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Hybrid Convolution neural Network and Graph Neural network for Detection of Leukocyte

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Abstract

In pathology and medical diagnostics, the identification of leukocytes, white blood cells essential for immune system function, is significant. The hybrid neural network model used in this study, which combines the strengths of convolutional neural networks (CNNs) and graph neural networks (GNNs), gives a unique method for the identification of leukocytes. Due to the intricate spatial and relational patterns visible in microscopic pictures of blood samples, leukocyte identification is difficult. The proposed hybrid model incorporates a GNN module to record the contextual associations among leukocytes in a blood sample and a CNN module to extract fine-grained characteristics from individual leukocyte pictures. Each leukocyte picture is seen in this paradigm as a node in a network, with the edges denoting the interactions between the cells' locations or contexts. While the GNN module uses graph-based representations to capture the connections and dependencies between leukocytes within a blood sample, the CNN module efficiently extracts local visual characteristics from leukocyte pictures. These two modules are used to produce a thorough and context-sensitive depiction of the leukocyte detection issue. The importance of this study resides in its potential to increase the precision and effectiveness of leukocyte identification in pathology and medical diagnostics, leading to better patient care and illness diagnosis. This hybrid CNN-GNN model may also be used for a variety of other medical image analysis tasks that call for taking both local and contextual information into account. In successfully identifying leukocytes in microscopic images, this hybrid CNN-GNN technique shows promising results. Accuracy, precision, recall, and F1-score are common assessment metrics used to assess the model's performance.

Keywords: Deep Learning, Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), White Blood cell, Image Classification.

I. INTRODUCTION

Leukocyte, or white blood cell, identification and categorization in medical images are essential tasks in pathology and medical diagnostics. The human immune system relies heavily on white blood cells to protect the body from illnesses and infections. For the proper diagnosis of a number of medical illnesses, such as infections, leukemia, and autoimmune disorders, leukocytes must be correctly identified [1],[2]. The development of automated techniques for the identification and categorization of leukocyte pictures has advanced significantly over time. The fusion of machine learning and deep learning methods, which have transformed medical image analysis, has been the driving force behind this development. These methods might improve leukocyte detection's efficiency and precision, enhancing patient care and disease diagnosis [3]. The growing accessibility of medical picture data and the unrelenting search for more precise and effective diagnostic techniques are driving the continued development of this discipline. Using a unique hybrid Convolutional Neural Network (CNN) and Graph Neural Network (GNN) technique, this article intends to enhance the state of the art in leukocyte image analysis as part of continuing efforts. This hybrid approach, which promises more developments in the field of medical image analysis, aims to use both local and contextual information for better leukocyte identification and categorization [4]. For precise disease diagnosis and patient care, leukocyte image recognition and classification are of utmost importance in the field of medical image analysis. The papers mentioned above show how machine learning and deep learning approaches have advanced significantly in addressing this important subject. These initiatives have opened the way for the creation of sophisticated automated systems that can process enormous amounts of medical image data in addition to laying the groundwork for more accurate diagnostic techniques. Neutrophils, lymphocytes, eosinophils, basophils, and monocytes are the different types of leukocytes that should be grouped. The many kinds of white blood cells (WBCs) are shown in Figure 1. This work introduces a unique hybrid CNN-GNN technique for the detection and classification of leukocyte images in an effort to advance the field of medical image analysis. The objective is to offer a more precise and contextually aware solution in line with the escalating requirements of the healthcare sector. By using this novel approach to tackle the challenges of leukocyte image interpretation, we hope to significantly enhance the field of medical science's continual search for more sophisticated diagnostic tools and better patient outcomes.

There are five sections in the paper's structure. The importance of leukocyte detection in medical diagnostics is described in the introduction. Leukocyte identification, machine learning, and deep learning approaches are covered in the literature review, which also identifies research needs. The hybrid CNN-GNN model's design, data preparation procedures, and particulars of the neural networks are covered in the methods section. In the fourth part, experimental findings are discussed with an emphasis on accuracy, precision, recall, and F1-score. This is followed by a discussion of the model's advantages and disadvantages. The conclusion, contributions, and prospective effects of the hybrid CNN-GNN model are included in the conclusion, along with recommendations for future research paths in cutting-edge neural network methods for medical image processing.

