Develop tool for automatic diagnosis of vessel disease using Deep Learning

Abstract:

We propose a clinical tool and develop deep learning technique to evaluated vessel wall automatically using imaging sequence. Gather a dataset of medical images, such as computed tomography angiography (CTA) scans, MRI or ultrasound images, that are annotated or labeled to indicate the presence or absence of atherosclerosis. The dataset should include a diverse range of cases to ensure the model's robustness. Developing a deep learning-based method that utilizes the UNet-VGG16 architecture for automated detection and segmentation of vessel region is a promising approach. VGG16 is a popular architecture known for its effectiveness in medical image segmentation tasks, and combining it with the VGG16 network can potentially enhance its performance.

The correlation coefficient is a statistical measure that quantifies the strength and direction of the relationship between two variables. In this case, it indicates how well the automatic estimations of the vessel areas align with the manual estimations. A correlation coefficient value of 0.81 suggests a substantial agreement between the automatic and manual measurements.

By utilizing an MR sequence, you can capture more comprehensive information about the vessel regions, enhancing the accuracy of the estimation. Different sequences may provide complementary information, such as T1-weighted and T2-weighted images, which can aid in distinguishing different tissue types and detecting abnormalities.

Introduction

cardiovascular disease (CVD) is a significant health concern in Canada and globally. It is the second leading cause of death in Canada and the number one cause of premature mortality. Atherosclerosis, characterized by the accumulation of plaque in the arteries, is the most common form of CVD.

Atherosclerosis involves a progressive process where lipids accumulate within the vessel walls, leading to the formation of plaques that narrow the arteries. This narrowing, known as stenosis, reduces blood flow to vital organs, such as the heart and brain, and can result in serious consequences like transient ischemic attacks (TIAs) or strokes. Plaques in the arteries can also become unstable or rupture, leading to the formation of blood clots that can further obstruct blood flow. These clots can result in severe complications such as heart attacks or ischemic strokes if they occlude blood flow to critical areas.

Preventing and managing atherosclerosis is crucial in reducing the risk of CVD. Lifestyle modifications, including adopting a healthy diet, engaging in regular physical activity, not smoking, and maintaining a healthy weight, play a significant role in reducing the development and progression of atherosclerosis.

Additionally, medical interventions may be necessary depending on the severity of the disease. These interventions can include medications to control cholesterol levels, blood pressure, and blood sugar, as well as surgical procedures such as angioplasty and stenting or bypass surgery in more advanced cases.

Raising awareness about the risk factors associated with atherosclerosis and implementing preventive measures is essential in combating the burden of CVD. Early detection, regular health check-ups, and timely management of risk factors are critical in reducing the impact of atherosclerosis and preventing adverse cardiovascular events. [1-3].

Non-invasive imaging techniques have greatly improved our ability to assess plaque characteristics and monitor the biological processes occurring during each stage of atherosclerosis development.

Vessel wall magnetic resonance imaging (MRI) has proven to be a powerful tool for studying atherosclerosis in various arteries, including the vessel, coronary, aorta, peripheral, and intracranial arteries. It provides detailed visualization of the vessel and enables assessment of plaque morphology, composition, and inflammation.

Accurate quantification of the vessel artery is clinically valuable for the diagnosis and prognostication of cardiovascular disease (CVD). One specific measure of interest is the vessel volume which provides information about the extent of atherosclerotic burden and disease progression.

However, the current method of quantifying vessel typically involves manual segmentation of individual images acquired from different MRI sequences. This manual segmentation process is time-consuming, requires extensive training, and is subject to variability based on image quality and the experience of the readers.

To address these challenges, there is a need for automated or semi-automated segmentation methods using advanced image analysis techniques such as machine learning and deep learning algorithms. These methods aim to streamline the quantification process, improve efficiency, and reduce inter- and intra-observer variability.

By training these algorithms on large datasets of annotated images, they can learn to automatically identify and segment the vessel from different MRI sequences. Automated segmentation methods have the potential to significantly improve the efficiency and consistency of vessel quantification, leading to more reliable and reproducible results.

