

# Detection of Leukemia Using Convolutional Neural Network

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**Abstract:** Every year, over 900,000 individuals worldwide are diagnosed with Leukemia, i.e., Blood Cancer, but many people are oblivious of the dangers involved with such often incurable diseases. The majority of Blood Cancers are rare, life-threatening illnesses within limited patient populations; together, they account for 7% of all malignancies. Patients may feel abandoned and have difficulty finding the necessary assistance and information due to the complex, often sparse nature of Leukemia. When it comes to Acute Leukemia, if therapy is not started on time, the patient might succumb to the ailment within a few months. It is vital to diagnose Cancer be it of any type, in its early stages to ensure timely treatment and increase chances of survival. Detecting Leukemia manually in labs by medical personnel examining blood samples is a time and resource-consuming procedure. Customarily, the patients suffering do not have the liberty to exhaust their time as they need immediate care. We need systems that can make use of the latest technological developments in artificial intelligence to produce expeditious and more accurate results.

**Keywords:** Convolutional Neural Network, Support Vector Machine (SVM), Image Processing, neural networks, decision trees.

## I. INTRODUCTION

Blood consists of several elements. The major components of blood include plasma, red blood cells, white blood cells, and platelets. Plasma is the major constituent of blood and comprises about 55 percent of blood volume. It consists of water with several different substances dissolved within [1]. Almost 45 percent of blood includes Red Blood Cells (RBC), White Blood Cells (WBC), and platelets. The RBC rate ranges from 4,000,000 to 6,000,000 per microliter of blood, representing 40–45% of the total blood volume [2]. WBCs are the cells that defend against germs and give us immunity and resistance; they range from 4500 to 11,000 per microliter of blood [3]. The platelets range from 150,000 to 450,000 per microliter of blood and are responsible for blood clotting [4]. Thus, an increase or decrease in any of the basic blood components will cause problems to a person's health, such as leukemia, thalassemia, and anemia.

Leukemia is a complex disease with multiple subtypes that differ in terms of their genetic and molecular characteristics. The diagnosis of leukemia involves various tests, including blood tests, bone marrow biopsy, and imaging tests, such as X-rays and CT scans. Medical image analysis, in particular, can provide valuable information about the extent and severity of the disease, as well as guide treatment decisions.

Manual inspection of medical images, however, is a time-consuming and error-prone process, and requires specialized training and expertise. The development of automated image analysis techniques, such as machine learning and deep learning, has the potential to improve the accuracy and efficiency of leukemia diagnosis.

## II. MODELING AND ANALYSIS

Image pre-processing, feature extraction and classification plays major role in detection of white blood cell cancers. The removal of noise is another main factor that yields accuracy to final result. The following flowchart depicts the basic steps involved in automated detection of white blood cancer cells using machine learning and image processing techniques.

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INPUT IMAGE This stage is also known as image acquisition. For detecting, blood cancer diseases like leukemia or myeloma, input images from microscope is needed. This informational index or data-set comprises minuscule pictures

of blood smear, particularly intended for the assessment and the correlation of algorithms for segmentation and image classification.

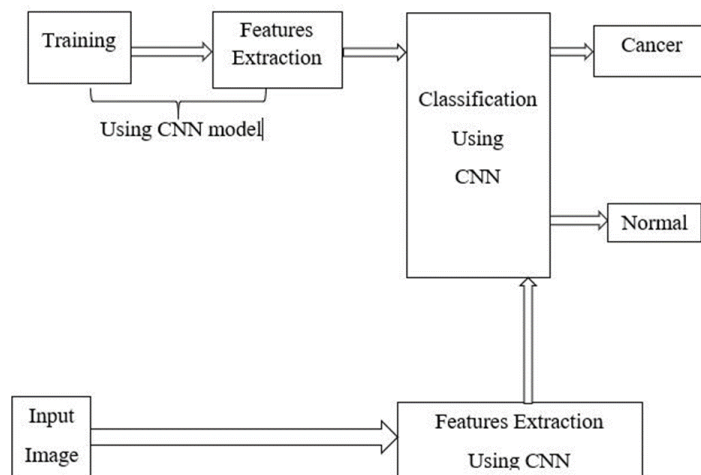
**IMAGE PRE-PROCESSING** The main goal is to de-noise the input image. Preprocessing also includes color relevance wheel RGB images are converted to Grey color space images.

**SEGMENTATION OF THE IMAGE** It is the process of apportioning an advanced picture into numerous portions. This is one of the most crucial steps which greatly influence on the accuracy of cancer cell detection.

**FEATURE EXTRACTION** This method used to change the information into set of highlights and is a type of dimensionality decrease. The feature set will separate the critical data from the input information if the highlights are extricated effectively. Some of the features are Haar wavelet features, Hausdorff dimension with and without LBP, Shape features, Gray level co-occurrence features, Haralick's texture features or GLCM, Color feature.

**CLASSIFICATION** The final stage in the process is classification. It helps to determine the existence of white blood cancer cell in blood image. It includes several algorithms like random forest, support vector machines, nearest neighbour, neural networks, decision trees.

