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WBC Detection and Classification using Optimization Deep Learning – A Review

Wasen Mohammed Najem, Nejood Abedyasir Ibadi, Ohood Ali Mohammed
Al-Diwaniya Technical Institute, AL-Furat AL-Awsat, Technical University

Annotation
One of the main components of blood is white blood cells (WBCs). These cells provide protection against organisms that cause infections, such as bacteria, viruses, and fungi. White blood cells come in five different varieties in the human body. Several names for these cells exist, such as neutrophils, eosinophils, basophils, lymphocytes, and monocytes. There are several conditions that might arise from an overly high or insufficient white blood cell count. There are four different White Blood Cell (WBC) classifications in the dataset of 12,500 JPEG photos : Eosinophil, Lymphocyte, Monocyte, and Neutrophil. Each class has more than 3,000 images. By selecting a collection of these images and analyzing the region of interest (ROI), the approximate color of the WBC has been determined. Using clustering algorithms, the obtained color was utilized as a centroid for image segmentation. A new segmented dataset was created by cropping the ROI bounding boxes. The results were gathered and trained using the CNN ResNet 50 model. The dataset was split between test and train sets in an 80:20 ratio. Following 25 epochs, the model's learning rate was 1.0000e-06, its accuracy was 0.9998, its validation accuracy was 0.9654, its validation loss was 0.1378, and its loss was 6.2305e-04. WBCs and specific types can be detected and recognised by the system.

Keywords: White Blood Cells, Image Processing, Machine Learning, CNN ResNet 50, Cell Classification.

1. Introduction

Human blood consists of blood cells and blood tissues, which make up 45% of the volume. The remaining 55% is plasma. Three types of blood cells have been identified: There are three types of blood cells: leukocytes that (white blood cells), erythrocytes (red blood cells), and platelets. White blood cells are divided into two types and occur in a variety of forms. Agranulocytes are composed of lymphocytes and monocytes, while granulocytes include neutrophils, basophils, and eosinophils.

White blood cells, or WBCs, are the immune system's security guards, protecting against bacterial and viral illnesses. A higher quantity of one of these white blood cell types indicates an infection, inflammation, soreness, or disease state. Each type of white blood cell has a specific defense role. For example, neutrophil cells treat infections and heal wounds, while eosinophils fight disease and combat viruses and germs.

picture processing involves converting a picture to a digital image and extracting important data from it. Image processing normally discusses all images as two-dimensional signals, using standard signal processing methods.

The process of transforming an image into a digital format and applying particular procedures to extract significant information from it is known as image processing. When using some predefined signal processing procedures, the image processing method often treats all images as two-dimensional signals.

A primary stage in various image and video applications is expressed by image segmentation techniques. This importance results from the segmentation technique's ability to identify regions of interest (objects). Greyscale, binary, or color images are the types of images used in the image segmentation process. Techniques for image segmentation include region growing, region shrinking, clustering, boundary detection, and morphological filtering.

Cluster segmentation is a method for achieving pixel-by-pixel image segmentation. This type of segmentation aims to create pixel clusters by assembling pixels with similar attributes. The segmentation by clustering process is carried out in two steps.

Machine learning enables computers to learn and access data automatically, improving user experience. It has made life easier and has developed into a crucial tool in many fields, including robotics, banking, agriculture, optimization, structural health monitoring, etc. It can be used with devices such as cameras to recognize patterns and objects in color images.

2. Literature Review

As a component of the cell classification process, recent research has proposed many techniques for blood cell image detection.Recent studies aim to identify and count three categories of white blood cells employing feature extraction and classification techniques. However, these methods are highly computational and designed for recognising specific cell types, as seen in the table below.

Table 1. literature Review

Ref No.	Pub. year	Study objectives	Software / Experiment / Theoretical	Conclusions
1	2021	Develop a system for detecting and classifying white blood cell subtypes using image processing and machine learning techniques.	utilize YOLOv3	Extensive experimental study reveals that the suggested work can classify with 90% accuracy and identify white blood cells with 99.2% accuracy. .
2	2021	Use object detection techniques to increase the categorisation effectiveness of white blood cells.	the Faster RCNN and Yolov4 based deep transfer learning models	96.25% and 95.75% accuracy percentages, respectively. Yolov4's one-stage model could detect at up to 60 frames per second while maintaining over 95% accuracy.

3	2005	Explain the concepts and the uses of image processing.	Theoretical study	The foundations of image processing and its uses in a variety of fields are covered in the book.
4	2001	Create an unsupervised technique for video and picture color-texture segmentation.	the JSEG algorithm	Images with complex colour textures can be effectively segmented using the suggested method.
5	2000	With an emphasis on applications in medical imaging, namely cardiac image processing and modelling, the article most likely attempts to investigate cutting-edge methods in pattern analysis and computer vision.	Experiment al study	Advanced image processing and pattern recognition methods can greatly enhance the analysis of cardiac images. Treatment planning and a better knowledge of heart problems are made possible by automated modelling techniques. AI integration in medical imaging improves the accuracy and effectiveness of diagnosis.
6	2015	Compare the picture segmentation clustering techniques K-means and Subtractive Clustering.	Experiment al study	The K-means algorithm performs greater than Subtractive Clustering in image segmentation.
7	2019	Use machine learning techniques to group together white blood cells.	6 different machine learning algorithms	The Multinomial Logistic Regression (MLR) algorithm fared better than the other methods, with an average test completion rate of 95%. The MLR can be used to automatically classify white blood cells.
8	2008	This study presents a smart device that simulates a human visual examination and distinction between the three types of blood cells.	Experiment al	The suggested approach successfully identifies blood cell types in spite of their unusual sizes, shapes, and orientations, according to testing data. This enables for the creation of a rotational and scale-invariant blood cell identification system that may be used to automate laboratory reporting in a quick, simple, and efficient manner.
9	2016	Create a morphologic and	mathematic	The suggested approach

