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EXPERT BIOINFORMATION SYSTEM FOR DIAGNOSING FORMS OF ACUTE LEUKEMIA BASED ON ANALYSIS OF BIOMEDICAL INFORMATION

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Анотація. В статті представлено значення лейкемії в здоров'ї людини та проблеми, пов'язані як з діагностикою, так і з терапією. Мета статті - надати інформаційно-технологічне рішення цієї проблеми, тим самим покращуючи доступ для пацієнтів і прогнозування. Запропонована концептуальна модель експертної системи діагностики острів лейкозів, яка дозволить знизити неоднозначність в інтерпретації об'єктів дослідження. Розглянуто фактори, що впливають на правильне розпізнавання складних об'єктів (виявлення бластних і небластних клітин крові) за допомогою експертної системи на основі методів комп'ютерної мікроскопії.

Ключові слова: гострий лейкоз, діагностика та терапія, біомедичне зображення, зображення бластних і небластних клітин крові

Abstract. The introductory chapter established the context for this paper by stressing the significance of leukemia in healthcare and the challenges associated with both diagnosis and therapy. The paper ultimate objective is to provide an information technology solution to these issues, thereby improving patient care and prognosis. A conceptual model of an expert system for the diagnosis of acute leukemia is proposed, which will reduce the ambiguity in the interpretation of research objects. Factors influencing the correct recognition of complex objects (images of blast and non-blast blood cells) using an expert system based on computer microscopy methods are considered.

Keywords: acute leukemia, diagnosis and therapy, biomedical image, images of blast and non-blast blood cells

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Introduction

Blood cancers, including leukemia, are a major global health concern because they affect people of all ages and demographics. The disease's annual incidence rate of 13 cases per 100,000 individuals illustrates how widespread it is and how much it strains international health systems (Begum et al, 2020). Acute leukemia, which makes up 1-2% of cases, is the deadliest subtype of malignant neoplasms. This cancer is associated with distinct demographic patterns: men are more susceptible than women, and the majority of victims are Caucasians (Rehman et al., 2018). While acute myeloid leukemia is more common in older adults, acute lymphocytic leukemia usually affects teenagers. Age is yet another crucial component (Singha et al., 2021). Moreover, chronic lymphocytic leukemia and chronic myelogenous leukemia differ in their epidemiological characteristics [1,2,3,4].

Leukemia's epidemiology demonstrates the diverse nature of this group of blood cancers, with differences observed in several demographic factors. One such component that exhibits intriguing patterns to help make sense of the intricate relationships between lifestyle, environment, and genetic factors is gender (Rehman et al., 2018). Men are frequently slightly more likely than women to develop leukemia. Gender differences in leukemia susceptibility point to potential underlying causes (Vosberg & Greif, 2019). All subtypes show a general consistency in this greater occurrence in men's pattern, suggesting a stable tendency. Acute lymphocytic leukemia is one notable exception, though. In this subtype, there is little recorded female predominance (Begum et al, 2020). It is a difficult challenge to identify the factors that contribute to these gender-specific variances in leukemia development, including genetic, hormonal, and environmental factors [5,6,7,].

Potential causes of these gender-based variances in leukemia incidence include genetic variations, hormonal variations, and differing exposures to environmental toxins. The genetic susceptibilities of men and women to leukemia may differ, thus influencing their respective risk profiles (Rehman et al., 2018). Hormonal differences may also be significant because they affect the development and progression of some leukemia subtypes, particularly those linked to puberty and pregnancy (Ansari et al., 2023). discrepancies in lifestyle and profession may also contribute to the observed discrepancies between men and women, as they often have distinct exposure patterns to possible carcinogens [8,9,10].

The purpose of this work is to develop a conceptual model of an expert system for diagnosing acute leukemia using computer microscopy methods, as well as to analyze the influence of factors that influence the result of recognition of poorly formalized objects (images of blast and non-blast cells).

Objectives: To design and implement an information technology system for the rapid and reliable detection of acute leukemia; To develop a forecasting model that can assist healthcare professionals in making informed treatment decisions based on the patient's condition and characteristics; To assess the performance and effectiveness of the developed information technology solution through rigorous testing and evaluation.

