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Optimizing the gallstone detection process with feature selection statistical analysis algorithm

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ABSTRACT

Early detection is one form of early anticipation in treating gallstone disease patients using medical images. However, the problem that exists is that there are still many shortcomings in medical images, such as noise in the image that causes the detection process to not run optimally. Based on this, this study aims to carry out the process of detecting gallstone objects in magnetic resonance cholangiopancreatography (MRCP) images by optimizing the performance of extraction techniques for feature selection. Optimization of extraction techniques in feature selection is carried out using the performance of the feature selection statistics analysis (FSSA) algorithm. The performance of the FSSA algorithm can provide improvements in the feature selection process by excelling in the performance of classification methods such as k-nearest neighbor (KNN), support vector machine (SVM), and artificial neural network (ANN), and the Pearson correlation (PC) method. Based on the tests that have been carried out, the performance of the FSSA algorithm in the detection process provides an accuracy level of 95.69%, a sensitivity of 89.65%, and a specificity of 98.43%. Overall, this study can contribute to the development of extraction and provide a significant technical impact on optimizing the gallstone detection process.

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1. INTRODUCTION

Gallstones are a disease that can attack the bile organs due to excessive cholesterol content [1]. The effects of excess cholesterol can have a negative impact by forming stone particles in the gallbladder area [2]. Not only that, this disease also causes pain for quite a long time so early prevention needs to be done [3]. Previous research stated that gallstones are a disease that can threaten human health [4]. Based on this, an early detection process is really needed by utilizing developments in medical image technology [5].

Medical images are a technology developed in the world of health that plays a role in supporting the diagnosis process [6]. Medical images or known as biomedical processing technology can contribute to decision making [7]. The active role of medical images in several previous studies has also had a significant impact on progress in the health sector [8]. One form of medical image can be seen from magnetic resonance cholangiopancreatography (MRCP). The implementation of MRCP can be used to assist medical personnel in the process of diagnosing disease [9]. Previous research explains that MRCP images have been widely used in the post-operative detection process [10]. Other research also states that MRCP images are a tool in the medical world that plays an active role in several disease detection processes [11].

MRCP images in detection cases have also been used to describe the location of gallstone objects [12]. However, the fact is that there are still visible shortcomings in MRCP images such as speckle noise [13], [14]. Based on this, the image processing process is needed to provide an optimal role in the detection process [15]. The concept of image processing is a technique for analyzing objects contained in an image [16]. Image processing can also be said to be a method that can manipulate images using color, shape, and texture [17]. Previous research explains that image processing can provide quite good image output in several processes such as detection [18], [19]. The image processing performance in the previous case has provided an identification accuracy level of [20]. The same research also reports that the role of image processing can contribute effectively to the object identification process [21]. Similar research has also proven that the implementation of image processing in the identification process provides quite good performance [22].

One technique that can be adopted in image processing can be seen based on the performance of segmentation and extraction techniques. Segmentation is a technique in image processing that is capable of solving problems in the disease diagnosis process [23]. Segmentation techniques are able to carry out the process of separating objects in an image quite well [24]. Previous research reported that image segmentation performance was able to identify gallstone image objects with an accuracy rate of 91% [25]. Furthermore, the same study has also reported that embed stone objects can be detected well with average precision, recall, and deviation ratio values of 94.56%, 96.56%, and 98.92% respectively [26]. Segmentation techniques have also been developed in accordance with the need for solving problems such as identification with fairly good results [27]–[29].

