Age Classification of Brain MRI using Transfer Learning and MATLAB

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Abstract

In recent years, deep learning has shown high potential for diagnostic prediction on medical images such as MRI. For example, it has been used to measure a patient's brain age, whose discrepancy from chronological age could serve as a biomarker of disease. The performance of the prediction is, however, often limited by the amount of training data sets as well as the availability of compute resources. In this work we present a lightweight approach with MATLAB that applies transfer learning to tune a pretrained deep neural network (ResNet-18) to perform chronological age classification on a brain MRI data set. This workflow is especially suitable for proof-of-concept studies since it requires less training data and compute power.

Background and Method

Introduction

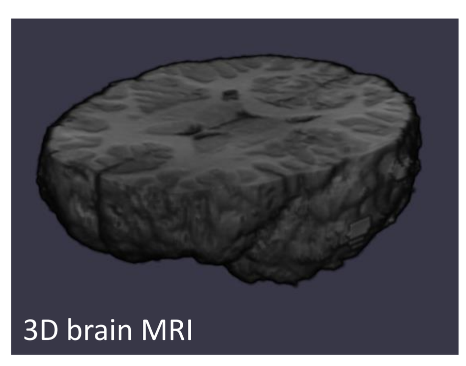
Standard machine learning algorithms work on arrays of numerical data and often do not need huge data set for their training. However, if one wants to apply them to images, one has to extract numerical features first, which is often challenging.

In turn convolutional neural networks (CNNs) are able to learn from images directly. But their development and training can be very time intensive and needs a lot of data. Either of the two issues can be bottlenecks for application of AI in proof-of-concept studies.

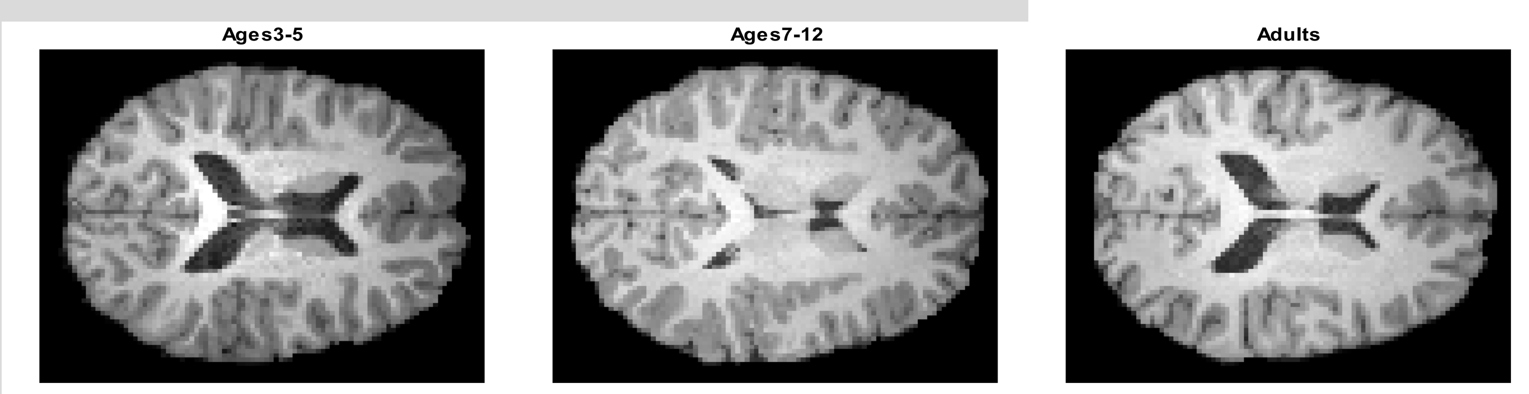
It is thus often easier to make use of pretrained CNNs and to retrain them. In this work we apply this concept of transfer learning to the problem of age classification from MRI images.

