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Speculative survey of Acute Lymphoblastic Leukemia Classification methods using Blood Smear Microscopic Images

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Abstract:
Rapid increase in the immature lymphocytic cells leads to Acute Lymphoblastic Leukemia (ALL), which is a type of blood cancer. The challenging task in the classification of ALL is the effective segmentation and the classification of the leukocytes using the Blood Smear Microscopic Images. This survey reviews the research works on the ALL Classification methods, research gaps and the future scope. For the literature review, 20 research papers based on the ALL classification are taken into consideration. The research papers are categorized into Machine learning classifiers, Ensemble classifiers, Deep learning classifiers and so on. The challenges and the research gaps faced during the classification of ALL are elaborated. The result and analysis of the ALL Classification methods are done based on the performance metrics, year of publication and the accuracy range. From the analysis, it is concluded that most of the research works are published in the year 2018. The most commonly used performance metrics is accuracy and the accuracy range for most of the ALL Classification methods ranges from 90% to 94%.

Keywords*: Acute Lymphoblastic Leukemia, Blood Smear Microscopic Images, leukocytes, image processing techniques, segmentation.*

1. INTRODUCTION

ALL is a type of blood cancer that occurs due to the abnormal growth of the leukocytes (WBC). The immune system of the body becomes vulnerable as the abnormal cell strikes the bone marrow and blood. This results in the suppression in the growth of the platelets and red blood cell thus, leading towards anemia [21]. Further, the abnormal WBC spreads into human blood destroying other body parts, like liver, kidney, brain, spleen and lymph nodes. Depending upon the infection level on the different white blood cells, the Leukemia is categorized into Myelogenous and Lymphoblastic Leukemia. In Myelogenous (AML), the infected cell occurs at monocytes and granulocytes, whereas in Lymphoblastic (ALL), the infected cell occurs at lymphocytes [22]. Based on French American British (FAB), the ALL is categorized into subtypes, such as L1, L2 and L3. The L1 type cells are homogenized and small in size with little cytoplasm. The nucleus of the L1 type cells is well structured and they occupied the full or small margin of cytoplasm. The L2 type cells are over-sized and have dissimilarity in shape. The nucleus of the L2 type cells contains variations in the cytoplasm and irregular. The L3 type cells are of normal size and have identical shape. The nucleus of the L3 type cells is oval or round in shape and they have adequate cytoplasm [4].Manual detection of ALL is affected by the skills and the tiredness of the pathologist [23]. The drawback of the manual ALL detection is overcome by the automatic detection of

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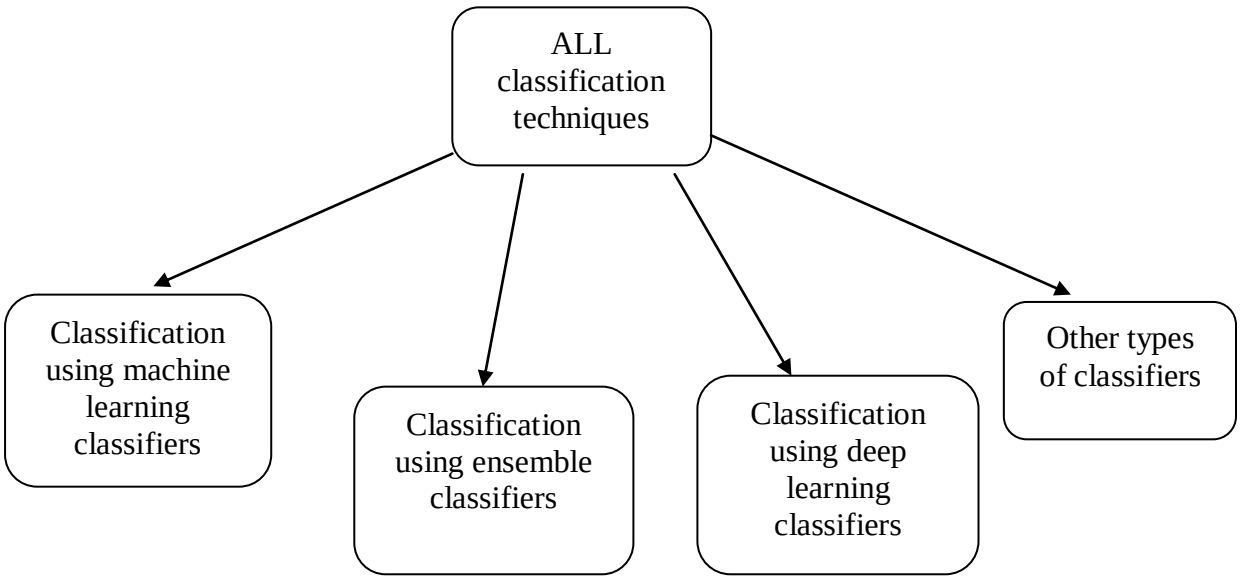
ALL. The automatic cancer detection is employed by applying the image processing techniques in the blood sample images. The automatic detection process has faster detection rate and they are economical too. Only the images of bone marrow or blood are processed in the image processing techniques. The three major components in the image are red blood cells, white blood cells, and platelets. The initial step in the detection of ALL is preprocessing. In preprocessing, the noise from the image is removed. After preprocessing, the white blood cells from the image are extracted during segmentation. The next step is the extraction of the features from the white blood cells [24]. The features are extracted from the lymphocyte images and classified. The final step is the classification of the input images into normal or blast cell by the classifier [12].The objective of the research is to provide a detailed survey of the ALL classification techniques. This review describes the existing ALL methods and the research gaps are summarized to provide motivation to the researchers for providing contribution in the field of ALL. The existing ALL classification methods are categorized into Machine learning classifiers, Ensemble classifiers, Deep learning classifiers and so on.

