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Design of A Convolutional Neural Network System to Increase Diagnostic Efficiency of Alzheimer's Disease

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Abstract. The most common degenerative neural disease, Alzheimer's disease (AD), is insidious and almost always requires imaging modalities to be diagnosed early. MRI is the most common one used, but requires timely interpretation. Here we develop a convolutional neural network (CNN)-based system that determines whether a brain MR image has AD or normal. First, feature extraction is performed to separate various parts of the brain. Then, the data is processed to differentiate normal brain from AD brain, solely using MR image. Finally, the neural network is supplemented using data from the patient's history and physical examination. In this first phase, we were able to extract features from the brain MR image, initially by masking the image and separating the white matter, grey matter, and cerebrospinal fluid called the grey level co-occurrence method (GLCM). This method is able to using a convolutional neural network.

1. Introduction

The nervous system's the most common degenerative disease, Alzheimer's disease, is a disease which is caused by damage to the brain cells associated with cognitive processes of reasoning, memorising, and actualising personality. Dementia or senility occurring in the elderly is assumed as a natural course of life by the majority of Indonesian because of its relationship to the aging process. In fact, there is a type of abnormal dementia namely Alzheimer's disease. An estimated 46 million people are Alzheimer's disease patients in worldwide, and one million of them live in Indonesia. This number is expected to increase dramatically to double in 2030[1].

Neuroscientists are fascinated in learning Alzheimer's disease (AD), not only because it is the most common of the degenerative central nervous disease, but also because of its insidious clinical progression, where the first symptoms are purely cognitive. This disorder affects the limbic system and the association cortices. Thus, the patients have impaired novel memory generation, first of trivial, and then important details of life. However, interestingly, motor and sensory functions of AD patients are often intact and show no pathological signs. The brain cortex of the patient shrivels up and shrinks severely, particularly in the hippocampus area, which is involved in thinking, reasoning and creating new memories. Brain ventricles, which produce cerebrospinal fluid, also become larger in an AD patient.

A well-timed diagnosis of this disease is crucial and requires good clinical assessment based on the patient's medical history. Several neuropsychological tests can be used to help to establish the diagnosis of AD, such as mini-mental state examination (MMSE), neuropsychiatric inventory questionnaire, clinical dementia rating and other pathological evaluations. National Institute of Aging Alzheimer's Association developed the first clinical criteria for AD diagnosis. Imaging tests, such as MRI, are required to accurately diagnose AD, but it needs an expert (neurologist or radiologist) to interpret the features, which often consumes a lot of time and money.

In the present, computer-aided diagnostic systems have been and are being developed by several researchers for accurate detection of AD. Some of the earliest expert systems are rule-based, and had been in development since the 1970s. In the 1990s, supervised models began replacing these rule-based systems, being trained with feature vectors taken from medical sources like computer tomography or MRI.. In this paper, we attempted to create a MRI-based expertise system that would allow a neurologist

or radiologist to interpret results quickly, that we hope will be able to increase the efficiency of AD diagnosis and therapy, whose number of patients are climbing at an ever-rising rate.

2. Methodology
2.1. Data
This project uses data from brain Magnetic Resonance Imaging (MRI). MRI is often the near gold-standard method when soft tissue delineation is necessary [2] (the gold standard for AD is brain autopsy, which would only be possible post-mortem, after the patient's death).

The Magnetic Resonance Imaging data for the model system has been earned from the Open Access Series of Imaging Studies (OASIS) dataset. OASIS is a freely distributed collection of neural imaging datasets made for the scientific development. The distributors hoped that the free dissemination would propel future discoveries in neuroscience. Currently, there are three OASIS datasets, with the first two, OASIS-Cross sectional and OASIS-Longitudinal have been used for data analyses, creation of anatomical reference, and development of algorithms to segmentate parts of the brain [3]. Its dataset also contains additional crucial information including age, sex, main complaint, systolic blood pressure, diastolic blood pressure, pulse, and axial head length and head width.

In the rst phase of system design, only MRI scan images is used, using the OASIS database as sources. Later, in advanced phases, we will be taking into account history-taking (anamnesis) and the patient's physical examination results as parameters of the dataset to be processed and programmed into the diagnostic system. The parameters can be seen in Table1. Then, from these, data testing is carried out and training data using Convolutional Neural Network.Table1 is the parameter that will be used in the system diagnose. In row of Code, A refer to result of history-taking (anamnesis), P refer to result of physical examination, and M refer to MRI result. The example of image in OASIS dataset shows in Figure1.

