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NAVIGATING THE EVOLVING FIELD OF BLOOD CANCER DETECTION: INSIGHTS FROM TRADITIONAL METHODS TO CUTTING-EDGE TECHNOLOGIES

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ABSTRACT

The complexity and heterogeneity of blood cancers make detection and classification difficult in the medical field. This survey paper examines the various techniques and methodologies used to detect and classify BCs. The paper begins with an overview of the multiple types of blood cancers, such as leukemia, lymphoma, and myeloma. Then, it delves into traditional diagnostic methods like blood tests, bone marrow biopsy, and imaging techniques. The paper also investigates the advancements in molecular diagnostics, such as genomic profiling and liquid biopsy, in understanding BC biology and personalised treatment strategies. It also looks at machine learning and artificial intelligence approaches to BC detection, segmentation and classification, offering insights into current challenges, emerging trends, and future directions in this critical area of oncology research.



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I. INTRODUCTION

Blood cancer, or hematologic or haematological malignancy, a classification of cancers affecting the blood, bone marrow, and lymphatic systems. [1] This type of cancer typically begins in the bone marrow, where blood cells are produced, and can affect various blood components, including leukocytes, erythrocytes, and platelets. There are several types of BC.

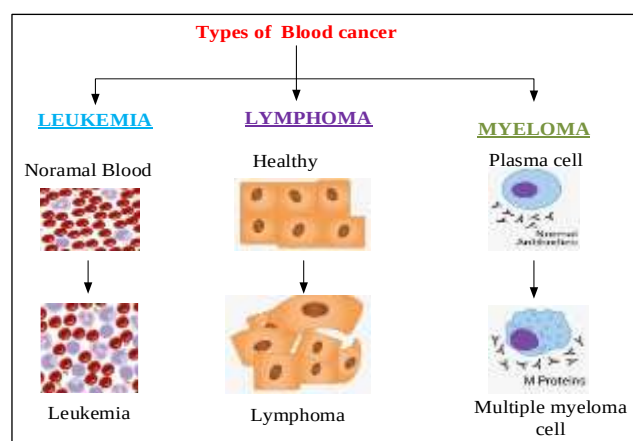


Figure 1: Types of Cancer from WBCs.

Source: Authors, (2026).

➤ **Leukemia:** It is a type of cancer affecting the blood and bone marrow, where blood cells are produced. It is defined as an abnormal production of WBCs. There are four types [2] ALL, AML, CLL, CML.

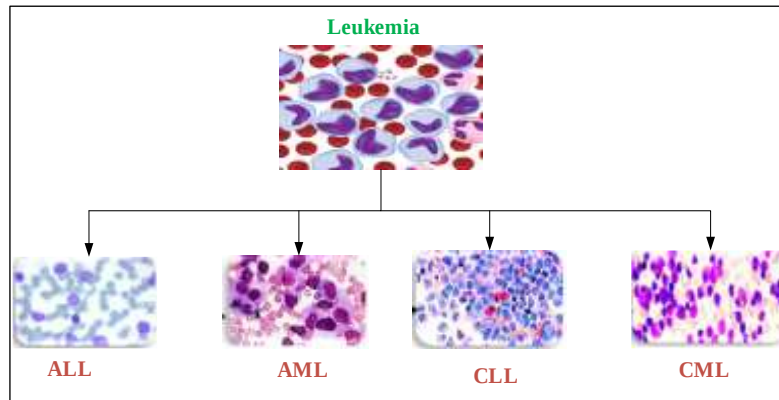


Figure 1: Types of Leukemia.

Source: Authors, (2026).

➤ **Lymphoma:** The lymphatic system, a component of the body's immune system, is where this cancer grows. It contains the lymph nodes, spleen, thymus, and bone marrow. There are two major types: Hodgkin lymphoma [3], a rare form of cancer, is characterised by the presence of Reed-Sternberg cells, which can spread to other lymph nodes or organs; NonHodgkin lymphoma [4] is a type of lymphoma that can occur at any age and may originate from B, T, or natural killer cells.

➤ **Multiple Myeloma:** The WBCs in the bone marrow called plasma cells are impacted by this kind of malignancy. [5] It results in an excess of aberrant plasma cells, which have the potential to displace healthy blood cells.

