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Computer-Vision Based CBC Test for Detecting Different Hematological Diseases

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ABSTRACT

Hematology is the branch of science that deals with blood diseases and disorders. Unlike other alternatives, computer vision technologies provide an uncostly precise tool for diagnosing such diseases. A cardinal issue that rises in the conventional techniques used to detect blood diseases is its dependency on external physical interferences which can significantly produce a deficiency in term of accuracy. In addition, the high cost of the analyzer is considered a major limitation with the currently used blood test devices. These drawbacks have motivated this study to come up with a more reliable non-expensive solution. In this paper, Hough Transform (HT) has been used in a computer-vision based model to recognize the different constituents of human blood. According to the sizes, shapes and count of blood cells, different hematological diseases are detected. Results showed promising efficiency the accuracy of diagnosing anemia, leukemia, myeloma and sickle cell anemia.

1. INTRODUCTION

According to WHO's report dated in May 2023, 40% of children, a total percentage of 30% of pregnant women, and 37% of adult females suffer from blood disorder diseases [1]. Many Hematologic diseases are mainly caused by abnormality in the number of blood cells as it is the case with anemia disease which is attributed to the low count of red blood cells [2-4]. Polycythemia on the other hand occurs when the marrow of bones overproduces red blood cells [5-7]. A decreased amount of white blood cells can be considered a sign of some viral infections like HIV or hepatitis [8-10]. In contrast, a sort of cancer hits bone marrow leading it to produce excessive amount of white blood cells [11, 12]. In addition, low count of blood platelets is a sign of a disease called thrombocytopenia [13]. In contrary, a decreased number of platelets in blood is termed as thrombocytosis which can be attributed to a certain disorder in bone marrow, steroid medications, or sorts of infections [14, 15]. Early diagnosis of such ailments can contribute to a large extent in saving human lives [16-18]. Not only the count of the different types of blood cells can be invested to detect relevant ailments, but instead, the differentiation in the shapes of blood cells gives critical diagnostic information as it is the case in sickle cells anemia where red blood cells are deformed [19-22].

Early diagnosis is considered a crucial factor in preventing unwanted complications. Early detection of leukemia for instance, can significantly lead to a better response to treatment [6]. In addition, HIV disease is a viral infection, where the delayed diagnosis can give the virus chance to continue replicating which can strongly threaten the infected individual's life. In contrary, prompt diagnosis of HIV and hence rapid treatment can be significantly beneficent when immune system is still stronger during the early stages of the disease. In addition, early detection of blood diseases makes it easier to control the symptoms like fatigue, or pain [8].

Automated Blood Analyzer (ABA), or most of the time referred to as Hematology Analyzer (HA) is the currently used electronic device for the purpose of counting different blood constituents. HA uses physical characteristics of blood stains to measure the approximate number of red blood cell, known as erythrocytes, white blood cells, leukocytes, and blood platelets, known as thrombocytes [23-25]. This operation of counting different blood components is termed Complete Blood Count (CBC). In addition to CBC test, Hematology Analyzer offers another important diagnostic service represented by measuring the amount of hemoglobin, the protein responsible of carrying oxygen to the different body cells [26-28]. Normally, erythrocytes should count 3.5-5 million per microliter in females, and 4-5.5 million per microliter in males [29]. Slight variation in these counts is permissible since these ranges are slightly dependable on some demographic factors such as age, sex and location [30]. Light passing though different constituents of blood experience different scattering levels. This physical property is employed in HA to differentiate among different kinds of blood cells and platelets. Developed analyzers use more than one physical property such as the amount of scattering experienced by light when subjected to the different blood particles, the level of light absorption, impedance and conductivity of blood smears, and flow cytometry of the blood specimen [31].

