Classification of Alzheimer Disease from MRI Image Using Combination Naïve Bayes and Invariant Moment

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Abstract. This study examines the classification of Alzheimer's disease. Alzheimer's is a memory disorder in an older person caused by degeneration of the central nervous system, which results in memory impairment and can cause death. Early detection of Alzheimer's can also be done based on image processing using magnetic resonance imaging (MRI) type images. Therefore, in this research, we use a feature extraction process to extract the characteristics of Alzheimer's disease that appear on MRI images using Moment Invariance and use the Naïve Bayes classification method to classify classes from images based on normal images, very mild disturbances, mild disturbances, and disturbances. Medium from brain images in the classification of Alzheimer's disease. The classification stage consists of several stages such as image acquisition, preprocessing (grayscaling), segmentation (canny edge detection, threshold), feature extraction using Invariant Moment, and image classification using Naïve Bayes. Based on the testing of the method proposed in this research, the results obtained for the accuracy of classifying Alzheimer's disease in this study are 94%.

Keywords: Alzheimers Disease, Image Processing, Invariant Moment, Naïve Bayes

1 Introduction

Memory disorders can generally be experienced by older people, and this is due to degeneration experienced by the central nervous system. The impact of this is the definition of Alzheimer's or Dementia [1]. Impaired memory, changes in personality, mood, and behavior are effects of Alzheimer's [2]. Disruption of Alzheimer's to sufferers occurs in a span of three to nine years with gradual impairment [3] .

In detecting the symptoms of Alzheimer's disease, if it is associated with the increasingly rapid technological era, it is possible to do so. For example, such as image technology based on Magnetic resonance imaging (MRI) [4]. In addition to Alzheimer's disease, in general, the use of MRI-based images is widely applied in various tasks, such as for early detection of the disease process in the body. Then detect cancer, fat, and spinal cord. Calculations based on MRI images are based on numerical calculations [5].

ICAE 2022, October 05, Batam, Indonesia

DOI 10.4108/eai.5-10-2022.2327750

As technology advances, it is possible to recognize Alzheimer's disease. One of them is the method of taking brain images using Magnetic Resonance Imaging (MRI). The results of MRI produce images that can be used to diagnose various diseases. Using an MRI image as a detector for Alzheimer's disease must first observe the characteristics of the image, and it is necessary to classify images to obtain the results of the observations.

Several related studies discuss the classification of Alzheimer's disease images, such as research by [4] regarding the detection of tumors in the brain with MRI images. In the preprocessing process, the MRI image is also extracted with GLCM to remove noise in the image. Then, the PNN method is used to classify the image. The accuracy obtained is 88.2%.

Sarraf & Tofighi in 2016 by researching the classification of the brain using MRI and fMRI (Flare Magnetic Resonance Imaging) images as datasets. The method used to process the image is the Brain Extraction Tool FSL-BET and Gaussian. In classifying, the method used is Deep Convolutional Neural Network [6] .

Research by [7] examined the detection of Alzheimer's disease using Naïve Bayes with Correlation Based Feature Selection. The test results with Naïve Bayes obtained an accuracy rate of 93.83%, while Naïve Bayes with feature selection with Correlation Based Feature Selection of 94.64%.

Research by [8] in the classification of Alzheimer's and Non-Alzheimer's uses the Fuzzy C-Mean method, feature extraction of Gray Level Co-Occurrence Matrix (GLCM), and the Support Vector Machine (SVM) method. The identification results obtained, namely, the classification, got good results with a system accuracy level of 93.33%.

From several studies that have been done and the existing problems, this study aims to classify Alzheimer's disease using MRI-based brain images using feature extraction with Invariant Moment. In contrast, classification is done using the Naïve Bayes method.

2 Methodology

The general description of this research is shown in Figure 1:

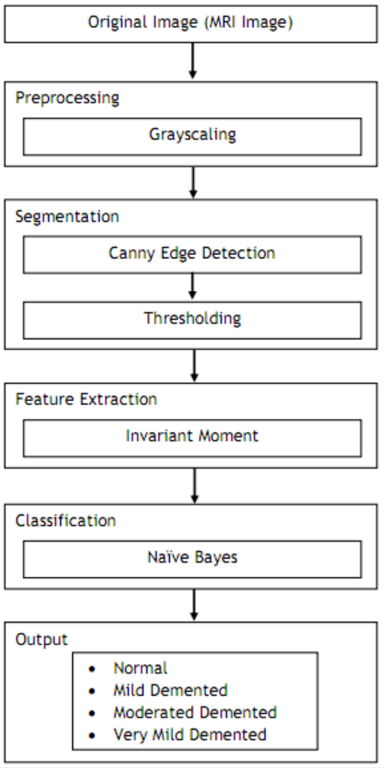


Fig. 1. Research Workflow

2.1 Image Dataset

The Magnetic Resonance Imaging (MRI) dataset of the brain used in this Alzheimer's classification study was taken from *https://www.kaggle.com/*. The number of image data is 600 images divided into 4 groups of normal brain images as many as 150, very mild demented 150, mild demented 150, and moderated demented 150 with an image resolution of 176 x 208 pixels and jpg extension.

