



Automatic Detection and Counting of Blood Cells using YOLOv3 and Dert

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Abstract: The procedure of counting various blood cells from a smear image will be substantially facilitated by an automated method. Applications for object detection and picture classification are improving in accuracy thanks to the development of machine learning algorithms. the approach for detecting various blood cells based on machine learning. You only need to look once when using cutting-edge object detection techniques like regions with convolutional neural network (R-CNN) (YOLOV3). In one evaluation, YOLOV3 employs a single neural network to forecast bounding boxes and class probabilities based on the entire image. Additionally, photos are annotated with the labelling tool, and the YOLOV3 framework uses the annotated images to automatically identify and count RBCs, WBCs, and platelets.

Keywords: YOLO, Machine Learning, YOLOv3, labelImg, RBC, WBC, Blood Cells

I. INTRODUCTION

As a crucial test frequently requested by medical practitioners to assess health status, a complete blood cell (CBC) count. Red blood cells (RBCs), white blood cells (WBCs), and platelets are the three primary cell types that make up blood. RBCs, sometimes referred to as erythrocytes, are the most prevalent form of blood cell and account for 40–45% of all blood cells. Blood contains a significant amount of platelets, also referred to as thrombocytes. Only 1% of all blood cells are WBCs, also referred to as leukocytes. Our body tissues obtain oxygen through RBCs, and the number of RBCs has an impact on how much oxygen is delivered to each tissue. WBCs ward off infections, while platelets aid in blood coagulation. Because there are so many of these blood cells, the accuracy of the traditional manual blood cell counting method using a hemocytometer rests, in most situations, greatly on the abilities of a clinical laboratory analyst. Therefore, the entire counting procedure will be substantially facilitated by an automated process to count various blood cells from a smear image. Applications for object detection and picture categorization are getting more reliable and accurate with the advancement of machine learning algorithms. Machine learning-based techniques are therefore being used in a variety of industries. Deep learning techniques are being used, in particular, in a variety of medical applications, including the automatic segmentation of the left ventricle in cardiac MRI and the detection of diabetic retinopathy in retinal fungal images. It is therefore worthwhile to investigate deep learning-based techniques that can be used to locate and count the blood cells in smear images. A method for counting blood cells based on machine learning has been suggested in this study. To identify various blood cells, we use an object detection technique based on machine learning. we chose the YOLOV3 framework, which is nearly three times faster than Faster R-CNN, out of cutting-edge object detection methods such regions with convolutional neural network (R-CNN) and you only look once (YOLOV3). In one evaluation, YOLOV3 employs a single neural network to forecast bounding boxes and class probabilities based on the entire image. We retrain the YOLOV3 framework to recognise and count RBCs, WBCs, and platelets automatically from images of blood smears.

II. PROBLEM STATEMENT

Existing system: Manually counting the cells in a patient's blood was done by using a microscope to examine a slide that had been produced with a sample of the patient's blood. These days, an automated analyzer is typically used to automate this process. The hemocytometer, sometimes known as a hemocytometer, is a tool that was initially made for counting blood cells. Louis Charles Malassez and has a rectangular depression that forms a chamber in a thick glass microscope slide. A grid of parallel lines has been laser-etched onto this chamber. The apparatus is carefully designed so that the depth of the chamber and the area delimited by the lines are both known. the fluid overall, it is therefore possible to count the number of cells or particles in a given volume of fluid. automated analyzer performing a full blood count. In the analyzer, the blood is well mixed and set on a rack. The several components of this device allow it to analyse the various components of blood. The cell counting component counts the number and varieties of various blood cells. For review, the results are printed out or emailed to a computer. A very small amount of the samples is aspirated by blood counting equipment using a thin tube. The results of an automated cell counter are extremely accurate since so many cells are

sampled and counted. The results of the instrument must be manually reviewed in order to identify any abnormal cells that it was unable to categorise due to the possibility that certain abnormal cells in the blood may not be appropriately detected. Along with measuring, counting, and examining red blood Automated haematology analyzers measure the quantity of haemoglobin in the blood and within each red blood cell in addition to measuring platelets, white blood cells, and haemoglobin.

Proposed system: Our The machine learning methodology we propose uses the YOLO algorithm to count and identify blood cells automatically. It also includes a training model with a modified configuration in which the final convolution layer is changed for three outputs, blood cell identification with the proper threshold, and blood cell counting from labels. We choose the suitable threshold for each type of cell that offers a minimum average absolute error in the validation dataset by computing the average absolute error between ground truths and our estimation at difference threshold value. In each platelet, we use the Knearest Neighbor (KNN) and intersection over union (IOU) algorithms to resolve this Overall, the identification and counting of blood cells using our suggested method is quick and precise.

