REVIEW OF DETECTION METHODS FOR LEUKEMIA IN MICRO IMAGES

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ABSTRACT: Health informatics has been qualified as prominent province in the headway of information technology. Ascribable to such a sophisticated evolution in the health care informatics, it is viable at the present period of time to diagnose several ailments in a short span of time. In relation to complaints, there is one disease dub leukemia which can be recognised by manipulating different detection techniques of information technology. In recent years the detection mechanisms are used widely in several medical areas for improving earlier detection and treatment stages. This review work studied about the details of various detection methods for Leukemia analysis in microscopic images. This review work has surveyed several detection methods utilized by prior authors such as Artificial Neural Network (ANN), Support Vector Machine (SVM), k Nearest Neighbour (kNN), Decision Tree (DT), Self Organizing Map (SOM) etc. The importance and issues of the every detection methods are experimented through a Leukemia Microscopic Images. These detection methods are successfully implemented in MATrix LABoratory (MATLAB) and measured using the accuracy.

INDEX TERMS: Leukemia Microscopic Images, segmentation, detection, classifiers, image processing, and computer aided diagnosis system .

1. INTRODUCTION

Leukemia is a cancer of blood cells. In leukemia, abnormal blood cells are produced in the bone marrow. Usually, leukemia involves the production of abnormal white blood cells which are responsible for fighting infection. The abnormal cells in leukemia do not function in the same way as normal white blood cells. The leukemia cells continue to grow and divide, eventually crowding out the normal blood cells. There are different types of leukemia, based upon how quickly the disease develops and the type of abnormal cells produced from http://www.hematology.org/, 2017. Leukemia can also cause symptoms in organs that have been infiltrated or affected by the cancer cells.

Diagnosis of leukaemia usually depends on the Complete Blood Count (CBC) in which doctors check the complete count of white blood cells, red blood cells, and platelets. This complete blood count test may show leukaemia cells, but, in most cases, it is not enough for doctors to confirm that the patient has leukaemia. Haematologist is using technique of image processing to analyze, detect and identify leukemia types in patients recently. Detection through images is fast and cheap method as there is no special need of equipment for lab testing. Technique of image processing is categorized into two types: Manual methods and automated methods.

In practice, manual microscopic evaluation of stained sample slide is used for diagnosis of leukaemia. But manual diagnostic methods are time-consuming, less accurate, and prone to errors due to various human factors like stress, fatigue, and so forth. Manual methods require a lot of effort and time. Also, highly trained medical professionals are required to perform these types of examining and hence it is labor-intensive task (https://curesearch.org, 2017).

On the contrary, automated diagnostic systems can overthrow these problems of manual diagnosis. Furthermore, it will reduce the burden of medical professional and will provide accurate and effective results as compared to manual diagnosing. In recent past, some computer-aided leukaemia diagnosis methods are presented. These automated systems are fast, reliable, and accurate as compared to manual diagnosis methods (https://www.cancer.org, 2017). This review work presents details of computer-aided diagnosis systems regarding their methodologies that include enhancement, segmentation, feature extraction, classification, and accuracy.

2. LITERATURE REVIEW

This section discusses about the review details of feature extraction methods, image classification and image segmentation methods.

2.1. REVIEW OF IMAGE SEGMENTATION METHODS

Sadeghian et al [2009] segmented the White Blood Cells (WBC) to its two dominant elements: nucleus and cytoplasm. The segmentation is conducted using a proposed segmentation framework that consists of an integration of several digital image processing algorithms. Twenty microscopic blood images were tested, and the proposed framework managed to obtain 92% accuracy for nucleus segmentation and 78% for cytoplasm segmentation. The results indicate that the proposed framework is able to extract the nucleus and cytoplasm region in a WBC image sample

Khashman and Al-Zgoul [2010] proposed the use of morphological analysis of microscopic images of leukemic blood cells for the identification purpose. Presented the first phase of an automated leukemia form identification system, which is the segmentation of infected cell images. The segmentation process provides two enhanced images for each blood cell; containing the cytoplasm and the nuclei regions. Unique features for each form of leukemia can then be extracted from the two images and used for identification.

Mohapatra and Patra [2010] presented two novel shape features i.e., hausdorff dimension and contour signature is implemented for classifying a lymphocytic cell nucleus. Support Vector Machine (SVM) is employed for classification. A total of 108 blood smear images were considered for feature extraction and final performance evaluation is validated with the results of a hematologist.

