STROKE SEVERITY ANALYSIS THROUGH CT-SCAN IMAGE TEXTURE ANALYSIS OF THE BRAIN WITH GRAY LEVEL RUN LENGTH MATRIX METHOD

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ABSTRACT

The condition of a stroke is when the blood supply to the brain is disrupted due to a blockage (ischemic stroke) or rupture of a blood vessel (hemorrhagic stroke). This condition causes certain areas of the brain to be deprived of the supply of oxygen and nutrients resulting in the death of brain cells. This study aims to determine the process of ischemic stroke assistance and hemorrhagic analysis through CT Scan image texture GLRLM brain method with the classification method using discriminant analysis and determine the level of accuracy. In this study there are 3 stages, namely preprocessing, learning stages and testing stages. The results of the assessment of stroke in the ischemic and hemorrhagic categories through texture analysis of CT scan images using the GLRLM brain method with a classification accuracy of 100%.

Keywords: Stroke; CT-Scan; Texture; GLRLM

Introduction

One of the causes of stroke is an unhealthy lifestyle. Almost all sources of disease come from an unhealthy lifestyle. Such as stroke which can arise due to blockages in blood vessels due to the accumulation of too much fat that is consumed daily.

In Islam, it is taught to maintain health to avoid various diseases. These include not overeating, not eating before you are hungry, avoiding Haram food, not drinking alcohol, fasting often, not sleeping on your stomach, maintaining environmental cleanliness, and maintaining body cleanliness.

Stroke is a major cause of mortality and high morbidity in causing disability and death in many countries, globally 5.5 million people die from strokes each year, in addition to more than 13.7 million new strokes each year and one in four over the age of 25 of them will have a stroke.[1]

Stroke is quite a serious problem because stroke is a medical emergency that can threaten disability and death in patients if it is not handled quickly and appropriately. In stroke, neuroimaging always plays an important role in the diagnosis of stroke, the majority of stroke patients undergo examination using Computerized Tomograph Scanning (CT scan) radiology modalities. However, the CT scan image results for each patient vary according to the amount of time that has passed since the stroke onset. So that a radiologist plays a major role in the management of stroke patients so that knowledge of the patient's radiological picture will determine the treatment that the patient will undergo.[2]

Stroke causes a reduction or stoppage of blood flow which results in the death of brain cells. Based on the cause, stroke is divided into two, namely ischemic stroke where the blood supply stops flowing to the brain due to a blockage and hemorrhagic stroke where bleeding occurs in the brain tissue.[3]

Accurate diagnosis is very important before stroke treatment begins, because

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treatment for stroke differs according to the type of stroke. If the patient fails to receive prompt and appropriate treatment, a stroke will have serious consequences and cause permanent brain damage to the patient's death. Treatment and diagnosis of stroke is carried out by clinical examination, then followed by examining radiological modalities such as a CT scan.[4]

Computed Tomography Scanning (CT-Scan) is a diagnostic support tool that has universal application for examination of organs such as the central nervous system, muscles, bones, throat to the abdominal cavity.[5] Reading the CT-scan images of the brain requires high accuracy to be precise in providing stroke care.

Texture analysis of CT-scan images of the brain is often used to diagnose disease. Structured analysis with statistics which includes the mean, standard deviation, variance extracted from object characteristics in the image can show the condition of healthy and diseased brains by comparing the respective statistical values of healthy images and images that detect abnormalities.[6]

Texture analysis with parameters of contrast, correlation, energy, homogeneity to differentiate the texture of brain tumor and normal images so as to produce a gold standard value based on the existing texture features. Training and testing of texture features using the backpropagation method of artificial neural networks classification accuracy of 96.55%.[7]

Research by analyzing CT scan images of lung cancer using the Grey Level Run Length Matrix (GLCM) texture feature extraction method and morphological features using a backpropagation neural network resulted in a classification accuracy of 98.83%.[8] Research by extracting CT-scan image features of the brain using ANN backpropagation resulted in a classification accuracy of 70%.[9]

In this study, texture feature extraction of brain CT scan images was performed to identify ischemic stroke and hemorrhagic stroke.

Methods

Materials and tools in this study were head CT scan image data for the stroke category of 51 ct scan images from PhysioNet under the supervision of the MIT Laboratory for Computational Physiology and image analysis using MATLAB software.