1.1 CAUSES AND SYMPTOMS OF BLOOD CANCER

BCs are malignancies that impact the lymphatic, stem cells, or blood pathways. These cancers develop in the cells of blood-forming tissues, disrupting average blood cell production and function [6]. The manifestations and signs can vary depending on specific type of BC.

❖ **Causes:** Although exact origins of these mutations are often unknown, a higher chance of having BC has been linked to various factors:

1. Genetic predisposition, including inherited mutations, can increase the risk of certain BC types, with individuals with a family history of the disease having a higher risk.
2. Exposure to certain chemicals or radiation: Carcinogenic substances like benzene, chemotherapy drugs, and ionising radiation can damage blood cell DNA, increasing the risk of BC.
3. Viral infections: Certain types of BC have been linked to Virulent illnesses, like Epstein Barr, human T cell leukemia, and human immunodeficiency virus.

❖ **Symptoms:** The symptoms of BC can differ depending on kind of cancer and its level of progression. Common signs that individuals may experience include fatigue and weakness, inexplicable loss of weight, enlarged lymph nodes, recurrent infections, straightforward bruises or haemorrhage, bone pain, fever, and night sweats.

1.2 IMPORTANCE OF EARLY DETECTION AND CLASSIFICATION

Accurate BC classification and early identification are essential for successful therapy and better patient satisfaction. Early detection allows healthcare professionals to intervene, reducing disease burden and improving treatment options. Accurate classification of BC subtypes will enable clinicians to tailor treatment based on specific characteristics, such as molecular abnormalities or cytogenetic markers [7], [8].

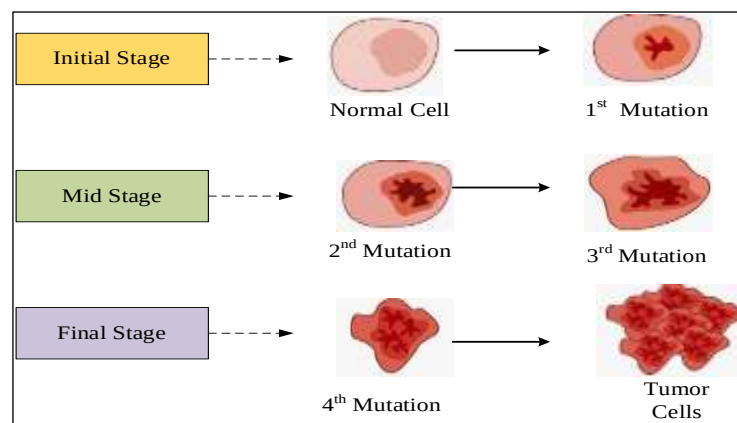


Figure 3: Different Stages of Blood Cancer.

Source: Authors, (2026).

This personalised approach enhances therapeutic efficacy and minimises side effects associated with broad-spectrum treatments. Additionally, it assists in recognizing those at risk who can benefit from more intensive therapy plans and stratifies patients into clinical trials for novel therapies. These early detection and classification serve as foundational pillars in comprehensive BC management, ensuring successful outcomes and improved patients' standard lives.

I.3 DIAGNOSIS AND TREATMENT OPTIONS

BC is typically diagnosed through a series of tests that confirm the presence of the disease and the type and stage. These diagnostic methods include blood tests such as a complete blood count, a peripheral blood smear, and flow cytometry to assess blood cell levels and properties [9]. A bone marrow biopsy and aspiration may also be performed to check for cancerous cells [10]. Imaging tests such as Xays [11], CTS and MRI may also be used to assess the disease's seriousness. [12]. At the same time, lymph node biopsy is performed in suspected lymphoma cases. The kind, stage, and unique patient characteristics influence the available treatment options. Chemotherapy uses drugs to kill cancer cells or inhibit growth, radiation therapy uses high-energy rays to target and destroy cancer cells, bone marrow or stem cell transplantation are common techniques., in immunotherapy, and targeted therapy [13]. Stem cell or bone marrow transplantation may be an option in some circumstances. Targeted therapy targets the growth chemicals associated with cancer, while immunotherapy employs the body's immune system to identify and combat cancer cells. Treatment choice depends on the cancer type, stage, and patient's overall health and preferences.

