



ADVANCED RETINAL BASED MULTIPLE DISEASE DETECTION SYSTEM

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ABSTRACT

Hypertension and heart attack is the leading risk factor of cardiovascular disease and has profound effects on both the structure and function of the microvasculature. Abnormalities of the retinal vasculature may reflect the degree of microvascular damage due to hypertension and heart attack, and these changes can be detected with fundus photographs. This project aimed to use deep learning and AI technique that can detect subclinical features appearing below the threshold of a human observer to explore the effect of hypertension and heart attack on morphological features of retinal microvasculature. retinal photographs are collected from data science domain with a diagnosis of hypertension and heart attack. By method of vessel segmentation, we removed interference information other than retinal vasculature and contained only morphological information about blood vessels. Using these segmented images, we trained a small convolutional neural networks (CNN) classification model and used a deep learning technique to generate heat maps for the class "hypertension" and "Heart attack". The main features are red patchy areas were mainly distributed on or around arterial/venous bifurcations. This indicated that the model has identified these regions as being the most important for predicting hypertension and little similar for heart attack.

Keywords : Morphological information, Heart attack and hypertension.

1. INTRODUCTION

Cardiovascular diseases are the world's biggest killers and these diseases have remained the leading causes of death globally in the last 15 years. Hypertension is the leading modifiable risk-factor, which affects 23.2% (estimated 244.5 million) of adult population aged ≥ 18 years. There is evidence that elevated blood pressure has a substantial impact on the microvasculature in end-organs, such as the brain, heart, kidney, eye and so on. In particular, retinal vasculature, measuring 100 to 300 μm in size, has attracted a lot of non-ophthalmological attention. Retinal microvascular abnormalities represent a manifestation of ongoing systemic microvascular damage and can be viewed directly and noninvasively, offering a unique and easily accessible "window" to study the human microcirculation in vivo. Advances in digital retinal photography and computer image analysis have now enabled more objective quantitative assessment of retinal microvascular structure and function, and may offer a potential non-invasive research tool to assess the pathophysiology of hypertension. Extensive researches on retinal microvascular phenotypes in fundus images have shown that hypertension can lead to abnormal signs on retina. These abnormal signs can be broadly divided into four groups: classic hypertensive retinopathy, isolated retinopathy (e.g., retinal hemorrhage, microaneurysm, or cotton wool spot), changes from retinal vascular caliber (e.g., generalized retinal arteriolar narrowing, focal arteriolar narrowing, arteriovenous nicking), and changes from retinal vascular architecture (e.g., retinal tortuosity, fractal dimension, branching angle). These signs probably reflect systemic microvascular damage and may be an early indicator of cardiovascular diseases. In addition, some prospective studies suggest that retinal microvascular abnormal signs are predictive of the subsequent

risk of hypertension independently of other known risk factors. Although a large number of studies have reflected the association between abnormal retinal microvascular signs and hypertension, some results were inconsistent with three reasons. Firstly, qualitative assessment of hypertensive retinopathy is mainly based on the experiences of the individual and the evaluation results lacks objectivity. Secondly, there is a variety of methods of computer-assisted quantification of retinal vasculature, such as retinal vessel caliber, and thus measurements given for the same fundus image often vary. Last but not least, variations in image brightness, focus, and contrast can significantly affect the measurement of retinal vasculature. Thus this study was designed to analyze retinal image using convolutional neural networks (CNN), also known as convnets, a type of deep-learning model almost universally used in computer vision applications. One fundamental characteristic of convnets that is composed of multiple processing layers is that it can find interesting features in training data on its own, without any need for manual feature engineering. This is especially useful in problems where the input samples are very high-dimensional, like retinal fundus images. It can detect subclinical and discrete features appearing below the threshold of a human observer and quantify minimal differences in feature expression.

