Web3 Journal: ML in Health Science

ISSN 2942-8726

2024. Vol. 1(2)

Original Article

TxnHash: 0x557e304cde91dd5de7a2754bd09c7a9c490db7c37cf760ac98caf6716e5c716c

DOI: 10.62487/82grqt38

Smartphone Camera for Angiographic Computer Vision in Vascular Medicine.

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Abstract.

Aim: This study aimed to develop a TensorFlow Lite algorithm for angiography classification and to deploy it on a basic mobile smartphone device, thereby verifying the proof of concept for creating a comprehensive end-to-end mobile computer vision application for vascular medicine. **Materials and Methods:** After ethical approval by the local ethics committee, we collected institutional and open source peripheral angiograms of lower limbs. The angiograms were labeled by a researcher with more than 10 years of experience in vascular surgery. The labeling included dividing the angiograms according to their anatomical pattern into the Global Limb Anatomic Staging System (GLASS). The model was developed using the open-source TensorFlow framework for general image classification and deployed as an Android application. **Results:** The model utilized 700 angiograms, distributed as follows within the femoropoliteal GLASS disease (fp) categories: fp0 – 187 images, fp1 – 136 images, fp2 – 128 images, fp3 – 97 images, fp4 – 152 images. The reference dataset included 372 non-angiographic images (not_angio). Consequently, the entire model included 1,072 images. After training and deployment, the model demonstrated the following performance: a mean accuracy of 0.72. The best self-reported accuracy per class was for fp0 0.72, fp4 0.83 and not_angio 1.0 classes. **Conclusion:** We discovered that a smartphone camera could be utilized for angiographic computer vision through end-to-end applications accessible to every healthcare professional. However, the predictive abilities of the model are limited and require improvement. The development of a robust angiographic computer vision smartphone application should incorporate an upload function, undergo validation through head-to-head human-machine comparisons, potentially include segmentation, and feature a prospective design with explicit consent for using collected data in the development of AI models.

Keywords: TensorFlow, Artery Disease, Smartphone Application, Machine Learning, Computer Vision, Artificial intelligence

Background:

Image classification in vascular medicine:

Vascular medicine is the field of medicine with very high concentration of imaging. Vascular specialists routinely use imaging every day for diagnostics and treatment of their patients. Imaging is a modality where we must interpret visual information, which inherently involves some subjectivity and is limited by our current individual understanding of what we know. Computer vision could standardize the interpretation of the information we visualize. It allows us to obtain a second, maximally independent, and at the same time, evidence-based opinion that could guide complex clinical decisions.

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Most of the available studies in vascular medicine are currently focused on the analysis of Doppler waveforms[1–4], ultrasound images[5], and peripheral angiograms[6–8], magnetic resonance and computed tomography images[9,10]. The models available today are primarily experimental in nature and find application in clinical practice only as laboratory or commercial tools. "Diamond open access"[11] and end-to-end mobile applications for computer vision, which could be applied by medical specialists across the field of vascular medicine, are currently not available.

TensorFlow Lite

TensorFlow Lite is a component of the TensorFlow image classification platform that offers the capability to deploy custom-made and optimized pre-trained models as mobile applications on smartphones[12,13].

Aim

This study aimed to develop a TensorFlow Lite algorithm for angiography classification and deploy it on a basic mobile smartphone device, thereby verifying the proof of concept for creating a comprehensive end-to-end mobile computer vision application for vascular medicine.

Material and Methods:

Data Collection

Our dataset comprised two subsets. The first subset included images collected through a web-indexed search and previously used for automated machine learning (AutoML) model development in our prior research[6]. The second subset was gathered through institutional channels following ethical approval of our study: Ethic Committee University Leipzig Medical Faculty, Protocol Nr. 333/23-ek from 24.10.2023.

The images consisted of digital subtraction angiograms (DSA) of the femoral, popliteal, and femoropopliteal segments of the lower limb arteries. These images were labeled according to the most applicable grade of femoropopliteal disease using the Global Limb Anatomic Staging System (GLASS)[14], as described in our previous research[6]. Additionally, we created a random reference set of non-angiographic images from the Kaggle platform[15]. Thus, our entire dataset included six subsets: Grades 0-4 of femoropopliteal disease according to GLASS, and a "non-angio" subset.

