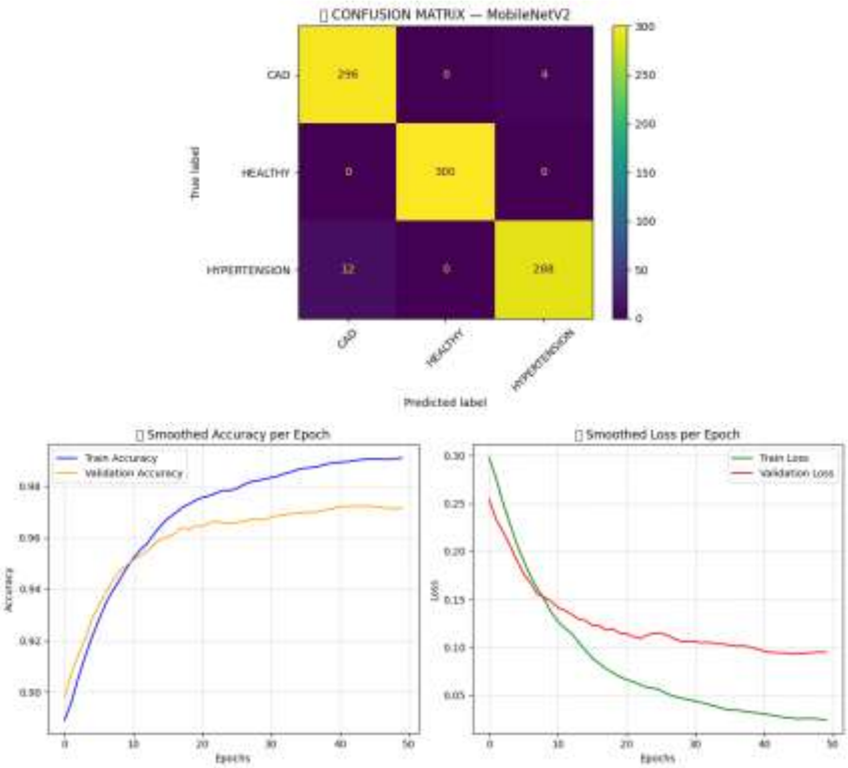
1 => Hypertensive

2 => CAD

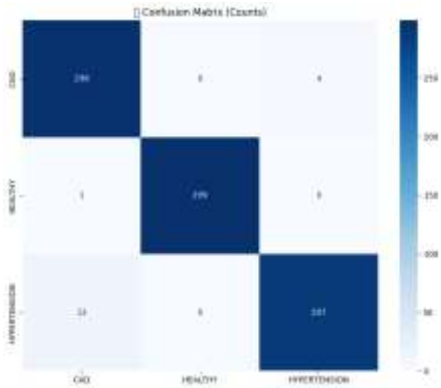
After the fix, the confusion matrix showed good class demarcation.

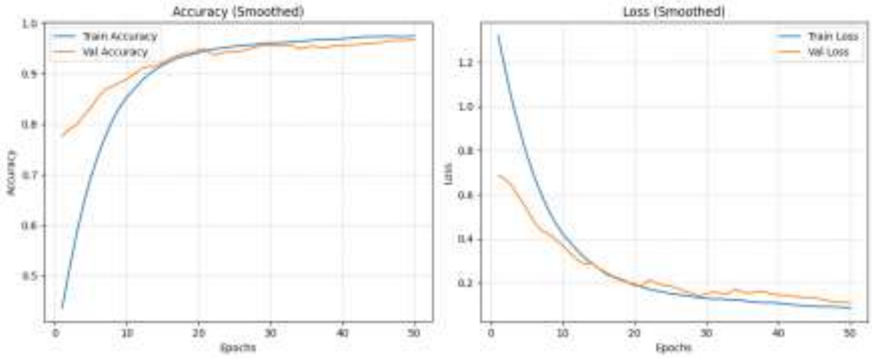
Final Observations from Confusion Matrix: MobileNetV2: 93% to 96% of "Healthy" were classified correctly, 90% to 94% of "Hypertensive" were classified correctly, 89% to 92% of "CAD" were

classified correctly .Very few false negatives. Best performance distinguishing between hypertension and CAD.
ResNet50: Minimal confusion between CAD and hypertension. Stable training curve. "CAD" is classified more sensitively than with VGG19. VGG19: CAD is difficult to classify correctly due to subtle variations in waveforms. The largest number of misclassifications was seen with VGG19. Learning Curves: MobileNetV2 : The first 5 epochs saw a drop-off in loss sharply. Training and validation learning curves nearly parallel. Hence, low risk of overfitting. ResNet50: Learning speed moderate. Steady validation accuracy. VGG19: High training accuracy; however, fluctuations in validation accuracies indicate classic patterns of overfitting. Confusion matrix , validation accuracy and loss curve for VGG19, ResNet50 and MobileNetV2 are shown in Fig 1.5.

