



Image Processing Techniques as a Tool for the Analysis of Liver Diseases

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Abstract:

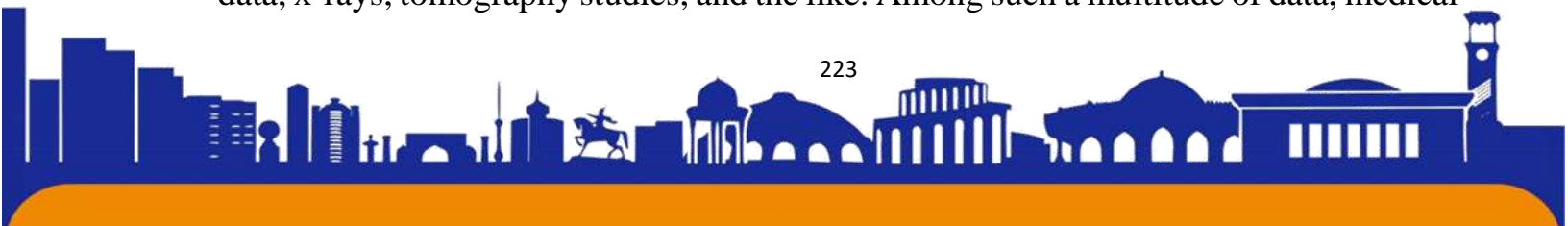
Identification of diseases and their successful treatment is largely determined by early diagnosis. This allows you to both prevent the development of the disease and get rid of possible negative consequences. Various data can be used for these purposes. We are looking at medical imaging techniques. Microscopic images of the liver, where manifestations of fatty disease are possible, were chosen as the object of study. The paper summarizes the general scheme of the corresponding analysis, and presents the results on real images.

Key words: Diagnostics, Analysis, Fatty liver disease, Image processing techniques, Medical imaging, Microscopic images

Introduction

Diagnosis is one of the ways to determine human diseases. This approach makes it possible to determine the possible occurrence of the disease at an early stage and apply methods to stop its development. Early diagnosis allows you to get rid of the severe consequences of the development of the disease, and in some cases to cure the patient [1]-[4]. At the same time, an important aspect is the study of data after the development of diseases that lead to death. This helps to understand the nature of the disease, its course, the impact on various human organs.

To diagnose and study the diseases of the patient, you can use different approaches that are based on different data. These can be empirical test results, ECG data, x-rays, tomography studies, and the like. Among such a multitude of data, medical





images should be singled out, which are photographs under a microscope [5]-[7]. In fact, this is a consideration of the disease and the state of human organs at the micro level. Various methods and approaches of medical image processing techniques can be used here [8]-[14].

Among the various human diseases, liver diseases should be distinguished. Improper diet and unhealthy lifestyle leads to fatty liver disease. This can lead to serious complications. But at the same time, such a disease in the early stages does not have symptoms [15], [16]. It is in this case that the analysis of medical images can be the tool that helps to carry out early diagnosis. This determines the relevance and significance of such a study.

Thus, the main purpose of the article is to consider the possibilities of using image processing techniques in the diagnosis of fatty liver disease.

