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Anemia Classification Based On Abnormal Red Blood Cell Morphology Using Convolutional Neural Network

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Abstract:
This study discusses the classification of anemia based on the types of morphology of abnormal red blood cells in the helmet cell, megaloblastic cell, normocytes cell, stomatocytes cell, and teardrop cell using the Convolutional Neural Network method to then be classified into two types of Anemia: Iron Deficiency Anemia and Megaloblastic Anemia. Which through morphological analysis is the starting point for a diagnostic approach of more than 80% of hematological disease. This study uses several testing parameters including epoch, learning rate, mini-batch and momentum to train the image during the classification process in order to obtain better testing accuracy of implementation

Background*:*
Iron and folidacid are very important elements for the body, thus the deficiency of iron and folidacidwill causes irondeficiencyanemia and megaloblasticanemia. As many as 24.8% of the world's population estimated 1.62 bilion people are affected by anemia and as many as 39% of cancer patients have anemiaat the time of diagnosis. That isalmosthalf of these cancer patients have irondeficiencyanemia.Morphologicalanalysisis the starting point for a diagnostic approach of more than 80 percent of haematologicaldisease. This study propose amethod for classifyingabnormalitiesbased on images of abnormalredbloodcells by using the CNN method. Previouslythereserealsomanystudiedthatdiscussed the classification of the anemiausing the CNN method. In thisstudyused 1.240 images of image data for training and used 251 image data for testing. From the experimentalresult, the accuracy value is 0.8725, precission value is 0.9074 and recall value is 0.9406.

Materials and Methods*: Data for this research were obtained from BCCD (Blood Cell Count and Detection) by downloading images on the site https://github.com/Shenggan/BCCD_Dataset (Blood cell dataset with a license from the Massachusetts Institute Of Technology) as many as 410 images of blood cells in the Joint Experts Group (.jpeg) format, Then the images will be sorted and cropped according to the region of interest (ROI) and resulting 1.491 images for 5 categories of abnormal red blood cell. The Training data used for this research were 1.240 images, consist of 70 helmet cells, 100 megaloblastic cells, 170normocytes, 500 stomatocytes cells, and 100 teardrop cells and the Test data used were 251 images consist of 20 helmet cells, 34 megaloblastic cells, 44 normocytes, 100 stomatocytes cells, and 53 teardrop cells.The method used for this research is Convolutional Neural Network. The first process is image data acquisition then pre-processing process: grayscale and resizing. And then proceed with the classification step in the CNN layer.*

Results*:The experimentalresult, the accuracy value is 0.8725, precission value is 0.9074 and recall value is 0.9406.*

Conclusion:
The results of the classification using the CNN method on the test data obtained, iron deficiency anemia can be classified correctly as many as 206 objects and megaloblastic anemia images correctly classified as many as 11 object images. This research used parameters epoch on 50, 100, 200, learning rate values are 0.1 to 0.0001 then mini-batch size 32, 64, 128, 256 and momentum values are 0.9, 0.95, 0.99. The highest training accuracy value is 0.97741 with parameter epoch 200, mini-batch 64, learning rate 0.01, momentum 0.95. The highest testing accuracy value is 0.8844 with parameter epoch 200, mini-batch 256, learning rate 0.1, momentum 0.9. This means that the classification result of the system is high accuracy. The accuracy value is 0.8725 , the precission value is 0.9074 and the recall value is 0.9406.

Key Word:*Red Blood Cells (RBCs); Convolutional Neural Network (CNN); Deep Learning*

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I. Introduction

In the medical field, the classification of red blood cells (RBC's) are used as an indicator to classify the type of abnormality presence in RBC's. The RBC's abnormal morphological nature of the cells gives anemia sign, hemoglobin reduction also the secondary effect of many other disorders. The diagnosis of RBC's gives more information on various related blood cell diseases In the medical field, the classification of red blood cells (RBC's) are used as an indicator to classify the type of abnormality presence in RBC's. The RBC's abnormal morphological nature of the cells gives anemia sign, hemoglobin reduction also the secondary effect of many other disorders. The diagnosis of RBC's gives more information on various related blood cell diseases. This research suggested the use of the CNN method to facilitate the classification of abnormal red blood cells into two types of anemia, because CNN can classify better even with very large datasets [2][4].

