Implementation of Data Augmentation to Improve Performance CNN Method for Detecting Diabetic Retinopathy

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***Abstract*— The most common causes of blindness in adults worldwide, 2.6% of them are caused by diabetic retinopathy, which is a progressive disease caused by complications of diabetes mellitus. Early detection and prompt treatment help save eyesight. The artificial intelligence technology can provide objective and accurate screening results. Deep learning, especially the Convolutional Neural Network (CNN), which is part of artificial intelligence, has proven successful in solving image problems and is very well used in medical image analysis. CNN works well on large datasets, but it will affect network performance to overfitting in fewer datasets. So to solve the problem of small data, data augmentation techniques can be used. There are various kinds of data augmentation techniques. This study used the CNN method to classify diabetic retinopathy disease, compared several suitable data augmentation techniques for retinal fundus images, and used Contrast Limited Adaptive Histogram Equalization (CLAHE) for image enhancement. This study found that the augmented random zoom technique, together with CLAHE, provided the best accuracy of 98% with 96% sensitivity and 100% specificity.**

Keywords—Diabetic Retinopathy, Contrast Limited Adaptive Histogram Equalization, Convolutional Neural Network, Data Augmentation

I. INTRODUCTION

Blindness cases caused by Diabetic Retinopathy (DR) are more than 2.6% worldwide [1], the most common blindness cases in adults aged between 20-74 years. Almost all patients with type 1 diabetes experience DR, and more than 60% of patients with type 2 diabetes experience too [2]. DR is a progressive disease [3] that occurs due to pathological changes in blood vessels that cause retinal damage in diabetes mellitus patients [4]. The initial stage of the emergence of the DR does not show symptoms that can be felt directly by the patient. Early detection of DR only can be observed through retinal fundus images characterized by the appearance of one or more retinal lesions such as Microaneurysms (MA), Hemorrhage (HE), Soft Exudate (SE), and Hard Exudate (EX) [5]. The difference between a healthy retina and a normal retina shows in Fig 1.

Blindness in DR patients should prevent early detection and appropriate treatment[6][7]. The need for technology in automatic screening for DR helps detect the disease early [8]. Besides, the technology can provide objective and accurate results compared to manual diagnosis [9]. Research to find the best method of computer-aided DR detection still has much room to develop. The technique that is very suitable in medical image analysis is a deep learning method based on convolutional neural networks. This method is very similar to the way human thinking [10]. Deep learning was popularized by Geoffrey Hinton in 2006 [11] and developed rapidly after the GPU discovery by Andrew et al. in 2009 [12].

Convolutional Neural Network (CNN), which is a sub-class of deep learning, is known to solve problems related to images successfully. CNN successfully outperformed traditional methods in object detection tasks [13], image segmentation [14], and classification [15]. Moreover, CNN very well uses in medical image analysis [16]. This study detects retinal DR by using the CLAHE image quality improvement method, which then uses CNN to classify normal retina and retina DR. CNN works very well with large amounts of data. However, because the amount of data held is still insufficient, the author will add to the augmentation data. And will compare several augmentation data methods to find the best matches data augmentation technique. The test will do using several scenarios and using a confusion matrix to get the value of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix results use to calculate the value of accuracy, sensitivity, and specificity, which are the parameters of the assessment of this study.

Retina normal Retina DR

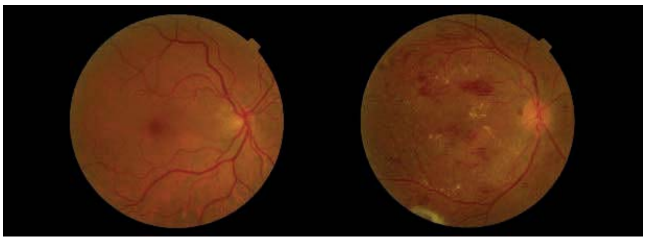


Fig. 1. Image of retinal fundus [17]

