

49275 Neural Networks and Fuzzy Logic

L10. DEMENTED AND NONDEMENTED
BRAIN MRI IMAGES CLASSIFICATION

Seminar 2

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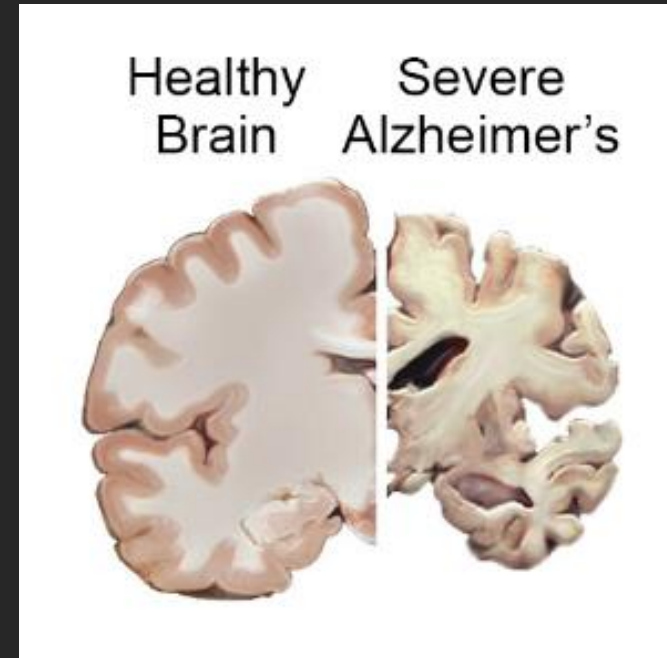
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Project: Classification of Demented and Non- Demented Brains

- Focusing on implementing machine learning algorithms to assist in distinguishing patients with Alzheimer's Disease
- Future applications focuses on creating assistive devices for clinicians to utilize for supported diagnosis to achieve higher accuracy.
- This concept can be up-scaled to future endeavors focusing on early detection of Alzheimer's disease, which currently do not exist.





(National Institute on Aging, 2021)

Project Motivations

- Alzheimer's is the most common form of dementia
- No cure for the disease
- According to WHO, more than 55 million people live with dementia globally.
- "In 2019, the estimated total global societal cost of dementia was US\$ 1.3 trillion, and these costs are expected to surpass US\$ 2.8 trillion by 2030 as both the number of people living with dementia and care costs increase" (World Health Organisation, 2021)

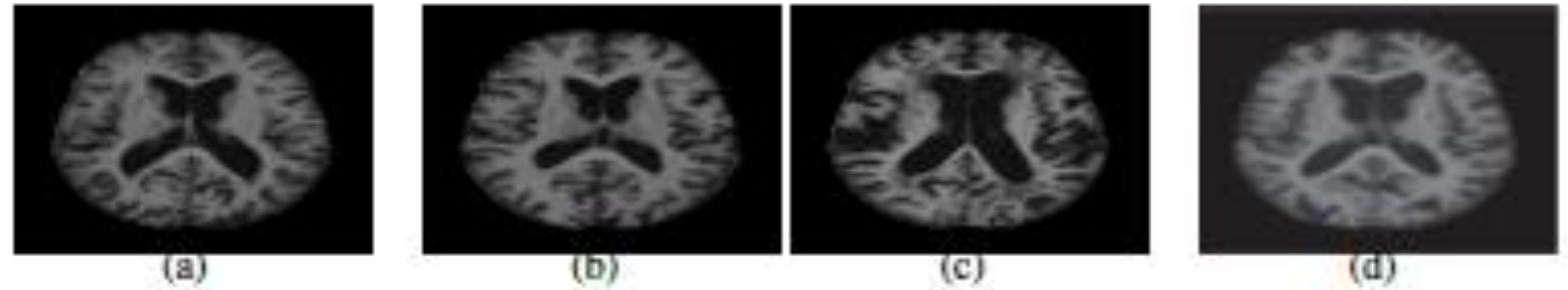


Figure 1: Example of different brain MRI images presenting different AD stage. (a) Nondemented; (b) very mild dementia ; (c) mild dementia; (d) moderate dementia.

Awate et al., 2018 figure 1.1

Aim / Objectives

- Aim: Classification and prediction of demented and nondemented brain MRI using neural networks
- Ideal outcome: High accuracy (>90%) performing model, low variance and not overfitting.
- Objectives:
 - Pre-processing data to select most relevant features.
 - Create neural network capable of predicting patients likely to develop Alzheimer's disease.
 - Verify constantly model is not overfitting