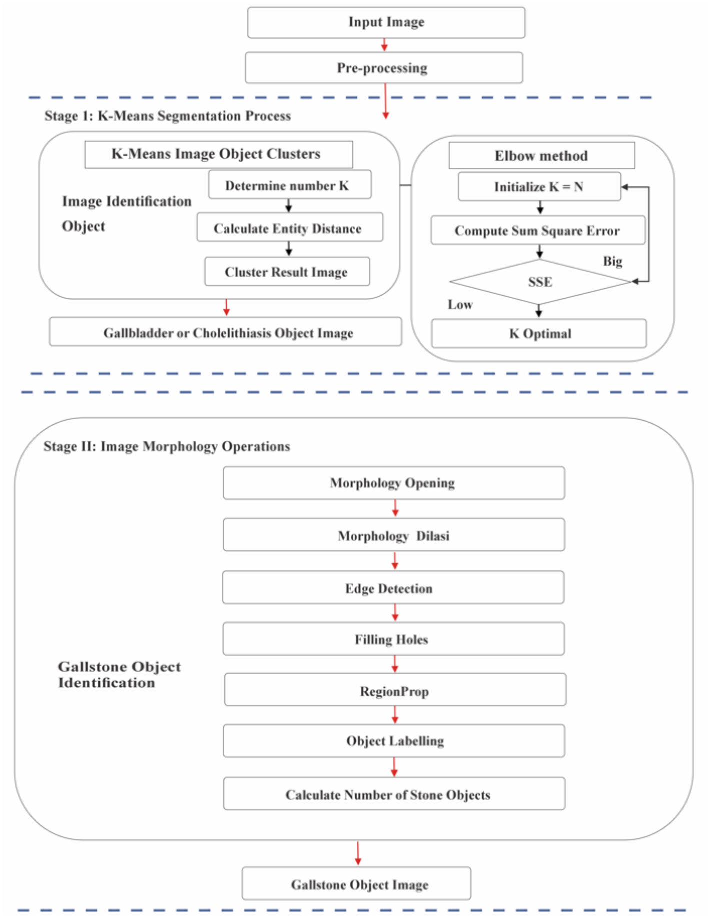
Extraction techniques can also play an important role in digital image processing. This technique is also experiencing development along with increasing performance in the identification process [30]. Previous research explains that extraction techniques can provide optimal results in the object classification process [31]. The development of extraction techniques is also presented in model form to provide increased accuracy values in the identification process [32]. The use of feature selection algorithms in the image extraction process is also able to make an active contribution to the image processing process [33]. Previous research reported that feature selection in the image extraction process was able to provide an object selection process by utilizing the attribute values of an image [34].

Based on previous research, the process of detecting gallstone objects in MRCP images needs to be optimized by developing a feature selection process in extraction techniques. This optimization is aimed at maximizing the detection process and results that will be carried out in the development of the feature selection process using the feature selection statistical analysis (FSSA) algorithm. The performance of the FSSA algorithm provides an analysis process in determining optimal characteristic patterns involving classification methods such as k-nearest neighbor (KNN), support vector machine (SVM), and artificial neural network (ANN) as well as the Pearson correlation (PC) method. The development of the FSSA algorithm in the feature selection process can also provide novelty in image extraction techniques used in detecting gallstone content. The performance of FSSA is also expected to be able to present optimal characteristic patterns from previously detected image objects. Overall, this research can contribute to helping medical parties in the process of diagnosing patients who have identified gallstone disease.