II. RELATED WORKS

Previous experiments detected DR in various ways, for example, by segmenting retinal morphology. By detecting and segmenting OD and FV, matching the DR-based histogram [18]. Extracting the retinal background based on binarization surgery and growth area [19]. To segmentation the blood vessel. Researchers used the vessel enhancement method is Frangi Filter. They claim it is the best method, combined with various other algorithms, such as contrast enhancement, Morphological Bottom Hat Transform, Laplacian of Gaussian (LOG) filters, and Fuzzy C-Means Clustering. The aim is to extract the BV edge structure and describe the BV structure [20]. By using CLAHE and a morphological process for feature extraction [21]. Supervised learning-based segmentation uses the Extreme Learning Machine (ELM) [22]. Zhou performed unsupervised classification with the PCA method to detect microaneurysms and solve the problem of class imbalance [23], but there were some false-positives (FP) during feature extraction. Some microaneurysms are opaque and low in contrast [24]. Then Jebaseeli classified NPDR using TPCNN (Tandem Pulse Coupled Neural Network) and DLBSVM (Deep Vector-Based Support Machine) methods for extraction and classification using one parameter. This experiment produces a high accuracy value [25], but the drawback is low sensitivity, where sensitivity indicates the ability of the algorithm to detect blood vessels correctly.

CNN based in [26][27][28] uses to define the label of each pixel sliding rectangular window for each iteration. The output from the CNN, combined with the output from the optical disc, can detect segment exudates accurately [29]. The other uses Dense U-net [30][31][32][33] to explore the location of blood vessel. In some studies using CNN to prevent overfitting, researchers use transfer learning methods such as the research was carried out by enhancing the image first and then using the CNN architecture, which adopted Alexnet [34], VGGnet [35], and ResNet [36]. Another study used data augmentation to segment blood vessels using warping non-linear and transformation techniques [37]. In other work, researchers use the CNN method with various data augmentation techniques such as warping [37]. Lighting variations, rotation, flipping [38]. Scaling, rotation, translation, flipping, and shearing [39]. Rotation, translation, mirroring, stretching, and zooming [40]. All of which yields outstanding curated values after adding augmentation data.

III. Proposed Method

A. *Dataset*

This research type is an experimental study using secondary datasets that have been provided by Messidor [17] for research needs on the diagnosis of computer-aided diabetic retinopathy. The total images use 700 images of the retinal fundus in the .tiff format that has been evaluated and labeled by ophthalmologists. The details of the dataset can show in table 1.

TABLE I Detail Dataset

Samples	Number	Repository
Normal retina	350	Messidor Dataset
Retina DR	350	
Total	700	

B. *Analysis Process*

The scenarios to test our CNN classification model using two types of datasets: (1) dataset without data augmentation, which will divide into two classes as in table 1, and (2) dataset using data augmentation. In this experiment, we will use three scenarios to try maximum results: (1) Using a simple CNN and image enhancement, (2) Comparing several data augmentation techniques to find suitable methods used in retinal fundus images, (3) Uses data augmentation to add variation to data together with CLAHE for image enhancement. The research flowchart in Fig. 2 will explain the process that we did. After determining the data and scenarios, the data will divide into 90% training data and 10% validation data. The next step is classification using the CNN method. Chapter 4 contains the analysis and discussion, and section 5 is the conclusion.

C. *Preprocessing*

Sometimes the data is not always in ideal conditions for processing. Therefore this stage of processing is needed to transform input data into data following the objectives to be achieved [41]. The selection of the right process at the preprocessing stage can improve classification performance [42]. The preprocessing steps carried out in this study were among others:

1) Resizing: All images in the dataset are resized to 224x224 to match the size and pixel input image used in the extraction process.

2) Green channel: selected because it can further highlight the contrast between features and background, also because green channels contain less noise [43]. The results of the green channel process can show in Fig. 3.