However, it is important to validate these automated segmentation methods against manual segmentation as the gold standard. Their performance should be assessed across different image qualities and patient populations to ensure accuracy, robustness, and generalizability [3-6]. Development of automated or semi-automated segmentation methods for quantifying vessel image has the potential to enhance the clinical assessment of atherosclerosis. By reducing the need for manual segmentation, these methods can save time, improve accuracy, and aid in the diagnosis and prognostication of CVD. Furthermore, In recent years, semi-automated or automated segmentation techniques have been developed to improve and accelerate the quantitative and qualitative analysis of vessel and plaque components in medical imaging.

These techniques aim to reduce manual intervention and improve efficiency in the analysis process. Machine learning techniques have been employed to classify image pixels into vessel and non-vessel classes, facilitating automated segmentation. By training models on labeled datasets, these methods can learn to distinguish between different regions in the image. Additionally, methods like Hough circle detection have been used to locate the artery of interest. They rely on the assumption that arteries have a circular shape and aim to find the center of the arterial wall. These approaches can provide initial localization, which is valuable for subsequent segmentation steps. While these methods reduce processing time and offer reasonable agreement with manual segmentations, they may still require some form of manual input. For example, seed-point initialization or user-defined input may be necessary to indicate the artery of interest. Image registration techniques may also be employed to align image sequences for consistent analysis.

It's important to note that these semi-automated or automated segmentation techniques are constantly evolving, and ongoing research aims to further improve their performance and reduce the need for manual input. The development of more advanced deep learning algorithms, such as fully convolutional networks (FCNs) and CNN, has shown promising results in automated segmentation tasks, including vessel segmentation.

Efforts to develop fully automated segmentation techniques without manual input are ongoing and are likely to have a significant impact on improving the efficiency and accuracy of vessel analysis. However, it remains important to validate and compare these automated techniques against manual segmentation by experts to ensure their reliability and clinical applicability. The development of semi-automated or automated segmentation techniques, including machine learning approaches and methods like Hough circle detection, has advanced the analysis of vessel wall volume and plaque components. While some manual input may still be required, ongoing research is focused on reducing manual intervention and improving the efficiency and accuracy of these techniques.

In recent years, deep-learning methods, including convolutional neural networks (CNNs), have shown significant advancements in cardiovascular image processing. These methods have demonstrated improved performance in various tasks, such as automatic quantification of left ventricle, retinal blood vessels, and coronary artery segmentation. CNNs, in particular, have emerged as a powerful deep-learning technique for analyzing cardiovascular images. They excel at capturing complex spatial patterns and features in the images, enabling accurate detection and segmentation tasks. By training CNNs on large datasets, they can learn to automatically detect and segment specific structures or regions of interest, such as the vessel regions.

The development of a deep learning-based method for fully automated detection and segmentation of the vessel labels is a promising approach. By leveraging a large dataset for training the algorithm, the model can learn from diverse examples and gain the ability to generalize well to new data. It is essential to have a separate dataset for testing the trained algorithm to assess its performance on new cases and evaluate its generalization capabilities.

By utilizing deep learning techniques, the proposed method aims to automate the process of vessel segmentation, eliminating the need for manual intervention and reducing human error.

This can lead to improved efficiency, consistency, and accuracy in the analysis of vessel regions.

However, it is important to note that the success of the deep learning-based method relies on various factors, such as the quality and representativeness of the training dataset, appropriate model architecture selection, optimization of hyperparameters, and careful evaluation and validation of the trained algorithm [7-11]. Developing and evaluating a deep learning-based method for fully automated detection and segmentation of the vessel regions is a promising direction. By leveraging a large dataset for training and utilizing CNNs, the method aims to improve the efficiency and accuracy of vessel analysis. Testing and validation are necessary to assess the performance and generalization capabilities of the trained algorithm.

Materials and Methods

1. Data Set

Collecting vessel MRI dataset from three major sources and utilizing an MRI sequence for the training and testing process is a comprehensive approach for developing and evaluating a deep learning-based method for vessel artery analysis.

The dataset consists of MRI sequence that capture complementary information about the vessel arteries. The sequence is the T1 weighted (T1W) sequence. This sequence allows for imaging of the entire length of the vessel artery, providing a comprehensive view of the vessel and surrounding structures. The T1W sequence captures tissue characteristics. Utilizing data from multiple sources further increases the diversity and generalizability of the dataset. Different MRI sources may employ distinct imaging techniques, protocols, and hardware, resulting in variations in image quality and appearance. By including data from multiple sources, the developed method can account for these variations and demonstrate robustness across different imaging systems.