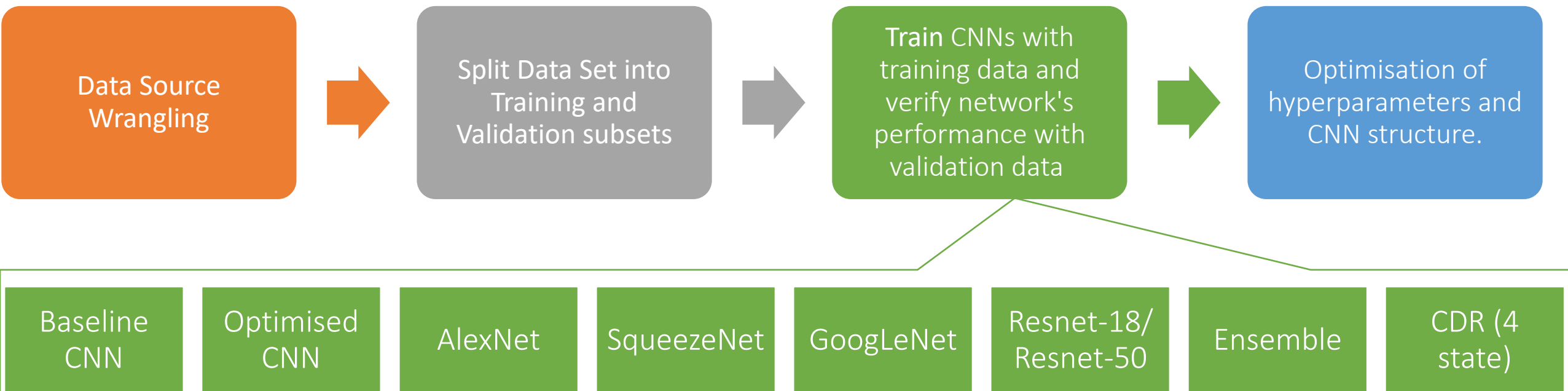
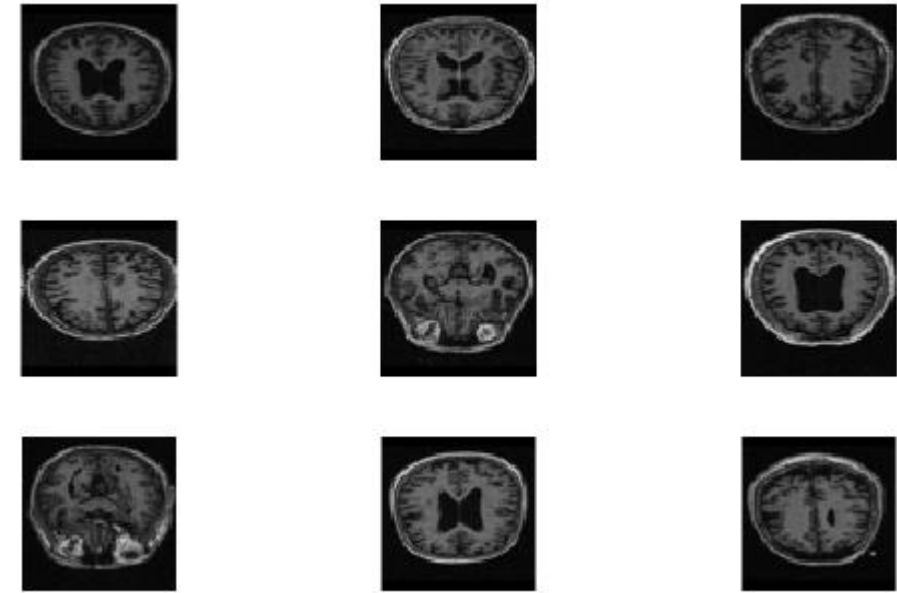
Methodology

- Converting MRI scans into computationally-feasible inputs (64x64 .bmp image files)
- Splitting OASIS-2 (373 MRI sessions | 150 Subjects) dataset into training and validation
- Evenly distributing Demented and Non-demented patients into training and validation sets.
- Implementing overfitting-controls to minimise likelihood of mis-representing accuracy of models.
- Development of various CNNs to classify patients.
- Optimising models to enhance performance, accuracy, and minimise loss.