2. LITRETURE SURVEY

2.1 STATUS OF HYPERTENSION IN CHINA

A stratified multistage random sampling method was used to obtain a nationally representative sample of 451 755 residents ≥ 18 years of age from 31 provinces in mainland China from October 2012 to December 2015. Blood pressure (BP) was measured after resting for 5 minutes by trained staff using a validated oscillometric BP monitor. HTN was defined as systolic BP (SBP) ≥ 140 mm Hg/or diastolic BP (DBP) ≥ 90 mm Hg or use of antihypertensive medication within 2 weeks. Pre-HTN was defined as SBP 120 to 139 mm Hg and DBP 80 to 89 mm Hg without antihypertensive medication. HTN control was defined as SBP < 140 mm Hg and DBP < 90 mm Hg. In addition, the prevalence of HTN (SBP ≥ 130 or DBP ≥ 80 mm Hg) and control rate (SBP < 130 and DBP < 80 mm Hg) of HTN were also estimated according to the 2017 American College of Cardiology/American Heart Association High Blood Pressure Guideline.

2.2 CORRECTION OF ARTERIAL STRUCTURE AND ENDOTHELIAL DYSFUNCTION IN HUMAN ESSENTIAL HYPERTENSION

Structural and functional alterations of the vasculature may contribute to complications of hypertension. Because angiotensin II may be pivotal in some of these vascular abnormalities, we tested the hypothesis that the angiotensin type 1 (AT_1) receptor antagonist losartan, in contrast to the β -blocker atenolol, would correct resistance artery abnormalities in patients with essential hypertension.

2.3 EVALUATION OF THE MICROCIRCULATION IN HYPERTENSION AND CARDIOVASCULAR DISEASE

The ability to investigate the microvascular structure and function is important in improving our understanding of pathophysiological processes in hypertension and related cardiovascular disease. A range of techniques are available or emerging for investigating different aspects of the microcirculation in animals and humans. Techniques such as experimental intravital microscopy and clinical intravital microscopy (e.g. orthogonal polarization spectral imaging) allow visualization at the level of single microvessels. Venous occlusion plethysmography can be used to measure blood flow in organs, and laser Doppler flowmetry to measure red cell flux in small areas of tissue. Positron emission tomography, myocardial contrast echocardiography, and magnetic resonance imaging provide three-dimensional imaging of local blood flow. The current and potential clinical usefulness of these different techniques is evaluated.

2.4 THE MACROCIRCULATION AND MICROCIRCULATION OF HYPERTENSION

Changes in vascular structure that accompany hypertension may contribute to hypertensive end-organ damage. Both the macrovascular and microvascular levels should be considered, as interactions between them are believed to be critically important. Regarding the macrocirculation, the article first reviews basic concepts of vascular biomechanics, such as arterial compliance, arterial distensibility, and stress-strain relationships of arterial wall material, and then reviews how hypertension affects the properties of conduit arteries, particularly examining evidence that it accelerates the progressive stiffening that normally occurs with advancing age.

2.5 MICROCIRCULATION ON A LARGE SCALE: TECHNIQUES, TACTICS AND RELEVANCE OF STUDYING THE MICROCIRCULATION IN LARGER POPULATION SAMPLES

The role of microcirculatory dysfunction is increasingly being recognized in the etiopathogenesis of cardiovascular disease. Whilst the importance of detailed mechanistic studies to determine the exact nature of these disturbances is without question, it was large-scale population-based studies that first identified the associations between deranged microvascular perfusion, autoregulation or structure, and subsequent target organ damage. This is the subject of considerable studies to establish whether there is a causal effect in either direction, or simply represents shared risk factors, although it is most likely to be a complex combination of bidirectional interactions. The techniques for investigating microcirculatory function have evolved almost exponentially over the last 75 years: So too have the strategies for investigation. Current epidemiological studies are focusing on attempting to untangle the inter-relationship between risk factors and pathological mechanisms to attempt to determine whether these represent therapeutic targets or simple markers of unmeasured risk. We plan to review the techniques used for these population-based studies, the advances made, and the clinical implications derived.

3. OBJECTIVE

To Import retinal images. To extract the features of the images and compares images with trained dataset. Produced the final result whether the retinal image is affected with hyper tension or possibility of having heart attack in the terminal.

