Detection of Arterial Occlusion on MRI Angiography of the Lower Limbs using Deep Learning

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I. Introduction

Lower extremity peripheral arterial disease (PAD) describes a condition which causes the partial or complete failure of delivery of oxygenated blood to the lower extremities, causing a range of symptoms from intermittent pain while walking up to gangrenous tissue [6]. The severity can be classified by the Fontaine or Rutherford classification system [12]. The overall prevalence of PAD is stated to be from 3 %- 10 % up to 15 %- 20 % at the age group above 70 years [3][8][16].

Besides the clinical examination common practice for the diagnosis of lower extremity PAD is the ankle-brachial index (ABI) calculated by the ratio of the blood pressure measured in the arm and leg [12]. After the initial screening using the ABI, further imaging diagnostics can be performed in order the evaluate the arteries supplying the legs. One of the imaging techniques is the contrast enhanced magnetic resonance (MR) angiography [12]. Although anatomical variances exists the main arteries of the lower limb are the Arteria iliaca externa, Arteria femoralis communis, -superficialis and -profunda, Arteria poplitea, Tractus tibiofibularis, Arteria tibialis anterior and -posterior and Arteria fibularis [14]. To quantify the occlusion of arteries radiological reports most often differentiate between no occlusion, none significant- and significant occlusion (above 50 % stenosis)[11].

In the last couple of years many technical advances in the field of Deep learning (DL) have been made with a wide range of applications in the field of medicine [15][10]. Regarding the detection of lesions or diseases in medical image data, DL systems have for example successfully been applied to chest radiographs [2] or the detection of nodule lesions in computer tomography (CT) of the lung [1]. Furthermore it also has been tested on the detection of vessel stenosis on lower limb CT angiography [4].

One of the difficulties of applying DL technologies to medical data is the lack of adequate labeled training data especially as radiological reports often take the form of free text [9].

In this study a DL approach to detect and classify arterial occlusions in contrast enhanced MR angiography of the lower limbs shall be examined.

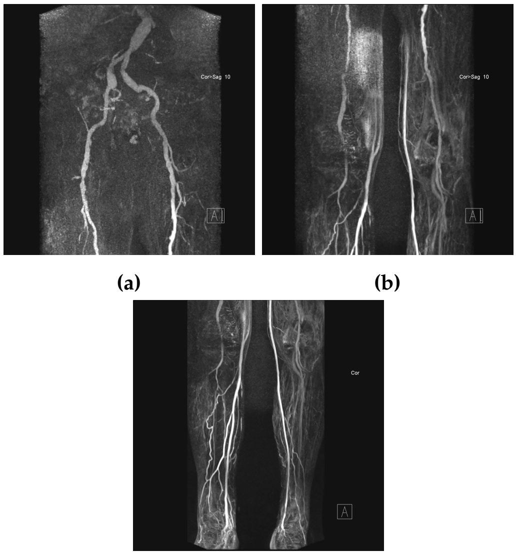
II. Methods

Approval by the research ethics committee of the Friedrich-Alexander-Universität Erlangen-Nürnberg was obtained.

For the study all image data was acquired retrospectively from clinical records from the institution Klinikum Fürth. Contrast enhanced MR angiography of the lower limbs is commonly performed in the clinical routine. The practice is to acquire vessel images in three levels, the abdominal pelvic-, the thigh- and the lower leg region.

Different image sequences are acquired and reconstructed by the attending radiographer. In this study the maximum intensity projection (MIP) and a derived 3D rotation reconstruction of the examination will be used for further examination as shown in Figure 1.

Labeling was be performed by a trained radiologist with several years of experience based on the radiological reports. A discrete numerical value between zero and five was used to encode the severity of the stenosis with zero denoting no occlusion and five a complete stenosis of the vessel. For the main arteries mentioned earlier in Section I and fur-



(a) (b)

(c)

Figure 1: *Exemplary frontal projection of the used 3D rotation derived from the MIP of the examination for the a) abdominal pelvic-, b) thigh- and c) lower leg region*

thermore for the right and left side, labeling was performed separately.

Additionally an exclusion label was introduced to denote artefacts e.g. by surgical material, previous bypass operations which alter the anatomy of the vessel structure and severe venous superposition. Patients which underwent an amputation of the lower limbs were excluded during the labeling process.

Overall data samples of roughly 500 examinations were collected.

For the preliminary training and testing of the neural networks (NN) labeling will be simplified by combining different vessels and severity labels.

Implementations of neural networks based on the ResNet- [7] and EfficientNet [17] architecture shall be examined.

Materials The implementation of the proposed networks will be done in Python using Pytorch-Lightning based on the deep learning framework PyTorch [5, 13]. As a hardware resource the Graphics Processing Unit cluster of the Pattern Recognition Lab of the Friedrich-Alexander-Universität Erlangen-Nürnberg shall be used.

Evaluation In order to evaluate the networks performance 50 data samples are be held out of the training and validation process and will be exclusively used for testing. Different metrics as Accuracy, F1 score and AUROC will be used for the performance evaluation.

III. Discussion

As the datasets will be acquired though one hospital using specific hardware and examination protocols, the trained network can be biased and not perform well on different image datasets using another setup for the image acquisition.

Furthermore labeling was done using a discrete level of severity and not strictly following the nomenclature of radiological reports. The labor and resource intensive manual labeling process also made it impossible to collect a vast amount of data which makes it necessary to apply some simplification e.g. the exclusion of patients with amputations (see Section II).

As mentioned, not the whole acquired image dataset will be used for training as that would overwhelm most hardware restrictions using common NN architectures. This however leads to a loss of information, for example the dynamic flood on the contrast agent in the vessels will not be taken into account.

Preliminary testing will be performed with a testing dataset. To evaluate true diagnostic relevance and accuracy a follow up study can be performed testing the network against trained radiologists.

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