Neural Networks for White Blood Cells Classiﬁcation

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***Abstract* - White blood cells, or leukocytes, are essential to human health because they strengthen immunity and fight infectious diseases. White blood cell categorization is essential for diagnosing disorders in humans. It can help identify illnesses that are brought on by immune system abnormalities, including as infections, allergies, leukemia, cancer, anemia, and acquired immune deficiency syndrome (AIDS). With the use of this classification, hematologists will have an easier time identifying the underlying causes of illnesses and differentiating between the many varieties of White Blood Cells found in the human body. In this topic, numerous studies are now being conducted. Given the importance and enormous potential of WBC classification, deep learning techniques like Convolutional Neural Networks (CNN) models like AlexNet and VGG19 will be used.**

***Index Terms – White Blood Cell Classification, Neural Networks, Classification Techniques, Convolutional Neural Network.***

I. INTRODUCTION

The sort of cell that is mostly present in blood that is created during hematopoiesis is called a blood cell. It is sometimes referred to as a hematopoietic cell, hemocyte, or hematocyte. Leukocytes, platelets, or thrombocytes, and erythrocytes, or red blood cells, are the three main types of blood cells. The blood's liquid component, plasma, makes up the remaining 55% of the blood tissue volume, with these three types of blood cells making up 45% of it. Numerous biological processes depend heavily on cell shape, which directly affects human health. Specifically, examining this feature of blood cells can aid in the provision of crucial data that aids in the diagnosis of certain illnesses or pathologies, such as hemolytic anemia inherited by autosomal recessive inheritance, melanocytic anemia (also known as sickle cell anemia), and variable, persistently severe anemia.

One important duty in image processing applications is AUTOMATIC segmentation. Acute lymphoblastic leukemia (ALL), acute myeloid leukemia (AML), and sickle cell anemia (SCA) all require it for identification, classification, and diagnosis, among other hematological disorders. Red blood cells (RBCs) with severe morphological abnormalities are caused by SCA. White blood cells (WBCs) are impacted by AML and ALL, though. Therefore, the diagnosis of hematological illnesses heavily relies on the examination of cell shape.

Cell segmentation and manual counting take a lot of time and are genuinely more difficult tasks. The presence of noise, undesired cells, overlapped cells, and low contrast makes this task more difficult. However, automatic segmentation

improves the robustness, leading to more accurate diagnosis and treatment planning.

In order to carry oxygen to tissues through the microvasculature, red blood cells (RBCs) need to be extremely malleable. The ability of red blood cells to expand can be lost due to disease, aging naturally, or storage in blood bags. This may hinder the cells' ability to operate as planned. Numerous techniques have been devised to assess RBC deformability; yet, they necessitate specific tools, extended measurement durations, and highly qualified staff. We looked into the possibility of using morphological characteristics from single-cell microscopy pictures in conjunction with a machine-learning technique to forecast donor RBC deformability as a workaround for this issue.

We arranged the RBCs according to their degree of deformability using the microfluidic ratchet apparatus. A deep learning model is built to identify red blood cells based on features associated with their deformability using sorted and imaged cells. The deformability of individual RBCs was accurately predicted by this model with an average accuracy of 81 ± 11% across ten donors. The accuracy of the score was 10.4 ± 6.8% when comparing the deformability score of RBC samples generated using this model to the resultant value from the microfluidic ratchet mechanism.

Our work is significant because it shows that Deep learning applied to single-cell microscope pictures can be used to quantify RBC deformability, a trait that is typically not measured by imaging. Machine learning techniques are often created to automate human image processing. The ability to quickly measure RBC deformability using a typical microscopy system makes it desirable as well. This may make it possible to do RBC deformability studies as standard clinical evaluations.

Highly specialized cells called red blood cells (RBCs) help tissues breathe by removing carbon dioxide and delivering oxygen to them. Approximately every sixty seconds, 1,2 red blood cells travel throughout the entire circulatory system. The RBCs go through the microvasculature, which consists of capillaries as small as 2 μm in diameter, and the 0.5–1.0 μm diameter inter-endothelial clefts of the spleen.3,4 RBCs lose their capacity to flex easily as a result of disease, aging naturally, or storage in blood bags. This makes it easier for phagocytes in the liver and spleen to remove the RBCs from circulation.5, 6 Thus, it is extremely desirable to develop methods for evaluating donated red blood cells (RBCs) for use in transfusions of blood as well as RBC

deformability as a potential biomarker for diseases including hemoglobinopathies and malaria.

