Vol. 16 (2026): Proceedings of the 2026 International Conference on AI and Technological Innovation Applications (AITIA 2026)
E-ISSN: 3105-0522 P-ISSN: 3105-0514
DOI: https://doi.org/10.70267/aitia.2026174181

The Utilization of Convolutional Neural Network (CNN) in Leukemia Detection

Yiren Liu*

School of Cyber Security, Southeast University, Nanjing, China

**Corresponding author: Yiren Liu.*

Abstract

Leukemia is one of the major types of cancer around the world; traditional detection methods of blood smear are time-consuming, subjective, and error-prone. This review provides an overview of the application of Convolutional Neural Networks (CNNs) for detecting leukemia in microscope images. This research investigates the main methods, latest developments, and root causes of the ongoing challenges in CNN-based leukemia detection. This review follows a systematic literature review approach. Grouping recent CNN models in technical routes: (i)pre-training architecture based on transfer learning (e.g., VGG19, AlexNet) and (ii)dataset augmentation and hyperparameter optimization, against the typical five-step diagnosis workflow. The key findings suggest that CNN significantly improves detection accuracy, speed, and automation. With transfer learning, one of the CNN designs achieved the best results, achieving 99.1% accuracy. Compared with other machine learning methods, accuracy has increased by 2% to 8%. However, most models still suffer from poor dataset quality and diversity, leading to overfitting and poor generalizability. This study proposes three complementary solutions: (i) transfer learning, (ii) unsupervised/semi-supervised learning, and (iii) multimodal data fusion. In conclusion, this review provides a clear roadmap that bridges current technical maps. By integrating three directions, future CNN models can be more robust, low-cost, and clinically viable, thus accelerating the reliable detection of leukemia worldwide.

Keywords

leukemia detection, CNN, deep learning

1. Introduction

Leukemia is a prevalent type of cancer marked by an abnormal increase in white blood cells in the blood or bone marrow. The cause of leukemia is multifactorial, including genetic and environmental factors; its exact etiology has not yet been fully elucidated. Leukemic cells are classified into four main subtypes: AML, CML, ALL, and CLL [1]. According to the 2025 research report, leukemia is a major cause of cancer death worldwide [2].

Leukemia detection currently suffers from several problems, including the low accuracy of conventional diagnostic approaches, the high cost and inconvenience of advanced approaches, and the reliance on experience and time. According to Hegde et al., the immaturity and non-specific nature of leukemic cells lead

to extensive experience and time requirements, as well as a high error rate in human observation [3]. Bodzas et al. emphasized that despite technological advances in medicine, morphology remains the frontline hematological diagnostic technique [4]. Visual examination of peripheral blood smears often provides a preliminary diagnosis of leukemia. Additionally, Hegde et al. noted that although methods such as fluorescence in situ hybridization can be used for leukemia detection, they are expensive and not readily available in many medical centers [3]. These significant drawbacks of conventional leukemia detection are the main reasons leukemia cannot be detected in a timely and accurate manner in today's medical context. Therefore, low-cost, high-accuracy, and highly repeatable leukemia detection models based on Deep Learning (DL) are urgently needed.

As Deep Learning (DL) and Machine Learning (ML) technologies have advanced rapidly in recent years, several studies have sought to apply them to the diagnosis of leukemia. Although these studies have proposed frameworks for detecting acute leukemia and its subtypes, few have proposed methodologies for detecting chronic leukemia or all leukemia subtypes [5]. Among all Deep Learning leukemia detection methods, models based on Convolutional Neural Networks are an appropriate choice that meets all performance metrics expectations, with high accuracy and rapid detection speed.

This review systematically investigates the application of convolutional neural networks (CNNs) to the automated detection of leukemic cells in microscopic blood smear images. The primary research question (RQ) is: What are the major methodologies, recent advancements, and persistent challenges of CNNs in leukemic cell detection? To address this overarching question, three specific sub-research questions are formulated:

RQ1: The key challenges faced by various models in the field of leukemia detection.

RQ2: The CNN models that have been applied in recent years for white blood cell detection and classification, along with their respective advantages and limitations.

RQ3: A few promising future directions for the application of CNN in leukemic cell recognition and classification, especially under the current constraint of limited annotated datasets.