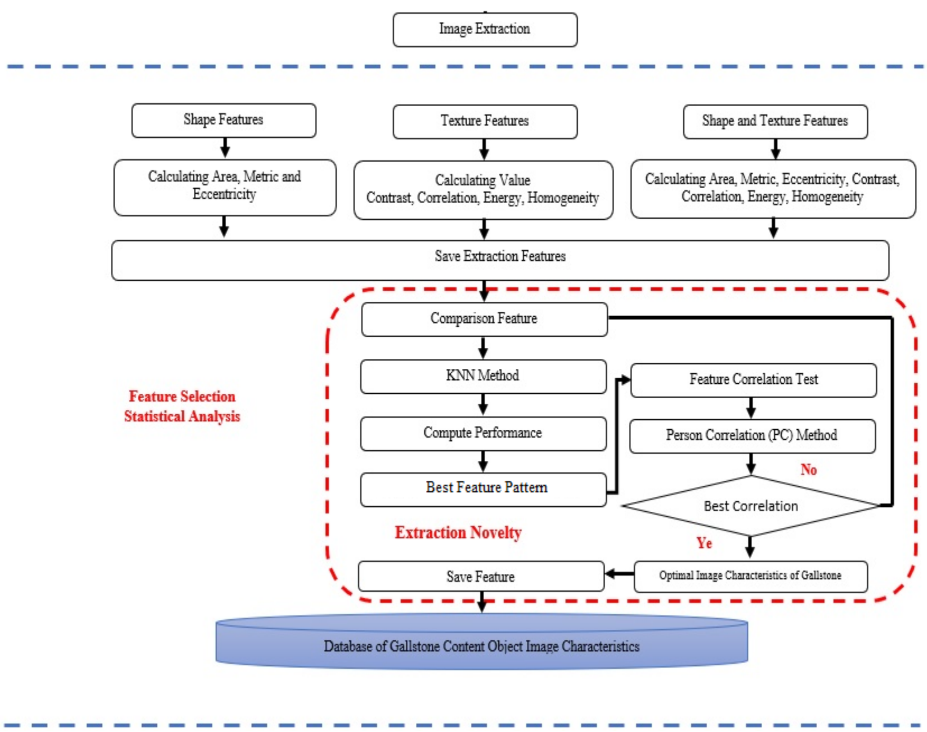
2. RESEARCH METHOD

The process of detecting gallstone objects in MRCP images is carried out by developing extraction techniques in the feature selection process based on the performance of the FSSA algorithm. The performance of the developed FSSA is aimed at providing accurate detection results for gallstone objects on MRCP images. The performance of the FSSA algorithm is presented in several stages starting from the preprocessing, segmentation and extraction stages. Based on these stages, the performance of FSSA in the process of optimizing the gallstone object detection process in feature selection will be able to present new extraction techniques in image processing. The performance of the FSSA algorithm in the gallstone object detection process is presented in the research framework in Figure 1.

Figure 1 is an illustration of the performance of the FSSA algorithm in detecting gallstone objects. The detection process based on the performance of the FSSA algorithm begins with the performance of the segmentation process which is based on the performance of the multistage segmentation algorithm (MSA) in Figure 1(a). The MSA algorithm involves k-means cluster-based segmentation (CBS) combined with morphological segmentation. The output of the segmentation results will later become input for the extraction process using the performance of the FSSA algorithm in Figure 1(b). The FSSA algorithm presents the development of the extraction process in feature selection by involving the performance of the KNN, SVM, and ANN classification methods as well as the PC method in measuring the correlation of each feature pattern produced. The performance results of the FSSA algorithm are able to provide optimization of the detection process for gallstone content objects.



(a)



(b)

Figure 1. Research framework of (a) segmentation process and (b) extraction with feature selection based on FSSA algorithm performance

Next, the performance stages of the FSSA algorithm can be explained as follows:
- Image preprocessing stage: this stage is the stage used for the process of improving the input image. Image improvement includes several processes including gray image transformation, image adjustment, and filtering. The output of the preprocessing image will later become the input image at the segmentation process stage.
- Image segmentation stage: the segmentation process is an advanced stage in FSSA performance in gallstone object detection. The segmentation process adopts the performance of the MSA algorithm by playing the role of the CBS method which is optimized with the elbow method in separating objects. The results of the segmentation process will later become input in the image extraction process.
- Image extraction stage: the extraction process using feature selection was developed by using statistical analysis methods on the performance of PC. The performance of the PC method can provide an optimal role in presenting optimal characteristic patterns of gallstone objects. Overall, the improvement in the feature selection process based on FSSA performance can provide novelty in the process of detecting gallstone objects.

2.1. Research dataset

The research dataset uses MRCP images sourced from patients at Santa Maria Hospital Pekanbaru and Siti Rahmah Hospital Padang. The dataset consists of 2371 images from 32 patients with indications of gallstone disease. The sample research dataset can be presented in Figure 2.