V. DESIGN FOR THE PROPOSED WORK

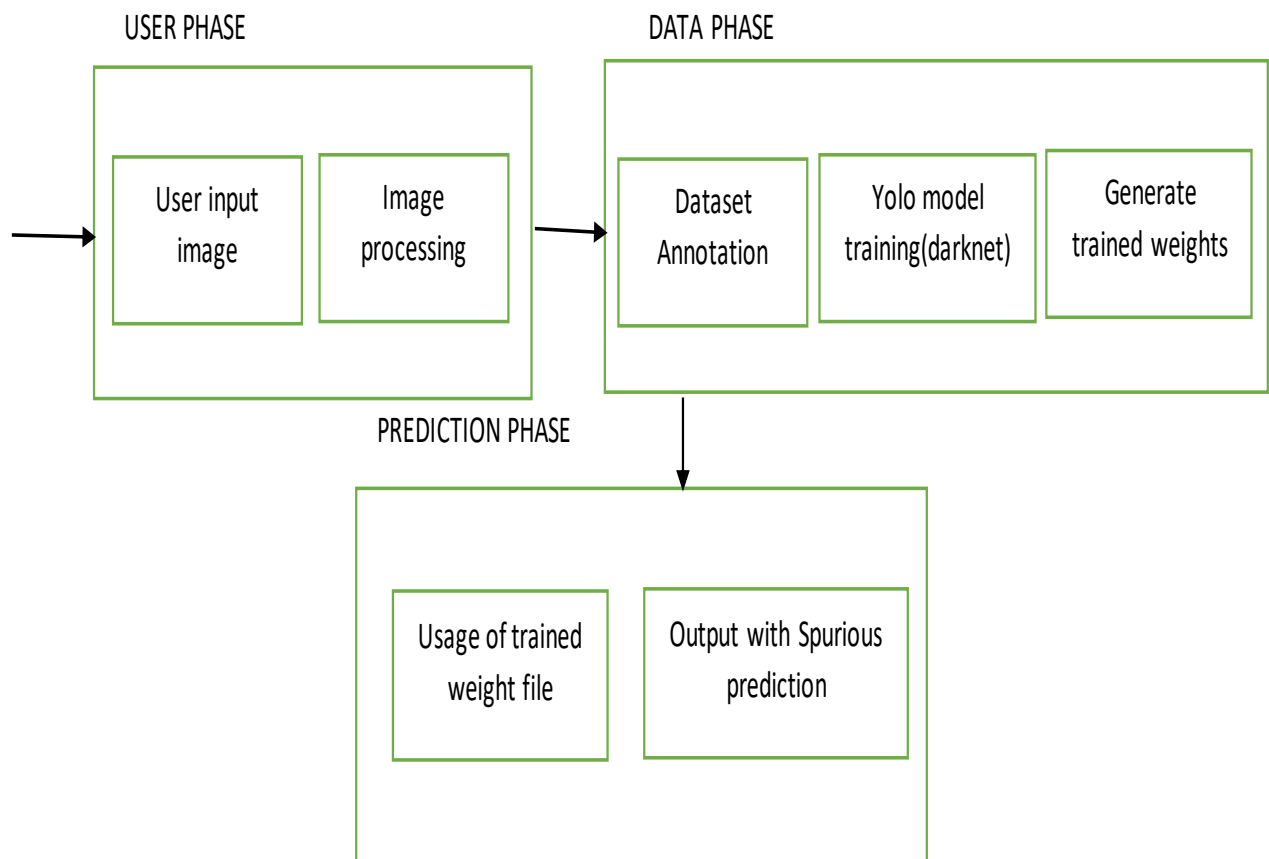


Fig .1 Proposed work diagram

The above Fig (Fig .1 A process flow Diagram) represents the flow diagram for a Blood Cells counting & detection. User Phase: Proposed system design do have user phase in which Input images are used to feed to trained model before feeding to trained model images needs to undergo image processing in which it will convert to numpy array or array format then enters to data model.

Data Phase: This is a phase where complete model training takes places in which before training the model, all the images are .jpg are annotated to .xml files usage labeling or labelme this is basically to get the co ordinates values and the region for the needed prediction. The annotated images will be feed to Darknet is an open source neural network framework for training, once training is completed weight file will be generated which will be further used for prediction phase.

Prediction phase: trained weight files are used or will load the saved/trained weight files for prediction final output will be the total count of wbc rbc and platelets along with prediction.