2.2. Preprocessing
The dataset's images have been processed by skull stripping and normalisation, so that the parts of the brain keep aligned properly at the relatively same coordinates, no matter how the image is transformed [4].

Brain image features consist of: White Matter (WM), Grey Matter (GM) and Cerebrospinal Fluid (CSF). The data are prepared (masked) to strengthen contrast and make a clear distinction between the WM, GM and CSF [5]. Image contrast is the difference in brightness between objects or region [6]. An image lacks contrast when it does not have strong difference between black and white. In a image, brightness refers to the overall its lightness or darkness. To change the contrast in an image, contras-stretching is performed by the Adjust Contrast tool. The better result of contrast enhancement could provide better segmentation accuracy at the anatomical structure of the brain, and digital image processing [7].The proposed design is showing in Figure 2.

Table 1. Parameters

No	Code	Parameters	Example
1	A	Name	Jhon
2	A	Sex	Male/M
3	A	Age	73
4	A	Main Complaint	Dementia
5	A	History of Headaches	Yes
6	A	History of Di culty Remembering the way home	No
7	A	History of Head Trauma	No
8	A	Family Medical History	Yes
9	A	Glasgow coma scale	15
10	P	Systolic Blood Pressure	120
11	P	Diastolic Blood Pressure	80
12	P	Pulse Rate	80
13	P	Respiratory Rate	16
14	P	Cranial Nervous Examination	Normal
15	P	Meningeal Re exes	Abnormal
16	P	Motor/Muscle Tones	Normal

17	P	Re exes	Normal
18	P	Sensory Function	Normal
19	P	Autonomous Nervous Function	Normal
20	P	Coordination	Normal
21	P	MMSE	18
22	M	Head length	20
23	M	Head Width	16
24	M	Cerebrum Density	Kg/m^3
25	M	Cerebellum Density	Kg/m^3
26	M	Ratio of Black Area/White Area	0.1
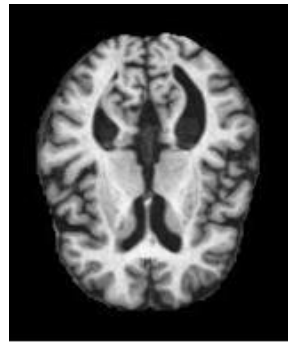
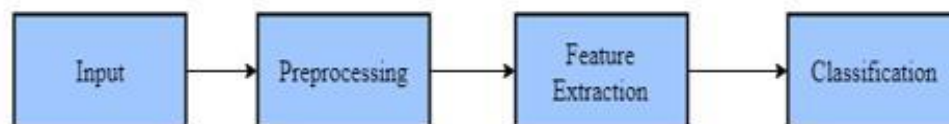Figure 1. Sample Image in the OASIS Dataset

Figure 2. Block Diagram System

2.3. Features Extraction
After thresholding, Grey Matter, White Matter, and CSF were extracted. This paper uses the following feature extraction by using Grey Level Co-Occurrence (GLCM). GLCM is is a matrix (number table) that represents the grey levels of each pixels in the image. The number of grey levels, G, is equivalent to the rows and columns. P is a matrix element (i,j) and represents the relative frequency in which two adjacent or non-adjacent pixels separated by the distance (x,y) , occur wiithin a specific neighbourhood. One of them has the intesnity 'i' and the other 'j' [8]. The equation that used in this phase by using eq(1), eq(2), eq(3) and eq(4).

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \qquad (1)$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma} \qquad (2)$$

$$Homogeneity = \sum_{i,j=0}^{N-1} P_{ij}\frac{(P_{ij}}{1+(i-j)^2} \qquad (3)$$

$$Entropy = \sum_{i,j=0}^{N-1} -ln(P_{ij})P_{ij} \qquad (4)$$

2.4. Convolutional Neural Network
CNN is an algorithm which can receive input image, assign importance to various aspect/object in the image and be able to di erentiate one from the other(Figure3) .

