

IMPROVED FEATURE SELECTION USING FEATURE SELECTION STATISTICAL ANALYSIS (FSSA) IN THE DETECTION OF GALLSTONE DISEASE

MUSLI YANTO^{1,*}, YUHANDRI¹, MUHAMMAD TAJUDDIN² AND VINA TRI SEPTIANA³

¹Department of Information Technology
Faculty of Computer Science
Universitas Putra Indonesia YPTK

Jl. Raya Lubuk Begalung, Padang, Sumatera Barat 25221, Indonesia
yuyu@upiyptk.ac.id

*Corresponding author: musli_yanto@upiyptk.ac.id

²Department of Computer Science
Faculty of Engineering
Universitas Bumi Gora

Jl. Ismail Marzuki No. 22, Cilinaya, Kec. Cakranegara, Mataram
Nusa Tenggara Barat 83127, Indonesia
tajuddin@universitasbumigora.ac.id

³Department of Radiology
Faculty of Medicine
Baiturahmah University

Jl. By Pass, Aie Pacah, Kec. Koto Tengah, Padang, Sumatera Barat 25586, Indonesia
s3ptavina@fk.unbrah.ac.id

Received February 2024; accepted May 2024

ABSTRACT. *Gallstones are a disease caused by large amounts of cholesterol. This disease is capable of causing continuous ill effects with a fairly high level of severity. Initial treatment has been carried out, such as early detection using medical images. However, this is not optimal so the diagnosis presented is not precise and accurate. Based on this, this research aims to improve feature selection using Feature Selection Statistical Analysis (FSSA) in the detection of gallstones. Improved feature selection is needed to ensure that the feature patterns are presented in image extraction. The detection is presented in the segmentation stage adopting the performance of the Multistage Segmentation Algorithm (MSA) and the extraction stage using the FSSA. The research dataset used 2371 MRCP from 32 patients with gallstone disease at Santa Maria Hospital Pekanbaru and Siti Rahmah Hospital Padang. Based on the testing that has been carried out, the results of detecting gallstone disease have provided an accuracy rate of 99%. The performance of the FSSA algorithm in improving feature selection has also been proven to be able to measure the correlation of image feature patterns with an average correlation level of 95.90%.*

Keywords: Detection, Gallstone, MSA, FSSA, MRCP

1. Introduction. Gallstones are a disease of the bile organ that can occur due to excessive cholesterol content [1]. The cholesterol content causes stone particles to form in the gallbladder and bile ducts, which results in a long illness, requiring quite intensive treatment for the sufferer [2]. Gallstone disease has main risk factors including obesity, increasing age, female gender, and lack of physical activity [3]. Gallstone disease can be said to be a disease that can affect the majority of the global population, with an estimated prevalence of 10-20% worldwide [4]. The same research also explains that gallstone disease is one of the diseases that are the main cause of surgical intervention in the bile

ducts. Based on reports more than 700,000 cholecystectomies are performed each year to treat more than 20 million people who have gallstones [5]. Gallstone disease also has a risk in developing countries by triggering other diseases such as obesity at 55.0%, dyslipidemia at 76.0%, and diabetes mellitus at 17.7% [6]. Previous research reported that 6% of men and 9% of women were diagnosed with gallstone disease in the United States [7]. Another explanation emphasizes that gallstone disease is also a factor that can threaten human health [8]. With this, an early diagnosis process is needed by utilizing technological developments in medical images [9].

Medical image is a technology that is developing in the world of health and plays an important role in supporting the performance of the disease diagnosis process [10]. Medical imaging can also be referred to as a biomedical processing technology that contributes greatly to early treatment measures [11]. The implementation of medical images is also capable of being active in several scientific studies such as the process of identifying and detecting a disease [12]. One form of medical imaging can be seen from Magnetic Resonance Cholangio Pancreatography (MRCP) images. MRCP images can be used to assist medical personnel in the process of diagnosing a disease [13].