Data Set

- MRI scans obtained from study done at MIT in Boston [2,3]
- Full brain MRI of 155 participants
- Brain areas extracted using statistical parametric mapping [4]
- Images collected and labelled in 3 age groups



3D brain MRI



Preprocessing

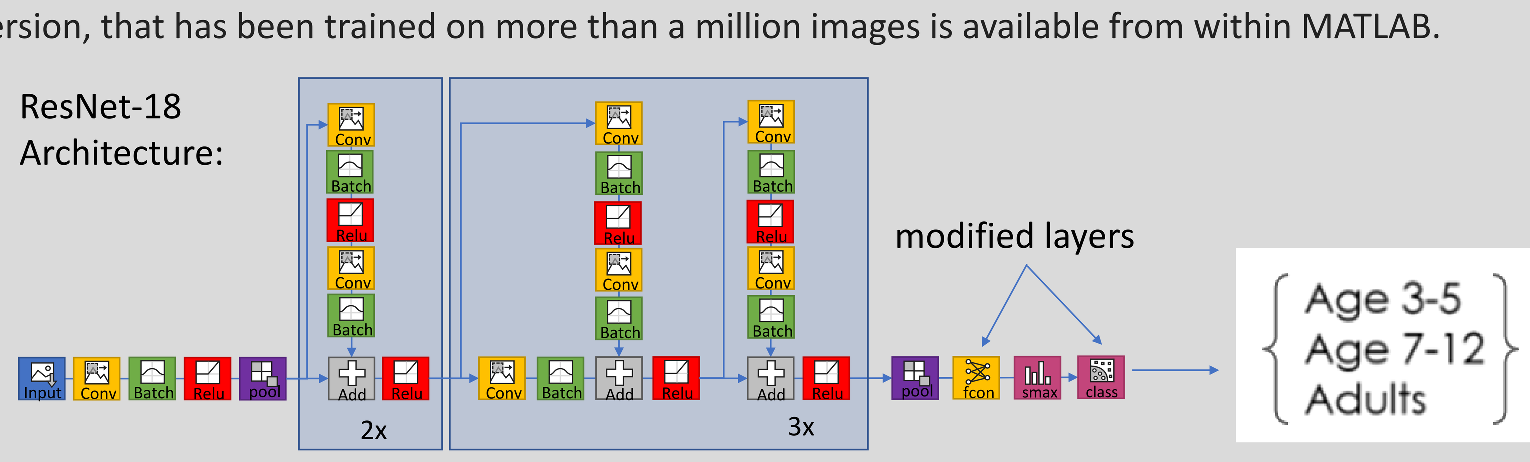
- Use axial midslice 2D images for training of CNN (depending on training setting 1-4 slices were used)
- Extensive data augmentation:
  - Flip images or rotate randomly (-30° to +30°) -> double size of training data set (310 images)
  - Adaption of image size to 224-by-224.
- Split data set into:
  - Training set (68%)
  - Validation set (17%, assess training accuracy)
  - Test set (15%, assess trained network)

	Ages 3-5	Ages 7-12	Adults	Total
Training	89	78	45	212
Validation	22	19	11	52
Test	19	17	10	46
Total	130	114	66	310

Transfer Learning of Deep Neural Networks

In this work we use ResNet-18, which is a readily available convolutional neural network. A pretrained version, that has been trained on more than a million images is available from within MATLAB.

ResNet-18 Architecture:

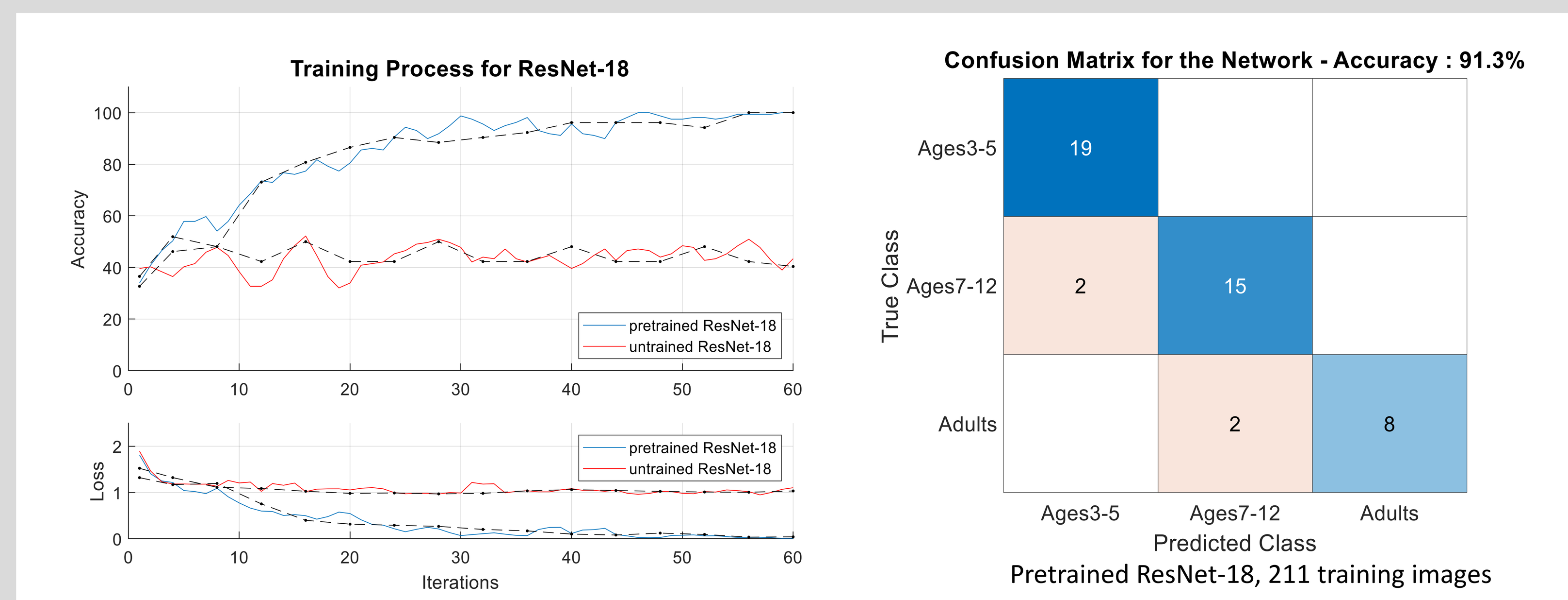


The pretrained network can classify images into 1000 object categories. As a result, the network has learned rich feature representations for a wide range of images. Instead of retraining all network weights, we directly apply this knowledge to our classification task. To achieve this, the last fully connected layer and the classification layer of the ResNet-18 are adapted to output only 3 classes. In this way, only the weights for the fully connected layer has to be trained from scratch.

Results

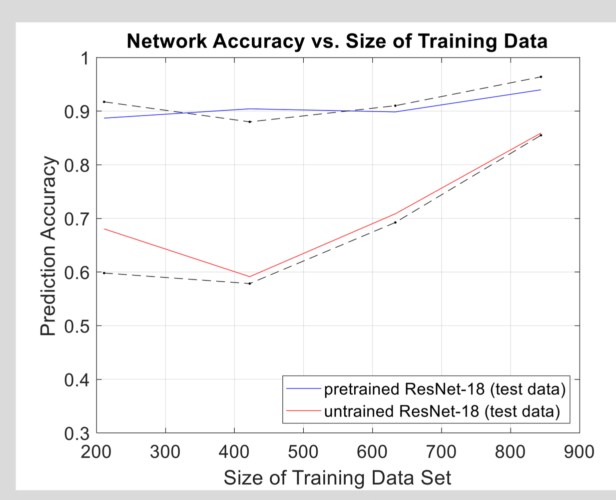
Transfer Learning vs. Learning from Scratch

For evaluation of the transfer learning approach, the training was repeated on the ResNet-18 with resetted weights. All trainings have been repeated 10 times using the same hyper parameters. Typical accuracies during the training process are shown below.



Pretrained ResNet-18, 211 training images

Network Accuracy vs. Amount of Training Data



(values are averages from 10 runs)

Repetition of training procedure using up to 3 additional midslices from the MRI data set:

- Observations for the **pretrained** network:
  - High accuracies already for small data sets
  - Enhancement of accuracy for bigger data sets
- Observations for the **initially untrained** network:
  - Very low performance for small data sets
  - Accuracy significantly increased with bigger data sets
  - Not able to catch up with the pretrained network for the largest data set used in this study.

