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Review RRJoOH

An Effective Convolutional Neural Network for Identifying Cancer Blood Disorder Cells Using Microscopic Images

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Abstract

Blood, bone marrow, and lymphatic systems are all impacted by hematological cancer is known as a cancer blood disorder. Blood malignancies and various blood disorders pose significant health challenges across all age groups. Early disease detection is essential for effective cancer blood disorder treatment and management. If a blood cancer is not identified in time, it may be hazardous. It results in abnormal white blood cell production by the bone marrow in the blood. It is possible to diagnose blood cancer early with deep learning algorithms. Our study presents a novel and highly effective approach to predicting cancer blood disorders from medical images. The convolutional neural networks (CNN) method will be used to extract characteristics from blood samples or images, followed by deep learning algorithms to separate malignant from non-cancerous samples. Many researchers have proposed various deep learning-based techniques to improve the accuracy of blood cancer diagnosis, such as feature selection and hybrid models. Our revolutionary DCNN classification architecture trains quickly. With 98% accuracy, our method is incredibly successful. To compare our system to existing classifiers to test its performance. We developed a complete system for segmenting and predicting cancer-related blood abnormalities, exceeding current methods. Based on the results, deep learning approaches have the potential to enhance blood cancer diagnosis and therapy by achieving high detection accuracy. The study also highlights this field's future directions. However further study is required to create more accurate and reliable models for therapeutic use.

Keywords: Blood Disorder, Deep Learning Techniques, Blood Sample Images, Classification, Convolutional Neural Network.

INTRODUCTION

The body's primary defense against infections and illnesses caused by external pathogens including bacteria, viruses, and fungus is comprised of white blood cells, also known as leukocytes. These blood cells are carried via the circulatory and lymphatic systems after being produced in the bone marrow [1]. Blood is another source of plasma [2]. Red blood cells carry oxygen from the lungs to the body's tissues, and vice versa. White blood cells are used by the body to fight infections and diseases. Platelets control bleeding and blood clotting. Leukemia causes immature white blood cells to multiply rapidly, which stops the remaining blood cells usually platelets and red blood cells from developing [3]. The following **Error! Reference source not found.**. Shows Sample blood sample.

Based on the rate of cell replication, acute and chronic leukemia are distinguished from one another. In acute leukemia, abnormal blood cells

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that are malfunctioning are frequently young cells, or immature blasts. These are rapidly growing cells. Acute leukemia quickly deteriorates if treatment is delayed. In addition to producing immature blood cells, chronic leukemia also creates mature functional cells [4][5]. In chronic leukemia, blast development is slow. The sickness takes longer to get worse. In this study, the literature review in Section II provides background information on prior studies, while the methodology section in Section III describes the suggested methodology and procedure. In section IV, the outcomes of the proposed technique are presented together with a comparison with previous approaches and methodologies. A review of its prospects for further advancement and improved reliability comes to a close with this study.

Literature Survey

Smear Blood Images for Machine Learning-Based Leukemia Detection and Classification. In this study, offers a complete and well-organized summary of the state of all known machine learning (ML)-based leukemia detection and classification models that analyze PBS images. Based on the average accuracy of machine learning approaches used to analyze PBS photographs for leukemia, machine learning might produce amazing outcomes when used for the detection of leukemia in PBS images. When it came to identifying distinct leukemia cases, deep learning (DL) outperformed all other machine learning (ML) algorithms in terms of sensitivity and accuracy. Leukemia detection using machine learning and microscopic image analysis. The machine learning technique Faster-RCNN is used in this work to predict the probability of the development of cancer cells [6]. To detect similar blood items identifying the object, figure out the matching item, and determine the leukemia count depending on the matching object. A review of machine learning techniques for the detection and classification of leukemia disease. The authors of this study look at several machine learning and image-processing methods that are used to classify leukemia diagnoses to offer an overview of the findings that will be useful to other researchers [7]. Additionally, they attempt to focus on the benefits and drawbacks of related studies. The authors conclude that the leukemia illness may be categorized using a range of contemporary machine learning techniques.

The images used in this research are taken from the online public dataset from the Kaggle platform. There were two sections to this dataset. There were 4850 training photos in all, 2835 of which featured healthy people, and 2015 of which featured blood cancer patients. The resolution of these pictures was 256x256. Three proposed methods consist of the following:

Preprocessing.

Convert to RGB: All leukemia pictures are converted to the RGB color model during this step. Resize all to 227x227: Because each image was captured using a different device, each one has a different pixel scale. With this operation, all images will have a fixed dimension of 227x227 pixels. Next Data Augmentation will be applied.

