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ASSESSMENT ITEM NUMBER/ TITLE
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Automatic Demented Detection Using Convolutional Neural Networks

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***Abstract*—Neurological degeneration is a significant and irreversible medical condition where the neuron structure within the brain is destroyed. Conditions such as Alzheimer's Disease, are slow processes which can cause issues with the patient's memory, social function and personal behaviour. Early detection of Alzheimer's Disease can allow for some intervention treatments to mitigate the impact. This paper proposes some novel detection methods for dementia through the use of convolutional neural networks (CNN) of MRI brain images. Some different CNN structures are presented in order to improve the classification performance. The OASIS dataset of 373 MRI images of dementia patients is used for training and classifying the CNNs. The ensemble method combining multiple CNNs had the best validation accuracy of 72%. This automatic method demonstrates viability and would supplement professional medical judgement in the early detection of Alzheimer's Disease and other similar conditions.**

Keywords—Convolutional Neural Networks, MRI, machine networks, Alzheimer's Disease

I. INTRODUCTION

A. Dementia

Dementia conditions affect at least 55 million people worldwide with various levels of neurological degeneration. The societal cost of dementia exceeds $1.3 trillion dollars (US) per year for managing the care of patients [1]. Currently there is no cure and as the condition is irreversible, most treatments involve reducing the rate of decline. Early detection allows for intervention to improve the quality of life for patients. As the majority of elderly people have some degeneration, manual diagnosis can be a challenging task for medical professionals [2].

As shown in Figure 1, Alzheimer's disease causes a reduction of the white matter and neurons in the brain [3]. This includes the extreme shrinkage of the cerebral cortex (the outer layer), shrinkage of the hippocampus (deep into temporal lobe), and severely enlarged ventricles (inner voids).

Figure 1: Pictorial Representation of Neurological Degeneration [4]

Brain magnetic resonance imaging (MRI) is a common method to get a scan of the internal structure of the human brain. MRIs use strong magnetic fields and radio waves to generate a three-dimensional image of the human brain. These images can be used by medical professionals to identify any degeneration beyond normal aging. This can be done through analysing static images or comparing images of the patient over time. [4]

B. Automatic Dementia Classification

There has been some recent related work using convolutional neural networks to automatically classify dementia with MRI images. Awate et al [5] used a convolutional neural network to classify dementia using the OASIS dataset [6] to successfully classify images albeit with a very small validation subset. The paper utilizes Tensorflow and CuDNN software tools for optimizing the hyperparameters of the CNN and utilizing the imaging processing of the Graphic Processing Unit (GPU). The results are promising but issues with the validation dataset structure may inflate results due to overfitting.

Islam et al [7] also used deep convolutional neural networks to classify dementia from MRI images. Islam used an ensemble model with three DenseNet CNNs to classify dementia from the same OASIS dataset [6]. The model achieved an accuracy of 94% using a four-point classification scale (non-demented, very mild, mild and moderate).

Folego et al [8] extended the application of CNN in MRI images by extending the input layer to include the whole 3D image rather than a segment. This extension utilises domain adaptation to allow the whole image space to fit within the input of a CNN. This novel method had promising results with an accuracy of 52.3% but would likely need much more training data and computational power to be successful.

Lee et al [9] used a multimodal approach to classifying dementia with deep learning. In addition to the MRI images, they also incorporated demographic information, cognitive performance, and cerebrospinal fluid (CSF) biomarkers to their recurrent neural network. This research was quite successful incorporating the holistic patient information to improve performance of their classification.

The objective of this paper to propose a robust and accurate automatic classification system for dementia using MRI images. The system will be able to automatically preprocess the image, train the CNN using a training dataset and then effectively classify new MRI images. The aim is to achieve high accuracy with low validation and avoidance of overfitting (where the model is only efficient at classifying the specific images of the training dataset, and not the general type of images).

C. Advanced Convolutional Neural Networks

For complicated image classification problems, some advanced pretrained CNNs can provide powerful capability. These include SqueezeNet [10], AlexNet [11], GoogLeNet [12], ResNet18 [13] and ResNet50 [14]. SqueezeNet is a compact CNN with a branched structure with 18 layers deep and a relatively smaller number of parameters. AlexNet is a linear CNN with a total of five convolutional layers. GoogLeNet is a CNN with an extensively branch structure including a total of 22 layers and utilizing inception modules allowing different filter sizes. ResNet18 and ResNet50 are powerful CNNs with 18 and 50 layers respectively and have a large number of parameters

These networks are typically applied to the ImageNet database [15] for classification of general images but can be applied to the MRI images. The structures of these networks often include branches and there is a large number of hyperparameters.

