Predicting Brain Age in Children and Adolescents Using Convolutional Neural Network

MELISSA PAX

Introduction

- A predicted age derived from neuroimages is considered someone's "brain age," a biomarker used to assess the state of a person's brain development (Franke and Gaser, 2019)
  - These predictions appear to have clinical relevance in disorders such as dementia and Alzheimer's (Biondo et al. 2022, Millar et al. 2023)
- Most of these models are centered around adults, yet there is a growing body of research around neurodevelopmental abnormalities associated with mental illness in childhood (Shaw et al. 2010, Kakuszi et al. 2020)
  - Brain age could be an interesting biomarker to monitor development. However, accurate models need to be developed and tested with typically developing children's brains
- Convolutional neural networks are particularly adept at handling image data. Studies have found that these networks can be effective with minimal preprocessing of medical images (Peng et al. 2020)
- This research project aims to create a simple regression convolutional neural network model that can closely predict the age of children and adolescents (ages 5 – 21) given a minimally processed T1 scan

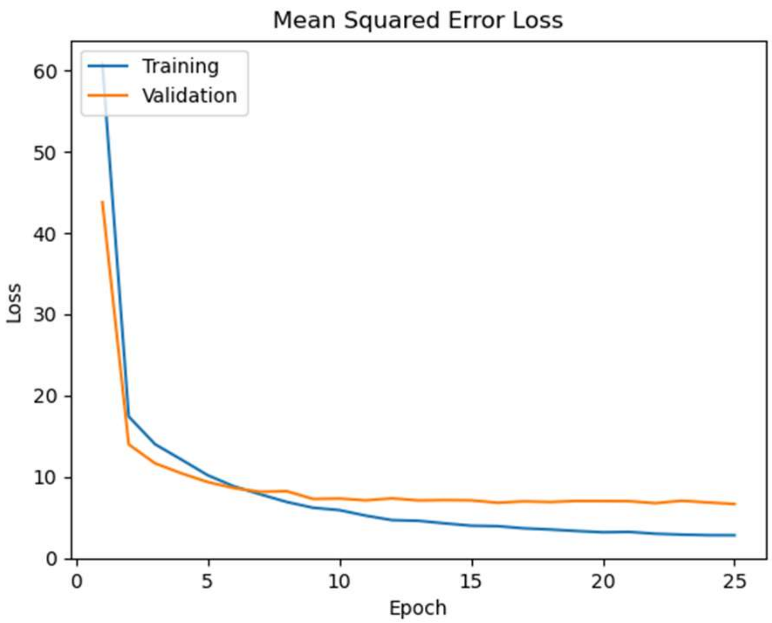
Methods

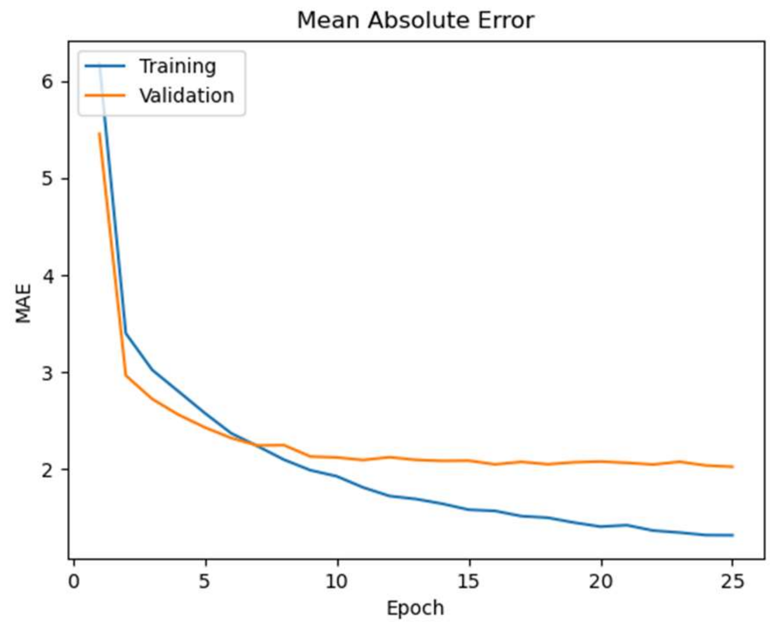
- MRI image data was obtained from the Human Connectome Development Project
  - 652 children and adolescents from the ages of 5 to 21 were included
  - Two subjects were excluded from the analysis due to missing MRI data
  - T1 images were already preprocessed on MNI152 model
- Skull-stripping completed using FSL and dimensions of T1 images were reduced from (227, 272, 227) to (113, 136, 113) using skTrans python module
- Data was split 80/20 for train and validation set. Due to small sample size, test set was excluded