The organization of the paper is as follows: Section 1 describes the introduction to ALL. Section 2 elaborated the literature review of ALL, Section 3 explains the research gaps and issues, Section 4 depicts the analysis of the research works and Section 5 concludes the paper.

2. Description of ALL classification methods

This section describes the research papers considered for the analysis of the ALL classification methods. The research papers are categorized into Machine learning classifiers, Ensemble classifiers, Deep learning classifiers and so on. Figure 1 describes the categorization technique of ALL classification methods.



2.1 Classification using Machine Learning Classifiers

Umamaheswari, D. *et al.* [1] developed a segmentation algorithm for the recognition of Acute Lymphocytic Leukemia. In this method, the segmentation of the image of the blood cell was performed using the Otsu's thresholding and morphological operators. Although this method had

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different training data sets for the reduction of the training time, it required improvement in the accuracy for the classification of four leukemia types.

Soni, F. *et al.*[2] designed a classification method for the identification of leukemic cell. This method classified the leukemia cells into three categories, such as ALL-L1, L2 or L3. This method had better robustness in the detection and the classification of the leukemia cells. However, this method failed to include the GLCM features and Haralick for classification

Bhattacharjee, R.*et al.*[3] modeled a lymphocytic cells classification approach using the blood smear images. In this method, the acute lymphoblastic leukemia was recognized by classifying the lymphocytic cells using the morphological operations. Although this method had good accuracy for the differentiation of the blast and normal lymphocytic cells, it failed to maintain the accuracy level while classifying the images in large dataset.

Shafique, S. *et al.*[4] developed a image processing technique for the detection of the acute lymphoblastic leukemia from microscopic blood images. This method separated the lymphocytes that were grouped using the Watershed segmentation approach and the lymphocytic cells were classified as normal and blast cells by employing the SVM classifier. This method provided good overall accuracy. However, this method failed to detect the different visual features from the image.

Asadi.*et al.*[9] modeled a blood cells extraction imagery and back propagation neural network algorithm for the classification of acute leukemia. The characteristics of the blood cells were extracted using the backpropagation neural network algorithm. The identification of the leukemia was done through the digital image processing. However, this method provided lower accuracy rate in the classification of acute leukemia.

Khosrosereshki, M. A. *et al.*[10] developed a ALL classification method using the fuzzy based classifier. This method classified the acute leukemia cells by identification of the characteristics of white blood cells. This method provided reliable, efficient and less time-consuming classification results thus, improving the accuracy. However, this method was prone to smaller errors.

Mishra, S. *et al.*[11] developed a two-dimensional discrete wavelet transform (2D-DWT) for the classification of ALL. In this method, the feature matrix was generated by the seperation of cytoplasm and nucleus region by applying 2D-DWT. The Bhattacharyya distance and PCA was employed for the selection of un-correlated and significant features. The classification of the lymphocyte cells was performed using the back propagation neural network. Although this method provided better accuracy, the combination of features consumed large amount of the time in the classification process.

Singhal, V.*et al.*[12] designed a automatic lymphocytes detection method from the blood sample images. The Local Binary Pattern (LBP) features and the geometric features were extracted from the blood sample images for the classification. The SVM classifier was trained with the extracted features for the classification of the lymphocyte cells. This method provided better accuracy during the classification. However, this method failed to include the texture variants.

Mohapatra, S.*et al.*[13] designed a lymphocytic cell classification method from the blood image. The irregularities in the boundary nucleus were measured using contour signature and hausdorff dimension features. The features, such as color, shape, and texture features were also extracted from the image. The initial segmentation was performed using K-means clustering for the segregation of WBC from other components of the blood. The roughness in the perimeter was measured using the hausdorff dimension for the classification of the nucleus of the lymphocytic cell.

