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Blood Type Identification System in Humans Based on Digital Image Processing

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A B S T R A C T

Humans strive to imitate expertise through artificial intelligence approaches, including in medical diagnosis such as distinguishing human blood types A, B, AB, and O. Artificial Neural Networks (ANN) have been developed as a generalization of mathematical models of human learning. This paper discusses the development of ANN software to detect human blood types through recognition of clotting patterns. The clotting patterns of the four blood types can be distinguished well by experts. ANN with the backpropagation learning method is applied as expert learning to recognize blood types based on the clotting pattern formed after antigen reagents are administered. Several image pre-processing stages are used, including edge detection and feature extraction, to improve the recognition process and support accurate blood type identification through artificial intelligence techniques.

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INTRODUCTION

Personal Computer (PC) as a means of helping humans complete daily work in all fields. At first, users only used computers as typewriters, now they have developed into control tools or controllers both in households, in industry and even in educational environments. With the help of video cameras and video blasters, the computer can recognize information from the image or image that is being observed. Image processing is a method or technique that can be used to process images or images by manipulating them into desired image data to obtain certain information (Ferraz et al., 2011; Mahmood, 2024a).

Humans try hard with all their abilities to imitate their greatness, for example, a doctor with his expertise can distinguish human blood types between A, B, AB, and O. With the artificial intelligence approach, humans try to imitate how patterns are formed. Artificial Neural Networks have been developed as a generalization of mathematical models of human learning. Some researchers have successfully applied artificial neural networks to solve the problem of identification. Among them are in the field of medicine that has been developed for the detection of cancer in the lungs, and for the detection and classification of liver disease conditions (Bukhari et al., 2021; Cacciari, 2005).

Develop artificial neural networks for identification with the learning process of an expert's ability to detect the degree of color damage on the monitor screen, and for the detection of red blood color diversity. This paper develops software that can be used to detect human blood type using image processing. The method used is to develop an Artificial Neural Network with a back-propagation learning method (Khan et al., 2024; Tyas et al., 2017).

LITERATURE REVIEW

Image Processing Subsystem

The entire hardware in this study is designed as an integrated system arranged in the form of a block diagram as shown in Figure 1. The system was developed to support the blood type identification process through a digital image processing approach. The hardware used consists of an image object in the form of a blood sample to be analyzed, a video camera as an image acquisition device, and a video blaster that functions to convert analog signals into digital signals so that they can be processed by computers (Lin et al., 2020; Polaków & Metzger, n.d.). The integration between these devices allows the image capture and processing process to be carried out in a more systematic and structured manner.

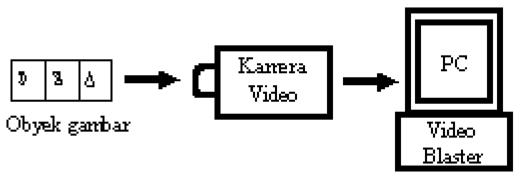

Figure 1. Hardware Diagram Blocks

In addition to the hardware, the system is also supported by a software subsystem arranged in the form of diagram blocks as shown in Figure 2. The software subsystem functions to manage the stages of image processing from data acquisition to the blood type classification process. The image used in the study has a resolution of 512 × 256 pixels with a grayscale of 256 grayscales. Image data is obtained through the acquisition process using a handycam camera, then converted into digital data using a video blaster card before being further processed by the system.

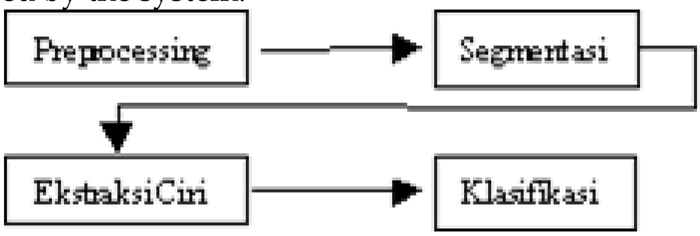

Figure 2. Software Diagram Blocks

Preprocessing

The preprocessing stage is carried out to simplify the image so that the object to be analyzed can be recognized more easily by the system. The process of simplifying the image is shown in Figure 3. In the field of digital image processing, one of the commonly used methods to simplify objects is the edge detection technique, which is a method to identify boundaries between objects in an image (Cui et al., 2008; Srujana et al., 2021). This technique works by detecting significant changes in color intensity or grayness between adjacent pixels. If the change in intensity value exceeds a certain sensitivity level, then the area is considered the edge of the object.