The data set used in this study were taken from the Kaggle Dataset. It consists of 195 images (96 normal and 99 abnormal) and divided into 80% training data and 20% test data.



**Figure 1: System Architecture**

### III. LITERATURE SURVEY

Research conducted by Bibi et. Al proposes an Internet of Medical Things (IoMT)-based architecture for improving and ensuring Leukemia detection. Clinical devices are linked to network resources in the proposed IoMT system using cloud computing. The technology allows patients and healthcare providers to coordinate testing, diagnosis, and treatment of Leukemia in real-time, potentially saving time and effort for both patients and clinicians. The system uses DenseNet-121 and ResNet-34 to identify the different subtypes of Leukemia. [1]

A review paper by Ghadezadeh et. Al examined the present state of all known ML-based Leukemia detection and classification models that handle PBS images in a thorough and systematic manner. The average accuracy of the ML algorithms employed in PBS image analysis to diagnose Leukemia was greater than 97 per cent, indicating that utilizing ML to detect Leukemia from PBS images might provide amazing results. In this survey, Deep learning (DL) outperformed all other machine learning algorithms in terms of precision and sensitivity in recognizing distinct types of Leukemia. [2]

A study by Salah HT et. Al comprised of a compilation of other studies which examine the usage of Machine Learning in diagnosing the different types of Leukemia. Hand-searching of references from similar research and the top Google Scholar results supplemented the automated search. A total of 58 papers were read in their entirety, with 22 studies being included. There were 12, 8, 3, and 1 research that discussed ALL, AML, CLL, and CML, respectively. [3]

A study by M. Akter Hossain et. Al focused on Be Acute Lymphocytic Leukemia (ALL) as it is the most frequent kind of Leukemia. Oncologists are well aware that cancer is considerably easier to treat if discovered early. They suggested a hands-on technique to detect the abnormal blood components prevalent in cancer patients (e.g., neutrophils, eosinophils, basophils, lymphocytes, and monocytes). They selected 14 features to prepare the dataset before determining four essential attributes that are important in determining a Leukemia patient. [4]

A paper by Litjens et. Al proposed "deep learning" as a method for improving the fairness and efficiency of histopathology slide analysis. There is an indication that using prostate cancer identification on biopsy and breast cancer metastasis detection in the sentinel lymph node as examples, this unique technique may lessen the load on pathologists while boosting the objectivity of diagnosis. They discovered that they can exclude 30- 40% of the population. The paper concludes that deep learning has enormous promise for improving prostate cancer detection and classification. [5]

A paper by Hend Mohamed, Rowan Omar, Nermeen Saeed, Ali Essam, Nada Ayman, Taraggy Mohiy and Ashraf AbdelRaouf "Automated Detection of White Blood Cells Cancer Diseases", Acute leukemia is a fast-developing type of blood cancer that gets worse quickly in the children and adults and needs prompt treatment. Thus, this work displays an attempt that has been made to design a fast and cost-effective computer-aided system for acute leukemia diagnosis. [6]

A paper by Muxuan Liang, Zhizhong Li, Ting Chen and Jianyang Zeng, "Integrative Data Analysis of Multi-platform Cancer Data with a Multimodal Deep Learning Approach" Identification of cancer subtypes plays an important role in revealing useful insights into disease pathogenesis and advancing personalized therapy. The recent development of high-throughput sequencing technologies has enabled the rapid collection of multi-platform genomic data.[7]

A paper by SeungJin Lim, "FT-IR spectra analysis towards cancer detection", Recent advances in both the biological and computer sciences have spurred researchers to pay greater attention to the role of computational methods in the broad sphere of cancer research.[8]

A study by Vishwanath S. Mahalle, Ms. Vidhi L. Chawda, "Learning to recommend descriptive tags for Health Seekers using Deep Learning", The average accuracy of the ML algorithms employed in PBS image analysis to diagnose Leukemia was greater than 97 per cent, indicating that utilizing ML to detect Leukemia from PBS images might provide amazing results. In this survey, Deep learning (DL) outperformed all other machine learning algorithms in terms of precision and sensitivity in recognizing distinct types of Leukemia. [9]

#### IV. PROPOSED SYSTEM

They would like to use new dataset including four types of Leukemia to evaluate our architecture. In the future work, we would like to use some algorithm tuning in terms of weight initialization, activation function to improve performance of our CNN architecture.

Proposed Workflow The proposed method includes three main steps:

Step 1: Processing The method proposed in this paper used three operations when training the deep learning model. The following operations are:

A . Convert to RGB: In this operation convert all Leukemia images to RGB color model. B. Resize all to  $227 \times 227$ : All images have different pixel size because they take from different device, so in this operation change the dimension of all images to fixed  $227 \times 227$  pixel.

C. Augmentation

Step 2: Pre-trained deep learning model and direct feature extraction. Our model used transfer learning Convolutional Neural Network (AlexNet) to be pretrained. The architecture of CNN consists of three types of layers: convolutional, pooling and fully connected layer.