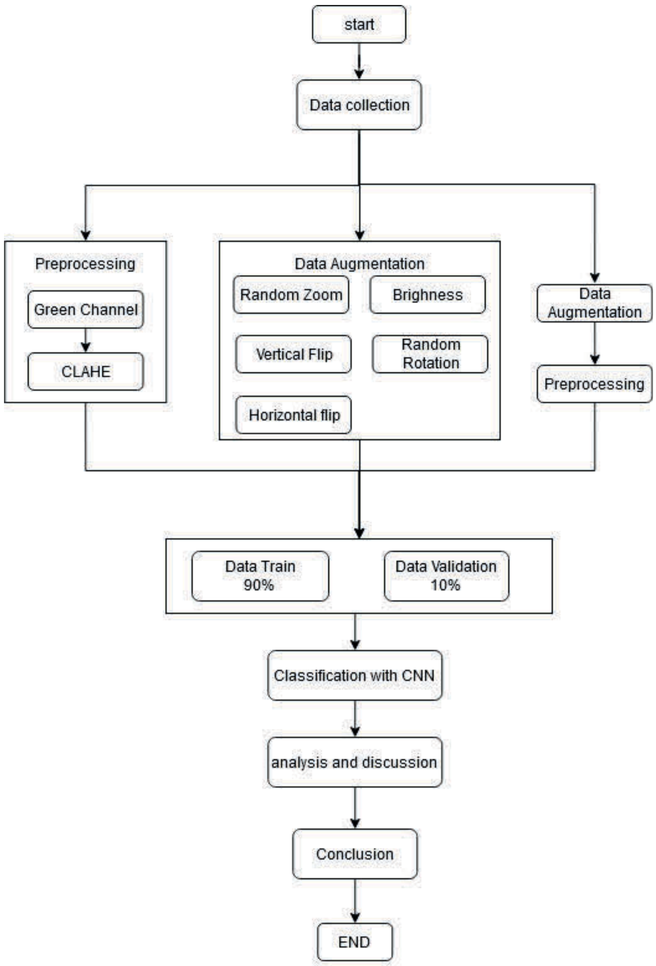


Fig. 2. Research flow

3) Contrast Limited Adaptive Histogram Equalization (CLAHE): is a contrast enhancement technique that can clarify the cross-section of blood vessels better than other contrast enhancement techniques [44]. The results of the green channel process and the CLAHE shows a very sharp contrast difference between each feature in the retinal image can show in Fig. 3.

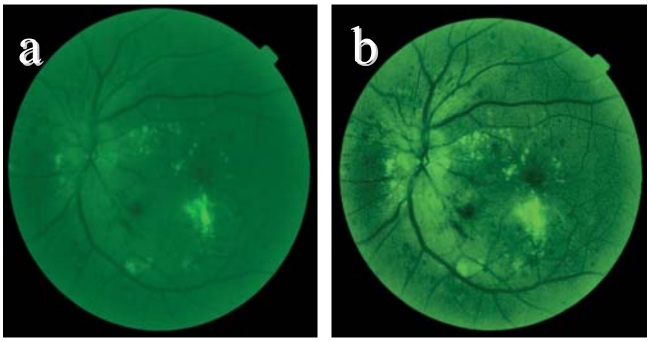


Fig. 3. (a) green channel, (b) CLAHE

D. Data Augmentation

Data augmentation is an increased technique of data variation, including a series of image manipulation operations such as random shifts, flips, random rotation, random zoom, and many more[36]. The technique aims to expand the dataset in a way that makes sense. The selection of data augmentation techniques is very influential on the results. The data augmentation used in this experiment is vertical flip, horizontal flip, random zoom, random brightness, and random rotation. Changes from augmentation results can show in Fig. 4.