Mohapatra et al [2011] aimed at leukocyte or white blood cell (WBC) segmentation which can assist in acute leukemia detection. A rough set based clustering approach is followed for color based segmentation of WBC. The segmented nucleus and cytoplasm can be used for feature extraction which can lead to classification of a leukocyte into mature lymphocyte or lymphoblast.

Mohapatra et al [2012] introduced a comparative approach to Acute Lymphoblastic Leukemia (ALL) detection based on WBC nucleus image segmentation and morphological analysis. Color based clustering is employed for segregating various blood components and obtaining the nucleus of the white blood cell. Further fractal geometry, contour signature and texture based techniques are employed for nucleus feature extraction which leads to automatic leukemia detection using a Support Vector Machine (SVM) classifier. The proposed approach is validated with the collected blood microscopic images and satisfactory results have been obtained.

Mohapatra et al [2012] proposed a fast and simple framework for lymphocyte image segmentation. Accurate segmentation of lymphocyte is essential as it facilitates automated leukemia detection in blood microscopic images. In this work image segmentation is considered as a pixel classification problem and a novel neural architecture is employed to classify each pixel into cytoplasm, nucleus or background region. The network tuned for a set of images works well for other similar stained blood images.

Fatma and Sharma [2014] presented a general review of algorithms that have been presented for the purpose of image segmentation. Image segmentation commonly known as partitioning of an image is one of the intrinsic parts of any image processing technique. In this image processing step, the digital image of choice is segregated into sets of pixels on the basis of some predefined and preselected measures or standards. There have been presented many algorithms for segmenting a digital image.

Arslan et al [2014] presented a new algorithm for segmentation of both normal and leukemic cells in peripheral blood and bone marrow images. In this algorithm, proposed to model color and shape characteristics of white blood cells by defining two transformations and introduce an efficient use of these transformations in a marker-controlled watershed algorithm. Particularly, these domain specific characteristics are used to identify markers and define the marking function of the watershed algorithm as well as to eliminate false white blood cells in a post processing step.

Sarrafzadeh and Dehnavi [2015] detected leukocytes from a blood smear microscopic image and segment them into their two dominant elements, nucleus and cytoplasm. The segmentation is conducted using two stages of applying K-means clustering. First, the nuclei are segmented using K-means clustering. Then, a proposed method based on region growing is applied to separate the connected nuclei. Next, the nuclei are subtracted from the original image. Finally, the cytoplasm is segmented using the second stage of K-means clustering.

ElDahshan et al [2015] applied the color segmentation for Acute Lymphoblastic Leukemia (ALL) images to segment each leukemia image into two clearly defined regions: blasts and background. The ALL segmentation process is based on two different color spaces: Red Green Blue (RGB) color space and Herpes Simplex Virus (HSV) color space. The comparison performance between the segmentation methods based on RGB and HSV color spaces are investigated to find the best method to segment the acute lymphoblastic leukemia images. The experimental results show that the segmentation of ALL images based on HSV color space yield better accuracy than RGB color space when compared with the manual segmentation image made by medical experts. Using HSV color space, the shape of blasts in ALL blood samples is closely preserved with segmentation accuracy over 99.00%. However, segmentation based HSV color space was chosen as it produced the highest ALL segmentation rate.

Dorini et al [2017] proposed a novel method to segment nucleus and cytoplasm of white blood cells (WBC). WBC composition of the blood provides important information to doctors and plays an important role in the diagnosis of different diseases. Use simple morphological operators and explore the scale-space properties of a toggle operator to improve the segmentation accuracy. The proposed scheme has been successfully applied to a large number of images, showing promising results for varying cell appearance and image quality, encouraging future works.

Choudhary et al [2017] proposed an image processing technique for the detection of leukemia in a human blood sample. Proposed work overcomes the problem of k-means clustering and thresholding method by using the image enhancement techniques and some arithmetic operation for the segmentation of nucleus from the white blood cells. Segmentation based on LAB color space (luminosity, chromaticity layer and chromaticity layer b) color space will be used in order to eliminate the White Blood Cells (WBC) from the background. The segmented image is used to calculate the shape based feature of the nucleus of the WBCs. k-nearest neighbor (k-NN) classifier has been utilized to classify blast cells from normal lymphocyte cells.