By synthesizing existing literature and proposing practical solutions centered on transfer learning, unsupervised/semi-supervised learning, and multimodal data fusion, this review seeks to provide a comprehensive roadmap that bridges current technical gaps and accelerates the clinical translation of CNN-assisted leukemia diagnostics.

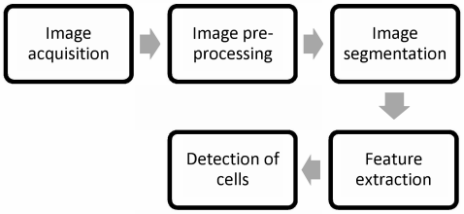
Building on the research questions, this paper makes the following key contributions: it meticulously examined recent CNN-based leukemia-detection models, classified them by structure, identified the boundaries they encountered, and analyzed the root causes of these boundaries. Based on the analysis of these boundaries, we discussed three aspects: multimodal fusion, transfer learning, and unsupervised learning, which could form a basic framework for leukemia detection models in the future.

2. CNN Models Used for Leukemia Detections

C. Raje et al. proposed a method that includes typical steps for automatic leukemia cell detection, from Image Acquisition to Image Preprocessing, Segmentation to isolate individual leukocyte cells from the background, Feature Extraction, Leukemia Detection, and Leukemia Classification [6].

Figure 1 demonstrates the steps described in the literature.

Figure 1: Typical steps for leukemia cell detection



Based on the typical workflow outlined in Figure 1, recent research has advanced CNN applications in leukemia diagnosis by innovating across key stages, including enhancing cell-isolation segmentation,

automating feature extraction with convolutional layers, and refining classification for subtype differentiation. These models often build on foundational steps by replacing manual processes with end-to-end deep learning, addressing common challenges such as computational efficiency, data variability, and overlapping cells. To highlight these progressions, the following discussion groups models by similar technical routes: first, those employing transfer learning from pre-trained architectures (e.g., AlexNet or VGG19) to streamline feature extraction and classification; second, those emphasizing dataset augmentation and hyperparameter optimization to bolster robustness in preprocessing and detection phases.

2.1 Transfer Learning

In the realm of transfer learning-based approaches, S. Sharma et al. proposed a model based on the VGG19 architecture to classify leukemia into four subtypes: Benign, Malignant Pre-B, Malignant Pro-B, and Malignant early Pre-B [7]. By leveraging transfer learning and fine-tuning on a dataset of leukemia cell images, the model effectively reduced training time while achieving higher accuracy, automating the feature extraction and classification steps in Figure 1 with pre-trained convolutional filters. Similarly, R. Arif et al. proposed a modified AlexNet-based CNN for segmenting and detecting leukemia cells in microscopic blood smear images, aligning closely with the segmentation and cell-detection phases [8]. Through pre-training and adaptation to a leukemia dataset, it attained efficient detection with lowered computational demands and enhanced precision in identifying abnormal cells. However, it highlighted the need for future improvements in handling overlapping cells to refine segmentation in complex scenarios. Extending this strategy, G.M. Devi et al. introduced a VGG16 CNN architecture tailored for computer-aided diagnosis of white blood cell leukemia, processing blood smear images for classification [9]. By leveraging transfer learning on preprocessed datasets, the model achieved high diagnostic accuracy, streamlined feature extraction, and enabled timely detection by pathologists. Collectively, these studies underscore the significant role that pre-trained DL models can play in automating hematological malignancy diagnostics, offering cost-effective alternatives to manual methods; however, they commonly point to broadening datasets—such as incorporating multi-center sources—as a key future direction to improve generalization and robustness across diverse imaging conditions. To provide a clearer comparison among the three transfer learning-based models, Tables 1 and 2 summarize their datasets, classification tasks, limitations, and core performance metrics.