Problems

There is no doubt that racial and ethnic disparities affect the prevalence of leukemia, with Caucasians having a larger risk than other racial groupings. The fundamental causes of the racial disparities in leukemia incidence have been the subject of extensive research (Singha et al., 2021). One important component that may account for these discrepancies is genetic predisposition. There is proof that some genetic mutations and circumstances increase the likelihood of developing leukemia (Vosberg & Greif, 2019). Caucasians may have greater rates of leukemia because some racial or ethnic groupings may have a higher prevalence of these genetic variants (Begum et al, 2020). Understanding the genetic underpinnings of leukemia across different ethnic groups is essential for more effective tailoring of diagnostic and treatment strategies.

A further factor influencing the variations in leukemia incidence throughout ethnic groups is environmental exposure. Exposure to toxins or carcinogens is one environmental element that may affect a person's risk of leukemia (Rehman et al., 2018). Examples of how various racial and ethnic groups may be more or less exposed to environmental risk factors include variations in lifestyle, occupation, and site of residence (Abdeldaim et al., 2018). Examining these environmental exposures within specific ethnic populations is essential to reduce disparities in leukemia incidence and to find effective preventive interventions [11,1213,14].

Furthermore, differences in healthcare access and consumption may potentially contribute to the differences in leukemia incidence throughout ethnic groups. Socioeconomic position, cultural barriers, and variations in the healthcare system can all affect the accessibility and quality of treatment (Abdeldaim et al., 2018). Minority populations could experience difficulties accessing healthcare services, which could lead to delayed diagnosis and less satisfactory treatment outcomes. Reducing these gaps in healthcare consumption and access is necessary to guarantee that all individuals, irrespective of their ethnicity, have equitable access to early diagnosis and appropriate treatment for leukemia (Begum et al, 2020). Work of this nature can help close the gap in leukemia incidence between different racial and ethnic groupings.

Age is a key demographic factor in the epidemiology of leukemia that significantly affects the variations in incidence and frequency of distinct leukemia subtypes. Age-specific patterns in leukemia offer valuable insights into the relationship between age and disease susceptibility, particularly in the context of acute myeloid leukemia (AML) and acute lymphocytic leukemia (ALL) (Rehman et al., 2018). When it comes to leukemia, age plays a big role in determining the prevalence of different disease subtypes. Acute lymphocytic leukemia (ALL) is largely a pediatric disease, with the majority of cases occurring in children between the ages of two and five (Abdeldaim et al., 2018). Because ALL mostly affects children, its age distribution highlights its unique traits.

Methodology

Because of the peculiar characteristics of pediatric ALL, including specific genetic alterations and treatment modalities, this age group needs specialist care. Acute myeloid leukemia (AML), on the other hand, has an extremely clear age-related pattern (Rehman et al., 2018). Over 60 years of age, the incidence of AML rises dramatically, leading to a higher diagnosis rate in this age group. The complex interplay between several aging-related factors, including alterations in the bone marrow microenvironment, cumulative genetic mutations, and exposure to environmental risk factors over time, result in this age-specific rise in AML incidence (Begum et al, 2020). Because older persons are more likely to develop AML, the disease mostly affects the elderly.

The age-related patterns in ALL and AML highlight the heterogeneity of leukemia and the importance of tailoring diagnostic and treatment strategies to the individual needs and characteristics of patients of different ages. Treatment strategies for pediatric ALL are often less aggressive than those for adults since children are more tolerant of rigorous therapy than adults are (Arber et al., 2017). On the other hand, for older persons with AML, therapeutic approaches specific to age-related comorbidities and treatment tolerance may be required. To make an accurate diagnosis and offer tailored therapy, medical professionals need to understand how aging impacts the epidemiology of leukemia (Williams et al., 2019). Additionally, it advances ongoing research that aims to develop age-specific strategies to improve treatment results for leukemia patients of all ages (Begum et al, 2020). By comprehending the minute variations in leukemia incidence among age groups, medical practitioners can enhance patient care and results.

