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Image Processing Techniques for Acute Leukaemia Detection

Ashwini P. Patil[1], Manjunatha Hiremath[2]

[1]PhD Scholar, of Computer Science, CHRIST (Deemed to be University), Bengaluru , Assistant Professor, Department of Computer Application, CMR Institute of Technology, Bengaluru, India, patil.ashwini.p@gmail.com

[2]Assistant Professor, Department of Computer Science,CHRIST(Deemed to be University), Bengaluru, India, manjunatha.hiremath@christuniversity.in

ABSTRACT

Every year a lot of people are diagnosed with blood cancer. This disease has a high mortality rate due to late and incorrect diagnoses. Acute leukaemia diagnosis requires an automated solution to facilitate early detection. This is one of the challenging problems and several machine learning techniques are proposed in recent years, however, image analysis using blood smear images remains the easiest and efficient technique to detect acute leukaemia. This study provides a literature review of the research work corresponding to the detection and classification of Acute lymphoblastic leukaemia (ALL) using digital image processing. The paper presents the analysis of various methods and techniques of image processing to detect leukaemia and highlights some of the research pros and cons. This literature review also introduces some of the research issues and challenges involved in this field of study

Key words : Acute lymphoblastic Leukemia, Classification, Image processing, Image segmentation..

1. INTRODUCTION

Leukaemia is one of the common blood cancers claiming many lives every year. Leukaemia is a blood cell cancer that originates in bone marrow spreading further to peripheral blood and other organs. Leukemic cancer can be classified into various types, based on the immaturity level of the cell it is divided as Acute or Chronic, and based on cell lineage it is divided into myeloid or lymphoid. Hence there are four different types of leukaemias i.e. Acute lymphoblastic leukaemia, Acute Myeloid leukaemia, Chronic lymphoblastic leukaemia, and Chronic Myeloid leukaemia. According to FAB Classification[1] two acute leukaemia are further divided into subcategories. Lymphoblastic leukaemia is subdivided into three types (L1, L2, and L3) whereas myeloid leukaemia is subdivided into six types (M1, M2, M3, M4, M5, and M6).

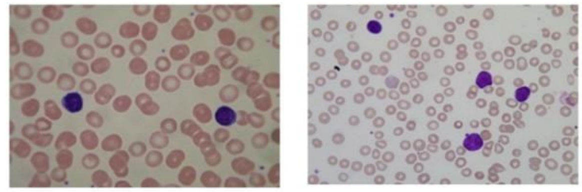
Acute leukaemia is considered riskier because it grows and spreads rapidly as compared to chronic and there would be very little time for diagnosis and treatment. Hence early detection of Acute leukaemia is very important. The diagnosis of leukaemia is done in three stages. First step is a complete blood count (CBC) test which gives the total count of hemoglobin, white blood cells, red blood cells, platelets and hematocrit. CBC test is one of the easiest and cheapest but it gives a complete analysis of your blood and is the most effective one. The second step is bone marrow aspiration; this test further helps in confirmation of leukaemia. The third step is to classify the type of leukaemia by analyzing the cancer cells characteristics.

This complete leukaemia diagnosis needs good infrastructure and an expert pathologist which might be a problem for underdeveloped as well as developing countries. Moreover this process if done manually will take a lot of time and diagnosis might get delayed. Due to these delays in diagnosis most of the patients are at advanced disease (stage 3-4) at the time of their diagnosis [21]. There is certainly a need to develop a completely automated, cost-efficient system to diagnose patients with leukaemia and detect the type of leukaemia.

A lot of studies have been done to find a better solution for leukaemia detection. Image processing using blood smear images serves as an efficient technique for early diagnosis of leukaemia. This paper reviews some of the studies and research work done in this area. The paper is organized as follows: Section1 defines the study; Section2 discusses the review protocol; Section3 gives details of the dataset; Section4 presents the review of methodology and summary of all the methods and techniques extracted from review papers; Section5 specify the research issues Section6 provides the conclusion.