Many problems appear when using Hematology Analyzer affecting the device accuracy, such as the existence of blood clots, impurities in the collected and specimen. Furthermore, air bubbles created due to the excessive shaking of the blood specimen during the pre-analytical stage can contribute to a substantial extent in deluding the counting process since some bubbles could be considered cellular particles. According to the study by Tadesse et al. [32], a total of 477 out of 2606, about 28%, of hematology tests were recorded incorrectly in St. Paul's hospital in Addis Ababa. Some of these errors were happened in pre-analytic stage, others in analytical stage, and some others occurred during the post-analytic stage. Furthermore, some diagnostic operations need manual processing to detect certain types of blood abnormalities, especially those abnormalities characterized by cell deformation such as hereditary spherocytosis and sickle cell anemia. In addition to the all-aforementioned issues, Hematology Analyzer is considered a high-cost device. In this paper a new computer-vision based method is proposed to analyze blood diseases. This method makes use of an image processing techniques and Hough Transform algorithm to identify a particular cellular particle, count the different blood components, diagnose the sort of ailment in an automatic manner. The proposed method outweighs the traditional CBC method mainly based on using Hematology Analyzer in terms of the cost, accuracy and diagnostic capabilities. In the capability's perspective, it offers an intelligent way to detect cells deformation, like sickle cell anemia, in an automatic manner. Clotting blood patches problem has also been resolved via using detaching and color facts. Section 2 in this paper reviews the necessary background for achieving the work of this paper. Section 3 on the other hand, shows the results of the proposed method and discusses these results. Finally, section 4 concludes this paper and suggests ideas for future work. To summarize, computer-vision based techniques outperform the traditional Hematology Analyzer-based detection in terms of the resulting accuracy, cost, speed, and covering a wider range of blood disorders.

2. METHODOLOGY

MATLAB programming platform has been utilized to analyze blood smears, recognize different types of blood particles, and finally give the corresponding diagnosis. A blood smear should pass through several analytic stations till a diagnosis result is given. MATLAB offers efficient facilities when dealing with image processing. Hough Transform algorithm and other image processing tools were invested in this work to recognize different types of blood cells and platelets according to predefined characteristics of the detected blood components. An image of blood smear obtained in phase-1 of the proposed scheme passes through another five phases to collect cardinal specifications of blood particles from each phase. All these resulting specifications gathered from the five phases are put together and analyzed to find out what and how many these particles are. These five phases are namely, extracting color planes, Hue-Lightness-Saturation (HLS), filtering, circular Hough Transform, and counting. The results of the counting phase are then fed to the diagnosis phase as shown in Figure 1.

2.1 Collecting specimen

This is the first phase in the proposed system where the blood smear sample is collected and a digital image is taken, then the image is imported by MATLAB. Coagulation is the major reason for the failure of CBC tests. According to the study by De la Salle [33-35], 57% of the failed CBC tests is attributed to coagulation. Consequently, appropriate measures should be considered when collecting specimens, such as using tubes supported with anti-coagulant agent.