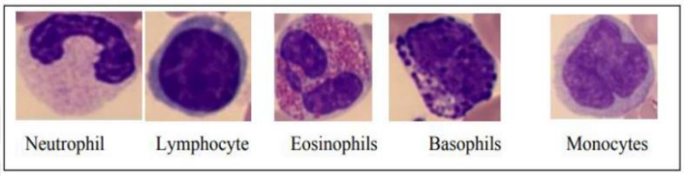

Figure 1 Types of leukocytes [1]

II. LITERATURE REVIEW

Recent years have seen substantial progress in the study of leukocyte identification and classification utilising various computational and deep learning approaches. With regard to identifying white blood cells (WBCs) and identifying disorders like leukaemia, this research seeks to improve the precision and effectiveness of medical diagnostics. The difficulties of leukocyte analysis have been addressed using a variety of approaches, including deep learning, picture segmentation, and machine learning algorithms. Additionally, the use of cutting-edge strategies like Graph Neural Networks (GNNs), Convolutional Neural Networks (CNNs), and YOLO (You Only Look Once) has created new opportunities for more precise and context-aware leukocyte identification. In this summary, significant studies and their contributions to leukocyte image analysis are highlighted. In [1] The goal of the study was to evaluate how well different deep learning techniques performed when used to automate the categorization of white blood cell pictures. The authors made significant contributions to our understanding of how various strategies function when used in the context of medical image analysis by contrasting them. The field of automated leukocyte categorization, a key element of illness detection and medical diagnostics, will benefit from the advancement of this effort. The authors offer a technique for accurately categorising medical photographs. The article probably covers the application of machine learning and image segmentation algorithms to improve the efficacy and accuracy of medical image categorization [3]. The application of several machine learning methods for the categorization of medical pictures is investigated by the authors. The work probably analyses several strategies and their efficacy in the context of classifying medical images, offering insights into how well certain algorithms function [5]. The authors outline a method for identifying peripheral leukocytes using deep learning techniques. The creation and use of deep learning models to automate and enhance the detection and categorization of leukocytes in medical images[6] are probably topics covered in the study. In [7], the authors provide a technique for the identification and categorization of leukocytes in photos of leukaemia that blends YOLO (You Only Look Once) with convolutional neural networks (CNNs) as shown in Figure 2. Most likely, this method covers the application of deep learning methods to automate the recognition and classification of leukocytes, especially in the context of leukaemia diagnosis.

In [8], the authors outline a technique for the quick and label-free separation of leukocytes using inertial and impedance cytometry. The use of this approach for profiling neutrophil extracellular traps (NETs) is also probably included in the study. In this work, a unique method for effectively separating and examining leukocytes and their extracellular components is presented. The application of machine learning approaches in the identification and categorization of leukemia using smear blood pictures is reviewed systematically by the authors in [9]. In order to provide insights into the efficacy of machine learning algorithms for leukemia diagnosis based on blood smear pictures, it is probable that the study summarizes and analyses the pertinent literature and research that has already been done in this area. The authors go through an approach for analyzing blood images in the context of leukemia that blends blob recognition techniques with deep learning. This most likely entails the use of image processing methods to locate and examine certain characteristics (blobs) within the pictures with the aim of enhancing leukemia diagnosis and comprehension. There are a huge number of researchers in this field the authors present some of the research as the comparison in Table 1.

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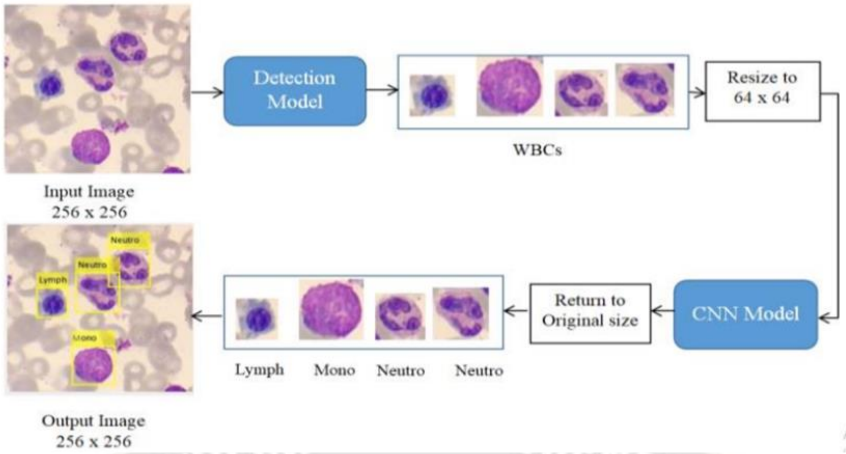

