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Quantification of hepatic fat level using gray level co-occurrence matrix (GLCM) and extreme learning machine (ELM) methods in ultrasonography image (USG)

Rahmat Fitriansyah[1], Hermina Sukmaningtyas[2], M. Irwan Katili[3]

[1]*Postgraduate Program Master of Applied Imaging Diagnostic, Semarang Health Polytechnic, Indonesia*
[2]*Dr. Kariadi Hospital Semarang, Indonesia*
[3]*Department of Radiodiagnostic and Radioteraphy Technic, Semarang Health Polytechnic Indonesia*
***Corresponding Author**: **Rahmat Fitriansyah**
Email id: rahmatfitriansyahsst@gmail.com

ABSTRACT

Ultrasonography (USG) is one of the alternative modalities used to avoid biopsies in evaluating Non-alcoholic Fatty Liver Disease (NAFLD). But having weaknesses is subjective and the results of the examination are very dependent on the ability, expertise, skills and experience of the operator. The application program of the GLCM and ELM methods provides a second opinion and increases the operator's subjectivity in interpreting the results of the ultrasound examination. Analyze the ability of the GLCM and ELM methods in the compatibility of fatty liver levels in ultrasound images, with indicators of sensitivity values, specificity and accuracy of the application program.

This study used a retrospective sample conducted at Semarang Medical Center (SMC) in Telogorejo Hospital, Semarang. The research test samples were 108 then carried out a diagnostic test to determine the sensitivity, specificity and accuracy of the application program.

Based on the diagnostic test obtained a high sensitivity value. At normal there are 93%, grade 1 is 74%, grade 2 is 78%, and grade 3 is 85%. Specificity of normal fatty liver is 100%, grade 1 is 98%, grade 2 is 86%, grade 3 is 93%. Normal accuracy is 98%, grade 1 is 92%, grade 2 is 84%, grade 3 is 91%..

The GLCM and ELM methods are good at detecting fatty liver levels in ultrasound images.

Keywords: *Fatty Liver, NAFLD, GLCM, ELM.*

INTRODUCTION

Non-alcoholic Fatty Liver Disease (NAFLD) is rapidly becoming a more common liver disease throughout the world. The prevalence of NAFLD in the general population of European countries is 20-30%. About 2-3% of these general participants are estimated to have non-alcoholic steatohepatitis (NASH), which can progress to cirrhosis of the liver and hepatocarcinoma. The prevalence of NAFLD is higher in males and increases with age and population characteristics, especially lifestyle habits. [1]

Obesity is a major risk factor for metabolic disorders of NAFLD, [2] Obese children and adolescents in the world are experiencing an increase in the incidence (22.5% -52.8%). Twenty percent of children and adolescents are obese in the United States, 44% in Italy and 74% in China. This disease is associated with type 2 diabetes mellitus. [3, 4] NAFLD covers several degrees of disease ranging from mild steatosis to Non-Alcoholic Steato Hepatitis (NASH) which can cause advanced fibrosis, cirrhosis, even hepatocellular carcinoma. [4, 5]

Reportedly an increase in Non-alcoholic Fatty Liver Disease (NAFLD) in several Asian countries, this is triggered a significant increase in the obese population. NAFLD in Japan in 1988 was around 9% -14% and experienced a significant increase in the last two decades along with an increase in obesity population. In the State of India about 5% - 28%, [6] in China there is a prevalence of 15% in the general population using ultrasound of the liver which is estimated to increase twice as the population of obesity increases. [7] In Indonesia, a study based on the general population has not yet been conducted, Hasan's study of the urban population has obtained a 30% prevalence using liver ultrasound. [8]

Liver biopsy remains the gold standard in diagnosing NAFLD, [9] but has a risk of bleeding in patients.[10] The clinical importance of NAFLD and the limitations of liver biopsy require further accurate and non-invasive imaging methods to evaluate NAFLD. To date, various imaging methods have been used to evaluate patients with NAFLD, including computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance spectroscopy (MRS), fibroscan and Ultrasonography (USG). [11]