Dhanachandra and Chanu, [2017] surveyed reviews on the different image segmentation strategies adopted by researchers in detecting leukemia from blood microscopic image to boost the clustering performance thereby eliminating noise in cell image. The primary stages of noise or outlier removal are image acquisition, preprocessing, image enhancement, image segmentation, feature extraction. Image Segmentation is a process of identifying blood cell types regardless of their irregular shapes, sizes, and orientation.

Karthikeyan and Poornima [2017] compared Fuzzy c means with k means for image segmentation, in which

Fuzzy c means (FCM) clustering gives higher accuracy than k means, Gabor Texture Extraction method is used to extract color features from images and finally extracted features are used for classification. FCM clustering gives 90% accuracy whereas k means gives 83% accuracy. SVM is used for classification. The whole work has been developed using MATLAB 7 environment.

Singh et al [2018] presented an automatic technique for the detection and classification of WBCs from microscopic blood images. The process of segmentation is implemented on microscopic blood image. The method firstly separates the leucocytes from rest of the image then it detects leukemia and finally it counts the total number of infected cells. Finally, a smart platform based on Graphical User Interface (GUI) in MATLAB is created to make the detection process much easier and user friendly inclusive of some interesting features like automatic blood cell coint and blood cell identification.

Thomas and Sreejith [2018] reviewed on some of the common segmentation methods are discussed. It includes K- mean segmentation, Otsu thresholding and Color based segmentation. This review also helps to get more details about the different types of segmentation and classification process. Currently blood smear's evaluation is important in the diagnosis of different diseases. Usually, the hematologists are curious on diagnosing white blood cells (WBCs) only. White Blood Cell (WBCs) detection is a vital evaluation method.

Moallem et al [2018] proposed a novel algorithm that can successfully detect and segment overlapping cells in microscopic images of stained thin blood smears. The algorithm consists of three steps. In the first step, the input image is binarized to obtain the binary mask of the image. The second step accomplishes a reliable cell center localization that utilizes adaptive meanshift clustering. Employ a novel technique to choose an appropriate bandwidth for the meanshift algorithm. In the third step, the cell segmentation purpose is fulfilled by estimating the boundary of each cell through employing a Gradient Vector Flow (GVF) driven snake algorithm.

2.2. REVIEW OF CLASSIFICATION METHODS

Scotti [2005] showed the effectiveness of an automatic morphological method to identify the Acute Lymphocytic Leukemia by peripheral blood microscope images. The proposed system firstly individuates in the blood image the leucocytes from the others blood cells, then it select the lymphocyte cells (the ones interested by acute leukemia), it evaluates morphological indexes from those cells and finally it classifies the presence of the leukemia.

Grimwade et al [2010] provided the framework for risk-stratification schemes in acute myeloid leukemia (AML); however, the prognostic significance of many rare recurring cytogenetic abnormalities remains uncertain. Studied outcome of 5,876 patients (16-59 years), classified into 54 cytogenetic subgroups, treated in the Medical Research Council trials. Similarly, additional abnormalities did not have a significant adverse effect in t(8;21) AML. Whereas in patients with inv(16), presence of additional changes, particularly +22, predicted a better outcome (p=0.004).

Putzu and Di Ruberto [2013] presented a complete and fully automatic method for White Blood Cells (WBCs) identification and classification from microscopic images. The proposed method firstly individuates WBCs from which, subsequently, are extracted morphological features necessary for the final stage of classification. The whole work has been developed using MATLAB environment

Mathur et al [2013] reviewed a novel based method ,peripheral Leishman blood stain images as the input and generates a count for each of the WBC subtypes. The digitized microscopic images are stain normalized for the segmentation, to be consistent over a diverse set of slide images. Active contours are employed for robust segmentation of the WBC nucleus and cytoplasm. The seed points are generated by processing the images in Hue-Saturation-Value (HSV) color space. An efficient method for computing a new feature, 'number of lobes,' for discrimination of WBC subtypes is introduced in this article. This method is based on the concept of minimization of the compactness of each lobe.