Brief critical review of the literature

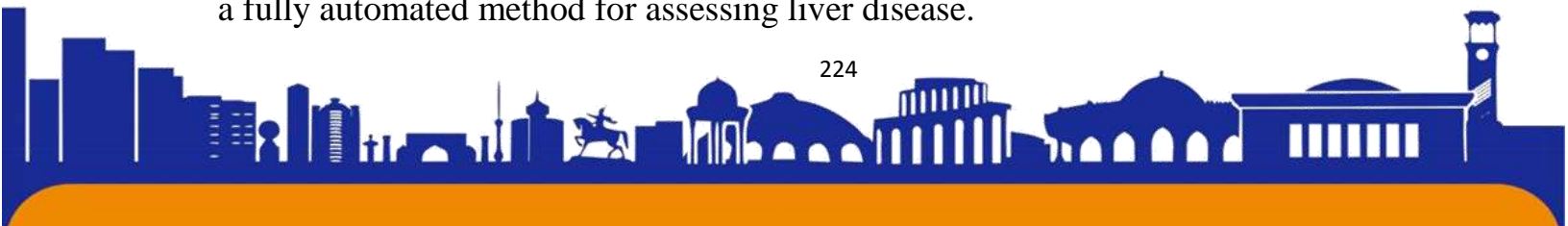
First of all, we note that for the appropriate analysis and creation of an expert system, various approaches can be used: from simple statistical analysis to artificial intelligence with training based on neural networks, evolutionary algorithms and machine learning [17], [18]. However, we will focus on pattern recognition and image processing.

In the study [19], the authors diagnose the state of the liver based on MRI data. For quantitative segmentation of the liver, a convolutional objective function is used in the work. However, the totals count of the part of the tissues of the affected liver remains outside the scope of research. This is the basis for continuing relevant research.

T. M. Hassan, M. Elmogy and E. Sallam consider various segmentation methods for the analysis of medical images [20]. Particular attention is paid to the analysis of images of the liver and the diagnosis of its various diseases.

K. Mala and V. Sadasivam perform segmentation of potentially interesting areas on the liver image using texture analysis and wavelet ideology [21]. It also uses a neural network to infer the final results.

The paper [22] considers an approach to liver image segmentation using morphological operations. This allows you to get more accurate estimates about the areas of interest in the liver region. Through this approach, the authors have developed a fully automated method for assessing liver disease.



However, it should be emphasized that efficient segmentation is not possible without preliminary processing of the input liver image [23], [24]. Here it is important to take into account both the increase in image contrast and the removal of noise. In this case, it is important in general not to spoil the quality of the input image, where quality is understood as the preservation of important information and the prevention of loss of necessary data. Moreover, sometimes pre-processing can have its own specific features of its application. This may be due to different methods of staining the studied tissue samples.

Also, when developing methods for analyzing medical images, one should not forget about the possibility of using simple classical approaches to highlight contours and conduct appropriate segmentation.

General methodology for image analysis of liver tissues

Before discussing the general methodology for analyzing liver images, let's look at a few examples. Figure 1 show some sample images of the liver.

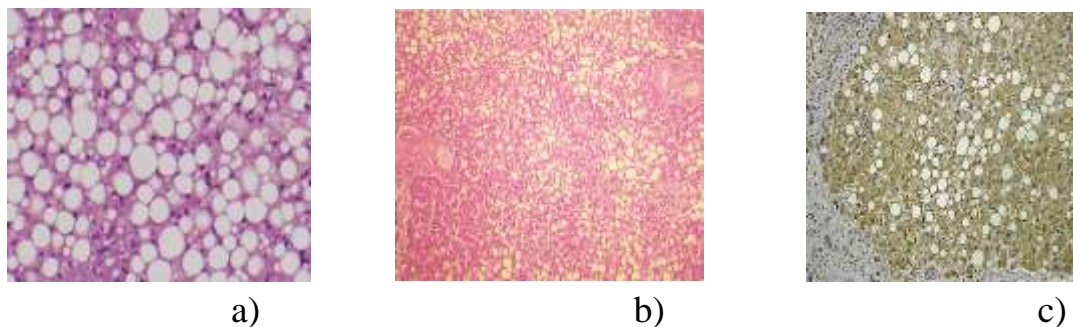


Figure 1: Selected examples of images of liver tissue [14]

We see foci of fatty liver disease of different concentrations. It should also be noted that these foci have a different shape, a different degree of readability of the outlines of such foci.

At the same time, we can state the applicability of different types of staining of the original samples. All this determines the specifics of the application of digital processing methods for the corresponding images.