Histopathological fatty liver levels were assessed by measuring macro vesicular steatosis and necro-inflammatory activity. Fatty liver level 1 has a maximal macro vesicular steatosis value of 33%, necro-inflammatory activity value ≤ 66%, found ballooning in zone 3, sporadic acinar neutrophils lymphocytes, minimal inflammation of the port. Fatty liver level 2 has a macro-vesicular steatosis value of 33% - 66%, necro-inflammatory activity value> 66%, zone 3 swelling and a slight presinusoidal fibrosis, intra-acinar PMN, swelling in the portal and intra-acinar. Fatty liver level 3 has macro vesicular steatosis value> 66%, Pan-acinar steatosis is widely distributed with Poly Morphonuclear Neutrophil (PMN), intra-acinar and portal swelling. [12]

Fibroscan is a non-invasive method that is able to evaluate fibrosis in the liver through ultrasonographic elastography. The probe, which is composed of an ultrasound transducer attached to the vibrator axis, produces mechanical impulses in the skin, inducing elastic shear waves that travel through the heart. Fibroscan has a relatively high cost compared to ultrasound of the liver and is rarely found in general hospitals. [13]

Ultrasonography (USG) is one of the modalities used to evaluate NAFLD, the advantage of evaluating using USG is that it is widely available in health care facilities, is easy to do, is cheaper. Besides having the advantage of ultrasonography also has disadvantages, has limitations in diagnosing fatty liver in grade 1 (mild), it is difficult to diagnose fatty liver in cases of Asites and Chronic Kidney Disease (CKD) because in that case there is also an increase in ecogenicity of the liver parenchyma and renal cortex. Another weakness is that the examination is operator dependent, meaning that the results of the ultrasound examination are highly dependent on the ability, expertise and skill of the operator conducting the examination. Retrieval techniques, ultrasound imagery, tissue texture and the experience of radiology specialists influence the results of interpretation of fatty grading of the liver so that the interpretation results are often subjective and often lead to diverse interpretations between radiology specialists. [11, 14]

Evaluation of fatty liver in ultrasonographic modalities usually consists of a qualitative visual assessment of liver ecogenicity, measurement of differences in ecogenicity between the liver and kidney, evaluation of echo penetration into the liver, and determination of clarity of the structure of blood vessels in the liver. The degree of fatty liver is usually judged by its ecogenicity. It is normal if the liver parenchyma has homogeneous echotexture, with the same ecogenicity as the normal renal cortex. Grade 1 Increased diffuse ecogenicity of the liver parenchyma compared to the renal cortex, but intra-hepatic blood vessels are still visualized normally. Grade 2 Increased moderate diffuse ecogenesits of the liver parenchyma compared to the renal cortex, with visualization of slightly blurred intrahepatic vessels. Grade 3 Increased ecogenicity of the liver parenchyma markedly compared to the renal cortex, with difficulty visualizing the portal vein wall and diaphragm. [15, 16] One alternative to overcome these shortcomings is with digital image processing technology. [17] In this research, image processing used is the application program creation in matlab using the Gray level Co-occurrence Matrix (GLCM) and Extreme Learning Machine (ELM) method in quantifying the degree of fatty tissue by extracting Ultrasonographic image characteristics (USG) using GLCM and the classification is carried out by ELM, as an objective additional information provider to improve diagnosis accuracy and avoid unnecessary biopsies, but does not replace the role of the doctor in diagnosis. [18]

Digital image processing in the last few decades there has been a rapid increase in research. Many researchers have published the latest theoretical and technological achievements in mathematical methods and various technical applications related to digital image processing. Examples are biomedical / nerve analysis, image transmission over wireless networks, 3-dimensional image processing, feature extraction and analysis, image capture, motion detection, display systems, imaging, image encoding and others. [19] Gray Level Co-occurrence Matrix (GLCM) and Extreme Learning Machine (ELM) are one of the digital image processing methods that are often studied.