Figure 2 is a sample of MRCP image results used as a research dataset in the gallstone object detection process. Figure 2(a) depicts an MRCP image of a gallstone patient on image slice 64, Figure 2(b) is also an MRCP image of a gallstone patient on image slice 65, and Figure 2(c) is also one of the MRCP images of a gallstone patient on image slice 66. The dataset on the MRCP image (.*jpg format) with an image resolution of 512×512 pixels. The dataset will later be divided into 1921 training data and 450 data for testing.

(a) (b) (c)

Figure 2. MRCP image dataset: (a) Slice 64, (b) Slice 65, and (c) Slice 66

2.2. Multistage segmentation algorithm

The segmentation process with the MSA algorithm adopts the performance of CBS combined with morphological segmentation. CBS segmentation involves the k-means cluster which is optimized using the elbow method. The performance of the elbow method can present optimal cluster (k) values based on the calculation of the sum square error (SSE) [35]. The equations used in the performance of the MSA algorithm are presented in (1)-(3) [36], [37].

In (1) is the formula used to measure distance using Euclidian distance in the k-means cluster process. Distance measurements are calculated on image intensity to group image objects. In (2) is the formula used to calculate the SSE in the elbow method. The formula is used as a form of optimizing the cluster process in CBS in separating image objects. The combination of (1) and (2) produces (3) in determining the optimal k value used in the CBS-based cluster process.

$$(x, y) = \sqrt{\sum_{1}^{k}(x_i - y_i)^2}\ ; k = 1,2,3, \ldots., n \tag{1}$$

$$SSE = \sum_{k=1}^{n} \|x_i - c_k\|^2 \tag{2}$$

$$\text{K\_Elbow}=\sum_{k=1}^{n} \left\| \sqrt{\sum_{1}^{k}(x_i - y_i)^2} - \frac{d(x,y)}{\sum_{1}^{k} d(x,y)} \right\| \tag{3}$$

2.3. Feature selection

Feature selection in image extraction is used as a detection process by utilizing the attribute values for each image feature. The feature selection process adopts the performance of the data classification process by taking the level of accuracy as a selection parameter [38]. The feature selection process uses several methods such as KNN, SVM, and ANN. KNN is an algorithm concept in supervised learning that considers the use of many k comparable patterns in the training [39]. SVM has contributed greatly to handling classification problems based on hyperplanes [40]. The performance of ANN has also been proven to provide maximum results such as identification, classification, and prediction problems [41], [42].

2.4. Person correlation

PC is a statistical analysis concept that is capable of measuring correlation [43]. PC methods can be combined to improve analysis performance with quite good output [44]. The PC method has also been used to review the accuracy of a model analysis [45]. Regarding PC performance, it can be seen in (4) and (5) [46].

In (4) and (5) is the formula used to calculate the value of cov (X, Y) which is the covariance between X and Y. The value of X, Y can be interpreted as a standard deviation value of the variables X and Y [47]. PC performance has contributed to maximizing the image processing process in a model that has been designed [48].

$$P\ X,Y = \left(\frac{\mathrm{cov}\ (\mathrm{X,Y})}{\sigma X.\sigma Y}\right) = \left(\frac{\mathrm{E}\ ((\mathrm{cov}\ (\mathrm{X}-\mu\mathrm{X})(\mathrm{Y}-\mu\mathrm{Y}))}{\sigma X.\sigma Y}\right) \tag{4}$$

$$P\ X,Y = \left(\frac{\mathrm{cov}\ (\mathrm{X,Y})}{\sigma X.\sigma Y}\right) = \frac{\mathrm{E}\ (\mathrm{XY}) - \mathrm{E}\ (\mathrm{X})\mathrm{E}\ (\mathrm{Y})}{\sqrt{\mathrm{E}\ (\mathrm{X.X}) - E.E(X)}\ \sqrt{B\ (Y.Y) - E.E\ (Y)}} \tag{5}$$