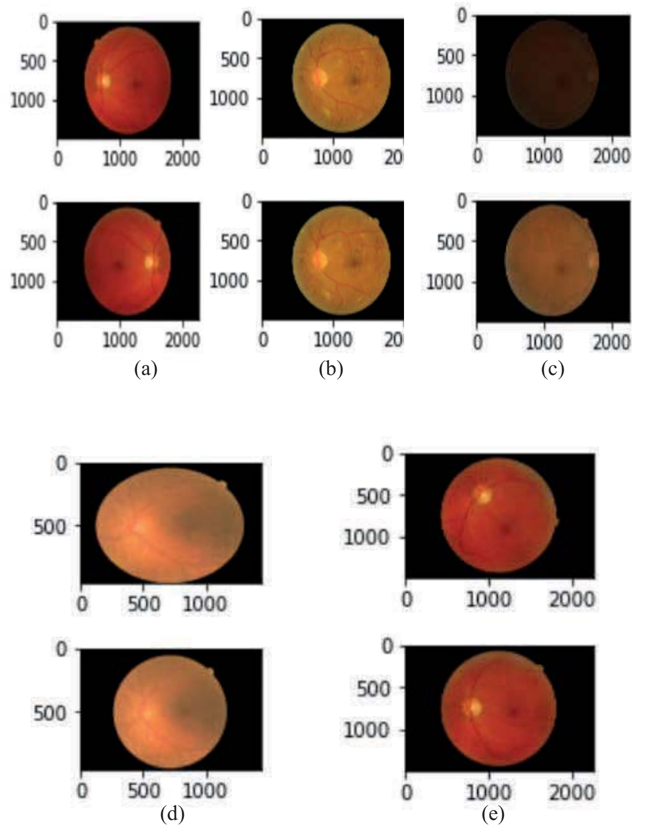


Fig. 4. Data Augmentation Technique (a) Horizontal Flip, (b) Vertical Flip, (c) Random Brightness, (d) Random Zoom, (e) Random Rotation

E. CNN Model Classification

We use a simple CNN network architecture using the convolution layer, which is the central core of CNN networks for extracting features. The next process is the pooling layer, which applies to speed up the calculation process, in this process using Max Pooling to take the output into a smaller grid. The last procedure is the Fully layer, use for classification. Our architecture can show in Fig. 5.

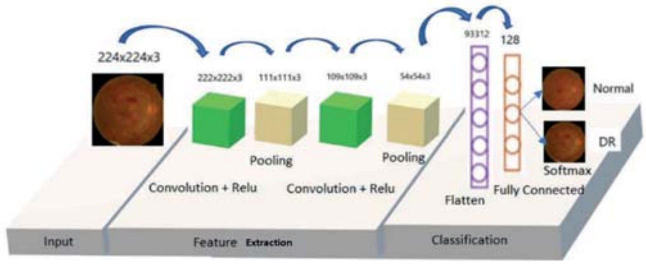


Fig. 5. Simple CNN Architecture

F. Confusion Matrix

The performance in our simple CNN proposed method for detecting DR in the retinal image is measured using the parameters of accuracy, sensitivity, and specificity obtained from the calculation of the Confusion Matrix (CM). CM is one of the methods used to measure the performance of classification results. The values and terms in the CM show in table 2 [45].

TP and TN are positive or negative correctly classified data, FP is negative but positively classified data, while FN is positive data but is classified negative. After getting the CM values, we can calculate the values of accuracy (AC), sensitivity (SS), and specificity (SP) with the equation [46]:

$$AC = (TP + TN) / (TP+FP+TN+FN) \quad (1)$$

$$SS = (TP) / (TP + FN) \quad (2)$$

$$SP = (TN) / (TN+FP) \quad (3)$$

TABLE II. CONFUSION MATRIX VALUE [47]

Class	Classified Positive	Classified Negative
Positive	TP (True Positive)	FN (False Negative)
Negative	FP (False Positive)	TN (True Negative)

IV. ANALYSIS

A. Experiment Configuration

Each scenario tests by measuring the performance of the verification method using the CM. The comparison of train data and validation data used is 90:10 with batch size 42 and l-rate 0.01.

B. The Results of The First Scenario Experiment

The first scenario compares the value of pure data accuracy with the addition of an image enhancement process, tested with different epoch values. The results of the experiment can show in table 3.

TABLE III. ENHANCEMENT AND SEGMENTATION TESTS RESULT

Epoch	Original data (%)	Preprocessing (%)
75	60	72,86
100	65,71	75,71
125	64,29	72,86

The experimental results in table 3 show an increase in accuracy from the addition of image enhancement to 10%. The best epoch value is epoch 100.

C. The Results of The Second Scenario Experiment

The second scenario is to find suitable data augmentation applied to the retinal fundus image. Not all data augmentation can improve results. The selection of techniques needed adjusting to the character of the data. Data augmentation techniques used for comparison were Random brightness [0.2,1.0], Vertical_flip, Horizonal_flip, Random zoom [0.5,1.0], and Random rotation = 90. Data augmentation will test with an epoch value of 100. The results of the experiment by applying data augmentation can show in table 4.