The primary objectives of this survey paper:

- The objective is to investigate methods for detecting and classifying BC thoroughly.
- The paper assesses the effectiveness, limitations, and clinical potential of various techniques for early detection and accurate classification of BCs.
- The survey synthesises current research findings and technological advancements.
- The goal is to choose the best technique to enhance diagnostic accuracy and therapeutic efficacy through comprehensive analysis.

II. DIAGNOSTIC TESTS FOR BLOOD CANCER

BC is a broad malignancy category affecting the blood, bone marrow, and lymphatic system. A timely and accurate diagnosis of BC is critical for initiating appropriate treatment and improving patient outcomes. [14] Diagnostic tests usually assess hematological parameters, bone marrow morphology, genetic abnormalities, and disease severity. Diagnosis usually entails a series of diagnostic tests designed to evaluate hematological parameters using diagnostic tests such as baseline and confirmation tests commonly used to assess BC [15]. Tables 1 and 2 provide the outline of these two tests.

Table 1: Baseline Test.

Test	Measures	Description
CBC	Count of RBC, WBCs, platelets	Abnormal levels of these cells can indicate various types of BCs.
Peripheral Blood Smear	Examination of blood cells under a microscope	Unusual blood cells, such as immature or misshapen cells, can suggest the presence of BC.
Blood Chemistry Tests	Measurement of electrolytes, proteins, enzymes	Abnormal levels could indicate organ dysfunction or metabolic disturbances related to BC.

Source: Authors, (2026).

Table 2: Confirmation Test.

Test	Measures	Description
Bone Marrow Aspiration/Biopsy	Examination of bone marrow for abnormal cells	It involves examining bone marrow samples from the hipbone or sternum for abnormal cells or signs of leukemia, lymphoma, or multiple myeloma.
Imaging Studies	PET scans, CT scans, MRI scans for disease evaluation	Identify abnormalities like enlarged lymph nodes, organ enlargement, or other BC-related issues.
Flow Cytometry	Analysis of cell surface markers and internal components	abnormal cells in blood samples and classify BCs based on their surface markers.
Cytogenetic Analysis	Examination of chromosomes for abnormalities	cancer cell chromosomes can identify genetic abnormalities, diagnose specific BC types, and predict their prognosis.
Molecular Testing	PCR, FISH, NGS for genetic mutations and rearrangements	utilised to identify specific genetic mutations or rearrangements linked to particular types of BC, thereby aiding in diagnosis and treatment planning.

Source: Authors, (2026).

III. DETECTION TECHNIQUES

BC detection techniques include traditional methods like biopsy and blood tests and emerging technologies like liquid biopsy and imaging techniques. Traditional methods include (i) biopsy, which is extracting a tissue sample from a suspected cancer site [16], such as lymph nodes or bone marrow, for histological examination. It provides a definitive diagnosis and allows for a detailed examination of cancer cells under a microscope. However, it is invasive, may cause discomfort, and requires specialised knowledge for interpretation. (ii) Blood Tests [17], including a smear of peripheral blood and a whole blood count are commonly used to detect abnormal blood cell counts and morphology that indicate BC. They are minimally invasive, easily accessible, and affordable. However, they may lack specificity, necessitating additional confirmatory tests for a correct diagnosis. Emerging technology, leveraging scientific advancements in molecular biology, genomics, imaging, and artificial intelligence, aims to improve BC diagnosis accuracy, sensitivity, and efficiency, enhancing early detection and monitoring, for example, liquid Biopsy and Imaging techniques. LB, a non-invasive method for real-time disease monitoring, analyses circulating tumour cells, cell-free DNA, and other biomarkers in bodily fluids, but may have lower sensitivity for early-stage cancers. Chen et al. [18] study explored liquid biopsy for early cancer screening and diagnosis, highlighting its potential for improved survival and reduced disease burden.