Training and evaluating a deep learning-based method on such a dataset can help optimize the algorithm's performance and ensure its ability to generalize to new cases. It is essential to properly validate and test the trained model's performance on separate validation and testing datasets to assess its accuracy, reliability, and generalization capabilities [6]. Using a vessel MRI dataset collected from three major sources and including complementary sequences (T1W) provides a comprehensive and diverse dataset for training and evaluating a deep learning-based method for vessel artery analysis. This approach increases the robustness and generalizability of the developed method, enhancing its potential clinical applicability.

2. Methodology: Deep Learning Network Architecture

We proposed technique of applying Convolutional Neural Networks (CNN) for delineating the vessel artery. This is innovative and promising technique as CNN is a well-established architecture for image segmentation, and our approach of using CNN architectures for detecting the vessel boundaries allows for a more specialized and focused analysis.

In this method, the vessel detection is treated as classification problem, where each pixel is categorized into one binary class. By estimating the non-linear mapping between each pixel and its corresponding label, your network can learn to accurately segment the vessel regions. The network structure incorporates four blocks of convolutional layers and max-pooling layers, followed by four blocks of convolutional layers and up-sampling layers. This arrangement enables the network to capture and process multi-scale information, from low-level to high-level features, which is crucial for accurate segmentation.

The U-Net is a classical fully-convolutional network for classification, localization, and segmentation in ultrasound images. It consists of an encoder (contracting path) and a decoder (expanding path). The output of the encoder is the feature map or vector that contains the information of the input. The decoder has the same structure as the encoder but takes feature maps as the input and provides a similar match to the actual input or intended output. Furthermore, concatenating feature maps from the contraction phase helps the expansion feature recover the information about the location of the respective object. The encoder process reduces the size of the input matrix by increasing the number of the feature maps. On the contrary, the decoder returns the matrix to its original size by minimizing the number of the feature maps. Therefore, the segmentation results can be compared with the ground truth (GT) in every pixel.

The VGG16 network has 13 convolutional layers, 5 pooling layers, and 3 fully connected layers in the end of the network. The VGG16 network features a homogeneous architecture that only performs 3×3 convolution and 2×2 max pooling from the beginning to the end. his allows the network to propagate both local and global information during the segmentation process. Finally, the convolution function in the last layer maps the network's output to the desired number of classes.

VGG16-UNet, similar to the networks, the final 3 fully connected layers of VGG16 were replaced with architecture that resembled the decoding part of U-Net, which formed the expanding path with convolution layers and upsampling layers. Hence, the VGG16 without the final 3 fully connected layers was retained as the contracting path. Additionally, 3 more modifications were performed in this study. (I) For the original rectified linear unit (ReLu) activation function in 7 convolution layers (the final four convolutional blocks), they were replaced with Leaky ReLu (α=0.1). (II) We used 4 skip connections (3 concatenations and a summation) to combine feature maps of different modules in contracting path and expanding path. (III) The size of the kernel for the upsampling operation was 4×4.

It is essential to train and optimize the network using appropriate loss functions, such as dice coefficient or cross-entropy, and employ suitable training strategies, including data augmentation and regularization techniques. Additionally, validating the performance of the network on independent datasets is crucial to assess its accuracy, generalization capabilities, and clinical applicability.

In summary, our proposed technique of utilizing CNN architectures for delineating the vessel artery holds great potential. The network's ability to capture multi-scale information and exploit both local and global context can enhance the accuracy and reliability of the segmentation results, contributing to improved vessel artery analysis.

- **Training Step**

Training CNN architectures with pre-processed data is a robust approach for vessel artery detection and segmentation.

In training dataset, there are MR images that are used for vessel detection and segmentation. This large dataset provides a diverse range of images to train the networks and helps capture the variability present in vessel artery anatomy across subjects.

For detection, the segmentation labels of the training dataset were based on expert annotations. The vessel regions were assigned a value of one, while the background regions were assigned a value of zero. This labeling scheme allows the CNN to learn to differentiate between the vessel and background regions accurately.