The use of MRCP images in disease diagnosis has provided results that can describe the presence of gallstone objects [14]. Based on several facts and conditions in the field there are still deficiencies in MRCP images such as speckle noise [15]. With this in mind, image processing is needed to maximize the diagnostic process using MRCP images. Image processing is a concept that can be adopted in handling various diagnostic problems [16]. Image processing is also a technique used in the process of analyzing an object in an image [17]. Previous studies have explained that image processing provides fairly good output results in the process of detecting image objects [18]. The results of this process can be seen based on the accuracy of the identification results of 93.95% [19].

Based on the results of previous studies, the concept of image processing has a fairly good performance in the identification process. One technique that has been used in this process is segmentation [20]. Segmentation techniques can handle problems in the process of diagnosing diseases [21]. Previous research explained that the identification results based on the performance of the gallstone image object segmentation process present an accuracy rate of 91% [22]. The same study also reported the results of the diagnosis of gallstone objects based on the performance of the segmentation process presenting the average precision, recall, and deviation ratio values were 94.56%, 96.56%, and 98.92%, respectively [23]. Furthermore, the segmentation process has developed according to the need for solving object identification problems [24]. The development of the segmentation process can present optimal results [25]. Based on previous research, the development of the segmentation process can present a fairly good output with an accuracy rate of 93% [26].

Image processing techniques that have been used in the identification process can be seen based on the image extraction process. The extraction process is also evolving along with improvements in the performance of the identification process [27]. One extraction process that provides optimal image characteristic patterns can be seen based on feature selection performance [28]. Feature selection is an algorithm developed to produce features in an image [29]. The feature selection algorithm adopts the performance of classification methods in selecting the best features [30]. The K-Nearest Neighbor (K-NN), Support Vector Machine (SVM) and Artificial Neural Network (ANN) methods can be used in the feature selection process by presenting quite good results [31-33].

Based on this explanation, research was carried out on the process of detecting gallstone objects in MRCP images. The detection process adopts feature selection which was developed using a statistical approach to the performance of the Feature Selection Statistical Analysis (FSSA) algorithm. The development of feature selection in the image extraction

process provides novelty for producing optimal feature patterns based on statistical analysis. The statistical analysis process on the performance of the FSSA algorithm is also able to maximize the role of feature selection so that the extraction output provides accuracy in detecting image objects. Overall, this research will contribute to the development of image extraction techniques and also have a significant impact in optimizing the gallstone disease detection process.

2. Methodology. Improved feature selection in the image extraction process with the Feature Selection Statistical Analysis (FSSA) algorithm is carried out using the Pearson Correlation (PC) method. The static analysis process aims to measure the level of correlation in the image characteristic patterns that have been produced based on the feature selection process. The performance of the PC method on the Feature Selection Statistical Analysis (FSSA) algorithm can validate pattern relationships. The performance of statistical analysis using the PC method in the FSSA algorithm is new and contributes to the image extraction process. The novelty produced by the FSSA algorithm also provides a level of accuracy in the image characteristic patterns that will be used in the detection process. The improvement in feature selection in the image extraction process with the FSSA algorithm is presented in Figure 1.