The results of this experiment indicate that data augmentation can use in a retinal image is a data augmentation technique that does not change the image position. The Random brightness or Horizonal_flip data augmentation techniques gives better results than other methods. Table 4 shows that the highest accuracy value increase by using a random brightness technique with an accuracy of 86.71%. Furthermore, the addition of extreme data is getting better to improve accuracy. After the information is augmented by data augmentation up to 3x the original data, the accuracy value increases to 88,57%.

TABLE IV. AUGMENTATION TECHNIQUE RESULTS

Types of Data augmentation	2x data fold (%)	3x data fold (%)
Random brightness [0.2,1.0]	85,71	**88,57**
Vertical_flip	77,86	83,33
Horizonal_flip	81,43	88,10
Random zoom [0.5,1.0]	52,86	68,10
Random rotation = 90	54,29	65,24

D. The Results of The Third Scenario Experiment

The third scenario uses the merging of original data and data augmentation. The data augmentation used is the best data from the second scenario experiment results using a random brightness technique. The data train was increasing the image with 2xfold and 3xfold data augmentation. The trial results show in Table 5. Visible results of data augmentation up to 3x the amount of data shows a very high accuracy until 98,57%.

TABLE V. RANDOM BRIGHTNESS AUGMENTATION TECHNIQUE AND IMAGE ENHANCEMENT RESULTS

Data Augmentation Multiples	Accuracy (%)
2x data fold	91,43
3x data fold	98,57

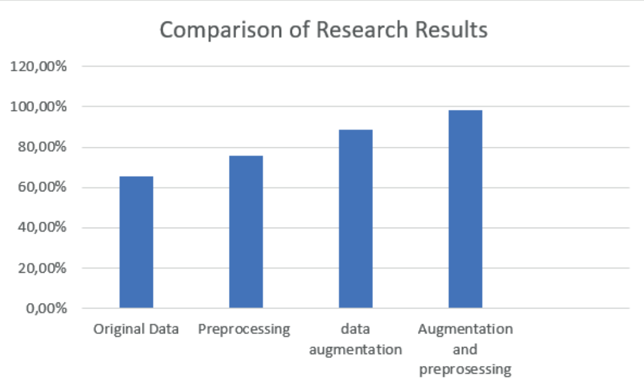
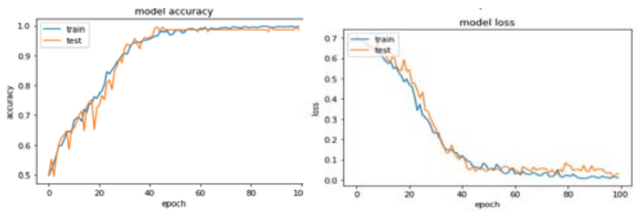


Fig. 6. Comparison of Research Results

Based on graph in Figure 6, the process carried out provides a significant increase in accuracy value. The best accuracy obtained by the original data is only around 60%. After adding preprocessing, the accuracy increased by 10%. If added the random brightness data augmentation technique, the accuracy can increase by more than 20%. The best accuracy is obtained by adding augmentation and preprocessing data to achieve an accuracy increase of more than 30%. The program performance is seen from the Confucius matrix graph in Fig. 7 shows that the model is going well. It looks overfitting still occur, but it is tiny.



(a) (b)

Fig. 7. Confusion Matrix Graph (a) Accuracy Curve, (b) Loss Curve

Configuration Matrix Calculation Results

From the results of the experiments we have done, we get the matrix confusion table shown in table 6. We get the value TP = 103, TN = 103, FP = 0, FN = 4. From the results, use Eq. (1), (2), and (3) we will get an accuracy value of 98%, and sensitivity is 96% and Specificity 100%. Accuracy shows that the positive or negative prediction of the patient's disease is correct according to reality. Sensitivity is the right percentage of a person suffering from the disease identified correctly. Specificity indicates that a person identified as unfavorable from a disease by the examination results is genuinely negative.