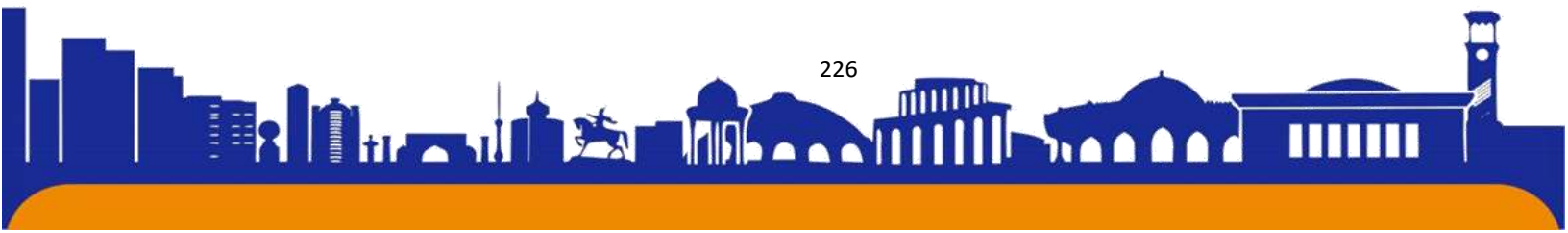
Two approaches can be applied to analyze and detect fatty liver disease.

The first approach is based on the identification of the contours of potential foci of liver damage. As can be seen from the data in Figure 1, such fatty foci have the shape of a circle or oval. To select the contour of an object of interest to us, we can use well-known operators (the so-called boundary detectors): Canny, Sobel, Prewitt, Laplace, and many others. We can also use a simple binarization threshold (Otsu's method). The main feature of this approach is the choice of the threshold, or the appropriate setting of the edge detector.

It should also be noted that we can search for lesions by their shape. The main problem in this case is to determine the geometric dimensions of such a shape. By choosing the wrong geometry, we can miss some foci of fatty liver disease.

The second approach can be based on segmentation methods where color segmentation should be applied. In this case, we are talking about splitting the image into some areas of interest. In some way, segmentation by color can be implemented by introducing separate color markers, according to which we must segment. Then the role of a person in this process is determined by the choice of certain color markers. On the one hand, this simplifies the task of segmentation, but on the other hand, the color of the marker can change and needs to be corrected.

Then, for example, based on the second approach, a generalized algorithm for the analysis of liver glycogen can be presented in accordance with Figure 2.



