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Ensemble-classifiers-assisted detection of cerebral microbleeds in brain MRI☆

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A B S T R A C T

Cerebral Microbleeds (CMBs) are considered as an essential indicator in the diagnosis of critical cerebrovascular diseases such as ischemic stroke and dementia. Manual detection of CMBs is prone to errors due to complex morphological nature of CMBs. In this paper, an efficient method is presented for CMB detection in Susceptibility-Weighted Imaging (SWI) scans. The proposed framework consists of three phases: i) brain extraction, ii) extraction of initial candidates based on threshold and size based filtering, and iii) feature extraction and classification of CMBs from other healthy tissues in order to remove false positives using Support Vector Machine, Quadratic Discriminant Analysis (QDA) and ensemble classifiers. The proposed technique is validated on a dataset of 20 subjects with CMBs that consists of 14 subjects for training and 6 subjects for testing. QDA classifier achieved the best sensitivity of 93.7% with 56 false positives per patient and 5.3 false positives per CMB.

1. Introduction

Cerebral Microbleeds (CMBs) are small brain hemorrhages that are caused by the leakage of blood from blood vessels [1]. These CMBs are also known as hemosiderin deposits [2]. The presence of CMBs and their patterns are considered as a crucial indicator of the cerebrovascular disorder. Recent studies show that CMBs are the root cause of many other brain disorders like intracerebral brain hemorrhage and stroke [34]. Aside from causing these vascular abnormalities, CMBs can also damage their neighboring tissues causing cognitive disabilities like dementia [2]. CMBs appear as small circular shaped spots [1]. They can be visualized through advanced Magnetic Resonance Imaging (MRI) techniques like Susceptibility-Weighted Imaging (SWI) and T2* weighted gradient-recalled echo. The SWI scans outperform T2* weighted sequences because CMBs are more clearly outlined in SWI [56].

Early detection of CMBs is very important because they are indicators of multiple life-threatening brain disorders. Therefore, a sound and reliable technique for the detection of CMBs is critical, which may assist neurologists to suggest medicines

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and anticipate the best solution. With the advancement in medical imaging techniques, minor organs in the brain can be visualized with more details that facilitate the diagnosis of CMBs [7]. Generally, manual inspection is performed to annotate CMBs that is based on visual analysis. It can be time consuming and monotonous task especially when there are a large number of subjects. It takes an observer about 30 min to detect all CMBs in a single Magnetic Resonance scan [8]. Manual detection of CMBs is also prone to errors due to their small size. They can be easily confused with other structures in brain Magnetic Resonance Imaging (MRI) such as blood vessels, calcium deposits etc. Moreover, as the number of CMBs increases, the time consumed to detect them manually also increase.

On the other hand, an automated procedure of CMB detection can achieve high sensitivity and reduce the workload for annotator. However, automating the detection of CMBs is a challenging task due to the similar morphological properties of CMBs and other structures in the brain, large variation in the size of CMBs and their widespread distribution in MRI scans. Many automated techniques proposed for CMBs detection are centered around native features based on size, intensity, and geometry of CMBs. Fazlollahi et al. [9] implemented radon transform to extract the local shape-based features of CMBs. However, only radon transform is not sufficient to capture complicated nature of CMBs. Kuijf et al. [10] used the Radial Symmetry Transform (RST) to detect CMBs. The accuracy of this system was not satisfactory. Therefore, it is not suitable for medical practices In order to differentiate CMBs from CMB mimics more accurately, Bian et al. [11] performed 2D fast RST to compute the geometric based features of CMBs but the results were not promising for this technique. Ghafaryasl et al. [12] extracted shape and intensity based features for CMB classification. However, their technique requires manual review for removal of false positives that is time-consuming. To make the automated process more efficient, some researchers, first, removed non-CMBs regions and then extracted a small number of candidates for classification based on some features [13,14]. However, the structure of these native features is dependent on the domain knowledge of CMBs. In addition, these features are not sufficient to capture the complicated nature of CMBs.

In this context, an automated technique is proposed for the detection of CMBs in SWI MRI scans. The objective is to develop a system that will be able to achieve high sensitivity and minimize the CMBs mimics. To overcome the limitations of existing techniques, we have explored a wide variety of features involving a total of 29 features. Out of these 29 features, 6 features are based on binary patches and 23 features are based on grayscale patches. These features are based on size, geometry and transform that differentiate CMBs from other similar structures. Some of these features haven't been used in the previous automated systems for CMB detection. To check the effectiveness of the proposed feature vector, three classifiers: Support Vector Machine (SVM), Quadratic Discriminant Analysis (QDA) and Ensemble classifiers are used. The proposed technique consists of three steps. (1) Preprocessing for brain extraction (2) Region of Interests (ROIs) extraction using statistical thresholding and hole filling. The extracted ROIs include both true CMBs and false positives. (3) Classification using SVM, QDA and ensemble classifiers to remove false positives. The proposed technique is validated on a dataset of 20 subjects. These 20 subjects have 167 CMBs in total. The training of classifiers is carried out with 14 subjects (104 CMBs) and testing is carried out with 6 subjects (63 CMBs). The proposed technique has the following contributions

1. A wide variety of features based on binary and grayscale patches are explored for CMB detection.
2. The proposed system achieves high sensitivity and also reduces the false positive rate considerably low.
3. Classification of CMBs is achieved without any post-processing step that requires manual review for removal of CMB mimics.

The remaining paper is organized as follows. In Section 2 we discuss previous techniques for CMBs detection, their effectiveness, and drawbacks. In Section 3 methodology is described in detail followed by Section 4 in which experimentation and results are reported.

2. Literature review

Many researchers have proposed automated techniques for CMBs detection using different classification algorithms. Most of the proposed techniques are a combination of image segmentation with features extraction and classification. Seghier et al. [15] proposed a unified probabilistic normalization segmentation technique using a mixture of Gaussians to detect CMBs in T2-Weighted MRI scans. Their proposed technique successfully detected CMBs in 8 out of 13 patients who had a single CMB and detected all CMBs in 9 patients who had two or more CMBs. Therefore, this method works well only for those patients that have multiple CMBs but did not work well for the patients having single CMB. Kuijf et al. [10] proposed a technique that computes the RST of MRI scans to detect CMBs. They achieved 65%, 78% and 84% sensitivities with an average of 20, 49 and 96 false positives per patient. Although their proposed system was reasonably efficient in terms of sensitivity their technique missed a significant number of CMBs. Barnes et al. [13] proposed a technique in which thresholding is applied first then shape and intensity based features were extracted and SVM classifier was used to remove false positives. They achieved 81.7% of sensitivity with 107 false positives per subject. Their system was not completely automated as they required to perform a manual review for the removal of leftover false positives. The manual removal of CMBs need human expertise and also consumes a lot of time.

Ghafaryasl et al. [12] used a large number of features based on local image descriptors and used four classifiers; QDC, Linear Discriminant Analysis (LDA), SVM, and Parzen classifier for CMB detection. Their system achieved high sensitivity but also produced a large number of false positives. Their system also requires manual review for the removal of false positives. Bian et al. [11] computed 2D fast RST to find geometric feature measurements followed by removal of false positives. They