2. DATASET

The first step in the detection of leukaemia disease is the acquisition of peripheral blood images. Most of the studies in this survey have used publicly available ALL-IDB database. The ALL-IDB dataset has two different versions (ALL-IDB1 and ALL-IDB2)[1]. Some of the studies which focus on ALL and AML classification have acquired images from The American Society of Hematology (ASH) Image Bank. ASH bank is a web-based image library containing a wide range of hematology images [2]. Some of the articles have collected a dataset from the local hospitals and pathology centres. Fig.1 shows an example of peripheral blood microscopic images. Table 1 provides a summary of acute leukaemia datasets used in reviewed research papers.



(a) (b)

Figure 1: Examples of images from ALL- IDB: (a) Healthy Blood (b) Blood with ALL blast

Table 1: Datasets used in reviewed research

#	Ref	Dataset	Number of Samples	Sources
1	[6]	Private Dataset	100 microscopic images (Training 62 images, Testing 38 images)	Medical Image and Signal Processing Research Centre (MISP)
2	[15] [17] [19]	Public Dataset	108 microscopic images Of resolution (2592×1944)	ALL-IDB
3	[3] [4]	Public Dataset	-	ALL-IDB2
4	[18]	Public Dataset	240 microscopic images (100 - healthy, 80 - AML, 60 - ALL)	American society of hematology (ASH) Image Bank
5	[9]	Public Dataset	80 single cell images of 60×60 pixels (40 – normal blood cells, 40 – abnormal blood cells)	ALL-IDB
6	[8]	Public Dataset and Private Dataset	14 images (2864×2909 pixel) 59 images (2592×1944 pixel) 215 images (300×300 pixel)	Cellavision database ALL-IDB database Jiashan database
7	[5]	Public Dataset	-	ALL-IDB1
8	[7]	Private Dataset	-	Ispat General Hospital, Rourkela Orissa and University of Virginia
9	[13]	Private Dataset	1500 (750 AML + 750 ALL) Images Training 1200 (600 AML+600 ALL) images, Testing 300 (150 AML + 150 ALL) images	Hematology Department at University Sains Malaysia Hospital (HUSM) in Kubang Kerian, Kelantan, Malaysia
10	[14]	Public Dataset and Private Dataset	115 public images (632×480 pixel) 642 private images	ALL-IDB
11	[16]	Public Dataset	260 images of resolution (257×257) pixel	ALL-IDB
12	[11]	Public Dataset	33 microscopic images	ALL-IDB1
13	[20]	Public Dataset	15 testing and 130 training images for cell counting 85 Images (1712 x 1368 pixels) for detection	ALL-IDB

3. REVIEW OF METHODOLOGY

Medical image processing is an analysis technique in which we apply machine learning to automate medical diagnosis. Image processing in leukaemia diagnosis can be broadly classified into four stages, Pre-processing, segmentation, feature extraction and classification. Figure 2 shows the detailed workflow of all the stages involved in acute leukaemia detection. This section reviews all the methods used in selected research articles. Table 2 summarizes the comparison of all the methodologies adopted by reviewed articles.

3.1 Pre-processing

Image pre-processing includes image restoration, transformation, filtering and enhancement. Images have to be pre-processed before feeding them into the detection system because it greatly impacts segmentation and feature extraction steps. In pre-processing [19] converts RGB image into a grayscale image, but most of the researchers propose that converting RGB model to other colour space like YCBR[6], CY[4], CMYK[17] is more effective. [14] proves that selecting only a green component from an RGB image can also result in better accuracy in segmentation.

[11,12,15,17,18,19] have used histogram equalization to improve image contrast. Some of the articles have used various filtering techniques such as Order statistic filter [18], wiener filtering [15, 10], Selective filtering [7] etc.

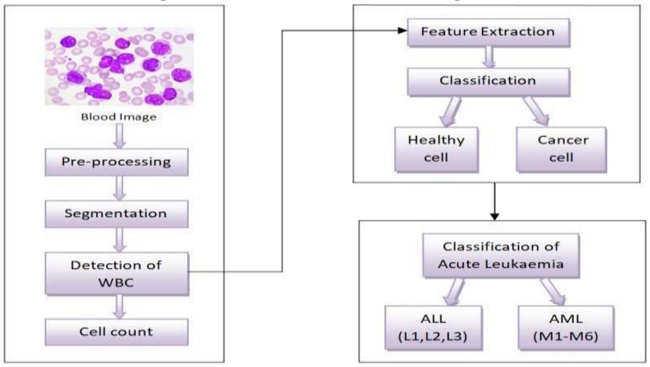


Figure 2: Stages of Acute Leukemia Detection using Image Processing

3.2 Segmentation

Image segmentation is one of the crucial steps in leukaemia detection.

