Prediction of Obstructive Coronary Artery Disease from Myocardial Perfusion Scintigraphy using Deep Neural Networks

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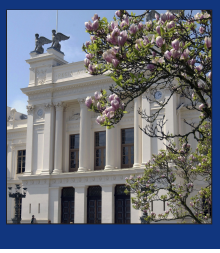
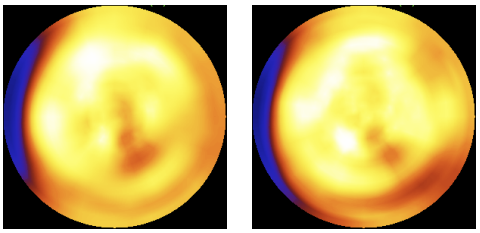


Overview

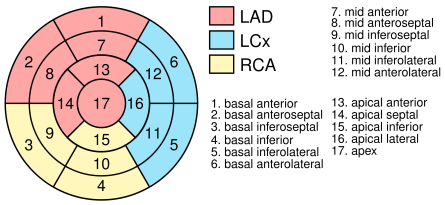
- For diagnosis of coronary artery disease (CAD) in patients with stable ischemic heart disease, myocardial perfusion scintigraphy (MPS) is commonly used.[1]
- Previous works, [2,3], have tried to automate this using neural networks.
- In this work, we extend the idea by using deep convolutional neural networks (CNN).
- To improve the performance, additional data such as angina symptoms are included by a second input layer.
- We investigate if the performance can be improved by using augmentation.

Data

Data from 588 patients was available. Examples of the scintigraphy images in artificial colouring are illustrated below for a patient with LCx defect (left: upright position, right: supine position). The original intensity (grayscale) images were reconstructed and used as input to the model.



The three arteries (left anterior (LAD), left circumflex (LCx) and right coronary (RCA)) for which CAD are predicted:

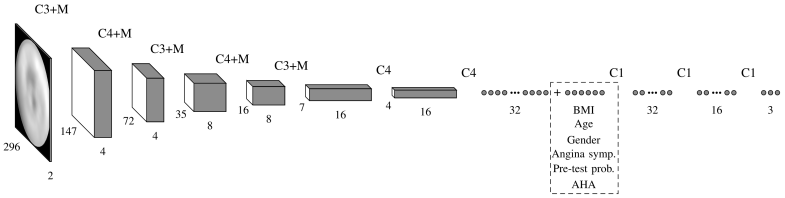


Six auxiliary parameters were used:

Parameter	Range of Values	Comment
Gender	$\{0, 1\}$	35% women
Angina symptoms	$\{0, 1\}$	-
AHA	$\{0, 1, 2, 3\}$	-
Age	$[21, 98]$	-
BMI	$[16, 52]$	14 values missing
Pre-test prob. ESC	$[0, 100]$	-

Method

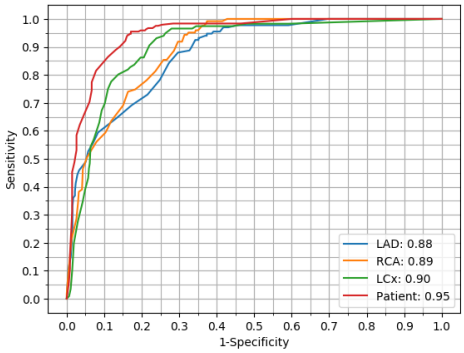
The CNN architecture, where the auxiliary parameters are concatenated with one of the latent layers, is shown below.



To train the network for multilabel classification with imbalanced classes, the loss was weighted such that each class and each label had the same importance.
The model was trained both with and without augmentation, both on the images (rotation, intensity clipping) and the auxiliary parameters.
Five-fold cross-validation was used to train and evaluate the method. Each fold had the same number of examples with and without disease.

Results

Receiver operating characteristic (ROC) curves for the three regions and per-patient level, using the model trained without augmentation but including the auxiliary parameters.



Area under ROC curve (AUC) for different configurations of the algorithm; trained with and without augmentation and including or excluding the auxiliary parameters.

Algorithm			AUC				
Incl. aux.	Augm. Im.	Augm. Aux.	LAD	RCA	LCx	Average	Patient
-	-	-	.84	.85	.86	.85	.89
-	x	-	.83	.85	.83	.83	.88
x	-	-	.88	**.89**	**.90**	**.89**	**.95**
x	x	-	**.89**	**.89**	**.90**	**.89**	**.95**
x	-	x	.88	.88	**.90**	**.89**	.94
x	x	x	.86	**.89**	.89	.88	.93

Conclusions

- CAD can with good performance be predicted based on MPS using deep learning.
- Additional information from the auxiliary parameters improves the performance.
- Augmentation, on images or auxiliary paramters, did not improve the performance significantly.

References

1. F. Nudi, et al. "Diagnostic accuracy of myocardial perfusion imaging with CZT technology: systemic review and meta-analysis of comparison with invasive coronary angiography," JACC: Cardiovascular Imaging, vol. 10, no. 7, pp. 787–794, 2017.
2. H. Fujita, et al. "Application of artificial neural network to computer-aided diagnosis of coronary artery disease in myocardial spect bull's-eye images," Journal of NuclearMedicine, vol. 33, no. 2, pp. 272–276, 1992.
3. J. Betancur, et al., "Deep learning analysis of upright-supine high-efficiency spect myocardial perfusion imaging for prediction of obstructive coronary artery disease: A multicenter study," Journal of Nuclear Medicine, vol. 60, no. 5, pp. 664–670, 2019.