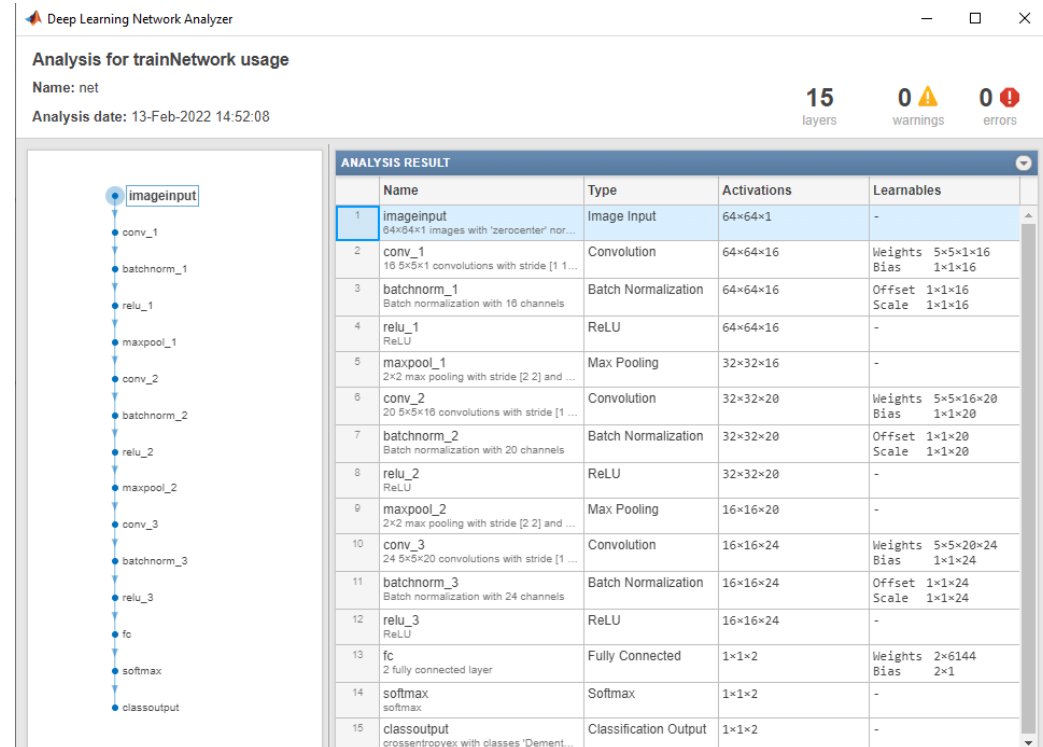
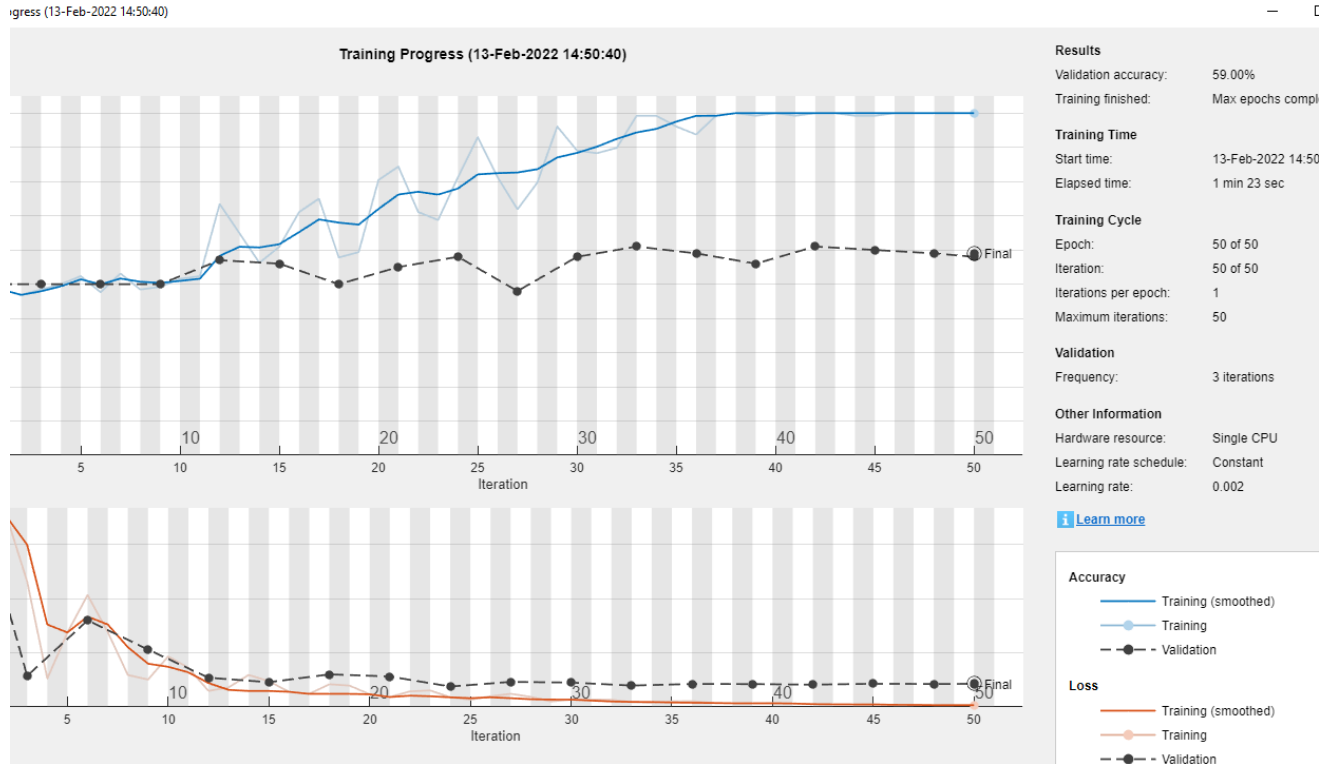


Functional Block Diagram

- Experiment with MRI Data from the OASIS Dataset
- Data pre-processing using MATLAB
- Nine models to evaluate: two basic CNN, five advanced CNNs, one ensemble model and one four state CNN



Experiment and Results: CNN Baseline (59% accuracy)



Experiment and Results: CNN Optimised (68% accuracy)