Mohapatra, S.*et al.*[18] designed a two stage WBC nucleus segmentation method from the blood smear images. Two methods, such as contour signature and

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hausdorff dimension were used for measuring the boundary irregularities on the nucleus. The features, like color, shape and texture were considered for the classification. The classification of the image was through the SVM classifier. The main drawback of this method was the inability to detect the sub types of the lymphoblast cells.

Bhattacharjee, R.*et al.*[20] developed a ALL segmentation and classification method from the blood smear image. In this method, the segmentation was done using the watershed transform and the classification models were used for diagnosing the ALL. This method adjusted the image contrast both manually and automatically. However, this method had high computational time.

Patil, T.G.*et al.*[7] developed a ALL classification technique. In this method, the texture features and shape features with contour signature were extracted from the image. The automatic segmentation of the image was based on Otsu's method. This method detected the leukemia at faster rate and analyzed the malignant and normal cells. This method segmented the overlapping cells and they were independent of the stains in the blood smear image. However, this method had high computational time.

Rawat, J.*et al.*[14] developed a computer aided diagnostic system (CAD) for the detection of ALL based on the shape based features and Gray level co–occurrence matrices (GLCM). The presence of leukemic cells was detected by the classification of the extracted features using the auto support vector machine (SVM) binary classifier. This method proved the importance of the shape of the nucleus in the detection of ALL. However, this method had high computational complexity.

2.2 Classification using Ensemble Classifiers

Mohapatra, S.*et al.*[16] designed a image processing-based tool for the detection and the classification of ALL. The lymphocyte image was segmented into cytoplasm and individual nucleus regions using the SCM clustering. The lymphocyte samples were classified into malignant or healthy by including the features, such as texture and shape features. However, the classifier had slower computation and it failed to include the sub classification types of ALL.

Moshavash, Z.*et al.*[5] designed a segmentation method for the detection of acute leukemia from blood microscopic images. The features, like color, shape, LBP-based texture features along with the feature based on hematologist visual criteria were extracted from the image for the recognition of leukocytes from the image. Although this method had better accuracy, it failed to provide robustness in detecting leukocytes in the image with touching cell and excessive staining.

Rahman, A. *et al.*[8] designed an automated system for the classification of ALL. In this method, the textural, morphological and color features were analyzed for the detection and the classification of ALL from the blood microscopic images. Although this method provided better accuracy for the classification of the malignancy and the detection of the white blood cell, the classification of ALL required more time.

2.3 Classification using deep learning Classifiers

Ghosh, A.*et al.*[15] developed a ALL detection method using deep learning approach from the blood smear images. The classification and the localization of WBC were simulated using the deep network. The WBC hotspots in the image were figured out using the average pooling layers. This method predicted the presence of ALL in the blood smear image but it failed to figure out all the lymphocytes in a whole-slide image successfully.

Rehman, A. *et al.*[17] modeled the deep learning and image processing method for the classification of ALL. The model was trained using the max-pooling layers and convolution layers. The image was classified using the softmax, fully connected layer and classification layer. This method achieved efficient processing time along with efficient accuracy. However, this method failed to segment the overlapped cells.

2.4 Other types of classifier

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Joshi, M.D.*et al.*[19] modeled a ALL detection method from the medical images. In this method, the blood cell segmentation was done through image enhancement and arithmetic process along with the Otsu's threshold blood cell segmentation method. The classification of the blast cells from the normal cells was performed through the kNN classifier. Although the accuracy of the detection was high, it failed to provide robustness for touching cells and excessive staining in the images.

Li, Y.*et al.*[6] designed an white blood cell segmentation approach based on dual-threshold method. The dual-threshold method was the combination of HSV and RGB color space. This method had three parts, such as preprocessing, threshold segmentation, and postprocessing. In pre-processing, a H component image and a contrast-stretched gray image was obtained from the image. The segmentation was performed using the dual-threshold method and the optimal thresholds were determined using the golden section search. The post-processing part removed the WBCs that were incomplete using median filtering and mathematical morphology operations. This method provided good segmentation accuracy but it had low computational time.

3. Research Gaps and Issues

This section describes the research gaps and issues of ALL classification methods. In the ALL classification methods, the major challenge lies in the segmentation of ALL in uneven image conditions. The uneven image conditions include the variation of the features in different laboratories. The detection of the acute lymphoblastic leukemia using Watershed segmentation approach and SVM classifier provided better accuracy in the classification but the issue in the classification method was the detection of different types of visual features from the image [4]. Although the classification method based on morphological operations provided better accuracy in the classification, the challenge lies in the image classification for large dataset [3]. In [2], the classification provided better robustness but the classification accuracy was reduced as the Haralick and the GLCM were not included in this method. The issue in the classification of ALL based on back propagation neural network algorithm was the lower accuracy rate [9]. The ALL classification based on fuzzy based classifier provided less time-consuming and reliable classification but the challenge was the removal of smaller errors that occurred during the classification [10]. In [12], the automatic lymphocytes detection method provided efficient classification accuracy but the texture variants were not included in this method.