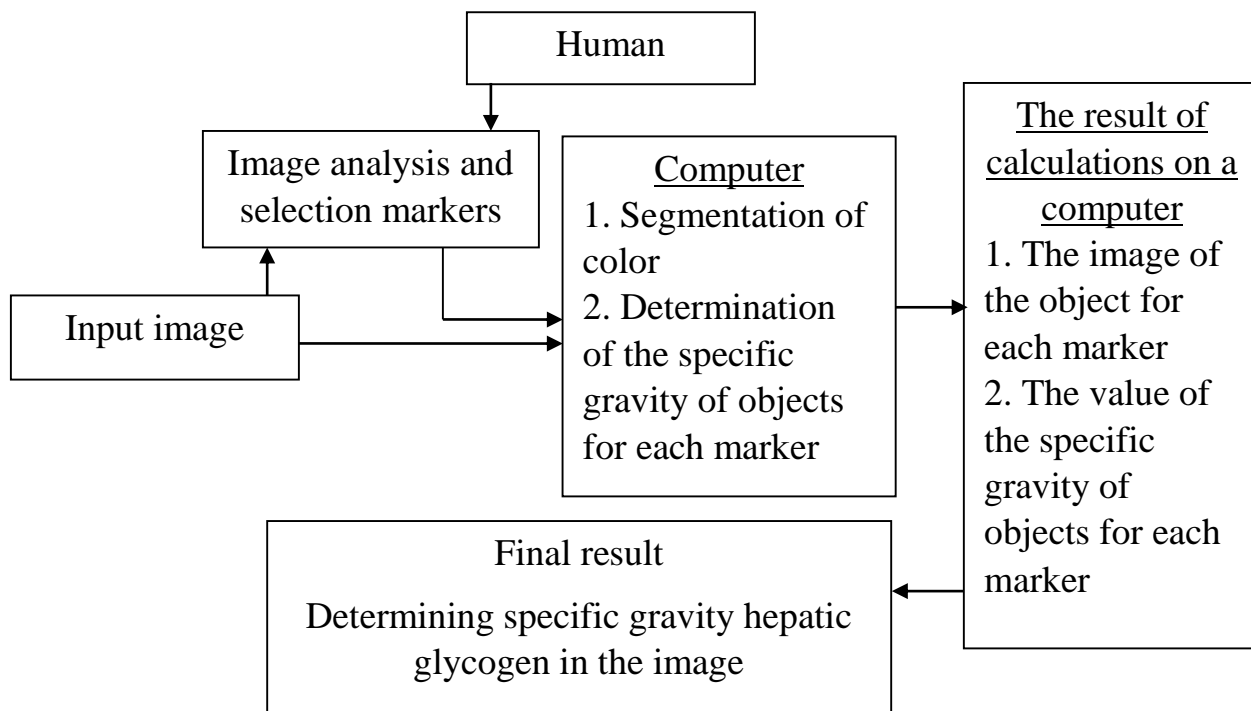


Figure 2: Generalized algorithm for the analysis of liver glycogen based on the color segmentation method

Thus, we consider an integrated human-computer system that allows the necessary analysis to be carried out.

Results

Figure 3 shows the results of detecting the boundaries of fatty liver lesions for the original image (Figure 1a) at different thresholds.

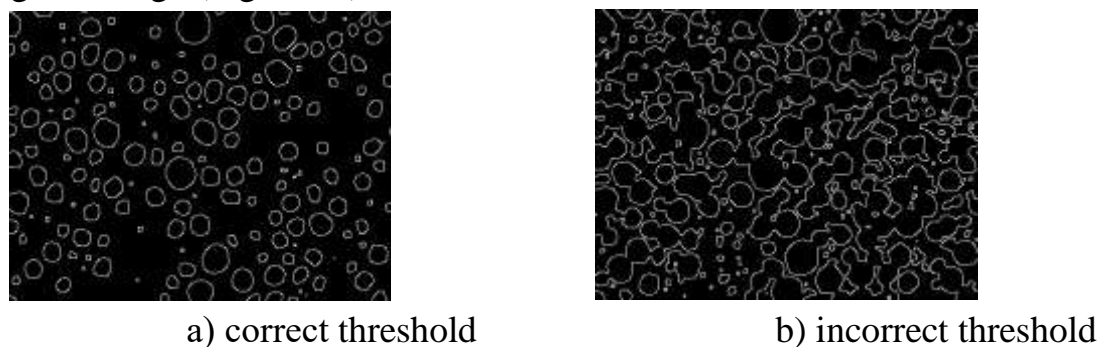
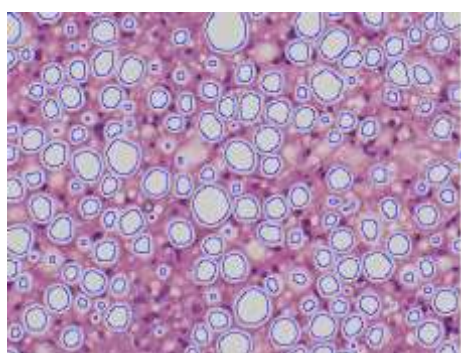
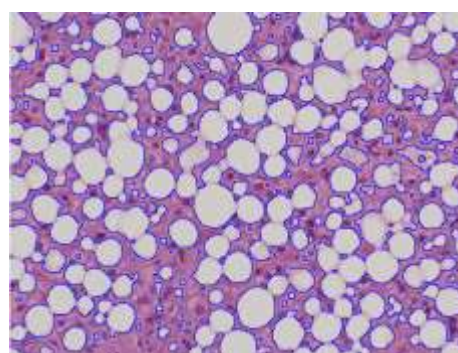