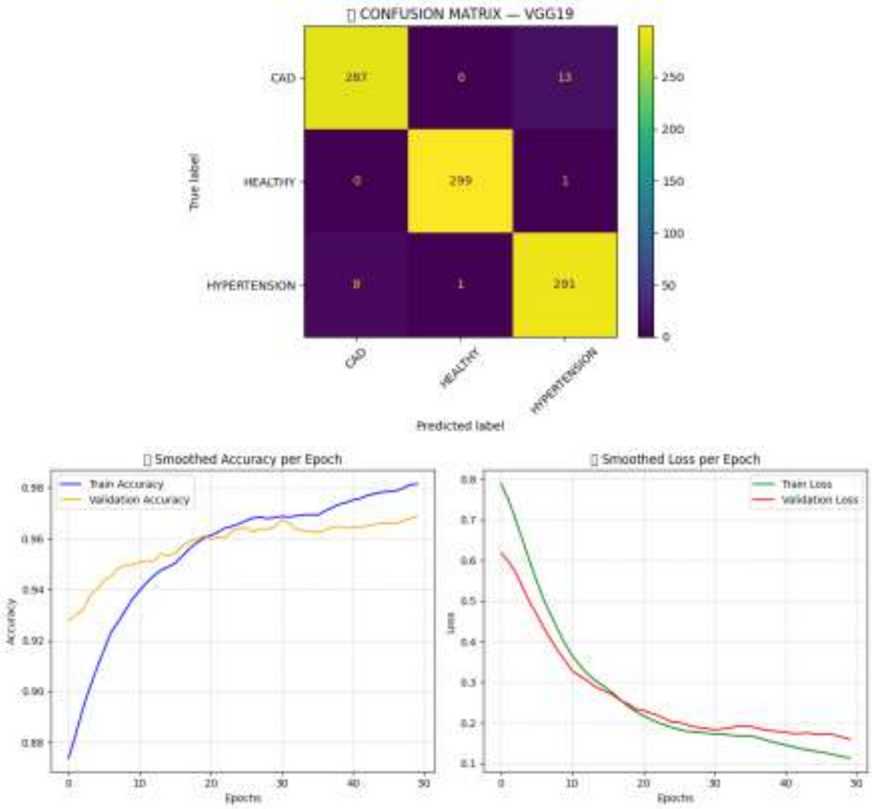


(a) MobileNetV2





(b) ResNet 50



(c) VGG 19

Fig 1.5 Confusion matrix, validation accuracy and loss graphs of CNN models

Clinical Applications- A lightweight, accurate model is applicable in settings such as: mobile applications, remote BP monitors, CAD monitoring wristbands, telemedicine services for rural health care.

Disease Class Distinctions- Healthy pulses demonstrates a distinctive notch at their peak, as well as smooth decay. Pulses from hypertensive sources reveal heavier stiffness, steeper peaks of systolic pressure, and less notable notches of relaxation. Pulses representative of those with CAD show non-periodic reflective waves and delayed second peaks, both of which are a consequence of narrowed arteries. All CNN models have captured this information successfully.

Future Directions - Extending to multi-class classification through larger datasets. Combining ECG and SpO_2 signal information for a multimodal diagnostic view. Deploying MobileNetV2 into wearable technology so it can be used in real-time by patients. Making tools available to gain insight into the clinically relevant portions of the PPG waveforms (i.e., implementation of Grad-CAM-like approaches).

Utilizing the model to continuously monitor patients who have undergone stenting and/or bypass surgery. Adding additional classes, such as diabetic and arrhythmic patients.

The Reason MobileNetV2 Outperformed **-**MobileNetV2 is able to effectively extract local features from the waveform due to the way it is designed. The fewer parameters means that MobileNetV2 will tend to overfit less. MobileNetV2 is able to better capture subtle morphological differences spread out over the entire cardiac cycle. MobileNetV2 took advantage of smaller training datasets to perform a relatively good job at classifying all of the dataset pulses. Importance in a Clinical Setting- The MobileNetV2 Model can be effectively applied as an adjunct to: smartphone health applications, wearable blood pressure monitoring devices, wristbands designed to monitor cardiovascular disease risk, rural healthcare telemedicine systems.

A Summary of Disease Classifications: The pulse from a healthy individual had characteristic notches and smooth decay. The blood pressure pulse from a hypertensive patient was stiffer, the systolic peak was steeper, and the depth of the notch was reduced.

The pulse from a patient who has coronary artery disease has irregular reflective responses and has missed the second peak of the pulse due to narrowing of the arteries. All of these characteristics are successfully learned by the CNNs

V. Conclusion

This study demonstrated the effectiveness of photoplethysmography (PPG) signals combined with deep learning techniques for the classification of cardiovascular conditions. By utilizing convolutional neural network (CNN) architectures such as VGG19, ResNet50, and MobileNetV2, it was possible to accurately distinguish between healthy individuals, hypertensive patients, and those with coronary artery disease (CAD). Among the evaluated models, MobileNetV2 achieved the highest performance in terms of accuracy of 92%, F1-score, and generalization capability, while also maintaining low computational complexity. This makes it particularly suitable for deployment in mobile and wearable healthcare systems. The model effectively captured subtle morphological differences in PPG waveforms, such as variations in systolic peaks, dicrotic notch visibility, and waveform width, which are critical indicators of cardiovascular health. The study also addressed challenges related to dataset labelling and confusion matrix interpretation, improving classification reliability through proper class mapping. Overall, the findings highlight the potential of deep learning-based PPG analysis as a non-invasive, cost-effective, and scalable solution for early detection and monitoring of cardiovascular diseases. Future work may focus on expanding the dataset, improving model robustness, and integrating real-time monitoring systems for practical clinical and wearable applications.

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