Lot of research work has been carried out in segmentation techniques and it is still one of the challenging steps in the entire process. In this step, the blast cell is identified and then nucleus and cytoplasm are segmented. Most common techniques used in this step are watershed algorithms, Otsu's thresholding and morphological operations. [9, 15] have proposed a novel marker-based segmentation (MBS) method for segmentation. [13] shows that the segmentation step could be excluded thus reducing computational and time cost.

3.3 Feature Extraction

In feature extracting and selection we extract desired features to identify or classify objects. Some of the common features that are used in leukaemia detection are colour, texture, contour, chromatic, geometric and statistical features.

3.4 Classification

Selected features from the previous steps are fed to the classification algorithm to detect leukaemia blast cells and healthy cells and further classify them into subcategories. The accuracy of classification largely depends upon features extracted and used to train the algorithms. Random forest, neural network, support vector machine (SVM), decision tree and k-nearest neighbour are the common methods used in leukaemia detection and classification.

Table 2: Comparison of reviewed literature

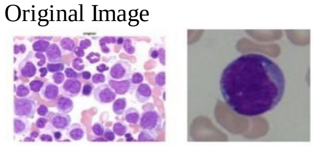
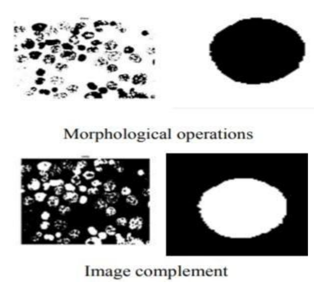
Author, year	Proposed work	Methods		Merits and Demerits	Results
Jha & Dutta, 2019 [3]	Detection of Acute Lymphocytic Leukemia using Mutual Information based hybrid model and deep learning	Preprocessing	Image Resizing	Merits: Proposed two novel approaches 1) MI based hybrid model used for segmentation 2)Chronological SCA based deep CNN classifier	98.7% Accuracy
		Segmentation	Mutual Information(MI) based hybrid model which employs Active contour and FCM based image Segmentation		
		Feature Extraction	Color histogram features, LDP features		
		Classification	Chronological Sine Cosine Algorithm (SCA) based Deep CNN		
Mohammed et al., 2014 [4]	Acute Lymphoblastic Leukemia Segmentation Using C-Y Color Space	Preprocessing	Convert image to CY color model, Extract Y component	Merits: By applying CY color space achieved better accuracy as compared to RGB color space	Segmentation accuracy is 98.38%
		Segmentation	Use histogram, median filter, convert final image to RGB		
Bhattacharjee & Saini, 2015 [5]	Compare four types of classifiers and develop graphical user interface using classifier with	Preprocessing	Contrast enhancement and Quality adjustment	Merits 1)Achieved better segmentation accuracy using morphological operations as compared to other techniques 2)developed GUI for	Segmentation accuracy is 96.67%
		Segmentation	Morphological Dilation and Erosion		
		Feature Extraction	Morphological features(Area, Perimeter, circularity, form factor)		

<table>
<tr><td></td><td>best output to detect ALL</td><td>Classification</td><td>KNN, SVM, ANN,
K-means clustering</td><td>segmentation and classification of lymphoid cells