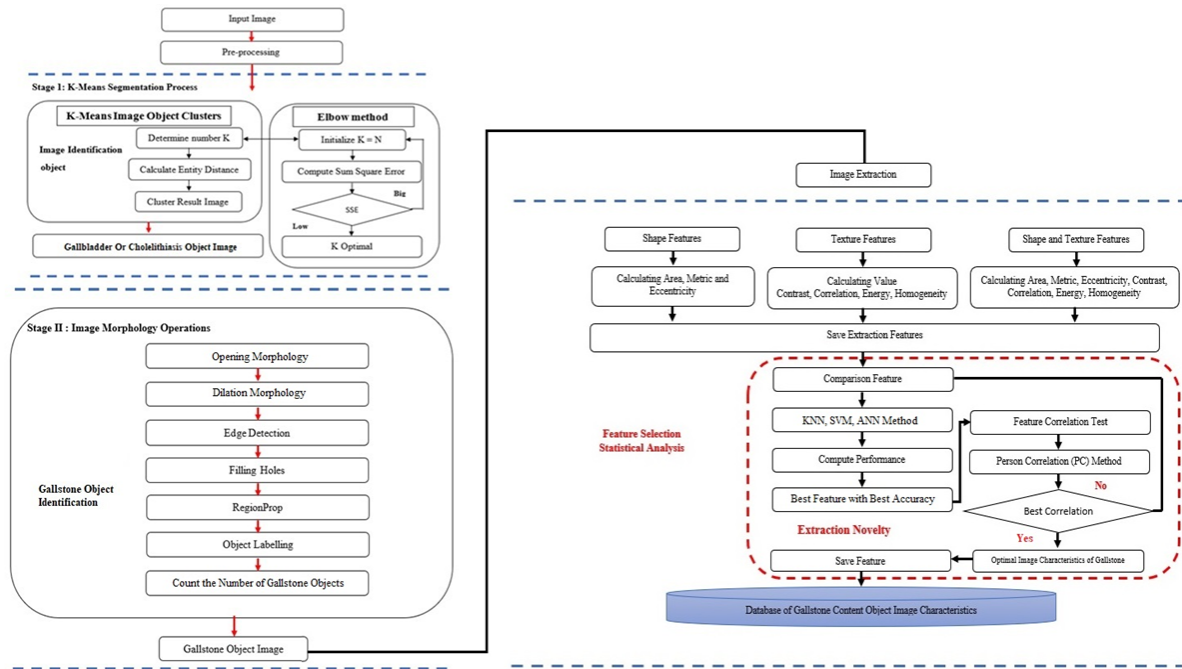


FIGURE 1. Research framework

Figure 1 is an overview of the research framework for improving feature selection in the image extraction process based on algorithm performance (FSSA). The detection process begins with preprocessing which is aimed at making improvements to image quality. The detection stage begins with a segmentation process using the Multistage Segmentation Algorithm (MSA) approach on the previous preprocessed image output. MSA segmentation is presented in Cluster Based Segmentation (CBS) which is optimized using the Elbow method for detecting gallstone objects. The performance of the Elbow method can provide optimal cluster values (K) so that CBS performance will work optimally in clustering objects in the image. The final stage of the detection process is presented in the extraction performance with the FSSA algorithm as a form of improving feature selection. The FSSA algorithm can carry out correlation measurements based on the Pearson Correlation (PC) method to produce optimal characteristic patterns. The FSSA performance

output will present the accuracy of the identification process in diagnosing gallstone disease. Overall, the improvement in feature selection in the image extraction process using the FSSA algorithm provides novelty in the process of identifying image objects.

2.1. Dataset. This research dataset will examine MRCP images in patients at Santa Maria Hospital Pekanbaru and Siti Rahmah Hospital Padang. The dataset consists of 2371 images of 32 patients with gallstone disease. The sample MRCP image test dataset used can be presented in Figure 2.

