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AUTOMATIC CLASSIFICATION OF LEUKOCYTES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

The human immune system's white blood cells (WBCs) guard against infection and shield the body from potentially harmful substances. WBCs are mainly composed of neutrophils, eosinophils, basophils, monocytes, and lymphocytes, each of which makes up a different proportion and has a particular job to do[1]. They differ in terms of texture, colour, size, and morphology. In order to count the different types of white blood cells as part of a complete blood count (CBC) test, which is used to assess a person's health, a clinical laboratory is typically used. Deep learning has enabled the fast and accurate classification of blood film images using a variety of algorithms. Detecting and classifying WBC kinds in blood is done automatically with computer assistance. This method attempts to classify WBCs using the latent features of their images. The methodology used in this system is Convolutional Neural Networks, a kind of ANN that is most frequently employed to analyse visual images.

Keywords: CBC, CNN, Eosinophil, Lymphocyte, Monocyte, Neutrophil.

Introduction

Multiple cell kinds and plasma constituents make up the specialized tissue known as blood. The tissues and systems of the body receive oxygen and nutrients from this vital fluid, which also transports them[6]. Waste products like carbon dioxide and ammonia are removed by the blood through its function. It also aids other biological processes such as oxygen transport, cell regeneration, clotting, body temperature regulation, and immunity[1]. The four vital biological components of blood are plasma, platelets, white blood cells (WBCs), and red blood cells (RBCs). RBCs typically make up between 40 and 50 percent of the overall volume of blood and transport oxygen from the lungs to all other vital tissues[1]. However, WBCs are also found in lymphatic organs in addition to blood. They are the immune system's first line of defense against external invaders, even though they only make up a small portion of blood volume—typically 1% or less in a healthy individual. In order to eradicate foreign proteins that are present in bacteria, viruses, and fungi, WBCs seek

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out, recognize, and bind to them. There are various varieties of WBCs, and each one contributes to various immune responses. Blood cell counts of WBCs can provide early warning signs of a number of potential abnormalities related to the number of cells in different WBC categories. Although WBC play a significant role in the body's immune system, a reduced WBC count can lead to blood cancer and many other disorders. Each type of cell plays a unique role in fighting infections or diseases. Neutrophils support the recovery of injured tissues and the eradication of pathogens. Severe blood diseases are brought on by excessive basophil levels. White blood cells known as eosinophils work to combat infection. Monocytes battle infections, eliminate dead or damaged tissues, and eradicate cancer cells, whereas lymphocytes combat bacteria, viruses, and cells that endanger their ability to perform their job[4,7]. Manual examination is challenging because the nucleus shapes, colors, and textures of these WBCs vary[7]. Making an early identification of likely diseases can be helped by calculating the WBC. Traditional methods for WBC-type detection are time-consuming and inaccurate, which increases the need for accurate methods for the rapid and exact analysis of WBC[3]. There are now several machine learning methods that can determine the type of WBC from microscopic pictures. Convolutional neural networks (CNN) were used in one of the studies. These machine learning methods analyze the morphology of the WBC types to categorize them.

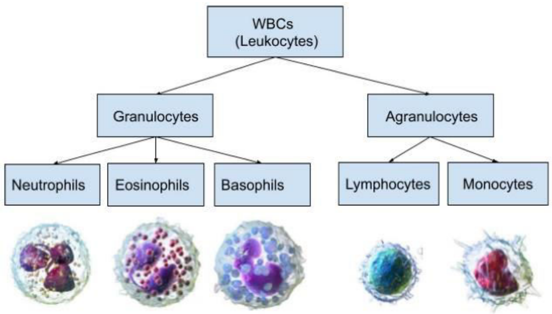

Fig.1. White Blood Cells Classification

Literature Survey

In the past, several machine learning techniques were used for blood cell classification, which were often difficult and time-consuming[7]. However, with the recent advancements in Convolutional neural networks (CNN), the accuracy of image classification and segmentation has significantly improved[8]. As a result, CNN has emerged as a powerful tool in various fields such as natural language processing, video analysis, and image recognition[9].