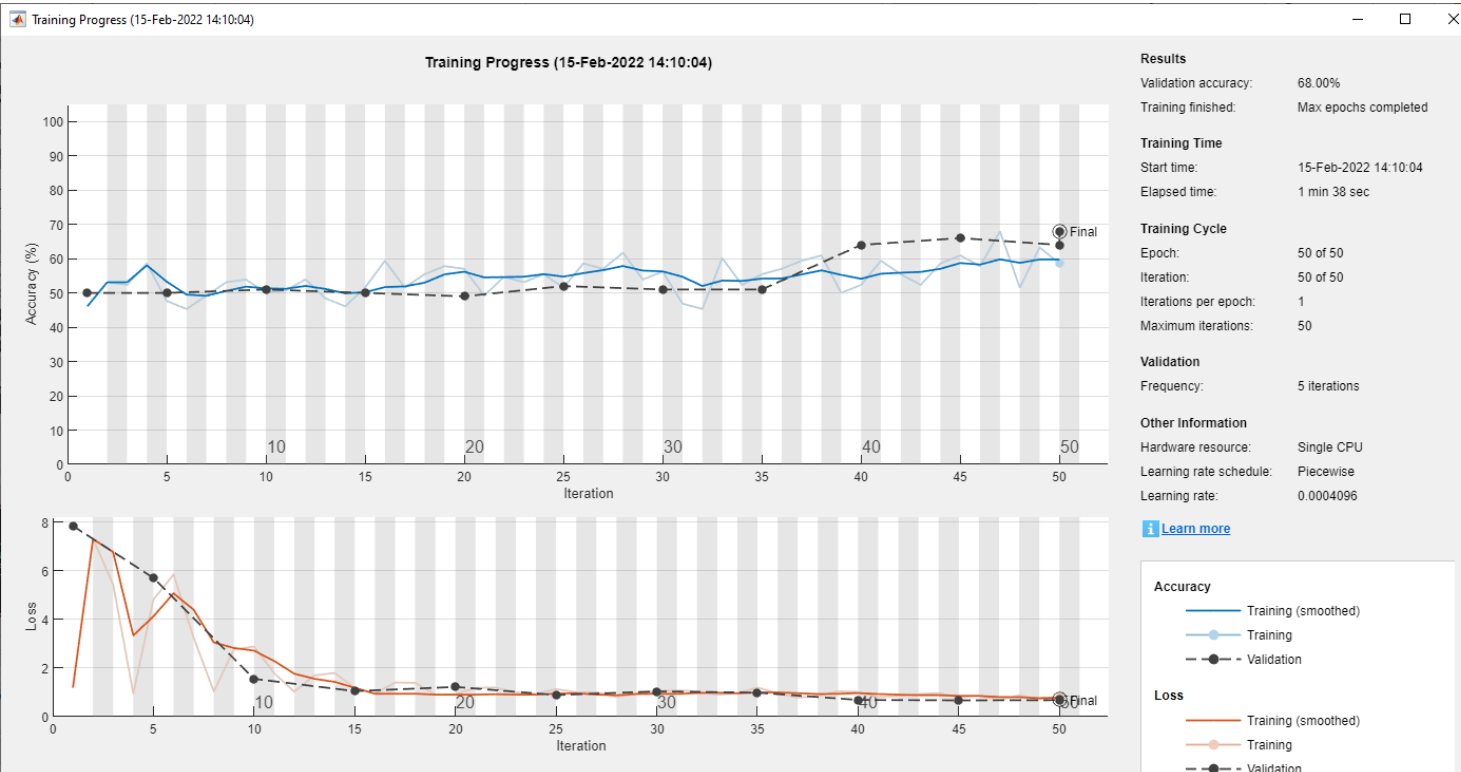
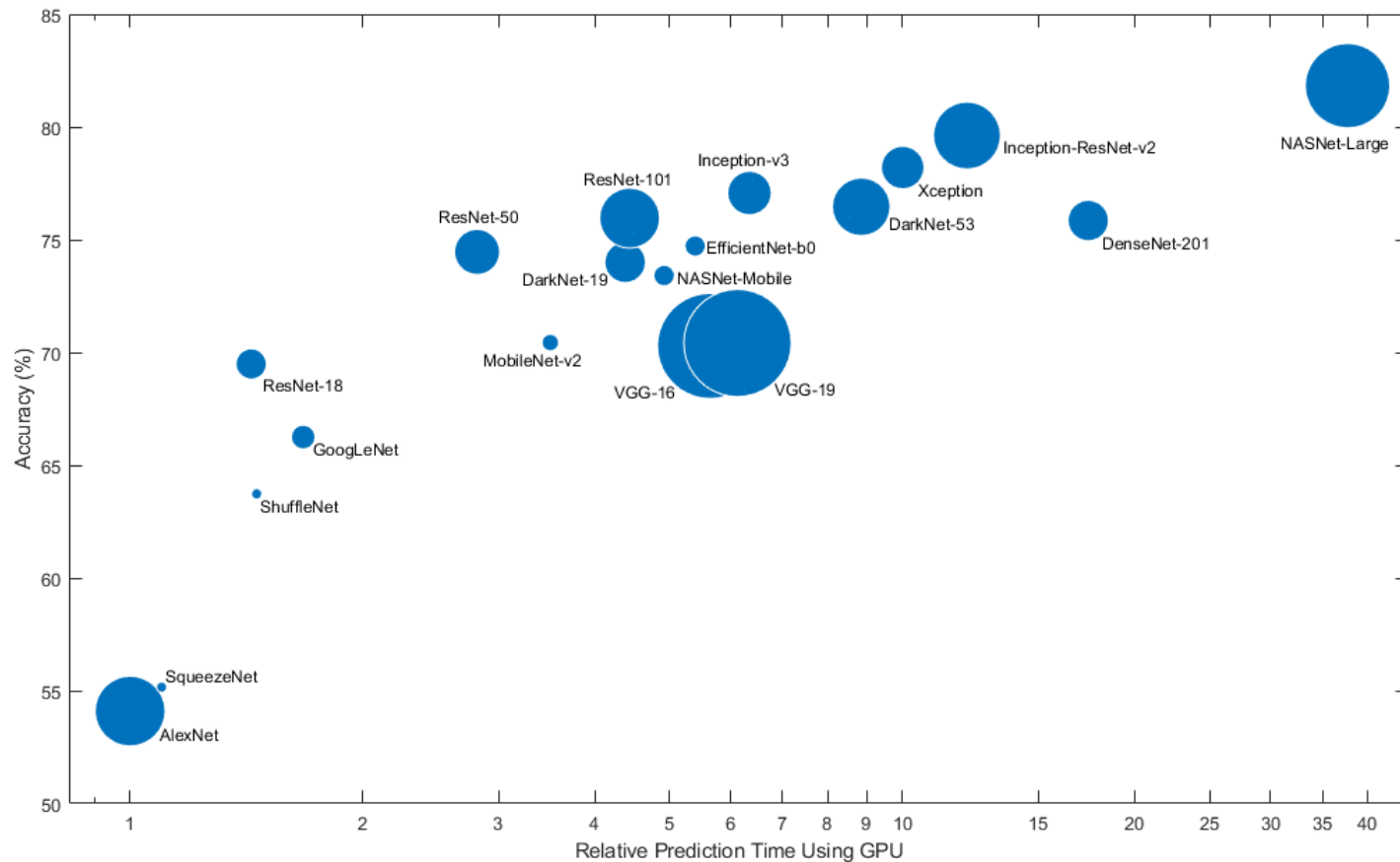