II. RELATED WORKS

Most of the research work is carried over as a classification problem. And some of the research works use neural networks to understand and analyze the model.

[1] Mishro presented a type-2 AWSFCM clustering method for brain MR tissue segmentation. The proposed method solves the problem of equidistant pixels by assigning bigger weights to the pixels that are closer to the expected decision border, combining them into a single cluster. The spatial data of the neighboring pixels is retrieved using the adaptive Gaussian filter; the filter's order decreases as the algorithm converges to the final cluster centers. In the presence of IIH and noise, a type-2 approach to membership value and cluster center calculation guarantees a more precise cluster center location than the conventional FCM clustering strategy. Moreover, more precise cluster centers are produced by the linguistic fuzzifier's fuzzy value (M) acquired use of the α-plane representation. By utilizing intuitionistic fuzzy set theory, a better intuitionistic FCM (IIFCM) clustering method is developed. A lower value of β yields better results, but more iterations are required to get there. Measures of Euclidean distance may not fairly account for underlying causes.

[2] Das proposed an effective technique for differentiating between healthy and diseased (ALL) lymphocytes. The suggested CLAHE successfully raises the image's contrast level while enhancing its quality. Leukocytes are then extracted using color-based k-means clustering. The process to extract texture features makes use of GLCM and GLRLM. Furthermore, it highlights the importance of extracting color and shape data. Ultimately, Support Vector Machines (SVM) with RBF kernel are used to separate WBCs into healthy and ALL-affected cells. The advantage of this work is that Principal Components Analysis, a feature reduction method reduces the feature for better classification. And drawback of this research work is that the Support Vector Machine takes more time to classify images.

[3] Das released a survey piece with a lot of advantages. The review's main goal is to provide a summary of the methods described in the literature for improving, segmenting, extracting properties from, and classifying images of red blood cells in order to identify sickle cell illness. Examined are the advantages and disadvantages of the most recent techniques. It is essential for the diagnosis of sickle cell illness as well as the overall therapy strategy. It could offer a deeper comprehension of the investigation of cutting-edge methods. These methods are quantitatively examined using a variety of performance metrics, including AUC, F1 score, J score, sensitivity, specificity, accuracy, and precision. This work has the benefit that the topological variation can be managed by the set technique over active contour. A significant disadvantage of common statistical mixture models, such as hidden Markov random fields and GMM, is their computational complexity.

[4] Zafari presented a technique that makes use of radial symmetry to divide several objects in silhouette photographs

that have roughly elliptical shapes and partially overlap. Three steps make up the suggested method: elliptical fitting for contour estimation, edge-to-seed point correspondence for extracting contour evidence, and Bounded Erosion and Quick Radial Symmetry Conversion for seed point extraction. Two real-world application datasets and one artificially generated dataset were used in the investigations. All datasets demonstrated that the suggested segmentation method and seed point extraction strategy outperformed the competing techniques, achieving high detection and segmentation accuracies. Particularly in models with many parameters, the computational cost of the task limitation is frequently considerable.

[5] As recommended by Prasad, this study employed a novel technique for elliptical fitting that is based on the geometric separation between an ellipse and a data point. The suggested approach divides the elliptical fitting mathematical issue into two operators, resulting in a non-iterative, numerically stable, and non-constrained optimization procedure overall. Even with extremely noisy data points (Gaussian noise for positive test results may be as high as 20%, while for negative test results, it may be as high as 30%.), the method's selectivity is higher than most current methods because the model is based on the geometric distance rather than the elliptical algebraic equation.

[6] Gonzalez-Hidalgo put forth a strategy for counting the amount of elongated and normal cells that make up a cell group. The approach is fully automatic and makes effective use of ellipse adjustment for cell detection. Additionally, it integrates a novel method for effectively locating concave or convex points of interest inside a contour. We don't preprocess the photos in order to shorten the execution time. Because our method can identify legitimate ellipses based on the stated criteria and has an effective point-of-interest detection method, the results are excellent. Circumference adjustments taking into account the new limitations and point-of-interest detection approach were used in trials to compare the performance with previously proposed methods.

[7] In addition to being affordable and simple to use, Tareef's MPFW approach can surpass the most advanced segmentation approaches. This effort attempted to expand the goals to encompass the application, speed, and simple implementation of the system. While there has been substantial progress in the previous five years in overlapping cell segmentation from cervical cytology pictures, the primary goal of current techniques is to obtain excellent performance in nucleus and cytoplasm segmentation on selected datasets.