II. Material And Methods

A dataset is a matrix representation of images along with image labels. The function of making a dataset is that the input format can be accepted during the convolution training process. This research uses two separate datasets namely train data and test data. This study uses 70% training data and 30% testing data which were trained 1.240 data and 251 testing data.

Table 1. Training Data Distribution and Testing Data

No.	Dataset	The Amount of Data
1.	Training Data Testing Data	1.240 251
2.	Training Data Testing Data	1.240 251

The data distribution for training in this study using 5 types of abnormal red blood cell image data, consist of 70 helmet cell image data, 100 megaloblastic cell image data, 170 normocytes cell image data, 500 stomatocytes cell image data, 400 teardrop cell image data. It can be seen in table 2.

Table 2. Training Data Distribution

No.	Abnormal Red Blood Cells Image	The Amount of Data
1.	Helmet Cell	70
2.	Megaloblastic Cell	100
3.	Normocytes Cell	170
4.	Stomatocytes Cell	500
5.	Teardrop Cell	400

The data distribution for testing in this study using 5 types of abnormal red blood cell image data, consist of 20 helmet cell image data, 20 megaloblastic cell image data, 44 normocytes cell image data, 100 stomatocytes cell image data, 53 teardrop cell image data. It can be seen in table 3.

Table 3 Testing Data Distribution

No.	Abnormal Red Blood Cells Image	The Amount of Data
1.	Helmet Cell	20
2.	Megaloblastic Cell	20
3.	Normocytes Cell	44
4.	Stomatocytes Cell	100
5.	Teardrop Cell	53

Read Dataset
The next process is reading the dataset. From the dataset training data and testing data are taken. The training data is then used to conduct CNN training. The output of this process is the best model for classification. The end of the training process is the best formulation that maps training data as shown by the level of training accuracy.

Model Accuracy
Model accuracy can be determined by conducting validation using test data.

Subjects & selection method:

The study population was taken from the BCCD (Blood Cell Count and Detection) by downloading the image on the site https://github.com/Shenggan/BCCD_Dataset (Blood cell dataset with a license from the Massachusetts Institute Of Technology) as many as 410 images of blood cells in the Joint Experts Group (.jpeg) format. Then the sorting and cropping process of the image based on ROI, and get 1.491 images abnormal red blood cell. This study classifies 5 kinds of abnormal red blood cells (helmet cell, megaloblastic cell, normocytes cell, stomatocytes cells and teardrop cells) into 2 type of anemia (Iron Deficiency Anemia and Megaloblastic Anemia). The comparison for training and testing data in this research is 70% and 30%.Data analysis method used in this study is Convolutional Neural Network for image classification of Iron deficiency Anemia and Megaloblastic Anemia. The division of images into training data sets is made to train system knowledge about types or categories of types anemia. And dataset testing to test the results of the image classification process according to the knowledge obtained by the system through training data.

Procedure methodology

The first is image acquisition , to collect image data then crop the image according to region of interest *(ROI)*. The next step is to pre-process the transformation of the RGB image into grayscale and resizing process. Then, the feature extraction process by CNN and continued with the image classification process by CNN. The next stage is training model and testing model to get training accuracy and testing accuracy of images.