		spectral categorisation system for white blood cells.	al morphology -based methods	outperforms conventional techniques in terms of classification accuracy by integrating both spectral and spatial data.
10	2020	Swarm optimisation of deep characteristics can be used to improve the categorisation of white blood cells.	Experimental study.	The outcomes surpass a number of convolutional network models and rank among the best obtained on these datasets. We anticipate that many additional image classification jobs may benefit from the combination of CNN feature extraction and SESSA feature optimisation.
11	2021	For feature selection and white blood cell categorisation, use an algorithm modelled after a bat.	Applied study	White blood cell classification is successfully accomplished by the suggested algorithm. With an accuracy of 97.69%, the suggested methodology chooses 11 features from a total of 35 features.
12	2020	Swarm optimisation of deep characteristics can be used to improve the categorisation of white blood cells.	Experimental study. Using SESSA	The outcomes surpass a number of convolutional network models and rank among the best obtained on these datasets. We anticipate that many additional image classification jobs may benefit from the combination of CNN feature extraction and SESSA feature optimisation.
13	2014	The fundamental science and art underlying the PBF are highlighted in this article. In light of different clinical illnesses, it broadens its clinical indications, laboratory uses, and interpretations.	Literature review.	For the haematologist, the PBF is still a crucial diagnostic test. The haematopathologist should guarantee a high-quality smear, a comprehensive examination, and an appropriate interpretation in accordance with the patient's clinical status.

14	1990	To find cerebral haemorrhage in CT scans, use convolutional neural networks.	Applied study	The fundamentals of image processing and its uses are covered in the book.
15	2019	offers a selection of two-dimensional image processing projects and algorithms.	Reference (book)	Advanced image processing techniques are presented in the book.
16	2021	Develop a Conflux LSTMs network for multi-view action recognition.	Experimental study using a pre-trained VGG19 CNN model	According to experimental results, the northwestern-UCLA and MCAD datasets have increased by 3% and 2%, respectively, as compared to benchmark datasets and state-of-the-art.
17	2019	Create a generative neural network that improves itself to support incremental learning in the classroom.	Experimental study SIGANN	The suggested network works well for incremental learning. With a median accuracy of 43%, SIGANN can identify new classes concealed in the data and move on with incremental class learning.
18	2019	The purpose of this work is to facilitate the use of convolutional neural networks (CNN) and deep learning algorithms for the detection of cerebral haemorrhage in computed tomography (CT) images.	Applied study	Haemorrhage can be detected with the use of convolutional neural networks. The suggested CNN networks achieve 98% F1 measurement, 97% recall, and 98% accuracy.
19	2017	Using machine learning and feature extraction techniques, examine the effects of a combination of several characteristics on aneurysm rupture rather than concentrating on a single factor at a time, as is commonly done in the literature.	Applied study	This study will be based on publicly accessible health statistics, meteorological data, and clinical and demographic information about patients at the Carlos Van Hospital who have been diagnosed with cerebral aneurysms.
20	2008	Analyze face images using convolutional neural networks.	Theoretical and experimental study.	With an error tolerance of 10% of the interocular distance, this method's detection rate is 96% for the AR database and 87% for the BioID database.
21	2021	Create a network of Conflux LSTMs to recognise actions	Experimental study	According to experimental results, the northwestern-

		in several views.	Using VGG19 CNN model	UCLA and MCAD datasets have increased by 3% and 2%, respectively, as compared to benchmark datasets and state-of-the-art.
22	2018	Describe the principles of neural networks and deep learning.	Theoretical study	The book covers the basics. of neural networks and deep learning.
23	2017	Give an initial explanation of convolutional neural networks.	Theoretical	The fundamentals and uses of convolutional neural networks are covered in the book.
24	2018	Introduce the key concepts of deep learning for computer vision.	Theoretical	The foundations of deep learning in computer vision are covered in the book. Several real-world case studies from computer vision provide an insight into the state-of-the-art in Deep Learning research.
25	2018	Explain deep learning and neural network concepts.	Theoretical	Neural networks are examined in this book from this contemporary angle. The book's chapters are arranged as follows.
26	2020	Examine the artificial neural network's activation functions.	Literature review	Neural network performance is greatly impacted by various activation functions.
27	2013	To forecast bridge scour, use a neural network with an adaptable activation function.	Applied study	When it comes to forecasting bridge scour, the neural network with adaptive activation works well.
28	2018	Examine convolutional neural networks' adaptable activation functions.	Experiment al study	Adaptive activation functions enhance neural network performance. Tests show that on benchmarks with different scales, the suggested activation functions outperform ReLU and its variations.
29	2020	the extension of a car-identification convolutional neural network (CNN.(	Experiment al study	These tests show how CNN generalisation is affected by changes in particular camera settings and image processing