Table 1: Comparison of Transfer Learning-based CNN Models for Leukemia Detection

Model	Dataset	Classification Task	Limitations
S. Sharma et al. (VGG19)	Leukemia cell images (specific name and size not provided)	4 subtypes: Benign, Malignant Pre-B, Malignant Pro-B, Malignant early Pre-B	Needs to broaden the dataset to include a wider variety of leukemia cases to strengthen robustness and applicability
R. Arif et al. (modified AlexNet)	ALL-IDB (Acute Lymphoblastic Leukemia Image DataBase)	2 classes: acute leukemia and chronic leukemia (segmentation and detection)	Requires advanced techniques for handling overlapping cells to improve performance in complex real-world scenarios
G. M. Devi et al. (AlexNet)	Pre-processed blood smear images (specific name and size not provided)	5 classes: Lymphocyte, Monocyte, Basophil, Eosinophil, Neutrophil	Needs improved generalization by incorporating multi-center data sources to handle diverse imaging conditions

Table 2: Core Performance Metrics of the Transfer Learning-based CNN Models

Model	Accuracy	Other Key Metrics	Efficiency Improvement
S. Sharma et al. (VGG19)	99.1%	Not reported	Successfully lowered training time
R. Arif et al. (modified AlexNet)	98.05%	Specificity: 97.59% Recall: 100% F1-score: 99.06%	Reduced computational demands
G. M. Devi et al. (AlexNet)	97.16% (average)	Lymphocyte: 98.53% Monocyte: 97.41% Basophil: 98.48% Eosinophil: 96.16% Neutrophil: 94.05%	Streamlined the feature extraction process

2.2 Dataset Augmentation and Hyperparameter Optimization

Transitioning to models that prioritize dataset enhancement and optimization techniques, A.Ullah et al. developed a CNN framework for classifying white blood cancer types from cellular images, leveraging

convolutional layers for automatic feature extraction [10]. By training on a comprehensive dataset and benchmarking against traditional methods, the model demonstrated superior accuracy and speed, outperforming human experts in consistency and reducing errors in resource-limited settings, particularly by addressing variability in preprocessing and segmentation. In a complementary vein, M. Idris et al. presented a ResNet-18 model for automated classification of acute lymphoblastic leukemia blood cells from microscopic images [11]. Employing convolutional operations and fine-tuning on annotated datasets, it achieved robust accuracy in distinguishing malignant subtypes despite varying image quality, with a focus on noise-resistant enhancements, such as advanced preprocessing filters, as a primary future direction to bolster reliability in noisy environments. Building on these data-centric innovations, V. Anand et al. optimized a CNN model for early detection of acute lymphoblastic leukemia using microscopic cell images, emphasizing the capture of morphological variations [12]. Through dataset augmentation and hyperparameter tuning, the model identified subtle abnormalities with high sensitivity, thereby aiding proactive treatment by improving detection and feature-extraction efficiency. This group of works demonstrates the transformative impact of deep learning in accelerating early-stage leukemia diagnostics and enhancing laboratory efficiency; however, they suggest future efforts to integrate diverse datasets to mitigate overfitting, alongside architectural refinements, such as hybrid models with attention mechanisms, to manage misclassifications in complex cellular structures better. Tables 3 and 4 summarize the datasets, classification tasks, limitations, and core performance metrics for these models.

Table 3: Comparison of Dataset Augmentation and Hyperparameter Optimization-based CNN Models for Leukemia Detection

Model	Dataset	Classification Task	Limitations
A. Ullah et al.	Comprehensive dataset (specific name and size not provided)	White blood cancer types from cellular images	Future developments should focus on integrating more diverse and large-scale datasets to mitigate overfitting and enhance generalization across varied patient populations
M. Idris et al.	Annotated datasets (specific name and size not provided)	Acute lymphoblastic leukemia blood cells (distinguishing malignant subtypes)	Primary future direction involves developing noise-resistant enhancements, such as advanced preprocessing filters, to increase reliability in noisy clinical environments
V. Anand et al.	Bone marrow lab at Taleqani Hospital / Kaggle (3256 original PBS images from 89 patients, augmented to 6000 images)	4 classes: Benign, Early, Pre, Pro	Model generalizability to other clinical datasets with different imaging conditions, staining methods, or demographic variations needs further validation; integration into real-world clinical workflows requires clinical trials

Table 4: Core Performance Metrics of the Dataset Augmentation and Hyperparameter Optimization-based CNN Models