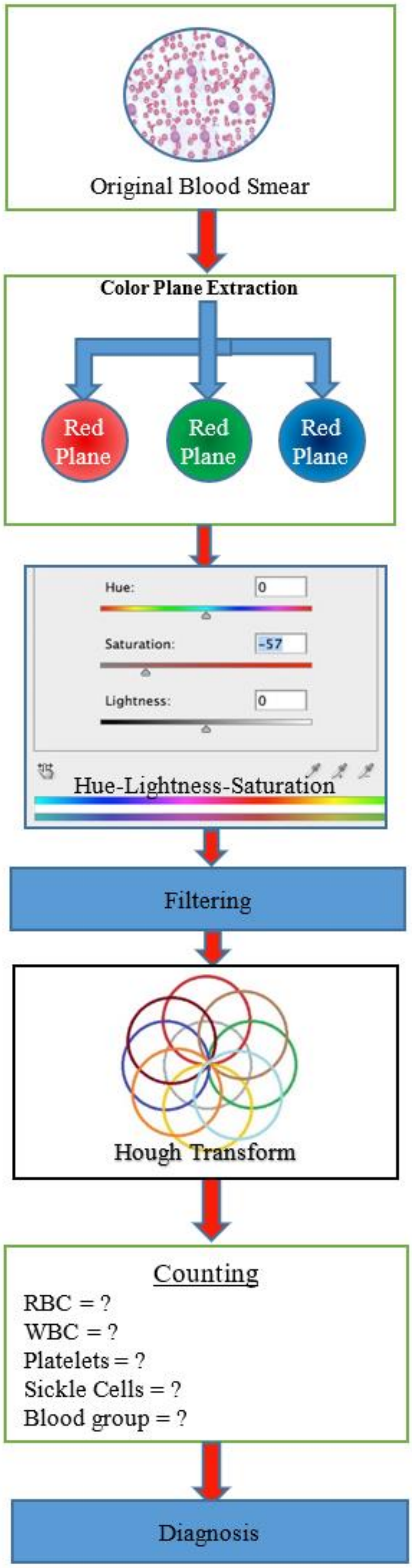

Figure 1. The proposed method chart

2.2 Extracting color planes

In this phase the, the specimen image is disassembled into its three-color planes, namely, red plane, green plane, and blue plane. Each plane contains important information about the specimen. This information can be utilized to recognize some cardinal facts about the blood that are used to make the proper diagnosis. Furthermore, White blood cells are colorless, and can look bluish when a dye is applied to the specimen, making it is easier to recognize the white blood cells by extracting the colors.

2.3 HLS

In this stage, lighting effects represented by shading and light spotting are eliminated using HLS filters. Light spots appear in the image of the specimen when the light is reflected from the specimen. These light spots can conceal very important information of the patch where they are located. Shading on the other hand can delude the system by making the program counting cells' shades as blood particle leading to a wrong count, and hence false diagnosis. These lighting effects can be resolved by applying hue, brightness, and saturation filters.

2.4 Noise filtering

Noise Filtering is the next phase, where the noise represented by air bubbles and impurities are eliminated from the treated image. These bubbles and impurities appear on the image as tiny objects and need to be filtered prior to applying the Hough Transform lest they will be falsely counted as blood particles, specifically blood platelets. MATLAB offers an efficient tool in doing such a task via using "bwareaopen" instruction. This instruction is used to remove tiny paches in black-and-white images. The sensitivity of this filter can be set within the instruction's arguments to select a suitable threshold size for the patches desired to be deleted. As a result of applying this filter, patches which are identified as contiguous white pixels are removed from the blood's binary image if and only if these patched have smaller sizes than the threshold specified within the instruction.

2.5 Hough Transform

Hough Transform is a tool used in the field of computer vision to recognize regular shapes such as circles, lines, and ellipses. It is a mathematical method used to connect disjoint points of a particular shapes if the original image is imperfect. Circular Hough Transform on the other hand is specialized in detecting circular objects. In Hough Transform, the algorithm walks through the edges of an image, after edge detection was performed, and considers each point on the edge as a center of a circle with a specific radius. The point where most of the circles intersect is the actual center of the circular object. Different radius values are tried to detect objects of different radiuses. The task of edge detection is achieved implicitly using the instruction "imfindcircles" which invests the capabilities of circular Hough Transform to identify circle-like shapes. This instruction takes two input arguments, the first is the image data variable, and the second is the range of radii of circles to be detected. The instruction can be executed twice but with different ranges of radii to detect the bigger WBCs and the smaller RBCs. This mathematical tool was used in this work to recognize blood cells and measure their sizes. Whenever a cell is detected, it is treated to remove its border line aiming to detach clotting cells.

2.6 Counting blood constituents

After applying circular Hough Transform, it is the time to count the number blood cells and inspect the existence of any deformation in cells. The results are directed to the diagnosis phase in order to find out whether there are any potential signs of blood diseases.