Hematologic diseases are blood-related conditions that affect red blood cells, platelets, lymph nodes, bone marrow, and spleen. Numerous problems can affect children; some are acquired, while others are hereditary. So, the watershed segmentation doesn’t detect the blood so it will yield subpar outcomes but improved segmentation. The ability of contemporary technology to differentiate between white blood cells (WBCs) and red blood cells (RBCs) in peripheral blood smear images is critical for the evaluation and diagnosis of several disorders, including infection, leukemia, and some

malignancies. Prior to the segmentation stage, images are often improved in quality using a variety of image processing techniques. Therefore, segmenting blood cells continues to be challenging. However, our approach separates red and white blood cells from blood smear images using a cutting-edge technique called deep learning semantic segmentation.

The proposed methodology captures the following key contributions to white blood cell classification:

 To identify every particle in a picture using a seed point is the primary goal of seed-point detection.

 Seed-point detection aims to accurately locate the cells in an image.

 To enhance the efficiency of this process, we plan to implement deep learning algorithms such as AlexNet, Resnet, and VGG19, which are variants of Convolutional Neural Networks (CNNs).

III. PROPOSED METHODOLOGY

The blood cell picture collection is used as input in the suggested system. The first step involves pre-processing the images, which includes resizing the original image and converting it to grayscale. Then, using the mean and standard deviation, features are retrieved from the pre-processed images. The photos are then divided into test and train sets, with the former being utilized for model evaluation and the latter for prediction. Following that, deep learning algorithms such as AlexNet, Resnet, and VGG19, which are variants of Convolutional Neural Networks, are implemented. The outcomes of the experiment show a number of performance indicators, including accuracy, loss value, and the capacity to identify or categorize distinct blood cell kinds. The planned work's process is depicted in Figure 1, along with the data flow for each stage.

the rest 1997 are used for model compilations' training purposes. The binary data is further processed for dimension expansion to increase the multispectral data dimensionality in a non-linear fashion.

*B. Convolutional Neural Network Model*

One type of deep learning technique that is particularly useful for commonplace tasks like object recognition and photo classification is convolutional neural networks. The CNN is composed of the following layers: input, pooling, fully connected, normalization, output, and convolutional. Convolutional layers apply several filters, each of which extracts a distinct pattern from the image. To put it simply, the image has little grids marked in it, each of which recognizes a different pattern. The pooling layer is further processed by reducing the dimension of the feature to obtain the most significant feature from the convolutional layer. In order to generate high-level representations and make predictions based on the features that have already been extracted, the fully connected layer is crucial. In order to avoid overfitting, the model is added with normalization layers and dropout layers. These layers either drop some neurons or normalize the layer by adjusting the activations to speed up and stabilize the training process. At last, an output layer is added with SoftMax prediction that predicts the possible outcomes, out of which output with a high probability score is considered.

A simple convolutional neural network (CNN) with two normalization layers, three max-pooling layers, three convolutional layers, and one fully linked layer, and one SoftMax layer is used in this investigation. Cross-entropy in binary and Adam's optimizer serve as the model's loss functions. The SoftMax layer is set to four due to four different classifications are performed.

*C. AlexNet Model*

Fig. 1 Workflow of Proposed Method

*A. Data Selection & Image Pre-processing*

The LISC dataset obtained has four different types of White Blood Cell Classification that include Eosinophil, Lymphocyte, Monocyte, and Neutrophil. All these images are stored in a separate directory. Image pre-processing is carried out in 2 steps that include resizing the images and color scaling of the images. The images are resized to 300x300 initially, then changed to 50x50 eventually. The resized images are converted to grayscale to get the binary data of the images. This binary data is then stored as separate data with labels as [0,1,2,3] referring to the four types. Out of the 2497 total photos obtained, 500 are used for testing purposes, while

A deep learning model called AlexNet is employed for sophisticated pattern recognition and computer vision. To produce predictions on photos, a CNN architecture has been updated. AlexNet is composed of two normalized layers, five convolutional layers, three max-pooling layers, two completely linked layers, and one SoftMax layer. All these layers perform as in a CNN model. This model uses SGD momentum as a learning optimizer. The overfitting in this model can be reduced by applying different formations on the same image. Increasing the size of the training dataset and using the original image to create a mirror image. Cropping the photos at random also aids in the model's analysis and prediction of the new features.