II. METHODS

A. Dataset

The OASIS [6] dataset is a longitudinal study of older adults with MRI images including both demented and non-demented adults. The dataset consists of 373 patients with brain MRI data. This is one of the largest open access databases of MRI images. The dataset also includes demographic and clinical information about the patients in the MRI images. CNNs with numerous tunable weight parameters need a large training data set in order to generate a robust and accurate model.

B. Software

Mathworks Matlab software will be used for the data preprocessing, CNN creation, CNN tuning and assessing performance [16]. Matlab's deep learning toolbox has a number of built-in functions to allow for easy application of various neural networks methods and provides powerful visualization tools for monitoring the training. Matlab also has built-in advanced CNN structures which include the pretrained weights on the ImageNet database [15]

C. Image Preprocessing

The MRI images [6] are preprocessed prior to being processed by the CNN. The MRI image files are contained in the Analyze 7.5 dataset format and are read into Matlab using built-in functions. The image files are converted from 256 x 256 x 128 pixel three dimensional images into a 64 x 64 pixel two-dimensional greyscale bitmap image file. A middle horizontal cross-section is chosen to extract from the 3D matrix to provide a representative image of the brain (see examples in Figure 2). The input size of 64 x 64 pixels for the CNN has been chosen to reduce the computational complexity of the training whilst retaining sufficient resolution for classification performance.

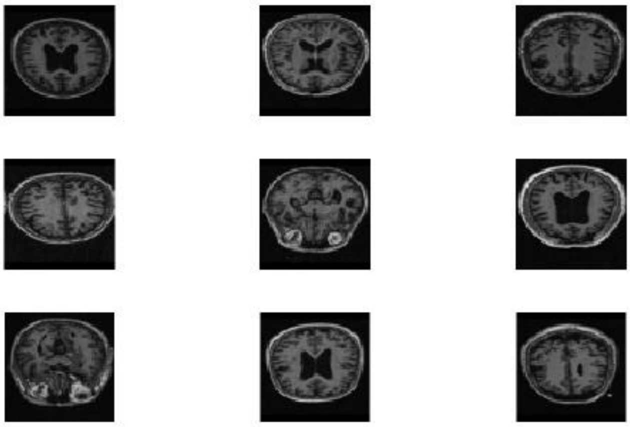

Figure 2: Some sample brain MRI cross-sections

These images have been collated into the image datastore data structure within Matlab for use with the built-in Matlab CNN functions [16]. Some further data processing has been conducted on the MRI metadata to classify the images within the image datastore. The main classification scheme will be demented / nondemented binary classification. The images have been randomly split between training (70%) and validation (30%) subsets. An extension item has been investigated using the clinical dementia rating (CDR) scale from the diagnosing doctor including non-demented; questionable (i.e., very mild); mild and moderate. It is noted that some of these CDR classes do not have sufficient images to allow for accurate classification.

D. Neural Network (NN) Theory

The machine learning structure of the neural network is based on the human neuron in the brain. The structure is shown in Figure 3, with the neuron summing multiple inputs multiplied by individual weights, and then adding a bias term. The neuron applies its own activation function to produce the output axon value. The weight functions are updated through training by comparing the outputs against the desired results and applying a learning function. These neurons are layered together to form a neural network which can process larger datasets and more complicated classifications.

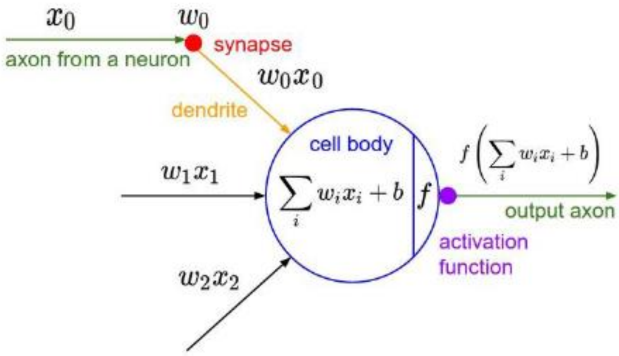

Figure 3: Neural Network Structure (Image Source: [5])