TABLE VI. CONFUSION MATRIX RESULTS

Class	Classified Positive	Classified Negative
Positive	103	4
Negative	0	103

E. Discussion

V. TABLE VII. COMPARING THE RESULTS OF PREVIOUS EXPERIMENTS

Author	Augmentation	SS (%)	SP (%)	AC (%)	Object-methods-Total Data
[37]	warping retinal fundus images with non-linear transformations	80	98	95	Retinal blood vessel segmentation -CNN-40
[39]	scaling, rotation, translation, flipping, and shearing	85.7	92.4	78.6	Liver lesion classification -GAN-182
[40]	rotation, translation, mirroring, stretching and zooming	90	100	81	Malarial Retinopathy-CNN-273
Proposed methods	Random brightness, Vertical_flip Horizonal_flip, Random zoom, Random rotation	96	100	98	Diabetic retinopathy classification -CNN-700

By comparing the results of previous experiments shown in table 7, our resulting 100% specificity is the same as the experiment [37]. Still, the method we propose has higher accuracy and sensitivity values than all previous studies. However, this research still needs to be improved, especially in terms of data limitations. Some other deficiencies to be resolved in future studies are to classify all stages of DR disease, improve the CNN network model to overcome overfitting. And also try several preprocessing methods such as lesion segmentation and other image enhancement techniques. Despite all the shortcomings, this technique is useful as a rapid screening for early detection of DR. We hope that by providing an accurate and fast diagnosis the symptoms of DR, it can save the patient's vision.

VI. Conclusion

By a series of trials that we did, we concluded that CNN works very well with large datasets, but if we use a small dataset, it will be a problem for this CNN network performance. To solve the problem of data, we can use data augmentation techniques are proven to be very significant in providing improve accuracy. Nevertheless, not all data augmentation techniques can use, make a wrong technique not to give a maximal result. From this study, we know the suitable data augmentation technique for image fundus retina is data that does not change the optic disk axis, such as the Random Brightness and Horizontal Flip method that we tested. To increase performance, preprocessing is very important. Enhancement techniques using CLAHE proved to increase the value of accuracy until 10%. From this experiment, we get the accuracy, sensitivity, and specificity values from the effects of image enhancement and data augmentation were 98%, 100%, and 96%.

REFERENCE

[1] R. R. A. Bourne *et al.*, “Causes of vision loss worldwide, 1990-2010: A systematic analysis,” *The Lancet Global Health*, vol. 1, no. 6, pp. 339–349, 2013.

[2] R. Williams, M. Airey, H. Baxter, J. Forrester, T. Kennedy-Martin, and A. Girach, “Epidemiology of diabetic retinopathy and macular oedema: A systematic review,” *Eye*, vol. 18, no. 10, pp. 963–983, 2004.

[3] A. Sharma and A. Sharma, “Retina and Vitreous,” *Mindmaps in Ophthalmology*, pp. 245–284, 2019.

[4] P. Porwal *et al.*, “IDRiD: Diabetic Retinopathy – Segmentation and Grading Challenge,” *Medical Image Analysis*, vol. 59, 2020.

[5] T. Y. Wong, C. M. G. Cheung, M. Larsen, S. Sharma, and R. Simó, “Diabetic retinopathy,” *Nature Reviews Disease Primers*, vol. 2, no. March, 2016.

[6] P. Vashist, S. Singh, N. Gupta, and R. Saxena, “Role of early screening for diabetic retinopathy in patients with diabetes mellitus: An overview,” *Indian Journal of Community Medicine*, vol. 36, no. 4, pp. 247–252, 2011.

[7] M. A. H. Graham, “Screening for diabetic retinopathy,” *Practical Diabetes International*, vol. 3, no. 6, pp. 315–315, 1986.

[8] Y. Ikedo, X. Gao, and X. Zhou, “Computer-aided diagnosis : The emerging of three CAD systems induced by Japanese health care needs,” vol. 2, pp. 238–248, 2008.

[9] M. I. Razzak and S. Naz, “Deep Learning for Medical Image Processing : Overview , Challenges and Future Deep Learning for Medical Image Processing : Overview , Challenges and Future,” no. August, 2017.

[10] G. Krizhevsky, Alex; Sutskever, Ilya; Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” in *Neural Information Processing Systems*, 2012.