The research sample in this study consisted of 26 CT scan images of the head in the ischemic category (a type of stroke that occurs when blood flow to the arteries in the brain is blocked) and 25 CT scan images of the head in the category of hemorrhagic stroke (a type of stroke due to rupture of blood vessels in the brain area).

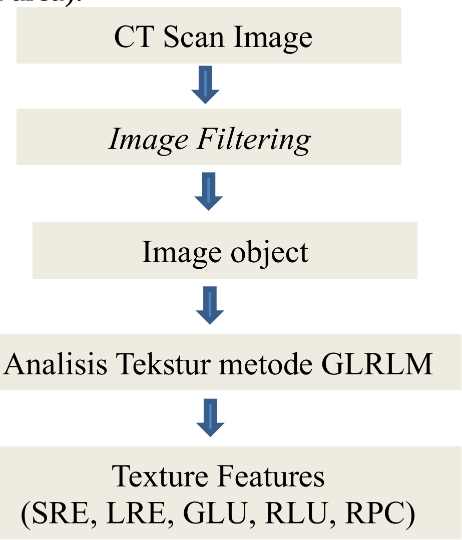

Figure 1. GLRLM method texture feature extraction step

Figure 1 illustrates the steps of texture feature extraction using the GLRLM method. The research steps were carried out in the following steps: 1) Preprocessing CT Scan images of the brain. 2) The main step in the GLRLM method is to take the normalized grayscale matrix values. Matrix values are used to find feature values in GLRLM, namely Short Run Emphasis (SRE), Long Run Emphasis (LRE), Gray-Level Nonuniformity (GLN), Run Length Nonuniformity (RLN), Run Percentage (RP), Low Gray-Level Run Emphasis (LGRE), High Gray-Level Run Emphasis (HGRE). 3) From the characteristics obtained, discriminant analysis is used to be able to see which features can distinguish CT scan images of the head from ischemic stroke and heragic stroke categories.

Schematically, the steps for texture feature extraction using the GLRLM method can be described as shown in Figure 1. After obtaining the textural features, we will proceed with classifying the CT scan images into two groups (ischemic group and hemorrhagic group) using discriminant analysis. With discriminant analysis, which features of the image texture will be obtained that differentiate between normal and those with stroke.

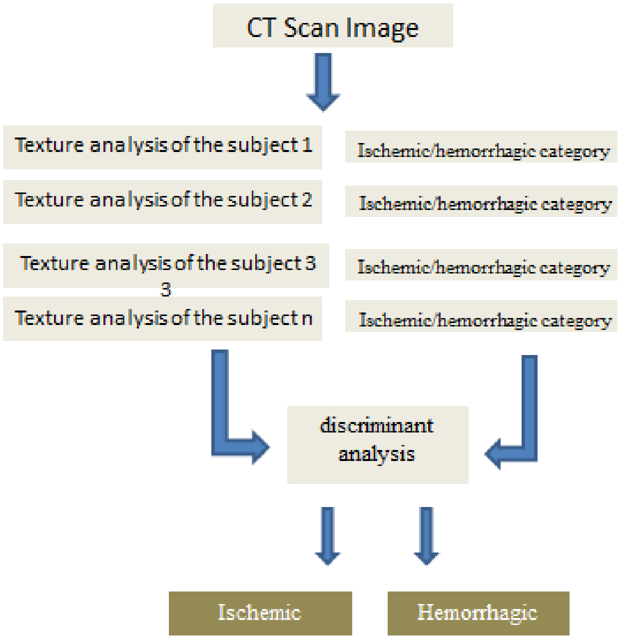

Figure 2. Discriminant analysis of image texture features

Figure 2 represents the discriminant analysis of image texture features. This analysis is a method used to differentiate or classify images based on their texture features, which include patterns, intensity distributions, and other characteristics found within the images. In this analysis, the image processing technique used to extract these features is the GLRLM method. After these features are extracted, discriminant analysis is conducted to identify patterns that differentiate between different classes of images, such as images with diseases and images without diseases, or images with different types of diseases. The results of this analysis can be used to support medical diagnoses or decision-making in various applications, such as medical diagnosis, environmental monitoring, or pattern recognition.

Result and Discussion

Data were 26 head CT scan images in the ischemic category (a type of stroke that occurs when blood flow to the arteries in the brain is blocked) and 25 head CT scan images in the hemorrhagic stroke category (a type of stroke due to rupture of blood vessels in the brain area).