The CNNs were trained using the TensorFlow library in Python. Training the networks for 70 epochs allows the models to learn and optimize their parameters by repeatedly iterating through the training dataset.

By training the CNN architectures with the provided dataset and leveraging the capabilities of a GPU, we make sure that the models can effectively learn the non-linear relationship between image features and the segmentation maps, ultimately improving the accuracy and

robustness of the inner region and outer region detection.
Further evaluation and validation of the trained models on independent datasets are crucial to assess their generalization capabilities and performance on unseen data.

- **Testing Step**

Performing testing on a separate set of subjects that were not included in the training dataset is a crucial step in evaluating the performance and generalization capabilities of the trained networks. By using around 10% of the dataset for testing, we ensure that the evaluation is performed on new data.
During the testing process, the new images undergo the same preprocessing steps described earlier to ensure consistency. This involves applying the necessary preprocessing techniques, such as rescaling, normalization, and noise reduction, to prepare the images for feeding into the network.
Once the preprocessed images are ready, they are fed into the trained network to obtain the segmentation maps. The reshaped image regions are passed through the network, and the network outputs predicted segmented region.
To evaluate the performance of the networks for new subjects, manual annotation is used as the reference standard. Expert annotators manually segment the vessel in the new images, providing ground truth labels for comparison.
By comparing the predicted segmented vessel generated by the network with the manual annotations, we can assess the accuracy and performance of the model in segmenting the vessels for the new subjects. This evaluation step helps validate the generalization capabilities of the trained model and provides insights into their performance on new data. It allows you to assess the reliability and accuracy of the model in segmenting the vessel artery and quantifying the vessel region. In summary, the testing process involves preprocessing the new images, passing them into the trained network, and obtaining the segmentation vessel. Manual annotation serves as the reference standard to evaluate the performance of the networks on new subjects. This step is essential for assessing the model performance and ensuring their applicability to new data in clinical settings.

Results

Evaluation of the Segmentation Model

The performance evaluation of the trained VGG16-UNet for vessel artery segmentation is a crucial step to assess the accuracy and conformity of the automatic segmentation results with the reference data. Various evaluation metrics and statistical analyses can provide insights into the performance of the segmentation algorithm. The performance evaluation of the proposed algorithm for vessel artery segmentation using overall accuracy is a valid approach to estimate the correctness of the automatic assessments compared to the total number of assessments. In this study, the trained network was utilized to automatically detect the vessel region on unseen testing images. After training the network for 70 epochs, the algorithm achieved accuracies of 0.81 for the detection of vessel region. This high accuracy value indicate a strong conformity between the automatically detected vessel regions and the ones manually labeled by the expert reader. The algorithm's ability to accurately detect the vessel region demonstrates its effectiveness in identifying these key components of the vessel artery. Overall accuracy provides a global assessment of the algorithm's performance by quantifying the proportion of correctly detected boundaries relative to the total number of assessments made. It is an essential measure for evaluating the algorithm's ability to correctly identify and segment the vessel artery structures. However, it's important to note that accuracy alone may not capture the full performance characteristics of the algorithm. It is recommended to validate the algorithm's performance on a larger and diverse dataset, comparing the automated results with expert manual annotations, and potentially incorporating additional evaluation metrics for a more comprehensive assessment.

Conclusion

Deep learning techniques, such as convolutional neural networks (CNNs), have demonstrated their effectiveness in medical image segmentation tasks, including the detection and segmentation of vessel arteries. Using radiology sequence in combination with a CNN can provide a reliable segmentation algorithm for vessel artery detection.

In conclusion, this study successfully developed a semi-automated vessel MR analysis system based on a CNN algorithm to estimate the vessel regions. The system was evaluated on new dataset that was not included in the training phase. Once the proposed CNN network architecture was trained using this dataset, it demonstrated the ability to automatically and accurately evaluate the vessel abnormality.

The semi-automated nature of the system allows for efficient and reliable analysis of vessel MR images. By leveraging the power of deep learning, the system can provide accurate and close to real-time evaluations of the vessel wall.

Overall, this study contributes to the advancement of vessel artery analysis by utilizing deep learning techniques to develop a semi-automated system that can accurately estimate the vessel regions. This has the potential to improve efficiency, consistency, and accuracy in clinical practice, ultimately benefiting patient care and management.

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