Model	Accuracy	Other Key Metrics	Efficiency / Optimization
A. Ullah et al.	Superior accuracy (not numerically quantified)	Superior speed, outperforming human experts in consistency	Training on comprehensive dataset and benchmarking against traditional methods; hyperparameter optimization for robustness in preprocessing and segmentation stages
M. Idris et al.	Robust accuracy (not numerically quantified)	Robust performance despite varying image qualities	Fine-tuning on annotated datasets; focus on noise-resistant enhancements via advanced preprocessing filters
V. Anand et al.	96% (with Adam optimizer)	Precision: 0.95	Dataset augmentation (vertical/horizontal flip, 90-degree rotation) + hyperparameter tuning (30 epochs, batch size 32, Adam vs Adamax optimizer)

3. Challenges and Future Directions for the Appliance of CNN in Leukemia Detection

In this Section, we discuss the major challenges and potential future directions in leukemia detection. Instead of describing the problems encountered during the process of specific studies, we focus on the root causes of these problems and offer a hint on how to address them in the current situation of insufficient datasets.

Building upon the typical workflow in Figure 1 and the grouped technical routes in Section 3, recent studies show that CNN-based approaches have clearly advanced from traditional image processing steps to end-to-

end automated detection. However, despite these advancements, according to the literature, most models still rely heavily on the quality and diversity of training datasets, which limits their real-world performance and stops CNNs from being widely applied in leukemia detection [13],[14]. When models are trained on small or homogeneous datasets, overfitting becomes common, and the generalizability of CNNs often falls short of clinical expectations [15]. Shaban et al. further confirmed that this dependence on annotated microscopic images remains the primary bottleneck preventing wider clinical adoption of CNN systems [16]. These issues explain why many current models perform well on laboratory datasets but struggle with noisy real-world blood smear images or overlapping cells.

One possible approach to reduce the damage caused by these problems is to apply advanced transfer learning techniques, such as few-shot domain adaptation and domain-incremental learning, using data from a source domain where large-scale, annotated images are available [17], [18], [19]. These methods are expected to achieve high performance by selecting an appropriate source domain and fine-tuning the model with limited target-domain data, thereby addressing the generalization issues observed in conventional transfer learning models mentioned before.

Another possible route is to develop unsupervised or semi-supervised systems to address these issues [20]. Compared with traditional CNN models, these systems use fewer datasets and have lower standards for the annotation quality of leukemia cell images, which could be well-suited to the current limited scale of usable datasets.

Furthermore, to complement the above strategies by expanding data dimensions rather than solely reducing dependency, multimodal data fusion is a promising approach that integrates diverse data types, such as microscopic images, clinical records, and genomic profiles, to enrich the feature space [21],[22]. This method mitigates the limitations of single-modality datasets by leveraging complementary information from multiple sources, thereby improving model robustness and generalization without requiring massive expansions in any one dataset. For instance, fusion techniques such as feature-level concatenation or attention-based integration can enhance detection accuracy for leukemia subtypes, as demonstrated in recent studies. However, challenges in data alignment and computational complexity remain to be addressed through optimized architectures.

In summary, these approaches—advanced transfer learning for knowledge borrowing, unsupervised methods for data efficiency, and multimodal fusion for information enrichment—collectively offer a multifaceted pathway to overcome dataset constraints, paving the way for more reliable CNN applications in clinical leukemia detection. As Kalnoor et al. demonstrated, combining attention mechanisms with multimodal fusion can effectively enrich feature space without needing massive single-modality datasets [23]. The multimodal fusion framework proposed in the IJISAE study also shows that integrating microscopic images with clinical records and genomic profiles can improve robustness and reduce the impact of limited annotation quality [24].

4. Conclusion

This review aimed to provide a comprehensive synthesis of the latest CNN models applied to automated detection and classification of leukemia. A wide range of research and datasets used as benchmarks for leukemia diagnosis has been compiled and systematically examined.

There are two main purposes for this research: (i) to find the root cause of the long-existing problems in the field of leukemia diagnosis, and (ii) to assist medical staff and future researchers in determining an effective and feasible technical route for developing future CNN leukemia detecting models that are more precise and usable. A fundamental challenge comes from current diagnostic methods: artificial diagnoses are time- and experience-consuming and inaccurate. We focused on transfer learning and dataset augmentation CNN models, including AlexNet and VGG19.