Poulet et al. [19] review emphasises the importance of standardising pre-analytical procedures for efficient clinical use of blood and effluents as liquid biopsy tools. Imaging modalities like CT, MRI, PET, and ultrasound are crucial for detecting BC related changes but may have limitations in detecting small lesions or distinguishing benign and malignant conditions. These traditional diagnostic methods offer high accuracy but have drawbacks like invasiveness and discomfort for patients and may lack specificity, requiring additional tests for confirmation. In addition to liquid biopsy, Advanced imaging techniques like CT, MRI, and PET are crucial detecting anatomical changes BC, aiding in disease staging and treatment planning by providing high-resolution images of lymph nodes, organs, and bone structures. Likhith et al. [20]. Used deep learning techniques to detect leukemia using a system architecture for YOLOv5-based detection, aiming to compile an extensive medical imaging database. Menagadevi et al. [21] utilised image processing and a CNN to predict ALL cells using blood samples for image acquisition. Azza et al. [22] utilised an ML classifier to identify blood disorders, specifically Leukemia, using microscopic images of blood samples for visual inspection. Each detection method has its strengths and limitations. This survey paper evaluates the effectiveness, limitations, and clinical applications of various BC detection methodologies, focusing on their integration to aid early diagnosis and personalised treatment strategies.

Table 3: Descriptions of detection technique.

Ref	Technique	Advantage	Disadvantage
[18]	Liquid biopsy	The potential of timely identification of cancer and monitoring	Limited sensitivity, specificity, especially in early-stage cancers
[19]	Standardised pre-analytical procedures	Efficient clinical use of blood and effluents as liquid biopsy tools	Requires standardisation and adherence to protocols for reliable results
[20]	DL-based detection	Capacity to recognize intricate patterns and characteristics from clinical images	needs substantial annotated datasets to be trained, and it might not be interpretable
[21]	Image processing using CNN	Possibility of automated detection of ALL cells from blood samples	It may be sensitive to variations in sample preparation and imaging conditions requires validation with clinical data
[22]	ML classifier	Ability to classify blood disorders, including leukemia, based on microscopic images of blood samples	Interpretability of results may be limited; performance is dependent on the quality of image samples and feature extraction methods.

Source: Authors, (2026).

III.1 SUMMARY OF DETECTION TECHNIQUES

Detection techniques provide insights necessary for timely diagnosis and effective treatment planning in the comprehensive evaluation of leukemia cancer. Traditional methods, such as biopsy and blood tests, provide clinically significant information in a minimally invasive and easily accessible manner, allowing for initial screening and monitoring. Emerging technologies, such as liquid biopsy and advanced imaging techniques, provide non-invasive alternatives and enhanced anatomical visualisation, increasing patient comfort and diagnostic accuracy. However, these methods may have limitations, such as low sensitivity or specificity, especially in early-stage cancers or distinguishing between benign and malignant lesions. Despite these challenges, combining various detection techniques allows for a more multifaceted approach, increasing the likelihood of accurate diagnosis and personalised treatment strategies. This survey paper aims to explore the landscape of leukemia cancer detection methodologies, evaluating their efficacy, advantages, and disadvantages, to provide a comprehensive understanding for clinicians and researchers alike.

III.2 SEGMENTATION TECHNIQUES

Segmentation techniques are essential for accurately detecting leukemia, a BC caused by abnormal white blood cell proliferation. These techniques partition medical images into meaningful regions, enabling the identification and analysis of leukemia cells amidst complex biological backgrounds. Image segmentation separates leukemic cells from normal tissues in medical images like blood smears, bone marrow aspirates, or histopathological slides. Various algorithms and methodologies have been developed, such as thresholding, edge detection, and ML-based approaches.

III.2.1. Thresholding Techniques

Thresholding methods use intensity thresholds to differentiate between leukemic and non-leukemic cells based on pixel intensity values. Toh et al. [23] used a colour thresholding technique using RGB color data from AL slide images and a median filter to separate leukemia cells from undesirable areas like surroundings and RBCs. Suryani et al. [24], the study utilised the Multi Otsu Thresholding Method for dynamic threshold value segmentation, involving two stages: detecting the nucleus and detecting WBC. This segmentation process aimed to identify the target cell accurately. Khairudin et al. [25] proposed segmentation procedures for automatically identifying and diagnosing leukemia cells from blood sample images, including contrast enhancement, hue component information extraction, and Otsu's thresholding and watershed technique. Abdulla et al. [26] used a thresholding based segmentation technique that performs better colour k means clustering for identifying leukemia, requiring WBCs separation from other objects like RBCs and platelets. Ananth et al. [27] demonstrated that leukemia could be identified and classified using a technique for segmenting images based on the presence of juvenile cells. The study by Agarwal et al. [28] utilized the KMeans method for segmentation, which separated the complete cell from the picture backdrop, in conjunction with the GD and Otsu adaptive thresholding for clustering. Ranjitha et al. [29] study suggested that a K-means clustering algorithm for segmenting blood samples, using colour and grayscale imagery, could result in inconsistent results, negatively impacting the classification of leukemia.