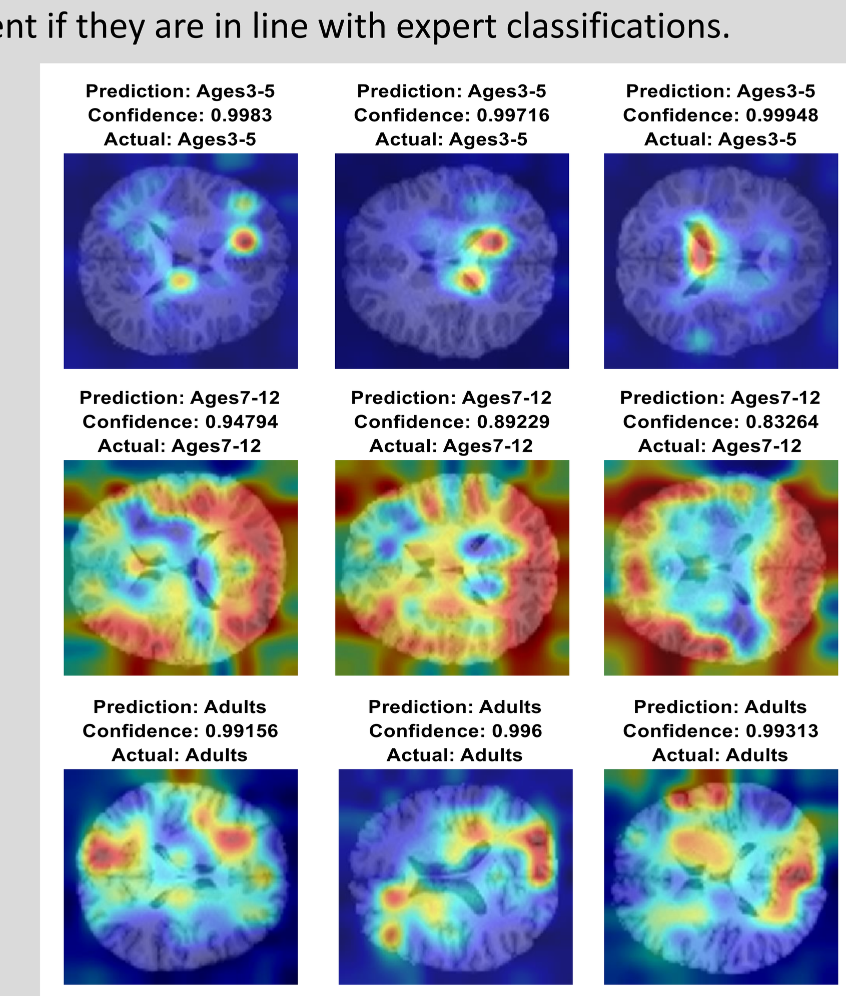
Interpretability

Occlusion maps indicate areas that were of importance for making the given prediction. They allow investigation of the learnt features and assessment if they are in line with expert classifications. Below are sample maps for all three age groups:

Group 'Age 3-5'
- High prediction accuracy
- Classification based on few, small features.
- Regions often close to the brain stem.

Group 'Age 7-12'
- Lower prediction accuracy
- Prediction based on larger features
- Regions further away from the stem
- Areas with large GM/WM interface

Group 'Adults'
- More isolated, medium size features
- More focus on areas with WM
- Features from the back part of the brain



Conclusions And Outlook

- Transfer learning can lower the requirements on the amount of training data and can thus reduce the time needed for training.
- Application of Deep Learning on Brain MRI allows classification into 3 patient age groups without the need of time intensive feature or parameter extraction.
- Occlusion maps reveal that the network training seems to be able to learn features of the Brain MRI that are related to brain age.
- Further optimization of training using misclassification costs might reduce number of wrong predictions.
- More applied brain age models could make use of regression on full 3D data sets.

References:

[1] Iyer, V., GitHub, Brain-MRI-Age-Classification-using-Deep-Learning. (2022)
[2] Richardson, H. et al., Nature Communications, 9(1), 1027. (2018)
[3] OpenNEURO.org, https://openneuro.org/datasets/ds000228/versions/1.1.0
[4] Friston, K.J. et al., Human Brain Mapping, 2(4), 189. (1994)
[5] Cole, J.H. et al., Neuroimage, 163, 115. (2016)
[6] Cole, J.H. et al., Trends in Neurosciences, 40(12), 681 (2017)
[7] *ImageNet*, http://www.image-net.org

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