				techniques.
30		the overfit controlling techniques and divides them into three groups: semi-active, active, and passive.	Experimental study	The paper highlights the distinctions between shallow and deep neural networks, offers a thorough analysis of overfitting control techniques, and illuminates current developments in the field. It can be an invaluable resource for machine learning practitioners and researchers.
31	2019	Examine how camera settings affect the generalisation of neural networks.	Experimental study	Neural network generalisation is greatly impacted by camera settings.
32	2019	Talk about the requirements for biological machine learning.	Literature review	There ought to be specific recommendations for using machine learning in biology.
33	2018	Give a succinct overview of computer vision deep learning.	Literature review.	In computer vision, deep learning yields encouraging outcomes.
34	2015	In order to speed up deep network training, implement batch normalisation.	Theoretical study.	Batch normalisation enhances deep network performance: surpass the accuracy of human raters and beyond the best publishing result on ImageNet classification, achieving 4.82% top-5 test error.
35	2019	Analyse white matter hyperintensities using automatic segmentation techniques.	Experimental study.	White matter hyperintensities can be effectively segmented using the suggested techniques.
36	2020	Build a temporal backpropagation algorithm for neural networks through pulses.	Theoretical and experimental study	The strategy suggested is a powerful way to train spiking neural networks.
37	2019	Examine the relative significance of optic disc traits for glaucoma and deep learning experts.	Applied study.	Experts in glaucoma can benefit from deep learning.
38	2019	Create a deep learning-based malware detection technique.	Applied study.	The suggested technique works well for identifying malware.

39	2018	Examine the significance of data augmentation in deep learning-based skin lesion classification.	Experimental study.	In conclusion, deep learning models perform better when data is supplemented. When compared to training with non-augmented data, the network that uses augmented data has performed better.
40	2012	Examine semi-supervised embedding in deep learning.	Theoretical study.	The performance of deep learning is enhanced by semi-supervised embedding. With competitive error rates when compared to current shallow semi-supervised techniques and deep learning approaches, this offers a straightforward substitute.
41	2017	Create a deep learning approach for optical flow estimates that is unsupervised.	Experimental study.	In conclusion, the suggested approach works well for estimating optical flow. promising outcomes on the benchmark datasets for KITTI, MPI-Sintel, and Flying Chairs. Our unsupervised approach performs better than its supervised learning-trained equivalent, especially on the KITTI dataset, which has a large number of unlabelled samples.
42	2015	For extensive convolutional neural networks, strengthen the arrangement of FPGA-based acceleration devices.	Applied study.	The proposed approach increases the performance of FPGA-based accelerators
43	2017	Create a convolutional neural network-based facial recognition technique.	Applied study.	The suggested approach works well for facial recognition.
44		Describe how convolutional neural networks use backpropagation.	Theoretical study.	One important technique for convolutional neural network training is backpropagation.
45	2020	presents a sophisticated transfer learning system that dynamically adjusts data distributions to improve model performance when	Experimental study Using MDDA & DDAN	Numerous tests show that MDDA and DDAN establish a solid baseline against the most recent deep and sophisticated

		knowledge is moved from a source domain to a target domain.		techniques in image classification, sentiment analysis, and digit recognition while also greatly enhancing transfer learning performance.
46	2020	how drug discovery procedures can be made more accurate and efficient by using transfer learning approaches, especially when there is a lack of or high cost for experimental data.	Experiment al study	A brief description of move learning and its current uses in the development of medicines is presented in this Perspective. It also offers insights on how transfer learning for drug discovery will advance in the future.
47	2019	We create a pretrained model library named XenonPy.MDL to enable the broad application of transfer learning.	Experiment al study.	Unlike nontrivial transferability across many qualities that transcend the several materials science disciplines, transfer learning has independently established transferability.
48	2021	We'll show off a hybrid mask-based detection model that mixes deep and routine machine learning.	Experiment al study	The stochastic support vector machine classifier's testing accuracy in RMFD was 99.64%. In LFW, it achieved 100% testing accuracy, and in SMFD, 99.49%.
49	2020	give a thorough examination of the various industrial areas in which deep transfer learning (DTL) techniques are being used for machinery fault diagnosis (MFD).	Applied study.	This supplies accurate guidance for identifying, constructing, or carrying down roots the deep transfer learning architecture in the field of machine failure diagnostics.
50	2020	Transfer educational objectives are for improving target learners' performance on target domains by spreading insight obtained from various but related source domains.	Applied study.	evaluating the efficacy among different transfer learning models; around 20 typical ones are used in the research projects.
51	2015	Using frequency-domain gait entropy characteristics and part-based analysis, this work sought to create a novel gait detection system with an emphasis on:	Experiment al study	In subject discrimination, time-frequency analysis-derived features performed better than conventional time-domain features. Compared to whole-body

				gait identification techniques, the accuracy was increased by 10-15%.
52	2015	This work offers a new image segmentation approach that combines texture analysis and boundary compression to improve segmentation of natural images.	Experiment al study	attains cutting-edge segmentation outcomes in contrast to other current techniques.

3. Experimental Model

This part presents the results of the suggested system. 12,500 photos were used to test and train this system. These pictures are a balanced dataset that includes four different WBC classes: neutrophils, monocytes, lymphocytes, and eosinophils. By calculating the percentage of each class in relation to the entire dataset, statistics have been performed to guarantee dataset balance. For certain photos, a histogram has been acquired in order to gain information regarding the colour of the target object. The picture segmentation technique has utilised the target colour as the cluster centroid. To create a fresh image for training solely on object features, the target segment has been clipped. The results of testing the entire suggested methods are listed below.

3.1 Case study

The plotting of several preprocessing picture techniques in order to provide explanations has been incorporated into the suggested method. Following the use of the training and assessment strategies, these techniques are detailed below.