Table 2: CNN-Layer-Details-(Baseline-and-Optimized)

Layer-Description	Key-Hyper-parameters	Size
Input-Image-Layer		$64 \cdot 64 \cdot 1$
Convolution-Layer	X-filters Baseline: 16-filters Optimised: 32-filters	$64 \cdot 64 \cdot X$
Batch-Normalization-Layer		$64 \cdot 64 \cdot X$
ReLU-Layer		$64 \cdot 64 \cdot X$
Pooling-Layer	Down-sample-by-factor-of-2	$32 \cdot 32 \cdot X$
Convolution-Layer	Y-filters Baseline: 16-filters Optimised: 32-filters	$32 \cdot 32 \cdot Y$
Batch-Normalization-Layer		$32 \cdot 32 \cdot Y$
ReLU-Layer		$32 \cdot 32 \cdot Y$
Pooling-Layer	Down-sample-by-factor-of-2	$16 \cdot 16 \cdot Y$
Convolution-Layer	Z-filters Baseline: 16-filters Optimised: 32-filters	$16 \cdot 16 \cdot Z$
Batch-Normalization-Layer		$16 \cdot 16 \cdot Z$
ReLU-Layer		$16 \cdot 16 \cdot Z$
Fully-Connected-Layer	2-classes	$1 \cdot 1 \cdot 2$
Softmax-Layer		$1 \cdot 1 \cdot 2$
Classification-Layer		$1 \cdot 1 \cdot 2$