Table 1: Description of Thresholding Technique.

Ref	Technique	Advantage	Disadvantage
[23]	Colour thresholding with median filter	It uses RGB color information to segment leukemia cells from the background and RBCs accurately.	The system may require adjustments to parameters for various image datasets.
[24]	Multi Otsu Thresholding Method	adaptable to varying intensity distributions within images	The process may necessitate manual adjustments to threshold values, as it may be sensitive to noise and image artefacts.
[25]	Otsu's thresholding, watershed	segmentation procedure incorporating multiple techniques for improved accuracy in identifying and diagnosing leukemia cells	Computational complexity, potential for over-segmentation or under-segmentation, sensitivity to parameter selection
[26]	Thresholding-based segmentation	Outperformed clustering methods for identifying leukaemia cells effectively separate WBCs from other cellular components like RBCs and platelets.	Sensitivity to variations in staining intensity and imaging conditions, potential for false positives or false negatives in segmentation results
[27]	Segmentation based on presence of juvenile cells	Focuses on specific cellular characteristics for segmentation	Limited applicability to diverse leukemia subtypes and sample variations may overlook other relevant morphological features of leukemic cells
[28]	GD, OAT, clustering	Integration of multiple techniques for robust segmentation, combining intensity-based and clustering methods for improved accuracy	Complexity in parameter selection and tuning.
[29]	K-means clustering algorithm	enabling automatic identification of leukemia cells from blood samples	Inconsistency in segmentation results may lead to variability in classification outcomes, potential sensitivity to noise and artifacts in images

Source: Authors, (2026).

The thresholding technique is computationally efficient and versatile for leukemia detection in medical images. However, it's susceptible to noise, artefacts, complex cell morphologies, and manual selection. Future research should focus on integrating advanced image preprocessing techniques, machine learning algorithms, hybrid segmentation methods, and standardised evaluation metrics to improve accuracy and efficiency. This will enhance patient care and outcomes.

III.2.2 Edge Detection Techniques

Edge detection algorithms analyse pixel intensity gradients for leukaemia detection, identifying abrupt changes in intensity corresponding to cellular structure transitions, separating leukemic cells from background elements, and quantifying spatial distribution. Bhagya et al. [30] utilised Otsu's thresholding, Watershed-based segmentation, Canny edge detection, and K-mean clustering to segment ALL datasets and their parameters. In previous research on the separation of touching cells, Fatonah et al. [31] utilised a technique for cell sorting using advanced edge detection, combining grayscale, Hue images for WBC segmentation results. A novel edge detection method used in the study by Dutta et al. [32] used two 5×5 masks and X and Y directions for both oriented horizontally and vertically. It provides an edge matrix that distinguishes specific hues, items, structures, or textures inside an image. A Stochastic Fractal Search algorithm based clustering model is proposed by Dhal et al. [33] for accurate segmentation of cytoplasm area in hematopathology images of ALL, delivering satisfactory outcomes in a reasonable amount of processing time. Al-Jaboriy et al. [34] conducted WBC segmentation using GA statistical features and ANN filtering, achieving accuracy close to that of the standard method. Edge detection segmentation techniques offer advantages in leukemia detection, including capturing fine details and irregular shapes and being less sensitive to noise and artefacts. However, their limitations include image contrast texture variations and complex cellular morphologies.

Table 5. Description Edge Based Segmentation

Ref	Technique	Advantage	Disadvantage
[30]	OT, Watershed, Canny edge detection, K clustering	potentially enhancing accuracy and robustness	Complexity in parameter tuning and optimisation
[31]	Combining grayscale and Hue images	improved WBC segmentation results	It may require manual adjustment of parameters
[32]	Novel edge detection method using masks	enhancing sensitivity to sharp changes in image content	Potential computational complexity
[33]	Stochastic Fractal Search algorithmbased clustering	delivering acceptable results within reasonable computational time	may require fine-tuning of algorithm parameters for optimal performance
[34]	GA statistical features and ANN filtering	achieving accuracy comparable to standard methods	Complexity in model training and optimisation

Source: Authors, (2026).