2.7 Diagnosis phase

It is the last phase of the proposed algorithm. Given the previously counted number of cells within a pre-determined volume of the blood specimen, the system decides which sort of illness is experienced, if any. Anemia, polycythemia, HIV, hepatitis, leukemia, thrombocytopenia, thrombocytosis, and sickle cells are examples of hematology diseases.

3. RESULTS

In Figure 2, the prepared blood specimen is imaged and fed into the proposed system. This image is then gray-scaled in Figure 3 to enhance the image contrast aiming to recognize the different types of blood components. This contrast of the blood sample can be further enhanced by changing the resulted image into binary one as shown in Figure 4. Results showed that the nucleus of cells appears in a different color in the microscopic specimen image. However, these nuclei can mislead the process of counting the number of cells or differentiating among the different types of these cells efficiently. To overcome this issue a kind of filtering is required to exclude these nuclei. MATLAB offers tremendous capabilities in processing and filtering images. Hence, filtering these nuclei is a very handy task through the use of *imfill* instruction. In addition, specimen impurities represented by dust particles and small air bubbles can also be removed through the use of this instruction. The obtained results after eliminating the nuclei and impurities are shown in Figure 5.

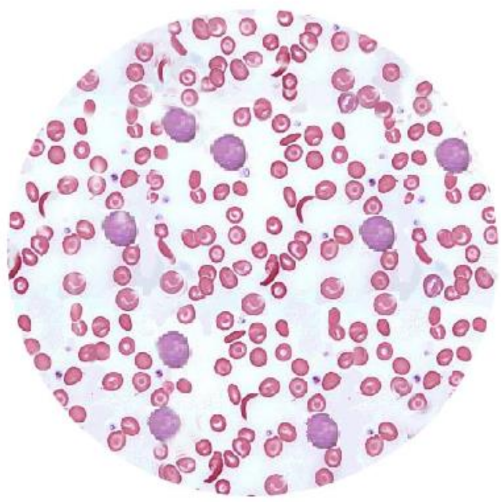

Figure 2. Original blood specimen

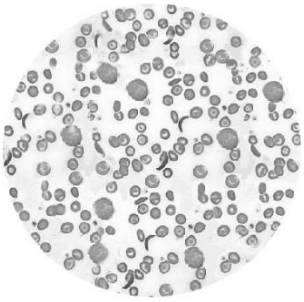

Figure 3. Grayscale specimen

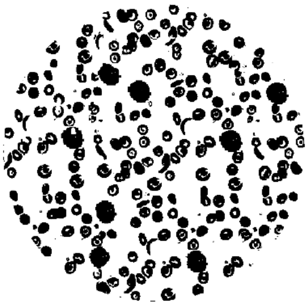

Figure 4. Black and white specimen

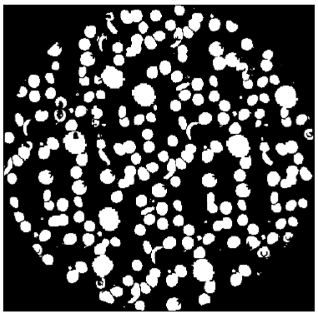

Figure 5. Inverted BW image after eliminating nuclei

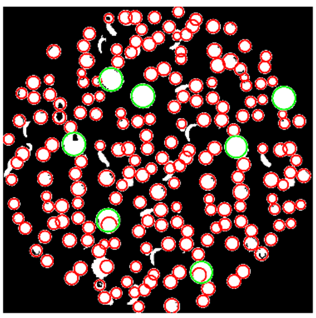

Figure 6. Counting red and white cells

The Hough Transform algorithm is then utilized to recognize circle-like objects in the resulting specimen image. Hough Transform is done twice in this work with different radius operands to recognize the large which cells and the relatively smaller red blood cells. Neither the white blood cells nor the red cells are all similar in size. Therefore, a further inspection algorithm needs to be used that makes use of the color planes to recognize the bluish colored white cells. In Figure 6, red blood cells are encircled with red borderlines, whereas white blood cells are encircled with green lines. A problem arises in the contiguous touching and clotting cells, where these cells can mislead the Hough Transform algorithm by showing these cells distorted or even these cells can appear as white blood cells, therefore, these touching cells are detached to resolve this confusion. This task is achieved by erasing the borderline of each circular object previously designated by Hough algorithm as shown in Figure 7.