Figure 3. Image Simplification Process

In this study, the Prewitt Operator method (Ye et al., 2018) was used as an edge detection technique. This method utilizes a matrix measuring 3 × 3 with a central point as the main processing target. The calculation is done by combining the difference in pixel values in the horizontal and vertical directions to determine the presence of the edges of the object. An explanation of the matrix structure can be seen in Table 1. Prewitt Matrix Operator. The calculation process is carried out using the following equation:

$$\textbf{Result}=|6+7+8-1-2-3|+|3+5+8-1-4-6|$$

In the equation, the numbers 1 to 8 represent the position of the pixel values in the Prewitt Operator matrix. The result of the calculation is used to determine whether a point includes the edge of an object or not. The use of this method is considered effective in clarifying the boundaries of blood objects so as to facilitate the extraction stages of traits in the next process.

Feature Extraction

The feature extraction stage is carried out after the object in the image has been successfully simplified through the preprocessing process. This stage aims to obtain certain characteristics of each object that can be used as a basis for blood type classification. The feature extraction process begins with determining the position of the leftern, rightern, topern, and bottommost objects in the image. After that, the image is divided into several parts in the form of an M row and an N column to form a number of observation boxes.

Each box is then scanned by pixels to identify the presence of objects in a specific area. If the number of pixels in a box exceeds the predetermined threshold value, then the box is given a value of 1. Conversely, if the number of pixels does not meet the threshold limit, then the box is given a value of 0. These values are then stored in a matrix measuring M × N as reference data to be used at the classification stage. The feature extraction process can be seen in Figure 4.

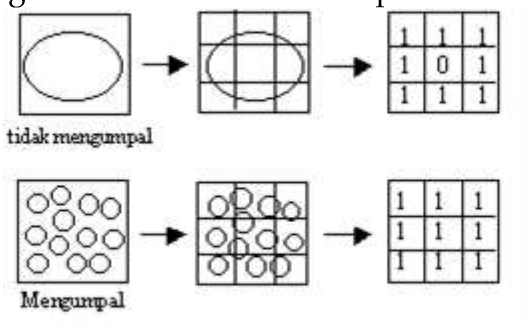

Figure 4. Feature Extraction Process

Classification

The classification process is carried out to determine the type of blood type based on the reaction of blood clots to certain reagents (Prasetyo et al., 2023; Reddy et al., 2025; Saleem et al., 2026). At this stage, three drops of blood samples were given anti-A, anti-B, and anti-AB reagents each. The reactions produced by each reagent are the basis for determining a person's blood type. The image information from the observation from the video camera is shown in Figure 5.

Figure 5. Image Data from Video Cameras

The image data obtained from each reagent is then analyzed to determine whether the blood is clotted or not. The condition of blood that clots is represented by logic 1, while blood that does not clot is represented by logic 0. To support the identification process, the Artificial Neural Network (JST) method with a backpropagation algorithm is used. The backpropagation method or generalized delta rule is one of the learning methods in JST that works using a gradient descent approach to minimize the total square error in the network output.

The stages in the backpropagation method include providing input patterns in the learning process, calculating errors and reverse propagation processes, as well as adjusting the network weight value (Mahmood, 2024b; Soma & Yashwantaray, 2019). The tissue structure used in this study consists of three layers, namely an input layer of 90 neurons, a hidden layer of 10 neurons, and an output layer of 1 neuron. The structure is designed to improve the system's ability to recognize blood clot patterns based on the image data obtained.

The results of the three reagents are then used to determine the type of blood type based on the clotting pattern that is formed. The combination of clot results from anti-A, anti-B, and anti-AB reagents is used as the basis for blood type classification decision-making as shown in Table 1. As below:

Table 1. Blood Type Detection Results

Masukkan			Keluaran
Anti A	Anti B	Anti AB	Golongan
0	0	0	O
0	0	1	X
0	1	0	X
0	1	1	B
1	0	0	X
1	0	1	A
1	1	0	X
1	1	1	AB

Keterangan: 0 (Tidak Menggumpal).
1 (Menggumpal).

