Semantic Segmentation of Retinal Blood Vessels from Fundus Images by using CNN and the Random Forest Algorithm

Ayoub Skouta[1][a], Abdelali Elmoufidi[2][b], Said Jai-Andaloussi[1][c] and Ouail Ouchetto[1][d]

[1]*Computer and Systems Laboratory, Hassan II University, Casablanca, Morocco*

[2]*Data4Earth Laboratory, Sultan Moulay Slimane University, Beni Mellal, Morocco*

{*ay.skouta, elmoufidi10, andaloussi.said, ouail.ouchetto*}*@gmail.com*

Keywords: Funds Images, Diabetic Retinopathy, CAD System, Semantic Segmentation, Blood Vessel Detection, Artificial Intelligence, Deep Learning, Convolutional Neural Networks.

Abstract: Abstract: In this paper, we present a new study to improve the automated segmentation of blood vessels in diabetic retinopathy images. Pre-processing is necessary due to the contrast between the blood vessels and the background, as well as the uneven illumination of the retinal images, in order to produce better quality data to be used in further processing. We use data augmentation techniques to increase the amount of accessible data in the dataset to overcome the data sparsity problem that deep learning requires. We then use the CNN VGG16 architecture to extract the feature from the preprocessed background images. The Random Forest method will then use the extracted attributes as input parameters. We used part of the augmented dataset to train the model (1764 images, representing the training set); the rest of the dataset will be used to test the model (196 images, representing the test set). Regarding the model validation phase, we used the dedicated part for testing the DRIVE dataset. Promising results compared to the state of the art were obtained. The method achieved an accuracy of 98.7%, a sensitivity of 97.4% and specificity of 99.5%. A comparison with some recent previous work in the literature has shown a significant advancement in our proposal.

1 INTRODUCTION

The human eye is a visual organ, similar to a sphere with a diameter of 2-3 cm, weighing about 8 grams. It receives the light emitted by objects, focuses it, then transmits the information to the brain for analysis. The eye is surrounded by a tough membrane called the sclera. The main structures of the eyeball are : The cornea is completely transparent and is located in front of the eye in front of the iris, but because it is transparent, it cannot be seen. It can be observed with a special microscope called a slit lamp. When we look at an eye, we can see that the iris is colored and shrinks depending on the light, and that the sclera is white and opaque and covers the entire back surface of the eye. The crystalline lens is a converging lens-like organ that reflects the image and directs it to the retina. The figure shows a human eye with all its parts (Abràmoff et al., 2010). The retina is the inner membrane of the eyeball. It is a light sensitive layer that captures light rays. The retina is made up of three layers of nerve cells: ganglion cells, bipolar cells and visual cells that are either cones or rods. Light passes through the upper layers of the retina to reach the cones and rods. After a series of photochemical reactions, the information is transmitted to the bipolar cells, then to the ganglion cells and finally to the optic nerves, which send information to the brain in the form of electrical signals, which in turn interpret the signals received as visual images. The cones are grouped in the center of the retina at the macula, where visual acuity is best. They are the color vision cells that work only in well-lit environments. The rods appear around the macula, they are the cells of black and white vision they react to very weak lights. Progressive damage to the macula leads to diseases such as macular degeneration or, in severe cases, creates a macular hole, which causes blood vessels in the macula to rupture (Jakobiec, 1982). Diabetes is a comprehensive metabolic disorder that can lead to various vascular complications in the body. There are two types of diabetes: type 1 diabetes and type 2 diabetes. Both result in high blood sugar lev-

[a] https://orcid.org/0000-0002-6176-910X
[b] https://orcid.org/0000-0002-8574-9584
[c] https://orcid.org/0000-0002-6864-1141
[d] https://orcid.org/0000-0001-8287-215X

Skouta, A., Elmoufidi, A., Jai-Andaloussi, S. and Ouchetto, O.
Semantic Segmentation of Retinal Blood Vessels from Fundus Images by using CNN and the Random Forest Algorithm.
DOI: 10.5220/0010911800003118
In *Proceedings of the 11th International Conference on Sensor Networks (SENSORNETS 2022)*, pages 163-170
ISBN: 978-989-758-551-7; ISSN: 2184-4380