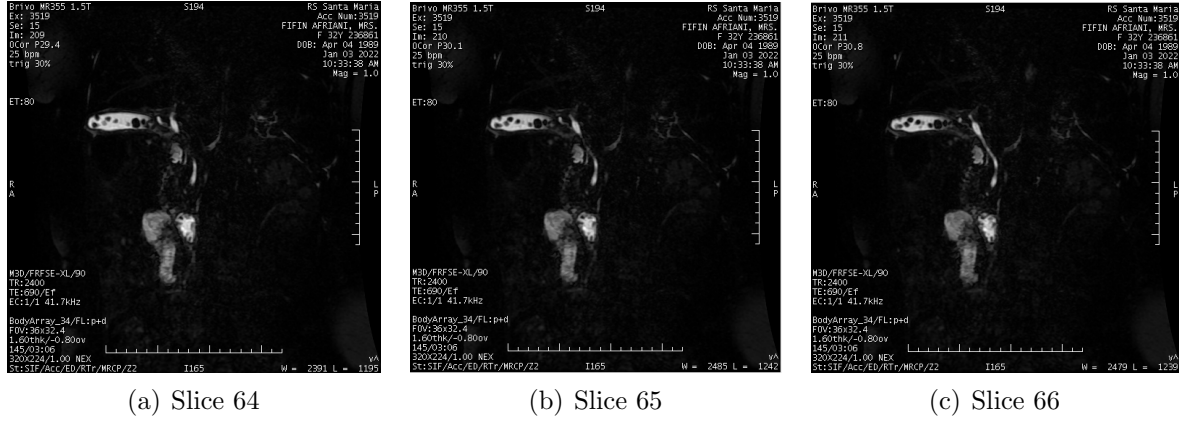


FIGURE 2. MRCP image dataset

Gallstone identification begins with an input process using MRCP images as a research dataset. The MRCP image is used to detect gallstone objects. This dataset will later become data to test the performance of the MSA and FSSA algorithms in the detection process.

2.2. Multistage segmentation. The segmentation process with the MSA algorithm adopts the performance of Cluster-Based Segmentation (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 is able to present optimal cluster (K) values based on calculating the Sum Square Error (SSE) value [34]. The equations used in the performance of the MSA algorithm are presented in Formulas (1)-(3) [35].

$$d(x, y) = \sqrt{\sum_{i=1}^k (x_i - y_i)^2}; \quad k = 1, 2, 3, \dots, n \quad (1)$$

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

$$K_Elbow = \sum_{k=1}^n \left\| \sqrt{\sum_{i=1}^k (x_i - y_i)^2} - \frac{d(x, y)}{\sum_{i=1}^k d(x, y)} \right\| \quad (3)$$

Formula (1) is used to measure distance using Euclidian distance in the K-Means cluster process. Distance measurements are calculated on image intensity to group image objects. Formula (2) is used to calculate the Sum Square Error (SSE) in the Elbow method. Formula (2) is used as a form of optimizing the clustering process in CBS in separating image objects. The combination of Formulas (1) and (2) produces Formula (3) in determining the optimal K value used in the CBS. After the CBS segmentation process using the

MSA algorithm, the segmentation process continues with morphological operations. Morphological segmentation is an advanced stage in the Multistage Segmentation Algorithm (MSA) involving opening and closing morphology.

2.3. Feature selection. Feature selection in the image extraction process in detecting gallstone disease uses a classification approach using the K-Nearest Neighbors (K-NN) method. K-NN is an algorithm concept in supervised learning, considering the use of many k comparative (closest) patterns in the training set [36]. K-NN performance can perform classification correctly based on the target class for instances that cannot be identified by calculating the class label with the highest frequency among the k closest instances [37].

2.4. Pearson Correlation (PC). Pearson Correlation (PC) is a statistical concept that is capable of performing calculations in carrying out a measurement process [38]. PC can be combined with several methods to provide better performance results [39]. PC-based techniques can also be used to select optimized features in reviewing an output from a model [40]. The PC calculation can be presented in Formulas (4) and (5) [41].

$$P_{X,Y} = \left(\frac{\text{cov}(X,Y)}{\sigma_X \cdot \sigma_Y} \right) = \left(\frac{E(\text{cov}(X - \mu_X)(Y - \mu_Y))}{\sigma_X \cdot \sigma_Y} \right) \quad (4)$$

$$P_{X,Y} = \frac{E(X \cdot Y) - E(X)E(Y)}{\sqrt{E(X^2) - (EX)^2} \sqrt{E(Y^2) - (EY)^2}} \quad (5)$$

Formulas (4) and (5) show the PC method used to measure the level of correlation in image characteristics. $P_{X,Y}$ is the result of Pearson correlation measurements tested on the X and Y values. The value of X , Y is the standard deviation value of variables X and Y . The value of $E(X)$ is the expected value of X . The application of the PC method will be developed in an image extraction algorithm to provide optimal feature patterns. The development of the algorithm is presented in the FSSA algorithm.