Based on the table, if the first drop of blood shows clots (1), the second drop of blood does not clot (0), and the third drop of blood clots (1), then the system will identify the blood sample as blood type A.

METHODOLOGY

This research is carried out through several stages which include literature study, observation, problem analysis, system design, and system implementation. These stages are carried out systematically to support the development of a blood type identification system based on digital image processing. The literature study stage is carried out by studying books, journals, and scientific references related to digital image processing, edge detection, feature extraction, and the Artificial Neural Network (JST) backpropagation method. This stage aims to obtain a theoretical foundation and determine the method that is appropriate for the research.

Furthermore, observations were made on blood samples that had been tested in the laboratory to understand the pattern of blood clots after the administration of anti-A, anti-B, and anti-AB reagents. The observation results are used as a basis in the process of identifying and classifying blood images.

The problem analysis stage is carried out to determine the limitations of the most effective system and method in the blood type identification process. After that, a system design was carried out which included image acquisition, preprocessing, edge detection using the Prewitt Operator method, feature extraction, and classification using JST backpropagation.

The final stage is the implementation of the system, which is to build software based on the design that has been made and conduct tests using blood image data to determine the system's ability to recognize blood types automatically.

RESEARCH RESULT AND DISCUSSION

This research succeeded in developing a human blood type identification system based on digital image processing by utilizing edge detection methods and Artificial Neural Network (JST) backpropagation. The system is designed to recognize blood clotting patterns after blood samples are administered anti-A, anti-B, and anti-AB reagents. The identification process is carried out through several main stages, namely image preprocessing, edge detection using the Prewitt Operator method, feature extraction, and classification process using JST.

Research on blood type identification based on image processing has actually been widely developed, especially through machine learning approaches and the recognition of medical image patterns. However, most previous studies have focused more on the use of microscopic images with relatively complex device specifications and high implementation costs (Ferraz et al., 2011; Khan et al., 2024). On the other hand, research combining simple edge detection methods with backpropagation of artificial neural networks on images of blood reagent reaction results is still relatively limited, especially in systems based on simple acquisition devices such as video cameras and video blasters. In addition, some previous studies have focused more on improving classification accuracy without explaining the stages of image simplification and feature extraction in a structured manner so that the pattern recognition process becomes less efficient when applied to devices with limited computing capabilities.

Based on these conditions, the research gap in this study lies in the lack of optimal development of a simple blood type identification system based on digital image processing that is able to work using low-cost image acquisition devices but still produces a good level of identification. This study also fills the gap of previous research by integrating the Prewitt Operator method as an image simplification process and JST backpropagation as a classification method in a structured identification system flow. This approach is important because most modern research is more oriented towards deep learning methods with the need for large datasets and high device specifications, while this research offers a lighter and more adaptive approach to the development of basic identification systems.

The main novelty of this study lies in the development of a blood type identification system based on blood clotting patterns using a combination of image preprocessing, extraction of binary matrix features, and classification of JST backpropagation on blood reagent images. This research not only focuses on the classification process, but also optimizes the stages of image simplification through the edge detection method so that the characteristics of blood clots can be recognized more clearly before the tissue learning process is carried out. In addition, the use of data representation in the form of binary matrices 9 × 10 provides a simpler and more efficient approach than the use of full image processing, thereby reducing computational complexity without eliminating the main pattern of blood objects. This approach is an important contribution because it shows that blood type identification systems can still be developed effectively using lightweight computing methods with a fairly good level of accuracy.

The results of the implementation showed that the system was able to recognize blood clotting patterns in each blood type quite well. In the preprocessing stage, the Prewitt Operator method manages to simplify blood imagery by highlighting the edges of objects so that clot patterns are easier to recognize by the system. The results of edge detection are shown in Figure 6. This process results in a simpler image than the original image, but still retains the main characteristics of the blood clot pattern. Thus, the feature extraction process can be performed more effectively as unnecessary noise and detail have been minimized.

