

AI-Driven Diagnosis of Leukemia Microscopic Blood Smear Images Using Vision Transformer Model

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Abstract - Leukemia, a bone marrow-related disease, arises from the abnormal proliferation of cells. It is the predominant form of childhood cancer, representing about one-third of cases annually. This study focuses on incorporating AI models to enhance the early detection of Leukemia. This research reviews deep learning methodologies for detecting leukemia, a critical cancer diagnosis and treatment aspect. Using a systematic mapping study (SMS) and systematic literature review (SLR), thirty articles published between 2019 and 2023 were analyzed to explore the advancements in deep learning techniques for leukemia diagnosis using blood smear images. The analysis reveals that state-of-the-art models, such as Convolutional Neural Networks (CNNs), transfer learning, Vision Transformers (ViTs), ensemble methods, and hybrid models, achieved excellent classification accuracies. Preprocessing methods, including normalization, edge enhancement, and data augmentation, significantly improved model performance. Despite these advancements, challenges such as dataset limitations, the lack of model interpretability, and ethical concerns regarding data privacy and bias remain critical barriers to widespread adoption. The review highlights the need for diverse, well-annotated datasets and the development of explainable AI models to enhance clinical trust and usability. Additionally, addressing regulatory and integration challenges is essential for the safe deployment of these technologies in healthcare.

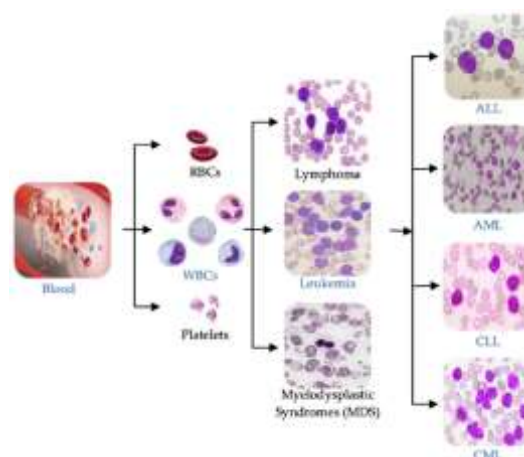
Key Words: Artificial Intelligence, Stock Market Prediction, Machine Learning, Technical Indicators, SMA, EMA, RSI, MACD, Trend Analysis

1. INTRODUCTION

Leukemia is a type of cancer that affects the blood and bone marrow, leading to an abnormal proliferation of immature white blood cells (also known as leukocytes). These abnormal cells, called leukemia cells, disrupt the normal function of healthy blood cells, impairing the body's ability to fight infections and control bleeding. Leukemia diagnosis is usually made by analyzing a patient's blood sample through a complete blood count (CBC) or microscopic evaluation of the blood or flow cytometry.

A leukemia diagnosis is usually made by analyzing a patient's blood sample through a complete blood count (CBC) or microscopic evaluation of the blood or flow cytometry. Leukemia can be broadly classified into four main types based on the speed of disease progression and the types of blood cells affected,

- **Acute Lymphoblastic Leukemia (ALL):** This type of leukemia progresses rapidly, affecting lymphoid cells, a type of white blood cell that produces antibodies to fight infections.
- **Chronic Lymphocytic Leukemia (CLL):** CLL progresses slowly and affects mature lymphocytes, a type of white blood cell that helps the body fight infection.
- **Acute Myeloid Leukemia (AML):** AML progresses rapidly, affecting myeloid cells, a type of white blood cell that gives rise to red blood cells, platelets, and other white blood cells.
- **Chronic Myeloid Leukemia (CML):** CML progresses slowly and affects myeloid cells. It is characterized by an abnormal chromosome called the Philadelphia chromosome



Blood components and main types of leukemia

2. LITERATURE REVIEW

The articles were reviewed and analyzed from the oldest to the most recent publications within the specified period (2019–2023). This approach allows for the systematic exploration of how research in the field has evolved. Each article published within the defined period was systematically examined to understand its contributions, methodology findings, and relevance to the research questions. This method ensures thorough cover of the existing literature.