E. Convolutional Neural Network (CNN) Theory

A convolutional neural network (CNN) is a type of neural network consisting of a number of layers with different specific functions. The input layer is the pixel values of the input image, and the output layer is the classification output values. The convolutional layers apply a sliding convolution filter which computes the dot product of the input (v) and the weights (w); then combined with the bias term (b) [17]. The output value (c) of the convolution at coordinates (x, y) is shown in Equation 1 below where p and q are the filter size:

$$c(x,y) = \sum_p \sum_q v(x-p, y-q)w(p,q) + b \qquad (1)$$

The batch normalization layer normalizes data across a batch of data. The Rectified Linear Unit (ReLU) layer removes negative values as per Equation 2 [17]:

$$f(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (2)$$

The max pooling layer reduces the input through down-sampling by taking the max value of each region [17]. These layers have a number of hyperparameters controlling the stride and padding of these operations. Care must be taken to ensure the input and output dimensions of the operations align.

F. CNN Models

A baseline basic CNN has been designed for comparison of the different CNNs. The structure of the CNN includes input image layer, three sets of convolutions, batch normalization, ReLU and max pooling layers. At the end is a fully connected layer, softmax and classification layer with two classes.

The optimized CNN has been developed through fine tuning the baseline hyperparameters, layer structure and training. Through iterative testing, the optimal parameters have been determined in order to optimize the performance. Some methods for avoiding overfitting have been utilized including the randomization of the training data set for each epoch through random rotations and pixel shifts.

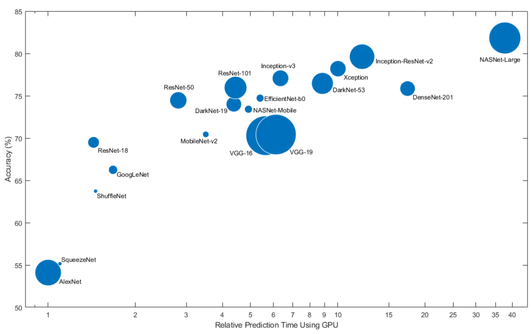

Figure 4: Advanced CNN Structures Accuracy plotted against the relative prediction time (Source: Matlab)

Five advanced CNNs will be evaluated to further optimize classification performance. From Figure 4, the selected CNNs include SquezeNet [10], AlexNet [11], GoogLeNet [12], ResNet18 [13], and ResNet50 [14]. The base layer structure is imported into Matlab without the pretrained weights for the ImageNet database [15]. The networks are modified to adjust the output classifications from the ImageNet database classes to the two dementia classes. Some additional preprocessing is required with an augmented image datastore to convert the 64 x 64-pixel greyscale (i.e., one channel) dataset to the typical 227 x 227 pixel colour (i.e., three channels) image dataset required as an input for these networks. Also, the dropout layers have been added to randomly set input values to zero between layers during training iterations which avoids overfitting to the training dataset. An example of the GoogLeNet structure is shown in Figure 5.

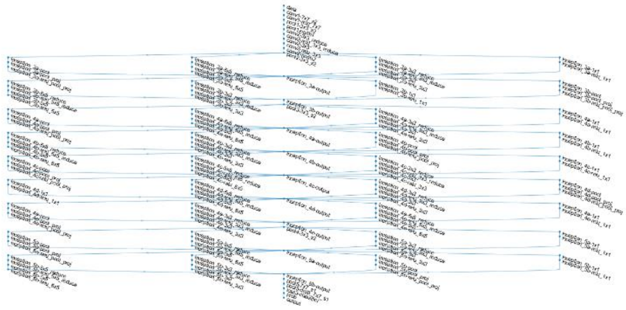

Figure 5: GoogLeNet layer structure. Note the amount of branching and different layers.

An ensemble method has been developed to combine multiple CNN's methods together using the "wisdom of the crowd" concept. The output softmax classification layer provides a confidence score (s_{ijk}, where s is the confidence score, i is the index of the image of the validation dataset, j is the class and k is the CNN model number) on the classification. The ensemble score (z_{ij}) is computed as the sum of the product of classification scores and CNN weights for the different CNNs (see Equation 3 below). The predicted ensemble classification is determined by the class with the highest score (z_{i1} $versus$ z_{i2}). This is repeated for all images (i) in the validation dataset. The ensemble model performance is evaluated similar to the other CNNs

$$z_{ij} = \frac{\sum_k w_k \times s_{ijk}}{\sum_k w_k} \qquad (3)$$

As an extension, a four-state clinical dementia rating (CDR) was tested using a basic CNN. The dataset was recreated with new labelling with the four states of the CDR scale, but otherwise using similar methods discussed above.