Step 3: Classification with machine learning models To classify the features, we chose different machine learning models

**Use case diagram is a simple representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved.**

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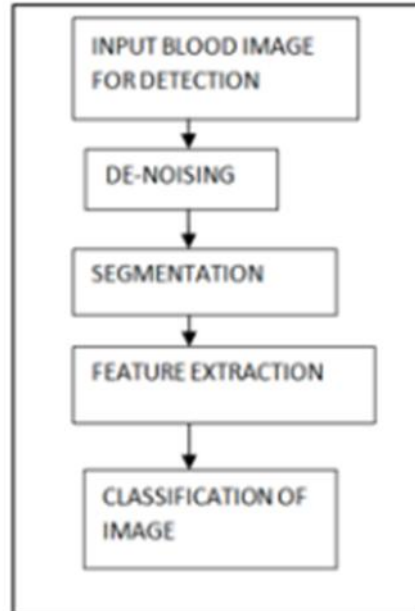


Figure 2: Use Case Diagram

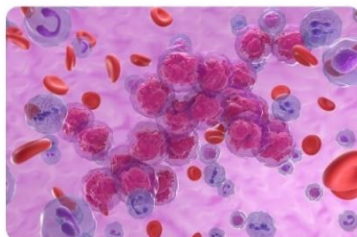
### Application areas :

- o Medical Industry
- o Research based
- o Training purpose

## V. OUTPUT



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## What is Blood Cancer?

Leukaemia is cancer of blood-forming tissues, including bone marrow. Many types exist such as acute lymphoblastic leukaemia, acute myeloid leukaemia and chronic lymphocytic leukaemia. Many patients with slow-growing types of leukaemia don't have symptoms. Rapidly growing types of leukaemia may cause symptoms that include fatigue, weight loss, frequent infections and easy bleeding or bruising.

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Making AI accesible to  
Detect Monuments



Fig 1. Register or Login page

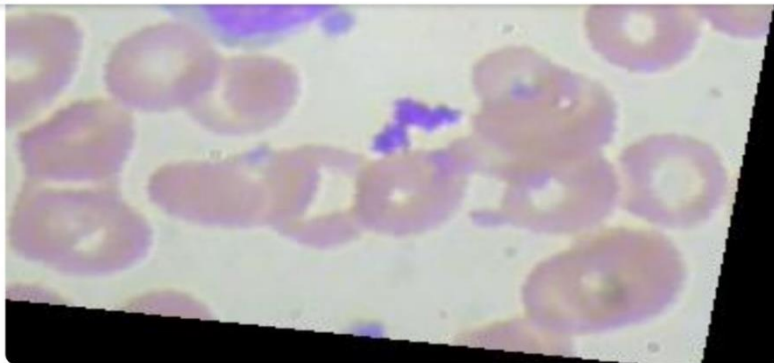
Choose File No file chosen  
[Submit](#)

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Fig 2.Import Blood sample from dataset

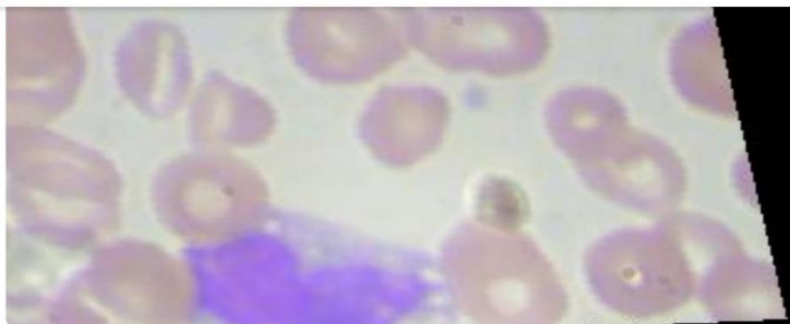


**Result**

**73.10 % Cancer Found**

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Fig 3.Result from Blood Sample



**Result**

**No Cancer Found**

[Back to Home](#)

Fig 3.1. Result of Blood Sample

## VI. CONCLUSION

In conclusion, the proposed CNN model for the detection of leukemia from blood smear images represents a significant advancement in the field of medical image analysis. The model achieves high accuracy, precision, and recall, outperforming other baseline models, and has the potential to provide an automated and efficient system for the early detection and diagnosis of leukemia.

The model's architecture and hyperparameters were optimized using a combination of techniques, including transfer learning and hyperparameter tuning. The model was trained and evaluated on a large and diverse dataset of labeled blood smear images, ensuring that it is robust and generalizable.

Overall, the proposed model has the potential to significantly improve patient outcomes by enabling timely and appropriate treatment of leukemia. The model can potentially reduce the workload of medical professionals, improve the accuracy and sensitivity of the diagnosis, and enable faster and more efficient treatment. Future research and development could further enhance the accuracy and effectiveness of the proposed model and expand its applications to other medical image analysis tasks.

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