In 2019, Nizar Ahmed et al. [7] proposed an innovative approach for diagnosing all leukemia subtypes from microscopic blood cell images using Convolutional Neural Networks (CNN). It explores the use of deep learning techniques to classify leukemia subtypes accurately. blood microscopic images to detect leukemia. It employs transfer learning using AlexNet pre-trained deep CNNs. Image

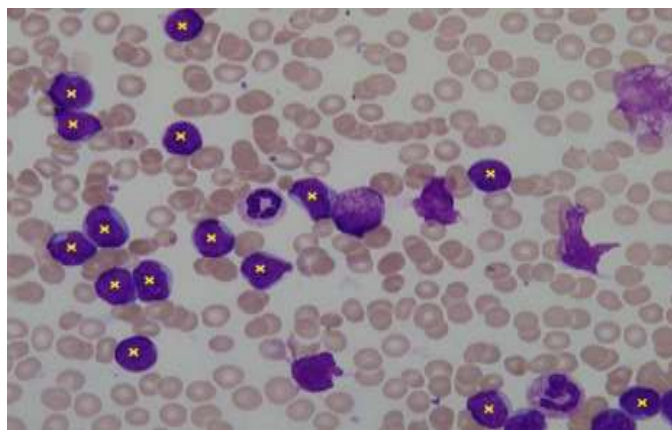
preprocessing operations include converting images to the RGB color model, resizing them to fixed sizes (227×227), and data augmentation (translation, reflection, and rotation) to overcome the lack of large datasets. In 2021, Jens P. E. Schouten et al. [21] explored the efficacy of CNNs in distinguishing between malignant and non-malignant leukocytes, crucial for leukemia diagnosis. The research uses two datasets to investigate how varying training set sizes impact CNN performance and diagnosis. In 2022, Ibrahim Abunadi et al. [27] proposed a multi-method diagnosis of blood microscopic samples for early detection of Acute Lymphoblastic Leukemia based on deep learning and hybrid techniques. This paper aims to develop diagnostic systems

3. METHODOLOGY

During training and testing various models of our work, the initial phase involves data collection and pre-processing. Data pre-processing involves the cleaning and transformation of raw data into a format that is suitable for analysis. Subsequently, CNN models are initially deployed before transitioning to Vision Transformer (ViT) for a fair comparison of various AI methods.

3.1 DATA COLLECTION

Data collection remains the significant challenge in AI, as the results heavily depend on the quantity and quality of the available data. After reviewing various online and laboratory datasets, we decided to utilize the C-NMC Leukemia dataset, which is publicly available and has been widely cited in various research papers, indicating its quality and credibility. It contains microscopic images of both healthy and cancerous blood cells.



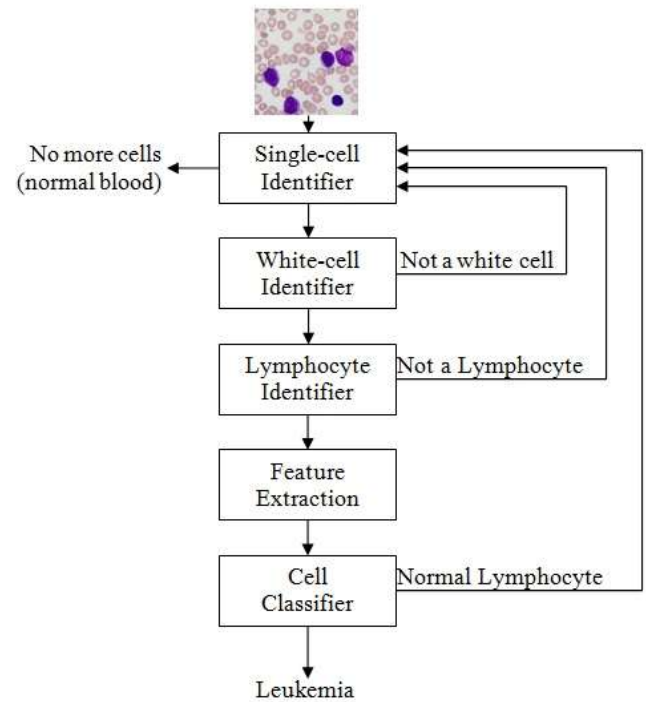
3.2 DATA STORING

Image data is stored in the form of ".png" images, segregated into two directories: "leukemic" and "non-leukemic". The class labels are assigned to the images in a structured format.