G. Performance Evaluation Metrics

Each CNN performance is evaluated on three metrics. Accuracy is the percentage of correct validation classifications compared to the total size of the validation dataset. Cross entropy loss is a measure of mutual exclusivity for the classes [18]. Finally, confusion matrices are used to observe the distribution of the classification results.

H. Functional Block Diagram

The overall system functional block diagram is shown in Figure 6. The different models discussed above will be trained and evaluated. There will be some iteration to experiment with different hyperparameters (such as number of convolutional filters), different layer structures and different training parameters (such learning rate and number of training epochs).

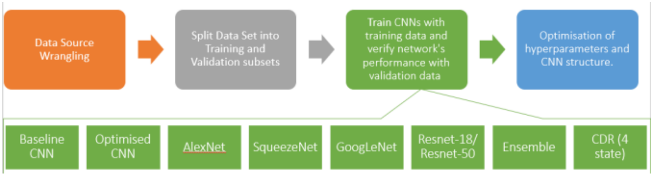

Figure 6: Functional Block Diagram

III. EXPERIMENTS AND RESULTS

The results of the experiment are shown in Table 1 with the validation data subset accuracy and validation loss metrics shown indicating the CNN performance.

Table 1:CNN Performance

Model	Layers Deep	Classes	Accuracy	Loss
Baseline CNN	3	2	59%	0.7552
Optimized CNN	3	2	68%	0.6822
SquezeNet	18	2	56%	0.6833
AlexNet	5	2	66%	0.7200
GoogLeNet	22	2	64%	0.6572
ResNet18	18	2	68%	0.7518
ResNet50	50	2	63%	0.6502
Ensemble	N/A	2	72%	N/A
CDR	3	4	54%	1.3537

The baseline CNN achieved an accuracy of 59%, with the CNN training performance shown in Figure 7. Table 2 shows the details of the layer structure and key hyperparameters for the baseline and optimized CNN models.

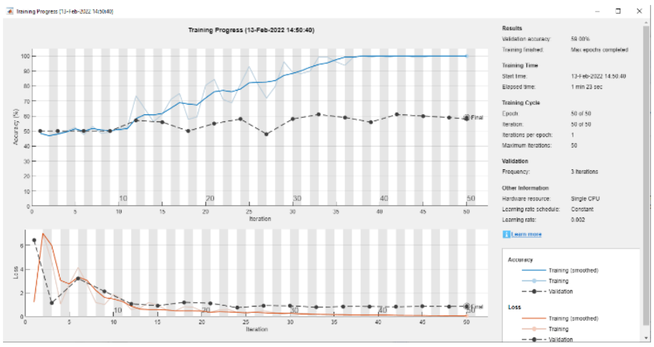

Figure 7: Baseline CNN Training Performance (accuracy of 59%) (training accuracy shown in blue, training loss in orange and validation accuracy/loss shown in black)

The details of the optimized CNN, including additional convolutional filters, are shown in Table 2. Other changes include dynamic training rate which decays through training and randomisation of training data each epoch (reflections, rotations and pixel shifts) to reduce overfitting. The optimized CNN achieved an accuracy of 68%, an improvement of 9%. These optimisations made the CNN more successful in the robustness of the network for identifying the key features in the images and versatility in accurate predictions of new images through less overfitting.

Table 2: CNN Layer Details (Baseline and Optimized)

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

Of the advanced CNNs, AlexNet achieved an accuracy of 66%, SqueezeNet 56%, GoogLeNet 66%, ResNet18 68% (Figure 8) and ResNet50 63%. As these networks were pretrained on the ImageNet database [15], the learning factor of the new two-state (demented / non-demented) classification output layer was configured to be twenty times faster than the rest of the network. Due to the large number of parameters and small training set, randomisation of training data each epoch (reflections, rotations and pixel shifts) and dropout layers were used to reduce overfitting.