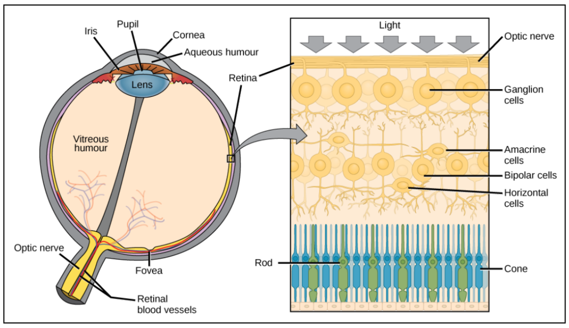

Figure 1: This anatomy of the eye and the retina.

els related to a hormone called insulin produced by the pancreas; this hormone is responsible for the regulation of blood sugar levels in the blood (Breiman, 2001a). Diabetic retinopathy is a microangiopathy that has the manifestations of occlusion and leakage of microvascular fluid and blood in the retina, it is essential to understand the signs of occlusion and leakage in the retina before understanding the pathogenesis and sign of diabetic retinopathy. In the presence of diabetes and hyperglycemia, several things happen in the blood vessels, the blood vessel walls that help nourish the retina deteriorate, the blood cells become distorted and the blood thickens and then finally a microvascular occlusion as there will be irregularities in the blood flow and a decrease in oxygen. This results in visual manifestations called lesions such as microaneurysms, hemorrhages, hard exudates, cottony spots (Agurto et al., 2010). This phenomenon due to diabetes can progressively damage the structure of the eyeball, leading to severe vision loss or even blindness (Kanski and Bowling, 2011). Several studies have focused on the use of automated techniques for the early diagnosis of diabetic retinopathy. These technologies are becoming increasingly advantageous in the healthcare sector, thanks to artificial intelligence (AI), which allows the creation of reliable software for decision support in the diagnosis of medical images (Tham Chen2014g,). The use of traditional machine learning (ML) approaches such as random forest algorithm, decision tree, nearest neighbor method (KNN), K-means, support vector method (SVM), etc. (Kotsiantis et al., 2007), (Liaw et al., 2002) are used to analyze fundus images to develop models that can predict outcomes without programming, through operations distributed over multiple layers (Kapoor et al., 2019). Machine learning techniques are divided into two categories: supervised and unsupervised learning. The supervised technique requires labeled data to train the segmentation model, but the unsupervised method requires no prior knowledge of the labeled data to train the segmentation model. Since the introduction of convolutional neural networks (CNNs), deep learning has been remarkably successful, and it is now considered the most successful AI model in all computer vision applications. It has proven to be very effective and useful in extracting features for use in various machine learning applications. The input layer, hidden layers and output layer are the three types of layers found in CNNs. These layers consist of linked nodes, each with its own output layer sending a weighted quantity to the activation function. Several strategies have been established to improve the quality of vascular segmentation, using classical machine learning or deep learning methods, but more can be done. The second section of this paper contains an overview of related previous work, and then the proposed method and materials used are described in the third section of this study. The results of our experiment are described in Section 4. A discussion is presented in Section Five. Finally, the main conclusions are presented in the last section.

