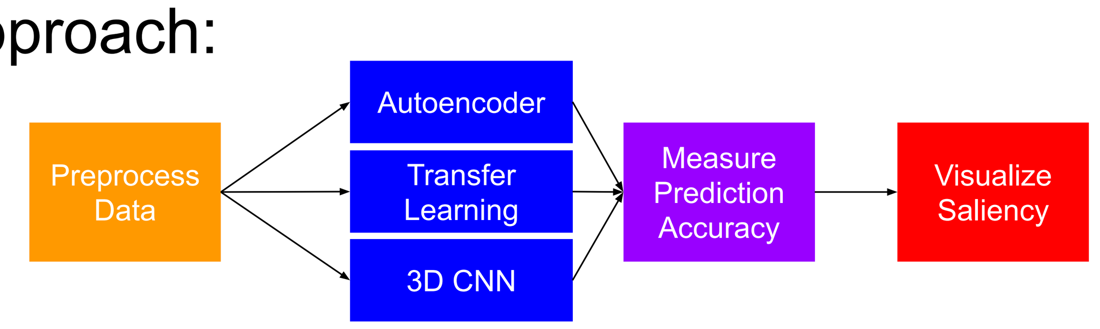
Healthcare: Alzheimer’s Disease Stage Diagnosis, Applying 3D Convolution Neural Networks to MRI Brain Scans

Utkarsh Tandon, Ben Moore, Mohammadhossein Shafinia

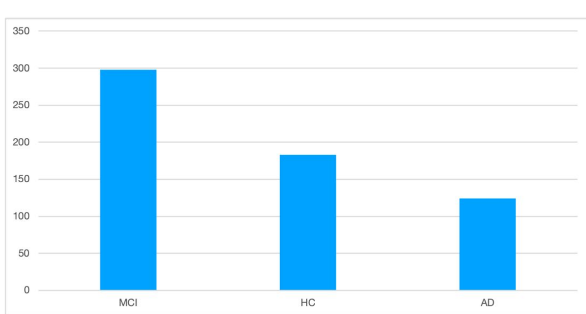
Introduction

- Alzheimer’s disease (AD) is an incurable, progressive neurological brain disorder and is the 6th leading cause of death in the USA
- Magnetic resonance imaging (MRI) is a technique used to diagnose Alzheimer’s disease in patients
- Highly skilled and experienced doctors are currently required to make a decision on the health status of a patient which could be costly
- There are no simple machine learning algorithm which could detect AD from MRI, we want to use deep learning to diagnose AD by using promising architectures for 3D brain images
- Challenges: Lack of preprocessed data, high dimensional input

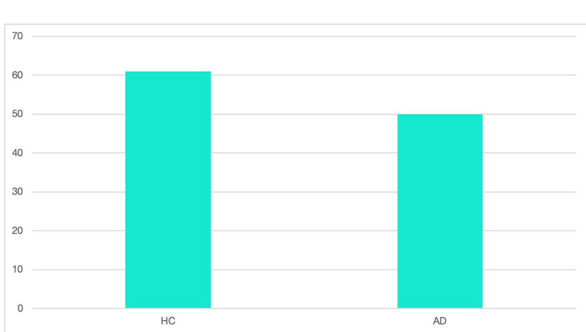
Approach:



Dataset and Features



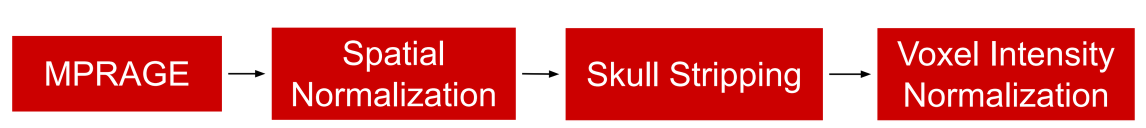
Histogram of ADNI datasets distribution, Raw