The Gray Level Co-occurrence Matrix (GLCM) method is a method that carries out an analysis of a pixel in an image and knows the gray level that often occurs. [20] This method is also for tabulation of the frequency combinations of pixel values that appear in an image. To analyze the image based on the statistical distribution of the pixel intensity, it can be done by extracting the texture features. [21] Gray Level Co-occurrence Matrix (GLCM) is a method for statistical based feature extraction, the acquisition of features is obtained from the matrix pixel value, which has a certain value and forms a pattern angle. [20]

Classification based on information systems is a technique of classifying data into one or several classes that have been previously defined. One classification technique that can be used is Extreme Learning Machine (ELM). Extreme Learning Machine (ELM) is a method of learning single-hidden layer feedforward network (non-parametric SLFN). In theory, this method is able to generalize very well in a very fast time compared to the Support Vector Machine (SVM) and Backpropagation methods. [22]

Previous studies have successfully distinguished the severity of NAFLD from normal liver which has a relationship with significant metabolic factors. They use extraction of 3 texture features, namely: autocorrelation, sum-average and sum-variance, signal to noise ratio, and slope of the center frequency downshift (CFDS slope). [23] In addition, previous studies have also succeeded in distinguishing normal and abnormal fatty liver with an accuracy rate of 96.75% using the classification of the Extreme Learning Machine (ELM) method. [24]

Based on the background described above, researchers are interested in conducting research on image processing techniques using the gray level co-occurrence matrix (GLCM) method and Extreme Learning Machine (ELM) in determining the degree of degree of fatty liver in the ultrasound image of the liver quantitatively.

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METHOD

Type and Design of Research

This study used a retrospective sample using a diagnostic test design by comparing the results of the interpretation of USG images using the GLCM and ELM methods with the results of interpretations by radiology specialists as the gold standard.

Population and Samples

The target population of this study were patients who performed an abdominal ultrasound examination at Semarang Medical Senter (SMC) Telogorejo Hospital, Semarang.

DATA ANALYSIS

The data obtained is collected and then checked the completeness and correctness of the data. The test results are in the form of a category of degrees of fatty liver through the reliability test (Kappa) which is at the level of "excelent agreement". Then followed by the analysis of the Diagnostic Test used to explain the calculation of sensitivity, specificity and diagnostic accuracy values. [25] The diagnostic study conducted was an analysis of the level of fatty liver using the GLCM and ELM method matlab program which was then matched with the doctor's interpretation as the gold standard. The Diagnostic Test Table is shown in table 1.

Tabel 1. Diagnostic Test Table

Interpretation of the GLCM and ELM Methods	Doctor's Interpretation (Gold Standard)		Total
	Positive	Negative	
Positive	a	b	a+b
Negative	c	d	c+d
Total	a+c	b+d	a+b+c+d

Note

a. Interpretation of positive image of fatty liver (grade.1, 2, 3) and Interpretation of Doctor positive fatty liver (grade.1, 2, 3)
b. Interpretation of positive image of fatty liver (grade.1, 2, 3 and normal) and Doctor's interpretation of negative fatty liver (grade.1, 2, 3 and normal)
c. Interpretation of negative images of fatty liver (normal) and Doctor's interpretation of positive fatty hearts (grade.1, 2, 3)
d. Interpretation of negative images of fatty liver (grades.1, 2, 3 and normal) and Doctor's interpretation of negative fatty hearts (grades.1, 2, 3 and normal)

In diagnostic tests, there are several things that can be determined [26]:

Sensitivity

Sensitivity shows the ability of diagnostic tools (in this study the GLCM method for texture and ELM for artificial nerves in detecting fatty liver (in each grade, namely grade 1, grade 2 and grade 3). Sensitivity is determined by the following formula:

$$Sensitivitas = \frac{a}{a+c} \times 100\%$$

Sensitivity

Specificity

Specificity shows the ability of diagnostic tools (in this study the GLCM method for texture and ELM for artificial nerves, determining that a subject is not sick (in this study patients who did not suffer from fatty liver in each grade, namely grade 1, grade 2 and grdae 3).

$$Spesifitas = \frac{d}{b+d} \times 100\%$$

Specifivity

Accuracy

Accuracy shows the ability of diagnostic tools (in this study the GLCM and ELM methods to correctly determine the degree of fatty liver of a subject (ultrasound image).

$$Akurasi = \frac{a+d}{a+b+c+d} \times 100\%$$

Accuracy

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RESULTS

This study aims to examine the application program in diagnosing the level of fatty liver whether it is in accordance with the interpretation of a radiology specialist. Through this diagnostic test will be known the level of sensitivity, specificity and accuracy of the application program. The results of the recapitulation of the suitability of the interpretation between the doctor and the application program, from the level of fatty liver are shown in table 2.