[1] This paper builds a new CNN model dubbed WBCNet, which extracts all the features of microscopic blood smear images. The WBCNet consists of 33 layers hence the category of WBC can be quickly identified compared to conventional CNN model. In order to test this model, 20400 additional unlabeled images are chosen. Approximately 83% of the extra chosen images were correctly classified, but 20% of them were incorrectly classified.

[2] This study concentrates on the classification of various types of WBCs using a model created by fusing convolutional neural networks and

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recurrent neural networks. Given the limited discriminativeness of the global visual features, it is challenging to identify small objects, and the CNN-RNN hybrid architecture performs better than CNN alone in about 6% of cases.

[3] For the four categories of WBC cell classification, the study assesses a multi-level CNN model. At the first level, a Faster R-CNN is used for detection, and Mobile Net, a CNN-based architecture, is used for cell-type categorization at the second level. This algorithm had an accuracy rate of 98.4%.

[4] In this paper, the authors proposed a model to detect the WBCs and then to classify the WBC into its subtype, using an appropriate algorithm in conjunction with a digital camera and microscope. This model has an of 90.62% but used a small dataset of 85 images. In addition, each parameter must be manually assigned to the segmentation technique.

[5] The authors proposed a method for classifying using the CNN algorithm at WBC. On the Kaggle WBC images dataset, they put the suggested technique to the test, and they were able to achieve an accuracy of 98.55%. Used publicly available dataset for state-of-the-art comparison with other research works and a smaller number of epochs for training.

[6] The categorization of leukocytes in this study uses a Pattern Net-fused Ensemble of Convolutional Neural Networks (PECNN). The design combines the results of CNNs that were generated at random. The main drawback of this model is that it takes more computational time.

Problem Identification

Traditionally, classifying blood cells has been a difficult and frequently time-consuming procedure[3]. Medical technologists physically count the patient's blood cells while examining a slide that had been made with the patient's blood sample under a microscope[2][5]. A hand count will also reveal details about additional cells that are not typically found in peripheral blood but may become active in certain diseases. Unfortunately, individual operator skills have a significant impact on how accurately cells are classified and counted. The identification and differential counting of blood cells is a particularly tedious and repetitive task that can be influenced by the operator's accuracy and fatigue.

Usually the percentage of erythrocytes (RBCs) in blood smears is always greater than that of leukocytes. One to three leukocytes would be present in a picture of about 100 erythrocytes[6]. The primary significant or essential factors with regard to haematology exams in a laboratory setting are the detection of blood disorders, the white blood cell amount as well as the red blood cell count. It is a difficult job to locate, identify, and count these cells. As a result, an automatic system is absolutely necessary for these processes. Because they are linked to numerous diseases, leukocytes are more important clinically than erythrocytes. In

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order to determine whether an illness is present in the human body, the appropriate differentiation of these cells is used.

Methodology

The initial step is to collect image data from the BCCD dataset. Following that, the data is pre-processed to ensure its suitability for training the CNN model. Pre-processing activities include image rescaling, reshaping, and array conversion. Training comprises 80% of the information, and testing comprises the remaining 20%. The training dataset is used to optimise the parameters of the model. The training dataset is fed into the CNN model[5]. The testing dataset is then used to evaluate how well the model predicts the future. After the model evaluation, the model can be deployed and can be used to work on other images.