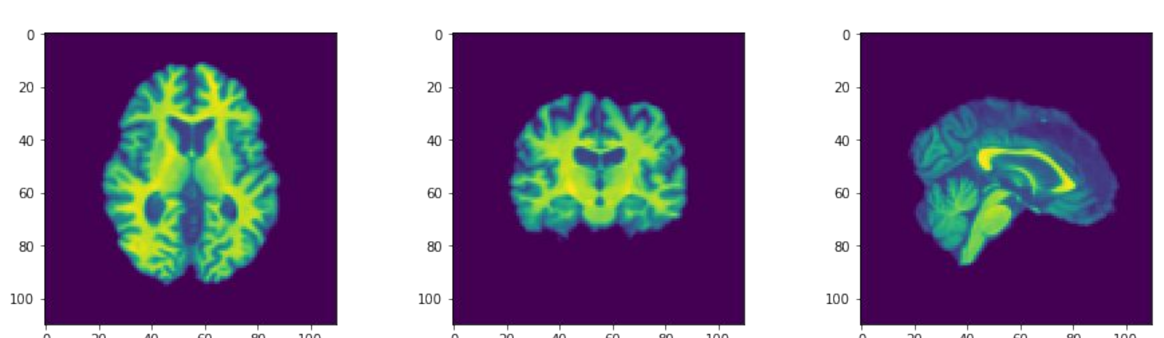


Histogram of ADNI datasets distribution, Preprocessed

- ADNI is currently the largest publicly available dataset for Alzheimer’s Disease - 600 unique subjects accounting for roughly 2300 scans in total.
- Many subjects are scanned multiple times over a 3 year span in an attempt to highlight longitudinal changes.
- Subjects are classified as either AD (Alzheimer’s Disease), MCI (Mild Cognitive Impairment),or NC (Normal Control).
- Data is considered "processed" by ADNI (MPRAGE),
  - Far more preprocessing necessary
- MRI: 3D voxel array format
- Varying dimensions, voxel intensities, and acquisition parameters (RAW).

Preprocessing Pipeline:

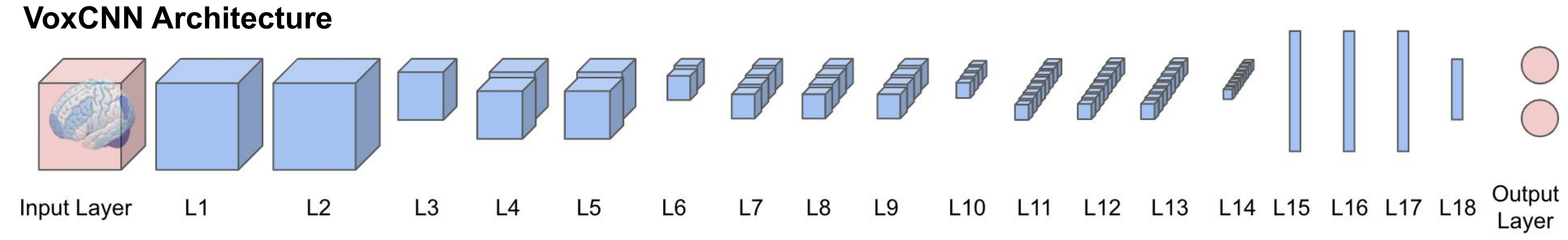




Preprocessed MRI images from sagittal, coronal, and axial plane

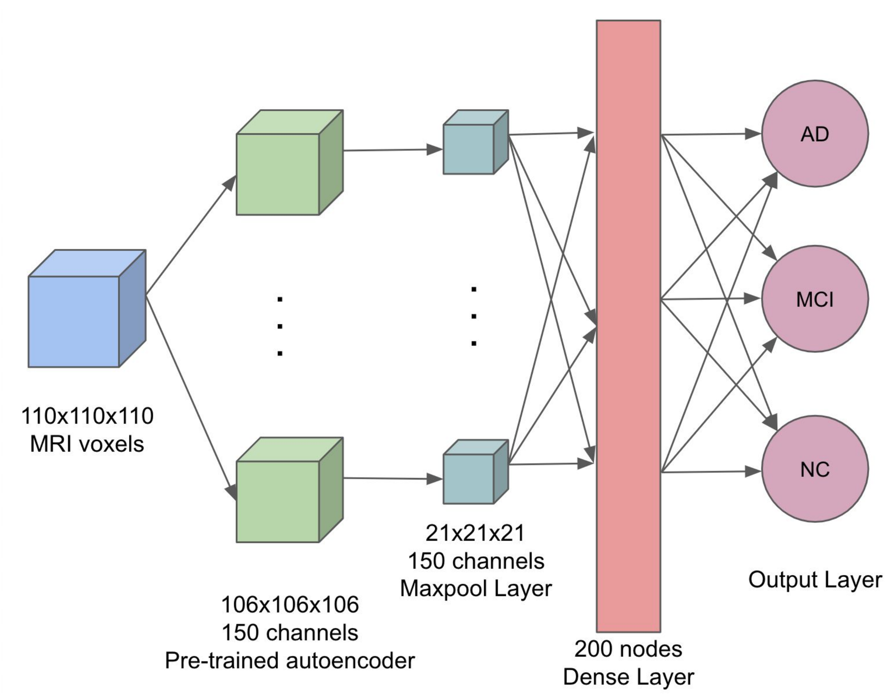
Model Training

VoxCNN Architecture



Hyperparameters: Learning Rate = 27*10^-6. Batch Size = 10. Optimizer = Adam. Loss = Cross-entropy

Autoencoder Architecture

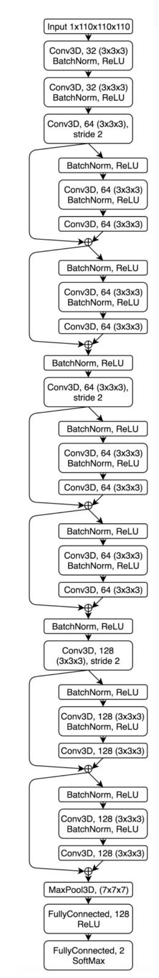


- Architectures
  - Voxnet CNN
  - 3D & 2D Resnet
  - Ground up 3D & 2D CNN
- Autoencoder
  - Over complete
- Loss functions:
  - Cross-entropy
  - Kullback-leibler divergence

$$-\sum_{c=1}^{M} y_{o,c}\log(p_{o,c}) \qquad D_{KL}(P||Q)=\sum_i P(i)\log\frac{P(i)}{Q(i)}$$

- Hyperparameter tuning
  - Learning rate
  - Adam parameters
  - Hidden units
  - Batch size
  - Regularization
    - Weights
    - Dropout
  - Frozen (non trainable) Layers

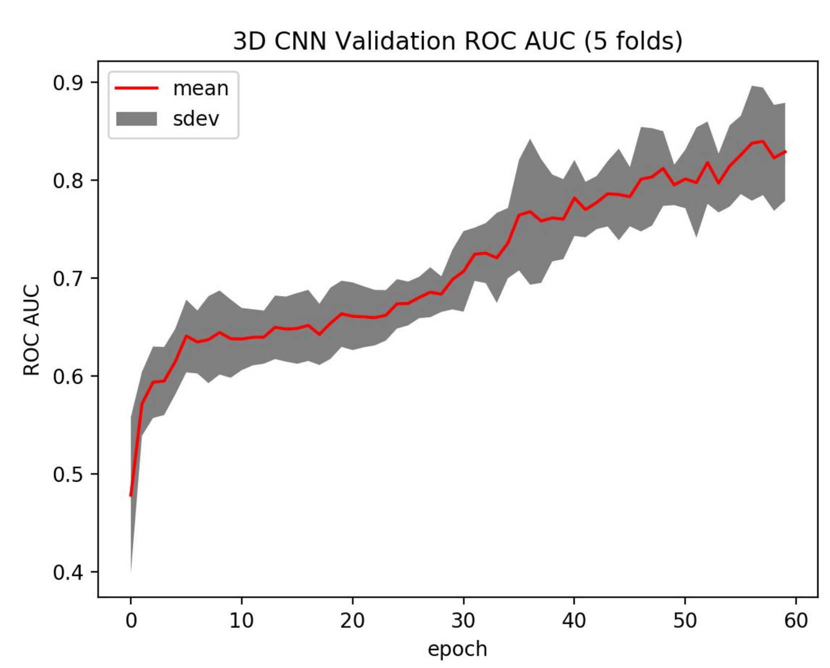
3D ResNet:

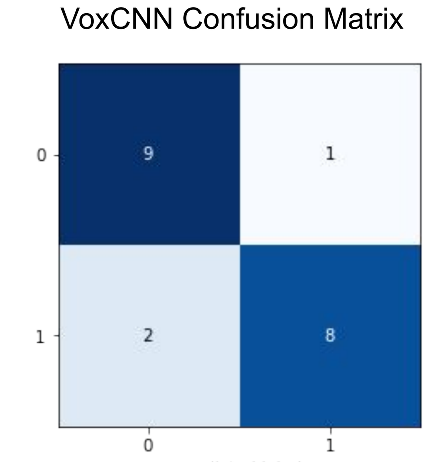


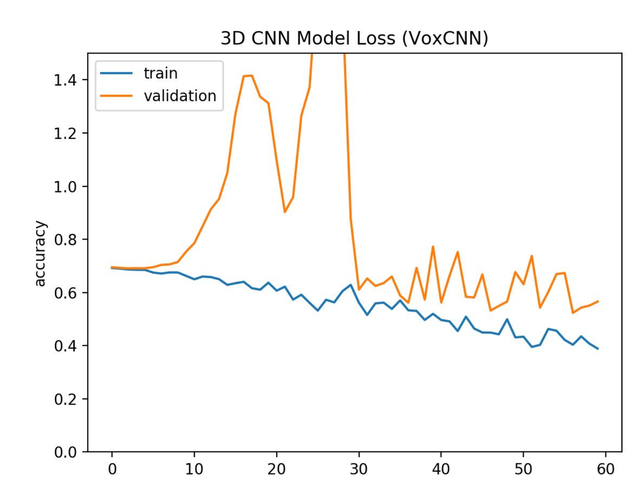
Results

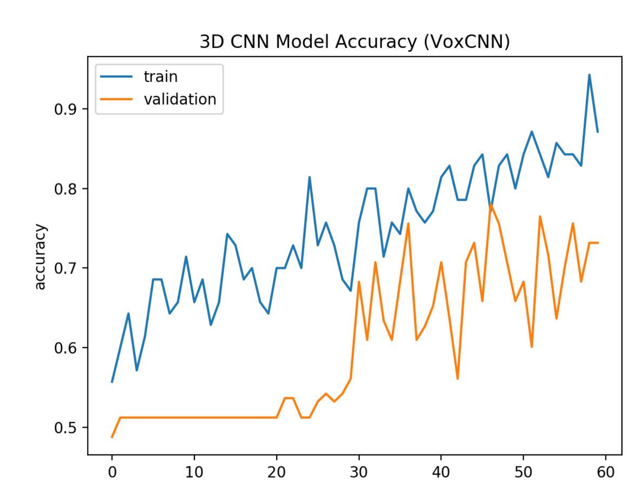
Table 1: Model performance comparison

	Accuracy (%)	F1 Total	F1 HC	F1 AD
VoxCNN	85.63	0.81	0.78	0.81
2D Resnet	86.92	0.82	0.90	0.82
3D Resnet	83.33	0.74	0.88	0.74
3D CNN Baseline	69.56	0.67	0.72	0.69