Nasir et al [2013] presented the classification of White Blood Cells (WBC) inside the Acute Lymphoblastic Leukaemia (ALL) and Acute Myelogenous Leukaemia blood samples by using the Multilayer Perceptron (MLP) and Simplified Fuzzy ARTMAP (SFAM) neural networks. Here, the WBC will be classified as lymphoblast, myeloblast and normal cell for the purpose of categorization of acute leukaemia types. Two different training algorithms namely Levenberg-Marquardt and Bayesian Regulation algorithms have been employed to train the MLP network. There are a total of 42 input features that consist of the size, shape and colour based features, have been extracted from the segmented WBCs, and used as the neural network inputs for the classification process.

Athira Krishnan [2014] discussed various image segmentation and feature extraction methods used for AML detection. .Acute Myelogenous Leukemia (AML) is a fast growing cancer of the blood and bone marrow. The need for automation of leukemia detection arises since current methods involve manual examination of the blood smear as the first step toward diagnosis. This is time consuming, and also the accuracy of the method depends on the operator's ability.

Putzu et al [2014] presented a complete and fully automated method for WBC identification and classification using microscopic images. In contrast to other approaches that identify the nuclei first, which are more prominent than other components, the proposed approach isolates the whole leucocyte and then separates the nucleus and cytoplasm. This approach is necessary to analyse each cell component in detail. From each cell component, different features, such as shape, colour and texture, are extracted using a new approach for background pixel removal.

Lipton et al [2015] presented the first study to empirically evaluate the ability of Long Short-Term Memory (LSTMs)to recognize patterns in multivariate time series of clinical measurements. Specifically, consider multi-label classification of diagnoses, training a model to classify 128 diagnoses given 13 frequently but irregularly sampled clinical measurements. First, establish the effectiveness of a simple LSTM network for modeling clinical data. Then demonstrate a straightforward and effective training strategy in which replicate targets at each sequence step.

Obragade et al [2015] proposed a method of detection of leukemia in patients from microscopic white blood cell images. They have focused on the changes in the geometry of cells and statistical parameters like mean and standard deviation which separates white blood cells from other blood components using processing tools like MATLAB and Lab VIEW. Images processing steps like image enhancement, image segmentation and feature extraction are applied on microscopic images.

Lashkari [2016] segmented the images and determined the region of interest. Then, 23 features that included statistical, morphological, frequency domain, histogram and gray-level co-occurrence matrix based features were extracted from the segmented right and left breasts. To achieve the best features, feature selection methods such as minimum redundancy and maximum relevance, sequential forward selection, sequential backward selection, sequential floating forward selection, sequential floating backward selection, and genetic algorithm were used. Contrast, energy, Euler number, and kurtosis were marked as effective features. The selected features were evaluated by FCM clustering as the unsupervised method and compared with the AdaBoost supervised classifier which has been previously studied. As reported, FCM clustering with a mean accuracy of 75% can be suitable for unsupervised techniques. FCM clustering can be a suitable unsupervised technique to determine suspicious areas in thermal images compared to AdaBoost as the supervised technique with a mean accuracy of 88%.

Manojbhai and Rajamenakshi [2016] focused on deriving knowledge from multiple data formats using intelligent analytics techniques. Medical analytics is a typical example, which encompasses data in multiple formats available as text, images and the data in the databases. Performing large scale image data analysis for near real time results is a challenging task. The challenge here is to extract features without compromising on the performance. Medical images are derived from multiple devices and are analyzed by health professionals manually which is qualitative. Automated deriving of intelligence and guidance will make the disease diagnosis accurate and faster.

Selvi [2016] presented the overall information about the Ewing's Sarcoma and overview of image processing techniques. Ewing's Sarcoma is a terrific form of cancer which affects the adjoining body areas such as bones and other supporting soft tissue of the body. It is a very rare cancer. About 1% among adult and 15% among the children is affected in this Ewing's sarcoma. For detection mainly biopsy, Computerised Tomography (CT) scan or Magnetic Resonance Imaging (MRI)is done and to pursue the treatment surgery, chemotherapy, radiation is given which may increase the survival rate of the patients. The image processing techniques are applied broadly in medical images for refining prior detection and treatment stages in Ewing's Sarcoma cancer.

Desai et al[2016] proposed an automation algorithm using image processing for the detection and classification of Leukemia using processing tool MATLAB. In this process inputs are the microscopic images, and these images are processed using image processing techniques such as Image enhancement, segmentation, feature extraction and classification.