*D. Resnet Model*

The ResNet50 is another cutting-edge deep learning model that is a modified version of the convolutional neural networks. Additionally, object detection and image classification are done with the ResNet. Microsoft created the ResNet, also referred to as the Residual Network, in 2015. ResNet50 is a powerful model for image classifications and as per the name, the model is comprised of 50 layers. This model

is separated into four major parts that include identity blocks, convolutional layers, fully connected layers, and convolutional blocks. ResNet50 overcame the problem of vanishing gradient that is found in conventional CNN algorithms. Gradient-based optimization is the primary technique to train the neural networks on backpropagations. This became a problem when the gradients of the loss function along the weights of the initial layers were reduced to small values. As a consequence, a very small or no weight is updated during backpropagation which leads to stagnation.

A Sequential model is created with the ResNet model as a base. It is composed of a fully connected layer, two convolutional layers, a SoftMax output layer, three max-pooling layers, two normalization levels, and one additional layer.

training and testing records are shown in Figures 2a and 2b. The training curve and testing curve synchronize from a particular point, as Figure 2a illustrates. At epoch 3, both the curves obtained 99.43% of accuracy and tend to coordinate at the same points. Similarly, the same trend is found in Figure 2b at epoch 3 obtained the same 0.56% and coordinates further.

*E. VGG19 Model* Fig. 2a CNN Accuracy for 5 epochs, 2b CNN loss for 5 epochs

The Visual Geometry Group, or VGG19, is a 19-layer convolutional neural network that has been modified. Typical picture recognition and classification tasks also employ this approach. The VGG19 model gets its name from the fact that it consists of three fully linked layers and sixteen convolutional layers. We increased the number of convolutional layers to two in addition to the preexisting layers, adding three max-pooling layers, one fully linked layer, two normalizing layers, and one softmax output layer. The model utilized in this paper has an input shape of (50,50,3), the Adam optimizer, and the binary cross-entropy as the loss function.

IV. RESULTS AND DISCUSSION

The Training and Testing phases should be used to evaluate the models' performance. The accuracy and loss at both phases are plotted to understand the trend at each epoch. The graphical understanding of these models is observed. An analysis is conducted on the overall metrics of accuracy and loss for all four models.

*A. Dataset*

The proposed work uses the LISC dataset, a public dataset available from Kaggle. Hematological pictures from healthy participants' peripheral blood are included in the dataset. These photos were taken at the Imam Khomeini Hospital in Tehran, Iran's Hematology-Oncology and BMT Research Center. This dataset is comprised of 2497 images of four different types including 623 images for Eosinophils, 620 images for Lymphocytes, 630 images for Monocytes, and 624 images for Neutrophils. Every image has a resolution of 320 x 240.

*B. Analysis of the CNN Model*

The CNN model is trained using the input shape of (50,50,3), the optimizer of Adam, and the binary cross-entropy loss function. The model is tested over five epochs using the 500 test images. It was found that the model obtained 99.4% average accuracy and 0.64% average error loss. The accuracy and error loss at each epoch of both

Fig. 3a AlexNet Accuracy for 5 epochs, 3b AlexNet loss for 5 epochs

*C. Analysis of the AlexNet Model*

The AlexNet model is trained using the input shape of (50,50,3), the SGD optimizer, and the binary cross-entropy loss function. Throughout five epochs, the model is tested using the 500 test images. It was found that the model obtained 99.3% average accuracy and 0.68% average error loss. The accuracy and error loss at each epoch of both training and testing records are shown in Figures 3a and 3b. Figures 3a and 3b show that the training curve and testing curve both do not synchronize and tend to be in parallel. The training and testing do not exactly synchronize like the CNN algorithm, but they are almost parallel to each other with little deviation.

*D. Analysis of the ResNet50 Model*

The ResNet50 model is trained using the binary cross-entropy loss function, the SGD optimizer, and the input form of (50,50,3). The model is tested over five and ten epochs using the 500 test images. It was found that the model obtained 99.4% average accuracy and 0.64% of average error loss. The precision and error loss for the training and test data for each period are shown in Figures 4a and 4b. The training curve and testing curve synchronize from a particular point, as Figure 4a illustrates. At epoch 3, both the curves obtained 99.43% accuracy and tended to coordinate at the same points. Similarly, the same trend is found in Figure 4b at epoch 3 obtained the same 0.56% and coordinated further.