2 RELATED PREVIOUS WORKS

In the medical domain, many computer-aided diagnoses have used to help in diagnosing of many deceases. Even more, many diseases are early-detected using artificial intelligence. And one of the newest examples is the creation of two models one to classify a COVID-19 test of a suspect patient as positive or negative, and the other to classify the hospitalization units of patients with COVID-19 (de Oliveira et al., 2021). Others diseases are breast cancer (Elmoufidi et al., 2018), (Elmoufidi et al., 2014), (Elmoufidi et al., 2015), (Elmoufidi, 2019) and diabetic retinopathy (Skouta et al., 2021), (El Hossi et al., 2021), (Stabingis et al., 2018), (Balkys and Dzemyda, 2012). In this paper, the purpose of determining retinal vascular segmentation is to predict abnormalities that can occur in the retina, including diabetic retinopathy and glaucoma. The advent of convolutional neural networks has led to improvements in reducing the burden on specialists with screening programs that have begun to generate high-accuracy segmentation (Salazar-Gonzalez et al., 2014). According to the literature presented in this section, different methods are applied to segment blood vessels in fundus images. In this paper, we focus on the use of deep CNNs, which have shown excellent performance in their application. The remainder of this section will be devoted to presenting related work on blood vessel segmentation from retinal fundus images; for example, the approach proposed by Khalaf et al (Khalaf et al., 2016) used a CNN to segment vessels, using an input patch derived from the original image as input. Three convolutional layers and a fully connected layer at the end of the network constitute the CNN. Their technique classifies each patch into three categories based on the center pixel: background, large vessels, and small vessels. Liskowski and Krawiec (Liskowski and Krawiec, 2016) presented another patch-based approach to determine the number of neurons in the final fully connected layer. Background and vessels are the two categories predicted by CNN. Segmentation is performed by connecting each pixel to a neuron, so that the CNN output is a two-dimensional vector. Yu et al (Yu et al., 2020) developed a CNN for hierarchical vessel division by first extracting vessel trees using a graph-based method and then classifying the retinal vasculature using two algorithms (PLDA and AHCA). The final layers of the CNN are fully connected layers. Shuangling Wang et al (Wang et al., 2015) designed a retinal blood vessel segmentation technique that combines a CNN as a feature extractor from raw images and a Random Forest (RF) algorithm as a classifier. Zhou et al (Zhou et al., 2017) propose a CNN solution to extract blood vessel features. The extracted features are then provided to the dense CRF to perform segmentation. The DeepVessel CNN published by Fu et al. (Fu et al., 2016) combines the output side layer and the CRF layer to model long-range pixel interactions and nonlocal pixel correlations. Hu et al (Hu et al., 2018) wrote a paper that performs binary segmentation by describing an RCF-inspired multi-scale CNN architecture that provides a comprehensive description of vascular features combined with an improved cross-entropy loss function. The emergence of the U-net architecture in 2015 (Ronneberger et al., 2015) has made a great contribution in the field of biomedical image segmentation. It has become popular in blood vessel segmentation. Several authors have customized this promising method to develop modified versions; Zhang and Chung (Zhang and Chung, 2018), Yan et al. (Yan et al., 2018), Yan et al. (Yang et al., 2017), Wu et al. (Wu et al., 2018), Wu et al. (Wu et al., 2020a), Wang et al. (Wang et al., 2020), Wu et al. (Wu et al., 2019), Wang et al. (Wang et al., 2019), Ma et al. (Ma et al., 2019), Mishra et al. (Mishra et al., 2020).

2.1 Materials

In this section, we outline the hardware used, the datasets used and the proposed methodology. We tested our solution in a GPU environment using the Keras library and TensorFlow.

2.2 Databases Used

The suggested approach has been trained, validated and tested using the Drive, HRF datasets. These datasets are freely accessible and are used in the vast majority of vascular segmentation studies. The DRIVE (Digital Retinal Image for Vessel Extraction) dataset is a series of 20 images that includes a manual segmentation of vessels for each image. There are 20 more photos in the test set. The images have a size of 768 x 584 pixels. the exception of seven photos that showed slight symptomatic RD, all images DRIVE were normal (Staal et al., 2004).

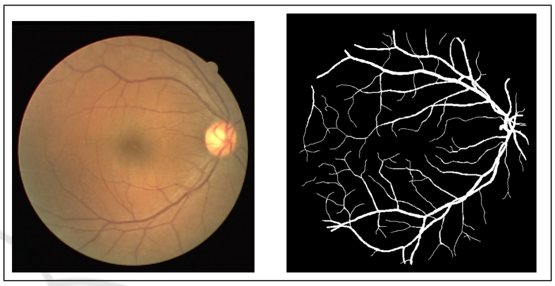

Figure 2: Left: Examples of fundus from the DERIVE database. Right: Examples of ground truth data from the DERIVE database.

Table 1: Presentation of the databases implemented in the proposed approach.

Datasets	Source	Images	Digitizer
Drive Available: Online	Staal et al. (Wu et al., 2019)	40 (33 healthy, 7 mild early DR) Resolutions : 768x584 Canon: CR5	non-mydriatic 3CCD fundus camera, FOV 45

2.3 Image Preprocessing

The high similarity in the fundus image between the vessels and the background can lead to erroneous segmentation. The data is optimized in the preprocessing step to provide a better image with a clear distinction between the vessels and the background, helping CNN to interpret the input images and allows for correct segmentation. This step starts by cropping the black border of the original images. After the original color image is cropped, the color order is BGR (blue, green, red) instead of RGB, so the first step is to convert the image from BGR to RGB. We then extract the green channel from the multichannel image after splitting it into several channels, which gives more contrast between the blood vessels and the background than the red and blue channels. The green channel is then smoothed and noise is reduced using a bilateral filter while vascular contours are preserved. Vascular information is further highlighted by applying contrast-limited adaptive histogram equalization (CLAHE) to the image generated by the bilateral filter. We used the image sharpening method to highlight each individual pixel, enhance the color it emanates, and increase the pixel density, making it more visible to CNN. Finally, a gamma correction, to correct the retinal image in order to remove the uneven light factor. The results of the pre-processing are shown in Figure 3.