Singh et al [2016] surveyed several methods utilized by prior authors such as Artificial Neural Network (ANN) , Linear Dependent Analysis (LDA), Self Organizing Map (SOM) etc. This procedure is relatively time-consuming; along with their proper accurateness depend upon the proficiency of operator's. So, prevention of leukemia is quite important.

Basima and Panicker [2016] reviewed the morphological evaluation of haemocytes performed manually by experts and counting of blood cells is done using a device called Haemocytometer. Yet, this approach has so many limitations, such as slow estimation, different standard, deviant accuracy and dependence on the operator's skill. For counting hardware solutions such as the Automated Haematology Counter exists, they are very expensive, unaffordable in every hospital laboratory and also use actual blood samples. So there consistently need a cost effective, simple and robust method for counting, analysis and classification of blood cells. The proposed method describes a complete automatic computerized method for WBC identification, counting and classification using microscopic images.

Vogado et al [2017] demonstrated that it is possible to build an automated, efficient and rapid leukemia diagnosis system. Results demonstrated that it is possible to improve the precision of current techniques from the literature using the description power of well-known Convolutional Neural Networks (CNNs). Extract features from a blood smear image using pre-trained CNNs in order to obtain a unique image description. Many feature selection techniques were evaluated and chose procoagulant cellular activity (PCA) to select the features that are in the final descriptor. To classify the images on healthy and pathological created an ensemble of classifiers with three individual classification algorithms such as Support Vector Machine(SVM), Multilayer Perceptron (MLP) and Random Forest(RF). In the tests obtained an accuracy rate of 100%. Besides the high accuracy rate, the tests showed that approach requires less processing time than the methods are analyzed. Considering these facts that approach does not use segmentation to obtain specific cell regions from the blood smear image.

Paswan, and Rathore, [2017] presented a technique for automatic detection and classification of AML in blood smear . K-means algorithm is used for segmentation. k-Nearest Neighbour Classifiers (kNN), Neural Network (NN), and Support Vector Machine (SVM) are used for classification. Gray level co–occurrence matrices (GLCM) is used for optimizing the spectral features. The local binary pattern is used for texture description. Blood microscope images were tested and the performance of the classifier was analyzed.

Rawat et al [2017] addressed the problem of segmenting a microscopic blood image into different regions, and then further analyzes those regions for localization of the immature lymphoblast cell. Further, it investigates the use of different geometrical, chromatic and statistical textures features for nucleus as well as cytoplasm and pattern recognition techniques for sub typing immature acute lymphoblasts as per French– American – British (FAB) classification. This can facilitate haematologist for acquiring essential information about prognosis and for an appropriate cure for leukemia. The exhaustive experiments have been conducted on 260 microscopic blood images (i.e. 130 normal and 130 cancerous cells) taken from ALL-IDB database.

Harjoko et al [2018] applied digital image processing with Active Contour Without Edge (ACWE) and Momentum Back Propagation Neural Network (BPNN) for AML subtypes M1, M2 and M3 classification based on the type of the cell. Six features required as training parameters from every cell obtained by using feature extraction. The features are: cell area, perimeter, circularity, nucleus ratio, mean and standard deviation. The results show that ACWE can be used for segmenting white blood cells with 83.789% success percentage of 876 total cell objects. The whole AML slides had been identified according to the cell types predicted number through training with BPNN.

TABLE 1. INFERENCE OF THE EXISTING WORKS

Author	Methods	Data	Advantages	Disadvantages
Mohapatra and Patra [2010]	two stage color segmentation	blood smear images	Extract useful characteristics from original image	Lesser accuracy
Mohapatra et al[2012]	Color based clustering	Human blood microscopic image	leads to automatic leukemia detection	Lesser accuracy
Mohapatra et al [2012]	NN	Human blood microscopic image	fast and simple framework	Lesser accuracy
Putzu et al [2014]	SVM with a Gaussian radial basis kernel	Blood sample images	provides excellent performances allowing an early diagnostic suspicion	Extracting irrelevant characteristics from original image
Sarrafzadeh and Dehnavi [2015]	K-means clustering	blood smear microscopic image	extract the nucleus and cytoplasm regions accurately	Time consuming
ElDahshan et al [2015]	RGB color space and HSV color space	blood samples	highest ALL segmentation rate	Time consuming
Lipton et al [2015]	LSTM networks	blood sample images.	powerful and increasingly popular models for learning from sequence data.	Trained only on raw time series
Desai et al[2016]	Neural Network	microscopic images	Solve leukemia cancer problems.	Needs more computation time
Basima and Panicker [2016]	automatic computerized classification	microscopic images	Provide a lot of valuable information to evaluate leukaemia	Lesser accuracy
Singh et al [2016]	ANN, LDA, and SOM	microscopic-images	quite time consuming	Accurateness depend upon the proficiency of operator's
Lashkari [2016]	FCM clustering algorithm	microscopic-images	determine suspicious areas in thermal images	time-consuming
Dorini et al [2017]	morphological operators	microscopic-images	Improve the segmentation accuracy	Time complexity
Choudhary et al [2017]	LAB color space	human blood sample images	fast growing technology	Lesser accuracy