<u>Demerits</u>
Lymphocytes in the image are individuated manually</td><td><table><tr><th>Figs. of Merit</th><th>kNN</th><th>SVM</th><th>ANN</th><th>K-means</th></tr><tr><td>True Positive</td><td>9</td><td>9</td><td>9</td><td>9</td></tr><tr><td>True Negative</td><td>20</td><td>19</td><td>20</td><td>18</td></tr><tr><td>False Positive</td><td>1</td><td>2</td><td>1</td><td>3</td></tr><tr><td>False Negative</td><td>0</td><td>0</td><td>0</td><td>0</td></tr><tr><td>Misclassification</td><td>4.76%</td><td>9.52%</td><td>4.76%</td><td>14.28%</td></tr><tr><td>Specificity</td><td>95.23%</td><td>90.47%</td><td>95.23%</td><td>85.71%</td></tr><tr><td>Sensitivity</td><td>100%</td><td>100%</td><td>100%</td><td>100%</td></tr></table></td></tr>
<tr><td rowspan="4"><u>Agrawal et al., 2019</u>
[6]</td><td rowspan="4">To develop automated system for early detection of WBC cancer i.e. Myeloma and Leukemia (ALL and AML)</td><td>Preprocessing</td><td>Convert RGB image to YCBCR color space</td><td rowspan="4"><u>Merits</u>
1) Detects Myeloma and types of Leukemia
2) This technique requires minimum preprocessing and excellent feature extraction</td><td rowspan="4">Detect ALL, AML and Myeloma with 97.3% Accuracy</td></tr>
<tr><td>Segmentation</td><td>Gaussian Distribution, Otsu’s Thresholding, Kmeans clustering</td></tr>
<tr><td>Feature Extraction</td><td>GLCM method to extract texture features.</td></tr>
<tr><td>Classification</td><td>CNN</td></tr>
<tr><td rowspan="4">Joshi et al..2013
[19]</td><td rowspan="4">This work propose automatic WBC segmentation and classify blast cells from normal lymphocyte cells</td><td>Preprocessing</td><td>Convert image into gray scale image, use histogram equalization, linear contrast stretching to adjust intensity of image</td><td rowspan="4"><u>Merits</u>
Good accuracy with minimal feature extraction

<u>Demerits</u>
Only classify blast cells and normal cell, does not detect type of leukemia</td><td rowspan="4">93% Accuracy</td></tr>
<tr><td>Segmentation</td><td>Otsu’s Thresholding, morphological opening, size test removal to discard unwanted objects</td></tr>
<tr><td>Feature Extraction</td><td>Shape feature (area, perimeter and circularity)</td></tr>
<tr><td>Classification</td><td>KNN</td></tr>
<tr><td rowspan="4"><u>Mohapatra et al., 2010</u>
[7]</td><td rowspan="4">Proposed work to classify a lymphocyte into normal or a ALL lymphoblast.</td><td>Preprocessing</td><td>Selective filtering, un-sharp masking, RGB to Lab color space</td><td rowspan="4"><u>Merits</u>
Two new features ie. Contour signature and hausdorff dimension are used to classify lymphocyte cell nucleus

<u>Demerits</u>
Does not include identification of types of leukemia</td><td rowspan="4">95 % Accuracy</td></tr>
<tr><td>Segmentation</td><td>FCM and Bounding box</td></tr>
<tr><td>Feature Extraction</td><td>Texture, color space, Fractals by hausdorff dimension, contour signature</td></tr>
<tr><td>Classification</td><td>SVM</td></tr>
<tr><td rowspan="4"><u>Zhao et al., 2017</u>
[8]</td><td rowspan="4">Automatic system to detect and classify WBC‟s from peripheral blood images</td><td>Preprocessing</td><td>R-B image</td><td rowspan="4"><u>Demerits</u>
It fails to detect all the WBC‟s, and it sometimes considers a few non WBCs as WBCs</td><td rowspan="4">92.8% Accuracy</td></tr>
<tr><td>Segmentation</td><td>Morphological operations</td></tr>
<tr><td>Feature Extraction</td><td>Extract Granularity features(PRICoLBP) from each WBC, use SVM to discern basophil and eosinophil, CNN to extract features from other types of WBC‟s</td></tr>
<tr><td>Classification</td><td>Random forest</td></tr>
<tr><td rowspan="4"><u>Khashman & Abbas, 2013</u>
[9]</td><td rowspan="4">Method to extract data from microscopic cell images without performing segmentation and using neural network classifier to identify normal and abnormal blood cells</td><td>Preprocessing</td><td>Crop single cell images , Otsu’s thresholding , median filter , edge detection(canny operator), pattern averaging (2×2 kernel)</td><td rowspan="4"><u>Merits</u>
Reduce computational and time cost without performing segmentation and extraction of local feature from the blood cell images</td><td rowspan="4">Accuracy
Learning Scheme I 90%,
Learning Scheme II 80%,
Learning Scheme III 75.1%.
<table><tr><th rowspan="2">Learning Scheme</th><th colspan="2">Training Accuracy Rate (%)</th><th colspan="2">Testing Accuracy Rate (%)</th><th colspan="2">Overall Accuracy Rate (%)</th></tr><tr><th>NBC[a]</th><th>ABC[b]</th><th>NBC</th><th>ABC</th><th>Training</th><th>Testing</th></tr><tr><td>LS-I</td><td>(30/30) 100</td><td>(30/30) 100</td><td>(9/10) 90</td><td>(9/10) 90</td><td>(60/60) 100</td><td>(18/20) 90</td></tr><tr><td>LS-II</td><td>(20/20) 100</td><td>(20/20) 100</td><td>(15/20) 75</td><td>(17/20) 85</td><td>(40/40) 100</td><td>(32/40) 80</td></tr><tr><td>LS-III</td><td>(10/10) 100</td><td>(10/10) 100</td><td>(22/30) 73.3</td><td>(23/30) 76.6</td><td>(20/20) 100</td><td>(45/60) 75.1</td></tr></table>[a] Normal Blood Cells. [b] Abnormal Blood Cells</td></tr>
<tr><td>Segmentation</td><td>-</td></tr>
<tr><td>Feature Extraction</td><td>-</td></tr>
<tr><td>Classification</td><td>ANN with 3 learning schemes. LS1, LS2 and LS3</td></tr>
</table>