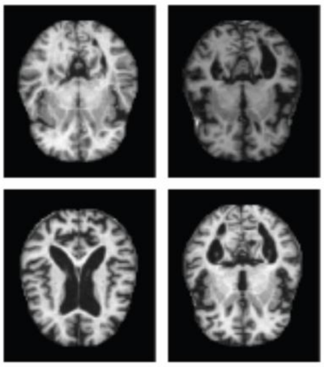


Fig. 2. MRI Based Brain Image

Then the data that has been collected is separated into two parts, the first part is training data and the second part is testing data as shown in Table 1.

Table 1. Sharing of Training and Testing Data

Image Class	Training	Testing	Amount
Normal	125	25	150
Mild Demented	125	25	150
Moderated Demented	125	25	150
Very Mild Demented	125	25	150
Jumlah	500	100	600

2.2 Preprocessing and Segmentation

Preprocessing and segmentation are carried out for image improvement so that image quality is better [9] , and can improve image classification capabilities. This study uses three stages, namely grayscaling, canny edge detection and thresholding. Grayscale aims to make the color uniformity in the image so that it has a gray value [10] , then canny edge detection gives results that match the image line points and are the results of the image edges [11] . Then thresholding aims to get the threshold value of black or white by using thresholding [12] .

1. Grayscaling

Grayscaling is a technique to change the color of the image that produces a gray image [10] . Grayscaling is used as a simplification of the color image which is divided into 3 levels, namely the red, green, and blue matrix layers to be gray. Grayscaling can be processed by finding the average value of the total number of RGB values. The process of calculating grayscale is in equation 1.

$$Grayscale = (R + G + B)/3 \tag{1}$$

The examples of grayscaling images are as shown in Figure 3:

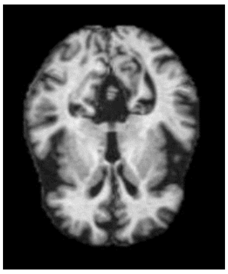


Fig. 3. Grayscaling Result Image

2. Canny Edge Detection

The next stage is canny edge detection which aims to provide results in the form of relocation of edge points of an image to be processed [13] . There are six steps to the Canny method process [14] .

Step 1: First, the image is filtered with the aim of eliminating noise using a Gaussian filter with a simple veil provided that the veil used is much smaller than the image size.

Step 2: After smoothing the image against noise, the next process is to get edge strength using the Gaussian operator. Image gradient can be calculated by the formula:

$$|G| = |G_x| + |G_y| \tag{2}$$

Step 3: Calculate the edge direction. The formula used is:

$$theta = tan^{-1}(G_x G_y) \tag{3}$$

Step 4: Associate the edge direction with an image traceable direction.

Step 5: The non-maximum removal is done along the edges and removes the pixels.

Step 6: Hysteresis process, this process removes dotted lines.

The examples of canny edge detection images are as shown in Figure 4:

Fig. 4. Image of Canny Edge Detection

3. Thresholding

The next stage is thresholding which is an image segmentation method that is useful for separating objects from the background of an image based on the difference in the threshold value of the brightness or darkness of an image pixel [12] . The thresholding calculation process can be seen in equation 4.

$$g(x,y) = \begin{cases} 1, if\ f(x,y) \geq T \\ 0, if\ f(x,y) < T \end{cases} \tag{4}$$

The examples of thresholding results images are as shown in Figure 5:

Fig. 5. Thresholding Result Image

2.3 Feature Extraction Using Invarian Moment

Feature extraction is useful for reducing the number of data sources required for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a particular analysis [15].

Invariant moment provide the properties of invariance to scale, position, and rotation [16]. The moment that transforms the image function f (x, y) is defined as [17]:

$$m_{pq} = \sum_{x=0}^{h-1} \sum_{y=0}^{w-1} x^p \, y^q f(x,y) \tag{5}$$

Where m is the moment you are looking for then p and q are integers i.e. 0.1,2, H is the image height,

W is the image width, x is the row, y is the column, and f (x, y) is the image intensity value. Furthermore, the central moment for an image is expressed in the equation 2.

$$\mu_{pq} = \sum_{x=0}^{h-1} \sum_{y=0}^{w-1} (x-\bar{x})^p \, (y-\bar{y})^q f(x,y), \tag{6}$$

$$where: \bar{x} = \frac{m_{10}}{m_{00}} \; and \; \bar{y} = \frac{m_{01}}{m_{00}}$$