3.1.1 Ensure dataset balancing

Making sure that the dataset is balanced is one of the crucial studies into each dataset. This is significant because it is necessary to calculate the accuracy for each class (per-class accuracy) if the data are not balanced.

Figure (4.1) explain the percent of class according to the dataset.

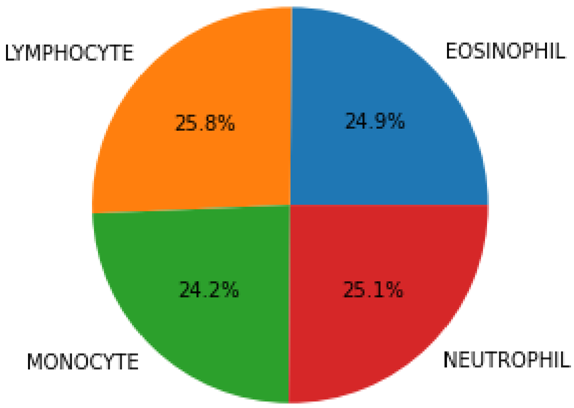

Figure (3.1) the percentage of each class according to the dataset.

3.1.2 Image Histogram

The image histogram is one of the mathematical examinations of an image that is used to give details about the distribution of colours in the image at that moment.. The image is displayed in figure (3.2), the image histogram is explained in figure (3.3), and the blue channel—the colour closest to the target object—is displayed in figure (3.4).

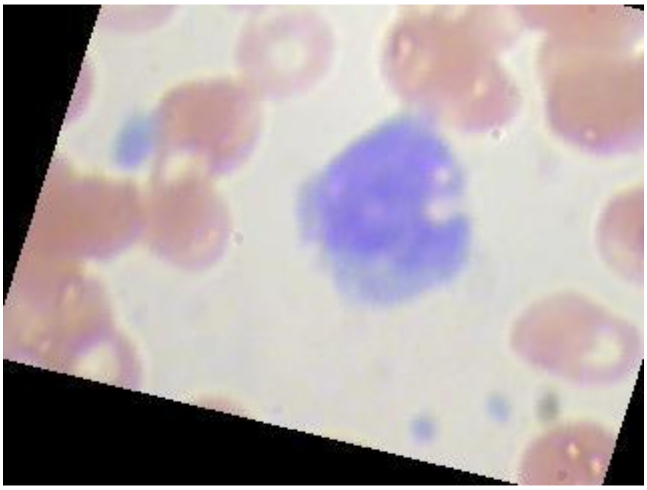

Figure (3.2) Row image from the dataset.

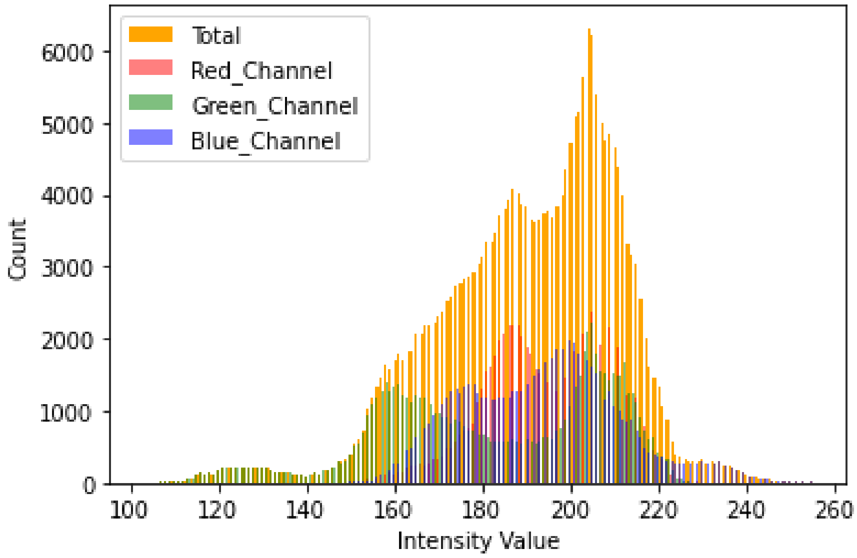

Figure (3.3) The histogram of the previous images.

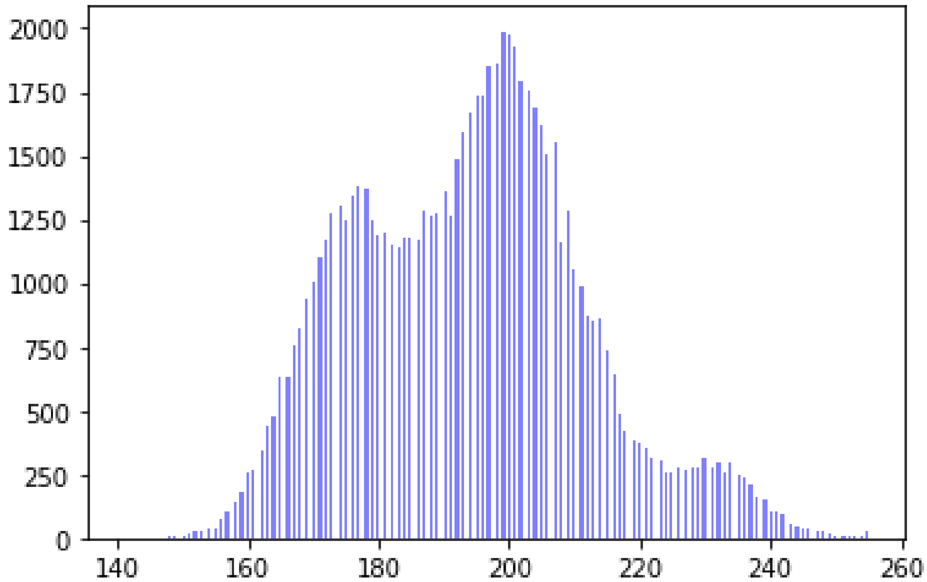

Figure (3.4) The blue channel of the histogram.