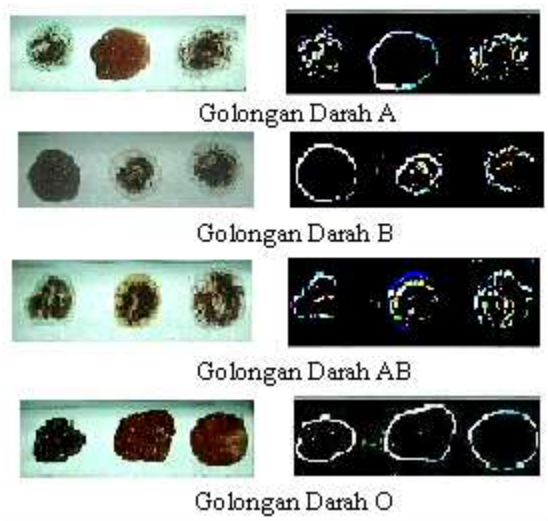

Figure 6. Blood Images and Edge Detection Results

The success of the Prewitt Operator method in this study shows that edge detection techniques are still relevant in simple medical image processing systems, especially to detect changes in pixel intensity in blood objects. These findings are in line with the research of Cui et al. (2008) and Srujana et al. (2021) which stated that edge detection is able to improve the system's ability to distinguish the boundaries of objects based on changes in the grayness of the image. In addition, the use of Prewitt operators also provides a relatively light computational process so that it is suitable for application to computer-based identification systems with simple specifications.

After the edge detection process is performed, the system proceeds with the feature extraction stage by converting the image pattern into a binary matrix shape of 9 × 10 as shown in Figure 7. This process is carried out by dividing the image into several parts, then scanning the pixels to determine the presence of the object based on the number of active pixels in each observation area. The results of the extraction of these traits are then used as input data on the artificial neural network.

```
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 1 1 1 0 0
0 0 0 1 1 0 0 0 1 0
0 0 0 1 0 0 0 0 0 1
0 0 0 1 0 0 0 0 0 0
0 0 0 1 0 0 0 0 0 0
0 0 0 0 1 1 1 0 0 0
0 0 0 0 0 0 0 0 0 0
```

Data XA22.dat

```
0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 0 0 0 0 0
0 0 0 1 1 1 1 1 0 0
0 0 1 1 1 0 0 1 1 0
0 0 0 1 1 1 1 0 0 0
0 0 0 1 1 1 1 0 0 0
0 0 0 0 1 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 1 0
```

Data XAB12.dat

```
0 0 0 0 0 0 0 0 0 0
0 1 1 1 1 1 0 0 0 0
0 1 0 0 0 1 1 0 0 0
1 0 0 0 0 0 1 0 0 0
1 0 0 0 0 0 1 0 0 0
0 1 0 0 0 0 1 0 0 0
0 1 1 1 1 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0
```

Data XO11.dat

```
0 1 1 1 1 0 0 0 0 0
1 1 0 0 0 1 0 0 0 0
1 0 0 0 0 0 1 1 0 0
1 0 0 0 0 0 0 1 0 0
0 1 0 0 0 0 0 0 0 0
0 1 1 1 1 0 1 0 0 0
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0
```

Data XB11.dat

Figure 7. Data from the 9×10 Matrix Scale

Image representation in the form of a binary matrix aims to simplify the input data before it is processed by artificial neural networks. The data reduction process produces numerical patterns that are easier to recognize by the classification system. An example of the results of image data reduction after the feature extraction process is shown in Table 2.