Table 1. CT Scan Image Data

Status	Amount
Ischemic	26
Hemorrhagic	25

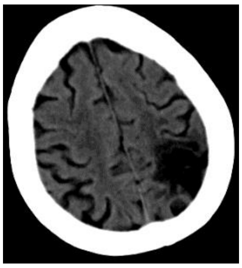

Figure 3. Example of a brain CT scan image of the ischemic category

Figure 3 presents an example of a brain CT scan image from the ischemic category, which is one of the serious conditions affecting blood flow to the brain. In this image, areas affected by reduced blood supply can be observed, which may lead to damage to brain tissue. By utilizing imaging technologies such as CT scans, doctors can better identify and analyze this ischemic condition, thereby aiding in treatment planning and management of patients with this brain blood flow disorder. The texture analysis using the GLRLM method on the CT scan image of the sample yields the results presented in Table 2.

Furthermore, from the texture feature data, discriminant analysis was carried out with the help of SPSS. Table 3 reveals variations in SRE, LRE, RLN, RP, LGRE, and HGRE values between the ischemic and hemorrhagic groups. These differences indicate their potential utility in classifying or detecting ischemic and hemorrhagic conditions.

In the advanced discriminant analysis, there are 6 characteristics, namely SRE, LRE, GLN, RLN, LGRE, and HGRE which are continued in the analysis. So we get the discriminant function,

Score = -254,133 + 370,849(SRE) – 0,541(LRE) + 0,0001(GLN) + 0, 0001(RLN) – 48,606 **(**LGRE**)** – 3,854 (HGRE)

Next calculate the Cut off score (Zcu) using the formula

$$Z_{cu} = \frac{N_A Z_B + N_B Z_A}{N_A + N_B}$$

So that the value of Zcv = 1.0786 is obtained

Table 2. Results of brain CT scan image texture analysis

No	SRE	LRE	GLN	RLN	RP	LGRE	HGRE	Status
1	0.859	86.314	3715983	6468567	0.196	0.0139	29.6298	Ischemic
2	0.8869	70.672	4552935	6290821	0.1546	0.0544	33.17	Ischemic
3	0.8657	83.825	3817981	6449234	0.1658	0.0479	30.241	Ischemic
4	0.9166	52.484	4920039	6402406	0.1479	0.0393	34.863	Ischemic
5	0.8784	73.223	4443162	6270147	0.1575	0.0607	32.414	Ischemic
6	0.8955	76.877	3253138	5266492	0.1587	0.0079	19.781	Hemorrhagic
7	0.8817	85.712	2979347	5314688	0.1646	0.0058	18.788	Hemorrhagic
8	0.786	146.897	1938389	5976711	0.2212	0.0259	13.572	Hemorrhagic
9	0.8851	83.563	2966916	5302156	0.1631	0.0135	18.631	Hemorrhagic
10	0.904	71.415	3532358	5240881	0.1533	0.0249	20.385	Hemorrhagic
Etc..								

Table 3. Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SRE	.783	13.553	1	49	.001
LRE	.905	5.167	1	49	.027
GLN	.999	.035	1	49	.853
RLN	.195	202.889	1	49	.000
RP	.850	8.670	1	49	.005
LGRE	.678	23.306	1	49	.000
HGRE	.617	30.425	1	49	.000

Table 4. Canonical Discriminant Function Coefficients

	Function
	1
SRE	370.849
LRE	.541
GLN	.000
RLN	.000
LGRE	-48.606
HGRE	-3.854
(Constant)	-254.133

Unstandardized coefficients

Table 5. Functions at Group Centroids

Status	Function
	1
1	26.954
2	-28.033

Unstandardized canonical discriminant functions evaluated at group means

Pattern identification using GLRLM involves several systematic steps. Firstly, the input image is processed to ensure its consistency and quality. Next, the image is converted to grayscale to enable more accurate texture analysis. The subsequent step involves selecting the direction and distance for GLRLM, followed by the computation of GLRLM matrices that yield the number of pixel runs with the same intensity in each direction and distance. These GLRLM matrices are then normalized to ensure consistency in texture features. Various texture features, such as Short Run Emphasis (SRE), Long Run Emphasis (LRE), and Run Length Non-uniformity (RLN), are extracted from the normalized matrices. These features are subsequently used in discriminant analysis to identify patterns or different classes within the image. The classification results show that the prediction accuracy is 100%, this indicates high accuracy. So that the characteristics of SRE, LRE, GLN, RLN, LGRE, and HGRE which are texture feature extraction can be used to detect or differentiate between ischemic and hemorrhagic strokes on brain CT-scan images.