3.1.3 Image segmentation

The picture segmentation procedure has made use of the clustering technique. The blue channel of the histogram has been used to identify the cluster centroid. Figure 3.5 displays the segmented image along with the bounding box enclosing the white blood cell.

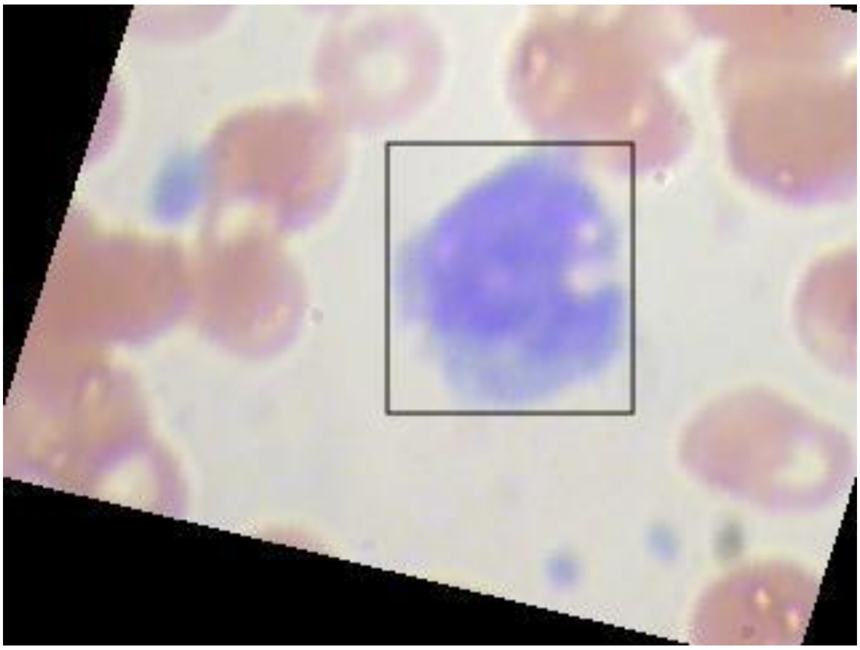

Figure (3.5) Image segmentation process by choosing the largest object.

Image cropping process used to extract the segmented area into a new image for the purposes of training. With black background without any features. Figure (3.6) shows the cropping technique.

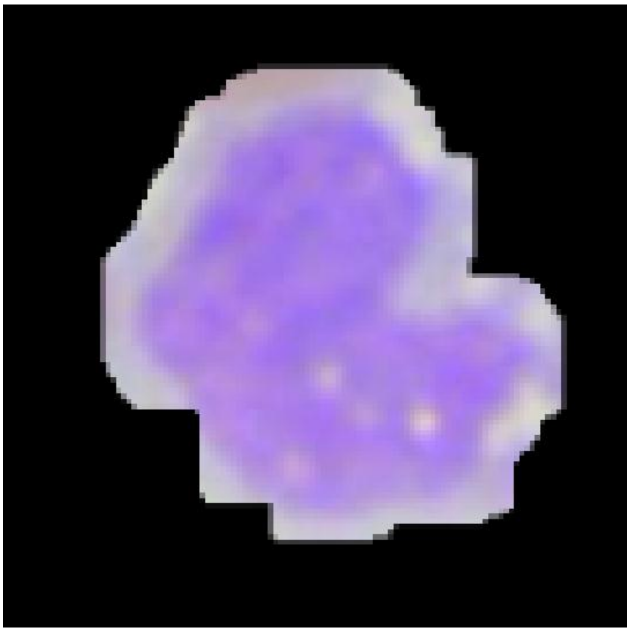

Figure (3.7) Cropping image.

Figure (3.8) shows the result of resizing the image into 120*120-pixel images.