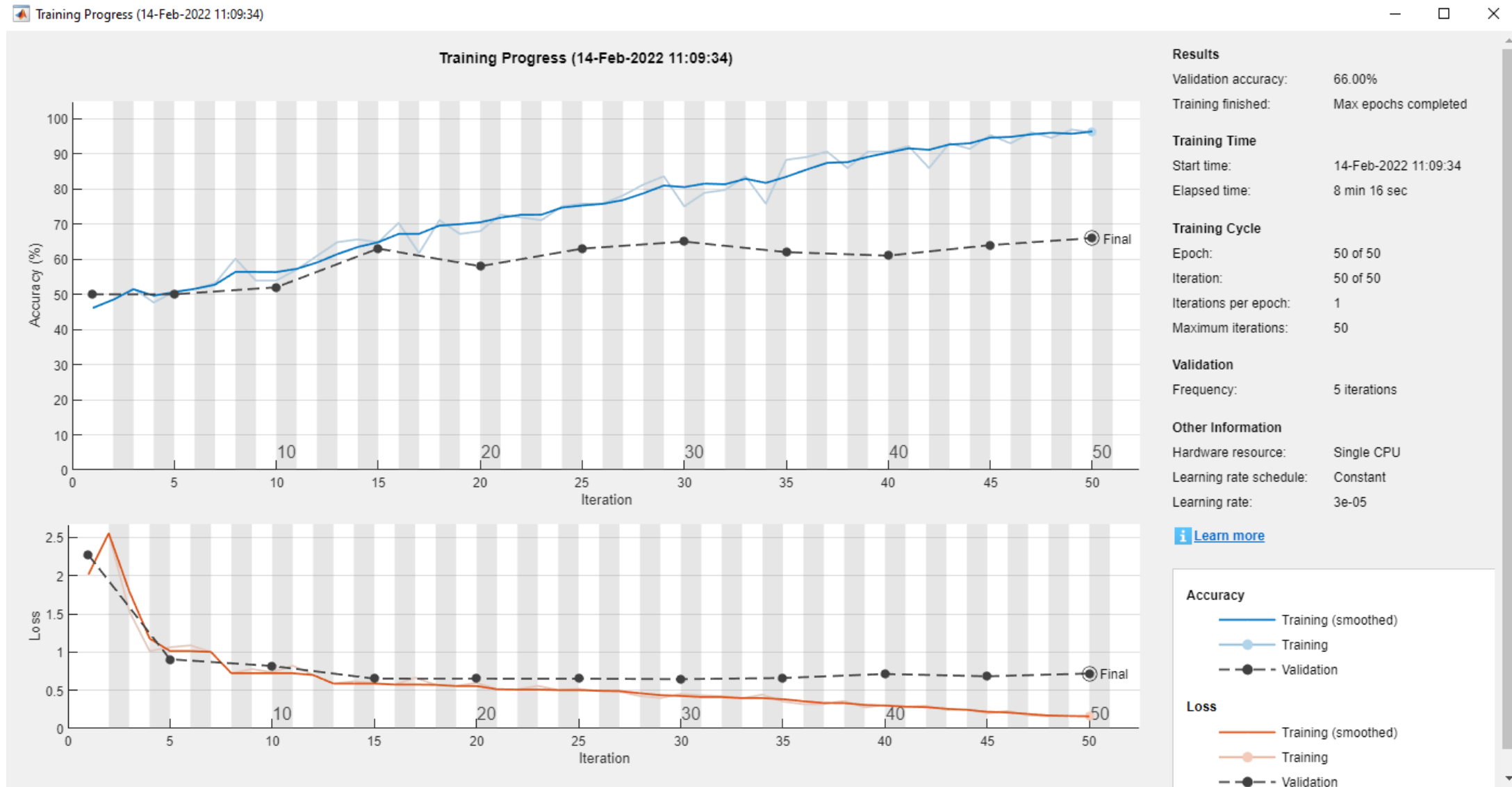
Advanced CNN Structures



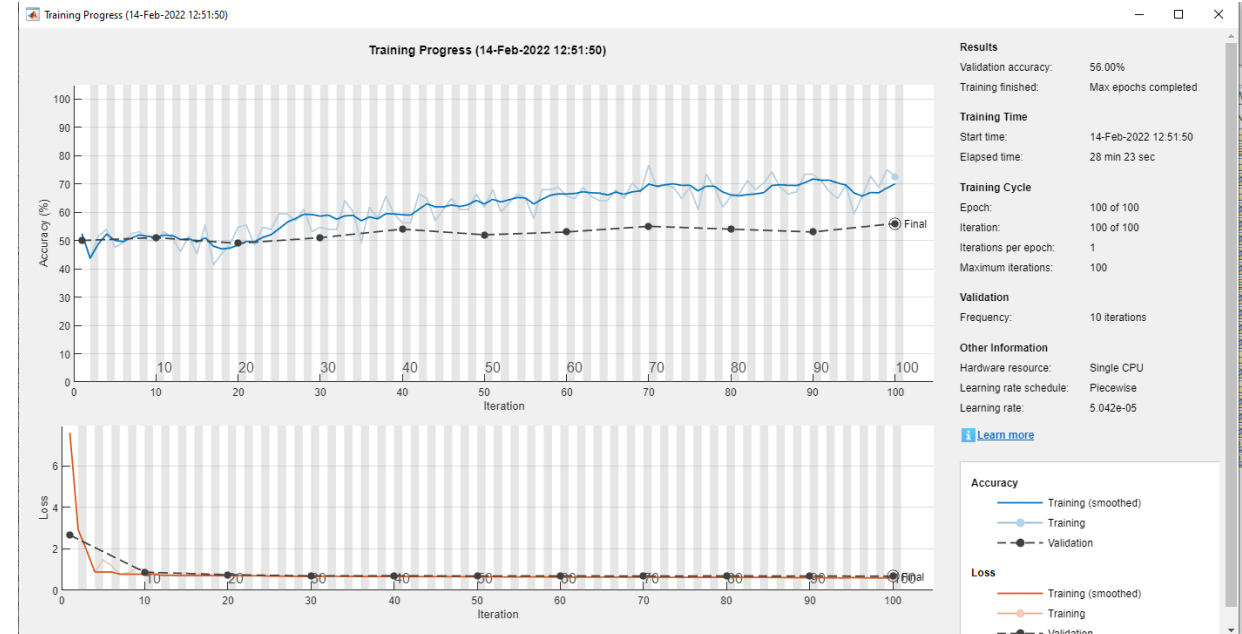
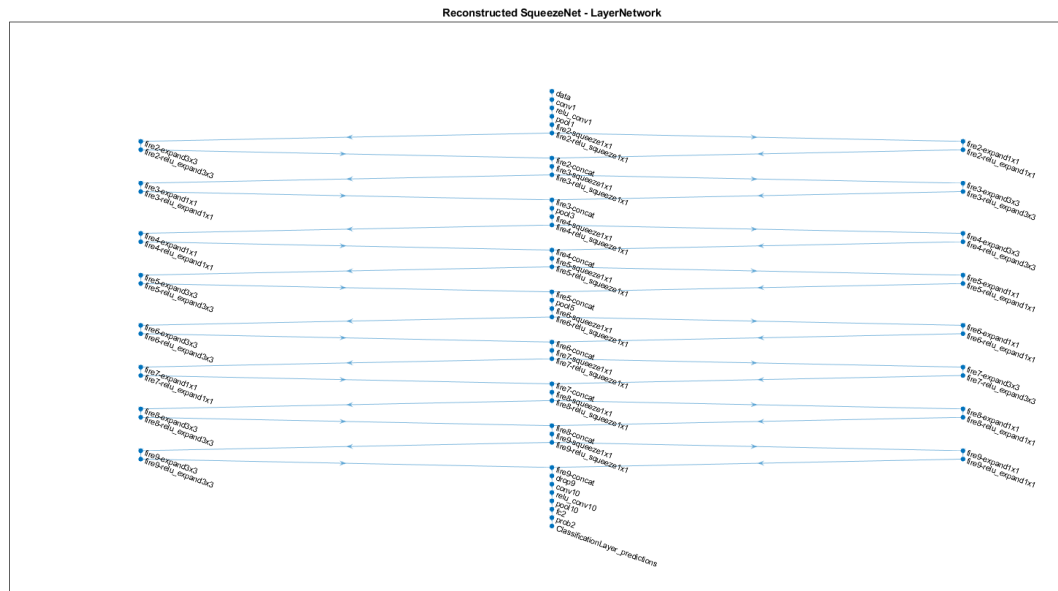
- Matlab has some built advanced CNN structures
- Require input image scaling (expect 227 pixel by 227 pixel with three colour channels) – use `augmentedimagestore` to adjust our training set
- Reconfigure classification layer to just two classes
- Use of dropout layers to avoid overfitting
- Train network