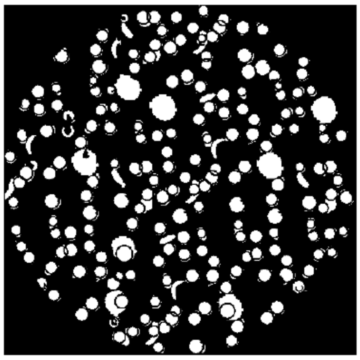

Figure 7. Detaching touching cells

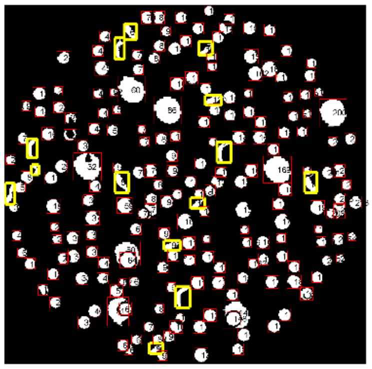

Figure 8. Counting sickle cells

Sickle cells are then investigated by measuring the dimensions of cells. Regularly, normal cells are depicted to have equal or close vertical and horizontal axes. Sickle cells on the other hand are distorted red blood cells and their different vertical and horizontal diameters. In order to permit an acceptable range of irregularity, a cell is considered sickled if one of its dimensions is at least as twice as the other dimension. Normal blood should not have any sickle cells. If any exists, then it is an inevitable sign of sickle cell anemia. For the purpose of diagnosis, white and red blood cells are counted and the concentration within a predefined sample's volume is calculated. Medical decisions can be made according to these automated measurements. For instance, the sample in Figure 8 is clearly diagnosed with sickle anemia ailment due to the presence of those deformed red blood cells they have crescent-like shapes. Sickle cells are surrounded by yellow boxes in Figure 8. The stage of investigating sickle cells is preceded by detaching the contiguous cells in order to resolve any illusion caused by these cells as they could look like sickle cells when stuck to each other. The proposed model has been tested on a number of different blood smear samples to quantify the efficiency and feasibility of the model. The results showed a range of accuracy exceeding 90% in terms of detecting and counting red blood cells. On the other hand, the process of white blood cells detection was a little more awkward due to the confusion caused by the smaller white blood cells which may be falsely considered red cells. However, this degradation in sensing white blood cells was overcome using color analysis method since the colorless white blood cells appear bluish when the smear is stained in the laboratory during the collecting phase.

4. CONCLUSIONS AND FUTURE WORK

This paper introduces a computer vision system to investigate hematological abnormalities as an alternative to the classical laboratorial Hematology Analyzer. The traditional analyzer is characterized by its high cost and relatively low accuracy compared to the proposed system. In addition, the proposed system outweighs the conventional analyzer in its capability to diagnose diseases attributed to cell distortion like sickle cell anemia. In this work, MATLAB programming language has been used to build a CBC system that considers different kinds of blood cells, counts them, and then detect any abnormality in these cells. Image processing tools and facilities were employed in this paper to recognize and differentiate among the different types of blood components. Circular Hough Transform capabilities have been invested here to identify white and red blood cells. Circle size and color is utilized to distinguish among the different constituents of the blood. Furthermore, cell distortion has also been investigated to identify any kind of hematological diseases. Results showed a promising level of efficiency in terms of detecting and counting blood cells accurately. A limitation of the proposed algorithm is represented by the incapability to classify different types of white blood cells. In fact, WBCs are not of a single type and each type has its own functions. White blood cells can be classified into neutrophils, eosinophils, basophils, lymphocytes, and monocytes. A low count of each type can be accompanied by underlaying ailment. Therefore, for further work, it is encouraged to improve the algorithm by granting it the power to identify the different types of WBCs and hence diagnose a wider range of immunological diseases.