Pre-Trained Deep Learning Model and Feature Extraction

Convolutional neural networks with transfer learning (AlexNet) were employed to train our model. Three different types of layers make up CNN's architecture: convolutional, pooling, and fully linked layers. The initial (convolutional)layer only learns low-level features. Increasing the layers will increase the features and the network will learn more specific training task patterns [8]. In our work, the pooling layer was employed to cut down on the number of features in the final data and to overcome the overfitting problem. Convolutional layers calculate the output by performing the activation function (rectified linear unit, ReLu).

Classification

The CNN is created to recognize patterns in two dimensions and is composed of layers of neurons. CNN employs three different types of layers: convolutional, pooling, and fully connected. Except for the input layer, our network has 11 tiers. An RGB color image with individual processing for each color channel is fed into the input layer [8]. The convolution network's first six layers are known as the convolution layer. In the first two convolution layers, a picture is subjected to 16 3x3 filters. The following Figure 1. shows the block diagram.

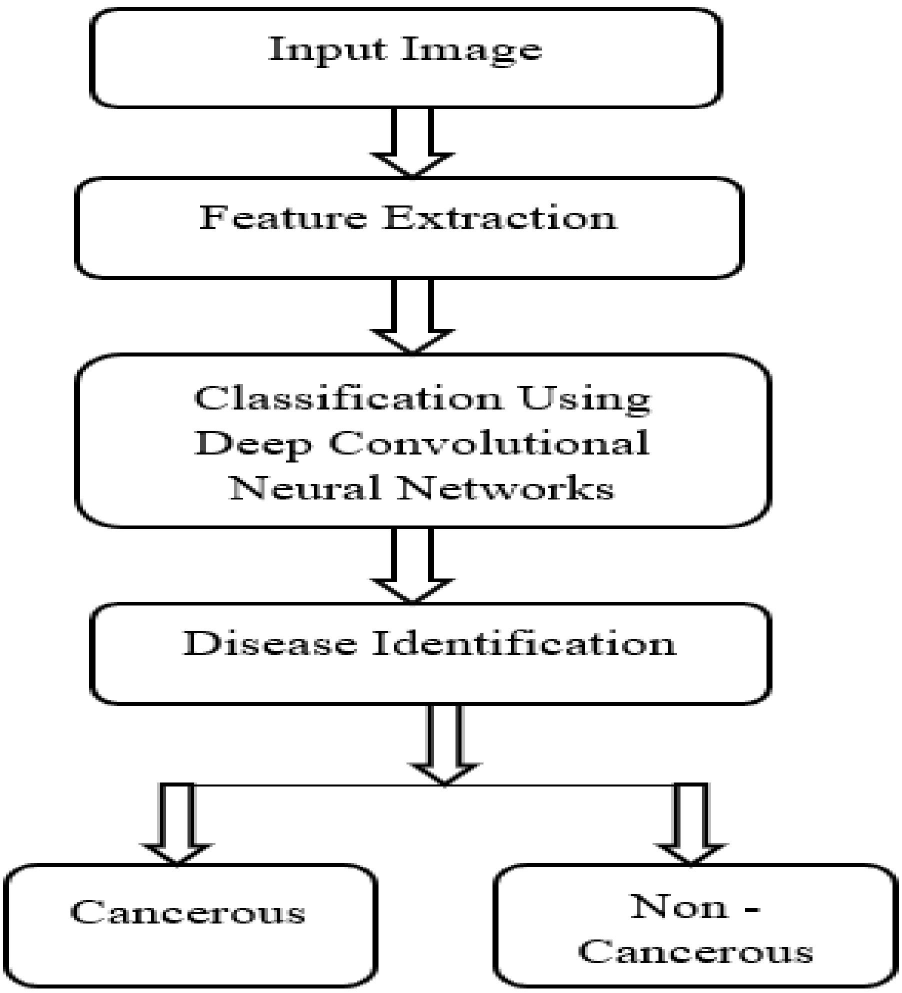

Figure 1. Block Diagram.

64 3x3 filters are applied to the picture on the last two convolution layers. In the nonlinear transformation sublayer, the ReLU activation function is used. Half of the image's size is lost as it passes through a 2*2 filter in the max pooling sublayer. For each of the 64 characteristics that the convolution network has retrieved thus far, a 32x32 array has been generated, one for each color channel. With the least amount of error in the two fully connected layers, we first train a convolution network using the data from the training set [9]. This process is continued until the convolution network has been trained for ten epochs. The performance of the convolution network is then assessed using the test set data [10].

Classification

Cancer blood disorder in microscopic blood samples is automatically detected using neural networks. Because the neural network technique is well known for being a classifier for most of the real-world scenarios, it is employed as a classification tool. To create a comprehensive process model utilizing DCNNs, the validation and training procedures are crucial. Using a feed-forward back propagation network, the DCNN model is trained and the correctness of the trained model is evaluated using a set of testing features [11].