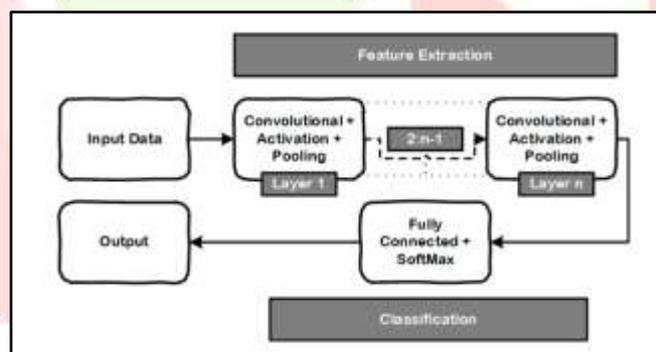


Fig. 1 Block Diagram

4. WORKING

CNNs are artificial intelligence architectures, mainly simulating the behavior of the visual system for the human brain. They are designed based on multi-layer neural networks that extract features from collected data. CNN can perform multiple tasks such as segmentation, detection, classification, and any data correlation. For classification applications, CNN is used to identify the labeled data by employing supervised learning techniques. Whereas supervised learning is one of the machine learning mechanisms for classifying collected data based on previously identified training process in order to find the target values. CNN has three main design ideas: weight sharing, spatial sub-sampling, and local receptive fields. The CNN is composed of four layers: convolutional layer, pooling layer, fully connected layer, and softmax layer. These layers comprise a set of neurons with biases, weights, and activation functions. The CNN network consists of two main stages which are the feature extraction stage and the classification stage. The feature extraction stage includes the convolutional layer and the pooling layer. While the classification stage involves both fully connected layer and SoftMax layer. The block diagram of a typical CNN architecture.

One of the key points that attracted the authors to use the CNN over the other techniques is that it includes feature extraction in its architecture. Accordingly, CNN can minimize the data pre-processing stages compared with other classification techniques. In CNN the feature extraction is done in the convolutional and pooling layers. The convolutional layer consists of neurons that are structured to form a set of filters (kernels) with specific heights and lengths (pixels). The filter is a matrix/vector of integers that is being used with the same size as the kernel on a part of the input pixels. Each pixel is multiplied by the kernel value and the result is added to a single and simple value for representing a grid cell in the output feature map like a pixel. In low level techniques, filters are configured manually for classification purposes, whereas CNN, with enough training dataset, has the ability to learn these filters in order to extract the main features that will improve the classification accuracy of the system. Two-Dimensional (2-D) CNN was applied on the steady state current signals directly to find the fault level. As reported in literature, 1-D and 2-D CNNs are mostly used in fault detection scenarios due to their high performance in feature extraction. The mechanism of learning main features from any raw signal by using 2-D extraction. The input is the raw signal amplitude with respect to time while the output of this feature extraction stage represents a set of local features extracted from the raw data. Typically, CNN consists of convolutional layers and pooling layers along with other supported layers (i.e. activations, normalizations, . . . etc.) which are grouped into submodules, then fully connected layers will be used at the end of the CNN structure based on the design requirements.

CONVOLUTION LAYER - It convolves an array of the raw signals that comes from the input layer with a set of filters with defined size to acquire the suitable feature maps. The feature maps are generated by moving these filters over the targeted dataset. Usually, Rectified Linear Unit (ReLU) is used in CNN model to generate the targeted output feature map. Moreover, Batch Normalization (BN) can be used to speed up the training speed of the CNN model by reducing the fluctuation and internal covariate shift.