III.2.3. ML-Based Approach

In recent years, ML techniques, like CNN, have revolutionised leukemia segmentation by detecting leukemic cells in digital pathology images. These deep learning-based approaches capture complex spatial relationships and morphological characteristics, improving segmentation accuracy and generalisation. Ikechukwu et al. [35] trained a DCN for segmenting WBC cells from minuscule photos with a same level of accuracy using the GPU of Google Colab. Leukocytes have both cytoplasm and nucleus, but ALL alter nucleus shape and texture. Segmentation of WBC nuclei helps identify ALL-related changes; in the study by Alagu et al. [36], U-Net is suggested for extracting nuclei from healthy and blast cells. SegGAN was a differentiable technique by Mercy et al. [37] that used a semantic segmentation model, which discriminated and generated separate pre-processed images. It used an end-to-end process to improve this hybrid construction. The generator network created an image based on the Segmentation Model's prediction layer. Devi et al. [38] utilised the HSV technique and anatomical processes in segmentation to distinguish between colors in the foreground and background.

The HSV colours were similar to the human eye's perception, with Hue encoding colour information from RGB, Saturation encoding purity and intensity, and Value encoding brightness, gloss, and shading, which improves prediction accuracy. Inbarani et al. [39] developed a rough k clustering method using a soft covering based rough approximation to segment leukemia nucleus images and extract the nucleus using a clustered index. Jha et al. [40] developed an MI-based hybrid model for segmenting blood smear images using Active contour and fuzzy membership models, utilising region-based segmentation and fuzzy membership for cluster centre computation. 11Eckardt et al. [41] conducted a human in loop cell segmentation using an FRCNN with a VGG annotator [42]. This method was trained with segmented images and created new segmentation proposals for unsegmented images. This improved segmentation quality through repetitions, removed the requirement for human correction. ML based segmentation techniques, particularly CNNs, offer advantages in leukemia detection by automating and accelerating the diagnostic process. CNNs can adapt to diverse sample types and imaging conditions, enhancing accuracy and generalisation. They can extract complex spatial relationships and morphological characteristics, enabling precise localisation of abnormal cell populations. However, these methods have limitations, such as requiring large amounts of annotated training data, influencing performance by dataset imbalance, annotation errors, imaging artefacts, computational complexity, and limited interpretability of results.

Table 6: Description of ML based Segmentation.

Ref	Technique	Advantage	Disadvantage
[35]	DCNN	Achieves equivalent accuracy on GPU accelerated platforms for the precise segmentation of WBC cells from microscopic pictures	Computational resource requirements and need for large annotated datasets for training.
[36]	U-Net	extracting nuclei from healthy and blast cells, potentially enhancing segmentation accuracy and robustness	sensitivity to variations in image quality and staining conditions
[37]	SegGAN	By combining semantic segmentation, discriminator, and generator for improved segmentation accuracy and end-to-end processing	complexity in implementation and training, computational resource requirements
[38]	HSV technique and morphological operations	enhanced segmentation performance in terms of distinguishing between foreground and background colors	Occur variations in imaging conditions.
[39]	Rough k-means clustering method	extracting nuclei from images using a clustered index.	Require clustering parameters for optimal segmentation results.
[40]	MI-based hybrid model using Active contour and fuzzy membership models	enhance accuracy and robustness of segmentation	Complexity in model implementation
[41]	FRCNN with VGG annotator	Improved accuracy, Robust	Potential for human error in manual annotation and dependency on expert annotators

Source: Authors, (2026).