A CNN is a type of feed-forward neural network (FNN) which has neurons that is inspired by an animal's visual cortex for all computer vision tasks [9]. The goal of a CNN is to learn-order features in the data via convolution. CNN's topology utilises spatial relationships to reduce the number of parameters which have to be learned [10]. In relation to the convolutional network, is to extract features from the input image. the major objective of convolution. CNN is inspired by the way human vision works, therefore layers of a convolutional network have neurons dispersed in three dimensions: height, width, and depth [11].

2.4.1. Transfer Learning
Transfer learning is the action of improving the learning in a novel task by tweaking and re-adjusting weights between neurons to classify an object of the same type but different category. Transfer methods is given huge ammount of resources to train CNN models or even larger datasets which the model are trained. Basically, it is the process of copying knowledge from an already trained network to a new network to solve similar problems [9]. In transfer learning, there are two forms of transfer learning which are inductive learning and inductive transfer that narrowed by using a model on not related task. For using transfer learning, we can use on two approaches such as develop model and pre-trained model. Furthermore, transfer learning has several models for image data especially MRI scan is VGG 16 model, ResNet, Inception from Google, and AlexNet.

2.4.2. AlexNet
The first major breakthrough in the architecture of CNN came in seven years ago. This award-winning CNN architecture is called AlexNet. At first run, a ReLU activation function and a dropout of 0.5 were used in the network to ght to over t [9]. AlexNet is an enormous network structure with 60 million parameters and 650.000 neurons.

The rst convolutional layers filter the 224 x 224 x 3 input images with 96 kernels of size 11 x 11 x 3, with a stride of 4 pixels (this is the distance between the receptive field centers of neighboring neurons in a kernel map).The second convolutional layer takes as input the
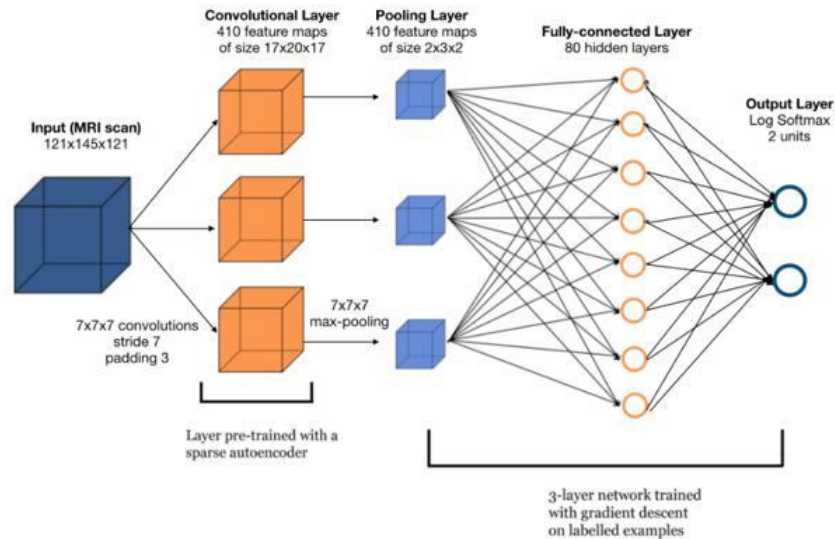
Figure 3. The Architecture of the naural network used for 2-way classi cation

(response-normalised and pooled) output of the first convolutional layer. The third, fourth, and fifth convolutional layers are connected to one another without any interventional pooling or normalisation layers. The third convolutional layer has 384 kernels which is connected to the (normalised, pooled) outputs of the second convolutional layer. The fourth convolutional layer has 384 kernels, and the fifth convolutional layer has 256 kernels. The fully-connected layers have 4096 neurons each.

3. Discusion

In this study method, we used brain images from OASIS dataset to analyze the method performance. The random datasets were marked for binary classi cation and the percentage data 75% for data training and 25% for data testing purpose. The dataset were preprocessing before through training and testing. The architecture of neural network are using Alexnet architecture with ve layer of convolution. Compare to another journal result, the study method mostly using ADNI database and LeNet or GoogleNet architecture. According to [10] used architecture of adopted LeNet and the average result for testing accuracy is 97.4%. In same study they also used architure of adopted GoogleNet and the highest result for testing accuracy is 98.84%.Other reseach by [12] used transfer learning and BellCNN got the result for nal testing accuary is 85.7%.

4. Conclusion

In this study we present a method of feature extraction from brain MR image input. The method is able to separate the white matter, grey matter, and the cerebrosipnal uid from each other.

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