After getting the values of µ20, µ02, µ30, µ03, µ12 and µ21 for each object, then to equation 2.5 normalize the value of the center moment.

$$\eta_{pq} = \frac{\mu_{pq}}{{\mu_{00}}^{y}}, where: \gamma = \frac{p+q}{2} + 1 \tag{7}$$

Then the value of the normalization of the center moment of each object will be obtained µ20, µ02, µ30, µ03, µ12 and µ21. After that, calculate with equation 3 to get 7 moment invariant values can be used for scale, position, and rotation invariant pattern identification as below [18].

$$\begin{aligned}
&\phi_1 = \eta_{20} + \eta_{02} \\
&\phi_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \\
&\phi_3 = (\eta_{30} + 3\eta_{12})^2 + (3\eta_{21} + 3\eta_{03})^2 \\
&\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
&\phi_5 = (\eta_{30} + \eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (3\eta_{21} + 3\eta_{03})^2] + \\
&\quad (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[(3\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\phi_6 = (\eta_{20} + \eta_{02})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + (4\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03}) \\
&\phi_7 = (3\eta_{21} + \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (3\eta_{21} + 3\eta_{03})^2] + \\
&\quad (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03})[(3\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{8}$$

2.4 Classification Using Naive Bayes

The next stage is the classification stage. At this stage, the Naïve Bayes will complete the classification process by finding the highest probability value based on the probabilities of all classes in the data. Naive Bayes includes a simple probability classification algorithm based on Bayes theory with solid assumptions on existing features [19] .

In general, the Naive Bayes performs well compared to other classification methods because of its simple procedure, less time complexity, small memory requirements, and good prediction accuracy. NBC can be expressed in the equation:

$$P(Ci|X) = \frac{P(X|Ci)P(Ci)}{P(X)} \tag{9}$$

Information:
C_i = Hypothesis data X
X = Data with unknown class.
$P(C_i|X)$ = Probability C_i based on condition X.
$P(X|C_i)$ = Probability X based on condition C_i.
$P(C_i)$ = Probability hypothesis C_i
$P(X)$ = Probability of data X.

2.5 Classification Evaluation

The evaluation aims to determine the level of classification accuracy of the test data. Several standard measurements are used to measure classification with two class labels: True Positive Rate, False Positive Rate, True Negative Rate, and False Negative Rate.

This research will use the Confusion Matrix, which is a concept that has data with the actual classification and prediction results of a classification that has been carried out by the classification method.

Table 2. Table of Confusion Matrix

		True Values	
		True	*False*
Prediction	*True*	TP	FP
		Correct Result	*Unexpected Result*
	False	FN	TN
		Missing Result	*Correct Absence of Result*

Then based on Table 2, some of the terms known in the *Confusion Matrix* are as follows [20]:

1. *True Positive* (TP): Recognized positive data Correct.
2. *False Positive* (FP): Negative data but correctly recognized.
3. *False Negative* (FN) is positive data that is recognized as negative data.
4. *True Negative* (TN) is negative data that is recognized as true.

Confusion Matrix parameters are *Accuracy, Recall, Precision,* and *F-Measure*. The formula for determining *Accuracy, Precision, Recall,* and *F-Measure based on the Confusion Matrix* Table.

$$Accuracy = \frac{TP+TN}{n} \quad (12)$$

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

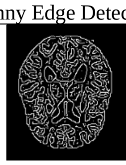
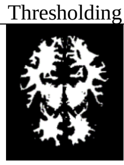
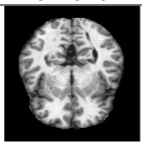
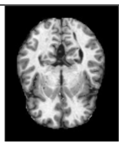
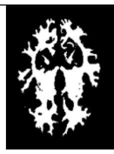
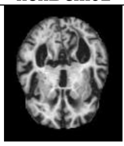
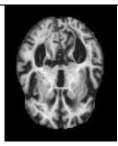
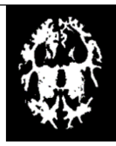
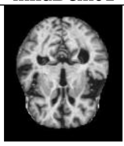
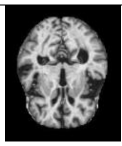
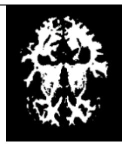
$$F-Measure = 2 * \frac{Precision * Recall}{Precision * Recall} \quad (15)$$