VI. SYSTEM ARCHITECTURE

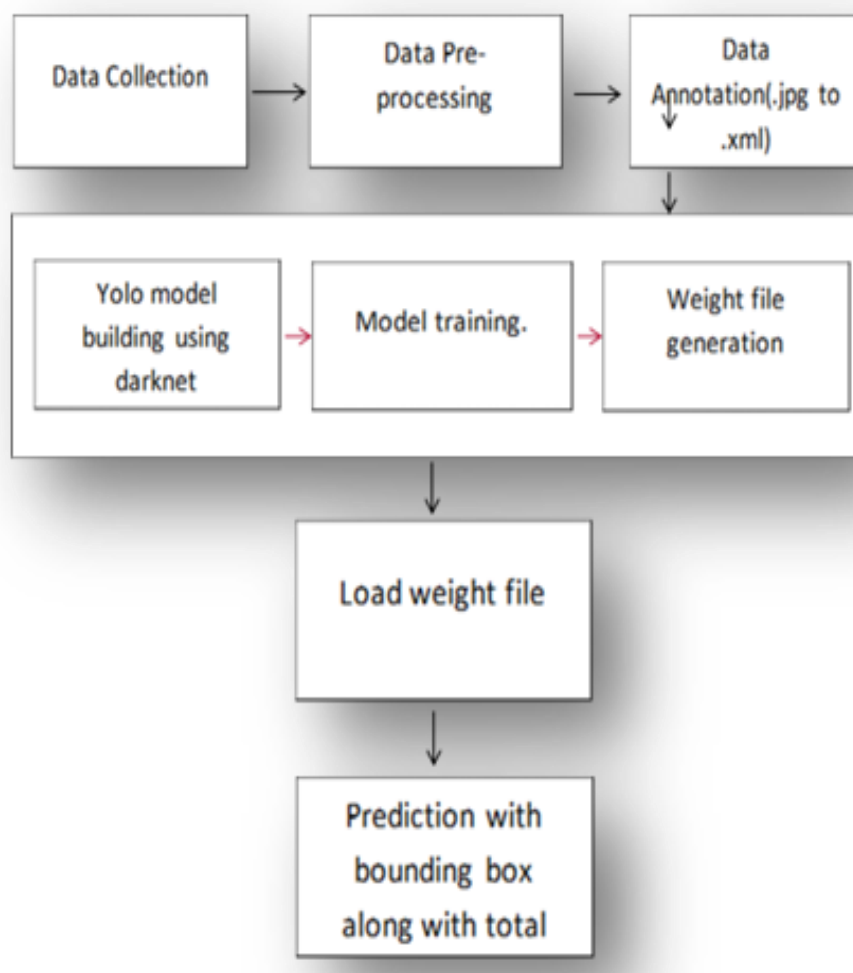


Fig .2 System Architecture

VII. DATASET

We employ the Blood Cell Count Dataset (BCCD [BCCD:<https://github.com/Shenggan/BCCD> Dataset], a publicly accessible dataset of annotated blood cell pictures. There are 364 annotated smear photos in all, but there are several serious problems with the collection. We discover that one annotation file in the test set does not contain any RBCs despite the fact that the picture has RBCs after dividing the data set into training (300) and testing (64) portions. We used the information from to test our model on a separate dataset. The dataset contains 100 high-resolution photographs that were taken with a Nikon V1 camera attached to a Nikon ECLIPSE 50 microscope with a 100x magnification.

VIII. YOLO

YOLO, or "You Only Look Once," is a cutting-edge object recognition and classification system. It views the detection of objects as a regression issue. To quickly forecast the image class and position, only one forward propagation pass over the network is necessary. Each grid cell predicts two bounding boxes and a confidence score for the boxes, resizing the image by and dividing it into grid cells. If an object's centre falls within a grid cell, that grid cell is in charge of detecting that object.

The PASCAL VOC dataset was used to evaluate the YOLO model's initial CNN implementation. Its network architecture, which was influenced by the Google Neural Network, consists of 24 convolutional layers and 2 fully linked layers.