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REFERENCES

[1] World Health Organization. (2023). Anaemia. https://www.who.int/news-room/fact-sheets/detail/anaemia.

[2] Chaparro, C.M., Suchdev, P.S. (2019). Anemia epidemiology, pathophysiology, and etiology in low-and middle-income countries. Annals of the New York Academy of Sciences, 1450(1): 15-31. https://doi.org/10.1111/nyas.14092

[3] KT, N., Prasad, K., Singh, B.M.K. (2022). Analysis of red blood cells from peripheral blood smear images for anemia detection: A methodological review. Medical & Biological Engineering & Computing, 60(9): 2445-2462. https://doi.org/10.1007/s11517-022-02614-z

[4] Elkhalifa, A.M., Abdul-Ghani, R., Tamomh, A.G., Eltaher, N.E., Ali, N.Y., Ali, M.M., Bazie, E.A., KhirAlla, A., DfaAlla, F.A., Alhasan, O.A.M. (2021). Hematological indices and abnormalities among patients with uncomplicated falciparum malaria in Kosti city of the White Nile state, Sudan: A comparative study. BMC Infectious Diseases, 21: 1-8. https://doi.org/10.1186/s12879-021-06228-y

[5] Lokesh Kumar, A., Devipriya, S., Gowtham, H., Jagadeesan, M. (2023). Cerebral venous thrombosis in polycythemia rubra vera: A rare case report. International Journal of Advances in Medicine, 10(3): 267-269. https://doi.org/10.18203/2349-3933.ijam20230373

[6] Raza, R., Ambreen, S., Mumtaz, H., Ahmad, S., Khan, H.D. (2021). Polycythemia secondary to pheochromocytoma. Journal of Rawalpindi Medical College, 25(4): 560-563. https://doi.org/10.37939/jrmc.v25i4.1655

[7] Miller, W.L., Strobeck, J.E., Grill, D.E., Mullan, B.P. (2021). Blood volume expansion, normovolemia, and clinical outcomes in chronic human heart failure: More is better. American Journal of Physiology-Heart and Circulatory Physiology, 321(6): H1074-H1082. https://doi.org/10.1152/AJPHEART.00336.2021

[8] Damtie, S., Workineh, L., Kiros, T., Eyayu, T., Tiruneh, T. (2021). Hematological abnormalities of adult HIV-infected patients before and after initiation of highly active antiretroviral treatment at Debre Tabor Comprehensive Specialized Hospital, Northcentral Ethiopia: A cross-sectional study. HIV/AIDS – Research and Palliative Care, 13: 477-484. https://doi.org/10.2147/HIV.S308422

[9] Wan, Z., Tao, R., Hui, J., Liu, X., Peng, X.R., Guo, Y.Z., Zhu, X.L., Huang, Y., Zhu, B. (2023). Efficacy and safety of lenalidomide in HIV-associated cryptococcal meningitis patients with persistent intracranial inflammation: an open-label, single-arm, prospective interventional study. Journal of Neuroinflammation, 20(1): 38. https://doi.org/10.1186/s12974-023-02717-w

[10] Koate, B.B.D., Didia, B., Monsi, T.P., Jeremiah, Z.A. (2021). Evaluation of the immunological status in occult hepatitis B virus-infected patients attending Rivers State University teaching hospital. International Journal of TROPICAL DISEASE & Health, 42(8): 1-9. https://doi.org/10.9734/ijtdh/2021/v42i830474

[11] Yang, X., Ma, R.C., So, W.Y., Ko, G.T., Kong, A.P.S., Zhao, H.L., Xu, G., Tong, P.C.Y., Chan, J.C.N. (2010). White blood cell count and renin-angiotensin system inhibitors for the risk of cancer in type 2 diabetes. Diabetes Research and Clinical Practice, 87(1): 117-125. https://doi.org/10.1016/j.diabres.2009.10.012