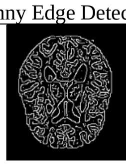
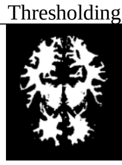
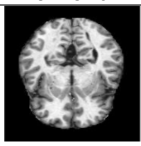
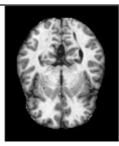
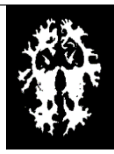
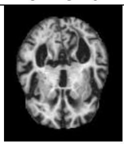
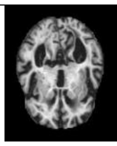
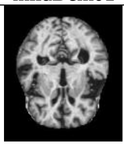
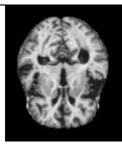
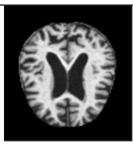
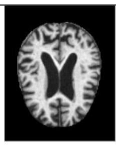
3 Results and Discussion

3.1 Preprocessing Dataset

In this section, the testing process on the test data will be carried out. The testing process is carried out using 25 normal images, 25 mild demented images, 25 moderated demented images, and 25 very mild demented images. The process begins with preprocessing and segmentation first. In Table 3, the following shows the results of preprocessing and segmentation of the 100 specified test data:

Table 3. Preprocessing Results

No.	Original Image	Grayscaling	Canny Edge Detection	Thresholding
1.	 nonDem01			
2.	 nonDem02			
3.	 mildDem01			
4.	 mildDem02			
⋮	⋮	⋮	⋮	⋮

No.	Original Image	Grayscaling	Canny Edge Detection	Thresholding
1.	 nonDem01			
2.	 nonDem02			
3.	 mildDem01			
4.	 mildDem02			
⋮ ⋮ ⋮	⋮ ⋮ ⋮	⋮ ⋮ ⋮	⋮ ⋮ ⋮	⋮ ⋮ ⋮
100.	 verymildDem05			

3.2 Results of Classification

Then after the preprocessing process, the next step is testing feature extraction using Invariant moment calculations and image classification processes using Naïve Bayes calculations to obtain the most significant probability value from all dataset classes. In the following Table 4 shows the classification results of the 100 specified image test data:

Table 4. Testing Data Results

No.	Image Name	Invariant Moment	Desired Output	Actual Output
1.	nonDem01	$\phi_{1=}$-1.25041 $\phi_{2=}$-0.68914 $\phi_{3=}$-0.23842 $\phi_{4=}$-0.27042 $\phi_{5=}$1.23793 $\phi_{6=}$0.21893 $\phi_{7=}$1.207921	Normal	Normal

2.	nonDem02	$\phi_{1=}$-1.36044 $\phi_{2=}$-0.69613 $\phi_{3=}$-0.26425 $\phi_{4=}$-0.24057 $\phi_{5=}$1.29369 $\phi_{6=}$0.23554 $\phi_{7=}$1.209032	Normal	Mild Demented
3.	mildDem01	$\phi_{1=}$-1.47051 $\phi_{2=}$-0.79812 $\phi_{3=}$-0.26545 $\phi_{4=}$-0.28054 $\phi_{5=}$1.20479 $\phi_{6=}$0.29928 $\phi_{7=}$1.223039	Mild Demeted	Mild Demeted
4.	mildDem02	$\phi_{1=}$-1.45351 $\phi_{2=}$-0.78112 $\phi_{3=}$-0.27245 $\phi_{4=}$-0.27854 $\phi_{5=}$1.28469 $\phi_{6=}$0.25958 $\phi_{7=}$1.213939	Mild Demeted	Mild Demeted
⋮	⋮	⋮	⋮	⋮
100.	verymildDem05	$\phi_{1=}$-1.35032 $\phi_{2=}$-0.71903 $\phi_{3=}$-0.26339 $\phi_{4=}$-0.24228 $\phi_{5=}$1.232123 $\phi_{6=}$0.24974 $\phi_{7=}$1.234539	Very Mild Demented	Very Mild Demented

Then an evaluation measurement is carried out from the results of the classification test on 100 testing datasets that have been carried out based on the Confusion Matrix evaluation and the results are in Table 5 and Table 6:

Table 5. Results Of Testing Classification

Index	Amount
True Positive (TP)	85
True Negative (TN)	9
False Positive (FP)	3
False Negative (FN)	3

Table 6. Calculation of Confusion Matrix

Index	Formula	Results
Accuracy	$\frac{TP+TN}{n}$	$\frac{85+9}{100}=\frac{94}{100}=0.94$
Precision	$\frac{TP}{TP+FP}$	$\frac{85}{85+3}=\frac{85}{88}=0.966$
Recall	$\frac{TP}{TP+FN}$	$\frac{85}{85+3}=\frac{85}{88}=0.966$
F-Measure	$2*\frac{Precision*Recall}{Precision*Recall}$	$\frac{85}{85+3}=\frac{85}{88}=0.966$

4 Conclusion

Based on the tests carried out using the proposed method, the classification of Alzheimer's disease using Invariant Moment feature extraction and Naïve Bayes classification obtained the best results with an accuracy value of 94%. Based on the results obtained, it can be concluded that this method is very suitable for the identification of Alzheimer's disease.

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