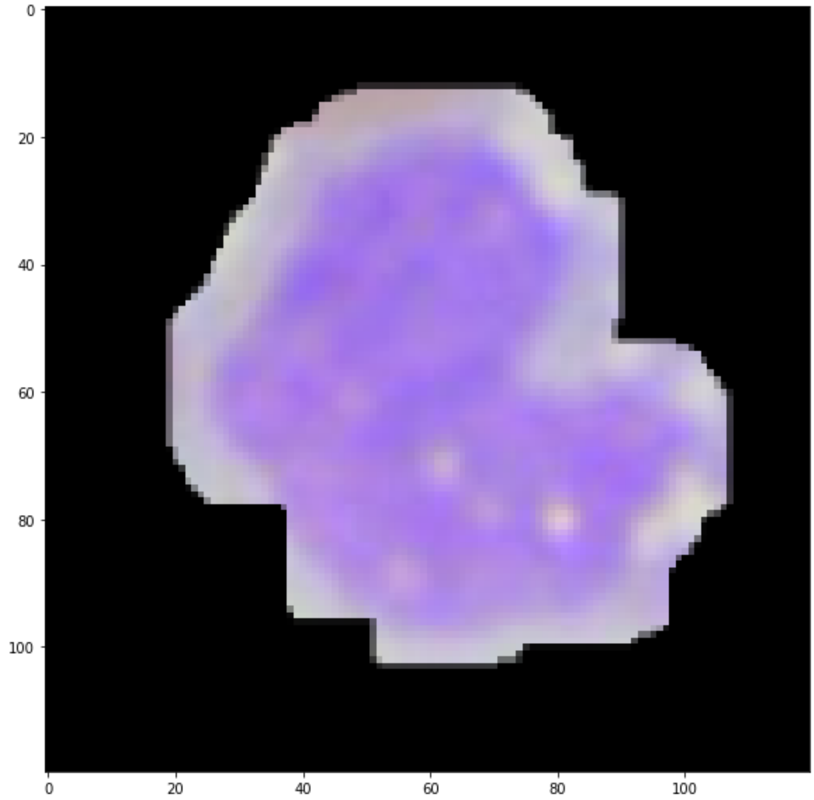

Figure (3.8) Resizing image to 120*120.

Preprocessing the images with the previous construct a new training set as shown in figure (3.9)

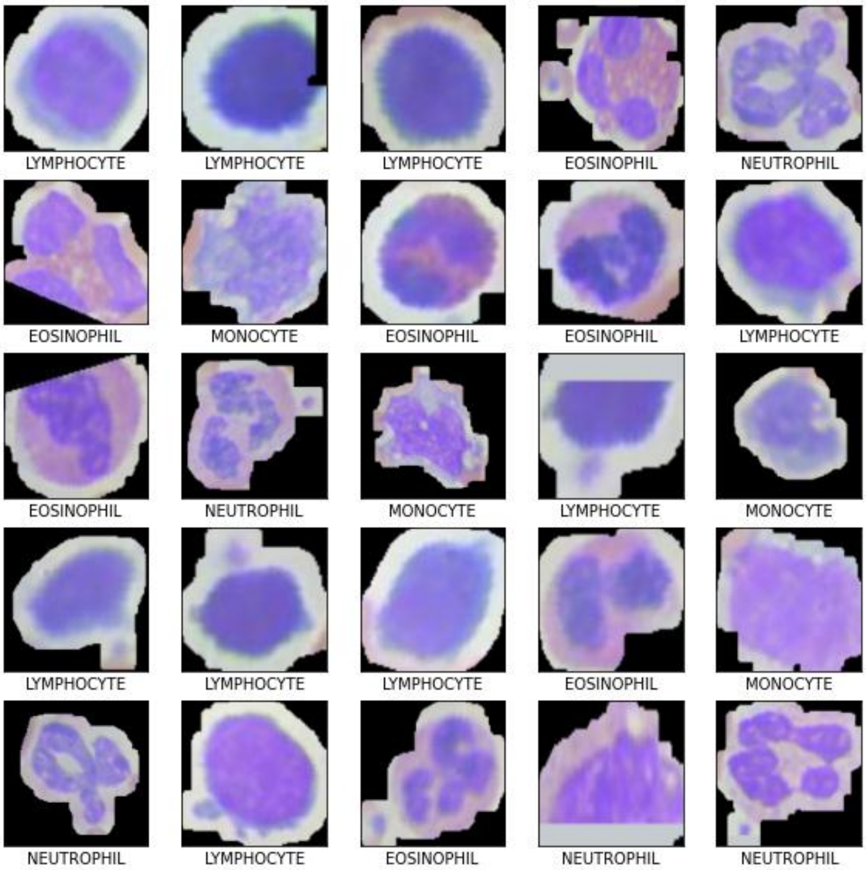

Figure (3.9) The new training set.

3.1.4 Training

Training and testing sets of 0.80%:0.20% have been utilised to distinguish the data assembling on multiple occasions. Figure 3.10 organises the dataset into training, testing, and validation sets. The model developed the following scores after 25 training epochs. In Figure (3.11), this is exhibited: Learning rate = 1.0000e-06, accuracy = 0.9998, val_accuracy = 0.9654, val_loss = 0.1378, and loss = 6.2305e-04.