3. Result and Discussion. The process of detecting gallstone disease objects is carried out by improving the feature selection process with the FSSA algorithm. This process is presented by carrying out several stages including preprocessing, segmentation with the MSA algorithm, and image extraction in the feature selection process.

3.1. MSA algorithm segmentation. The segmentation work process with the MSA algorithm presents segmentation stages starting with CBS segmentation by adopting the Cluster-Based Segmentation (CBS) approach and morphological operations. The MSA segmentation algorithm presents a novelty in optimizing CBS performance using the Elbow method to maximize the K value used in image clusterization. The CBS segmentation output results will also be used in the segmentation process with morphological operations to obtain an image of the gallstone object. The output results of the segmentation process with the development of the MSA algorithm can be presented in Figure 3.

Figure 3 shows that the CBS segmentation output provides quite optimal results in depicting the gallbladder and cholelithiasis. The performance of the MSA algorithm has been able to describe the disease object containing gallstones quite well. The segmentation results of the MSA algorithm will be used as input for the image extraction process.

3.2. Feature Selection Statistical Analysis (FSSA). The feature selection process in feature extraction will be improved by using the FSSA algorithm in detecting gallstone content objects. The performance stages of the FSSA algorithm adopt the classification and correlation measurement stages with the PC method. The classification stage involves several performance methods such as K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), and Artificial Neural Network (ANN). Testing the FSSA algorithm will also involve shape, texture, and a combination of shape and texture features. The output of

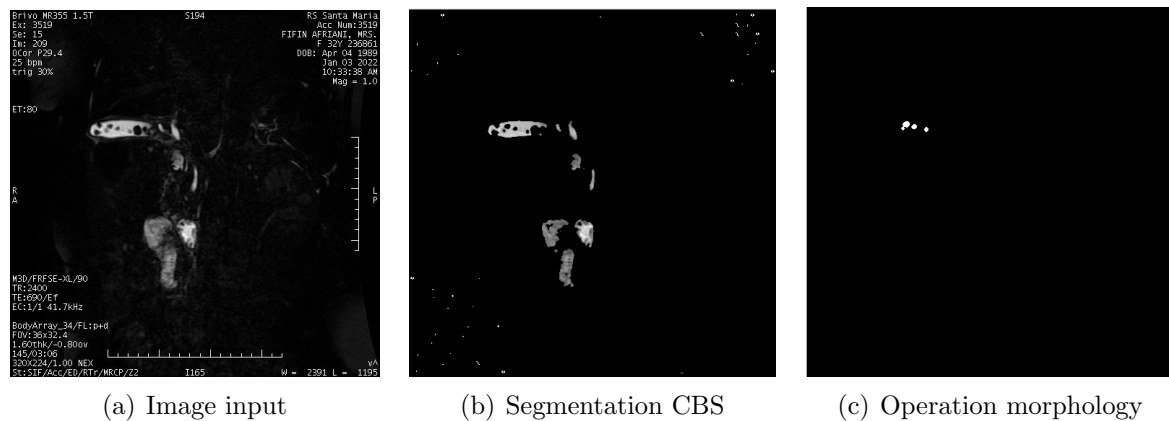


FIGURE 3. Segmentation CBS

TABLE 1. Performance results of the FSSA algorithm

Extraction features	K-NN accuracy			SVM accuracy			ANN accuracy			Correlation analysis
	Training	Testing	Total accuracy	Training	Testing	Total accuracy	Training	Testing	Total accuracy	
Shape	61.53%	100%	80.76%	69.23%	100%	84.61%	99.46%	99.99%	99.73%	80.04%
Texture	69.23%	100%	84.61%	80.76%	100%	90.38%	99.93%	99.97%	99.95%	95.90%
Combination	65.38%	100%	82.69%	69.23%	100%	84.62%	99.90%	99.94%	99.92%	87.96%

the FSSA algorithm will provide accurate image characteristic patterns. The results of the FSSA algorithm testing can be presented in Table 1.