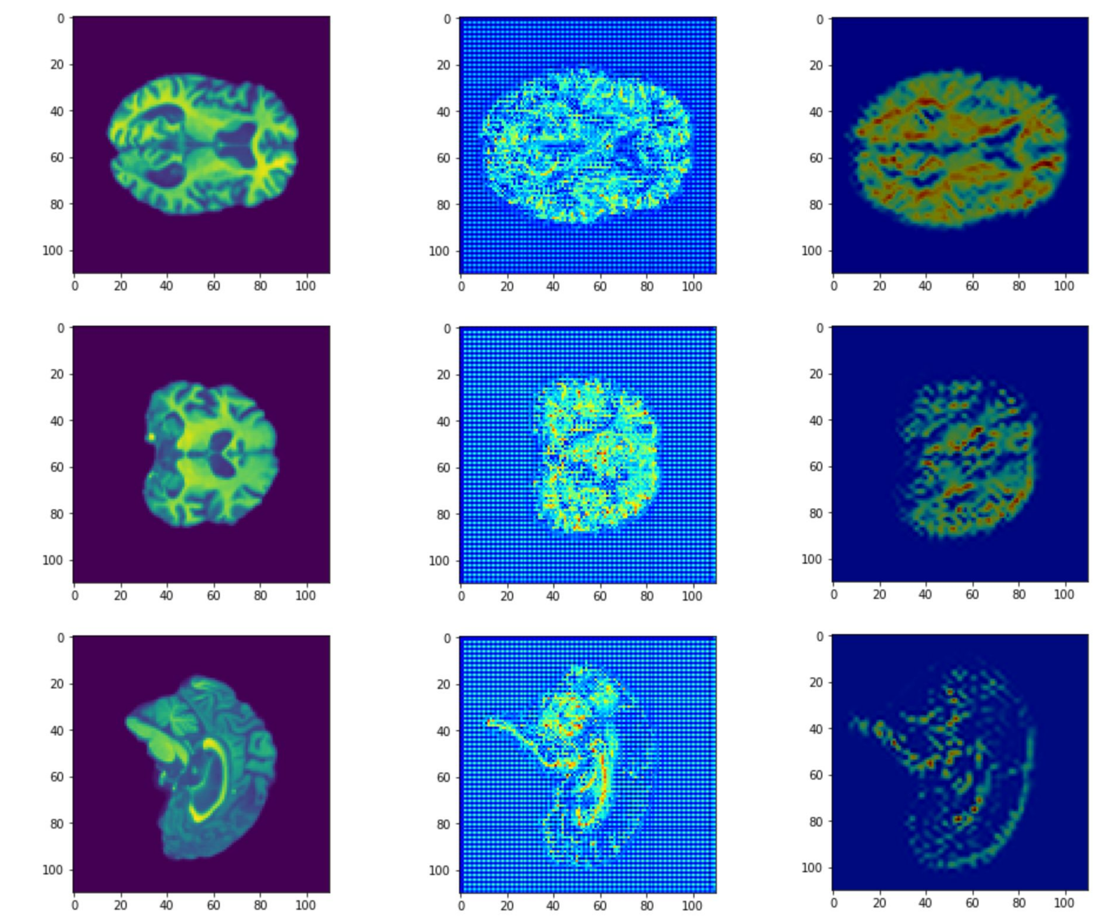






Analysis

2D Transfer Learning Saliency



- The class activation map shown above visualizes the attention of the model over the input by taking gradients with respect to the second to last layer.
- This enables the retention of spatial information in the map before it is enters the dense layer.
- Bottom right: Can see that the model is focusing on matter in the hippocampus region and in the other layers we can see that the model is looking at areas of general white matter decay which are indicative of Alzheimer’s disease
- 3D attention maps would also hopefully highlight the same information, although they are much harder to visualize

Conclusion

- Several approaches to tackle the problem
- 3D CNNs the VoxCNN algorithm had the best results
- The 3D ResNet also had comparable accuracies however the result on validation set fluctuates
- The transfer learning provided us with the best accuracy (87%) due to the ability to augment our data easily using 2D generators
- Autoencoder couldn't perform well as the architecture was minimal under memory constraints - leading to poor encodings.

Future works

- Manually preprocess and clean more data
- Increase the autoencoder's capacity so that it can properly translate encoded info down the network.

Hosseini-Asl, Ehsan, Keynto, and Ayman. Alzheimer’s disease diagnostics by adaptation of 3d convolutional network, Jul 2016.

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Sergey Korolev, Amir Safiullin, Mikhail Belyaev, and Yulia Dodonova. Residual and plain convolutional neural networks for 3d brain MRI classification. CoRR , abs/1701.06643, 2017.