Figure 2 Visualization model process for detection images [7]

Reference	Method Used	Dataset	Types of Leukemia	Aim	Object
[1]	Deep Learning	Not specified	Not specified	Automated classification of WBC images	Leukemia detection using deep learning
[2]	Algorithm Evaluation	Not specified	Not specified	Classification of leukocyte images	Evaluation of classification algorithms
[3]	Image Segmentation & ML	Not specified	Not specified	Effective medical image classification	Medical image classification
[4]	Deep Learning	Not specified	Not specified	Detecting leukemia in real images	Leukemia detection using deep learning
[5]	Various ML Algorithms	Not specified	Not specified	Medical image classification	Medical image classification
[6]	Deep Learning	Not specified	Not specified	Peripheral leukocyte recognition	Leukocyte recognition using deep learning
[7]	YOLO & CNN	Not specified	Leukocytes	Detection and classification of leukocytes in leukemia	Leukocyte detection and classification
[8]	Inertial-Impedance Cytometry	Not specified	Leukocytes	Label-free leukocyte isolation and NETs profiling	Leukocyte isolation and NETs profiling
[9]	Machine Learning	Smear blood images	Leukemia	Detection and classification of leukemia	Leukemia detection using machine learning
[10]	Blob Detection & Deep Learning	Not specified	Leukemic blood images	Leukemic blood image analysis	Blood image analysis using blob detection
[11]	Not specified	Not specified	Vascular infections	Diagnosis of vascular infections	Diagnosis of vascular infections
[12]	Deep Learning	AML blood smear images	Acute Myeloid Leukemia	Feature extraction of white blood cells	Leukemia diagnosis using feature extraction

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[13]	Detection Transformer	Peripheral blood leukocytes	Leukocytes	Peripheral blood leukocyte detection	Peripheral blood leukocyte detection
[14]	CMYK-moment Localization & Deep Learning	AML blood smear images	Acute Myeloid Leukemia	Feature extraction of white blood cells	Leukemia diagnosis using feature extraction
[15]	Deep Learning	Peripheral blood smear images	Acute Leukemia	Feature extractor for leukemia diagnosis	Leukemia diagnosis using deep learning
[16]	Deep Learning	Not specified	Not specified	Automatic classification of WBCs	White blood cell classification
[17]	Blob Detection & Deep Learning	Not specified	Leukemic blood images	Leukemic blood image analysis	Blood image analysis using blob detection
[18]	Convolutional Deep Learning & SIFT	Not specified	Leukocytes	Detection of white blood cells using hybrid approach	White blood cell detection
[19]	Convolutional Neural Network	Not specified	White Blood Cells	Type identification of white blood cells	White blood cell type identification
[20]	Refractive Index Tomography & Deep Learning	Not specified	White Blood Cells	Label-free white blood cell classification	White blood cell classification
[21]	Deep Learning	Not specified	Erythrocytes and Leukocytes	Classification of erythrocytes and leukocytes	Erythrocyte and leukocyte classification
[22]	Deep Learning	Microscopic Images	Leukemia	Diagnosis of leukemia disease	Leukemia diagnosis using deep learning
[23]	Traditional Image Processing & Deep Learning	Peripheral blood smear images	White Blood Cells	Classification of white blood cells	White blood cell classification
[24]	Deep Learning (Squeeze and Excitation Learning)	Microscopic blood samples	Leukemia	Leukemia cancer detection in microscopic blood samples	Leukemia detection using deep learning

III. METHODOLOGY

For leukocyte identification in medical image analysis, notably in the field of pathology and medical diagnostics, the proposed approach integrates convolutional neural networks (CNNs) with graph neural networks (GNNs), offering a unique and cutting-edge method. Leukocytes are critical white blood cells required for the proper operation of the immune system, and this combination of CNNs and GNNs intends to solve the inherent difficulties and obstacles associated with precisely identifying them. In order to successfully categories these blood cell pictures into their respective categories, this model aims to develop a neural network architecture that blends convolutional neural networks (CNNs) and graph neural networks (GNNs). Figure 3 present the overall structure of the procedure, while Figure 4 shows the architecture of the hybrid model. The number of classes (four different cell types), the size of the input for the GNN module, and the image's dimensions (64x64 pixels with three color channels). The convolutional layers, max-pooling, and flattening steps of the CNN model are used to extract visual features from the input pictures. The GNN model, on the other hand, is a straightforward feedforward neural network that outputs class probabilities from a vector with a predetermined input dimension. In the end, a hybrid neural network model made up of both CNN and GNN modules is created. The GNN module processes extra data while the CNN module processes the picture data. The outputs from these two modules are combined and placed through more thick layers for processing.

