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Detection and classification of white blood cells with an improved deep learning-based approach

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Abstract: The analysis of white blood cells, which defend the body against deadly infections and disease-causing substances, is an important issue in the medical world. The concentrations of these cells in the blood, examined in 5 classes, i.e. monocytes, eosinophils, basophils, lymphocytes, and neutrophils, vary according to the types of diseases in the body. The peripheral blood smear is widely used to analyze blood cells. Manual evaluation of this method is laborious and time-consuming. At the same time, many environmental and humanistic parameters affect the method's performance. Therefore, in the presented study, a real-time detection process is realized. Firstly, YOLOv5s, YOLOv5x, and Detectron 2 R50-FPN pretrained models in the object recognition framework are used. Next, two original contributions are made to the study to improve the model's performance. The first contribution includes optimizing the activation function, an essential criterion in training the model, and an arrangement provided in the architecture. With this proposed approach, an improvement of 0.006 is achieved in the recognition rates of all classes. The second contribution is the combined use of the YOLO and Detectron2 frameworks, which have two different object evaluation processes. The success rate achieved with this hybrid structure provided an improvement between 3.44% and 14.7% compared to the outputs obtained from the YOLO and Detectron2 pretrained models. In addition, the maximum accuracy rate of this hybrid structure on the test dataset for detection and classification of white blood cells is obtained as 98%.

Key words: Classification of white blood cells, peripheral blood smear, object detection, YOLOv5, Detectron2

1. Introduction

Blood is the living fluid that controls the body's metabolism rate [1]. It makes it perform various vital functions such as clotting and immunity. Oxygen, carbon dioxide, and minerals are circulated in the body thanks to the blood fluid [1, 2]. The essential components of this vital fluid are plasma, platelets, red blood cells (RBC), and white blood cells (WBC) [2]. Analyzing the blood, which consists of organic and inorganic structures, provides the opportunity to evaluate the person's health status. Blood tests are important biomarkers to evaluate the patient's current condition with minimum cost. Peripheral blood smear, one of the available blood tests, is a widely preferred approach in the medical world [3]. Peripheral blood smear involves the process of staining blood spread on a glass slide. After staining, the glass slide is placed under the microscope and evaluated with different magnifications [4]. Identification of subtypes of white blood cells (WBC) is easy as various cell types give different responses to dye [3]. Morphological analysis is performed with this process, which allows manual

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blood examination. However, the manual evaluation process is laborious and time-consuming. In addition, this evaluation can also vary according to the physician's knowledge, experience, and medical knowledge [4]. On the other hand, the ratio of white blood cells to red blood cells is 1/600 and constitutes about 1% of the total blood volume. The fact that the contrast situation in the images is also included in the analysis process during the application of this method is another factor that negatively affects the final decision [1, 3, 4]. Due to such situations, the manual evaluation processes of WBCs with the peripheral blood smear method involve extra difficulties [2, 5]. White blood cells are vital structures that defend the body against disease-causing agents and deadly infections [2]. These structures protect the body. It is evaluated in 5 different classes monocytes, eosinophils, basophils, lymphocytes, and neutrophils. The abnormal ratio of subtypes of white blood cells produced in the bone marrow and lymphoid tissues is the cause of various diseases. In this direction, neutrophil structures are seen above the standard value in the blood in cases of metabolic disorders, hemolysis, or bleeding. The increase in the monocyte ratio is associated with bacterial and viral infections. The increase in the eosinophil ratio is associated with allergic or atopic disorders. Hemolytic anaemia or malignant myeloproliferative affect the number of basophil structures. While hepatitis viruses, leukemia, or brucella diseases increase the lymphocyte rate in the blood, chickenpox and tuberculosis diseases decrease the lymphocyte rate in the blood [6]. The peripheral blood smear hemogram test is preferred in the medical world in order to examine and interpret subtypes of white blood cells [6].

Many studies have been carried out in the world of informatics to make automatic recognitions that produce reliable, consistent, and high accuracy rates. In this context, a segmentation approach is proposed in the first stage of the study in [7], which aims to classify five different white blood cells. With the proposed segmentation approach, features are extracted from the segmented cells. These features are then classified by multilayer perceptron, support vector machine, and hyperrectangular composite neural networks approaches. It is stated that the highest overall correct recognition rate could reach 99.11%. The study in [8] made an analysis of white blood cells. Firstly, statistical and geometric features are extracted from microscopic blood images. Next, classification successes are evaluated with decision tree (DT), k-nearest neighbor (k-NN), multiterm logistic regression (MLR), naïve Bayes (NB), random forest (RF), and support vector machine (SVM) algorithms. Maximum success rate is obtained as 95% with the MLR approach. The study in [9] used a new end-to-end convolutional deep network architecture, the WBCsNET approach, to identify white blood cells. Highest accuracy score is 96.1% for Dataset3 and 92.9% for Dataset_All. In the study in [3] for evaluating white blood cells, which are vital in body defense, capsule networks are used to compensate for the deficiencies of the deep learning method. The proposed model obtained 96.86% accuracy rate. The study in [6] used regional-based convolutional neural networks to detect the types of white blood cells (WBC). Thus, it is stated that simultaneous detection of different cell types in the same image is achieved. Moreover, the system has 100% success in deciding WBC cells. A new method is proposed in [10], which is carried out to detect and quantify white blood cells and red blood cells on microscopic blood images. It is stated that successful cell suggestions are reached even for scattered or complex cells with the edge boxes used in this method. The ellipse detection approach is used in the study [11] to detect white blood cells, which play a vital role in diagnosing hematological diseases. In this approach, the selected candidate ellipses are effectively matched to white blood cells using an artificial electric field algorithm. The proposed algorithm found an overall detection accuracy of 96.90%. The study in [12] evaluated white blood cells, which are structures that are examined in diagnosing blood-related diseases. A new WBC kernel segmentation method based on color space transformation and the k-means algorithm was used. Reached average accuracy is 98.61% on each public database. The study in [13] used a

lightweight convolutional neural network approach to identify different hematological disorders. The obtained accuracy rate is 98.63% and 91.95% for multiclass and binary classification, respectively. Defining and counting WBC structures is necessary for examining the person's health status. For this purpose, the features extracted from the images with the CNN frame in [14] are fed into a fully connected blood cell classification layer using CNN, VGGNet, and GoogleLeNet. Accuracy of GoogLeNet is 93.43% and 91.72% for Relu and LRelu activation functions. The study in [15] presented the canonical correlation analysis method, which is the merging model of CNN and RNN. It is stated that this method provides higher accuracy than modern blood cell classification techniques. Deep learning-based transfer learning methods are used to classify white blood cells in the study in [16]. Highest accuracy achieved is 94% with the proposed DenseNet121 model. In [2], a CNN structure is proposed for the classification of white blood cells. Obtained accuracy is 98.55% by the proposed approach. Analysis of white blood cells, which are an important part of the human immune system, is handled in [17]. With the proposed fine-grained interactive attention learning (FIAL) semisupervised approach, the classification of white blood cells is achieved. The obtained average accuracy is 93.2% on the BCCD dataset by the FIAL approach. The study in [18] used object recognition algorithms to classify platelets, red blood cells, and white blood cells. YOLOv3 approach is found to be faster and more successful than SSD, Faster R-CNN, and R-FCN object recognition algorithms with 99% accuracy. In the literature on machine learning and deep learning, it is seen that alternative approaches or improvements made to existing structures increase the final success rate [19, 20].