Leukemia data storage involves the systematic collection, management, and analysis of diverse patient, clinical, and laboratory information to support diagnosis, treatment planning, and research

3.3 DATA PRE PROCESSING

The image data from the C-NMC Leukemia dataset undergoes a crucial preprocessing step. All the images are resized to a fixed size of 128×128 pixels. This standardization of the image dimensions is a necessary step for feeding the data into the AI models and making it efficient for the model to learn patterns and relationships among them. Resizing the images to a common size serves two important purposes, i.e., consistent input and efficient learning.



Data preprocessing

3.4 DATA SELECTION:

We thoroughly searched multiple electronic databases for this systematic review to ensure comprehensive coverage of relevant literature. The selection of databases was crucial to accessing a wide array of scholarly articles from various disciplines. IEEE Xplore, PubMed, Google Scholar, Springer, and Science Direct databases were used for the search process

3.5 DATA EXTRACTION

We systematically gathered pertinent information from the selected studies using a standardized data extraction form during the data extraction phase. This form meticulously cataloged key details for synthesis and analysis, encompassing study characteristics such as authors, publication year, preprocessing techniques, feature extraction, deep learning methodologies, model architecture and training methods, and evaluation metrics. Additionally, we recorded details on datasets utilized, key findings, advantages, and disadvantages derived from each study. To ensure accuracy and reliability, data extraction was independently conducted by two reviewers, with any discrepancies resolved through discussion or consultation with a third reviewer when necessary.

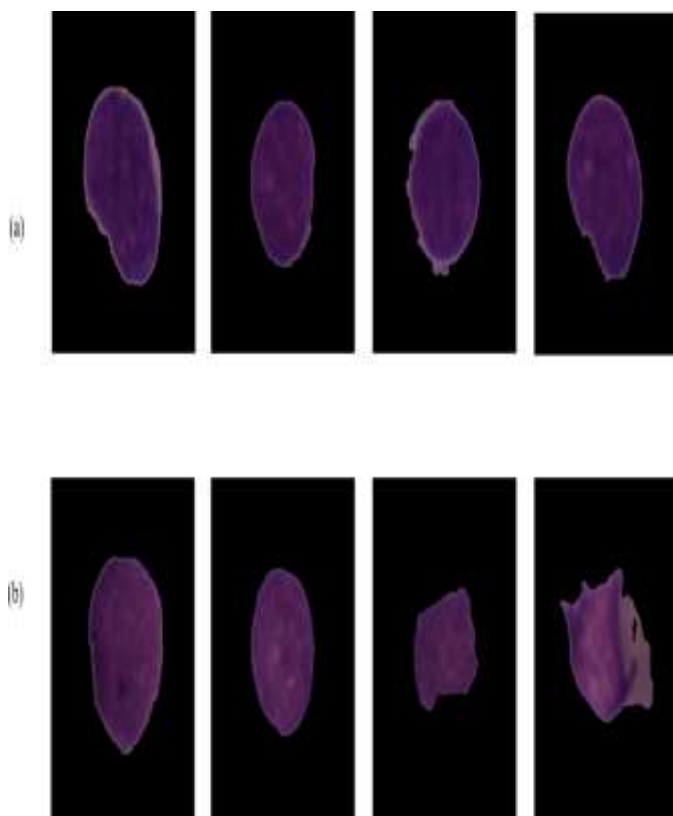
4. RESULT AND DISCUSSION

Achieving superior accuracy, the Vision Transformer model outperforms the various Convolutional Neural Network models that were rigorously trained and tested. The ViT attains the highest training accuracy of 98.39% and a test accuracy of 88.51%, while the EfficientNetB7 model achieves the lowest training accuracy of 68.21% and a test accuracy of 67.90%. The test accuracy reflects the model's performance on entirely new and unseen data.