Table 1 is a form of testing the stages of the extraction process with the performance of the FSSA algorithm. The feature selection stage using the K-NN classification method produces texture features as optimal features in describing the characteristic patterns of gallstone disease. The correlation test stage using PC statistical analysis was also able to show a very strong level of correlation in each variable with an average correlation value of 95.90%. These values include the variables contrast (X_1), correlation (X_2), energy (X_3), and homogeneity (X_4), each of which shows a very strong correlation with (Y). Based on the overall results of correlation testing on each variable, it has shown significant results so that the characteristic pattern can be used as a knowledge-based system in the process of identifying gallstone disease.

4. Conclusions. Improved feature selection using the FSSA algorithm has been proven to provide optimal performance in the process of detecting gallstone disease. This performance can be seen in the statistical analysis performance of the PC method which produces characteristic patterns with an average correlation level of 95.90% for texture features. Based on this, the detection process provides the correct output with an accuracy level of 99%. The output of the extraction process based on improved feature selection can produce characteristic patterns of objects containing gallstones and can be used as a knowledge-based detection system. Overall, this research has been quite successful in providing novelty in feature selection algorithms in image extraction.

REFERENCES

- [1] D. A. Goldman, Gallbladder, gallstones, and diseases of the gallbladder in children, *Pediatr. Rev.*, vol.41, no.12, pp.623-629, DOI: 10.1542/pir.2019-0077, 2020.
- [2] A. M. Madden, Modified dietary fat intake for treatment of gallstone disease, *Cochrane Database Syst. Rev.*, vol.2021, no.6, DOI: 10.1002/14651858.CD012608.pub2, 2021.
- [3] H. Gellert-Kristensen, N. Dalila, S. Nielsen, B. Nordestgaard, A. Tybjærg-Hansen and S. Stender, Identification and replication of six loci associated with gallstone disease, *Hepatology*, vol.70, no.2, pp.597-609, DOI: 10.1002/hep.30313, 2019.