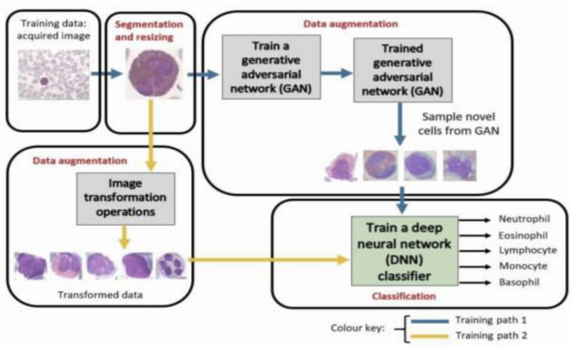

Fig.2. Proposed Methodology

A. Convolutional Neural Networks (CNN)

The neurons in convolutional neural networks have learnable weights and biases, just like in the ordinary neural networks from the prior chapter. Every nerve takes in multiple inputs, weights the total of those inputs, then sends the result through an activation function to produce an output. The better performance of convolutional neural networks with inputs such as images, speech, or audio signals sets them apart from other neural networks. They consist of the following four layers:

- Convolutional layer
- ReLu layer
- Pooling layer
- Fully-connected (FC) layer

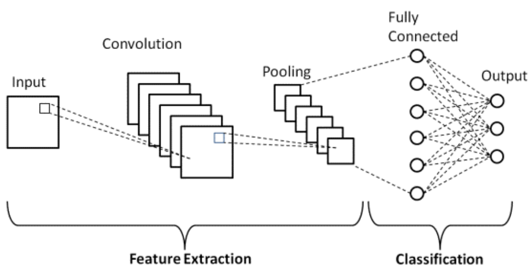

Fig.3. Basic CNN Architecture

i. Convolutional Layer:

The layer of convolution is the central component of the CNN algorithm along with it's here that the bulk in calculation takes place[10]. It needs raw data, a filter, and a feature map, among other things. A color picture made up of a three-dimensional pixel matrix will be used as the input. As a result, the data being provided will have the following parameters: length, breadth, and broad terms, which are equivalent to RGB in an image's format. Additionally, we have a feature detector, also referred to as a core or organize, which will travel throughout the receptive fields of an image and determine whether an attribute is present. Convolution describes this procedure[11].

ii. ReLu Layer:

Rectified Linear Unit (ReLu) is a trigger function that only starts a node if its value exceeds a predetermined threshold Otherwise, the outcome is zero. However, the connection between the data input and the variable of interest becomes linear once the input goes above a particular boundary[10]. The primary goal is to clear the convergence of every adverse value. All of the benefits stay identical, but zero is substituted for every lower one.

iii. Pooling Layer:

The key objective is to clear the convergence of every adverse value. All of the benefits stay identical, but zero is substituted for every lower one. In contrast, the result matrix is filled by the kernel using an accumulation function applied to the numbers in the field that is open. The combination generally comes in two flavors:

- Max pooling: The one with the highest value is chosen by this filter to be sent to the result array as it travels throughout the input stream.
- Average pooling: The mean amount within the field of reception is determined as the filter moves across the input, and it is then sent to the output array.

iv. Fully-connected (FC) layer:

Each cell in each layer below it is connected to every neuron in the completely connected layer. Based on the characteristics that were extracted from the prior levels and their various effects, this layer conducts the labeling task.

Implementation

A. Data Collection:

The BCCD blood cell dataset was used. 9957 pictures from 4 different classes, including "EOSINOPHIL", "LYMPHOCYTE", "MONOCYTE," and "NEUTROPHIL," are included in this dataset[5]. The dataset needs to be pre-processed because it is raw and cannot be utilised directly in the model.

B. Data Pre-processing:

Raw data is transformed into a format appropriate for model training during pre-processing. First, libraries like NumPy, Pandas, Matplotlib, TensorFlow, and Keras are loaded. In order to optimise the model's parameters and assess the precision of its predictions, The training set comprises 80% of the dataset, while the testing set comprises the remaining 20%. The training dataset is subsequently subjected to a number of transformations, including rescaling, reshaping, and array conversion, in order to guarantee or enhance performance, and transformation is applied to each image in the dataset.