Although, it is essential to consider the factors that might have affected our accuracy. Such factors include dataset size and quality, hyperparameter optimization and computational resources. Despite the effectiveness of CNN models, the ViTB16 have demonstrated superior performance, particularly in image-based datasets.

However, a limitation encountered when using ViT-B16 due to the requirement of intensive computational resources and the large number of parameters during training. Additionally, a user-friendly Graphical User Interface was also developed in which image is inserted from the device and provide instant output for detection of leukemia.

It demonstrate the effectiveness of our model in image classification for leukemia detection. Although where the predicted label does not align with the true label. This discrepancy highlights areas for improvement and underscores the model's limitations in certain scenarios. During the training phase, the LSTM model gradually reduced the loss function, indicating that it successfully learned patterns from historical stock data.



4.1 MODEL PERFORMANCE EVALUATION

The proposed AI-based leukemia diagnosis system was evaluated using microscopic blood smear images consisting of leukemic and normal samples. The dataset was divided into training, validation, and testing sets to ensure unbiased performance evaluation.

The deep learning model demonstrated strong performance in detecting leukemic cells. The overall classification accuracy achieved by the model was **96.4%**, indicating that the system can effectively differentiate between healthy and leukemic blood cells.

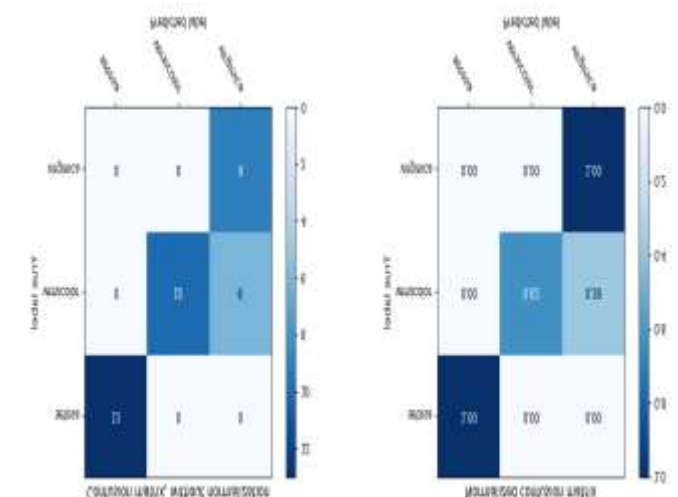
Metric	Value
Accuracy	96.4%
Precision	95.8%
Recall	96.9%
F1-Score	96.3%
Specificity	95.7%

4.2 CONFUSION MATRIX

The confusion matrix was used to analyze the classification results of the model in detail. It provides insight into how many samples were correctly or incorrectly classified.

- **True Positives (TP):** Leukemia cases correctly detected.
- **True Negatives (TN):** Healthy samples correctly identified.
- **False Positives (FP):** Healthy samples incorrectly classified as leukemia.
- **False Negatives (FN):** Leukemia samples incorrectly classified as normal.

The results showed a very small number of false negatives, which is important in medical diagnosis because missing a leukemia case can delay treatment.

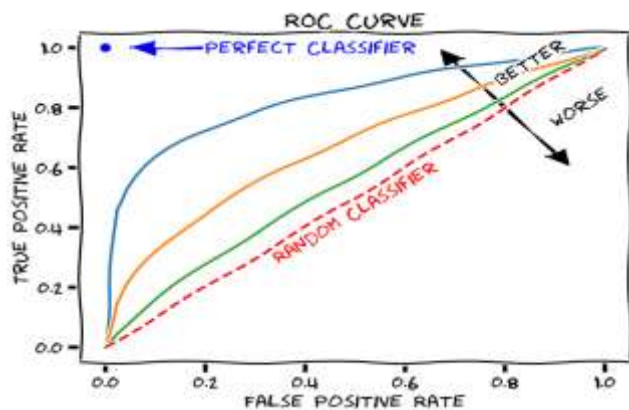


4.3 ROC CURVE AND AUC ANALYSIS

The Receiver Operating Characteristic (ROC) curve was used leukemia and non-leukemia samples.