Beyond general demographic trends, distinct subtypes of leukemia display age-related patterns and distinctive characteristics. These variations highlight the complexity of leukemia as a blood cancer class with a

broad spectrum of risk factors and clinical presentation (Rehman et al., 2018). This variety is best demonstrated by the age distribution of two subtypes: chronic lymphocytic leukemia (CLL) and chronic myelogenous leukemia (CML). The age distribution of chronic myelogenous leukemia (CML) is unique; it is bimodal. This suggests that the incidence rates of CML show two distinct peaks at different phases of life (Ansari et al., 2023). In early adulthood, the initial peak often occurs between the ages of 25 and 30. There may be a link between specific genetic abnormalities or risk factors that impact this age range and the early start of CML. The incidence of CML peaks again after late adulthood, with greater rates observed in individuals over 60 (Begum et al, 2020). It is critical to comprehend this bimodal age distribution to adapt therapy and diagnostic strategies to individuals at different phases of life.

However, there is a notable difference in the age-related pattern of chronic lymphocytic leukemia (CLL). The majority of patients with this subtype of leukemia are elderly adults; the typical diagnostic age is almost 70 years (Zolfaghari & Sajedi, 2022). When compared to bimodally distributed CML, late adulthood is the primary age at which CLL affects individuals. This age-related tendency in CLL may result from the intricate interactions between immunological changes, genetic variables, and cumulative exposure to environmental factors throughout time. Because these age-related trends in CML and CLL affect diagnosis and treatment decisions, healthcare providers need to be aware of them (Ansari et al., 2023). The unique characteristics of these subtypes—such as the bimodal distribution in CML and the prevalence of elderly persons in CLL—require specialized methods of care. The patient's age, comorbidities, and potential drug adverse effects may need to be considered in treatment approaches (Begum et al, 2020). Moreover, leukemia epidemiology research continues to explore the underlying causes of these diverse age-related trends, providing insights into the mechanisms driving the formation of distinct leukemia subtypes over a range of age ranges.

An approach to solving the problem of diagnosis and treatment of leukemia

Leukemia diagnosis and treatment provide complex problems for medical professionals, necessitating a multimodal approach to address the complex psychological, emotional, and physical elements of this illness. Leukemia patients deal with the emotional toll of managing their illness and its effects on their lives in addition to the physical difficulties of the disease (Shah et al., 2021). Further highlighting the need for sophisticated, precise, and quick diagnostic techniques are the complexity of leukemia subtypes, variations in patient demographics, and the wide range of survival rates.

The unchecked growth of abnormal white blood cells, which compromises the body's capacity to fight infections and generate healthy blood cells, is a hallmark of leukemia, a kind of blood cancer. Blood counts, bone marrow biopsies, and cytogenetic analysis are among the tests used in the diagnosis of leukemia to identify the particular subtype of the disease (Ahmed et al., 2023). Treatment strategies differ based on the kind of leukemia, patient age, and general health, and frequently entail stem cell transplantation, radiation therapy, and chemotherapy. For patients and their families, receiving a leukemia diagnosis and treatment can be extremely taxing emotionally. Anxiety, despair, and social isolation might result from treatment-related adverse effects, uncertainty about the disease's course, and dread of recurrence (Zolfaghari & Sajedi, 2022). To address these issues and improve patients' quality of life, effective communication, emotional support, and psychological treatment are essential.

The wide range of leukemia subtypes, each with unique genetic abnormalities and clinical manifestations, makes fast and correct diagnosis extremely difficult. Although helpful, traditional diagnostic approaches can be time-consuming and interpreted differently (Zolfaghari & Sajedi, 2022). It is critical to have reliable diagnostic instruments that can quickly and precisely detect leukemia subtypes. There are notable differences in leukemia incidence and survival rates among various demographic groups. Social class, age, gender, and ethnicity can all affect treatment outcomes, access to high-quality care, and the likelihood of developing leukemia (Shah et al., 2021). Comprehending these demographic disparities is crucial in formulating focused preventive measures and enhancing healthcare parity.