In this scope, in our study, YOLOv5s, YOLOv5x, and Detectron2 R50-FPN pretrained object recognition approaches were used. In order to optimize the performance ratio, 2 separate contributions (proposed YOLOv5x and hybrid structure) were made and the maximum accuracy rate reached with the hybrid structure was 98%.

2. Methodology

The peripheral blood smear method used in the medical world for the detection and classification of white blood cells is a hematology test [6]. This test contains many humanistic and environmental effects [21, 22]. In order to reduce these effects, a computer-aided automatic recognition and classification system is created in the presented study. In this system, the object recognition approach, which provides real-time output, is preferred. The object recognition approach is used for identifying objects on target images, displaying them with bounding boxes, expressing the confidence value and classifying them. This approach includes detecting and classifying objects with two separate methods. These methods are based on the region proposed approach and regression/classification approach. Region proposed-based methods are structures that create region proposals in the first stage and then classify each offer presented for suggestions according to object categories. Regression/classification-based methods are structures that solve the object detection process as a regression or classification problem [23]. The training time and success rates produced by both approaches on the same dataset will be different. Therefore, YOLO in the scope of regression/classification-based methods and Detectron2 in the scope of region proposal-based methods are the preferred frameworks in the study. However, the main goal is to produce output by optimizing the training time and success parameters in the detection and classification of white blood cells. Therefore, two different suggestions are made. The first proposal covers improvements realized in the architecture and activation function of the YOLO approach. The other proposal involves the hybrid use of YOLO and Detectron2 constructs, which are handled under two different approaches for object detection. Detailed description of each method used is given below.

2.1. Dataset

The free and public Raabin Health Database is used in this study. Digitized images of monocytes, eosinophils, basophils, lymphocytes, and neutrophil blood cells in the dataset are obtained from https://raabindata.com/. Cells stained with the Glemsa staining type in this dataset are obtained using Olympus CX18 and Zetss microscopes at 100× magnification rates with Samsung Galaxy S5 and LG G3 phone cameras [24, 25]. A visual representation of these cells is given in Figure 1.

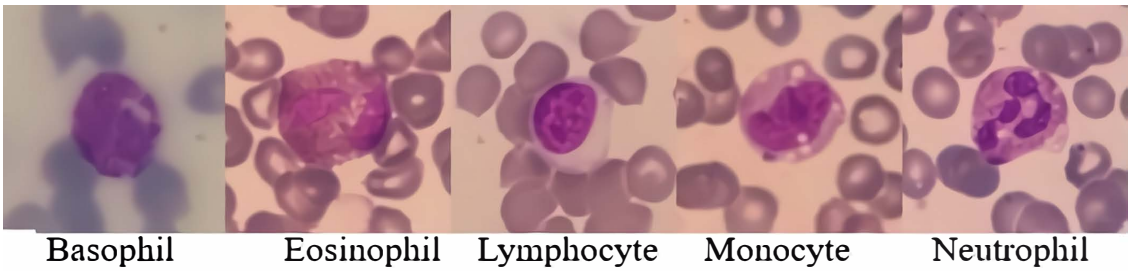

Figure 1. Components of white blood cells obtained from the Raabin dataset.

There are no repetitive samples in the Rabbin Health dataset. The labeling process of cells is carried out by two experts [25]. In the study, 200 images for each cell type and 1000 images in total are used. All images are resized to 575 × 575 pixels. The segmentation process, which plays a role in the successful realization of the training process, is done meticulously and the segmented images are labeled. Seventy percent of the dataset is divided as a training set and 30% as a test set. Subsequently, the object detection approaches described below for the detection and classification of blood cells are realized using Python language on Google Colab by activating the GPU feature.

2.2. YOLOv5 approach

YOLO has a single-stage structure. It is a deep learning-based object recognition algorithm in which different features are developed and combinations are produced in order to strengthen the accuracy of convolutional neural networks [26, 27]. It is developed over time as YOLO, YOLOv2, YOLOv3, YOLOv4, and YOLOv5 [28]. The architecture of the YOLOv5 structure, which consists of the backbone, neck, and head parts, is given in Figure 2.

The YOLOv5 architecture shown in Figure 2 has a structure that consist of neural networks [29]. Detailed descriptions of the modules in the architecture are given below:

Backbone Network: It is the part that produces feature maps of different sizes of the input image presented to the network. It contains 4 different feature maps in 152 × 152, 76×76, 38×38, and 19×19 pixel sizes. The focus module in the backbone network is the part that separates and then combines images for a more successful extraction of features during downsampling. The spatial pyramid pooling (SPP) module provides compression of the input feature map and represents the image features at a high abstraction level. Cross-stage partial (CSP) module connecting the front and back layer of the network reduces the model size and improves the inference speed. The CONV-BN-Leaky RELU (CBL) module performs the convolution and normalization processes [29].

Neck Network: The part where the features extracted from the convolutional neural networks are combined. The CSP module in here is formed by replacing residual units with CBL modules. It enables feature maps to be combined in order to obtain more contextual information from feature maps in the backbone. During combining feature maps at different levels, feature pyramid network (FPN) and path aggregation network (PAN)