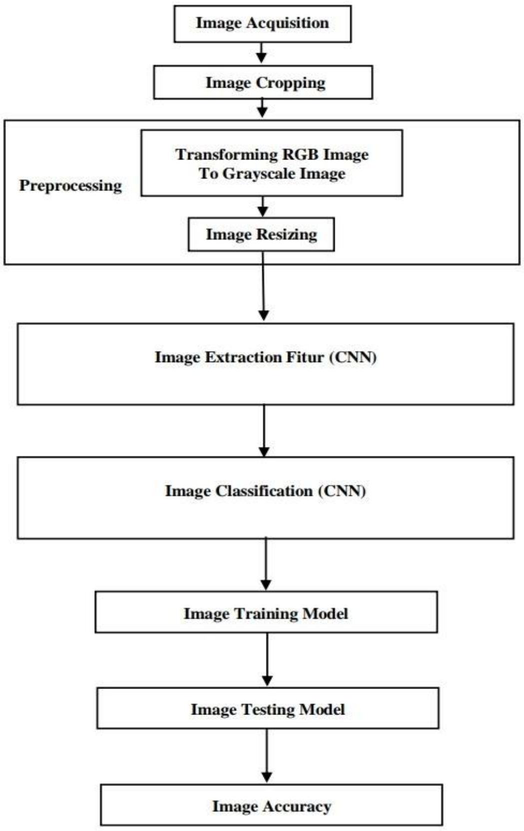

Fig. 1: Research Method Scheme

Image Acquisition

This study uses secondary data obtained from the BCCD on the site: https://github.com/Shenggan/BCCD_ Dataset. The dataset consist of 410 images in jpeg format. The data needed is abnormal red blood cell image data.

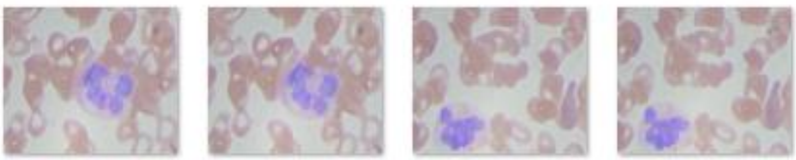

Fig. 2: Dataset of Blood Cell

Image Cropping

At this step images of blood cells will be crop according the region of interest *(ROI)* and obtained 1.491 images in jpeg format. This research focuses on discussing 5 tyoes of abnormal red blood cells namely helmet cells, normocytes cells, stomatocytes cells, teardrop cells for Iron Deficiency Anemia type and megaloblastic cells for megaloblastic anemia type.


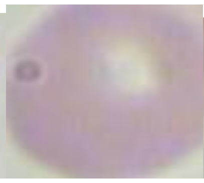


Fig 3. Helmet Cell Fig 4. Normocyte CellFig 5.Stomatocyte Cell


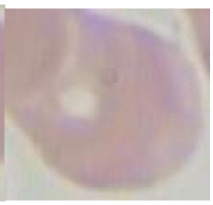

Fig 6. Teardrop Cell Fig 7. Megaloblastic Cell

Pre-Processing

Transforming RGB Image to Grayscale Image

At this step, the RGB color transformation is made to a grayscale to simplify the image model. Out put from this step is a picture with gray, then the file will be used to build the data set.

Image Resizing

This step, the image will be converted into a matrix as input for the classification process with convolutional neural network.

Image Extraction Fitur

Input Layer

In this step the color images will be input, then the image will go through a convolution process. The number of convolution layers will determine the accuracy of the classification model. Then the process of ReLu activation to grayscale to get the results of binary image segmentation, to be able to recognize objects in the image required parameters that characterize objects. The parameter value is then used as input data in the classification process.

Hidden Layer

The next process is fully-connected layer. This layer is a hidden layer in general in neural networks that are shaped in one dimension. Input on fully-connected layer comes from processes that exist in the previous convolution layer.

Image Classification

Output Layer

The final process in the CNN classification step is the output layer, which is the last layer and consist of 2 neurons representing 2 types of anemia that want to be classified, namely Iron Deficiency Anemia and Megaloblastic Anemia. This layer is the softmax layer, it is the command used to classify objects in this research.

Statistical analysis

Training Hyperparameter

In this research the classification process on CNN uses 4 hyperparameters namely epoch, mini-batch, learning rate and momentum. The function of these hyperparameters is to able to carry out the classification process accurately:

a. Batch

A batch is a hyperparameter that controls the number of samples in training that must be carried out before the internal parameters of the model are updated. Batch size is more than one sample and less than the size of the training dataset, the learning algorithm is called a mini-batch. The best batch size is 32, 64 and 128 samples [5].

b. Epoch

Epoch is a hyperparameter that functions to control the number of complete passes through the training dataset. Epoch consists of one or more groups. The number of epochs commonly used is 10, 100, 500 and 1.000 [5].

c. Learning rate
Learning rate is a hyperparameter that controls the speed or speed of the learning model. In general, a large level of learning rate allows the learning model to be faster but with less optimal accuracy. While the small level of learning rate allows the model to get more optimal or even globally optimal accuracy but may take a little longer to practice, learning rate range value of 1.0 until 10^{-6} [5].