4. Analysis and discussion

This section describes the analysis and discussion of the ALL classification methods based on the analysis of the performance metrics, accuracy range and the year of publication.

4.1 Analysis based on the year of publication

This section describes the various ALL classification methods based on the year of publication. In this research work, 20 papers are considered for the analysis of the ALL classification methods. From the analysis, it is concluded that most of the research works on the classification of ALL are published in the year 2018. Figure 2 depicts the analysis of the ALL classification methods based on the year of publication.

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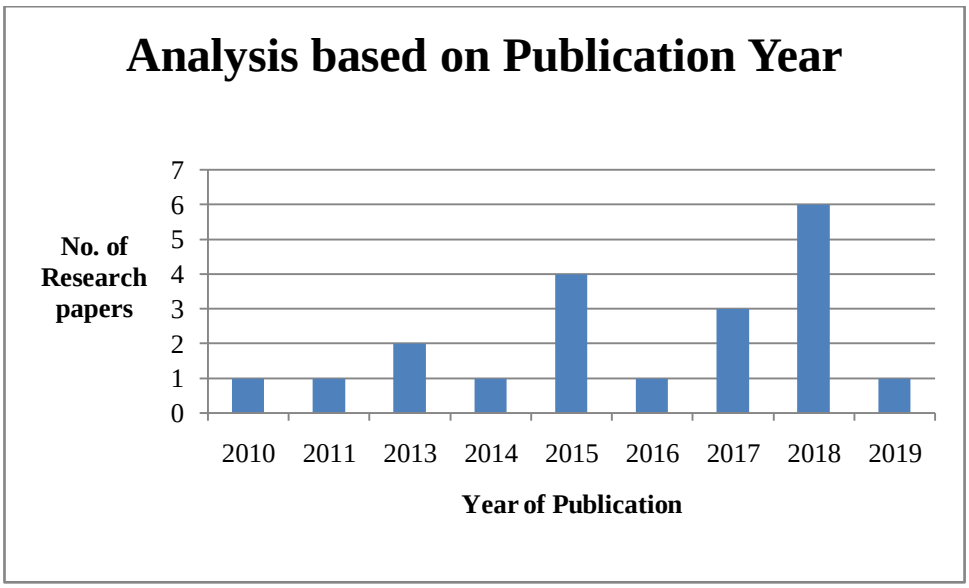

Figure 2. Analysis of the ALL Classification methods based on the year of publication

4.2 Analysis based on performance metrics

This section shows the analysis of the ALL Classification methods based on the performance metrics. In the ALL classification methods, the performance metrics, like accuracy, sensitivity, specificity, recall, precision, Error rate and misclassification are considered. From the table 1, it is concluded that the mostly used performance metrics in the ALL classification method is accuracy.

Table 1. Analysis of the ALL Classification methods based on the performance metrics

Performance metrics	Research paper
accuracy	[1], [4], [5], [6], [8], [9], [10], [11], [12], [14], [15], [16], [18], [19]
sensitivity	[1], [3], [4], [12], [16], [20]
specificity	[1], [3], [4], [12], [16], [20]
recall	[2]
precision	[2]
Error rate	[1]
missclassification	[3], [12], [20]

4.3 Analysis based on accuracy range

This section describes the analysis of the ALL classification methods based on the accuracy range. Table 2 shows the analysis of the ALL classification methods based on the accuracy range. From the analysis, it is shown that the accuracy range in most of the ALL classification methods ranges from 90% to 94%.

Table 2. Analysis of the ALL classification methods based on the accuracy range

Accuracy range	No. of research papers
70%-80%	[14]
80%-90%	[9], [12]
90%-94%	[2], [4], [8], [10], [15],

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	[18], [19]
94%-98%	[1], [6] [11], [17]
98%-99.5%	[5]

Conclusion

This research presented the survey of different ALL classification methods. In this research, 20 previous research papers are taken into consideration for review and analysis of ALL classification methods. The research papers are taken from Google Scholar, IEEE, and Science Direct. The research papers are categorized into Machine learning classifiers, Ensemble classifiers, and Deep learning classifiers and so on. The research gaps and challenges faced during the ALL classification methods are elaborated. The existing ALL classification methods are analyzed in terms of year of publication, performance metrics and the accuracy range. From the analysis, it is concluded that the most commonly used performance metrics is accuracy and the accuracy range of the ALL classification methods ranges from 90% to 94%, whereas most of the research works on ALL classification methods are published in the year 2018. The future enhancement can be done by including more features in the classification of ALL for improving the efficiency of the classification.

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