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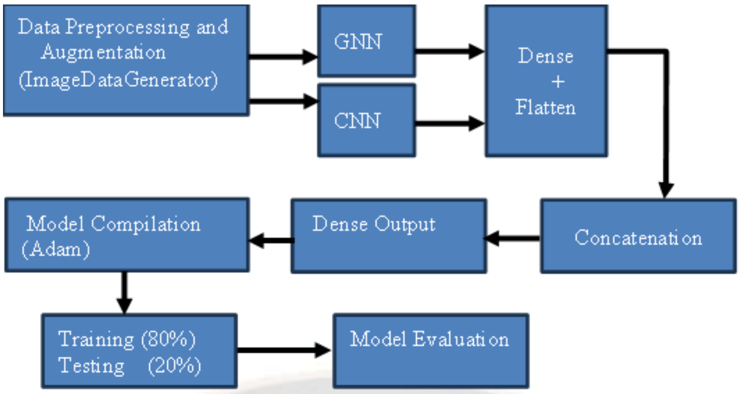

Figure 3 Procedure of the proposed hybrid CNN with GNN Model

The procedure of the hybrid model shown in figure 3 have the following steps:

- **Data Preprocessing and Augmentation:** Both CNN and GNN inputs are preprocessed and enhanced using ImageDataGenerator in the code. To normalize pixel values to the range [0, 1], rescaling is used.
- **CNN and GNN Components:** A CNN and a GNN are part of the architecture. Convolutional layers and max-pooling layers make up the CNN, which uses them to extract features. In this illustration, a thick layer is used to illustrate the GNN. Each component's output is represented by a distinct block.
- **Concatenation and Flattening:** The concatenation layer's input specifications are met by flattening the GNN output to match them. The outputs of the CNN and GNN are combined in the concatenation layer.
- **Dense Output Layer:** For classification, the concatenated features are then sent via one or more dense output layers, including one that uses softmax activation.
- **Model Compilation:** The Adam optimizer and categorical cross-entropy loss are used to construct the model.
- **Training:** Using unique data generators and the model.fit technique, the model is trained. There are several epochs in the training process.
- **Model Evaluation:** Using the model.evaluate method, the trained model is assessed against the test dataset.

Layer (type)	Output Shape	Param #	Connected to
conv2d_input (InputLayer)	[(None, 64, 64, 3)]	0	[]
conv2d (Conv2D)	(None, 62, 62, 32)	896	['conv2d_input[0][0]']
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0	['conv2d[0][0]']
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18496	['max_pooling2d[0][0]']
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0	['conv2d_1[0][0]']
input_1 (InputLayer)	[(None, 64)]	0	[]
flatten (Flatten)	(None, 12544)	0	['max_pooling2d_1[0][0]']
dense (Dense)	(None, 64)	4160	['input_1[0][0]']
concatenate (Concatenate)	(None, 12608)	0	['flatten[0][0]', 'dense[0][0]']
dense_1 (Dense)	(None, 128)	1613952	['concatenate[0][0]']
dense_2 (Dense)	(None, 1)	129	['dense_1[0][0]']

Total params: 1,637,633
Trainable params: 1,637,633
Non-trainable params: 0

Figure 4 The Hybrid CNN with GNN Model Structure

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IV. RESULT AND ANALYSIS

This collection includes 12,500 enhanced blood cell photos in JPEG format, along with associated CSV cell type descriptions for each image. Four distinct cell types—Eosinophil (2497 image for training and 150 images for testing), Lymphocyte (2483 image for training and 150 images for testing), Monocyte (2487 images for training and 150 images for testing), and Neutrophil (2499 images for training and 150 images for testing—are represented by these images, with over 3,000 images of each one arranged into separate folders. 410 original blood cell photos (pre-augmentation) with two subtype labels (WBC vs. WBC) and bounding box annotations supplied in XML metadata format are also included in the dataset. This collection is placed in the 'dataset-master' folder. The 'dataset2-master' folder also includes four extra subtype labels in CSV format and 2,500 enhanced photos, one for each of the four cell types. the use of CNN and GNN to construct a hybrid neural network model. For a computer vision problem, namely for picture categorization, this model was created. The blood cells in the dataset used for this work are supposed to be images of four different cell types: eosinophils, lymphocytes, monocytes, and neutrophils. The evaluation of the proposed model as shown in Figure 5 a confusion matrix.