Figure 3: Detection of the boundaries of fatty lesions in liver tissues

We see that the choice of threshold significantly affects the correctness of detection of lesions. In the first case, such lesions stand out clearly and without overlap with neighboring areas of interest. In the second case, we see many intersections of such foci of liver damage. This breaks the understanding of the development of fatty liver disease. The results obtained can be seen in Figure 4, which is the result of combining the data of Figure 1a and Figures 3a,b in turn.



a) correct selection



b) incorrect selection

Figure 4: Result of selection of lesions in the case of using the edge detection method

Figure 5 shows the final result, which helps to make further analysis (counting fatty liver lesions, taking into account their size).

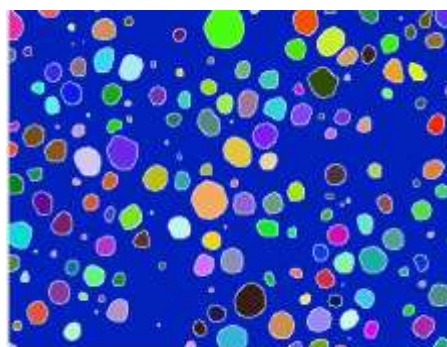


Figure 5: The result of identification of foci of fatty lesions of the liver



Identification of foci of fatty liver lesions is one of the important steps in the processing of the corresponding images. We can visually assess the scale of the lesion; assess the dynamics of the development of fatty liver disease.

We also pay attention to the effectiveness of color prompts in solving the task. Color solutions make it possible to facilitate the process of calculating the total area of liver lesions, to carry out a complete identification of such objects, and to build their classification system. Our system also has the ability to automatically determine the area of liver lesions, which is important for constructing an appropriate histogram. Below is a fragment of such data, which shows the number of the lesion and its area in pixels:

- Object # 17 180
- Object # 18 203
- Object # 19 270
- Object # 20 1
- Object # 21 1
- Object # 22 154
- Object # 23 34
- Object # 24 324
- Object # 25 213
- Object # 26 58
- Object # 27 392
- Object # 28 185
- Object # 29 14
- Object # 30 292
- Object # 31 159
- Object # 32 10
- Object # 33 189
- Object # 34 176
- Object # 35 586
- Object # 36 24
- Object # 37 228
- Object # 38 13
- Object # 39 147



Object # 40 82
Object # 41 303

In the following figure (Figure 6a), objects with the same intensity are shown with the help of colors from the point of view of the original image (Figure 1b). This allows the most significant lesions to be identified (see Figure 6b).