Table 6. Classification Results[b,c]

		Status	**Predicted Group Membership**		**Total**
			1	2	
Original	Count	1	26	0	26
		2	0	25	25
	%	1	100.0	.0	100.0
		2	.0	100.0	100.0
Cross-validated[a]	Count	1	26	0	26
		2	0	25	25
	%	1	100.0	.0	100.0
		2	.0	100.0	100.0

a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b. 100.0% of original grouped cases correctly classified.

c. 100.0% of cross-validated grouped cases correctly classified.

In this study, texture analysis of brain CT-scan images using the GLRLM method provides insights into stroke severity. By referring to the data obtained from CT-scan images of stroke patients' brains, texture patterns associated with the severity of stroke can be identified. The analysis results show significant variations in texture features among CT-scan images of patients with mild, moderate, and severe strokes. For example, there is a significant increase in the SRE (Short Run Emphasis) value and a decrease in the LRE (Long Run Emphasis) value with increasing stroke severity. These findings indicate that texture analysis using the GLRLM method can be a useful tool in objectively evaluating stroke severity and assisting doctors in planning appropriate treatment. By employing this approach, a positive contribution to the understanding and management of stroke can be made more effectively.

Texture features are important features in an image that show information on the surface structure of an image.[10] Texture is a characteristic that contains values for the level of roughness, granularity, and regularity of the arrangement of pixels.[11] Image data taken panoramically can then be processed statistically through its texture. Texture is understood as a pattern of pixels of gray intensity in a certain direction starting from a reference pixel (PoI). Texture analysis focuses on spatial complexity and heterogeneity of grayscale patterns through high-level graylevel statistics that can be calculated through programming languages.

Run is a term used to indicate a pixel search sequence that has the same intensity value as the straight direction of the original pixel.[12] while run length is the number of adjacent pixels that are skipped from the original pixel (PoI) and have gray intensity. -the same gray in a certain direction. So that GLRLM is a high-order texture extraction method using the run-length concept in order to obtain statistical characteristics of pixels with the same gray value.[13] GLRLM is a two-dimensional matrix where each element $(i,|\theta)$ contains the number of run-length j, with the intensity of the gray level i, in the direction of orientation θ. GLRLM has four different orientation angles that are commonly used, namely 0°, 45°, 90° and 135°.

From the results of the discriminant analysis, the texture features of SRE can be used to differentiate ischemic and hemorrhagic CT scan images. Table 2 shows that SRE has a small value for coarse textures and a large value for fine textures. SRE states the number of textures with short paths in an image in a certain direction. Smoother textures tend to have more short runs with similar gray intensities.[14] The finer the image, the greater the SRE value.

The texture features of the LRE can also be used to differentiate CT scan images of ischemic and hemorrhagic strokes. LRE depends on the long run distribution. LRE has a large value for coarse textures and small values for fine textures. LRE states the number of textures with long paths in an image in a certain direction.[15] Coarse textures tend to have more long runs with significantly different gray levels. The coarser the image, the higher the LRE value.

GLN texture features can also be used to differentiate CT scan images of ischemic and hemorrhagic strokes. GLN measures the similarity of the gray level values in all images and has a small value if the gray level values are the same in all images.[16,17] The lower GLN indicates the similarity of the higher intensity values in the image at each pixel.

The texture features of RLN can also be used to differentiate CT scan images of ischemic and hemorrhagic strokes. RLN measures the similarity of run lengths across all images and has a small value if the run lengths are evenly distributed throughout the image.

The texture features of LGRE can also be used to differentiate CT scan images of ischemic and hemorrhagic strokes. LGRE measures the distribution of low gray level values which will be of great value for images with low gray levels. The texture features of HGRE can also be used to differentiate CT scan images of ischemic and hemorrhagic strokes. HGRE measures the distribution of high gray level values, which will be of great value for images with high gray level values.

Conclusion

Texture analysis of the GLRLM method of brain CT scan images can be used as a method for identifying ischemic and hemorrhagic stroke categories with a classification accuracy of 100%. The texture features used are SRE, LRE, GLN, RLN, LGRE, and HGRE.

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