[12] Wang, Y.L., Ge, X.X., Wang, Y., Xu, M.D., Gong, F.R., Tao, M., Wang, W.J., Shou, L.M., Chen, K., Wu, M.Y., Li, W. (2018). The values of applying classification and counts of white blood cells to the prognostic evaluation of resectable gastric cancers. BMC Gastroenterology, 18: 99. https://doi.org/10.1186/s12876-018-0812-0

[13] Lippi, G., Plebani, M., Henry, B.M. (2020). Thrombocytopenia is associated with severe coronavirus disease 2019 (COVID-19) infections: A meta-analysis. Clinica Chimica Acta, 506: 145-148. https://doi.org/10.1016/j.cca.2020.03.022

[14] Odimegwu, C.L., Ikefuna, A.N., Okafor, H.U., Nwagha, T., Ubesie, A., Chinawa, J.M. (2022). Haemostatic profile of children with nephrotic syndrome attending University of Nigeria Teaching Hospital Ituku-Ozalla, Nigeria. BMC Nephrology, 23(1): 274. https://doi.org/10.1186/s12882-022-02894-5

[15] Gu, H., Devine, M., Hedrick, H.L., Rintoul, N.E., Thom, C.S. (2022). High rate of extreme thrombocytosis indicates bone marrow hyperactivity and splenic dysfunction among congenital diaphragmatic hernia patients. Platelets, 33(5): 787-789. https://doi.org/10.1080/09537104.2021.1994546

[16] Lindert, J., Sancassiani, F., Massa, E., Nardi, A.E. (2021). An overview of the international literature on health-related quality of life, mental health and psychosocial issues in people with cancer. Clinical Practice and Epidemiology in Mental Health: CP & EMH, 17(Supp-1): 253. https://doi.org/10.2174/1745017902117010253

[17] Rus, I., Tertis, M., Pop, A., Fizeşan, I., Bogdan, D., Matei, E., Oprea, D., Diculescu, V., Sandulescu, R., Cristea, C. (2023). The use of a new selective AB3 aptamer for the hematologic tumor cells' detection. Sensors and Actuators B: Chemical, 394: 134389. https://doi.org/10.1016/j.snb.2023.134389

[18] Wu, E., Jensen, I.S., Cyr, P., Kisner, H. (2017). Economic model shows that guideline recommended testing of patients with early symptoms of myeloma results in improved patient outcomes and decreased hospital costs. Blood, 130: 4698. https://doi.org/10.1182/blood.V130.Suppl_1.4698.4698

[19] Adegboyega, L.O. (2021). Psycho-social problems of adolescents with sickle-cell Anaemia in Ekiti State, Nigeria. African Health Sciences, 21(2): 775-781. https://doi.org/10.4314/ahs.v21i2.37

[20] Al-Momin, M., Almomin, A. (2021). A MATLAB model for diagnosing sickle cells and other blood abnormalities using image processing. International Journal of Electrical and Computer Engineering, 11(6): 5060. https://doi.org/10.11591/ijece.v11i6.pp5060-5065

[21] Clavería, V., Connes, P., Lanotte, L., Renoux, C., Joly, P., Fort, R., Gauthier, A., Wagner, C., Abkarian, M. (2021). In vitro red blood cell segregation in sickle cell anemia. Frontiers in Physics, 9: 737739. https://doi.org/10.3389/fphy.2021.737739

[22] Nader, E., Romana, M., Connes, P. (2020). The red blood cell—inflammation vicious circle in sickle cell disease. Frontiers in Immunology, 11: 454. https://doi.org/10.3389/fimmu.2020.00454

[23] Ragav, N.V., Sinduja, P., Priyadharshini, R. (2021). Automated blood analysers and their testing principles: A comparative study. Journal of Pharmaceutical Research International, 33(63A): 294-301. https://doi.org/10.9734/jpri/2021/v33i63a35633