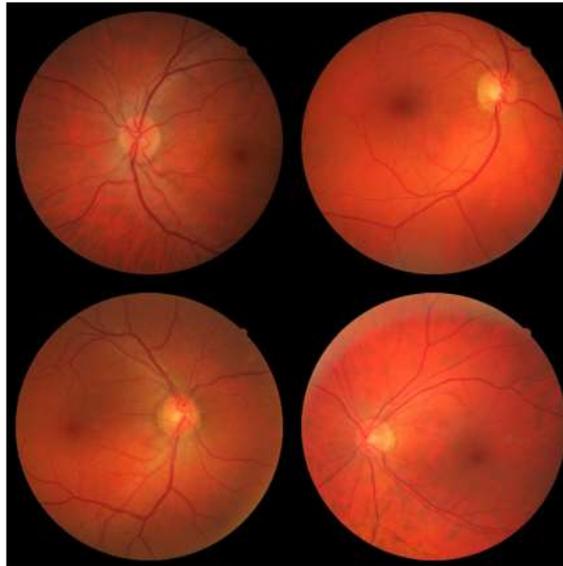
POOLING LAYER - It comes directly after the convolutional layer in order to decrease the dimension of the resulted convolved features. Indeed, this can be done by down sampling the feature signs that are constructed by the previous layer. The input signals are divided into sub-parts and a pooling function is applied to each part to evaluate a new value. Among pooling functions, there are two widely used functions which are the average pooling function and the max pooling function. The average pooling function evaluates the average value of all selected inputs while the max pooling function evaluates the maximum value by using a suitable filter and stride values and then the resulted values will be propagated to the next layer. As mentioned before, this layer minimizes the dimension of the extracted feature maps by changing them into a single output. Therefore, the computational time is reduced and the most important features are extracted.

FULLY CONNECTED LAYER - The main goal here is to take the output feature maps resulted from the convolution and pooling layers and use them to classify the input data into a label. In the fault detection problem, the output of the fully connected layer represents the class of a specific fault.

SOFTMAX LAYER - It allows a multi-class task to be run by the CNN. It reproduces a vector of labels into a set of values between 0 and 1, and the summation of all values is equal 1. Therefore, the number of outputs will be the same as the number of classes.

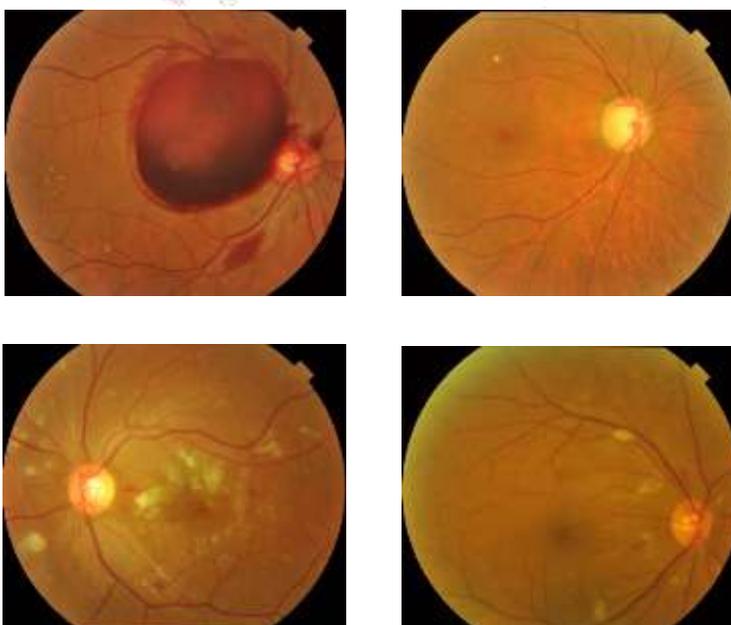
5. DATASET

The dataset is collected from Kaggle data science website in the form of images with three classes namely hypertension, heart attack, normal fundus images some of the example images are given below



6. RESULT & CONCLUSION

In this project, we have proposed a reliable and robust method for Hypertension and Heart attack detection in highly cluttered images using CNN. The cluttered images are obtained using retinal images. The image sequences also provide the candidate affected region proposals done by multilevel graph cut. We have introduced a verification step in which the proposed region is classified into Hyper Tension or Heart attack classes, Thus, determining whether the proposed region is truly affected or not. We applied CNN features to machine learning algorithm to achieve better performance, even the dataset size was small for deep learning. Although we use some strategies for mitigating overfitting and maximizing generalization, such as reducing the size of the model, using dropout layers, and data augmentation, the model eventually started over-fitting after a certain number of iterations. Because these techniques couldn't produce new information and could only remix existing information—the inputs the model sees are still heavily inter-correlated. So we interrupted the training process when the validation loss was no longer improving. Using “segmented dataset”, the accuracy and the precision of the model on the “test set” is slightly higher than using “enhanced dataset”, and the recall and the AUC is apparently higher.



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