Identifying Dementia in MRI Scans Using Artificial Neural Network and K-Nearest Neighbor

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***Abstract*—Artificial Neural Network (ANN) and K-Nearest Neighbor (KNN) models are used to detect dementia in MRI scans. Each scan is segmented and then normalized into four discrete color areas corresponding to white matter, dark gray matter, light gray matter and black background, the former three constituting the feature set. Thresholding technique is used in segmentation and nearest neighbor interpolation technique is used in normalization of the images. The ANN implementation resulted into 69.81% accuracy and the KNN implementation resulted into 81.13% accuracy in classification of demented and non-demented scans.**

***Index Terms*—ANN, Dementia, KNN, MRI**

I. Introduction

Dementia is a broad category of neuro-degenerative diseases, including, but not limited to, Alzheimer 's Disease, that causes a long term and often gradual decline in the patient's ability to think and remember [1].

Dementia is a leading cause of deaths today; it affects more than 44 million people worldwide with every 1 out of 20 patients under the age of 65. The global cost of caring for dementia is estimated to be $605 billion, which is equivalent to 1% of the global gross domestic product [1].

Diagnosis of dementia is conventionally done through cognitive, neurological and neuropsychological evaluation of a patient's mental state. These tests, however, can not provide tangible measure of severity and proper indication of the suitable treatment [2].

Neuroimaging in dementing illness has undergone revolutionary changes in recent years with the wide availability of an unprecedented array of new techniques. Magnetic Resonance Imaging (MRI), in particular, has aided in objective analysis for determining the presence and subsequently the type of dementia. Radiological findings may support the diagnosis of specific neurodegenerative disorders and sometimes radiological findings are necessary to confirm the diagnosis. It is a challenge for neuroimaging to contribute to the early diagnosis of neurodegenerative diseases such as Alzheimer's disease. Early diagnosis includes recognition of pre-dementia conditions, such as Mild Cognitive Impairment (MCI) [3].

Timely diagnosis of Dementia is vital in developing early treatments and designing management strategies to this fatal disease, but only 1 in every 4 people with Alzheimer's or related dementia have been properly diagnosed [1]. This raises a need for easy and non-invasive technique for dementia diagnosis.

Previous researches in this field have used naive Bayesian classifier [4], [5]; C4.5 decision tree[4], [6], [8]; Support Vector Machine (SVM)[5], [7]; Neural Network[7] and multi-modality classification framework [9]. These have resulted in average accuracy of around 80%.

This project uses Artificial Neural Network and K-Nearest Neighbor approaches to classify MR Images into demented and non-demented categories.

II. Data

This project uses a dataset containing 436 neurological MRI scans made available by the Open Access Series of Imaging Studies (OASIS) project. This data set consists of a cross-sectional collection of 416 subjects covering the adult life span aged 18 to 96 including individuals with early to mild to moderate Alzheimer's Disease. For each subject, 3 or 4 individual T1-weighted MRI scans obtained within a single imaging session are included. Each scan includes age, sex, education level, socioeconomic status, intracranial volume, and normalized brain volume, and two indicators of dementia: the Clinical Dementia Rating (CDR) and Minimental State Exam (MMSE) associated with additional information about the subject.

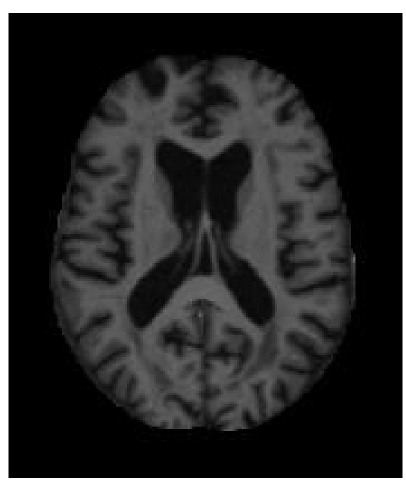

Fig. 1: Original Image Slice

All images are in 16bit Bigendian Analyze 7.5 format. Each scan consists of 3D images of dimension 176x208x176 voxels which have been preprocessed to remove the skull, leaving only brain matter in the images [10].