Model training, deployment, and extraction

We employed the most straightforward method of TensorFlow Lite model development using the Teachable Machine platform and a standard color image model with an input resizing of 224x224 pixels. The labeled data were trained with the following settings: 10 epochs, a batch size of 16, and a learning rate of 0.001, standard data split. The model's performance was assessed using a confusion matrix and accuracy per class. After deployment, the model was extracted as a quantized TensorFlow Lite file.

Application Deployment Using TensorFlow Lite Model with Android Studio

We utilized the standard TensorFlow Lite example model from the GitHub repository for image classification on the Android system[16]. The model was extracted from the repository and modified within Android Studio Flamingo (2022.2.1 Patch2) by adding the previously created TensorFlow Lite quantized model into the assets category, as shown in **Figure 1.**

APK Deployment and Installation on a Smartphone

After incorporating our customized model, we customized the TensorFlow Lite application by adding a unique name, "ML GLASS," and an icon and deployed on an Android Smartphone Sony Xperia XQ-AS52 Android 12, as shown in **Figure 2.**

Testing with Unknown Angiograms

After deployment, the application was used to identify previously unknown random static angiograms using a smartphone camera with the following presets: Standard frame: 640x480, Crop: 224x224, View: 480x480, Rotation: 90 degrees, Threads: 9, Model: Quantized_MobileNet, Device: CPU.

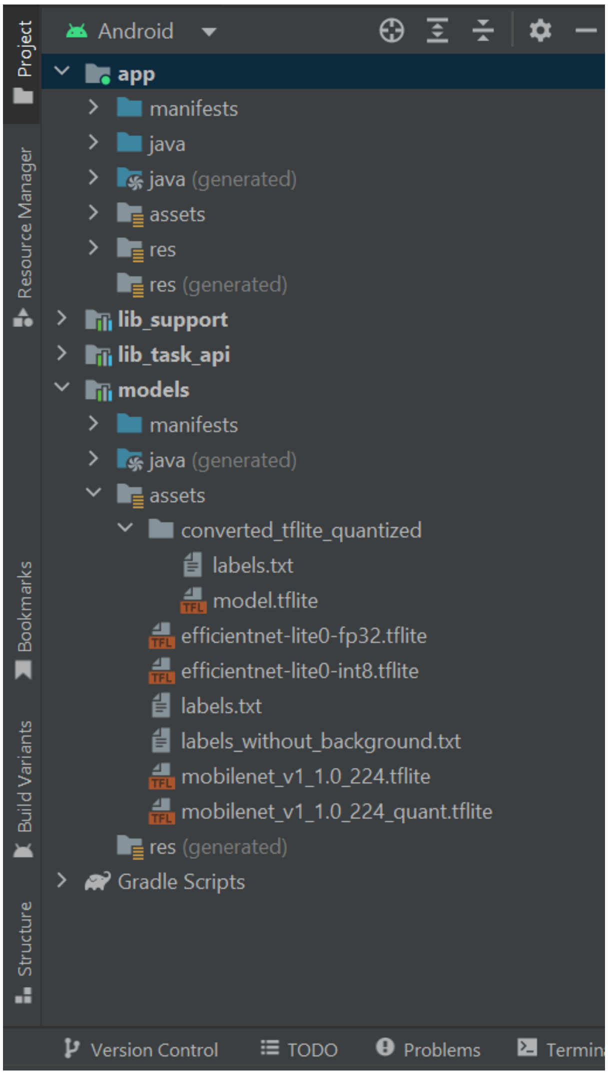

Figure 1: Incorporation of TensorFlow Lite quantized model into the assets category

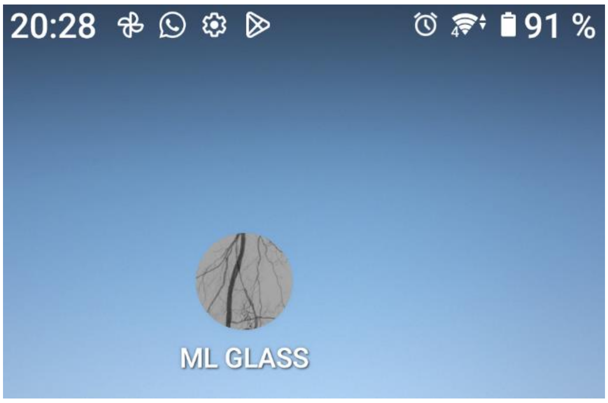

Figure 2: Installed APK on the smartphone

Results:

Dataset

We analyzed a total of 700 angiograms, distributed as follows within the femoropoliteal GLASS disease (fp) categories: fp0 – 187 images, fp1 – 136 images, fp2 – 128 images, fp3 – 97 images, fp4 – 152 images. The reference dataset included 372 non-angiographic images (not_angio). Consequently, the entire model included 1,072 images.