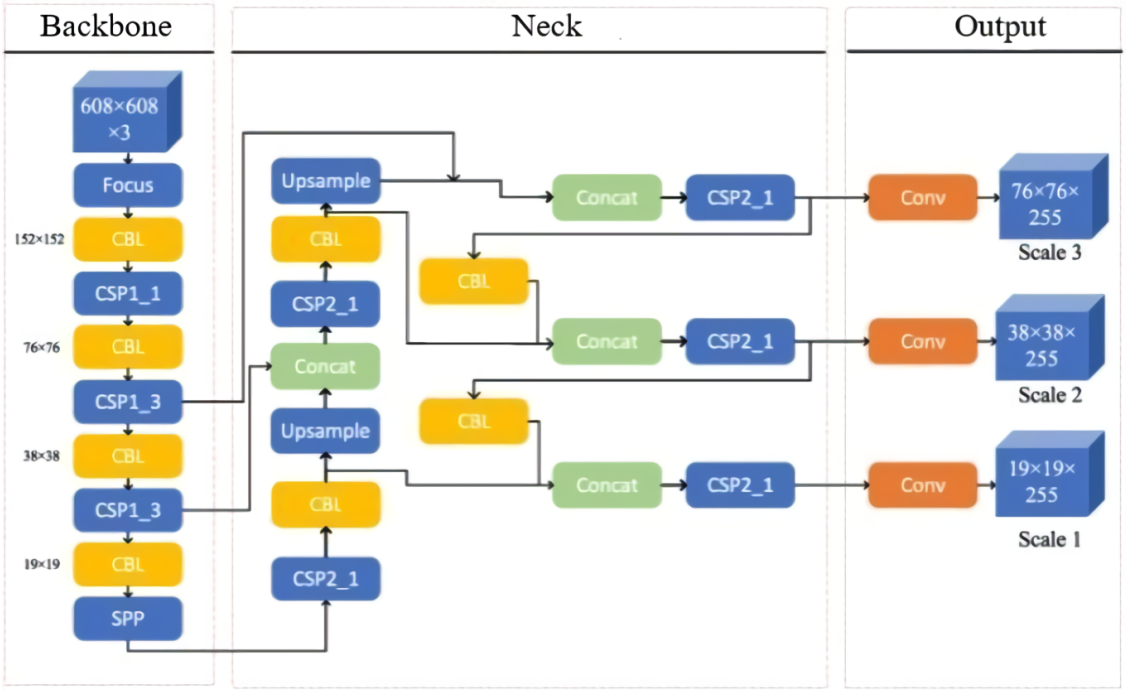

Figure 2. The architecture of the YOLOv5 approach [29].

structures are used, which strengthens the feature combining ability of the neck structure. FPN transmits strong semantic features from top-feature maps to subfeature maps. PAN transmits localization features from low-feature maps to high-feature maps. The concat module is the module that allows tensors to be combined [29].

Output Network: Objects are detected and classified using feature maps. $19 \times 19 \times 255$ feature maps are suitable for identifying large objects. $76 \times 76 \times 255$ feature maps are more suitable for identifying small objects [29].

The YOLOv5 approach has pretrained YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x models. The letters s, m, l, x, and v are small, medium, large, extralarge, and version designations, respectively. These models are trained with the COCO dataset. The difference between the models is the number of convolution kernels and feature extraction modules. The pretrained YOLOv5s and YOLOv5x models evaluated in the YOLOv5 framework are trained for 200 epochs for training the target dataset. Batch size is selected as 16. The training time for the YOLOv5s architecture is 0.544 h, and the training time for the YOLOv5x architecture is 2.717 hours.

2.3. Detectron2 approach

The Detectron2 is a library. It is the successor of the Detectron and the MaskRCNN. Compared to these structures, it offers a higher output performance. Detectron2 structure performs object detection and segmentation operations on images [30]. Segmentation is examined in two sub-sections: semantic segmentation and instance segmentation, among deep learning techniques. Semantic segmentation is an approach that provides a pixel-based classification of shapes. However, it does not distinguish different samples within the same category. Therefore, an instance segmentation approach is used to obtain the objects' unique structure [31]. This study

preferred Detectron 2 structure that uses the instance segmentation approach. This structure uses a JSON-based image file system. The JSON-based image file system informs about the labeling of objects. This file has a format consisting of images, categories, and descriptions. Categories provide saving for classes related to a group. The descriptions include the category of the targeted object and the array of coordinates of the polygon related to the box surrounding the area it occupies [30]. The use of pretrained models during the realization of the training is a preferred technique to obtain effective outputs. Pretrained models are used in the framework of the target dataset with this technique, which is defined as transfer learning. It is important to fine-tune according to the target dataset before training the model [32]. In this study, the R50-FPN model is used as the transfer learning architecture. The R50 part states that Resnet50 is used as the feature extraction backbone of the model [32]. The Detectron2 algorithm, which originated from the MaskRCNN structure, is trained for 4000 epochs with a learning rate of 0.0005. The batch size is selected as 16. The training lasted 0:30:30 h.

2.4. Proposed YOLOv5 approach

The YOLO approach proposed in this study includes the arrangements made in the architecture and the activation function, which has a key role in training the neural network. Arrangement in architecture is provided on the convolution module. The convolution module, which is responsible for extracting the information from the input is organized as the depthwise convolution module to compress the network parameters. With this structure, which allows for the reduction of the parameter and process size, the power of the model has been increased, and it has been possible to extract spatial feature information in different dimensions [33].

Another improvement is achieved through the activation function. The activation function has a significant impact on learning real-world data and improving training performance [34]. It should be carefully selected to prevent the loss of information about the inputs during the forward propagation [35]. Thus, the activation function will provide a realistic connotation and will be optimized to find the most appropriate solution [36]. For this purpose, the SiLU activation function derived from the sigmoid function is inspired. The SiLU activation function is obtained by multiplying the input value with the sigmoid function [37]. The mathematical expression of the SiLU activation function is given in equation 1.

$$SiLU(x) = x * sigmoid(x) \tag{1}$$

In this study, an improvement is made to the sigmoid activation function in order to teach nonlinear states to the neural network. The golden section search approach is used to improve the sigmoid activation function for the proposed YOLOv5. A detailed description of this method is given below:

Golden Section Search: This approach, which is proposed within the framework of problems that are not differentiable or difficult to distinguish, is preferred in many applications such as optimization or computation. With this method, calculation related to 2 points is provided to find the minimum point of the function in the interval [a,b]. Next, a comparison is made to find the optimal point on the points defined as x1 and x2. The [-a, x2] point is determined in case of that the f(x1) structure, in which the function is characterized as f, is smaller than the f(x2) structure. Otherwise, the [x1,b] point is determined as the optimal point. In order to find the optimal point, the search process continues until the value (b-a) is less than the stopping criterion we have determined as "1e-5" [38].

Mathematical definitions of x1 and x2, which are expressed as optimal points, are given in equations 2–4.

$$c = \frac{-1 + \sqrt{5}}{2} \tag{2}$$

$$x1 = ca + (1 - c)b \tag{3}$$

$$x2 = (1 - c)a + cb \tag{4}$$

In our study, the interval and the function are determined as [-1,+1] and sigmoid, respectively. This optimization method is preferred in many fields such as computer science, biomedicine and chemistry [38].

2.5. Hybrid approach

In the scope of the object recognition approach, there are two different approaches for the detection and classification of images (region proposal-based and regression/classification-based) [23]. Detectron 2 and YOLO frameworks used in this study are evaluated in the scope of region proposed-based and regression/classification-based approaches, respectively. Regression/classification-based approaches make more localization errors than region proposal-based approaches [23]. This is a criterion that affects the success of the object detection process. On the other hand, YOLO is a single-stage object recognition framework and Detectron is a two-stage object recognition framework. The detection speed in single-stage object recognition approaches is faster than in two-stage object recognition approaches [28]. Therefore, the training time, accuracy of detecting and classifying images will differ. In this direction, the hybrid use of YOLO and Detectron2 approaches, which have strengths and weaknesses, has been realized.