Vogado et al [2017]	SVM, MLP and RF	blood smear image	obtained an higher accuracy rate	does not use segmentation to obtain specific cell regions
Paswan and Rathore [2017]	kNN, NN, and SVM	Blood microscope images	enhanced accuracy	Lesser quality of the input images.

3. INFERENCES FROM RECENT WORK

Health informatics has been qualified as prominent province in the headway of information technology. Ascribable to such a sophisticated evolution in the health care informatics, it is viable at the present period of time to diagnose several ailments in a short span of time. In relation to complaints, there is one disease dub leukemia which can be recognised by manipulating different detection techniques of information technology. Diagnosis of leukaemia usually depends on the Complete Blood Count (CBC) in which doctors check the complete count of white blood cells, red blood cells, and platelets. This complete blood count test may show leukaemia cells, but, in most cases, it is not enough for doctors to confirm that the patient has leukaemia. Haematologist is using technique of image processing to analyze, detect and identify leukemia types in patients recently. Technique of image processing in practice, manual microscopic evaluation of stained sample slide is used for diagnosis of leukaemia. But manual diagnostic methods are time-consuming, less accurate, and prone to errors due to various human factors like stress, fatigue, and so forth. Manual methods require a lot of effort and time. Also, highly trained medical professionals are required to perform these types of examining and hence it is labor-intensive task.

4. SOLUTION

Acute leukaemia is a type of cancer that affects the blood and the bone marrow. Detection and classification of white blood cells is a challenge in image processing, as manual data analysis is time-consuming and most often it is not accurate. Research in this area is essential because a fully automated classifier tool can prove to be an effective ancillary tool for physicians. In past years, some computer-aided leukaemia diagnosis methods are presented for diagnosis of leukaemia. These automated systems are fast, reliable, and accurate as compared to manual diagnosis methods. The goal of future work is to develop a new whole image system that performs automated classification of peripheral blood images of acute lymphoblastic leukaemia containing multiple nuclei. Furthermore, it will reduce the burden of medical professional and will provide accurate and effective results as compared to manual diagnosing.

5. RESULTS AND DISCUSSION

Propose a new public and free dataset of microscopic images with 100 of blood samples, specifically designed for the evaluation and the comparison of algorithms for segmentation and image classification. The initiative is focused on Acute Lymphoblastic Leukemia (ALL), a serious blood pathology that can being fatal in as little as a few weeks if left untreated, most common in childhood with a peak incidence at 2-5 years of age.The images of the dataset has been captured with an optical laboratory microscope coupled with a Canon PowerShot G5 camera. All images are in JPG format with 24 bit color depth, resolution 2592 x 1944.The ALL_IDB1 version 1.0 can be used both for testing segmentation capability of algorithms, as well as the classification systems and image preprocessing methods. This dataset is composed of 108 images collected during September, 2005. It contains about 39000 blood elements, where the lymphocytes have been labeled by expert oncologists. The images are taken with different magnifications of the microscope ranging from 300 to 500.