[24] Litvinenko, A.L., Nekrasov, V.M., Strokotov, D.I., Moskalensky, A.E., Chernyshev, A.V., Shilova, A.N., Karenko, A.A., Maltsev, V.P. (2021). Blood platelet quantification by light scattering: From morphology to activation. Analytical Methods, 13(29): 3233-3241. https://doi.org/10.1039/d1ay00431j

[25] Maharani, E.A., Astuti, D. (2020). Stability of routine hematology sample using the Medonic m-series analyzer. Medical Laboratory Technology Journal, 6(2): 108-114. https://doi.org/10.31964/mltj.v0i0.305

[26] Wittenmeier, E., Lesmeister, L., Pirlich, N., Dette, F., Schmidtmann, I., Mildenberger, E. (2019). Assessment of haemoglobin measurement by several methods-blood gas analyser, capillary and venous HemoCue®, non-invasive spectrophotometry and laboratory assay-in term and preterm infants. Anaesthesia, 74(2): 197-202. https://doi.org/10.1111/anae.14481

[27] Risqi, N.K.A.C., Sarihati, I.G.A.D., Dharmawatii, I.G.A.A. (2022). Differences in hemoglobin level examination results using HB meter and Hematology Analyzer on whole blood components of donors in blood donation unit palang merah Indonesia, gianyar regency. Jurnal Analis Laboratorium Medik, 7(1): 54-59. https://doi.org/10.51544/jalm.v7i1.2820

[28] Aydın, Ö. (2022). Discordant hemoglobin values determined by blood gas analyzer and Hematology Analyzer synchronously is a warning for inappropriate blood sampling. Indian Journal of Clinical Biochemistry, 37(2): 250-252. https://doi.org/10.1007/s12291-020-00938-x

[29] Liu, Z., Zhu, Y., Zhang, L., Wu, M., Huang, H.B., Peng, K., Zhao, W.J., Chen, S.H., Peng, X., Li, N., Zhang, H., Zhou, Y.Y., Peng, Y.Q., Fan, J., Zeng, J.P. (2023). Red blood cell count and risk of adverse outcomes in patients with mildly reduced left ventricular ejection fraction. Clinical Cardiology, 46(10): 1276-1284. https://doi.org/10.1002/clc.24108

[30] Badireddy, M., Baradhi, K.M., Wilhite Hughes, A. (2021). Chronic Anemia (Nursing). Treasure Island (FL): StatPearls Publishing.

[31] Gupta, T., Basu, D. (2020). Utility of scatterplot patterns of automated hematology analysers in white blood cell disorders – A comparative study with peripheral blood smears. Asian Journal of Medical Sciences, 11(5): 29-34. https://doi.org/10.3126/ajms.v11i5.29049

[32] Tadesse, H., Desta, K., Kinde, S., Hassen, F., Gize, A. (2018). Errors in the hematology laboratory at St. Paul's hospital millennium medical college, Addis Ababa, Ethiopia. BMC Research Notes, 11: 420. https://doi.org/10.1186/s13104-018-3551-y

[33] De la Salle, B. (2019). Pre-and postanalytical errors in haematology. International Journal of Laboratory Hematology, 41: 170-176. https://doi.org/10.1111/ijlh.13007

[34] Gollapalli, M., Alfaleh, A. (2022). An artificial intelligence approach for data modelling patients inheritance of sickle cell disease (SCD) in the eastern regions of Saudi Arabia. Mathematical Modelling of Engineering Problems, 9(4): 1079-1088. https://doi.org/10.18280/mmep.090426

[35] Sevinc, O., Mehrubeoglu, M., Guzel, M.S., Askerzade, I. (2022). An effective medical image classification: transfer learning enhanced by auto encoder and classified with SVM. Traitement du Signal, 39(1): 125-131. https://doi.org/10.18280/ts.390112