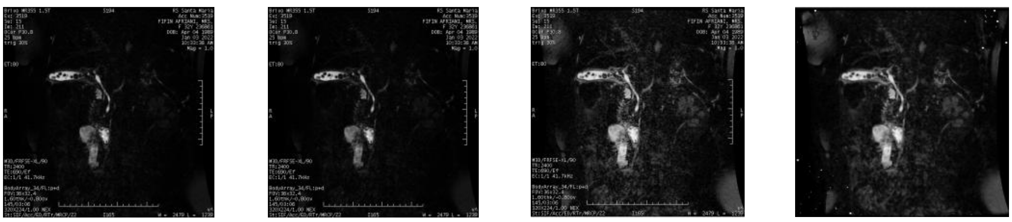
3. RESULTS AND DISCUSSION

Optimizing the gallstone object detection process by developing feature selection using FSSA is the main topic of research. The development of feature selection based on the performance of the FSSA algorithm in the extraction process is a novelty to provide improvements in the detection of gallstone objects. The performance of the FSSA results that have been developed will be able to provide a detection model that provides accuracy.

3.1. Image preprocessing

The preprocessing stage is the initial stage of the gallstone object detection process. This process plays a role in providing an increase in the quality of the input image used. Preprocessing results involve several processes including gray image transformation, image adjustment, and filtering. The preprocessing results can be presented in Figure 3.

Figure 3 is the output of the preprocessing stage using the gray image transformation process, image adjustment, and filtering. Figure 3(a) is the input image in the detection process. Figure 3(b) is the gray image transformation process which is the beginning of preprocessing. Figure 3(c) is the result of continued preprocessing involving the image adjustment process. Figure 3(d) is the final stage of preprocessing, which presents the image output from the filtering process. In the preprocessing stage can be seen that there is an improvement in the quality of the input image used previously. The output of the preprocessing image will be the input in the detection process.



(a) (b) (c) (d)

Figure 3. Preprocessing result (a) input image, (b) gray transformation, (c) image adjustment, and (d) results filtering

3.2. Multistage segmentation algorithm

The segmentation process using the MSA algorithm is part of the gallstone object detection process. The performance of the MSA algorithm adopts a CBS approach and operational morphology to guarantee the accuracy of segmented objects with precise and accurate results. The performance results of the MSA algorithm in segmentation can be presented in Figure 4.

Figure 4 is the result of the segmentation process of the MSA algorithm performance in detecting gallstone disease. Figure 4(a) is the result of the previous preprocessing image which is used as the input image in the segmentation process with the MSA algorithm. Figure 4(b) is the result of CBS segmentation which is one part of the segmentation process in the MSA algorithm. Figure 4(c) is the result of morphological segmentation which is the next stage in the segmentation process in the MSA algorithm. Figure 4(d) is the final output of the MSA algorithm segmentation process in detecting gallstone objects. The performance of the MSA algorithm has been able to describe the object of gallstone disease quite well. The results of the MSA algorithm segmentation will be used as input in the image extraction process.

(a) (b) (c) (d)

Figure 4. Results of the MSA algorithm segmentation process (a) preprocessing result, (b) CBS results, (c) morphology results, and (d) MSA results

3.3. Feature selection statistical analysis algorithm extraction

Development of feature selection in the delay image extraction process using FSSA for the process of increasing detection. The FSSA performance process plays the role of the classification method and correlation examiners found in the image characteristic pattern. Classification methods such as KNN, SVM, and ANN are involved in finding optimal feature patterns. The performance results of the FSSA algorithm in the feature selection process can be presented in Table 1. Based on Table 1, it can be seen that the feature selection process by adopting the performance of the FSSA algorithm has gone well in determining image characteristic patterns. The results of the feature selection process which involves several classification methods with PC statistical analysis methods have been able to illustrate a more effective feature selection process. The performance test results of the FSSA algorithm can be presented in Table 2.

Table 1 is the result of measuring the performance of the FSSA algorithm in detecting gallstone objects. Based on this table, it can be seen that the texture feature outperforms other features in presenting optimal image characteristic patterns. This characteristic pattern can be seen based on the total performance accuracy of the KNN classification method of 84.61%, SVM 90.38%, and ANN 99.95%. The results of correlation measurements using the PC method have presented a correlation level of 95.90%. Based on these results, the performance of the FSSA method is quite good, providing an improvement in the detection process for gallstone objects.