Tabel 2. The recapitulation results of the suitability of interpretation

Doctor's Interpretation	Application Program				
	Normal	Grade I	Grade II	Grade III	False -
Normal	25	2	0	0	2
Grade I	0	20	7	0	7
Grade II	0	0	21	6	6
Grade III	0	0	4	23	4
False +	0	2	11	6	

The following is a recapitulation of the appropriateness of interpretations between doctors and application programs, from the level of fatty liver for each grade:

Normal

		Medical specialist	
		Normal	**Not normal**
Application	Normal	25	0
	Not Normal	2	81

Accuracy = 98%; Sensitivity = 93%; Specificity = 100%; PPV = 100%; NPV = 98%.

Grade1

		Medical specialist	
		Grade 1	**Not Grade 1**
Application	Grade 1	20	2
	Not Grade 1	7	79

Accuracy = 92%; Sensitivity = 74%; Specificity = 98%; PPV = 91%; NPV = 98%.

Grade 2

		Medical specialist	
		Grade 2	Not Grade 2
Application	Grade 2	21	11
	Bukan Grade 2	6	70

Accuracy = 84%; Sensitivity = 78%; Specificity = 86%; PPV = 66%; NPV = 92%.

Grade 3

		Medical specialist	
		Grade 3	Not Grade 3
Application	Grade 3	21	6
	Bukan Grade 3	4	77

Accuracy = 91%; Sensitivity = 85%; Specificity = 93%; PPV = 79%; NPV = 95%.

ALL CASEs	Total	FP	FN	TP & TN all cases	overall accuracy (TP+TN) / total	sensitivity = TP / (TP + FN)	specificity = TN / (FP + TN)
	108	19	19	89	82%	82%	82%

DISCUSSION

Quantification of degree of fatty liver study using GLCM and ELM methods on USG images was done by retrospective Gray level co-occurrence matrix (GLCM) is a matrix that describes the frequency of appearance of two pixel pairs with a certain intensity in distance (d) and has a direction orientation with certain angle (θ) in an image, image extraction is obtained from the value of energy, contrast, correlation and homogeneity [27]. ELM serves to classify, this method leaves the traditional algorithm that adjusts all network parameters iteratively, but determines the weight between hidden neurons and neuron output from a single hidden layer analytically. ELM parameters such as input weight and hidden neuron bias are chosen randomly, so ELM has a fast learning time and is able to produce high accuracy even with large amounts of data. [28]

The ability of the application to detect fatty liver grade is carried out by several processes ranging from the application of the GLCM extraction method to the application of ELM for classification. GLCM is based on a suitable second order texture and statistics method, this is in accordance with research conducted by Dulce. GLCM is stated to be able to offer an appropriate method for characterizing the statistical distribution of grayscale values in the case of liver texture patterns, this is because GLCM can provide relevant information about pixel-to-pixel relationships, periodicity, and spatial gray level dependencies. [29]

ELM trains Single Layer Feed Forward Neural Network (SLFFNN) where the weight of the input-to-hidden layer is initialized randomly. ELM only trains the hidden-to-output layer weights using the smallest square loss model that uses the closed-form solution provided by Moore-Penrose pseudo-inverse. In the simplest sense, errors are minimized and tend to prove more accurate or at least comparable to iterative neural network models. This capability is proven to be able to display high suitability (not significantly different) and provide fast classification access. This was stated by researchers before, [24] where with SVM as a comparison, ELM is superior with classification 40% faster than using the SVM method.

This application program begins with a process of introducing the characteristics of ultrasound images of the liver with fatty levels that have been validated by radiology specialists. The level of fatty liver is grouped into Normal, if: Liver parenchyma has homogeneous echotexture, with the same ecogenicity as normal renal cortex. Grade 1, if: Increased diffuse ecogenicity of the liver parenchyma compared to the renal cortex, but intra hepatic blood vessels are still visualized normally. Grade 2, if : Increased diffuse ecogenesits moderate hepatic parenchyma compared with renal cortex, with visualization of slightly blurred intrahepatic vessels. Grade 3, if : Increased ecogenicity of the liver parenchyma is markedly compared to the renal cortex, with difficulty visualizing the portal vein wall and diaphragm. [16]