d. Momentum
Momentum serves to accelerate learning on the problem of high dimensional weight space, especially in the face of high curvature, small but consistent gradients. Momentum values can be set greater than 0.0 and less than 1. Where the commonly used momentum value is 0.9 and 0.99 [5].

e. Confussion matrix
Confussion matrix is a method to represent the result of classification evaluation.The accuracy of classification of a specific example can be viewed in one of four possible ways [14]:
a. The predicted class is Y, and the actual class is also Y - this is a TruePositive or TP
b. The predicted class is Y, and the actual class is N - this is a False Positive or FP
c. The predicted class is N, and the actual class is Y - this is a False Negative or FN
d. The predicted class is N, and the actual class is also N - this is a True Negative or TN

Table 4. Confussion Matrix
(Source : Vijay Kotu and Bala Deshpande, 2019)

		Actual Class (Observation)	
		Y	**N**
Predicted class (expectation)	Y	*TP* correct result	*FP* unexpected result
	N	*FN* missing result	*TN* correct absence of result

TP, *true positive;* FP, *false positive;* FN, *false negative;* TN, *true negative.*

Accuracy is defined as the ability of the classifier to select all cases that need to be selected and reject all cases that need to be rejected. For a classifier with 100% accuracy, this would imply that FN = FP = 0. Note that in the document search example, the TN has not been indicated, as this could be really large. The Formula of accuracy is [6]:
Accuracy = (TP + TN) / (TP + FP + TN + FN) (1)

Precission is defined as the proportion of cases found that were actually relevant. From the example, this number was 70, and thus, the precision is 70/100 or 70%. The 70 documents were TP, whereas the remaining 30 were FP. The Formula of precission is [6]:

Precission = TP / (TP + FP) (2)

Recall is defined as the proportion of the relevant cases that were actually found among all the relevant cases. Again, with the example, only 70 of the total 110 (70 found + 40 missed) relevant cases were actually found thus giving a recall of 70/110 = 63.63%. It is evident that recall is the same as sensitivity The Formula of recall is [6]:

Recall = TP / (TP + FN) (3)

III. Result

Training and Testing Accuracy
Test results on epoch 50, mini-batch with values varying between 32, 64, 128, 256 and learning rate with values of 0.1 to 0.0001 and momentum values of 0.9, 0.95, 0.99 then the highest accuracy is obtained for training 0.92096 and lowest accuracy for training is 0.91935. While the highest accuracy results for testing obtained by 0.86852 and the lowest accuracy for testing obtained by 0.86454. The fastest result of the processing time is obtained in 2 minutes 45 seconds and the longest processing time is obtained in 14 minutes 48 seconds. The results can be seen in table 5.

Table 5. Classification Performance using Epoch 50

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing Processing	Accuracy Training	Accuracy Testing
1.	50	32	0.1	0.9	14 min 48 sec	0.92016	0.86454
2.	50	64	0.1	0.9	7 min 18 sec	0.92096	0.86454
3.	50	128	0.001	0.9	3 min 40 sec	0.91935	0.86454
4.	50	256	0.1	0.95	2 min 45 sec	0.92096	0.86852

Test results on epoch 100, mini-batch with values varying between 32, 64, 128, 256 and learning rate with values of 0.1 to 0.0001 and momentum values of 0.9, 0.95, 0.99 then the highest accuracy is obtained for training 0.962097 and lowest accuracy for training is 0.91935. While the highest accuracy results for testing obtained by 0.88047 and the lowest accuracy for testing obtained by 0.86055. The fastest result of the processing time is obtained in 5 minutes 27 seconds and the longest processing time is obtained in 29 minutes 28 seconds. The results can be seen in table 6.