Improving the gallstone object detection process using the FSSA algorithm can provide novelty in the feature selection process in extraction techniques. Testing the performance of FSSA in increasing detection has been proven to be quite good with an accuracy of 95.83%, sensitivity of 96.96%, and specificity of 95.23%. Testing based on several previous studies is also a process of proving the performance of the FSSA algorithm in improving the process of detecting gallstone objects presented in Table 3.

Table 3 is a form of testing the performance results of the FSSA algorithm with previous research in the detection process. Based on these results, it can be stated that the FSSA algorithm can provide accurate image characteristic patterns in the gallstone object detection process. Overall, this research has been quite successful and can contribute to optimizing the process of diagnosing gallstone disease.

Table 1. The performance results of the FSSA algorithm in the feature selection process

	Shape features			Texture features			Combination of shapes and textures		
Area	100	119	418		-		100	119	21
Perimeter	38.117	40.466	86.540		-		38.117	40.466	12.756
Metric	0.864913	0.913222	0.701378		-		0.864913	0.913222	1.6261
Eccentricity	0.833286	0.847956	0.693967		-		0.833286	0.847956	N/A
Y	1	1	1	1	1	1	1	1	1
Contrast		-		0.003256	0.002554	0.002527	0.003256	0.002554	0.0009
Correlation		-		0.627183	0.704434	0.849754	0.627183	0.704434	0.569403
Energy		-		0.99835	0.998167	0.995909	0.99835	0.998167	0.9199
Homogeneity		-		0.999722	0.999732	0.999661	0.999722	0.999732	0.9999
K-NN (%)		80.77			84.62			82.69	
SVM (%)		88.40			88.46			86.54	
ANN (%)		99.98			99.98			99.97	

Table 2. The performance test results of the FSSA algorithm (%)

Features	K-NN accuracy			SVM accuracy			ANN accuracy			Analysis (PC)
	Training	Testing	Total accuracy	Training	Testing	Total accuracy	Training	Testing	Total accuracy	
Shape features	61.53	100	80.76	69.23	100	84.61	99.46	99.99	99.73	80.04
Texture features	69.23	100	84.61	80.76	100	90.38	99.93	99.97	99.95	95.90
Combination of shapes and textures	65.38	100	82.69	69.23	100	84.62	99.90	99.94	99.92	87.96

Table 3. Comparison of the performance of the FSSA algorithm in improving the process of detecting gallstone objects with previous research

No	Previous research results	Performance results of the FSSA algorithm
1	The results of the tests that have been carried out show that the performance accuracy level of the multiclass classification method combined with deep learning reaches 93.4% and 94.36% [48].	Presents the development of the image extraction process with the FSSA feature in detecting gallstone objects. Performance testing of FSSA performance in increasing detection provided an accuracy rate of 95.83%, sensitivity of 96.96%, and specificity of 95.23%. Based on these results, the FSSA algorithm can present a novelty in the form of an effective and efficient algorithm for improving the gallstone object detection process.
2	The CNN classification method with feature extraction and feature selection in the detection process provides output with an accuracy level of 0.6536% and 0.8942% for the training and testing [38].	
3	The MSA algorithm uses coarse network segmentation with shape operations in object detection providing a detection accuracy rate of 90% [49].	
4	MSA algorithm development was carried out using the Enhancement technique using the feature improvement pyramid network (multi-stage FEPN) providing an accuracy rate of 92.1% [50].	

4. CONCLUSION

Improving the gallstone object detection process by developing feature selection with the FSSA algorithm has provided maximum output results. These results are based on the results of FSSA performance testing with an accuracy rate of 95.83%, sensitivity of 96.96%, and specificity of 95.23%. Based on these results, it can be proven that the FSSA algorithm can provide optimal results in the process of detecting gallstone objects. The overall performance of the FSSA algorithm can be used as a novelty in extraction techniques, especially in the feature selection process.

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