C. Model Training:

To generate an output prediction, the CNN processes the incoming image layer by layer. The error is calculated by comparing the output prediction to the dataset label and is propagated backwards through the network. This entails computing the error gradients with respect to the weights and then using these gradients to update the weights. The preceding steps are repeated for a predetermined number of epochs or until a stopping criterion is reached. The

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weights are updated after each epoch to further reduce the error. After training, the model is evaluated on a test set to see how well it performs on new data. Particularly when working with large datasets and complicated models, the training process can be long and computationally demanding. Yet, it is feasible to enhance the training procedure and attain high accuracy on a specific job by modifying the architecture, hyperparameters, and optimization techniques.

D. Classification:

Following training, the model is capable of classifying unlabelled images of blood cells. When an image is fed into the model, it compares the extracted features with those of the training and testing images and generates an output specifying the WBCs subtype.

Results

This study highlights the significance of White blood cell classification.

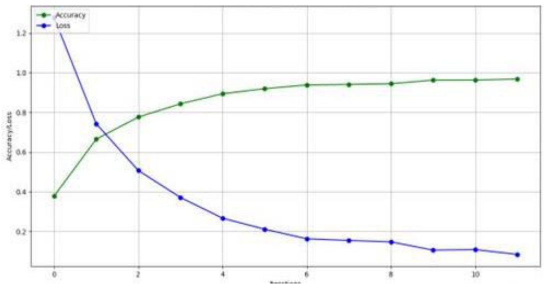

Fig.4. Accuracy and Loss Graph

The x-axis in the graph above shows EPOCH/iterations, and the y-axis shows accuracy/loss numbers. There are 12 epoch and at each epoch CNN accuracy get increased and loss value get decreased which means at each layer, CNN model gets better and better.

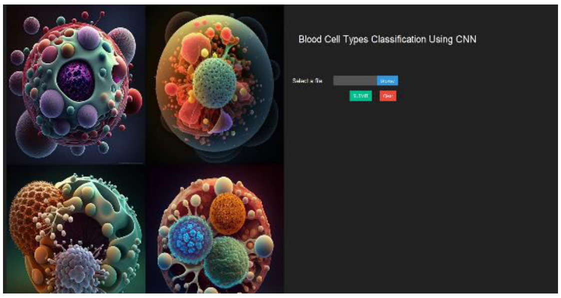

Fig.5. Image Upload Page

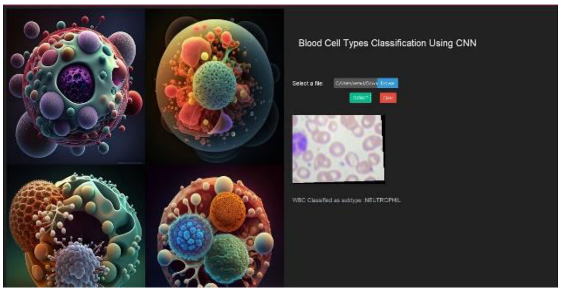

Fig.6. Output Page

Conclusion

White blood cells are critical components of the defense system protecting the organism from illnesses and foreign objects. The significance of WBC classification is illustrated by the fact that WBCs are divided into various types, and that abnormalities in one type of WBC may indicate a disease. It takes a lot of time and energy for specialists to manually classify blood cells visually. It has been effectively proven that the technique discussed below is capable of categorizing various types of lymphocytes using CNN with an accuracy of 96.7%.

Future Scope

The next stage of creating a computational method for the WBC classification is to extend the model to categorize multiple white blood cells in a single image. This step presents a very interesting avenue for future research because it would involve incorporating both classification and image segmentation techniques into the model. The identification of abnormal white blood cells is another area for future research because, in addition to the four main WBC types, the presence of abnormal WBCs also has medical value for aiding doctors in patient diagnosis and treatment. The end result of combining these research paths is to create an online application that enables medical professionals to upload an image of a stained blood smear, which can be prepared domestically before a patient sees their doctor, and receive the results of the WBC count and WBC differential by the time the doctor meets with their patient. If accomplished, this would be just another example of how computer modelling may enhance healthcare and patient outcomes.

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