Table 6. Classification Performance using Epoch 100

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing	Accuracy Training	Accuracy Testing
1.	100	32	0.01	0.95	29 min 28 sec	0.96209	0.88047
2.	100	64	0.1	0.95	8 min 3 sec	0.91935	0.86454
3.	100	128	0.1	0.95	6 min 49 sec	0.94274	0.86055
4.	100	256	0.1	0.95	5 min 27 sec	0.93225	0.87251

Test results on epoch 200, mini-batch with values varying between 32, 64, 128, 256 and learning rate with values of 0.1 to 0.0001 and momentum values of 0.9, 0.95, 0.99 then the highest accuracy is obtained for training 0.97941 and lowest accuracy for training is 0.95080. While the highest accuracy results for testing obtained by 0.88442 and the lowest accuracy for testing obtained by 0.82868. The fastest result of the processing time is obtained in 12 minutes 31 seconds and the longest processing time is obtained in 30 minutes 38 seconds. The results can be seen in table 7.

Table 7. Classification Performance using Epoch 200

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing Processing	Accuracy Training	Accuracy Testing
1.	200	32	0.01	0.9	30 min 38 sec	0.97903	0.86852
2.	200	64	0.01	0.95	21 min 44 sec	0.97941	0.87251
3.	200	128	0.1	0.9	30 min 26 sec	0.95080	0.82868
4.	200	256	0.1	0.9	12 min 31 sec	0.95403	0.88442

The highest accuracy results for training are obtained with a value of 0.97741 if the epoch value is 200, mini-batch size is 64 , learning rate value is 0.001 and then momentum value is 0.95. the results can be seen in the table 8.

Table 8. The Highest Value Of Training Process

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing Processing	Accuracy Training	Accuracy Testing
1.	50	256	0.1	0.95	2 min 45 sec	0.92096	0.86852
2.	100	32	0.01	0.95	29 min 28 sec	0.96209	0.88047
3.	200	64	0.01	0.95	21 min 44 sec	0.97741	0.87251

The highest accuracy results for testing are obtained with a value of 0.88442 if the epoch value is 200, mini-batch size is 256 , learning rate value is 0.1 and then momentum value is 0.9. the results can be seen in the table 9.

Table 9. The Highest Value Of Testing Process

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing Processing	Accuracy Training	Accuracy Testing
1.	50	256	0.1	0.95	2 min 45 sec	0.92096	0.86852
2.	100	32	0.01	0.95	29 min 28 sec	0.96209	0.88047
3.	200	256	0.1	0.9	12 min 31 sec	0.95403	0.88442

Time Processing Result

The fastest processing time obtained with parameters epoch is on 50, mini-batch size 256, learning rate value is 0.1 then momentum value is 0.95 is 2 minutes and 45 seconds. It can be seen at table 10.

Table 10. Time Processing

No	Epoch	Mini-Batch	Learning Rate	Momentum	Timing Processing	Accuracy Training	Accuracy Testing
1.	50	256	0.1	0.95	2 min 45 sec	0.92096	0.86852
2.	100	256	0.1	0.95	5 min 27 sec	0.93225	0.87251
3.	200	256	0.1	0.9	12 min 31 sec	0.95403	0.88442

Confussion Matrix Of Training Accuracy

Based on table 11 we can see the confussion matrix, which means that the classification results are not entirely able to read correctly by the program according to the category. In the Iron Deficiency Anemia images object only 1.129 images were detected in the category of 1.146 image objects tested on the training data and megaloblastic anemia image objects as many as 11 image objects were detected in the category of 94 image objects tested on the training data. From the experiment results the accuracy value is 0.9774 , precision value is 0.9903and recall value is 0.9851.

Table 11 Confussion Matrix Of Training Accuracy

Predicted Class	Actual Class	
	Iron Deficiency Anemia (+)	Megaloblastic Anemia (-)
Iron Deficiency Anemia (+)	1129	11
Megaloblastic Anemia (-)	17	83

Confussion Matrix Of Testing Accuracy

Based on table 12 we can see the confussion matrix, which means that the classification results are not entirely able to read correctly by the program according to the category. In the Iron Deficiency Anemia images object only 213 images were detected in the category of 238 image objects tested on the training data and megaloblastic anemia image objects as many as 4 image objects were detected in the category of 13 image objects tested on the training data. From the experiment results the accuracy value is 0.8844, precission value is 0.9815, recall value is 0.8949.