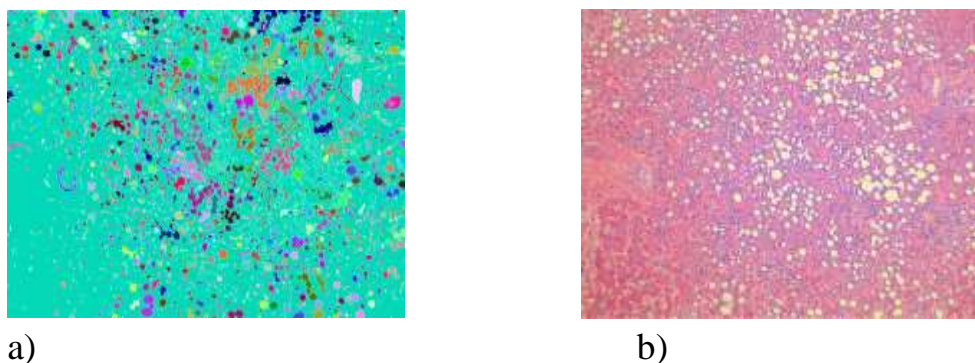


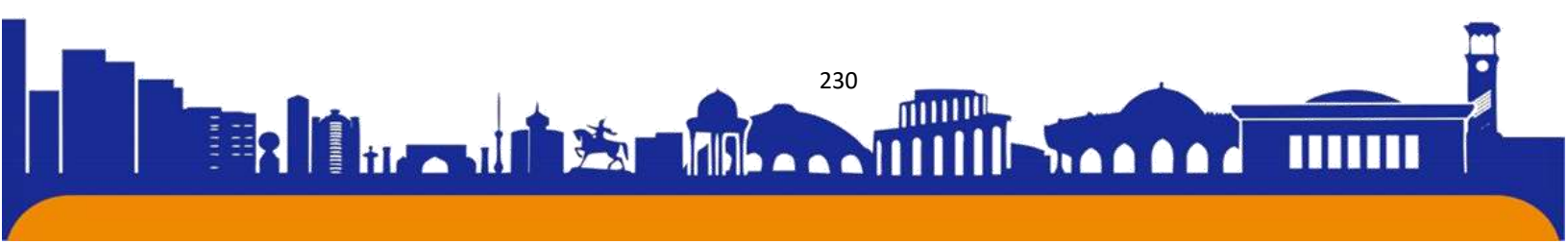
Figure 6: Color segmentation results for the original Figure 1b

The data in Figure 6 illustrate well the benefits of color segmentation in identifying the most intense lesions. This simplifies the overall task of localizing fatty liver disease. It is also an effective tool for illustrating proposed solutions in the course of treatment.

As noted earlier, we can also implement color segmentation based on the selection of color markers. Figure 7 shows the results of this liver lesion segmentation for the original image in Figure 1c.

Figure 7a is a set of color markers that display the primary colors of fatty liver lesions as circles or oval conglomerates (see Figure 1c).

Figure 7b is the result of color segmentation using markers, where fatty liver lesions are highlighted in black. Other colors characterize different components of the liver tissue structure (see Figure 1c).



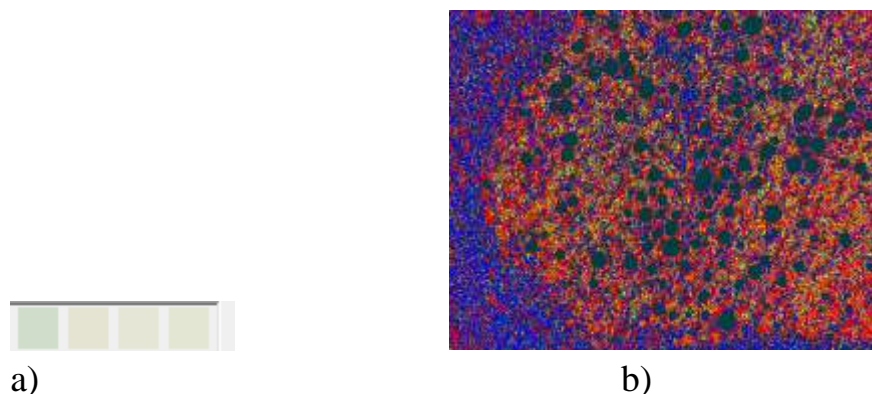


Figure 7: Result of color segmentation based on color markers

Thus, in general, the considered system of approaches to the processing of medical images can solve various problems of analysis and diagnostics.