[11] G. E. Hinton, S. Osindero, and Y.-W. Teh, “A Fast Learning Algorithm for Deep Belief Nets,” *Neural Computation*, vol. 18, no. 7, pp. 1527–1554, Jul. 2006.

[12] R. Raina, A. Madhavan, and A. Y. Ng, “Large-scale deep unsupervised learning using graphics processors,” in *Proceedings of the 26th Annual International Conference on Machine Learning - ICML ’09*, 2009, pp. 1–8.

[13] R. L. Galvez, A. A. Bandala, E. P. Dadios, R. R. P. Vicerra, and J. M. Z. Maningo, “Object Detection Using Convolutional Neural Networks,” in *TENCON 2018 - 2018 IEEE Region 10 Conference*, Oct. 2018, pp. 2023–2027.

[14] D. Liao, H. Lu, X. Xu, and Q. Gao, “Image Segmentation Based on Deep Learning Features,” in *2019 Eleventh International Conference on Advanced Computational Intelligence (ICACI)*, Jun. 2019, pp. 296–301.

[15] N. Jmour, S. Zayen, and A. Abdelkrim, “Convolutional neural networks for image classification,” in *2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET)*, Mar. 2018, pp. 397–402.

[16] G. Litjens *et al.*, “A survey on deep learning in medical image analysis,” *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017.

[17] E. Decencière *et al.*, “Feedback on a publicly distributed image database: The Messidor database,” *Image Analysis and Stereology*, vol. 33, no. 3, pp. 231–234, 2014.

[18] R. J. Chalakkal, W. H. Abdulla, and S. S. Thulaseedharan, “Automatic detection and segmentation of optic disc and fovea in retinal images,” *IET Image Processing*, vol. 12, no. 11, pp. 2100–2110, Nov. 2018.

[19] R. Romero-Oraá, M. García, J. Oraá-Pérez, M. I. López, and R. Hornero, *A robust method for the automatic location of the optic disc and the fovea in fundus images*. 2020.

[20] P. Dhal and C. Azad, “A novel approach for blood vessel segmentation with exudate detection in diabetic retinopathy,” in *2020 International Conference on Artificial Intelligence and Signal Processing (AISP)*, Jan. 2020, pp. 1–6.

[21] S V Viraktamath, V. Koti, S. Ragi, and N. Pai, “Blood Vessels Extraction of Retinal Image Using Morphological Operations,” *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, no. Icirca, pp. 1185–1189, 2018.

[22] C. Zhu, B. Zou, Y. Xiang, J. Cui, and H. Wu, “An Improved Retinal Vessel Segmentation Method Based on Supervised Learning,” in *2015 14th International Conference on Computer-Aided Design and Computer Graphics (CAD/Graphics)*, Aug. 2015, pp. 216–217.

[23] W. Zhou, C. Wu, D. Chen, Y. Yi, and W. Du, “Automatic Microaneurysm Detection Using the Sparse Principal Component Analysis-Based Unsupervised Classification Method,” *IEEE Access*, vol. 5, pp. 2563–2572, 2017.

[24] S. Wang *et al.*, “Localizing Microaneurysms in Fundus Images Through Singular Spectrum Analysis,” *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 5, pp. 990–1002, 2017.

[25] T. J. Jebaseeli, C. A. Deva Durai, and J. D. Peter, “Retinal blood vessel segmentation from diabetic retinopathy images using

tandem PCNN model and deep learning based SVM," *Optik*, vol. 199, no. October 2018, p. 163328, 2019.

[26] Q. Jin, Q. Chen, Z. Meng, B. Wang, and R. Su, "Construction of Retinal Vessel Segmentation Models Based on Convolutional Neural Network," *Neural Processing Letters*, Mar. 2019.

[27] B. Al-Bander, W. Al-Nuaimy, B. M. Williams, and Y. Zheng, "Multiscale sequential convolutional neural networks for simultaneous detection of fovea and optic disc," *Biomedical Signal Processing and Control*, vol. 40, pp. 91–101, Feb. 2018.