IX. AUTOMATIC BLOOD CELL IDENTIFICATION AND COUNTING SYSTEM

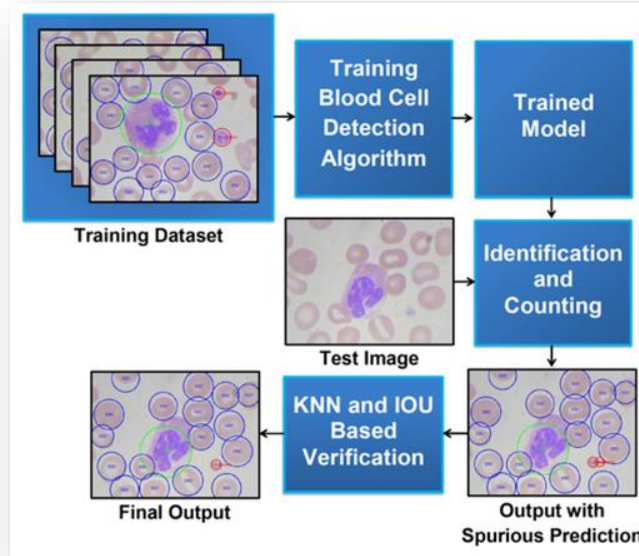


Fig .3 Automatic Blood Cell Identification & Counting System

A complete blood count is a crucial test in the medical diagnosis process to assess general health. It is a laborious and time-consuming process to manually count blood cells using a hemocytometer, additional laboratory equipment, and chemicals. The 'you only look once' (YOLO) object detection and classification technique is used by the authors of this work to provide a machine learning strategy for the automatic identification and counting of three types of blood cells. To automatically recognise and count red blood cells, white blood cells, and platelets in blood smear images, the YOLO framework was trained using a modified configuration BCCD Dataset. The learnt models are generalised, according to testing done on smear images from a separate dataset using the trained model.

X. FLOW CHART

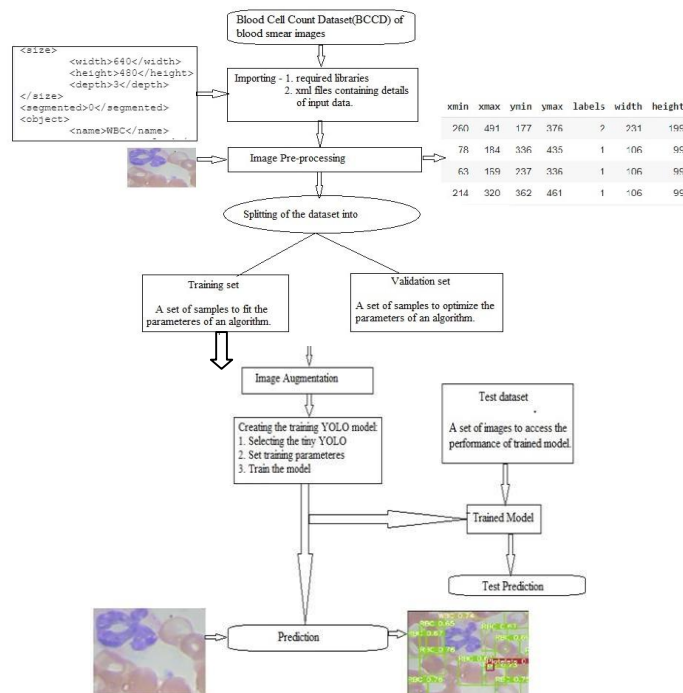


Fig .4 Flow Chart for Proposed Algorithm



From the blood smear photos, the suggested model will automatically identify and count the RBCs, WBCs, and Platelets. The 60-test data set, which contains the known ground truth, has been used to test the model. In the beginning, this model counts the various cells that are present in the validation sets of the smear image with various confidence truths. As the YOLO method uses this threshold for the grid cells rather than the entire image, it has been noted that the threshold plays a significant part in the process. The cells are not contained in grid cells. Consequently, by selecting an acceptable confidence level, we may eliminate the unnecessary and erroneous predictions. The average absolute error between the estimated number of cells in the validation set and the ground truth is then determined with a low degree of confidence.

XI. CONCLUSION

Based on the YOLO algorithm, we suggested a machine learning method to automatically recognise and count blood cells from a smear image. The method used KNN and IOU based methods to eliminate multiple counting of the same object in order to increase accuracy. On publicly accessible datasets, our suggested methodology is assessed. For the test dataset, it has been found that our technique correctly identifies RBCs, WBCs, and Platelets. It can be observed that our method accurately counts even part of the dataset's unlabelled cells. In the YOLO back-end, various neural network models have also been tested. Furthermore, it has been found that different models might offer the optimum accuracy for various cells. Despite trying many models with various depths, it is found that the procedure is remarkably quick for counting and labelling the smear images. Additionally, a different dataset of smear photos was used to test the suggested strategy, and it did so satisfactorily. The proposed method has the potential to simplify the manual procedure of counting and identifying blood cells given its accuracy and detection performance. Therefore, by utilising the algorithms and methodologies we examined, blood cell diseases and changes in haematological parameters can be easily discovered and treated. The results produced will also be more accurate, but it will take more time and money.

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