Architecture

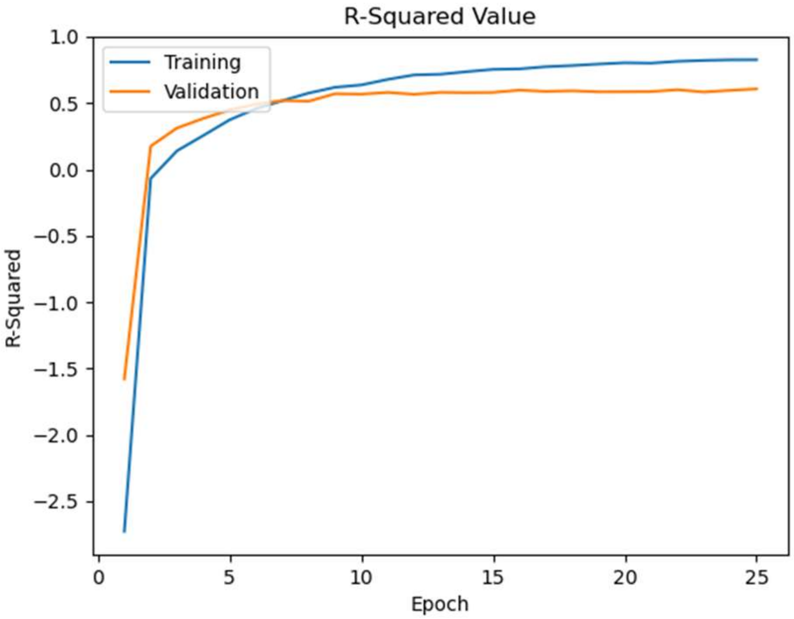
- Architecture of the convolutional neural network
  - 5 blocks, each consisting of a 3-D convolutional layer with a kernel size of 3 x 3 x 3 and ReLU activation (filter size 64-128-256-512-128), batch normalization layer, and a max pooling layer with pool size 2 x 2 x 2
  - Last block consists of a global average pooling layer, a dropout layer with a 30% dropout rate, and a fully connected Dense layer with linear activation
- Model was compiled using mean squared error as the loss function, an Adam optimizer, and a learning rate of 0.000001
- Training occurred over 25 epochs with r-squared and mean absolute errors collected as metrics

Results


Mean Squared Error Loss
Training
Validation
Loss
Epoch
0
10
20
30
40
50
60
0
5
10
15
20
25


Mean Absolute Error
Training
Validation
MAE
Epoch
2
3
4
5
6
0
5
10
15
20
25

Results



Epoch	Train MSE	Train MAE	Train R^2	Val MSE	Val MAE	Val R^2
5	10.22 ± 0.88	2.55 ± 0.12	0.38 ± 0.05	9.38 ± 0.83	2.43 ± 0.11	0.44 ± 0.05
10	5.93 ± 0.52	1.93 ± 0.10	0.64 ± 0.03	7.35 ± 0.73	2.12 ± 0.14	0.567 ± 0.04
15	4.02 ± 0.28	1.58 ± 0.06	0.75 ± 0.02	7.13 ± 0.97	2.09 ± 0.15	0.58 ± 0.06
20	3.21 ± 0.19	1.41 ± 0.05	0.80 ± 0.01	7.04 ± 0.76	2.08 ± 0.12	0.59 ± 0.04
25	2.84 ± 0.26	1.32 ± 0.05	0.83 ± 0.02	6.68 ± 0.68	2.03 ± 0.13	0.61 ± 0.04

Discussion

- The r-squared value suggests this model is a moderate fit in regards to predicting age based on a minimally-processed T1 MRI scan
  - Compared to other models, 650 is a relatively small sample size. The r-squared value may be improved with a larger, more balanced dataset
  - Data augmentation can be explored to see if the r-squared value increases
- The mean absolute error is comparable to another paper by Peng et al (2020) with a similar range of ages.
  - However, with children and adolescents, it may be more important to have a model that has a lower mean absolute error. Due to rapid development during this period of life, two years may be too large of an error margin
- A paper by Hong et al. (2020) had a similar dataset size, but used slices from the MRI image and extensively did data augmentation to increase the sample to over 10,000 images. A direction to accomplish a more accurate prediction for this dataset would be to follow this approach and create a 2-dimensional convolutional neural network

Conclusion

Currently, the model has moderate success in accurately predicting age. Increasing the dataset size with data augmentation may be worth exploring to see if the network can more accurately predict age

Citations

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