III.3 SUMMARY OF SEGMENTATION TECHNIQUES

The survey on leukemia detection segmentation techniques emphasises the importance of precise cell delineation in medical images for effective diagnosis and classification. Traditional methods face challenges due to intricate morphologies and overlapping clusters, resulting in inaccuracies and inconsistencies, potentially impacting diagnostic assessments' reliability. ML based approaches, particularly CNNs, have significantly improved leukemia segmentation accuracy by learning intricate patterns and features from annotated training data. These techniques adapt and generalise across diverse sample types and imaging conditions, offering more accurate and reliable diagnostic outcomes. However, challenges persist, such as achieving consistently high accuracy across various leukemia subtypes and sample variations and issues like sample preparation artifacts and staining inconsistencies. Addressing these challenges requires concerted efforts from researchers and practitioners, including developing and validating strategies to mitigate the impact of sample artefacts and staining variations on segmentation accuracy. Despite the promise of ML segmentation techniques for leukemia detection, significant challenges remain to be addressed. By leveraging technological advancements and fostering interdisciplinary collaboration, researchers can continue to enhance segmentation accuracy and reliability, ultimately advancing leukemia diagnosis and classification in clinical practice.

IV. CLASSIFICATION TECHNIQUES

These methods are crucial for diagnosing and classifying leukemia, a group of hematological malignancies characterised by abnormal WBC proliferation. They help identify subtypes based on morphological, immunophenotypic, cytogenetic, and molecular characteristics, enabling personalised treatment strategies and prognostic assessment. They include traditional morphological analysis, molecular profiling, and machine learning. The classifier uses the extracted features to decide whether a cell is typical or malignant. It is accomplished by contrasting logical, empirical, appearance, and dimension ratio features attained during the segmentation process to norm sets of attributes. The outcomes are analysed to determine types and subtypes of AL. ML-based classification approaches, including ensemble methods and deep learning algorithms, have shown promising performance in classifying leukemia subtypes by integrating diverse data modalities. The classification process utilised the Support Vector Machine classifier Ananth et al. [43] for binary classification problems requiring significant variable separation between classes.

Features extraction methods applied to a dataset by cell count and cell area would classify images as normal or abnormal and create a confusion matrix to provide the classification results in study of Al-Ghraibah et al. [44]. Ali et al. [45] introduced the analysis by comparing SVM, KNN, and DT algorithms. The paper suggested that the optimal choice of ML or SC algorithms depends on the data set's ability to achieve 95% accuracy in cancer detection. Sharma et al. [46] developed an automatic leukemia cell nucleus segmentation model for BC classification from microscopic images. They selected the best segmentation approach and developed a cancer classification model using a CNN, achieving a classification accuracy of close to 99%. The model was trained by an optimised Dense CNN framework presented by Kumar et al. [47] accurately predicted cancer type in cells, achieving a 97.2% accuracy rate, making it suitable for bone marrow malignancy detection. Rahman et al. [48] research utilised seven ML classifiers for multi-class malignant classification SCV, RF, DT, NB, XGB, KNC, and LR, achieving 98.43% accuracy without relying on FS or nature inspired algorithms.

Gondal et al. [49] used two classifiers to classify ALL and its subtypes, utilising attributes from the last FC layer of CNN to achieve 100% accuracy for binary classification and 97.43% for subtypes classification of ALL. The study by Loey et al. [50] introduced two classification models for distinguishing leukemia free and affected blood microscopic images. The first uses AlexNet for feature extraction, while the second uses other classifiers like DT, LD, SVM, and KNN. The SVM classifier was found to be superior in performance metrics. Kadhim et al. [51] developed a CNN deep learning model for a leukemia diagnosis, achieving over 98% accuracy in classification using the AML dataset. Ghany et al. [52] developed an automated ALL classifier based on the Efficient Net B3 CNN model. The model used a practice loss ratio to compare the loss value at each epoch, outperforming conventional methods with a fixed learning rate and achieving high performance. Ansari et al.

[53] developed a DL model for detecting AL using lymphocyte and monocyte pictures. The model, which includes multiple hidden layers significantly improved the diagnosis of AL cells. Bodzas et al. [54] developed research for automated blast cell detects and classify the cells from peripheral blood smear images using ANN and SVM classifiers. The neural network model achieved 100% sensitivity and 97.52% accuracy. Menagadevi et al. [55] study utilized a CNN model to forecast ALL cells in blood samples. This model segmented the nucleus using k clustering and L*a*b colour space, classifying the segmented image into normal and ALL photos. Saeed et al. [56] proposed an automated system for diagnosing ALL diseases using the CNN technique.