Confusion Matrix

The effectiveness of a classification model is evaluated using a confusion matrix, often known as a table. The percentage of precise and imprecise predictions the model produced is shown in a matrix. The confusion matrix is frequently used in supervised learning contexts when the model is trained on labeled data and then used to create predictions on fresh, unlabelled data. The model's performance on this new data may be assessed using the confusion matrix. The statistics for true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) make up the confusion matrix. Whether the model anticipated the positive or negative class accurately or not determines these numbers. Using the confusion matrix, additional performance metrics like as accuracy, precision, recall, and F1-score may be computed to evaluate the model's effectiveness. For 1500 samples our model made the following predictions which shown in

.:

No of Predictions: 1500	Actual :Yes	Actual : No
Predicted: Yes	130(TP)	10(FN)
Predicted: No	10(FP)	1350(TN)

Table 1. Confusion Matrix.

- Accuracy = (TP+TN) / (TP+TN+FP+FN)
- Precision = (TP) / (TP + FP)
- Recall = (TP) / (TP + FN)
- F1-score = 2 * (Precision * Recall) / (Precision + Recall)

Results and Analysis

The application of deep learning and machine learning models for the identification of cancer blood disorders has been the subject of numerous studies. Although there is a lot of promise for the application of machine learning for cancer blood disorder detection, there are still issues that must be resolved, including the lack of readily available labeled data and the requirement for more reliable and understandable models. The below Figure 2 shows the color image and Figure 3 depicts Grayscale image

Deep Convolutional neural networks (DCNNs), in particular, have demonstrated promising outcomes in the detection of blood cancer. These models may identify characteristics in medical images (such as microscopic images of blood) and utilize those characteristics to categorize the images as cancerous or non-cancerous. In several studies, DCNNs have outperformed traditional machine learning models. Using the DCNN model provides efficient results with an accuracy of 98%. The following Figure 5 depicts a cancerous cell image and Figure 6 shows a non-cancerous cell image.

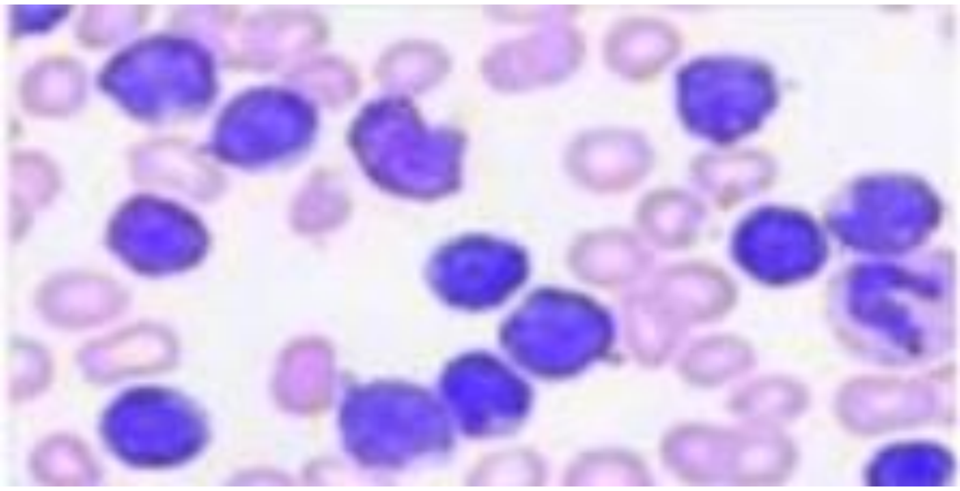

Figure 2. Color Image.