Excessive production of abnormal blood cells occurs in the bone marrow, the source of leukemia, a group of blood malignancies. Even though leukemia therapy has advanced significantly in recent years, survival rates for the various cancer subtypes still vary significantly (Ahmed et al., 2023). In the continuous efforts to create more effective medicines and individualized treatment plans for leukemia patients, an understanding of these discrepancies is essential. The increase in survival rates is one of the most positive advances in leukemia research and treatment (Ansari et al., 2023). This advancement is the result of numerous variables, such as improved leukemia patient supportive care, more precise treatment protocols, focused therapy development, and advancements in diagnostic techniques (Shah et al., 2021). Many people with leukemia now have higher survival rates and improved quality of life as a result of these advancements.

Significance of the Study

The creation of an efficient and reputable technique for identifying acute leukemia is one of the main goals of this research. This is significant because it can revolutionize the present diagnostic procedure, which is

laborious and dependent on human interpretation (Arber et al., 2017). Healthcare practitioners now have access to a diagnostic tool that is more accurate and efficient thanks to information technology solutions. This may result in the early identification of acute leukemia, allowing for the timely start of treatment and maybe enhancing the prognosis for affected individuals (Singha et al., 2021). Quick diagnosis is especially important when it comes to acute leukemia because of its quick and aggressive progression.

Another important factor contributing to the study's significance is its emphasis on predictive capacities. Making predictions about how acute leukemia patients will progress and respond to therapy could completely change how medical practitioners make decisions (Arber et al., 2017). The research can provide clinicians with valuable insights about the expected course of a patient's sickness by utilizing computer processing techniques and biomedical data (Ahmed et al., 2023). This in turn makes it easier to make well-informed treatment decisions, enabling a more efficient and individualized method of providing care (Shah et al., 2021). Patients with leukemia may experience better results and a higher quality of life as a result of this customized care.

This study's potential to solve current gaps in leukemia management highlights its significance. Leukemia is a broad and complicated group of diseases, each having specific traits, treatment options, and prognoses (Singha et al., 2021). By facilitating a systematic and data-driven approach to leukemia care, information technology solutions can assist in harmonizing the diagnosis and treatment procedures. This harmonization can be especially helpful in raising the standard of care across medical facilities and geographical areas, guaranteeing that patients receive the finest care available wherever they seek care. Furthermore, the study has significant ramifications for medical practitioners that go beyond leukemia treatment (Arber et al., 2017). Through the utilization of computer processing techniques and information technology, this research can provide physicians with a multitude of data-driven insights (Kadia et al., 2016). In turn, these insights are a potent tool that enables medical practitioners to make decisions based on accurate forecasts and verifiable data.

This shift in the process of making decisions has broad implications. With these cutting-edge resources at their disposal, healthcare professionals may feel more confident in the treatments they choose to administer (Arber et al., 2017; Rose-Inman & Kuehl, 2017). They can now make decisions based on tailored insights derived from each patient's biology data, rather than on guesswork or broad methods, which gives them a sense of confidence (Ahmed et al., 2023). The reduction of the uncertainty that sometimes accompanies the treatment of complicated medical illnesses, including leukemia, is one very notable feature of this transition. Even the most skilled medical practitioners may encounter difficulties due to the complexities and particular patient-specific characteristics that these illnesses frequently exhibit (Kadia et al., 2016). Information technology solutions have the potential to greatly lessen this uncertainty load.

Healthcare providers can handle leukemia cases more skillfully if they have a deeper comprehension of the unique requirements and prognosis of each patient. Consequently, this opens the door for the provision of more patient-centered care (Singha et al., 2021). Instead of depending exclusively on traditional, one-size-fits-all methods, medical professionals can customize treatment regimens to meet the unique needs of every patient. As a result, patients now receive care at a higher standard that is more sensitive to the unique circumstances of each patient and the dynamic nature of leukemia (Shah et al., 2021). This study essentially serves as a cornerstone in the effort to equip medical personnel with the information, resources, and understanding necessary to provide more efficient, individualized, and patient-centered treatment (Arber et al., 2017). The research eventually helps patients and healthcare professionals by contributing to a larger paradigm shift in healthcare through the reduction of ambiguity, improvement of evidence-based decision-making, and provision of customized insights.