Convolutional Neural Network plays a vital role in automated leukemia detection. In recent years, by improving the typical workflow of CNN-based leukemia detection models, such as preprocessing and detection phases, some models have achieved promising results, showing significant improvements in accuracy and speed. Apart from that, future development directions such as advanced transfer learning, unsupervised learning, and multimodal learning have begun to address CNN models' long-standing drawbacks of relying on dataset size and diversity.

While progress has been made, there remain problems to be solved. The lack of repeatability and explainability of diagnostic results hinders clinical development of these models. Apart from that, there is also a gap between successful trials and clinical application. To address these difficulties, future research should prioritize developing generalizable and explainable CNN models, integrating attention-based models (e.g., ViTs) and XAI methods (e.g., LIME and SHAP). Apart from that, lightweight solutions that can be embedded in common hospitality systems are necessary for implementing CNN models in actual leukemia detection. Finally, the application of artificial intelligence in hospitals and clinics remains limited; most methods are still in the experimental stage, and very few have undergone rigorous prospective validation or integration with clinical decision support systems.

In conclusion, this review provided a thorough and systematic overview of CNN-based methods for leukemia diagnosis, aiming to help future researchers advance the development of leukemia detection. By deeply analyzing the root causes and possibly directions, this view can contribute to the development of more robust, low-cost, and clinically viable diagnostic systems.

References

[1] Hu, C., Chen, W., Zhang, P., Shen, T., & Xu, M. (2025). Global, regional, and national burden of leukemia: Epidemiological trends analysis from 1990 to 2021. *PLOS ONE*, *20*(6), Article e0325937. https://doi.org/10.1371/journal.pone.0325937

[2] Siegel, R. L., Kratzer, T. B., Giaquinto, A. N., Sung, H., & Jemal, A. (2025). Cancer statistics, 2025. *CA: A Cancer Journal for Clinicians*, *75*(1), 10–45. https://doi.org/10.3322/caac.21871

[3] Hegde, R. B., Prasad, K., Hebbar, H., Singh, B. M. K., & Sandhya, I. (2020). Automated decision support system for detection of leukemia from peripheral blood smear images. *Journal of Digital Imaging*, *33*(2), 361–374. https://doi.org/10.1007/s10278-019-00288-y

[4] Bodzas, A., Kodytek, P., & Zidek, J. (2020). Automated detection of acute lymphoblastic leukemia from microscopic images based on human visual perception. *Frontiers in Bioengineering and Biotechnology*, *8*, Article 1005. https://doi.org/10.3389/fbioe.2020.01005

[5] Shah, A., Naqvi, S. S., Naveed, K., Salem, N., Khan, M. A. U., & Alimgeer, K. S. (2021). Automated diagnosis of leukemia: A comprehensive review. *IEEE Access*, *9*, 132097–132124. https://doi.org/10.1109/ACCESS.2021.3114059

[6] Shafique, S., & Tehsin, S. (2015). Detection of leukemia in microscopic images using image processing. In *Proceedings of the 2015 International Conference on Communication, Signal Processing and Systems (ICCSP)* (pp. 187–193). https://doi.org/10.1109/ICCSP.2015.7322621

[7] Sharma, S., Gupta, S. S., & Gupta, R. (2025). Leukemia classification using CNN and VGG19 architecture. In *Proceedings of the 2025 IEEE International Conference on Artificial Intelligence and Big Data (ICAIBD)* (pp. 1–6). https://doi.org/10.1109/ICAIBD60510.2025.10957277

[8] Arif, R., Setiawan, A., & Setiawan, A. A. (2022). Automatic detection of leukemia through convolutional neural network. In *Proceedings of the 2022 5th International Conference on Vocational Education and Electrical Engineering (ICVEE)* (pp. 1–6). https://doi.org/10.1109/ICVEE57061.2022.10043089

[9] Devi, G. M., Shah, M. A., & Wani, M. A. (2022). Computer-aided diagnosis of white blood cell leukemia using convolutional neural network. In *Proceedings of the 2022 International Conference on Advanced Computing, Communication and Applied Informatics (ICACCAI)* (pp. 1–6). https://doi.org/10.1109/ICACCAI54546.2022.9985611