- [4] A. K. Rahardjo, T. Lesmana, H. S. Wibowo, R. Prabowo and E. Rosita, One-stage laparoscopic cholecystectomy with intraoperative endoscopic retrograde cholangiography bile duct stone extraction is a feasible option in Indonesia within the national health insurance system, *Int. J. Surg. Case Rep.*, vol.109, 108550, DOI: 10.1016/j.ijscr.2023.108550, 2023.
- [5] F. Alemi, N. Seiser and S. Ayloo, Gallstone disease: Cholecystitis, Mirizzi syndrome, Bouveret syndrome, gallstone ileus, *Surg. Clin. North Am.*, vol.99, no.2, pp.231-244, DOI: 10.1016/j.suc.2018.12.006, 2019.
- [6] H. Hendarto, F. N. Akbar, J. B. Muzakki, R. A. Amri, S. N. A. Nugraha and H. Adlani, Obesity, dyslipidemia, and diabetes mellitus as risk factors in cholelithiasis, *Electron. J. Gen. Med.*, vol.20, no.6, 2023.
- [7] A. Z. Lysandra et al., Risk factor of dietary habit with cholelithiasis, *J. Community Med. Public Heal. Res.*, vol.3, no.1, pp.1-11, DOI: 10.20473/jcmphr.v3i1.27931, 2022.
- [8] L. Pan et al., The treatment of cholecystitis and cholelithiasis by Tibetan medicine, *Evidence-Based Complementary and Alternative Medicine*, vol.2021, DOI: 10.1155/2021/9502609, 2021.
- [9] J. Wang, H. Zhu, S. H. Wang and Y. D. Zhang, A review of deep learning on medical image analysis, *Mob. Networks Appl.*, vol.26, no.1, pp.351-380, DOI: 10.1007/s11036-020-01672-7, 2021.
- [10] S. Suganyadevi, V. Seethalakshmi and K. Balasamy, A review on deep learning in medical image analysis, *Int. J. Multimed. Inf. Retr.*, vol.11, no.1, pp.19-38, 2022.
- [11] X. Liu, L. Song, S. Liu and Y. Zhang, A review of deep-learning-based medical image segmentation methods, *Sustainability*, vol.13, no.3, 1224, 2021.
- [12] W. Zhou, H. Wang and Z. Wan, Ore image classification based on improved CNN, *Comput. Electr. Eng.*, vol.99, 107819, 2022.
- [13] M. A. S. Ai et al., Real-time facemask detection for preventing COVID-19 spread using transfer learning based deep neural network, *Electronics*, vol.11, no.14, 2250, 2022.
- [14] M. Higashi, M. Tanabe, K. Ihara, E. Iida, M. Furukawa and K. Ito, Bile flow dynamics in patients with cholelithiasis: An evaluation with cine-dynamic magnetic resonance cholangiopancreatography using a spatially selective inversion-recovery pulse, *Tomography*, vol.8, no.2, pp.815-823, DOI: 10.3390/tomography8020067, 2022.
- [15] S. Bilal, I. U. L. Hassan, N. Haroon, S. Ameer, M. Ali and M. I. Nazir, Determination of the diagnostic accuracy of MRCP in detection of choledocholithiasis taking per-operative findings as gold standard, *Pakistan J. Med. Heal. Sci.*, vol.14, no.4, pp.1534-1536, 2020.
- [16] E. Cabal-Yepez, Introduction to the special section on image processing in security applications (VSI-ipsa), *Computers and Electrical Engineering*, vol.89, DOI: 10.1016/j.compeleceng.2020.106935, 2021.
- [17] T. D. Shashikala, Some studies on measurement of worn surface by digital image processing, *Int. J. Image Graph.*, DOI: 10.1142/S021946782350016X, 2022.
- [18] M. Ji and Z. Wu, Automatic detection and severity analysis of grape black measles disease based on deep learning and fuzzy logic, *Comput. Electron. Agric.*, vol.193, 106718, 2022.
- [19] K. Buschbacher, D. Ahrens, M. Espeland and V. Steinhage, Image-based species identification of wild bees using convolutional neural networks, *Ecol. Inform.*, vol.55, 101017, DOI: 10.1016/j.ecoinf.2019.101017, 2020.
- [20] S. Tavakoli, A. Ghaffari, Z. M. Kouzehkanan and R. Hosseini, New segmentation and feature extraction algorithm for classification of white blood cells in peripheral smear images, *Sci. Rep.*, vol.11, no.1, pp.1-13, DOI: 10.1038/s41598-021-98599-0, 2021.
- [21] X. Chen et al., Diverse data augmentation for learning image segmentation with cross-modality annotations, *Med. Image Anal.*, vol.71, DOI: 10.1016/j.media.2021.102060, 2021.
- [22] S. Pang et al., A novel YOLOv3-arch model for identifying cholelithiasis and classifying gallstones on CT images, *PLoS One*, vol.14, no.6, pp.1-11, DOI: 10.1371/journal.pone.0217647, 2019.
- [23] D. Li, B. Du, Y. Shen and L. Ge, Artificial intelligence-assisted visual sensing technology under duodenoscopy of gallbladder stones, *J. Sensors*, vol.2021, 2021.
- [24] A. Garcia-Molsosa, H. A. Orengo, D. Lawrence, G. Philip, K. Hopper and C. A. Petrie, Potential of deep learning segmentation for the extraction of archaeological features from historical map series, *Archaeol. Prospect.*, vol.28, no.2, pp.187-199, DOI: 10.1002/arp.1807, 2021.
- [25] H. Wang, W. Zhang, S. Li, Y. Fan, M. Feng and R. Wang, Development and evaluation of deep learning-based automated segmentation of pituitary adenoma in clinical task, *J. Clin. Endocrinol. Metab.*, vol.106, no.9, pp.2535-2546, DOI: 10.1210/clinem/dgab371, 2021.
- [26] C. P. Jayapandian et al., Development and evaluation of deep learning – Based segmentation of histologic structures in the kidney cortex with multiple histologic stains, *Kidney Int.*, vol.99, no.1, pp.86-101, DOI: 10.1016/j.kint.2020.07.044, 2021.