Table 2. Image Data Reduction Results

No	Gol A	Skala	Gol B	Skala	Gol AB	Skala	Gol O	Skala
1	XA11	BENAR	XB11	BENAR	XA11	BENAR	XO11	BENAR
2	XA12	BENAR	XB12	BENAR	XA12	BENAR	XO12	BENAR
3	XA13	BENAR	XB13	BENAR	XA13	BENAR	XO13	BENAR
4	XA21	SALAH	XB21	BENAR	XA21	BENAR	XO21	BENAR
5	XA22	BENAR	XB22	BENAR	XAB22	BENAR	XO22	BENAR
6	XA23	SALAH	XB23	SALAH	XAB23	SALAH	XO23	BENAR
7	XUA11	BENAR	XUB11	BENAR	XUAB11	SALAH	XUO11	BENAR
8	XUA12	SALAH	XUB12	BENAR	XUAB12	BENAR	XUO12	BENAR
9	XUA13	SALAH	XUB13	SALAH	XUAB13	BENAR	XUO13	BENAR
10	XUA21	BENAR	XUB21	BENAR	XUAB21	BENAR	XUO21	BENAR
11	XUA22	BENAR	XUB22	SALAH	XUAB22	BENAR	XUO22	SALAH
12	XUA23	BENAR	XUB23	SALAH	XUAB23	BENAR	XUO23	BENAR
13	XUA31	SALAH	XUB31	BENAR	XUAB31	BENAR	XUO31	SALAH
14	XUA32	BENAR	XUB32	BENAR	XUAB32	BENAR	XUO32	BENAR
15	XUA33	BENAR	XUB33	SALAH	XUAB33	SALAH	XUO33	BENAR
16	XUA41	BENAR	XUB41	BENAR	XUAB41	BENAR	XUO41	SALAH
17	XUA42	BENAR	XUB42	SALAH	XUAB42	SALAH	XUO42	BENAR
18	XUA43	BENAR	XUB43	BENAR	XUAB43	BENAR	XUO43	BENAR

The results of the data reduction showed that the feature extraction process successfully changed the blood image pattern to a simpler numerical data form without eliminating the main characteristics of the object. However, the data simplification process also causes some image information to be reduced, affecting the level of system accuracy in the classification process.

The next stage is the classification process using the Artificial Neural Network backpropagation method. The system conducts a learning process based on the data pattern of the characteristic extraction to distinguish the condition of blood that clots and non-clotting. The test was carried out directly using a video camera to find out the system's ability to recognize human blood type.

The results of the system tests showed that the software was able to identify blood types with a fairly good success rate. The data from the system test results is shown in Table 3.

Table 3. Blood Type Identification System Test Results

No	Gol A	Hasil	Gol B	Hasil	Gol AB	Hasil	Gol O	Hasil
1	XUA1	dikenali	XUB1	dikenali	XUAB1	dikenali	XUO1	dikenali
2	XUA2	tidak	XUB2	dikenali	XUAB2	tidak	XUO2	dikenali
3	XUA3	dikenali	XUB3	tidak	XUAB3	dikenali	XUO3	dikenali
4	XUA4	dikenali	XUB4	dikenali	XUAB4	dikenali	XUO4	dikenali
5	XUA5	dikenali	XUB5	dikenali	XUAB4	tidak	XUO5	dikenali

Based on the test results in Table 3, the number of correct detections was obtained as many as 16 data and the number of false detections as many as 4 data. Thus, the accuracy level of the system in recognizing blood types reaches about 80%. The success rate shows that the JST backpropagation method has a fairly good ability to recognize blood clot patterns based on digital images.

Nonetheless, the results show that the accuracy level of the system is still influenced by several external factors, such as the quality of the video camera, the intensity of the lighting, the position of the image shooter, and the quality of the blaster video device. In addition, the data reduction process at the feature extraction stage causes some image details to be lost so that in some conditions the system experiences misclassification.

The learning process of JST during training is shown in Figure 8. The graph shows that the error value decreases as the number of training iterations increases. This condition shows that the network learning process is running well and the network weight is able to adjust the input data pattern to the expected output target.