Table 12 ConfussionMatriksOf Testing Accuracy

Predicted Class	Actual Class	
	Iron Deficiency Anemia (+)	Megaloblastic Anemia (-)
Iron Deficiency Anemia (+)	213	4
Megaloblastic Anemia (-)	25	9

An accuracy rate of 0.8725 means that the system performance of the method used can be done with a percentage rate of 0.8725 out of 100%. It means the system is able to classify image data correctly at 0.8725, and 0.1275 means that systems cannot classify images correctly

IV. Discussion

Hung Ning,Hu Yu-Li,ShenChe-Cheng et al., explained their research about the classification of red blood cells in sickle cell anemia. They used CNN method. Their dataset consisted of 434 raw microscopy images of 8 different SCD patients collected from two different hospitals. Then based on the obtained raw images, 7206 single RBC image patches were extracted by using the CNN method. The classification used a deep convolutional neural network for classification of red blood cells in sickle cell anemia in Sickle Cell Disease, which was quite difficult due to the heterogeneous shapes of RBCs and the existence of touching and overlapped RBCs in the raw microscopy image, and existing software cannot be directly used to obtain RBC boundaries and cannot distinguish among the many different types of RBCs. By using the CNN neural network to realize the classification of red blood cells and successfully classifying sickle red blood cells automatically with high accuracy. Their classification result obtain recall value was 0.938 and precision value was 0.60 [4].

Besides classification of red blood cells in sickle cell anemia, other studies have studied classification in another language and dataset. Acevedo Andrea, Alferez Santiago, Merino Anna et al., explained their research about the Recognition of peripheral blood cell images. They used convolutional neural networks method. Their dataset consisted of 17,092 images of eight classes of normal peripheral blood cells was acquired using the CellaVision DM96 analyzer. All images were identified by pathologists as the ground truth to train a model to classify different cell types: neutrophils, eosinophils, basophils, lymphocytes, monocytes, im- mature granulocytes (myelocytes, metamyelocytes and promyelocytes), erythroblasts and platelets. The morphological differentiation among different types of normal and abnormal peripheral blood cells is a difficult task that requires experience and skills. This research proposes a system for the automatic classification of eight groups of peripheral blood cells with high accuracy by means of a transfer learning approach using convolutional neural networks. With this new approach, it is not necessary to implement image segmentation, the feature extraction becomes automatic and existing models can be fine-tuned to obtain specific classifiers. The performance obtained when testing the system has been truly satisfactory, the values of precision, sensitivity, and specificity being excellent. In conclusion, the best overall classification accuracy was 0.962 [2].

Another research, AliyuAbdulkarimHajara, SudirmanRubita, Razak Abdul AzharMohd et al., explained their research about the Red Blood Cell Classification: Deep Learning Architecture versus Support Vector Machine. They used SVM and Deep Learning method. Their dataset consisted of 105 images of red blood cells, which have a spread of 5 class labels (normal cell, elliptocyte cell, sickle cell, teardrop cell, achantocyte cell). This research proposed a method to classify abnormalities based on deformed shaped RBCs image by using SVM and Deep learning in comparison on the RBCs cell classification. Classifying normal cells of RBCs indicate of healthy patient and classifying elliptocyte cell, sickle cell, teardrop cell, achantocyte cell indicate presence of disease. This study suggested that SVM clasifier out performed deep learning classifier because the SVM can classify the cells in all condition either small or large dataset and deep learning performs mainly on large dataset only[3].

V. Conclusion

The results of the classification using the CNN method on the test data obtained, iron deficiency anemia can be classified correctly as many as 206 objects and megaloblastic anemia images correctly classified as many as 11 object images. This research used parameters epoch on 50, 100, 200, learning rate values are 0.1 to 0.0001 then mini-batch size32, 64, 128, 256 and momentum values are 0.9, 0.95, 0.99. The highest training accuracy value is 0.97741with parameter epoch 200, mini-batch 64, learning rate 0.01, momentum 0.95.The highest testing accuracy value is 0.8844 with parameter epoch 200, mini-batch 256, learning rate 0.1, momentum 0.9. This means that the classification result of the system is high accuracy. The accuracy value is 0.8725 , the precission value is 0.9074 and the recall value is 0.9406.

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