Performance

After training and deployment, the model demonstrated the following performance: a mean accuracy of 0.72, accuracy per class (**Figure 3)**, the confusion matrix (**Figure 4)**, and accuracy per epoch (**Figure 5)**.

Accuracy per class

CLASS	ACCURACY	# SAMPLES
fp0	0.72	29
fp1	0.52	21
fp2	0.55	20
fp3	0.67	15
fp4	0.83	23
not_angio	1.00	56

Figure 3: Accuracy of the model per class

The model's performance was also assessed with previously unseen angiograms. The results are illustrated in **Figures 6, 7**. A sufficient head-to-head Kappa comparison with an independent human researcher was not possible because the model's predictive values varied depending on external light, image position on the monitor, and movement of the smartphone. However, the model was able to correctly recognize the angiograms within the provided accuracy, as shown in **Figures 6, 7**.

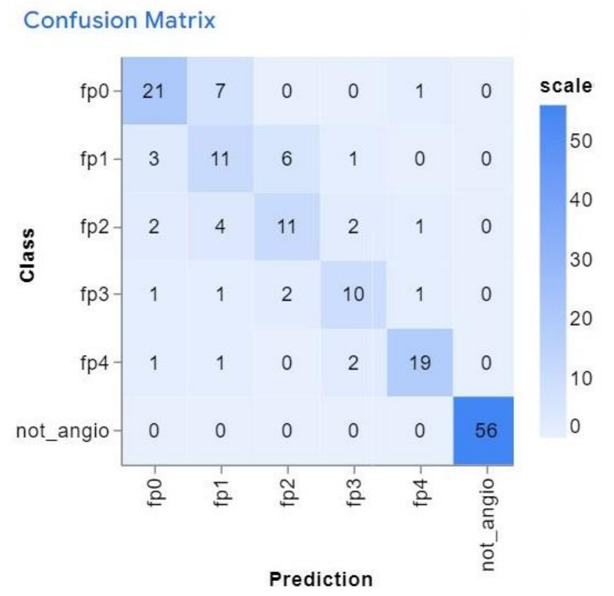

Figure 4: Confusion Matrix: demonstrating the model's performance.

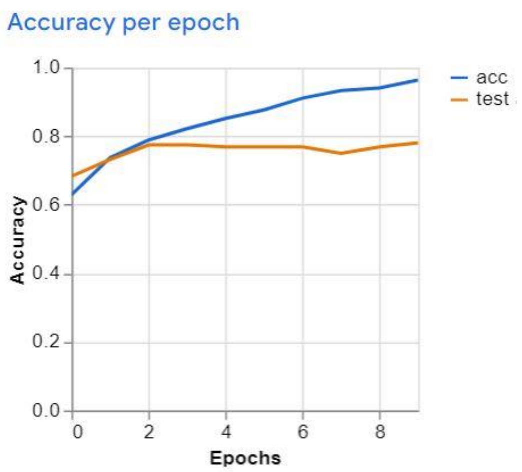

Figure 5: Model accuracy by epoch during training

Discussion:

Practical standpoint

This research validated the concept of creating a mobile application for angiogram classification using computer vision on a smartphone camera. The deployment is feasible on essentially any Android smartphone. The application was able to perfectly distinguish between angiographic and non-angiographic images with an accuracy of 1.0. Good results were also observed for diseases categorized as fp0 and fp4 due to the definitive disease patterns. However, lower performance was noted for fp1 and fp2. The model's predictive abilities were influenced by external factors such as external light and camera movement, which limit its application within healthcare settings. Nonetheless, it has the potential to be used by non-vascular specialists and vascular trainees as a supportive tool.