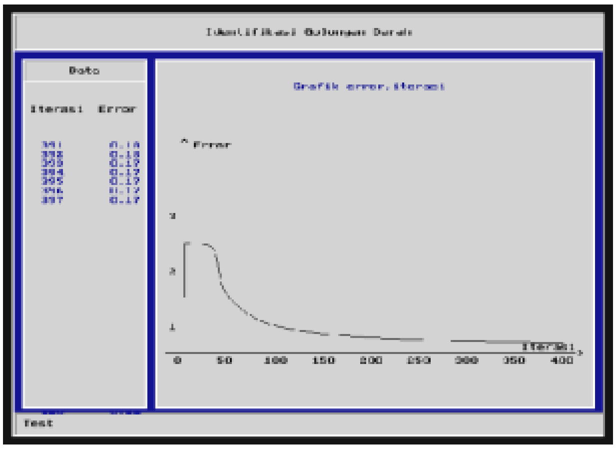

Figure 8. Graph of Data Training on Artificial Neural Networks

The results of this study support the research of Mahmood (2024b) and Soma and Yashwantaray (2019) who stated that the JST backpropagation method can be used for the blood image classification process through the recognition of digital patterns. In addition, the research of Khan et al. (2024) also showed that the combination of image processing and artificial intelligence is effectively used in the identification of blood structures in microscopic medical images. The difference is that this study uses a classification approach based on blood reagent clotting patterns with a simpler image acquisition system. Thus, this study shows that the JST-based digital image processing approach can be an alternative to an automatic blood type identification system with a relatively low cost and a faster process than manual observation.

The contribution of this research lies not only in the success of blood type identification, but also in the development of a simple system model that can be implemented in environments with limited digital laboratory facilities. The use of simple preprocessing methods and binary matrix representations suggests that identification systems do not necessarily require complex computations to produce adequate classifications. This is a practical and theoretical contribution to the development of a light-scale artificial intelligence-based medical image processing system.

However, the results show that the accuracy level of the system is still influenced by several external factors, especially the quality of the image acquisition device. Lighting intensity, camera position, blaster video quality, and blood image conditions greatly affect the success of the identification process. In some conditions, the process of data reduction during image simplification causes the loss of some important information so that the system experiences misclassification. This is one of the reasons why four data are still found that are not recognized correctly.

In addition, the amount of training data used in this study is still relatively limited, so the generalization ability of the network is not optimal. This condition causes the system to be more sensitive to changes in image patterns that are different from previous training data. Therefore, further research is recommended to use a larger number of datasets, more stable image quality, as well as develop more modern classification methods such as Convolutional Neural Network (CNN) so that the accuracy level of blood type identification can be improved more significantly.

CONCLUSIONS AND RECOMMENDATIONS

Based on the results of observations, tests, and discussions that have been carried out, this study shows that the digital image processing method using Prewitt Operator edge detection can be used to simplify blood images so that clotting patterns can be recognized more clearly. The developed system also successfully identified blood types A, B, AB, and O using the Artificial Neural Network backpropagation method with a fairly good level of accuracy. The results of the study show that a combination of image preprocessing, trait extraction, and JST classification can be used as an alternative to automatic blood type identification based on digital images. However, the success of the system is still greatly influenced by the condition of the supporting devices, such as the quality of the video camera, video blaster, and the intensity of the lighting during the image-taking process.

This research is expected to add insight and reference in the development of a blood type identification system based on artificial intelligence and digital image processing. For further development, it is recommended that the research use more modern classification methods and a larger number of datasets so that the accuracy level of the system can be improved. In addition, the use of image acquisition devices with better quality and more stable lighting conditions is also needed so that the identification process can run more optimally, quickly, and accurately.

ADVANCED RESEARCH

Further research is expected to develop a blood type identification system using more modern artificial intelligence methods, such as Convolutional Neural Network (CNN) or Deep Learning, so that the level of classification accuracy can be improved more optimally. In addition, the use of larger blood image datasets, variations in lighting conditions, and better quality image acquisition devices are also needed to improve the generalization capabilities of the system. The development of a real-time system based on mobile devices or the Internet of Things (IoT) is also an opportunity for further research so that the blood type identification process can be carried out faster, more practically, and more efficiently.

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REFERENCES

Bukhari, M. M., Alkhamees, B. F., Hussain, S., Gumaei, A., Assiri, A., & Ullah, S. S. (2021). An improved artificial neural network model for effective diabetes prediction. Complexity, 2021, 1–10. https://doi.org/10.1155/2021/5525271.

Cacciari, M. (2005). Nomes de lugar: Confim. Revista de Letras, 45(1), 13–22. https://doi.org/10.2307/26459823.

Catenary System. (1991). ZIP image processing. Catenary System.

Catenary System. (1992). Victor image processing library. Catenary System.

Creative Labs. (1994). Video Blaster SE100PI user's guide. Creative Technology Ltd.

Cui, F. Y., Zou, L. J., & Song, B. (2008, September). Edge feature extraction based on digital image processing techniques. In IEEE Conference Proceedings. IEEE.