The ResNet50 is again trained for 10 epochs and an improvement in accuracy and reduced loss error is observed. The curves shown in Figures 4a and 5a clearly depict the improvement of the ResNet50 on more epochs. Consequently,

a 99.4% accuracy rate on average and a 0.57% error loss on average. The accuracy and error loss at each epoch of both training and testing records are shown in Figures 5a and 5b. The model is found to follow the same linearity of horizontal line even after epoch 5, which means the model does not learn more than this. And is only able to obtain an accuracy of 99% as the max outcome.

*E. Analysis of the VGG19 Model*

The VGG19 model is also shown to follow the same curve patterns for both accuracy and loss graphs, as illustrated in Figures 6a and 6b, similar to models such as CNN and ResNet50. It is found that this model achieves 99.4% accuracy and an average error loss of 0.64%. According to the ResNet50 which is trained for 10 epochs, we also found the same trend of no increase in accuracy even after 10 epochs of the VGG19 model is performed.

with minute differences in decimal points, which made it a tedious task to understand the nature of each model.

The only neural network that differed from others is AlexNet. As the lines of curves do not synchronize and tend to be in parallel, unlike other models. The accuracy of each algorithm at each epoch is depicted in Figure 7a showing a keen difference in the working of different models. The lines of CNN, VGG19, and ResNet50 are found to be similar. While the line curve of AlexNet is found to be contrastive even though it obtained an accuracy of 99%. A similar trend is observed in error loss curves also as shown in Figure 7b.

Fig. 7a Accuracy for 5 epochs, 7b Loss for 5 epochs for all models

Fig. 4a ResNet50 Accuracy for 5 epochs, 4b ResNet50 loss for 5 epochs

Fig. 5a ResNet50 Accuracy for 10 epochs, 5b ResNet50 loss for 10 epochs

Fig. 6a VGG19 Accuracy for 5 epochs, 6b VGG19 loss for 5 epochs

*F. Analysis of all the models*

A comparative analysis of different neural networks is carried out and their patterns and trends at each epoch are observed. The neural networks used in this work include CNN, AlexNet, ResNet50, and VGG19. All these models are modified versions of the conventional neural algorithm CNN. Though they share the same approach, they are comprised of different layers in between. We tried to understand how different sets of layers and different epochs impact the model’s growth. All these algorithms are found to be optimal and produced an average accuracy of more than 99% each

Fig. 8 Average accuracy of all the four models

Figure 8 shows that the CNN model has gained more accuracy compared to other algorithms and Figure 9 shows that the AlexNet has more error loss compared to other algorithms. By contradiction, CNN, ResNet50, and VGG19 are found to be more accurate even in both training and validation phases. While AlexNet is found to produce a high accuracy and reduced loss, but the training and validation phases don’t sync and tend to be in parallel. As a conclusion, AlexNet needs to be optimized so as to satisfy the training and validation trends like other algorithms. This work is considered as future work and more neural algorithms will be observed to analyze the trends and patterns at each training and testing epoch.

Table I depicts the accuracy and loss of each model after 5 epochs. And observed that AlexNet obtained a decimal-less score and more error rate compared to other neural networks. And other 3 models outperformed and obtained similar outcomes. It is evident from Figures 2a, 4a, and 6a, that the curves are smooth and Figure 3a is parallel for the AlexNet

model. Even though Table I values are closer, the curves show the difference in the performance of the model.

Fig. 9 Average loss of all the four models

TABLE I

**TRAINING SCORE AND LOSS OF ALL FOUR MODELS**

**Model** **Accuracy** **Loss**

Convolutional Neural Network 99.4% 0.64% AlexNet 99.3% 0.68% ResNet50 99.4% 0.64% VGG19 99.4% 0.64%

VI. SUMMARY AND NEXT WORKS

In this work, we suggest to compare multiple neural networks and document the techniques applied to training and testing at each epoch. The neural networks used in this research work include CNN, VGG19, AlexNet, and ResNet50. All these models are found to optimize a 99% accuracy with minimal difference in decimal points. It is also found even though AlexNet has obtained a 99.3% accuracy, its training and testing curves at the compilation do not coincide and the model does not synchronize as like other models. Hence, we conclude that other models tend to synchronize in both training and testing phases and are found to follow the same trend for more epochs. The CNN model is found to obtain a higher accuracy and AlexNet has obtained a higher error loss rate. This work can be extended to optimize the AlexNet and also include other neural networks to analyze their patterns and trends along the training and testing phases.

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