Conclusion

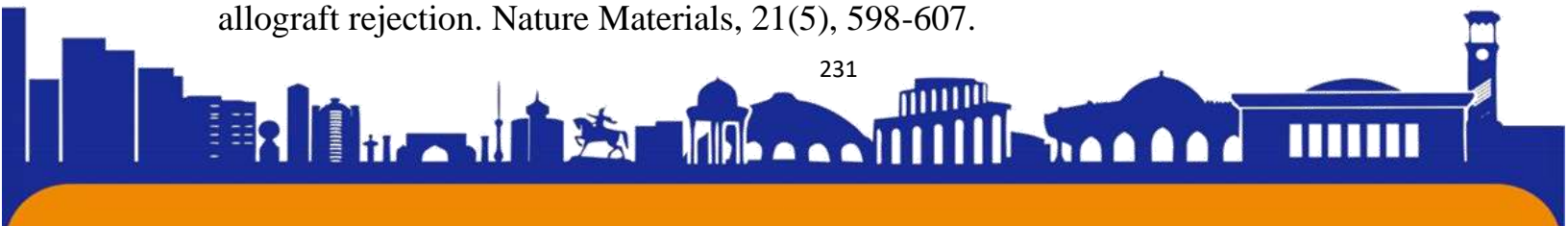
The article deals with the use of classical methods of image analysis for the study of medical data. For this purpose, we have chosen digital images of fatty liver disease.

The paper considers approaches for identifying potential foci of fatty liver disease in the image. Different ways of solving the problem are shown. All results are presented on real images.

The results of the work can be useful for medical professionals, researchers and educators. As a development of this direction, generalization and consideration of an expert system for the diagnosis and analysis of liver diseases is expected.

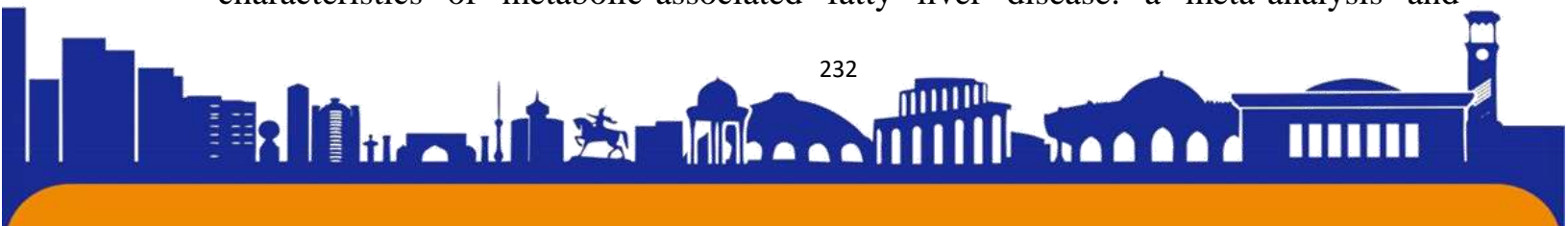
References:

1. Parsa, S. F., & et al.. (2018). Early diagnosis of disease using microbead array technology: a review. *Analytica chimica acta*, 1032, 1-17.
2. Poggiali, E., & et al.. (2020). Can lung US help critical care clinicians in the early diagnosis of novel coronavirus (COVID-19) pneumonia?. *Radiology*, 295(3), E6-E6.
3. Shernazarov, F., Tohirova, J., & Jalalova, D. (2022). Types of hemorrhagic diseases, changes in newboens, their early diagnosis. *Science and innovation*, 1(D5), 16-22.
4. Huang, J., Chen, X., Jiang, Y., Zhang, C., He, S., Wang, H., & Pu, K. (2022). Renal clearable polyfluorophore nanosensors for early diagnosis of cancer and allograft rejection. *Nature Materials*, 21(5), 598-607.