Experiment and Results: AlexNet (66% accuracy)

- data
- conv1
- relu1
- norm1
- pool1
- conv2
- relu2
- norm2
- pool2
- conv3
- relu3
- conv4
- relu4
- conv5
- relu5
- pool5
- fc6
- relu6
- drop6
- fc7
- relu7
- drop7
- fc
- softmax
- classoutput

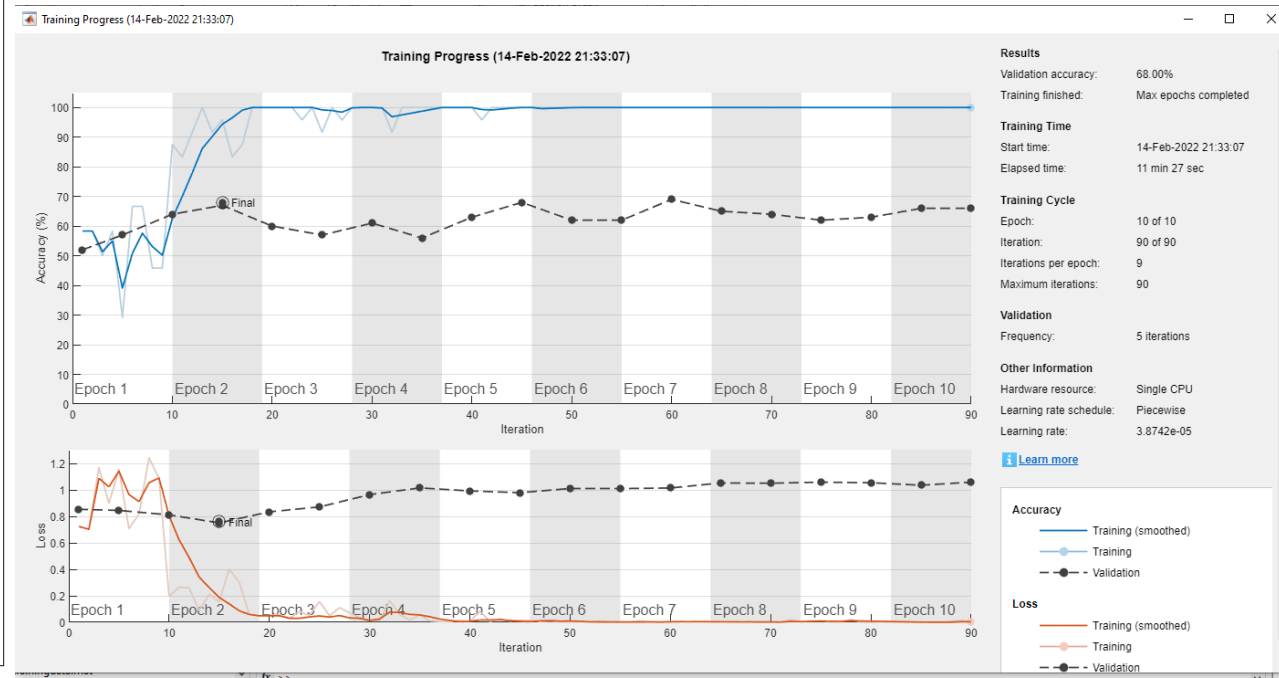
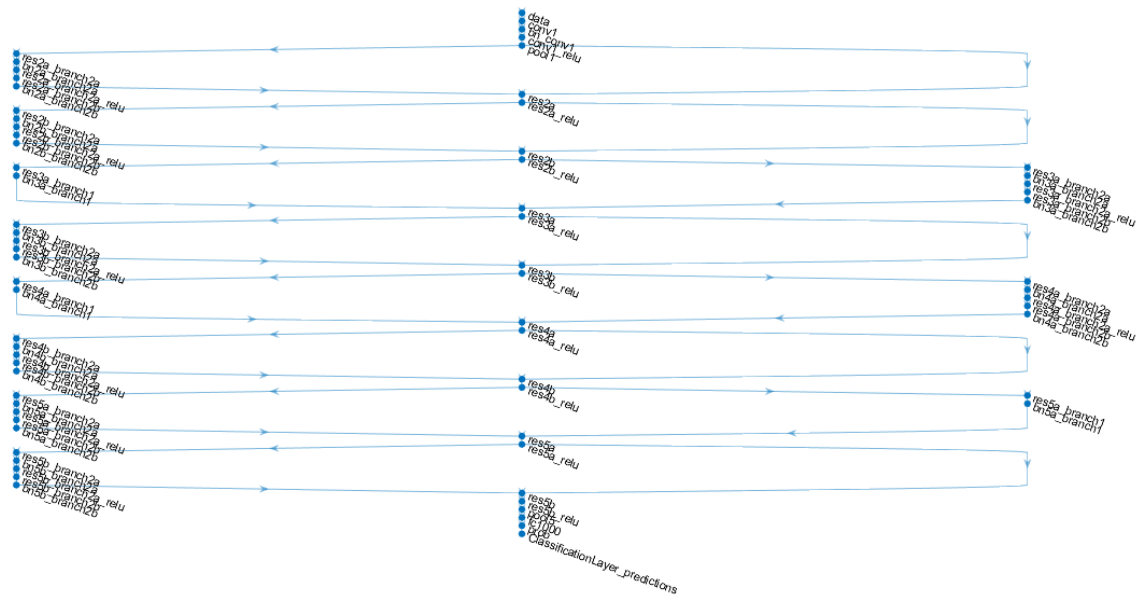