Method

One of the first stages in the diagnosis of acute leukemia is the study of peripheral blood for the presence of blast cells. This procedure is associated with a number of difficulties, the main of which is the high variability of blast cells and the similarity of the images of some of them with non-blast cells, which causes errors in their classification. It should be noted that such an expert system serves as a tool for a hematologist in diagnosing acute leukemia.

The main advantage of the system being developed is a reference selection of digital images, the descriptions of which are stored in the knowledge base. An important component of the system is the analytical subsystem, which includes many rules by which decisions are made [15,16,17,18].

Mathematical models based on spatially connected preparation have been developed. The essence of spatially connected preparation (SCP) consists in finding the intensity differences between readings of the discretized image according to the eight ranks of connectivity (Fig. 1), forming two-level detection signals, transforming the collection of detection signals into a collection of SCP, forming SCP functions and forming by summing masked ones separately functions of CSP of positive, negative and zero generalized spatially connected preparations (GSCP).

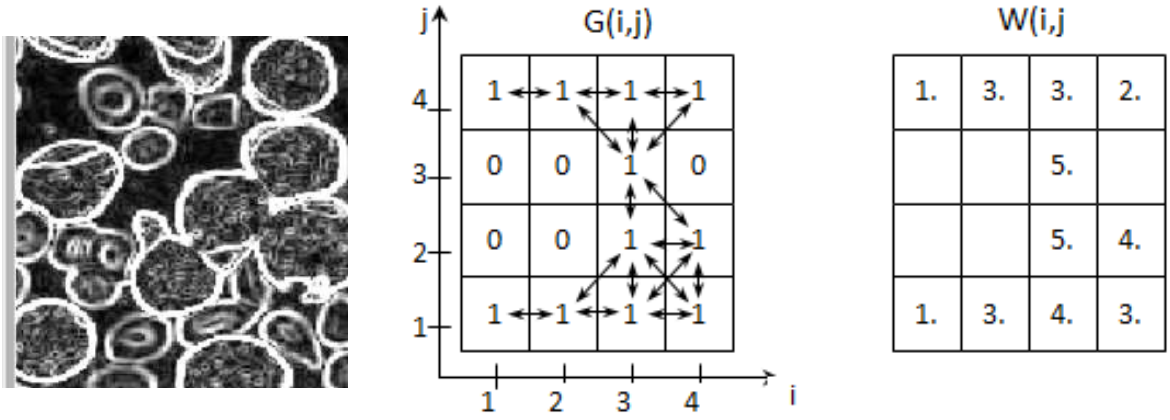


Figure 1 – Finding the intensity differences between counts of the discretized image by eight ranks of connectivity

We form the functions of spatially connected preparations, obtaining a system of functions of the PZKP:

$$\begin{cases} f_{i,j(\beta)}^{(\vec{\alpha}_1)} = \begin{cases} 1, & if \quad r_{i,j(\beta)}^{+(\vec{\alpha}_1)} = \beta \\ 0, & that, \end{cases} \\ \quad \ldots \\ \quad \ldots \\ f_{i,j(\beta)}^{(\vec{\alpha}_8)} = \begin{cases} 1, & if \quad \partial_{i,j(\beta)}^{-+(\vec{\alpha}_8)} = \beta \\ 0, & that \end{cases} \end{cases}$$

In accordance with the method of generalized spatial connectivity, we form the system of functions of SCP from the system of functions of GSCP in the form [19, 20, 21]:

$$\begin{cases} F_{|\vec{a}|_V=1(\beta)}^{i,j} = \sum_{V=1}^{8} (f_{i,j|\vec{a}|_V=1(\beta)} \omega_{i+l,j+\tau}, \xi_k, \eta_k) \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ F_{|\vec{a}|_V=S(\beta)}^{i,j} = \sum_{V=1}^{8} (f_{i,j|\vec{a}|_V=S(\beta)} \omega_{i+l,j+\tau}, \xi_k, \eta_k) \end{cases}, \quad (1)$$

where $F_{\vec{\alpha}_V(\beta)}^{i,j}$ - is the generalized SCP function.