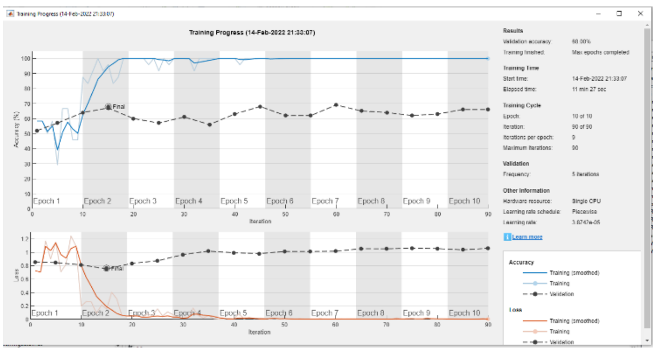

Figure 8: ResNet18 Training Data Plot (Accuracy of 68%) (training accuracy shown in blue, training loss in orange validation and accuracy/loss shown in black)

The ensemble method results are shown in the form of a confusion matrix in Figure 9 with an overall accuracy of 72%. The best individually performing CNNs were weighted higher than the lesser performing ones. This method achieved 4% higher accuracy than any individual CNN model performance.

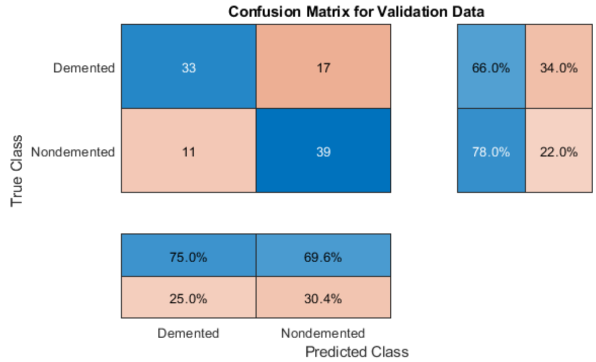

Figure 9: Ensemble Method Confusion Matrix (blue is correct classification, red is incorrect)

Finally, some experimentation was conducted on a CNN with the four-state classification using the CDR score. Shown in Figure 10, this achieved an accuracy of 54%. It is noted the classes with limited sample sizes (Mild and Moderate dementia classes) performed poorly due to insufficient training data. It was determined to focus on the two-state classification problem.

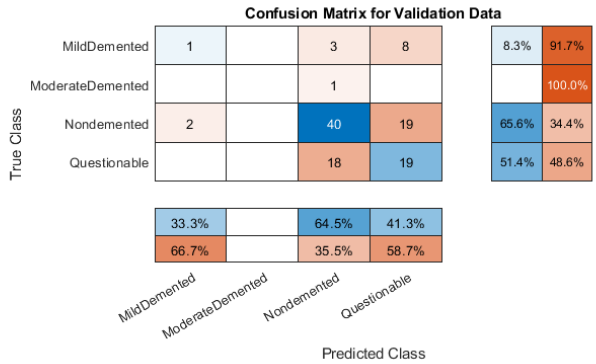

Figure 10: Four State Classification Confusion Matrix (Blue is correct classification, red is incorrect classification).

IV. DISCUSSION

The results presented above are promising in the automatic classification of dementia from MRI images. Compared to the related work in the literature, there is some room for improvement to achieve similar high accuracy scores in classification. The limitations of the research include the computational power of experiment, CNN image resolution and the size of the training data. These will be discussed in more detail below.

The baseline CNN model achieved modest classification accuracy of 59%. The structure of the model with three convolutional layers and a small number of filters did not have the capability to discriminate the dementia features as accurately as required. The training graph shown in Figure 7 shows overfitting of the training data with the blue line hitting 100%, which reduced the ability of the CNN to improve further.

The Optimised CNN achieved a significant improvement on the Baseline CNN. Experiments were conducted with four and five layer convolutional layer structures with down-sampling in between each layer, but these did not improve performance. It is inferred that with an input image size of 64 x 64 pixels, the optimal number of layers is three, otherwise the down-sampled images became too small. Of all the hyperparameters changed, increasing the number of convolutional filters as shown in Table 2 had the biggest improvement on performance. Other changes include a dynamic learning rate for the 'adam' training algorithm starting at 0.001 and decaying by 80% every ten epochs. This was more effective at training the network than the flat learning rate of the baseline CNN. The dynamic learning rate tailored the learning to the requirements of different stages of the training. Also, the training data was randomized using pixel shifts and reflections each epoch to reduce overfitting, making the training dataset seem larger than it was.