The available data is divided into 12 discs with a total of 235 datasets containing enough information about Dementia. Undemented MRI scans have Clinical Dementia Rating (CDR) value 0. Demented MRI scans have Clinical Dementia Rating(CDR) value of 0.5, 1, 1.5 or 2 depending on the severity of dementia.

III. Methodology

A. Image Preprocessing

Image files of the MRI scans from OASIS consists of raw information about each voxel. This image cannot be used directly to model a image classification system since this image consists of large number of features and analysis of such features increases the complexity in modeling a classifier. So, image preprocessing should be performed in order to reduce some unnecessary features and preserve others that bear significance in dementia detection. Image preprocessing includes format conversion, image re-sampling, grayscale color enhancement, noise removal, segmentation, image normalization and finally feature extraction.

1) Segmentation: Thresholding technique is used for segmentation of 3D images into four different volumes which are image background, white matter or the cerebro-spinal volume of the brain, the dark gray matter or the tissues inside the brain and the light gray matter (intermediate tissues between Gray matter and Cerebro-Spinal Fluid, CSF).

Fig. 2: Segmented Image Slice

The grayscale values and representative values of each of the volumes are:

Particulars	Grayscale Value	Representative Value
Background	0-5	0
Dark Gray Matter	5-38	85
Light Gray Matter	38-72	170
White Matter	72-255	255

TABLE I: Range of Grayscale values for Image Segmentation

2) Normalization: 7 layers from the top and 25 layers from the bottom of the image were removed as they contain only black voxels, which is an irrelevant information to our cause. The 3D image size is hence reduced from 176 X 208 X 176 to 144 X 208 X 176. Nearest neighbour interpolation was then performed. Nearest-neighbor interpolation (also known as proximal interpolation or point sampling) is a simple method of multivariate interpolation in one or more dimensions. It has been used in approximating the grayscale value of a non-given point in some space when given the value of that function in points neighboring that point. The nearest neighbor algorithm yields a piecewise-constant interpolant. This process is repeated four times to reduce image data to 9 X 13 X 11, with a total of 1287 voxels.

B. Feature Extraction

From the above normalized image data, three volumes: dark gray matter, light gray matter and white matter, are considered. These values are measured from normalized segmented brain volume. Total volume of the matters is 398. These extracted volumes are hence normalized into the range 0 to 1 by dividing each value by 398. Thus the features for the machine learning model are:

- Normalized volume of Dark gray matter (Tissues)
- Normalized volume of White matter (CSF)
- Normalized volume of Light gray matter (Intermediate tissues between Gray matter and CSF)

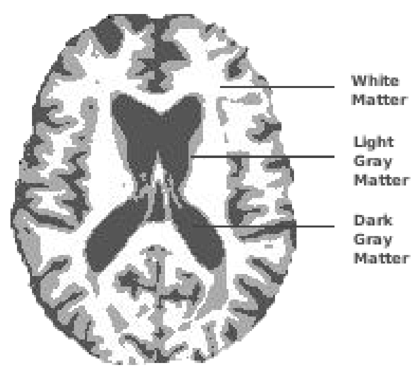

Fig. 3: Extracted Features

C. ANN Implementation

A neural network is modeled with a three neuron input layer, each corresponding to one of the extracted features. This model consists of two hidden layers and an output layer with two neurons each. The hidden layers use hyperbolic tangent function as activation function, mathematically expressed as:

$$f(x) = tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

The model uses back propagation method for training.

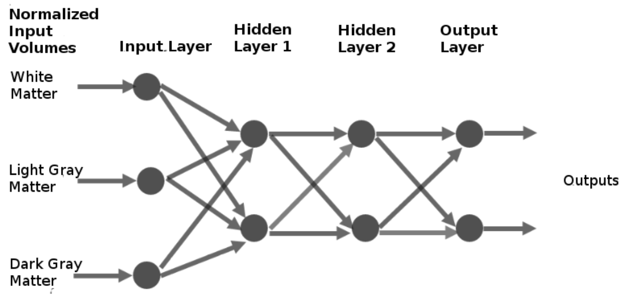

Fig. 4: ANN Model

D. KNN Implementation

A KNN model is designed where the 5-fold cross validation technique resulted in 7 as the best value of K (value of K for minimum classification error). So, the majority class of the 7 nearest neighbors of each input scan is assigned as the class for that scan.