Experiment and Results: SqueezeNet (56% accuracy)



Experiment and Results: ResNet-18 (68% accuracy)

Reconstructed ResNet18 - LayerNetwork



Experiment and Results: Ensemble Method (72% accuracy)

1	Vote between multiple CNNs discussed above
2	Use the output softmax scores (% confidence)
3	Scale each network by a weight factor
4	Sum and normalise the different contributions
5	Analyse results

Confusion Matrix for Validation Data

True Class	Demented	33	17	66.0%	34.0%
	Nondemented	11	39	78.0%	22.0%
		75.0%	69.6%		
		25.0%	30.4%		
		Demented	Nondemented		
		Predicted Class			

Experiment and Results: Four State CDR

54% accuracy (four classes)

Confusion Matrix for Validation Data

True Class	Confusion Matrix for Validation Data					
	MildDemented	ModerateDemented	Nondemented	Questionable		
MildDemented	1		3	8	8.3%	91.7%
ModerateDemented			1			100.0%
Nondemented	2		40	19	65.6%	34.4%
Questionable			18	19	51.4%	48.6%
	33.3%		64.5%	41.3%		
	66.7%		35.5%	58.7%		
	MildDemented	ModerateDemented	Nondemented	Questionable		
	Predicted Class					

Experiment and Results: Summary

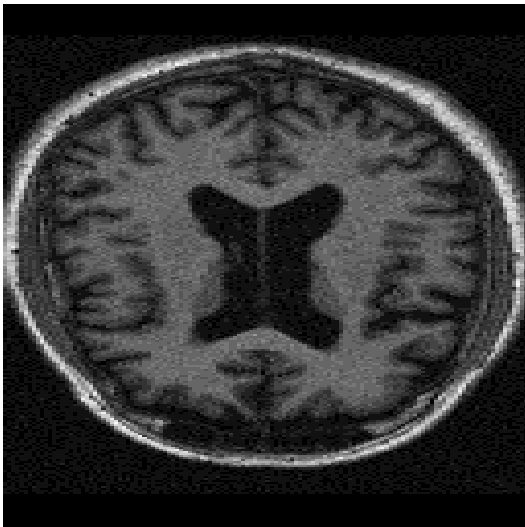
Model	# of Classes	Accuracy	Loss
Baseline CNN	2	59%	0.7552
Optimized CNN	2	68%	0.6822
SqueezeNet	2	56%	0.6833
AlexNet	2	66%	0.7200
GoogLeNet	2	64%	0.6572
ResNet18	2	68%	0.7518
ResNet50	2	63%	0.6502
Ensemble	2	72%	N/A
CDR	4	54%	1.3537

Analysis and Discussion: Optimisation

- Training/Validation split $\sim 70/30$.
- Implementing `imageDataAugmenter` to implement rotations, pixel shifting, and reflections.
- Even distribution of Demented and Non-demented patients to ensure lack of biased classifications.
- Greater depth generally leads to higher performance, however Resnet-18 and Resnet-50 failed to demonstrate this leading to early halt of further development of Resnet-50.
- Average loss of models is 0.7, all networks achieved a loss within 1-2 standard deviations.

Analysis and Discussion: Limitations

- Training and validation split limited potential of models.
- Re-sizing images into 64x64 pixel .bmp image files resulting in lower resolution.
- Detailed features such as ventricles and hippocampus were unclear.
- Limited dataset size.



256x128 pixels

MRI scan of same patient



64x64 pixels

Conclusion

Best performing model was ensemble network.

Models could not achieve the 90% accuracy due to the limitations encountered during optimisation.

Limitations need to be addressed before future work can be continued.

Future work to improve performance

- Testing higher computational CNNs.
- Higher resolution input images.
- Better image pre-processing
- Larger dataset
- Interweaving multiple modalities.
 - Age.
 - Ethnicity.
 - Biomarkers: Derivatives of beta amyloid concentrations.
 - Genetics: TREM2.

Individual Project Contributions:

Yuk Leong

- Literature Review
- CNNs optimisation

Robert Makepeace

- Data wrangling
- CNN Experiments and Optimisation
- Advanced CNNs and optimisation
- Method

Sannjit Saha

- Feasibility

Reference

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