# Next-Generation Architectures for Leukemia Subtype Identification: A Review of CNN, Vision Transformers, and Hybrid Models

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**Abstract:** One of the most urgent issues is the possibility to provide reliable and repeatable leukemia subtype diagnosis based on the hematological image due to the minimal morphological variations, inter-rater error, and due to the disadvantages of the traditional diagnostic procedures. These dilemmas are viewed in this review by conducting a systematic examination of next-generation deep learning architectures, including convolutional neural networks (CNNs), Vision Transformers (ViTs) and novel hybrid CNN-transformer models to automatically identify the subtypes of leukemia. The paper is an overview of the current advances in feature extraction, attention and multi-scale representation learning and how hybrid architecture can effectively combine local spatial feature learning and global contextual learning. Important results have shown that transformer-based and hybrid strategies are always better than the traditional CNN models in accuracy, robustness, and generalization on different datasets, and they also allow better interpretability when used in combination with explainable AI methods. In addition, the review also identifies the significant gaps in the research related to the heterogeneity of data, complexity of computation, and clinical validation. These are the lessons that suggest how the next-generation architecture will enhance the scalability and reliability of the diagnostics. Its results can be particularly relevant in the framework of developing AI-based clinical decision-support systems, which would enable an earlier diagnosis, less subjective diagnosis, and implementation in a healthcare environment with scarce resources.

**Keywords**: Leukemia Subtype Classification; Convolutional Neural Networks; Vision Transformers; Hybrid Deep Learning Models; Explainable Artificial Intelligence

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## Introduction

Leukemia is a heterogeneous group of hematological cancers that is characterized by the inappropriate growth of the white blood cells and appropriate and timely subtypes of the leukemia are required to facilitate proper treatment planning and prognosis. The traditional diagnostic techniques employed in the conventional diagnostic rely on the microscopic examination of peripheral blood smears and bone marrow samples which are highly dependent on the services of expert hematopathologists and can be subject to inter-observer variability, and diagnostic variability.

A typical automated system of leukemia diagnosis includes multiple successive phases, which include image preprocessing, image segmentation, feature extraction, classification and evaluation, as depicted in Fig. 1. Images are first improved in terms of noise, stain normalization and contrast enhancement. This is after which procedures of segmentation are followed which isolate areas of interest (ROI) and separate over-lapping cells.

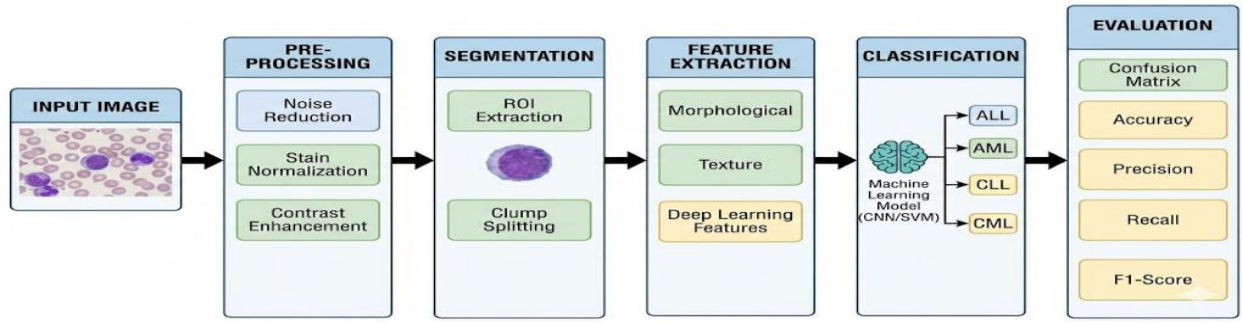


*Figure 1. General pipeline for automated leukemia subtype classification from hematological images*

This review aims to critically analyze the state-of-the-art deep learning architectures in order to determine the hematological images of leukemia subtypes. This research synthesizes the recent studies and indicates the weaknesses and strengths of current methodologies, and especially the hybrid and attention-based models. It is anticipated that the mentioned insights will aid the creation of strong, interpretable, and clinically viable AI systems, which will help in the progression of smart healthcare solutions in the diagnosis of leukemia.