Based on the results of diagnostic tests, the sensitivity of the normal fatty liver level is 93%, specificity 100%, accuracy 98%. At grade 1 the sensitivity is 74%, the specificity is 98% and the accuracy is 92%. While in grade 2 the sensitivity is 78%, specificity is 86% and accuracy is 84%. Grade 3 sensitivity 85%, specificity 93% and accuracy 91%. PPV in normal samples is 100%, Grade 1 is 91%, grade 2 is 66%, grade 3 is 79%. NPV in normal samples is 98%, grade 1 is 98%, Grade 2 is 92%, grade 3 is 95%. These results are in accordance with previous studies where there is an accuracy of 96.75%, which only distinguishes between normal and abnormal fatty liver. [24] The strength of this study is that it is able to classify the level of normal fatty liver with an accuracy of 98%, grade 1 with an accuracy of 92%, grade 2 with an accuracy of 84% and grade 3 with an accuracy of 91%. Application program diagnostic test results are shown in Figure 1

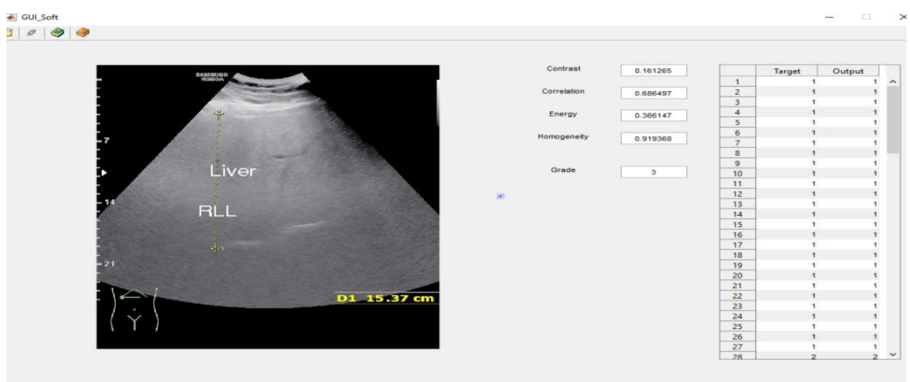

Figure 1: Application program diagnostic test results

The four indicators applied to GLCM as a condition for feature extraction (energy value, contrast, correlation and homogeneity) have their respective roles in the successful extraction of USG image characteristics well before classification using ELM. GLCM shows the spatial relationship of adjacent pixels by calculating the rate of occurrence of pixels with a certain level or intensity compared to their neighbors in a number of directions. The feature is calculated based on the statistical distribution of pixel intensity.

These results are in line with the support of previous studies in which the application of GLCM shows results with high diagnostic testing. Application of GLCM as a feature extraction method and compared to other extraction methods, the result is that GLCM is able to show an extraction accuracy rate of 75.75%, higher than GLRLM which displays a value of 54.53%. [30] Being an advantage in this study when GLCM is able to be combined with ELM as a classification method.

ELM in classifying pathology in the liver, especially Fatty Liver, implements SLFFNN which can be trained on one track, making it faster than contemporary Machine Learning algorithms. There are three layers of neurons (or nodes) in SLFFNN, where weights between hidden inputs and nodes are randomly initiated and then fixed without any iteration (called input-to-hidden weights). The only weight to be learned is the weight between the hidden layer and the output layer. The resulting application accuracy is in accordance with previous studies when comparing ELM with other classification methods. ELM is stated to show a higher accuracy of 96.7% when compared to SVM which shows an accuracy of 89.01% when distinguishing normal liver tissue and fatty liver. [24]

Determination of the level of fatty liver by the application program of the GLCM and ELM methods is a study that uses retrospective samples, so that the ultrasound images used in the study mostly have markers of size and organ naming that result in reducing the lack of accuracy of the application program in analyzing the level of fatty liver.

CONCLUSION

Based on the results and discussion in this study, it can be stated that the application of the GLCM and ELM Method is able to properly detect the level of fatty liver in the ultrasound image.

RECOMMENDATION

The combination of GLCM and ELM in the application of this application program has a significant impact in the diagnostic tests conducted. The high value of sensitivity, specificity, accuracy, PPV and NPV proves the success of this application as a Decision Support System (DSS) in the classification of the level of fatty liver using USG modality.

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