- [27] T. S. Priya et al., Resnet based feature extraction with decision tree classifier for classification of mammogram images, *Turkish J. Comput. Math. Educ.*, vol.12, no.2, pp.1147-1153, DOI: 10.17762/turcomat.v12i2.1136, 2021.
- [28] P. Hu, J.-S. Pan and S.-C. Chu, Improved binary grey wolf optimizer and its application for feature selection, *Knowledge-Based Syst.*, vol.195, 105746, 2020.
- [29] H. Alazzam, A. Sharieh and K. E. Sabri, A feature selection algorithm for intrusion detection system based on pigeon inspired optimizer, *Expert Syst. Appl.*, vol.148, 113249, 2020.
- [30] M. Farooq, F. Hussain, N. K. Baloch, F. R. Raja, H. Yu and Y. B. Zikria, Impact of feature selection algorithm on speech emotion recognition using deep convolutional neural network, *Sensors*, vol.20, no.21, 6008, 2020.
- [31] N. Maleki, Y. Zeinali and S. T. A. Niaki, A k-NN method for lung cancer prognosis with the use of a genetic algorithm for feature selection, *Expert Syst. Appl.*, vol.164, 113981, 2021.
- [32] Y. Guo, Z. Zhang and F. Tang, Feature selection with kernelized multi-class support vector machine, *Pattern Recognit.*, vol.117, 107988, 2021.
- [33] E. Ileberi, Y. Sun and Z. Wang, A machine learning based credit card fraud detection using the GA algorithm for feature selection, *J. Big Data*, vol.9, no.24, 2022.
- [34] A. B. Habib, Elbow method vs silhouette co-efficient in determining the number of clusters, DOI: 10.13140/RG.2.2.27982.79688, 2021.
- [35] S.-S. Yu, S. W. Chu, C. M. Wang, Y.-K. Chan and T. C. Chang, Two improved k-means algorithms, *Appl. Soft Comput. J.*, vol.68, pp.747-755, DOI: 10.1016/j.asoc.2017.08.032, 2018.
- [36] H. Salem, M. Y. Shams, O. M. Elzeki, M. A. Elfattah, J. F. Al-amri and S. Elnazer, Fine-tuning fuzzy KNN classifier based on uncertainty membership for the medical diagnosis of diabetes, *Appl. Sci.*, vol.12, no.3, pp.1-26, DOI: 10.3390/app12030950, 2022.
- [37] G. Liu, H. Zhao, F. Fan, G. Liu, Q. Xu and S. Nazir, An enhanced intrusion detection model based on improved KNN in WSNs, *Sensors*, vol.22, no.4, pp.1-18, DOI: 10.3390/s22041407, 2022.
- [38] H. Pan, Pearson correlation coefficient-based pheromone refactoring mechanism for multi-colony ant colony optimization, *Appl. Intell.*, vol.51, no.2, pp.752-774, DOI: 10.1007/s10489-020-01841-x, 2021.
- [39] P. Waldmann, On the use of the pearson correlation coefficient for model evaluation in genome-wide prediction, *Front. Genet.*, vol.10, DOI: 10.3389/fgene.2019.00899, 2019.
- [40] J. Cai, Model of freight vehicle energy consumption based on Pearson correlation coefficient, *Journal Transp. Syst. Eng. Inf. Technol.*, vol.18, no.5, pp.241-246, DOI: 10.16097/j.cnki.1009-6744.2018.05.035, 2018.
- [41] H. Zhu, Multiple ant colony optimization based on pearson correlation coefficient, *IEEE Access*, vol.7, pp.61628-61638, DOI: 10.1109/ACCESS.2019.2915673, 2019.