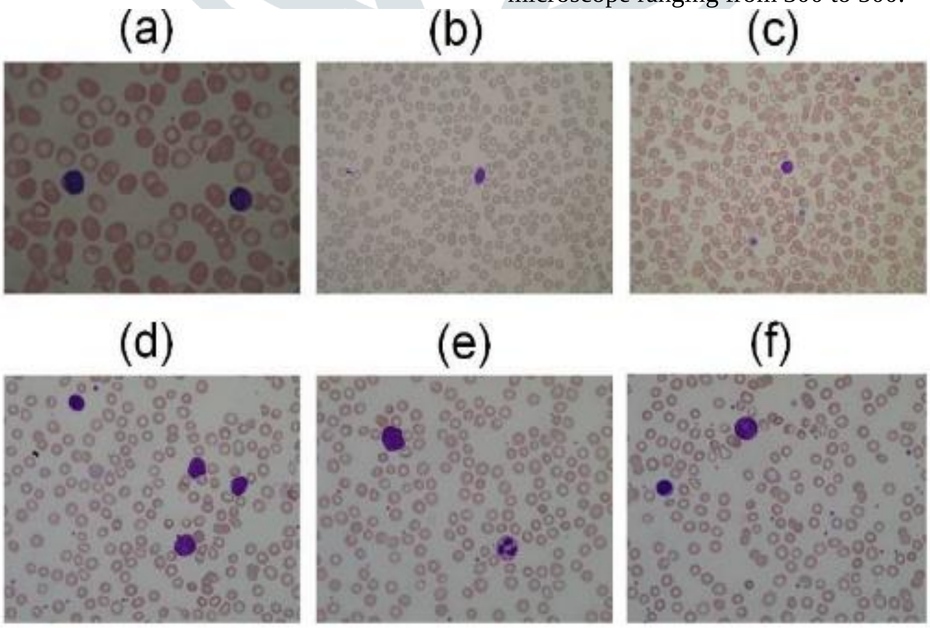

Figure 1. Examples of the images contained in ALL-IDB1

Healthy cells from non-ALL patients (a-c), probable lymphoblasts from ALL patients (d-f).

Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions model got right. For binary classification, accuracy can also be calculated in terms of positives and negatives as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

The performance of the classifier is evaluated using the following standard measures. The results are discussed in table 2. In this research, employ the MLP, kNN and SVM for ALL classification. Several evaluation strategies are applied to assess the system efficiency.

Table 2. Performance metric comparison

Classifiers	Accuracy (%)
kNN	87.00
MLP	90.00
SVM	93.00

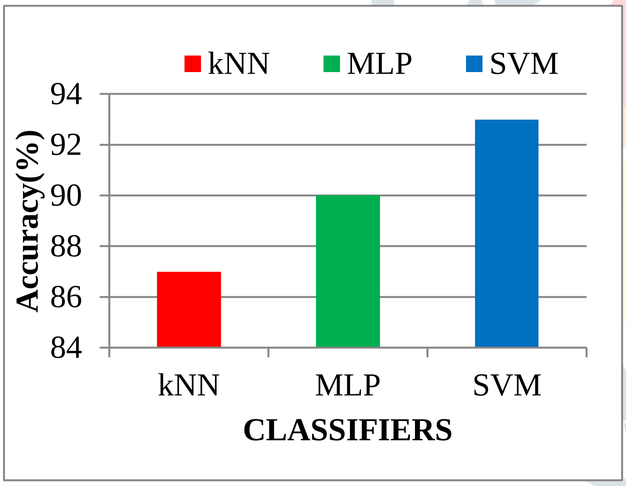

Figure 2. Accuracy results comparison vs. classifiers

From the results it concludes that the proposed SVM classifier produces higher accuracy results of 93.00%, whereas other methods such as k-NN, and MLP classifiers produces only 87.00% and 90.00% values respectively shown in figure 2.

6. CONCLUSION AND FUTURE WORK

Leukaemia is a type of cancer pertaining to white blood cells (WBCs), whereby abnormal and immature WBCs are produced by the bone marrow and enter the bloodstream. In the recent years leukemia detection can be recognised by manipulating different detection techniques of information technology. proposed an innovative method for the automatic identification and classification of leukocytes using microscopic images, providing an automated procedure to support the recognition of ALL. Our results indicate that the proposed method is able to efficiently identify the WBCs present in an image and to properly classify leuko blasts with great accuracy. Also proposed a new method for feature extraction from a cropped image that is excellent, and it can be used for feature extraction in many fields and for many applications. This review work majorly focused on the detection methods are experimented through a Leukemia Microscopic Images. The next step for this work will include further development of the identification phase. Further prospective studies are required to validate the sensibility and specificity of this method, especially in different lightning and resolution conditions.

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