3. Discussion and results

In this study, a computer-aided structure was designed for the analysis of white blood cells, which is an important biomarker in the evaluation of the body health of individuals. Experiments were carried out with different methods in order to obtain the final output with optimum parameters. In the first stage, YOLOv5s architecture, which has the smallest network structure, and YOLOv5x architecture, which has the largest network structure, were used in the YOLOv5 framework. The curves of the performance criteria obtained with architectures with different network sizes were given in Figure 3.

The predictions' success for 5 different categories of images is important in terms of the quality of the decision to be made. For this purpose, F1-confidence curve, precision-confidence curve, and recall F1-confidence curve were examined to evaluate the classification success. If the area under these drawn curves is 100%, it is stated that all the predictions are correct. For this reason, obtaining a rate close to 100% as a result of applying the trained models to the test data set is a necessary process to create a successful model. In this direction, when the performance curves given in Figure 3 are examined, it is seen that the model trained with the YOLOv5x architecture is more sensitive in distinguishing 5 different cell classes. On the other hand, accuracy analyzes are carried out to measure its applicability to real-world problems of the architecture. The confusion matrix used in the evaluation of deep learning models shows the frequency at which classes produce the same output by the doctors and the model being trained. Therefore, a strong inference was provided with help of the confusion matrix [31, 39]. The confusion matrices produced by the YOLOv5s and YOLOv5x architectures as a result of the training are presented in Figure 4.

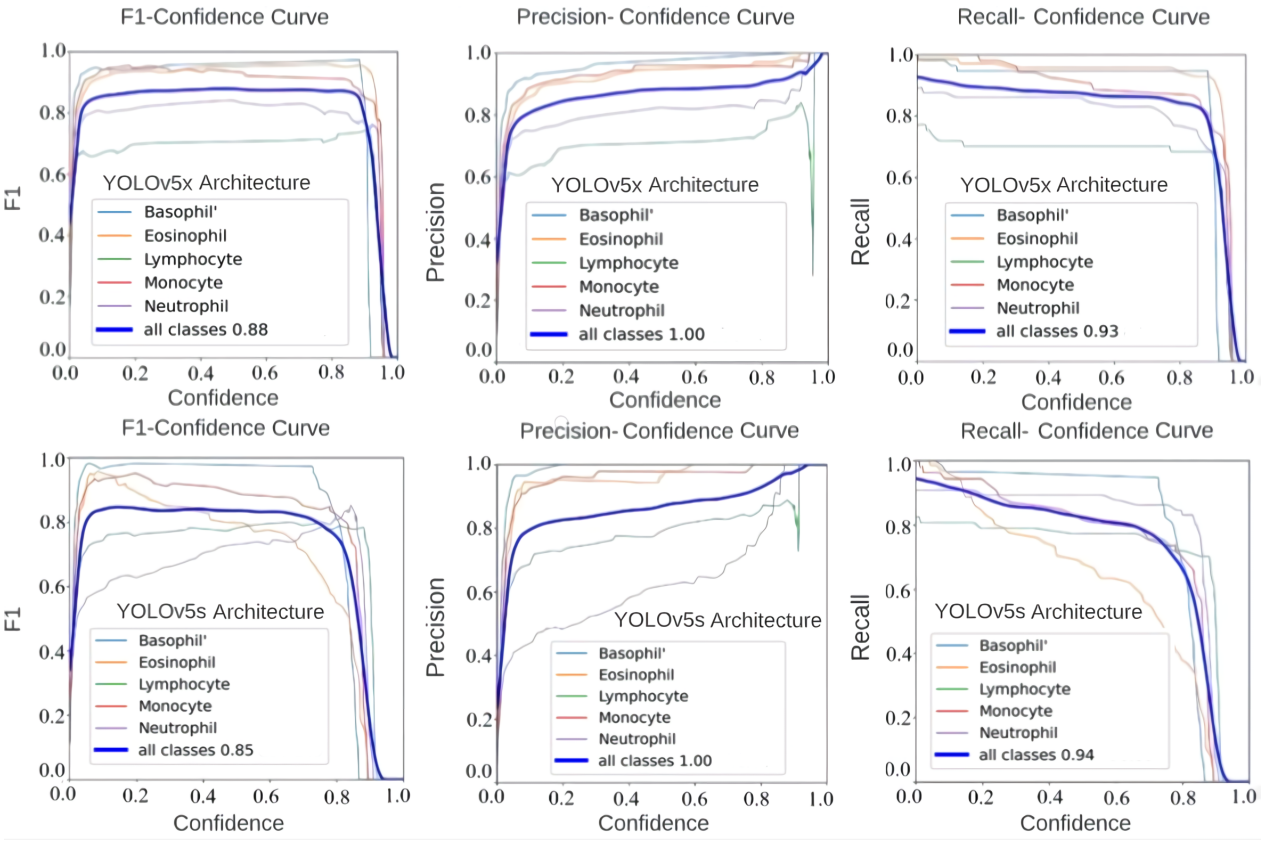

Figure 3. Performance curves obtained with the YOLOv5s and YOLOv5x architectures.

Realized training times using YOLOv5s and YOLOv5x architectures are 0.544 and 2.717 hours, respectively. In addition, the results produced using the YOLOv5s and YOLOv5x models are 83.3% and 94.66%, respectively. When the results are examined, it is seen that the YOLOv5x model trained in a wide time period is more successful than the YOLOv5s model.

The detection power of the Detectron 2 architecture compared to YOLO architectures was also examined. For this purpose, the R50-FPN pre-trained model of the Detectron 2 frame was used. The confusion matrix obtained as a result of the 0:30:30 hour training is presented in Figure 5.

		YOLOv5s Model				
		Predicted				
		0	1	2	3	4
Actual	0	53	0	2	0	0
	1	0	40	2	0	29
	2	0	0	52	0	3
	3	0	1	10	41	1
	4	0	0	0	0	64

		YOLOv5x Model				
		Predicted				
		0	1	2	3	4
Actual	0	55	0	0	0	0
	1	0	69	0	1	1
	2	0	2	53	0	2
	3	0	0	9	43	1
	4	0	0	0	0	64

Figure 4. Confusion matrices architectures.

		Detectron2 Model				
		Predicted				
		0	1	2	3	4
Actual	0	54	0	0	1	0
	1	0	71	0	0	0
	2	0	0	53	3	1
	3	0	0	3	48	1
	4	2	4	1	2	55

Figure 5. Confusion matrix.