The performance of the advanced CNN was lower than anticipated as these models are optimized for a different classification problem of general images. The dementia dataset is too small to effectively train these models with a large number of parameters without overfitting. Whilst the methods of the dropout layers and training data randomization limited overfitting somewhat, these networks need significantly larger training datasets to be highly accurate and robust.

The SqueezeNet performance was poor at 56%, 2% lower than the baseline system. The CNN is designed to be computationally less intensive with less parameters but did not seem effective at distinguishing the subtle features of dementia in the brain. Some experimentation was done with different learning rates, but it offers little value in differentiating the images.

The AlexNet model achieved 66% accuracy. The randomization of training data and dropout layers were critical in improving AlexNet performance in allowing training that was robust and transferrable to the validation dataset. The training was amplified on the new output classification layer by a factor of twenty compared to the other pretrained layers. These settings achieved the best combination of utilizing the power of the pretrained AlexNet and focusing training on the output layers for the MRI images.

Similar to AlexNet, the GoogLeNet model achieved good results with 64% accuracy. The inception blocks allowing convolutions of different sizes were a powerful feature in analyzing the images of the brain as the information required collating information spread across the MRI image. The key improvement in the GoogLeNet was also in effectively managing the overfitting through dropout layers and training data randomization.

The ResNet18 and ResNet50 achieved mixed results. ResNet18 was the equal highest performing individual model, however it suffered from overfitting with the training data reaching 100% accuracy after only two epochs even with the mitigation measures discussed above. It is suspected the training dataset was too small with the large number of trainable parameters within the ResNet CNNs. ResNet50 also suffered from overfitting issues. No combination of training rate was found to be effective in improving performance.

The ensemble classifier performance was higher than expected utilising the confidence scores between the different CNNs to generate a more accurate combined class prediction. It worked best with multiple different models to provide different perspectives on the validation images. The weight factors allowed for tuning to strengthen the votes from high performing individual CNNs (such as Optimised CNN and ResNet18) and soften votes from weaker performing CNNs (such as SqueezeNet). Improving the performance of individual CNNs would improve the ensemble model performance. The ensemble model allows the advantages of different CNNs to be combined to achieve higher accuracy than individual CNNs.

The four state (CDR) classification problem would benefit from using a larger dataset of MRI images especially of the higher dementia levels to improve training performance. As seen in the confusion matrix of Figure 10, the classes with larger sizes achieve reasonable accuracy, but the smaller classes were ineffective at classification. With a larger dataset the other CNNs could also be applied to the four-state problem.

V. CONCLUSION

The results presented above show the feasibility of automatic detection of dementia using convolutional neural networks. This paper presented the performance of a number of CNN models which have moderate accuracy in predicting dementia status from MRI images. With further performance improvements this novel technology has the potential to assist doctors in the early diagnosis of patients to improve the medical outcomes.

Future work for this paper includes better preprocessing of the MRI images. There was some variation in the location of the head within the input images. More effort could be invested into ensuring a consistent cross section of the head is taken, and for the images to be scaled and cropped respective to the size of the head rather than the scope of the MRI image. This consistency would reduce the noise, training overfitting and improve classification accuracy.

Another area for future work is experimenting with more computationally powerful equipment to allow for using the full resolution of MRI images in the CNNs. The reduced resolution blurred some of the features of the brain around ventricles, hippocampus and cerebral cortex size reducing the ability of the CNNs to distinguish these features. Higher computational power could also assist with more computationally intense CNNs (such as DenseNet) or novel methods of Bayesian optimization of hyperparameters. These methods would improve the classification performance.

There is also future work in terms of the dataset of MRI images. As discussed above, with the small size of the OASIS dataset, there is evidence of overfitting of training data. The performance of the system could improve with the utilisation of a larger dataset of MRI images. Training with a larger dataset would reduce the amount of overfitting and improve validation classification, especially for the advanced CNNs with large numbers of parameters. Another area for further work is incorporating other modalities into the CNN including age, demographics, biomarkers and genetics to improve performance by utilising other information about the patients.

VI. APPENDIX: MATLAB SOFTWARE

The Matlab scripts used for this research paper are available through UTS OneDrive here: https://1drv.ms/u/s!AvVvu1NLzg7ltF8R-zAbeW3NUvCW?e=PXCbSE

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