**Related work**

Artificial intelligence (AI) in the diagnosis of leukemia has been greatly revolutionized, transitioning through the conventional machine learning methods to deep learning and hybrid models. Initial studies were mainly based on convolutional neural networks (CNNs) to detect and classify leukemia automatically.

*Table 1. Comparison of Related Work*

| Methodology Category | Key Characteristics | Representative References | Limitations |
|---|---|---|---|
| **Traditional Machine Learning** | Handcrafted features (morphology, texture) with classical classifiers | [12], [17] | Limited feature representation, poor generalization |
| **Standard CNN-Based Models** | Automatic feature extraction using deep convolutional layers | [1], [3], [9], [10], [15], [19] | Limited global context understanding |
| **Attention-Enhanced CNN Models** | Incorporation of attention mechanisms to focus on important regions | [2], [7] | Increased complexity, still partially local |
| **Transformer-Based Models (ViT)** | Global feature learning using self-attention mechanisms | [13] | High computational cost, data dependency |

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|---|---|---|---|
| **Hybrid CNN-Transformer / Ensemble Models** | Combines CNN (local) + Transformer (global) or ensemble learning | [6], [13], [16], [18] | Computational overhead, integration complexity |
| **Dataset & Review-Based Studies** | Dataset creation, surveys, and benchmarking studies | [4], [11], [14], [20] | Lack of direct classification contribution |
| **Clinical/Non-Image Techniques** | Flow cytometry and laboratory-based diagnostic approaches | [8] | Limited automation and scalability |

**Methodological Analysis of Deep Learning Architectures**

Automated leukemia subtype recognition has been developed with great force due to the advances made in deep learning architectures. Here, the authors comment on three primary categories, i.e., convolutional neural networks (CNNs), Vision Transformers (ViTs), and hybrid CNN-transformers models, their methodology, their advantages, and their drawbacks in the hematological image analysis.

*Table 2. Comparative Analysis of Deep Learning Architectures*

| Architecture Type | Feature Learning | Strengths | Limitations | Representative References |
|---|---|---|---|---|
| **CNN** | Local spatial features | Efficient, strong feature extraction | Limited global context | [1], [3], [9], [15] |
| **Attention-CNN** | Local + focused regions | Improved accuracy, interpretability | Partial global understanding | [2], [7] |
| **Vision Transformer** | Global context via self-attention | Captures long-range dependencies | High computational cost | [13] |
| **Hybrid CNN-Transformer** | Local + global features | Best performance, robust | Complex architecture | [6], [13], [16], [18] |

**Challenges, Research Gaps, and Future Directions**

This section critically evaluates these limitations and identifies possible future research directions in safeguarding the limitations.

**A. Dataset Limitations and variability**

The absence of large, varied and standardized datasets is one of the key issues to leukemia image analysis. Most studies are based on limited or one-source datasets and this limits the generalizability of trained models in different clinical environments.

**B. Generalization and Cross-Dataset Performing.**

Most deep learning models are found to be extremely accurate on benchmark datasets but not reproductible on new or multi-center datasets.

**C. Resource Constraints and Computational Complexity**

Information: Upstream architecture, especially Vision Transformers and hybrid architectures, have huge computing requirements, such as high memory and processing power.

**D. Lack of Interpretability and Clinical Trust**

The many black-box systems regarding deep learning models render them unacceptable in clinical practice.

**E. Limited Inter-Professional Integration with Clinical Workflows**

The available literature aims at model development and evaluation but does not cover any practical implementation factors including interconnection with hospital information system, real-time processing, and a user-friendly interface.

## Conclusions

The topic of this review related to the challenging issue of the accurate and consistent identification of leukemia subtypes based on hematological imaging in which inter-observer bias, fine morphological variations, and constraints of manual diagnostic tests frequently obstruct and hinder the reliable identification of the subtypes. This was a push to see how the next-generation artificial intelligence can enhance the diagnostic reliability, scalability, and clinical decision-making. The paper concluded that CNN-based models are more effective in local features extraction, whereas transformer-based ones are good at obtaining global contextual relationships. Close-ended models combining CNNs and transformers are better in terms of accuracy, robustness, and generalization. The future developmental efforts should be directed at creating models that are lightweight and efficient, enhancing quality and variety of datasets, multimodal data incorporation and better explainability.

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