Ferraz, A., Carvalho, V., Soares, F., & Leão, C. P. (2011). Characterization of blood samples using image processing techniques. Sensors and Actuators A: Physical, 172(1), 308–314. https://doi.org/10.1016/j.sna.2011.02.022.

Khan, R. U., Almakdi, S., Alshehri, M., Haq, A. U., Ullah, A., & Kumar, R. (2024). An intelligent neural network model to detect red blood cells for various blood structure classification in microscopic medical images. Heliyon, 10(4), Article e26149. https://doi.org/10.1016/j.heliyon.2024.e26149.

Lin, R., Ramesh, R., Chi, C., Jain, N., Nuqui, R., Dutta, P., & Hartmann, B. (2020). Polymorphic blocks: Unifying high-level specification and low-level control for circuit board design. In Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology (pp. 529–540). ACM. https://doi.org/10.1145/3379337.3415860.

Mahmood, M. F. (2024). Recognition and categorization of blood groups by machine learning and image processing method. Innovative Biosystems and Bioengineering, 8(2), 53–68. https://doi.org/10.20535/ibb.2024.8.2.298201.

Patterson, D. W. (1995). Artificial neural networks: Theory and applications. John Wiley & Sons.

Penedo, M. G., Carreira, M. J., Mosquera, A., & Cabello, D. (1998). Computer-aided diagnosis: A neural-network-based approach to lung nodule detection. IEEE Transactions on Medical Imaging, 17(6), 872–880. https://doi.org/10.1109/42.746622.

Polaków, G., & Metzger, M. (n.d.). Dynamically generated block diagrams as a visualisation method.

Prasetyo, A. B., Wahyudi, R., Tahyudin, I., Kusuma, S. F., Oktaviana, L. D., Barkah, A. S., & Artono, B. (2023). Comparative analysis of image on several edge detection techniques. TEM Journal, 12(1), 111–117. https://doi.org/10.18421/TEM121-15.

Purnomo, M. H., et al. (1997). An artificial neural network approach for the quality classification of tile product. In Proceedings of the International Conference on Nonlinear Theory and Its Applications (pp. 779–781).

Purnomo, M. H., et al. (1998a). Identification of color uniformity defect on the electronic displays by learning the human perception records. IEEJ Transactions on Electronics, Information and Systems, 118-C(7–8), 1164–1169.

Purnomo, M. H., et al. (1998b). Operator skill acquisition for re-setting the adjuster position of an energy meter. In Proceedings of the IEEE Instrumentation and Measurement Technology Conference (pp. 286–288).

Reddy, G. C., SaiKrishna, G., & Annie Micheal, A. (2025). Automated blood group detection system using image processing for non-invasive antigen feature extraction and classification. In 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT 2025) (pp. 2199–2208). IEEE. https://doi.org/10.1109/IDCIOT64235.2025.10914768.

Saleem, R., Ashish, Kazmi, S. M. H., & Qadeer, M. A. (2026). ABO blood type and rhesus factor detection system: An automated approach. In 2026 6th International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT 2026). IEEE. https://doi.org/10.1109/IMPACT68503.2026.11468288.

Soma, S., & Yashwantaray, P. (2019). RGB image cluster evaluation for human blood group identification by MLP classification. International Journal of Recent Technology and Engineering, 8(3), 4197–4202. https://doi.org/10.35940/ijrte.C6005.098319.

Srujana, P., Priyanka, J., Patnaikuni, V. Y. S. S. S., & Vejendla, N. (2021). Edge detection with different parameters in digital image processing using GUI. In Proceedings of the 5th International Conference on Computing Methodologies and Communication (ICCMC 2021) (pp. 795–802). IEEE. https://doi.org/10.1109/ICCMC51019.2021.9418327.

Tyas, D. A., Ratnaningsih, T., Harjoko, A., & Hartati, S. (2017). The classification of abnormal red blood cell on the minor thalassemia case using artificial neural network and convolutional neural network. In ACM International Conference Proceeding Series (pp. 228–233). ACM. https://doi.org/10.1145/3177404.3177438.

Ye, H., Shen, B., & Yan, S. (2018). Prewitt edge detection based on BM3D image denoising. IEEE Press.