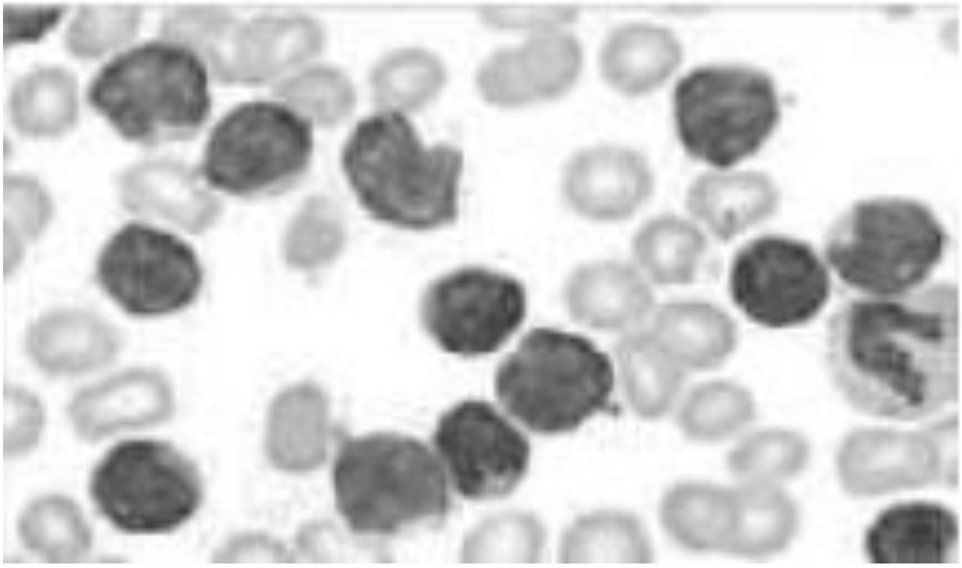

Figure 3. Grayscale Image.

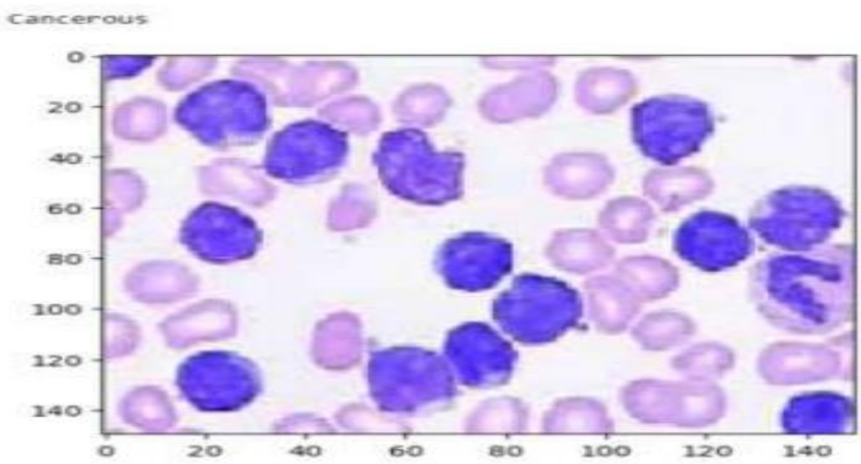

Figure 4. Cancerous Cell.

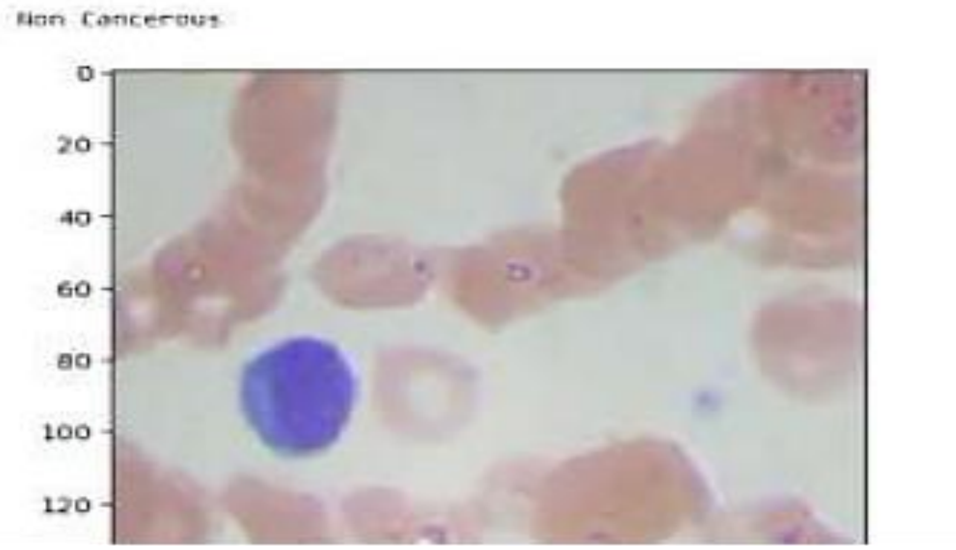

Figure 5. Non-Cancerous Cell.

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	0.768	0.7842	0.7236	0.8289
K-means Clustering	0.884	0.7945	0.7678	0.8367
DCNN	0.985	0.8820	0.8829	0.8920

The above **Error! Reference source not found.** shows the comparison of different features using different algorithms and approaches.

CONCLUSION

The application of computer-based methods for image processing allows for the categorization of. The system should be able to classify cancer blood disorders with high reliability based on pictures of microscopic blood samples. classification methods of cancer blood disorder identification need the time-consuming transportation of sample tissue to a facility for cancer diagnosis since cancer blood problem is a quickly spreading disease. Nonetheless, treating cancer blood disorders early on is probably going to increase cancer patients' chances of survival. Deep learning models provide fast and accurate results, which help with early detection and allow for low-cost diagnostics

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