Patel & Mishra, 2015 [10]	Automated approach for leukemia detection	Preprocessing	Median filtering, wiener filtering and image cleaning using solidity	Merits Important part of this work is to segment lymphocyte and myelocytes Demerits Only classify cancerous cells from healthy cell. Type of leukemia is not detected	93.57% Accuracy
		Segmentation	K means clustering, histogram equalization, Zack algorithm, Bounding Box		
		Feature Extraction	Color, Geometric, texture and statistical features		
		Classification	SVM		
Putzu et al., 2014 [11]	Proposed and automated method to identify and classify WBC from microscopic images	Preprocessing	CMYK color model, Contrast stretching operations, Histogram equalization	Merits 1) Innovative technique for identification and classification of leukocytes. 2)Developed a new method to extract features from cropped images which is excellent for both chromatic and texture features	93% Accuracy, 98% Sensitivity
		Segmentation	Zack algorithm, Bounding Box, grouped WBC identification by roundness analysis, Watershed segmentation operation, Distance transform image calculation, Watershed line refining.		
		Feature Extraction	Developed a new method to calculate background pixels using previously calculated binary mask and remove this pixels from the histogram. This technique allows to extract chromatic features from whole WBCs , nucleus and from the cytoplasm, for 21 color descriptors		
		Classification	SVM with Gaussian radial basis kernel		
Dharani & Haripra sath, 2018 [12]	Develop methodology to detect leukemia affected cells from healthy cells	Preprocessing	Enhance image using “imadjust” command in MATLAB, Convert RGB to gray image, histogram equalization	Demerits 1) This research work only proposes method to segment and identify affected cells. 2)No performance analysis	Original Image  Final Image 
		Segmentation	Otsu’s Thresholding, Morphological operation and complement		
		Feature Extraction	Centroid, perimeter, roundness		
		Classification	-		
Supardi et al., 2012 [13]	Classification of blast cell in ALL and AML using KNN	Preprocessing	-	Merits Used large data set for training and testing Demerits	Highest accuracy using cosine distance in identifying ALL is 84.67% and AML is 87.33%
		Segmentation	-		
		Feature Extraction	12 features extracted manually from the image		