Nearest neighbor approximation is done by the measure of Eucledian Distance as given by:

$$\delta = \sqrt{(G_{ip} - G_{tr})^2 + (g_{ip} - g_{tr})^2 + (W_{ip} - W_{tr})^2} \quad (2)$$

Where,
δ = Eucledian Distance
W_{ip} = Normalized volume of white matter of input image
g_{ip} = Normalized volume of light gray matter of input image
G_{ip} = Normalized volume of dark gray matter of input image
W_{tr} = Normalized volume of white matter of training image
g_{tr} = Normalized volume of light gray matter of training image
G_{tr} = Normalized volume of dark gray matter of training image

IV. Results

A. ANN Model Validation

The following confusion matrix shows performance of the ANN model:

		Actual		
		Positive	Negative	Total
Predicted	Positive	18	9	27
	Negative	7	19	26
	Total	25	28	

TABLE II: Result from ANN Implementation

Accuracy : 69.81 %
Sensitivity : 72.00%
Specificity : 67.85%

Out of the 53 test data, the ANN model resulted in 18 true positives and 19 true negatives along with 9 false positives and 7 false negatives. This means that the ANN model is able to identify positive dementia with a Positive Prediction Value (PPV) of 0.6666 and negative dementia with a Negative Prediction Value (NPV) of 0.7307.

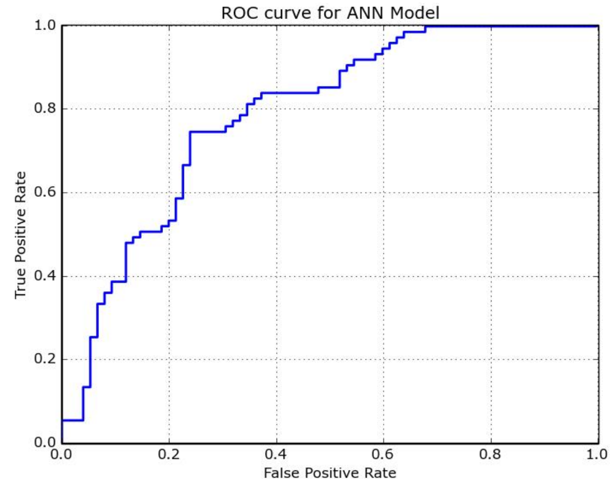

Fig. 5: ROC Curve for ANN Model

B. KNN Model Validation

The following confusion matrix shows performance of the KNN model.

		Actual		
		Positive	Negative	Total
Predicted	Positive	19	4	23
	Negative	6	24	30
	Total	25	28	

TABLE III: Results from KNN Implementation

Accuracy : 81.13%
Sensitivity : 76.00%
Specificity : 85.71%

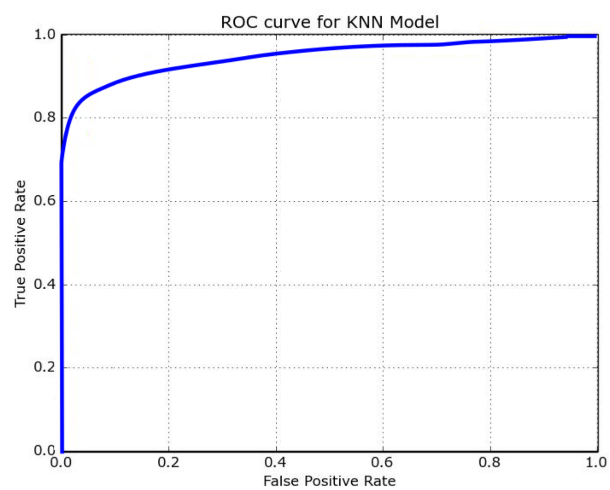

Fig. 6: ROC Curve for KNN Model

Out of the 53 test data, the KNN model resulted in 19 true positives and 24 true negatives along with 4 false positives and 6 false negative. This means that the KNN model is able to identify positive dementia with a Positive Prediction Value (PPV) of 0.8260 and negative dementia with a Negative Prediction Value (NPV) of 0.80.