Simulations were conducted on ALL IDB 1 and Leukemia IDB 2 datasets, focusing on automatic feature extraction using a CNN deep learning model. The A2M-LEUK algorithm, an attention-augmented method for children's BC detection, was proposed in the study by Talaat et al. [57], enhancing accuracy and efficiency in detecting and classifying leukemia cells. This innovative approach could improve leukemia diagnosis and treatment, reducing medical professionals' workload and enhancing patient experience. A hybrid classification approach for WBC Leukaemia is utilised in the study by Sahlol et al. [58], using a DCNN VGGNet and a statistically enhanced Salp Swarm Algorithm. This approach achieved high efficiency and lowered level of complexity, reducing computation time and resource consumption. The SESSA optimisation successfully narrows down features from 25K to 1K, improving performance.

Table 7: Classification Techniques.

Ref	Technique	Advantage	Disadvantage
[43]	Binary classification with feature extraction	enabling efficient detection of leukemia	Require dependency on specific dataset characteristics
[44]	SVM, KNN, and DT	Reduced time consumption	Image processing techniques are improved for diagnosing different types of diseases.
[45], [49], [51], [55], [56]	CNN	achieving high classification accuracy	computational complexity may require large annotated datasets for training
[47]	Optimised Dense CNN	cancer type cells are accurately predicted, demonstrating high accuracy rates	potential complexity in model optimisation
[50]	Alex Net	demonstrated superior classification accuracy compared to previous studies on a larger dataset of 2820 images	The text does not provide any information on whether images are leukemia-free or leukemia-affected.
[52]	EfficientNet-B3 CNN for ALL classification	The system is capable of performing various automated processing tasks, including color correlation, nucleated cell segmentation, and efficient validation and categorization.	To enhance performance, more samples will need to be collected.
[54]	ANN, SVM for blast cell identification	The likelihood of overfitted areas near these cells is high.	The need for extensive medical data is significant, and expanding the learning set can help reduce overfitting and increase the probability of specific classifications.
[57]	A2M-LEUK algorithm for BC detection	The system has demonstrated high accuracy rates, suggesting its potential to reduce medical professionals' workload and enhance the diagnosis of leukemia in children.	scalability and generalizability
[58]	DCNN with VGGNet and SESSA	while enhancing performance, the power and resource consumption is reduced	Highly complex model to perform better in some necessary cases.

Source: Authors, (2026).

IV.1. SUMMARY OF CLASSIFICATION TECHNIQUES

The survey about classification techniques is critical in accurately diagnosing and managing leukemia, providing information about disease subtypes, prognosis, and treatment options. Traditional methods, such as morphological analysis and immunophenotyping, provide clinically relevant information that is simple to interpret, thereby facilitating initial diagnosis. Despite resolution limitations, cytogenetic analysis improves classification by identifying genetic alterations necessary for prognosis and treatment decisions. Molecular profiling technologies provide comprehensive genomic insights into leukemia subtypes and potential therapeutic targets, but they require specialised expertise and can be costly. Furthermore, machine learning-based approaches promise improved classification accuracy by integrating multidimensional data. Still, they may need help with challenges such as the need for large annotated datasets and limited interpretability, preventing widespread clinical adoption. Despite their limitations, classification techniques significantly impact leukemia detection and patient care, highlighting the need for continued research to address challenges and optimise their utility in clinical practice.

V. CONCLUSION

Blood cancer diagnosis has improved significantly over the past decade as a consequence of technological innovation, groundbreaking research. This survey paper has thoroughly examined this changing landscape, beginning with an overview of various blood cancer types, including leukemia, lymphoma, and myeloma. Traditional diagnostic modalities were reviewed alongside molecular diagnostics research, including genomic profiling and liquid biopsy.

The combination of these molecular diagnostic approaches has transformed our understanding of blood cancer biology and paved the way for personalised treatment strategies. Furthermore, the survey investigated the use of ML and artificial intelligence techniques in blood cancer detection, including segmentation methods such as thresholding, edge detection, and ML-based approaches. It also provided insights into classification techniques using ML and DL methodologies, illuminating current challenges, emerging trends, and future directions in oncology research. This comprehensive survey highlights the dynamic evolution of blood cancer diagnosis, providing a path to better patient care and treatment outcomes.

VI. AUTHOR'S CONTRIBUTION

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