When the confusion matrix is evaluated, produced success rate is 93.66%. This ratio shows that the architecture trained with the YOLOv5x model is more successful on the test dataset than Detectron 2 R50-FPN architecture. A graph showing the loss of labeling with incorrect classes over bounding boxes estimated along 4000 iterations with the R50-FPN architecture of the Detectron2 framework is given in Figure 6.

Another criterion used to evaluate the data is the Intersection over Union standard [31]. It expresses the ratio of similarity between the predicted bounding box and the actual bounding box. The mathematical expression of the object accuracy detection standard is given in equation 5 [28].

$$IoU = area(box(Pred) \bigcap box(Truth))/area(box(Pred) \bigcup box(Truth)) \tag{5}$$

The IoU rates produced by the YOLO and Detectron 2 approaches on test images labeled with 5 different classes (0-basophil,1-eosinophil,2-lymphocyte,3-monocyte,4-neutrophil) are given in Figure 7.

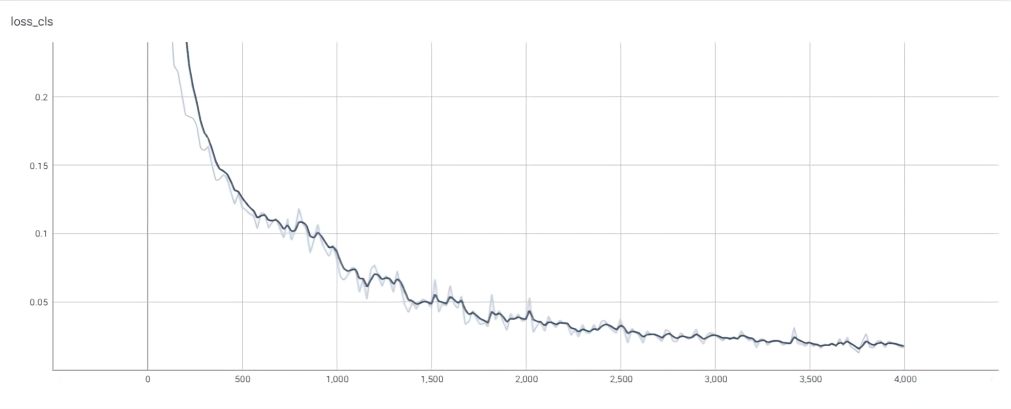

Figure 6. Loss of bounding boxes predicted with wrong classes along 4000 iterations.

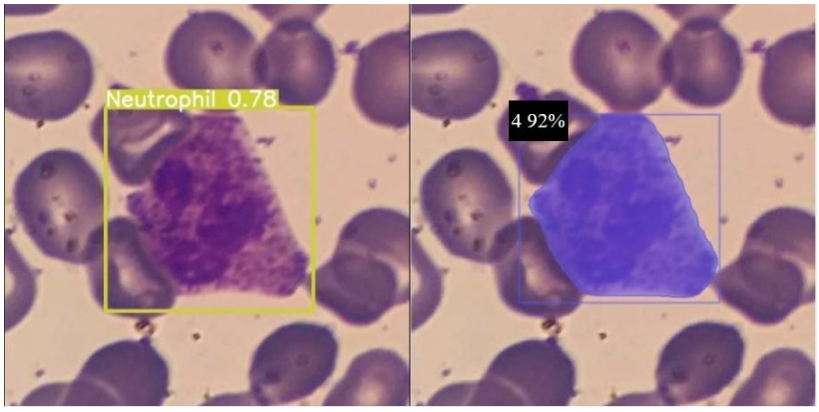

Figure 7. Outputs produced with YOLO and Detectron2 approaches.

In the Figure 7, the similarity of the image predicted with ground truth is 78% and 92%, respectively. IoU rate is expected to be 100% or close to 100%.This situation shows that the trained model is successful.

Despite the long training time, the YOLOv5x architecture is more successful than the YOLOv5s and Detectron2 architectures. Therefore, the architecture used in the proposed YOLO approach was chosen as

YOLOv5x. The precision recall curve of the performance produced by the YOLOv5x architecture on the test dataset was given in Figure 8 and compared with the proposed YOLOv5x architecture.

The area under all curves in the precision-recall graph is targeted to be 100%. This indicates that all images in the test dataset are predicted correctly.

The proposed YOLOv5 approach produced an increase in the recognition rates of images belonging to the neutrophil and lymphocyte categories, while it produced lower performance outputs in the recognition rates of the basophil, eosinophil and monocyte categories. However, an improvement of 0.006 was achieved in all classes. But, the improvement rate of the results achieved using the proposed YOLOv5x approach is not enought. For this reason, also a hybrid structure in which YOLOv5 and Detectron structures are used together was designed.

In this part, firstly, the success rates of YOLOv5s, YOLOv5x and Detectron2 approaches are examined. Outputs produced on the same image are given in Figure 9.

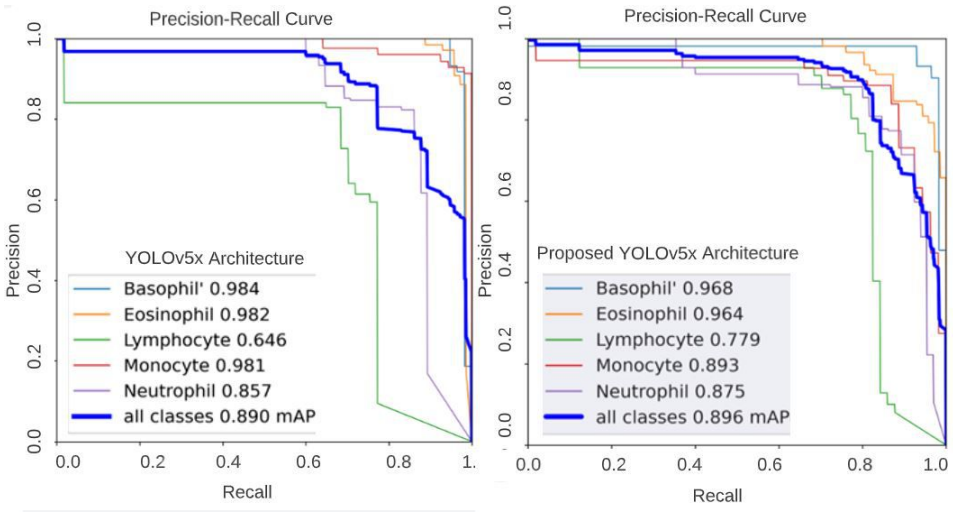

Figure 8. Performance curves obtained with the YOLOv5x and proposed YOLOv5x architectures.