The local spectrum of spatial connectivity (SCP) $W_{\wedge(i,j)}^{\vec{Z}_\vee(\beta)}$ is defined by the expression:

$$W_{\wedge(i,j)}^{\vec{Z}_\vee(\beta)} = \sum_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}(\beta)}^{i,j} = \sum_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}(0)}^{i,j} \bigcup \sum_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}(-1)}^{i,j} \bigcup \sum_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}(+1)}^{i,j}. \quad (2)$$

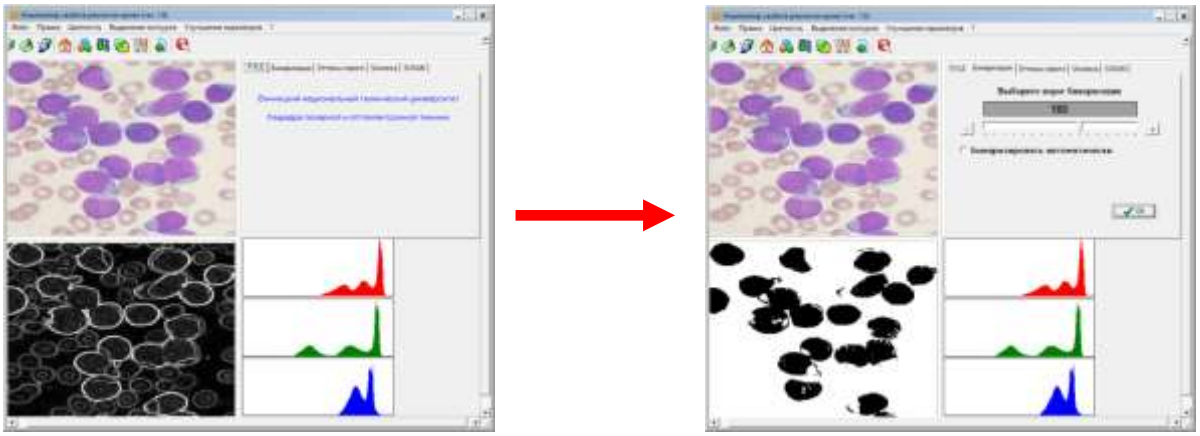
Then the full SCP $W_n^{\vec{a}(\beta)}$ of the image $g(i,j)$ can be determined using expression (1), obtaining the input information for the PI transformation [22,23].

$$W_n^{\vec{\alpha}(\beta)} = \begin{pmatrix} \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{1,1} & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{1,2} & \cdots & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{1,m_g} \\ \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{2,1} & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{2,2} & \cdots & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{2,m_g} \\ \cdots & \cdots & \cdots & \cdots \\ \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g-1,1} & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g-1,2} & \cdots & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g-1,m_g} \\ \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g,1} & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g,2} & \cdots & \sum\limits_{|\vec{\alpha}_\vee|=1}^{S} F_{\vec{\alpha}_\vee(\beta)}^{n_g,m_g} \end{pmatrix}. \quad (3)$$

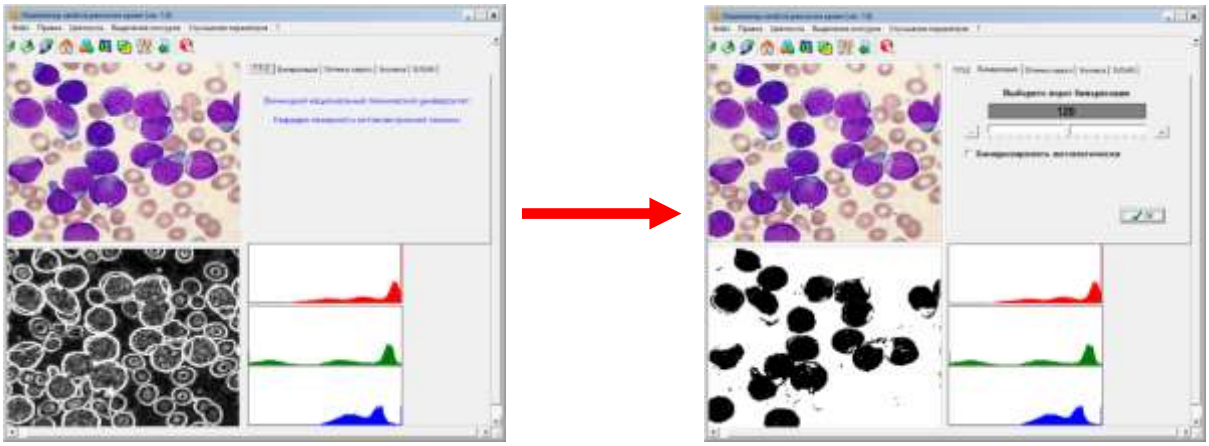
Realization of expert system is of peripheral blood for the presence of blast cells