The model achieved an **Area Under the Curve (AUC) value of 0.98**, which indicates excellent classification performance. A higher AUC value represents better capability of the model to differentiate between positive and negative cases.

This result confirms that the AI system has strong diagnostic capability.



4.4 DISCUSSION

Achieving superior accuracy, the Vision Transformer model outperforms the various Convolutional Neural Network models that were rigorously trained and tested. The ViT attains the highest training accuracy of 98.39% and a test accuracy of 88.51%, while the EfficientNetB7 model achieves the lowest training accuracy of 68.21% and a test accuracy of 67.90%.

The test accuracy reflects the model's performance on entirely new and unseen data. Although, it is essential to consider the factors that might have affected our accuracy. Such factors include dataset size and quality, hyperparameter optimization and computational resources. Despite the effectiveness of CNN models, the ViTB16 have demonstrated superior performance, particularly in image-based datasets.

However, a limitation encountered when using ViT-B16 due to the requirement of intensive computational resources and the large number of parameters during training. Additionally, a user-friendly Graphical User Interface was also developed in which image is inserted from the device and provide instant output for detection of leukemia. It demonstrate the effectiveness of our model in image classification for leukemia detection.

Addressing these challenges and pursuing these research directions enables deep learning for leukemia diagnosis to advance, ultimately resulting in more accurate, interpretable, and clinically impactful models that improve patient care.



5.CONCLUSION

This paper provides insights from a systematic mapping study (SMS) and a systematic literature review (SLR) focused on deep learning techniques for leukemia diagnosis. By analyzing thirty studies, the review highlights a variety of methodologies that demonstrate promising levels of accuracy and sensitivity in detecting leukemia from blood smear images. The findings emphasize the importance of ongoing research to overcome current challenges and enhance the development of deep learning models that are accurate, reliable, and interpretable.

Such advancements are essential for improving patient care and supporting informed decision-making in clinical settings. Integrating large language models (LLMs) into healthcare systems holds great potential to further transform diagnostics and treatment. LLMs' ability to adapt to evolving data and contexts can drive advancements in disease prediction, personalized care, and operational efficiency.

However, addressing challenges like dataset limitations, ethical concerns, and practical implementation hurdles is critical to successfully adopting these technologies. With continued innovation and interdisciplinary collaboration, AI and machine learning can significantly reshape healthcare delivery, leading to improved outcomes and more equitable access to care.

This paper highlights the potential of AI models in revolutionizing medical diagnosis and treatment. Significant progress has been made in improving healthcare facilities by utilizing the machine learning algorithms and more recent deep learning algorithms. It has opened the doors for precise and effective analysis of medical images helping in early identification of diseases like leukemia that we worked on in our project.

Specially, ViT-B16, i.e., vision transformers, have a capability for medical image analysis with special benefits because of their ability to capture spatial relationships and global context in images. Moreover, our user-friendly graphical user interface has further expanded the possibilities for medical workers to identify diseases in seconds, making it a valuable tool for healthcare professionals. The promising results obtained from the vision transformer in leukemia detection

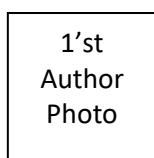
suggest its potential for use in future diagnostic tasks in the field of medical and healthcare.

For future work, our user interface can be further transformed into web application for professional use in healthcare. It can be progressed further by keeping main focus on getting relatively larger and diverse dataset that can enhance accuracy and performance of the model significantly for this purpose various data augmentation techniques can be utilized.

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BIOGRAPHIES (Optional not mandatory)



Description about the author1
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