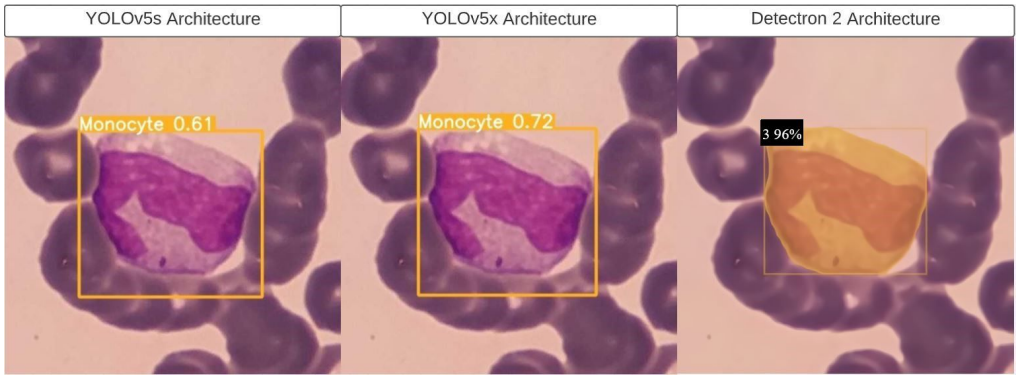

Figure 9. Outputs produced with YOLOv5s, YOLOv5x and Detectron2 R50-FPN architectures.

Recognition accuracy is 61% for YOLOv5s architecture, 72% for YOLOv5x architecture, and 96% for Detectron 2 architecture to detect monocyte cell type belonging to category 3. On the other hand, the prediction category produced on the same image with these architectures can be different. This situation is given in Figure 10.

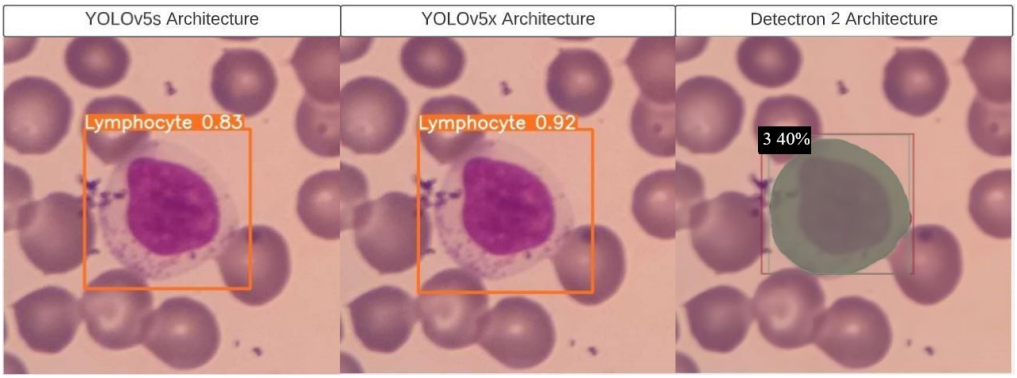

Figure 10. Outputs produced with YOLOv5s, YOLOv5x and Detectron2 R50-FPN architectures.

Recognition accuracy is 83% for YOLOv5s architecture and 92% for YOLOv5x architecture to detect lymphocyte cell type belonging to category 2. However, the Detectron 2 architecture produced false detection accuracy with 40% recognition rate in the monocyte cell type identification belonging to category 3. When Figures 9 and 10 are examined, the recognition accuracy of the images differs on the YOLOv5s, YOLOv5x and Detectron 2 R50-FPN pretrained models.

In this study, hybrid use of YOLO and Detectron2 approaches, which have strengths and weaknesses, is aimed in order to produce better quality outputs. Firstly, the recognition rates produced by the YOLOv5 approach and the Detectron2 approach on images are handled. Next, the recognition rates of test images predicted incorrectly by the Detectron2 frame are compared with the recognition rates produced by the YOLOv5 approach on the same images. The recognition rate in the YOLOV5 approach is evaluated for images that are incorrectly predicted in the Detectron2 approach. In such a case, if the recognition accuracy in the YOLOV5 approach is higher than the recognition accuracy produced in the Detectron2 approach, the new answer for the created hybrid structure is decided as the category predicted by the YOLOv5 algorithm. On the other hand, comparison is not made for correctly predicted images in the Detectron2 framework. The success rate of this hybrid approach trained on the test dataset is obtained as 98% for both the YOLOv5s+Detectron2 structure and the YOLOv5x+Detectron2 structure. The confusion matrix reached as a result of the study is shown in Figure 11.

		YOLOv5s + Detectron2 Model				
		Predicted				
		0	1	2	3	4
Actual	0	54	0	0	1	0
	1	0	71	0	0	0
	2	0	0	57	0	0
	3	0	0	3	48	1
	4	0	0	0	0	64

		YOLOv5x + Detectron2 Model				
		Predicted				
		0	1	2	3	4
Actual	0	54	0	0	1	0
	1	0	71	0	0	0
	2	0	0	56	1	0
	3	0	0	2	50	1
	4	0	0	0	1	63

Figure 11. Confusion matrices.

A new array is created using the algorithm of hybrid structure. For each image in test datasets, 2 comparisons are made depending on a query. In such a case, the operating time is O(N) according to the big

o notation. The accuracy rates achieved in the YOLOv5s+Detecron2 and YOLOv5x+Detectron2 approaches using this new array are 98% and 98%, respectively. The reason for this is that architectures with different dimensions in the YOLO framework are estimated to produce the same or close result, as they are evaluated with the same evaluation metric in the scope of the regression/classification-based approach. This hybrid study enabled the calculation of categories related to images by different evaluation approaches.

Different studies have been carried out in the literature about the evaluation of blood cells. Some of the studies carried out in the last 3 years are given in Table.

Table . Comparison of related studies

Authors	Aim	Methods	Performance criteria
Anita and Yadav 2020 [11]	Automatic detection of WBCs on blood smear images	Artificial electric field algorithm with novel velocity and position bound (AEFA-C)	The accuracy rate is 96.90%.
Makem and Tiedeu, 2020 [40]	Detection of white blood cell nuclei	An adaptive fusion based on principal components analysis	A dice similarity coefficient is 97.06%, 94.75% and 90.79%, respectively for Cellavision, BloodSeg, and JTSC datasets.
Kutlu et al., 2020 [6]	Detection of WBC types on blood images	Regional convolutional neural network	The accuracy rate is 100%.
Ridoy and Islam, 2020 [13]	Detection and classification of WBCs	Lightweight convolutional neural network	The accuracy rate is 98.63%.
Kousalya et al., 2021 [14]	Classification of white blood cell images	GoogleNet approach using ReLU and LReLU activation function	The accuracy rate is 93.43%.
Patil et al., 2021 [15]	White blood cell image classification	Canonical correlation analysis that merges models of CNN and RNN	The accuracy rate is 95.89%.
Baby et al., 2021 [41]	To automatic detection and classification of WBC	Hybrid use of transfer learning architectures and multiclass support vector machine	Highest accuracy is 90.76%.
Sharma et al., 2021 [42]	White blood cells subtypes classification	Fast traditional convolutional neural network model	The accuracy rate is 84.64%.
Iqbal et al., 2021 [43]	To identify multiple myeloma and to distinguish between myeloma and nonmyeloma cells	MASK-recurrent CNN and EfficientNet B3	The accuracy rates are 93% and 95%, respectively.
Shakarami et al., 2021 [44]	Detecting white blood cells, red blood cells, and platelets	Fast and efficient YOLOv3 (FED)	The average precision rates are 98.92%, 80.41%, and 90.25% for WBC, RBC, and platelets, respectively.
Shah et al., 2022 [18]	Detection of different types of blood cells	YOLO_v3, SSD, faster R-CNN, R-FCN	The accuracy rate is 99%.
Ha et al., 2022 [17]	Classification of white blood cells	Fine-grained interactive attention learning (FIAL) semisupervised approach	The accuracy rate is 93.22%.
Xu et al. 2022 [45]	Detecting white blood cells, red blood cells, and platelets	Tiny and efficient YOLOF (TE-YOLOF)	The maximum mean average precision is 91.9 with TE-YOLOF-B3.
Our study	Detection and classification of WBCs	Hybrid model	The maximum accuracy rate is 98%.