The result of the work of the expert system is a conclusion about whether a cell belongs to a certain type, indicating a probabilistic assessment, which requires the creation of the required volume of a representative reference sample of cell images. The peculiarity of the expert system under consideration is that, along with the knowledge of experts accumulated in it, a database is created based on the results of measuring quantitative characteristics obtained as a result of automated image processing. The authors developed an automated method for processing and isolating blast cells and software “Blood Rheology Analyzer” for a hematologist. In Fig. 2. An example of the processing of blast and non-blast cells is presented.

a) Determination of blast cells against the background of lymphocytes



b) an example of an atypical monoclear



c) Determination of blast cells

Figure 2 – Example of processing blast and non-blast cells

Recommendations for the development of an expert system for studying peripheral blood for the presence of blast cells

We formulate recommendations for the creation of a system for assessing dynamic changes in biomedical images using the application of monitoring peripheral blood for the presence of blast cells in the following way (Figure 3):

- Processing of images taken per hour of one patient visit;
- Preservation and preservation of the results of digitalization and maintenance of the image database;
- Visualization of the results of the main stages of processing, analysis and alignment of blood cells;
- Organization of interactive interaction with the computer behind an additional graphical interface, which allows you to control the necessary parameters in the process of tracking and data processing, which will ensure the output of the necessary inputs and output data to the doctor in a manual format for processing;
- Notify and prompt the doctor of the results of syntactic and logical control of the data that is entered;
- Formation of a report on the results of processing both one and several biomedical images;
- Implementation of classification algorithms, saving parameters of mask templates, forming a selection with valued sign values, assessing the reliability of diagnosis.
- The adherence to such recommendations gives doctors a low priority, and itself:
- improve all the main structures and change the microcirculatory bed;
- the system is simple, easy to use and easy to use;
- the establishment of a clear scoring gradation will facilitate quantitative analysis and statistical processing of tracking results;
- detailed assessment of dynamic indicators that change during biomedical investigations and course treatment.

A comprehensive characterization of dynamic indicators makes it possible to assess the adequacy of the administered drug dose, the course of treatment, the correction of doses of pharmacological drugs and drug therapy regimens, as well as There are other methods of bathing.

For the system under consideration, instrumental factors can be classified into two groups: the first – factors determined by the instrumental capabilities of the equipment; the second is factors determined by the influence of external conditions. The first group of instrumental factors includes image sensor noise, color and brightness distortions of the camera, diffraction effects of the optical system of the microscope, uneven spectral characteristics of the illuminator in the microscope, uneven illumination of the sample in the field of view of the camera, etc. The factors of the second group include factors determined by the external conditions of use of the system.

When developing measurement techniques, it is necessary to resolve the problems of ambiguity in the interpretation of the measured quantities (for example, cell size, nucleus size, taking into account the variety of shapes of these objects). When choosing measurement models, one should take into account (and for this it is necessary to conduct preliminary studies) the achievable accuracy in measuring the parameters under consideration (for example, the accuracy of measuring the nuclear-cytoplasmic ratio, which is one of the signs widely used by doctors to differentiate cells by type, depends on the accuracy of image segmentation nucleus and cytoplasm).