		Classification	KNN	It is not a fully automated approach. Features are manually extracted	
Negm et al., 2018 [14]	Decision support system that comprises of panel selection, segmentation using k-means clustering feature extraction and image refinement to identify leukemia cells	Preprocessing	Select green component	Merit High accuracy	Accuracy is 99.517% Sensitivity is 99.348% Specificity is 99.529%
		Segmentation	K means algorithm, data normalization		
		Feature Extraction	WEKA tool		
		Classification	ANN and decision tree		
Mishra et al., 2017 [15]	ALL detection using (MBS) marker-based segmentation, (GLCM) gray level co-occurrence matrix based feature extraction, and (PPCA) probabilistic principal component analysis based feature reduction.	Preprocessing	Histogram equalization, wiener filtering	Merits Proposed new technique for identification and classification of lymphoblast	Accuracy Segmentation 96.29% , Classification 99.004% and nucleus and cytoplasm 96%
		Segmentation	marker-based segmentation (MBS)		
		Feature Extraction	GLCM and PPCA		
		Classification	Random Forest		
Muntasa & Yusuf, 2019 [16]	A detection model for ALL using principal object characteristics of the color image	Preprocessing	Separate the image into Red, Green, Blue channels. Image enhancement, Merge all 3 Channel images and convert RGB to HSV channel	Merits Proposed system has two novelties: 1) image enhancement using 3 color channels. (red green blue), 2) feature extracted using Densitometry components extension. Demerits Main focus is on image enhancement and feature extraction. This work do not include classification of ALL and its subtypes	81.54% accuracy for Euclidean Distance, 76.92% accuracy for Manhattan, Canberra, 82.31% accuracy for Chebyshev
		Segmentation	Filtering(Hue channel, MatMask), local entropy threshold, Morphological operations, color image segmentation		
		Feature Extraction	Feature extraction using Energy (EN), Shanon Entropy HX, Entropy(EP), Log Energy Entropy (EE), Variance (VA), Mean (ME), and Correlation (CO), Normalize features, calculate similarity measurement using Euclidean Distance, Manhattan, Canberra, and Chebyshev methods		
		Classification	-		
Pathirage et al..	Image processing	Preprocessing	Noise removal, edge detection		

2016 [20]	techniques to count RBC, WBC and platelet cells and classify ALL and CLL	Segmentation	Circular Hough transform		
		Feature Extraction	Geographical and color based feature extraction		
		Classification	-		
Shafique et al., 2019 [17]	Develop automated system for Acute Lymphoblastic leukemia detection	Preprocessing	RGB image converted to CMYK color space, Histogram equalization	Demerits Only classification of blast cell and normal cell. Do not include ALL subtype detection. No novelty in this work	93% Accuracy 92% sensitivity 91% specificity
		Segmentation	Zack algorithm, watershed segmentation, morphological operations		
		Feature Extraction	Color, shape and texture features		
		Classification	SVM		
Rawat et al., 2017 [18]	Develop system to identify leukemic cells from healthy cells and classify them into ALL and AML and further classify them into their subtypes	Preprocessing	Nucleus sub image selection, Histogram equalization, Order statistic filter	Merits 1)Classification of leukemia into ALL, AML and their subtypes with high accuracy 2)Used genetic algorithm for feature selections	Acute lymphoblastic cells, Acute myeloid cells and healthy cells classification accuracy is 99.5%, Classification accuracy for L1, L2 and L3 is 97.1% , Classification accuracy for M2, M3 and M5 is 98.5%.
		Segmentation	Otsu's thresholding, morphological opening, image refining(hole filling and border cleaning)		
		Feature Extraction	shape features, GLRL, FOS, GLDS, NGTDM, SFM, EDGE and GLCM, signal processing based features, transform domain based models (FPS and 2-D Gabor transformation features using three scales) and color features. Feature selection using genetic algorithm		
		Classification	SVM with various kernel functions. Quadratic kernel, Multilayer perceptron (MLP) kernel, Linear kernel, polynomial kernel Gaussian Radial basis function kernel		

4. RESEARCH ISSUES

A lot of studies and research works are being conducted on automatic leukaemia detection. Many studies are achieving better accuracy and reliability, but researchers have to face a lot of challenges regarding dataset. Most of the research works do not use the same dataset which makes the comparison of accuracy and efficiency difficult. Low sample size and noise in the dataset are also some of the difficulties. Further challenges in this research area are extracting features from blood smear images to classify leukaemia into its various types and subcategories, hence researchers mostly focus on classifying cancerous cells and non-cancerous cells.

5. CONCLUSION

This review paper presents details of various methods and techniques, their merits and demerits which are summarized in a table. There is a lot of scope for future work in the development of automatic leukaemia detection system. Researchers should expand the size of their dataset and develop a system with high reliability and accuracy. Detection system should also be faster and economical. A lot of novel technologies could also be implemented to enhance the accuracy of segmentation and classification. Researchers should also focus on classifying leukaemia into various types and sub categories.

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