The common point of the studies is the evaluation of blood elements. Creating new approaches, using

existing pretrained architectures, making improvements on existing models or creating hybrid structures are distinguishing parts of the studies.

In this study, a hybrid structure was created for the classification of white blood cells on blood smear images. The hybrid use of the region proposal-based Detectron2 pretrained model and the regression/classification-based YOLOv5 pretrained model provides combining forces of two separate object recognition approaches. The output obtained using the hybrid model provides an improvement between 3.44% and 14.7% from the outputs obtained using two separate object recognition approaches. Compared to the existing studies in the literature, this study created a different perspective. It is thought that the study will contribute to the literature.

4. Conclusion

Blood is the fluid of life that enables realizing vital events. Analysis of blood elements in this fluid is an important process used in the diagnosis process of hematological diseases. In this study, white blood cells were recognized and classified. In the study performed using YOLOv5s, YOLOv5x, and Detectron2 R50-FPN pretrained object recognition approaches, 83.3%, 94.66%, and 93.66% success rates were obtained, respectively. However, two more different approaches have been proposed to improve the achieved result. The first approach is the proposed YOLOv5x architecture. With this proposed architecture, an improvement of 0.006 was provided in the recognition rates of all classes. The second approach is a hybrid structure. It enables the hybrid use of YOLO and Detectron2 algorithms, which have two different object evaluation processes. This hybrid structure provided an improvement between 3.44 and 14.7 in the accuracy rate compared to the outputs obtained from the YOLO and Detectron2 pretrained models.

In the future, it is planned to make more powerful inferences using metaheuristic optimization algorithms or to construct a hybrid structure with high inference power using the fuzzy logic algorithm.

References

[1] Al-jaboriy SS, Sjarif NNA, Chuprat S, Abduallah WM. Acute lymphoblastic leukemia segmentation using local pixel information, Pattern Recognition Letters 2019:85-90 doi: 10.1016/j.patrec.2019.03.024

[2] Girdhar A, Kapur H, Kumar V. Classification of White blood cell using Convolution Neural Network, Biomedical Signal Processing and Control 2022: 71 doi: 10.1016/j.bspc.2021.103156

[3] Baydilli YY, Atila Ü. Classification of white blood cells using capsule networks, Computerized Medical Imaging and Graphics 2020: 80 doi: 10.1016/j.compmedimag.2020.101699

[4] Scotti F. Automatic Morphological Analysis for Acute Leukemia Identification in Peripheral Blood Microscope Images, CIMSA 2005-IEEE International Conference on Computational Intelligence for Measurement Systems and Applications 2005: 20–22.

[5] Kasim Ö, Emin AK. Lökosit Hücrelerinin Preparat Görüntüsünden Tespiti ve Sınıflandırılması, Journal of the Faculty of Engineering and Architecture of Gazi University 2015;3 (1): 95–109

[6] Kutlu H, Avci E, Özyurt F. White blood cells detection and classification based on regional convolutional neural networks, Medical Hypotheses; vol. 135, no. November 2019; 135:109472 doi: 10.1016/j.mehy.2019.109472

[7] Su MC, Cheng CY, Wang PC. A neural-network-based approach to white blood cell classification, Scientific World Journal 2014 doi: 10.1155/2014/796371

[8] Elen A,Turan MK. Classifying White Blood Cells Using Machine Learning Algorithms, International Journal of Engineering Research and Development 2019: 141–152 doi: 10.29137/umagd.498372

[9] Shahin AI, Guo Y, Amin KM. and Sharawi AA. White blood cells identification system based on convolutional deep neural learning networks, Computer Methods and Programs in Biomedicine 2019;168 :69–80 doi: 10.1016/j.cmpb.2017.11.015

[10] Ruberto CDi, Loddo A,Putzu L. Detection of red and white blood cells from microscopic blood images using a region proposal approach, Computers in Biology and Medicine 2019:116 doi: 10.1016/j.compbiomed.2019.103530

[11] Anita,Yadav A. An Intelligent Model for the Detection of White Blood Cells using Artificial Intelligence, Computer Methods and Programs in Biomedicine 2021: 199 doi: 10.1016/j.cmpb.2020.105893

[12] Banik PP, Saha R,Kim KD. An Automatic Nucleus Segmentation and CNN Model based Classification Method of White Blood Cell, Expert Systems with Applications 2020;149 doi: 10.1016/j.eswa.2020.113211

[13] Ridoy MAR, Islam MR. A Lightweight Convolutional Neural Network for White Blood Cells Classification, ICCIT 2020 - 23rd International Conference on Computer and Information Technology 2020;19–21 doi: 10.1109/ICCIT51783.2020.9392649

[14] Kousalya K, Krishnakumar B, Mohana RS,Karthikeyan N. Comparative analysis of White Blood Cells Classification using Deep Learning Architectures, Proceedings of the Second International Conference on Smart Electronics and Communication (ICOSEC); 1220–1225, 2021, doi: 10.1109/ICOSEC51865.2021.9591771

[15] Patil AM, Patil MD,Birajdar GK. White Blood Cells Image Classification Using Deep Learning with Canonical Correlation Analysis, IRBM 2021;42 (5):378–389 doi: 10.1016/j.irbm.2020.08.005

[16] Bozkurt F. Classification of Blood Cells from Blood Cell Images Using Dense Convolutional Network, Journal of Scientific, Technology and Engineering Research 2021; 2:81–88 doi: 10.53525/jster.1014186

[17] Ha Y, Du Z,Tian J. Fine-grained interactive attention learning for semi-supervised white blood cell classification, Biomedical Signal Processing and Control 2022; 75 doi: 10.1016/j.bspc.2022.103611