V. Conclusion

From the above result, we can see that the KNN model has performed better than ANN model in all statistical measures of performance of binary classification models.

The KNN model produces adequate accuracy to be termed as a medically acceptable level of diagnosis accuracy($>$80%) for the dataset used. This level of accuracy as given by the KNN model is better in comparison to many existing systems and within comparable bounds of several others.

Machine learning and artificial intelligence can produce significant accuracy in classification of demented and non-demented MRI scans. Further, artificial intelligence, if researched extensively, may some day surpass human accuracies in disease diagnosis and replace human expertise in the same.

VI. Future Work

The OASIS repository provides limited datasets that can be used in KNN implementation and in training the ANN model. A larger dataset covering a wide range of subjects could improve the accuracies of these models and in verification of the results obtained.

Further experimentation on the ANN could result into a better model for implementation in Dementia diagnosis.

Also the use of filters like median filter and fuzzy filter could reduce noise in the image leading to better accuracy.

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References

[1] Alzheimer’s Association, *2015 Alzheimer's Disease Facts and Figures*. Alzheimer’s & Dementia 2015.

[2] Alzhiemer's Australia, *Dementia Q&A: Tests Used in Diagnosing Dementia*, 2014.

[3] J. Valk, F. Barkhof and P. Scheltens, *Magnetic Resonance in Dementia*: Springer-Verlag Berlin Heidelberg, New York, 2002.

[4] W. R. Shankleab, S. Mania, M. B. Dickc and M. J. Pazzania, *Simple Models for Estimating Dementia Severity Using Machine Learning*, Studies in Health Technology and Informatics: University of California at Irvine, Irvine, California, 1998.

[5] V. Miller, S. Erlien, and J. Piersol, *Identifying dementia in MRI scans using machine learning*, Stanford University, Stanford, CA.

[6] W. R. Shankle, P. Datta, M. Dillencourt and M. Pazzani, *Improving Dementia Screening Tests with Machine Learning Methods*, Alzheimers Research: University of California at Irvine, Irvine, CA, 1996.

[7] J. A. Williams, A. Weakley, D. J. Cook and M .Schmitter-Edgecombe, *Machine Learning Techniques for Diagnostic Differentiation of Mild Cognitive Impairment and Dementia*, AAAI 2013 Workshop, Expanding the Boundaries of Health Informatics using Artificial Intelligence, Washington State University, Pullman, WA.

[8] P. Datta, W. R. Shankle and M. Pazzani, *Applying Machine Learning to an Alzheimer’s Database*, AAAI-96 Spring Symposium, AI in Medicine: Applications of Current Technologies: University of California at Irvine, Irvine, CA, 1996.

[9] K. R. Gray, *Machine learning for image-based classification of Alzheimers disease*, Imperial College London, UK.

[10] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, *OASIS Fact Sheet: Cros-Sectional Data Across The Adult Lifespan*, Journal of Cognitive Neuroscience, 2007.

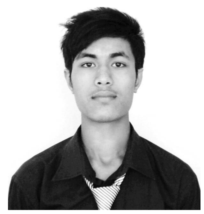
[11] M. Sezgin and B. Sankur, *Survey over image thresholding techniques and quantitative performance evaluation*, Journal of Electronic Imaging 13(1), 146165,January 2004.

[12] L. M. Surhone, M. T. Timpledon and S. F. Marseken, *Nearest - Neighbor Interpolation*, VDM Publishing, 2010.

[13] M. Hassoun, *Fundamentals of Artificial Neural Networks*: The MIT Press, Cambridge, Massachusetts, 1995.

[14] E. Deza, M. M. Deza, *Encyclopedia of Distances*: Springer-Verlag, Berlin, Heidelberg. 2009.

[15] Gerardnico, *Machine Learning - K-Nearest Neighbors (KNN) algorithm - Instance based learning*



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