INTERNATIONAL JOURNAL OF TECHNO-ENGINEERING
IJTE

ISSN: 2057-5688

A SYSTEMATIC REVIEW ON RECENT ADVANCEMENTS IN DEEP AND MACHINE LEARNING BASED DETECTION AND CLASSIFICATION OF ACUTE LYMPHOBLASTIC LEUKEMIA

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ABSTACT:

Automatic Leukemia or blood cancer detection is a challenging job and is very much required in healthcare centers. It has a significant role in early diagnosis and treatment planning. Leukemia is a hematological disorder that starts from the bone marrow and affects white blood cells (WBCs). Microscopic analysis of WBCs is a preferred approach for an early detection of Leukemia since it is cost-effective and less painful. Very few literature reviews have been done to demonstrate a comprehensive analysis of deep and machine learning-based Acute Lymphoblastic Leukemia (ALL) detection. This article presents a systematic review of the recent advancements in this knowledge domain. Here, various artificial intelligence-based ALL detection approaches are analyzed in a systematic manner with merits and demits. The review of these schemes is conducted in a structured manner. For this purpose, segmentation schemes are broadly categorized into signal and image processing-based techniques, conventional machine learning-based techniques, and deep learning-based techniques. Conventional machine learning-based ALL classification approaches are categorized into supervised and unsupervised machine learning is presented. In addition, deep learning-based classification methods are categorized into Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and the Autoencoder. Then, CNN-based classification schemes are further categorized into conventional CNN, transfer learning, and other advancements in CNN. A brief discussion of these schemes and their importance in ALL classification are also presented. Moreover, a critical analysis is performed to present a clear idea about the recent research in this

field. Finally, various challenging issues and future scopes are discussed that may assist readers in formulating new research problems in this domain.

INDEX TERMS Acute Lymphoblastic Leukemia, blood cancer, classification, deep learning, machine learning, segmentation.

I. INTRODUCTION

Leukemia is a blood cancer that affects white blood cell (WBC) replication in the bone marrow. It causes an increase in the number of abnormal WBCs, which leads to a decrease in immunity [1]–[8]. WBC is an important component of blood like other two crucial components: Erythrocyte (Red Blood Cell) and platelet [1], [7], [9]–[11]. WBC contains a nucleus and cytoplasm, as presented in Fig.1. Leukemia is classified mainly into two types: acute and chronic [1], [2], [4], [6], [8], [10]–[12]. Acute Leukemia develops very quickly and gets to the worse stage, whereas chronic Leukemia takes comparably more time to worsen. According to the French-American-British (FAB) classification model, Acute Leukemia is further categorized as ALL and Acute Myeloid Leukemia (AML) [8], [10]–[12]. Similarly, chronic Leukemia is of two subtypes: Chronic Lymphocytic Leukemia (CLL) and Chronic Myeloid Leukemia (CML) [11]. Hence, Leukemia is of four types: ALL, AML, CLL, and CML.

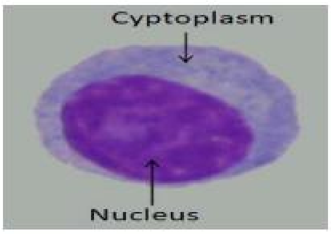


FIGURE 1. Structure of WBC.

2. Methodology

The block diagram below shown the proposed classification method for acute leukemia images which consist of several image processing techniques such as image enhancement, color thresholding, feature extraction and classification.

Image Processing: The effectiveness of the image enhancement process will make it easier for image segmentation, features extraction and classification of the blood sample slide images to identify leukemia. Thus, local contrast stretching has been implemented on B and T types of ALL images. By implementing this algorithm, each red, green and blue color space will be distributed linearly over the whole histogram so that the dynamic range of the histogram is fulfilled (0 – 255)[6][7]. After that, automatic color thresholding based on HSI (Hue, Saturation, Intensity) color space has been applied. In order to segment white blood cell (WBC) from the background and red blood cell (RBC), Hue component has been extracted from HSI color space. Based on the previous study, Hue component can provided a fully information about WBC while saturation component contains information about nucleus only [8]. The threshold value is set to 0.5. Any region which has greater than 0.5 will be considered as the WBC and the rest will be eliminated from the images

Feature Extraction: Feature extraction is used to measure the properties of WBC. A number of approaches have been developed for feature extraction in acute leukemia identification system, such as the geometrical features [10][11], texture features [12][13], and the combination of geometrical ,texture and color features[14][15][16]. Before that, all of the WBC should be crop manually in order to extract features efficiently. There are some shape and geometrical based features that have been extracted such as area, perimeter, convex area, eccentricity, solidity, circularity and Affine Moment Invariant. For texture-based features such as contrast, correlation, energy and entropy have been extracted from segmented WBC images. Finally, color-based features are also extracted such as standard deviation and mean of RGB (Red, Green,Blue) color space. In total, there are 25 features have been extracted from the segmented WBC of both types of ALL which were then fed up as the neural network inputs for the classification. Beforehand, the features must be normalized between 0 to 1 in order to achieve high performance of classification. Noted that these features have been implemented on whole images in this study and the choice of the features has been driven by suggestions of the experts in HUSM and validate by them.