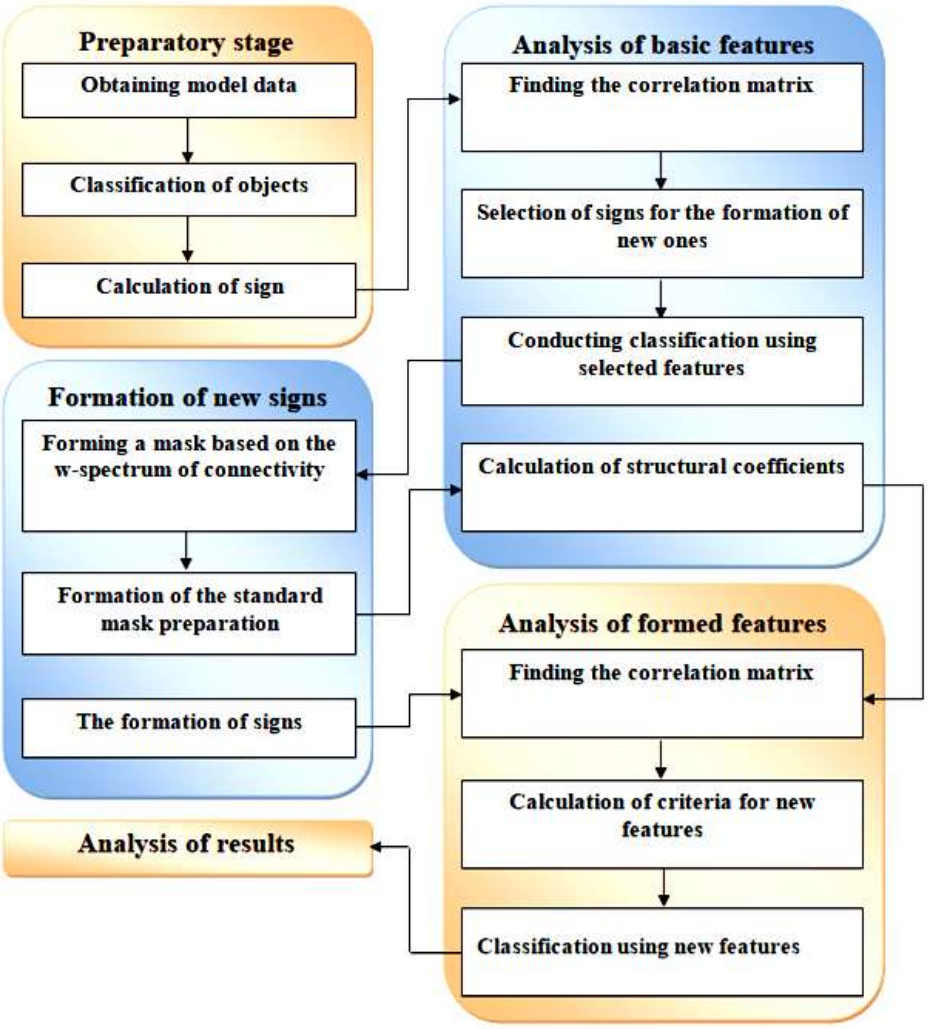


Figure 3 – Scheme of the robotic expert system algorithm for examining peripheral blood for the presence of blast cells

Conclusion

The introductory chapter established the context for this paper by stressing the significance of leukemia in healthcare and the challenges associated with both diagnosis and therapy. The paper ultimate objective is to provide an information technology solution to these issues, thereby improving patient care and prognosis. A conceptual model of an expert system for the diagnosis of acute leukemia is proposed, which will reduce the ambiguity in the interpretation of research objects. Factors influencing the correct recognition of complex objects (images of blast and non-blast blood cells) using an expert system based on computer microscopy methods are considered.

The upcoming chapters will address the impact of the suggested information technology system on the diagnosis and treatment of acute leukemia in addition to a thorough study of the research methodology, data analysis, and conclusions.

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ЕКСПЕРТНА БІОІНФОРМАЦІЙНА СИСТЕМА ДІАГНОСТИКИ ФОРМ ГОСТРОГО ЛЕЙКОЗУ НА ОСНОВІ АНАЛІЗУ БІОМЕДИЧНОЇ ІНФОРМАЦІЇ

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