5. Dabeer, S., Khan, M. M., & Islam, S. (2019). Cancer diagnosis in histopathological image: CNN based approach. *Informatics in Medicine Unlocked*, 16, 100231.
6. Liu, X., Song, L., Liu, S., & Zhang, Y. (2021). A review of deep-learning-based medical image segmentation methods. *Sustainability*, 13(3), 1224.
7. Vijayalakshmi, A. (2020). Deep learning approach to detect malaria from microscopic images. *Multimedia Tools and Applications*, 79, 15297-15317.
8. Lyashenko, V. V., Babker, A. M. A. A., & Kobylin, O. A. (2016). The methodology of wavelet analysis as a tool for cytology preparations image processing. *Cukurova Medical Journal*, 41(3), 453-463.
9. Rabotiahov, A., & et al.. (2018). Bionic image segmentation of cytology samples method. In 2018 14th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET) (pp. 665-670). IEEE
10. Lyubchenko, V., Matarneh, R., Kobylin, O., & Lyashenko, V. (2016). Digital image processing techniques for detection and diagnosis of fish diseases. *International Journal of Advanced Research in Computer Science and Software Engineering*, 6(7), 79-83.
11. Lyashenko, V., Matarneh, R., & Kobylin, O. (2016). Contrast modification as a tool to study the structure of blood components. *Journal of Environmental Science, Computer Science and Engineering & Technology*, 5(3), 150-160.
12. Mousavi, S. M. H., Lyashenko, V., & Prasath, S. (2019). Analysis of a robust edge detection system in different color spaces using color and depth images. *Компьютерная оптика*, 43(4), 632-646.
13. Babker, A., & Lyashenko, V. (2018). Identification of megaloblastic anemia cells through the use of image processing techniques. *Int J Clin Biomed Res*, 4, 1-5.
14. Mousavi, S. M. H., Victorovich, L. V., Ilanloo, A., & Mirinezhad, S. Y. (2022, November). Fatty Liver Level Recognition Using Particle Swarm optimization (PSO) Image Segmentation and Analysis. In 2022 12th International Conference on Computer and Knowledge Engineering (ICCKE) (pp. 237-245). IEEE.
15. Duan, Y., Pan, X., Luo, J., Xiao, X., Li, J., Bestman, P. L., & Luo, M. (2022). Association of inflammatory cytokines with non-alcoholic fatty liver disease. *Frontiers in immunology*, 13, 880298.
16. Chan, K. E., & et al.. (2022). Global prevalence and clinical characteristics of metabolic-associated fatty liver disease: a meta-analysis and





systematic review of 10 739 607 individuals. *The Journal of Clinical Endocrinology & Metabolism*, 107(9), 2691-2700.

17. Zhou, L. Q., & et al.. (2019). Artificial intelligence in medical imaging of the liver. *World journal of gastroenterology*, 25(6), 672.

18. Gore, J. C. (2020). Artificial intelligence in medical imaging. *Magnetic resonance imaging*, 68, A1-A4.

19. Irving, B., Hutton, C., Dennis, A., Vikal, S., Mavar, M., Kelly, M., & Brady, J. M. (2017). Deep quantitative liver segmentation and vessel exclusion to assist in liver assessment. In *Medical Image Understanding and Analysis: 21st Annual Conference, MIUA 2017, Edinburgh, UK, July 11–13, 2017, Proceedings 21* (pp. 663-673). Springer International Publishing.

20. Hassan, T. M., Elmogy, M., & Sallam, E. (2015). Medical image segmentation for liver diseases: a survey. *International Journal of Computer Applications*, 118(19), 38-44.

21. Mala, K., & Sadasivam, V. (2005, December). Automatic segmentation and classification of diffused liver diseases using wavelet based texture analysis and neural network. In *2005 Annual IEEE India Conference-Indicon* (pp. 216-219). IEEE.

22. Huo, Y., & et al.. (2019). Fully automatic liver attenuation estimation combing CNN segmentation and morphological operations. *Medical physics*, 46(8), 3508-3519.

23. Lupsor-Platon, M., Serban, T., Silion, A. I., Tirpe, G. R., Tirpe, A., & Florea, M. (2021). Performance of ultrasound techniques and the potential of artificial intelligence in the evaluation of hepatocellular carcinoma and non-alcoholic fatty liver disease. *Cancers*, 13(4), 790.

24. Lafci, B., & et al.. (2023). Multimodal assessment of non-alcoholic fatty liver disease with transmission-reflection optoacoustic ultrasound. *Theranostics*, 13(12), 4217.