[10] Ullah, A., Khan, M. A., Murtaza, S., Mehmood, A., & Sharif, M. (2022). Deep learning for classifying of white blood cancer. In *Proceedings of the 2022 2nd International Conference on Digital Futures and Information Security (ICDIFIS)* (pp. 1–6). https://doi.org/10.1109/ICDIFIS54539.2022.9736372

[11] Idris, M., Mazlan, S. A., & Mat Isa, N. A. (2025). Acute lymphoblastic leukemia blood cell image classification system using convolutional neural network. In *Proceedings of the 2025 IEEE International*

Conference on Artificial Intelligence and Engineering Technologies (IICAIET) (pp. 1–6). https://doi.org/10.1109/IICAIET59459.2025.11182698

[12] Anand, V., Bachhal, P., Koundal, D., & Dhaka, A. (2025). Deep learning model for early acute lymphoblastic leukemia detection using microscopic images. *Scientific Reports*, *15*(1), Article 29147. https://doi.org/10.1038/s41598-025-13080-6

[13]Taha, A. A., & Hanbury, A. (2019). Going deep in medical image analysis: Concepts, methods, challenges, and future directions. *IEEE Access*, *7*, 40938–40972. https://doi.org/10.1109/ACCESS.2019.2907934

[14] Achir, A., Boughrara, A., Bouhedda, M., & Meziane, S. (2025). Advances in leukemia detection and classification: A systematic review of AI and image processing techniques. *Frontiers in Artificial Intelligence*, *8*, Article 1384919. https://doi.org/10.3389/frai.2025.1384919

[15] Shah, W. H., et al. (2026). A systematic review of machine and deep learning techniques for acute lymphoblastic leukemia diagnosis. *Artificial Intelligence in Medicine*. https://doi.org/10.1016/j.artmed.2026.103456

[16] Shaban, W. M., et al. (2025). An AI-based automatic leukemia classification system. *Scientific Reports*, *15*(1), Article 98400. https://doi.org/10.1038/s41598-025-98400-6

[17] Chossegros, M., Delhommeau, F., Stockholm, D., & Tannier, X. (2024). Improving the generalizability of white blood cell classification with few-shot domain adaptation. *Journal of Pathology Informatics*, *15*, Article 100405. https://doi.org/10.1016/j.jpi.2024.100405

[18] Kumari, P., Bozorgpour, A., Reisenbüchler, D., et al. (2025). Domain-incremental white blood cell classification with privacy-aware continual learning. *Scientific Reports*, *15*, Article 25468. https://doi.org/10.1038/s41598-025-08024-z

[19] Wang, X., Ou, C., Pan, G., Hu, Z., & Cao, K. (2025). Few-shot leukocyte classification algorithm based on feature reconstruction network with improved EfficientNetV2. *Applied Sciences*, *15*(17), Article 9377. https://doi.org/10.3390/app15179377

[20] Asghar, R., Hussain, A., Nazir, Z., Shorfuzzaman, M., Alabdulwahab, J., & Fouad, S. (2024). Classification of white blood cells (leucocytes) from blood smear imagery using machine and deep learning models: A global scoping review. *PLOS ONE*, *19*(6), Article e0301913. https://doi.org/10.1371/journal.pone.0301913

[21] Vinurajan, I. (2024). Multi-modal feature fusion with machine learning approach for leukemia detection and classification. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(21s), 3174–3185. https://ijisae.org/index.php/IJISAE/article/view/6006

[22] Yadav, D. P., Kumar, D., Jalal, A. S., et al. (2023). Morphological diagnosis of hematologic malignancy using feature fusion-based deep convolutional neural network. *Scientific Reports*, *13*, Article 16988. https://doi.org/10.1038/s41598-023-44210-7

[23] Kalnoor, G., et al. (2025). Advanced leukocyte classification using attention mechanisms and dual channel U-Net architecture. *Scientific Reports*, *15*(1), Article 96918. https://doi.org/10.1038/s41598-025-96918-3

[24] Jeyanthi, J. E. S. A. S. N., et al. (2024). Multi-modal feature fusion with machine learning approach for leukemia detection and classification. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3), 6006–6015. https://ijisae.org/index.php/IJISAE/article/view/6006

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.