	Predicted value			
Actual Value	**134**	**10**	**0**	**6**
		135	**10**	**5**
	0	**16**	**130**	**4**
	0	**15**	**0**	**135**

Figure 5 Confusion Matrix Of the Proposed Model

A crucial tool in machine learning and classification is a confusion matrix, commonly referred to as an error matrix. It is used to assess how well a classification method or model performs on a dataset with known real values (ground truth). The model's predictions and the data's actual class labels are broken down in great detail by the confusion matrix. True Positives (TP): The number of instances that were correctly identified as belonging to the positive class is represented by true positives. In binary classification, the expected or interesting class is often represented by the positive class. True Negatives (TN): The number of cases that were accurately identified as not being within the positive category are represented by true negatives. This is a term used in binary classification to describe occurrences that were accurately recognized as not belonging to the targeted class. False Positives (FP) are Type I errors that happen when a model predicts a positive class label but the actual class label is negative. These are situations that the model mistakenly categorizes as falling under the positive category. False Negatives (FN): Also referred to as Type II mistakes, false negatives happen when the model predicts a negative class label but the actual class label is positive. These are cases that the model mistakenly categorizes as not being within the positive class. Accuracy: The degree to which the model's predictions for all classes are generally accurate. Precision is the capacity of the model to accurately identify instances of a given class among all examples that the model predicted to belong to that class. Recall (Sensitivity): The capacity of a model to accurately identify examples of a given class among all real occurrences of that class. Specificity: The model's capacity to appropriately distinguish between examples that do not belong to a given class from all other instances that do not. The harmonic means of recall and accuracy, which strikes a balance between the two, is the F1-score. The result shown in table 2. It may learn how well your model is performing for each class separately by analyzing the confusion matrix and related metrics. You can also gain insight into potential areas for model improvement or fine-tuning.

Table 2 Accuracy, F1-Score, Recall, and Precision of Proposed Model

	(Class 1)	**(Class 2)**	**(Class 3)**	**(Class 4)**
Precision	**0.9301**	**0.8933**	**0.9286**	**0.9574**
Recall	**0.9571**	**0.931**	**0.963**	**0.9718**
F1-Score	**0.9434**	**0.912**	**0.9451**	**0.9645**
Accuracy	**0.9687**			

The presented result comprises multiple assessment measures for a 4-class classification issue, each of which sheds light on the effectiveness of the model. These metrics offer a thorough picture of the model's overall performance as well as how well it performs for each specific class. Particularly in a multi-class categorization context, they assist in determining the model's advantages and disadvantages. The table 3 shows the comparative result of the proposed model with related work.

Table 3 Comparative Accuracy result of the proposed model	
Models	Accuracy
CNN AlexNet [25]	96.06%
feature extraction used SVM [26]	93%
Proposed Model	**96.87%**

V. CONCLUSION

Convolutional neural networks (CNNs) and graph neural networks (GNNs) have been expertly combined in the proposed approach for leukocyte identification in medical image analysis. In pathology and medical diagnostics, leukocyte identification is crucial because of their crucial function in the immune system. In order to overcome the inherent difficulties in leukocyte identification, the hybrid model combines the strengths of CNNs for image data processing and GNNs for extra data processing. Data preprocessing, CNN and GNN components, concatenation, flattening, dense output layers, model assemblage, training, and assessment make up the hybrid model's overall architecture. This thorough technique guarantees that the model can accurately classify blood cell pictures into their appropriate subgroups. The 12,500 enhanced blood cell photos from four different cell types—eosinophil, lymphocyte, monocyte, and neutrophil—make up the training and testing dataset. A confusion matrix, which divides the model's predictions and actual class labels into True Positives, True Negatives, False Positives, and False Negatives, is used to evaluate the model's performance. Accuracy, Precision, Recall, Specificity, and the F1-Score are important assessment measures that offer information about the model's overall performance and its capacity to accurately categorise each class. Particularly the F1-Score achieves a compromise between recall and precision, making it an important metric in multi-class classification settings. The proposed approach outperforms existing approaches like CNN AlexNet and feature extraction paired with SVM, achieving an excellent accuracy of 96.87%, according to a comparative study with relevant work. The usefulness and promise of the hybrid CNN-GNN technique for leukocyte identification are highlighted by this discovery, which opens up the possibility of additional improvements in medical picture analysis and diagnosis.

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