[18] Shah R, Shastri J, Bohara MH, Panchal BY, Goel P. Detection of Different Types of Blood Cells: A Comparative Analysis, 2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE) 2022; 1–5 doi: 10.1109/icdcece53908.2022.9793132

[19] Zhao Z et all. Real-time detection of particleboard surface defects based on improved YOLOV5 target detection, Scientific Reports 2021;11 (1):1–15 doi: 10.1038/s41598-021-01084-x

[20] Alakus TB,Turkoglu I. Comparison of deep learning approaches to predict COVID-19 infection, Chaos, Solitons and Fractals 2020; 140 doi: 10.1016/j.chaos.2020.110120

[21] Scotti F. Automatic morphological analysis for acute leukemia identification in peripheral blood microscope images, IEEE International Conference on Computational Intelligence for Measurement Systems and Applications - CIMSA; 96–101, 2005, doi: 10.1109/CIMSA.2005.1522835

[22] Al-jaboriy SS, Sjarif NNA, Chuprat S,Abduallah WM. Acute lymphoblastic leukemia segmentation using local pixel information, Pattern Recognition Letters; 125, 85–90, 2019, doi: 10.1016/j.patrec.2019.03.024.

[23] Zhao ZQ, Zheng P, Xu ST, Wu X. Object Detection with Deep Learning: A Review, IEEE Transactions on Neural Networks and Learning Systems 30 (11); 3212–3232, 2019, doi: 10.1109/TNNLS.2018.2876865

[24] Tavakoli S, Ghaffari A. Kouzehkanan ZM and Hosseini R. New segmentation and feature extraction algorithm for classification of white blood cells in peripheral smear images. Scientific Reports 2021; 11 (1): 1–13 doi: 10.1038/s41598-021-98599-0

[25] Kouzehkanan ZM et all. A large dataset of white blood cells containing cell locations and types, along with segmented nuclei and cytoplasm, Scientific Reports 2022;12 (1):1–14 doi: 10.1038/s41598-021-04426-x

[26] Karaci A. Detection and classification of shoulder implants from X-ray images: YOLO and pretrained convolution neural network based approach, Journal of the Faculty of Engineering and Architecture of Gazi University 2022;37 (1):283–294 doi: 10.17341/gazimmfd.888202

[27] Bochkovskiy A, Wang CY,Liao HYM. YOLOv4: Optimal Speed and Accuracy of Object Detection, Arxiv; 2020.

[28] Song Q. et all. Object detection method for grasping robot based on improved yolov5, Micromachines 2021; 12 (11) doi: 10.3390/mi12111273.

[29] Zhu L, Geng X, Li Z, Liu C. Improving yolov5 with attention mechanism for detecting boulders from planetary images, Remote Sensing; 2021; 13 (18): 1–19 doi: 10.3390/rs13183776

[30] Yagu FJ. et all. Defect detection and segmentation in X-Ray images of magnesium alloy castings using the Detectron2 framework, Arxiv; 2022.

[31] Carvalho OLF et all. Instance segmentation for large, multi-channel remote sensing imagery using mask-RCNN and a mosaicking approach, Remote Sensing 2021;13 (1):1–24 doi: 10.3390/rs13010039

[32] Yang D. et all. A Mask R-CNN based particle identification for quantitative shape evaluation of granular materials, Powder Technology 2021;392:296–305 doi: 10.1016/j.powtec.2021.07.005

[33] Chen J, Lu Z, Xue JH, Liao Q. XSepConv: Extremely Separated Convolution, Arxiv; 2020,

[34] Şafak E, Doğru İ, Barışçı N,Toklu S. Derin öğrenme kullanılarak nesnelerin interneti tabanlı mobil sürücü yorgunluk tespiti, Journal of the Faculty of Engineering and Architecture of Gazi University 2021;37 (4): 1869–1881 doi: 10.17341/gazimmfd.999527

[35] Hayou S, Doucet A ,Rousseau J. On the impact of the activation function on deep neural networks training, Arxiv; 2019.

[36] Seyyarer E, Karcı A, Ateş A. Stokastik ve deterministik hareketlerin optimizasyon süreçlerindeki etkileri, Journal of the Faculty of Engineering and Architecture of Gazi University 2021;37 (2):949–965 doi: 10.17341/gazimmfd.887976

[37] Elfwing S, Uchibe E, Doya K. Sigmoid-weighted linear units for neural network function approximation in reinforcement learning, Neural Networks 2018;107: 3–11 doi: 10.1016/j.neunet.2017.12.012

[38] Koupaei JA, Hosseini SMM , Ghaini FMM. A new optimization algorithm based on chaotic maps and golden section search method, Engineering Applications of Artificial Intelligence 2016;50 :201–214 doi: 10.1016/j.engappai.2016.01.034

[39] Akalın F, Yumuşak N. DNA genom dizilimi üzerinde dijital sinyal işleme teknikleri kullanılarak elde edilen ekson ve intron bölgelerinin EfficientNetB7 mimarisi ile sınıflandırılması, Journal of the Faculty of Engineering and Architecture of Gazi University 2021; 3: 1355–1371doi: 10.17341/gazimmfd.900987

[40] Makem M, Tiedeu A. An efficient algorithm for detection of white blood cell nuclei using adaptive three stage PCA-based fusion, Informatics in Medicine Unlocked 2020;20 doi: 10.1016/j.imu.2020.100416

[41] Baby D, Devaraj SJ, Hemanth J, MM AR. Leukocyte classification based on feature selection using extra trees classifier: A transfer learning approach, Turkish Journal of Electrical Engineering and Computer Sciences 2021;29 (8):2742–2757 doi: 10.3906/elk-2104-183

[42] Sharma A. et. all. White Blood Cells Subtypes Classification Using Fast Traditional Convolutional Neural Network, 2021 International Conference on Emerging Techniques in Computational Intelligence - ICETCI 2021;113–117 doi: 10.1109/ICETCI51973.2021.9574045

[43] Iqbal A, Ahmed MF, Suvon MNI, Das Shuvho S, Fahmin A. Towards Efficient Segmentation and Classification of White Blood Cell Cancer Using Deep Learning, 2021 Emerging Technology in Computing, Communication and Electronics - ETCCE 2021; 1–6. doi: 10.1109/ETCCE54784.2021.9689839

[44] Shakarami A, Menhaj MB, Mahdavi-Hormat A, Tarrah H. A fast and yet efficient YOLOv3 for blood cell detection, Biomedical Signal Processing and Control 2021;66 doi: 10.1016/j.bspc.2021.102495

[45] Xu F, Li X, Yang H, Wang Y, Xiang W. TE-YOLOF: Tiny and efficient YOLOF for blood cell detection, Biomedical Signal Processing and Control 2022;73 doi: 10.1016/j.bspc.2021.103416