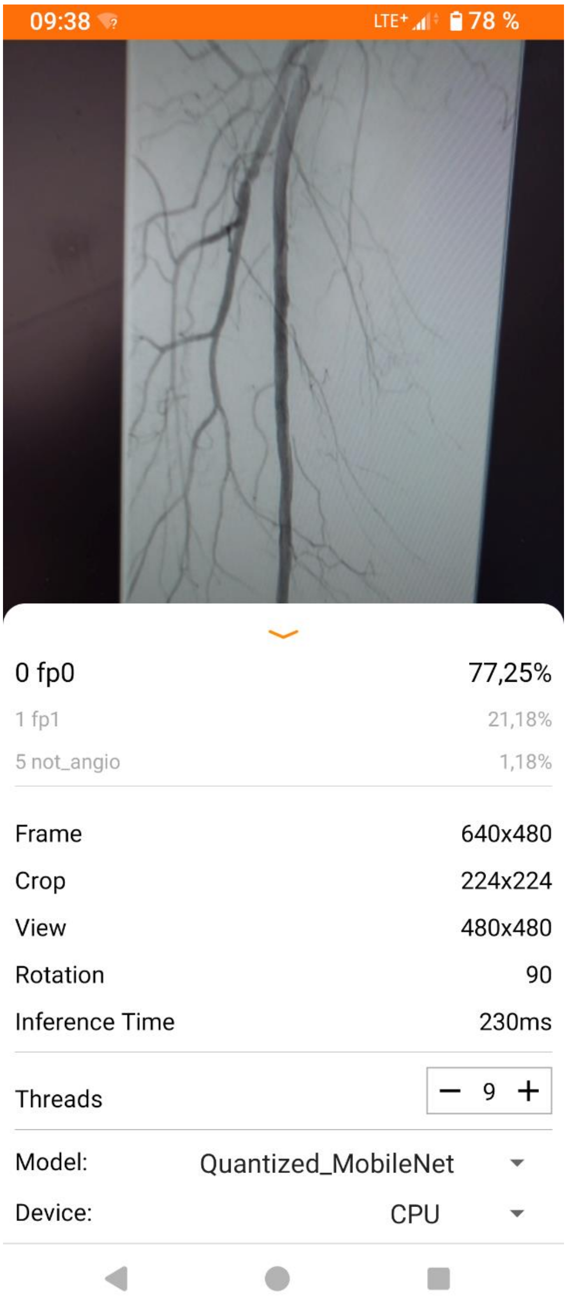

Figure 6: Screenshot of working application

Figure 7: Screenshots of disease classification according to the most applicable grade of femoropoliteal disease in GLASS

Limitations

The main limitation of this research is the application of a holistic image classification algorithm for our computer vision model. Segmentation could potentially outperform our algorithm and yield better performance. However, the primary goal of this study was not to build a powerful model but to prove the concept of developing a mobile application for computer vision in vascular medicine.

The second limitation is that the camera was used in movie mode; therefore, the predictive value changes with angulation or light exposure. For example, the upload function for screenshots could provide a constant predictive value and improve the model.

The third limitation is the absence of a head-to-head human-machine comparison, due to the proof-of-concept study design and the challenging interpretation of results caused by the camera's movie mode, as mentioned in the second limitation.

Another limitation of our research is its retrospective nature. Therefore, the patient data used and consents obtained were only for general research purposes, not specifically for the development of an artificial intelligence (AI) model. As a result, our current model will remain an experimental project. The development of a powerful angiographic computer vision smartphone application should incorporate an upload function, be proven in head-to-head human-machine comparisons, potentially include segmentation, and feature a prospective design with explicit consent for using collected data in the development of AI models[17].

To the best of our knowledge, this is the first study to explore the development of an end-to-end smartphone application for angiographic computer vision in vascular medicine.

Conclusion

We discovered that a smartphone camera could be utilized for angiographic computer vision through end-to-end applications accessible to every healthcare professional. However, the predictive abilities of the model are limited and require improvement. The development of a robust angiographic computer vision smartphone application should incorporate an upload function, undergo validation through head-to-head human-machine comparisons, potentially include segmentation, and feature a prospective design with explicit consent for using collected data in the development of AI models.

Conflict of Interest: Authors state that no conflict of interest exists.

Authorship: YR: Concept, data analysis, original draft, survey. YR, VR, MD: Review and editing.

The Web3 rewards were donated to water.org by the corresponding author.

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