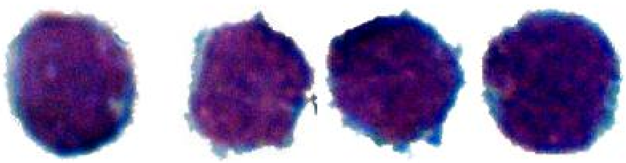
ISSN: 2057-5688

3. Results&Discussions

In this section, the classification performance based on overall features will be elaborated here. For this purpose, a total of 25 input features have been fed into the MLP network. There are two different analyses that have been conducted which are analysis of finding the best number of states and the best number of hidden nodes. All of this can be obtained when the MLP network achieved the highest testing result. The states refer to the initial values assigned to the function when a random number of generator is called. Different initial random values will produce different results. Hence, the testing has been done in five states to choose the best structure for MLP network. . In order to avoid the problem of over-fitting, it is necessary to determine the best number of hidden nodes. Table 2 and Figure 6 show the analysis of number of hidden nodes for classification between B and T using MLP(LM) network.Based on Table 2, the best classification performance is obtained at state 5 and number of hidden nodes of 4 with testing accuracy of 96.99%.The results also show that the testing accuracy better than 90% has been archieved for other state.

Table 1. Input data division for classification method

Overall Dataset	Training Dataset (70%)	Testing Dataset (30%)
B = 601 T = 461	B = 421 T = 323	B = 180 T = 138
Total = 1062	Total = 744	Total = 318



(a) Type B

(b) Type T

Figure 2. Zooms of Segmented images of acute lymphoblastic leukemia (ALL).

ISSN: 2057-5688

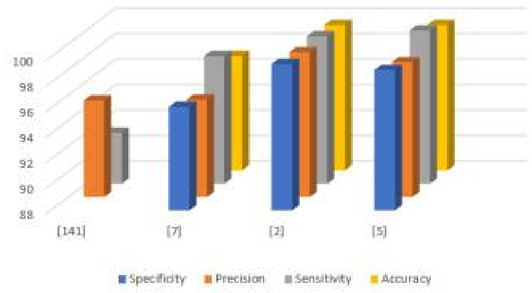


FIGURE 3. Graphical representation of deep learning-based classification performance

4 CONCLUSION

This article presents a brief analysis of recent advancements in deep and machine learning-based detection and classification of ALL. We have analyzed various existing methods of segmentation, feature extraction, and classification, which are employed to detect ALL efficiently. From this review, we also observed that among classical machine learning schemes, unsupervised schemes are preferred for segmentation tasks, whereas supervised schemes are preferred for classification tasks. However, Deep learning, particularly transfer learning, has emerged as a preferred approach for automatic and more robust detection and classification of ALL since it yields excellent performance even in small datasets. From this study, we have also observed that the MobileNetV2- ResNet18 architecture yields the best ALL detection performance in ALLIDB1 dataset due to the combined benefits of both schemes. In the ALLIDB2 dataset, MobileNetV2-SVM depicts admirable classification performance by integrating the pros of both approaches. Furthermore, we have discussed the challenging issues and future scope in this research field. We hope this article will help researchers to analyze recent advancements in ALL detection and will inspire researchers to do further research.

5 REFERENCES

[1] P. K. Das, S. Meher, R. Panda, and A. Abraham, ‘‘An efficient blood-cell segmentation for the detection of hematological disorders,’’ IEEE Trans.Cybern., early access, Mar. 18, 2021, doi: 10.1109/TCYB.2021.3062152.

[2] P. K. Das and S. Meher, ''An efficient deep convolutional neural network based detection and classification of acute lymphoblastic leukemia,''Expert Syst. Appl., vol. 183, Nov. 2021, Art. no. 115311.

[3] P. P. Banik, R. Saha, and K.-D. Kim, ''An automatic nucleus segmentation and CNN model based classification method of white blood cell,'' Expert Syst. Appl., vol. 149, Jul. 2020, Art. no. 113211.

[4] L. H. Vogado, R. M. S. Veras, F. H. D. Araujo, R. R. V. Silva, and K. R. T. Aires, ''Leukemia diagnosis in blood slides using transfer learning in CNNs and SVM for classification,'' Eng. Appl. Artif. Intell., vol. 72, pp. 415–422, Jun. 2018.

[5] P. K. Das, B. Nayak, and S. Meher, ''A lightweight deep learning system for automatic detection of blood cancer,'' Measurement, vol. 191, Mar. 2022, Art. no. 110762.

[6] P. K. Das, A. Pradhan, and S. Meher, ''Detection of acute lymphoblastic leukemia using machine learning techniques,'' in Machine Learning, Deep Learning and Computational Intelligence for Wireless Communication. Singapore: Springer, 2021, pp. 425–437.