[28] J. H. Tan, U. R. Acharya, S. V. Bhandary, K. C. Chua, and S. Sivaprasad, "Segmentation of optic disc, fovea and retinal vasculature using a single convolutional neural network," *Journal of Computational Science*, vol. 20, pp. 70–79, May 2017.

[29] P. Prentašić and S. Lončarić, "Detection of exudates in fundus photographs using deep neural networks and anatomical landmark detection fusion," *Computer Methods and Programs in Biomedicine*, vol. 137, pp. 281–292, 2016.

[30] Q. Jin, Z. Meng, T. D. Pham, Q. Chen, L. Wei, and R. Su, "DUNet: A deformable network for retinal vessel segmentation," *Knowledge-Based Systems*, vol. 178, pp. 149–162, 2019.

[31] D. Yang, M. Ren, and B. Xu, "Retinal Blood Vessel Segmentation with Improved Convolutional Neural Networks," *Journal of Medical Imaging and Health Informatics*, vol. 9, no. 6, pp. 1112–1118, Aug. 2019.

[32] C. Wang, Z. Zhao, Q. Ren, Y. Xu, and Y. Yu, "Dense U-net Based on Patch-Based Learning for Retinal Vessel Segmentation," *Entropy*, vol. 21, no. 2, p. 168, Feb. 2019.

[33] Y. Jiang, N. Tan, T. Peng, and H. Zhang, "Retinal Vessels Segmentation Based on Dilated Multi-Scale Convolutional Neural Network," *IEEE Access*, vol. 7, pp. 76342–76352, 2019.

[34] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Alexnet_Tugce_Kyunghee," *Nips*, 2015.

[35] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings*, pp. 1–14, 2015.

[36] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 770–778.

[37] A. Oliveira, S. Pereira, and C. A. Silva, "Augmenting data when training a CNN for retinal vessel segmentation: How to warp?," *ENBENG 2017 - 5th Portuguese Meeting on Bioengineering, Proceedings*, 2017.

[38] S. Chaichulee *et al.*, "Multi-Task Convolutional Neural Network for Patient Detection and Skin Segmentation in Continuous Non-Contact Vital Sign Monitoring," in *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*, May 2017, pp. 266–272.

[39] M. Frid-Adar, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, "Synthetic data augmentation using GAN for improved liver lesion classification," in *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*, Apr. 2018, pp. 289–293.

[40] A. Kurup, P. Soliz, S. Nemeth, and V. Joshi, "Automated Detection of Malarial Retinopathy Using Transfer Learning," in *2020 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)*, Mar. 2020, pp. 18–21.

[41] R. Karthick, "Preprocessing of Various Data Sets Using Different Classification Algorithms f or Evolutionary Programming," *International Journal of Science and Research (IJSR)*, 2015.

[42] S. F. S. Syeda Farha Shazmeen, "Performance Evaluation of Different Data Mining Classification Algorithm and Predictive Analysis," *IOSR Journal of Computer Engineering*, vol. 10, no. 6, pp. 1–6, 2013.

[43] T. A. Soomro, T. Mahmood Khan, M. A. U. Khan, J. Gao, M. Paul, and L. Zheng, "Impact of ICA-Based Image Enhancement Technique on Retinal Blood Vessels Segmentation," *IEEE Access*, vol. 6, no. c, pp. 3524–3538, 2018.

[44] Erwin, "Improving Retinal Image Quality Using the Contrast Stretching, Histogram Equalization, and CLAHE Methods with Median Filters," *International Journal of Image, Graphics and Signal Processing*, vol. 12, no. 2, pp. 30–41, 2020.

[45] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing and Management*, vol. 45, no. 4, pp. 427–437, 2009.

[46] A. Kwasigroch, B. Jarzembinski, and M. Grochowski, "Deep CNN based decision support system for detection and assessing the stage of diabetic retinopathy," in *2018 International Interdisciplinary PhD Workshop (IIPhDW)*, May 2018, pp. 111–116.

[47] M. Rich, R. Mills, T. Dube, and S. Rogers, "Evaluating Machine Learning Classifiers for Defensive Cyber Operations," *Military Cyber Affairs*, vol. 2, no. 1, Dec. 2016.