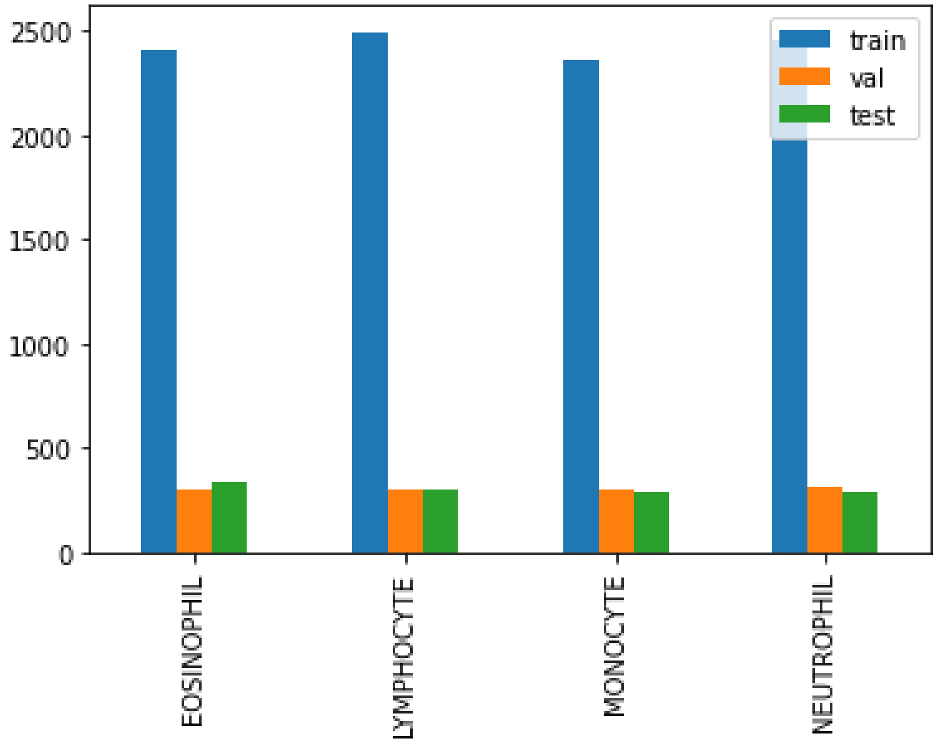

Figure (3.10) Spliting the dataset to training set and testing set.

Figure (3.11) shows training and validation accuracy and figure (3.12) training and loss

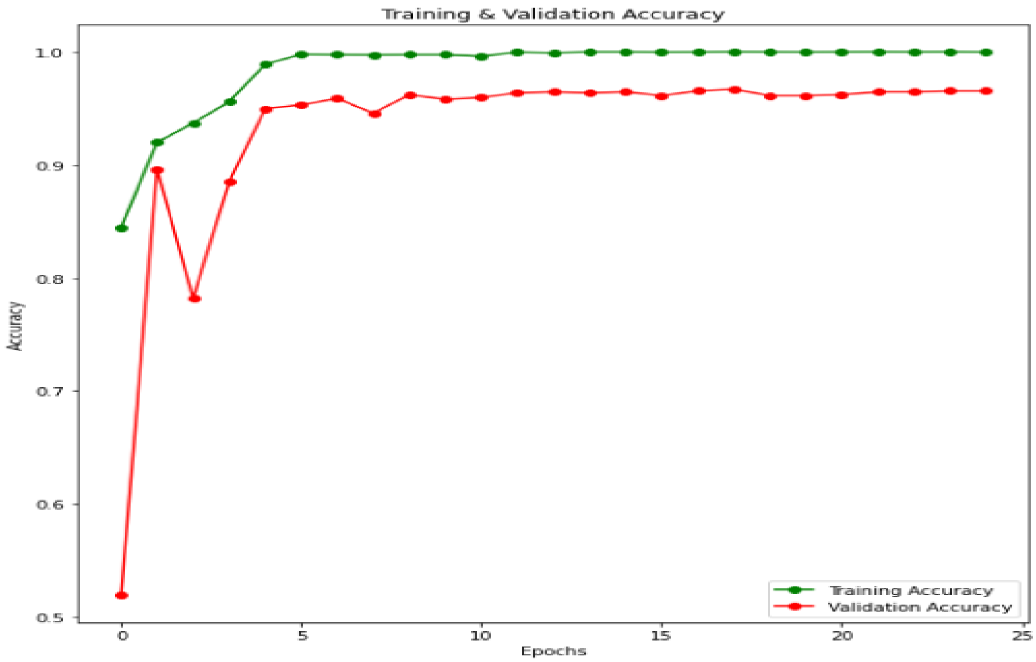

Figure (3.11) Training and validation accuracy.