[7] P. K. Das and S. Meher, ''Transfer learning-based automatic detection of acute lymphocytic leukemia,'' in Proc. Nat. Conf. Commun. (NCC), Jul. 2021, pp. 1–6.

[8] S. Mishra, B. Majhi, and P. K. Sa, ''Texture feature based classification on microscopic blood smear for acute lymphoblastic leukemia detection,'' Biomed. Signal Process. Control, vol. 47, pp. 303–311, Jan. 2019.

[9] P. K. Das, S. Meher, R. Panda, and A. Abraham, ''A review of automated methods for the detection of sickle cell disease,'' IEEE Rev. Biomed. Eng.,vol. 13, pp. 309–324, 2020.

[10] P. K. Das, P. Jadoun, and S. Meher, ''Detection and classification of acute lymphocytic leukemia,'' in Proc. IEEE-HYDCON, Sep. 2020, pp. 1–5.

[11] N. Patel and A. Mishra, ''Automated leukaemia detection using microscopic images,'' Proc. Comput. Sci., vol. 58, pp. 635–642, Jan. 2015.

[12] J. M. Bennett, D. Catovsky, M.-T. Daniel, G. Flandrin, D. A. G. Galton,H. R. Gralnick, and C. Sultan, ''Proposals for the classification of the acute leukaemias

ISSN: 2057-5688

French-American-British (FAB) co-operative group,''Brit. J. Haematol., vol. 33, no. 4, pp. 451–458, Aug. 1976.

[13] T. Terwilliger and M. Abdul-Hay, ''Acute lymphoblastic leukemia: A comprehensive review and 2017 update,'' Blood Cancer J., vol. 7, no. 6, p. e577, Jun. 2017.

[14] K. AL-Dulaimi, J. Banks, K. Nugyen, A. Al-Sabaawi, I. Tomeo-Reyes, and V. Chandran, ''Segmentation of white blood cell, nucleus and cytoplasm in digital haematology microscope images: A review–challenges, current and future potential techniques,'' IEEE Rev. Biomed. Eng., vol. 14,pp. 290–306, 2021.

[15] S. Shafique and S. Tehsin, ''Acute lymphoblastic leukemia detection and classification of its subtypes using pretrained deep convolutional neural networks,'' Technol. Cancer Res. Treatment, vol. 17, Sep. 2018, Art. no. 1533033818802789.

[16] S. Mishra, B. Majhi, and P. K. Sa, ''GLRLM-based feature extraction for acute lymphoblastic leukemia (ALL) detection,'' in Recent Findings in Intelligent Computing Techniques. Singapore: Springer, 2018, pp. 399–407.

[17] S. Mishra, B. Majhi, P. K. Sa, and L. Sharma, ''Gray level co-occurrence matrix and random forest based acute lymphoblastic leukemia detection,'' Biomed. Signal Process. Control, vol. 33, pp. 272–280, Mar. 2017.

[18] J. Laosai and K. Chamnongthai, ''Classification of acute leukemia using medical-knowledge-based morphology and CD marker,'' Biomed. Signal Process. Control, vol. 44, pp. 127–137, Jul. 2018.

[19] Z. Moshavash, H. Danyali, and M. S. Helfroush, ''An automatic and robust decision support system for accurate acute leukemia diagnosis from blood microscopic images,'' J. Digit. Imag., vol. 31, no. 5, pp. 702–717, Oct. 2018.

[20] S. Kumar, S. Mishra, and P. Asthana, ''Automated detection of acute leukemia using K-mean clustering algorithm,'' in Advances in Computer and Computational Sciences. Singapore: Springer, 2018, pp. 655–670.

[21] T. Ojala, M. Pietikäinen, and T. Mäenpää, ''Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 7, pp. 971–987,Jul. 2002.

[22] T. Jabid, M. H. Kabir, and O. Chae, ‘‘Local directional pattern (LDP) for face recognition,’’ in Proc. Dig. Tech. Papers Int. Conf. Consum. Electron. (ICCE), Jan. 2010, pp. 329–330.

[23] S. Drabycz, R. G. Stockwell, and J. R. Mitchell, ‘‘Image texture characterization using the discrete orthonormal S-transform,’’ J. Digit. Imag., vol. 22, no. 6, p. 696, 2009.

[24] R. M. Haralick, K. Shanmugam, and I. Dinstein, ‘‘Textural features for image classification,’’ IEEE Trans. Syst., Man, Cybern., vol. SMC-3, no. 6, pp. 610–621, Nov. 1973.

[25] X. Tang, ‘‘Texture information in run-length matrices,’’ IEEE Trans. Image Process., vol. 7, no. 11, pp. 1602–1609, Nov. 1998.

[26] E. H. Houssein, M. M. Emam, A. A. Ali, and P. N. Suganthan, ‘‘Deep and machine learning techniques for medical imaging-based breast cancer: A comprehensive review,’’ Expert Syst. Appl., vol. 167, Apr. 2021, Art. no. 114161.