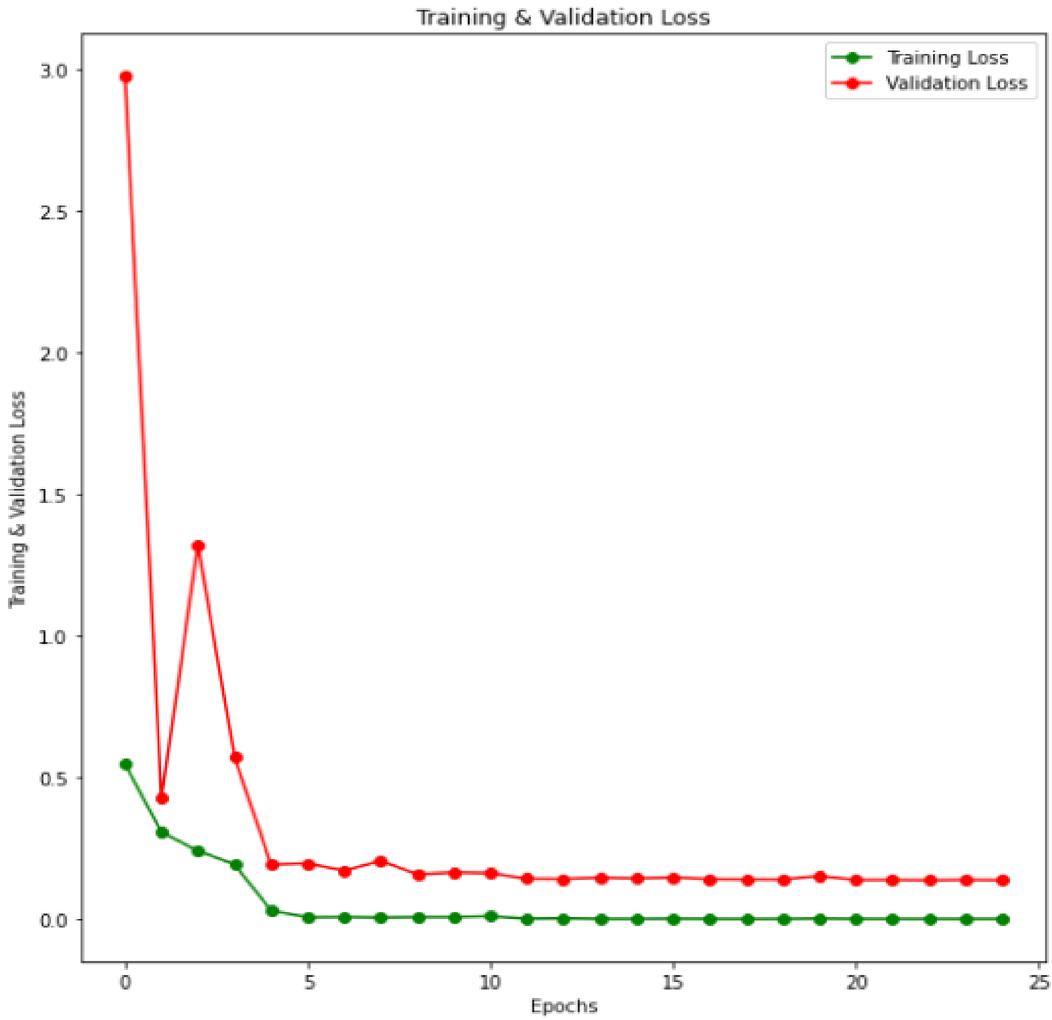

Figure (3.12) Training and validation loss.

Table (3.1) explain precision, recall, F1-score, support and accuracy.

Table 1. precision, recall, F1-score, support and accuracy.

	Precision	Recall	F1-score	support
EOSINOPHIL (Class 0)	0.95	0.93	0.94	337
LYMPHOCYTE (Class 1)	0.98	1.00	0.99	303
MONOCYTE (Class 2)	0.99	0.98	0.98	286
NEUTROPHIL (Class 3)	0.91	0.92	0.92	289
Accuracy			0.96	1215
macro avg	0.96	0.96	0.96	1215
weighted avg	0.96	0.96	0.96	1215

Figure (3.13) explain the confusion matrix for Resnet50 CNN model.

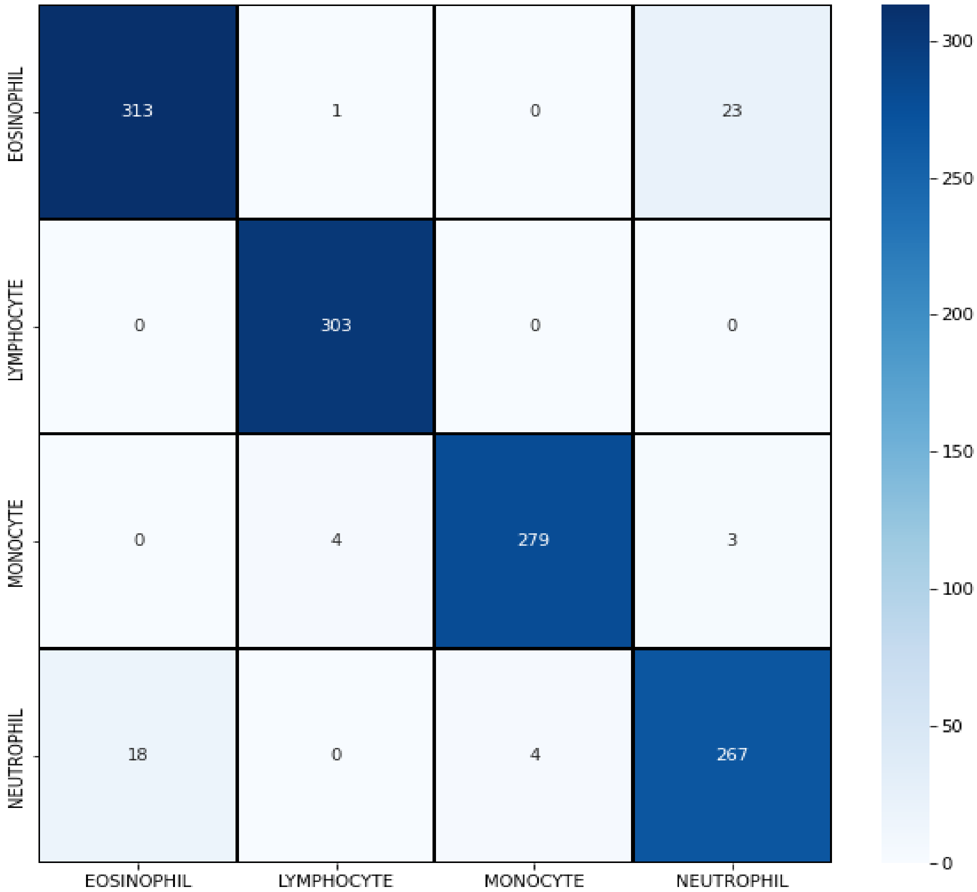

Figure (3.13) Confusion matrix for Resnet 50 model.

4. Conclusions

Some of the troubles required to be established themselves as well as discussed during the stages of the system that is suggested are as follows:

1. Make sure the data set is balanced at this critical point, as the testing set's sampling procedure should have the same percentage. For non-balanced datasets, calculating the accuracy per class is crucial for system testing.
2. Using information from the picture a histogram the Region of Interest (RoI) was derived from the row image based on the colour of the region. A centroid for the picture segmentation clustering algorithm has been established using the colour information.
3. Because the training process will focus on the key characteristics that are part of the target region in the images, the CNN model trained with ROI is more accurate.

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