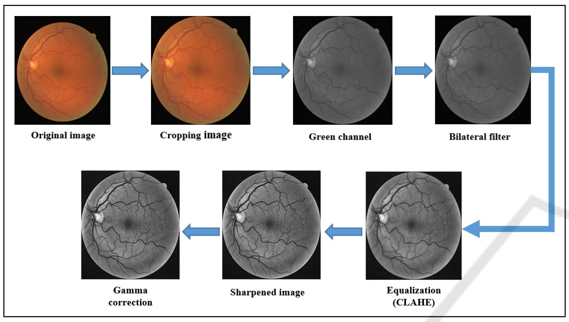

Figure 3: Result of preprocessing step.

2.4 Data Augmentation

The step of data augmentation is proposed of this study; it consists in modifying the existing preprocessed images in the original database as well as its associated mask in order to increase the size of the dataset that will be used for the training and testing of the proposed method. Data augmentation strategies reduce overfitting and give the proposed model more power while also enhancing accuracy and resilience. Having a CNN with a huge dataset increases the model's capacity to generalize to new pictures from other databases. To achieve this, we employ a number of techniques to generate various kinds of sample while preserving the attributes of the source images: The original images and the images obtained after the preprocessing stage, together with their accompanying ground-truth masks, are rotated from 0 to 360° at a 30° angle each time. Randomly, we add noise, change the brightness, change the colorimetry, vertical and horizontal flips and horizontal and vertical flips to each image created by the loop that rotates the image from 0 to 360 degrees. These are the transformations used in the data update process. The total data recovered from the original photos and the images acquired after the pre-processing step is equal to 1960 images, which are divided into 1764 images, representing the training set (90 percent of the generated images) and 196 images, representing the validation set (ten percent of the total generated images).

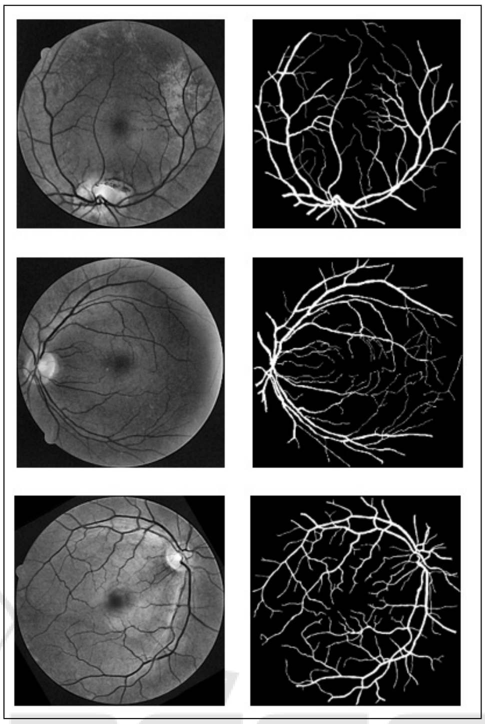

Figure 4: An example of images after the data augmentation procedure.

3 PROPOSED METHODOLOGY

3.1 Feature Extraction by CNN

Segmentation is the classification of pixels, where each pixel, rather than the whole picture, is assigned to a distinct category. The feature extraction approach is critical for a successful segmentation process. Extraction is a critical operation because the features used to define the candidate areas have a direct impact on the accuracy with which each pixel in the input image is classified as a blood vessel or background. The CNN has recently demonstrated the capacity to recognize the most sophisticated, basic, and significant visual elements such as edges, corners, orientated edges, and so on. This is crucial information for the analysis and categorization of pixels. Following that, subsequent layers integrate these characteristics to capture higher order features (Wang et al., 2019). In this technique, the CNN VGG16 architecture is utilized as a feature extractor for pixels in terms of quantifiable metrics that can be used in the classification stage to determine if the pixels correspond to real blood from the vessel or not. The Random

Forest classifier (Breiman, 2001b) takes the role of the VGG16 model's last fully connected layer. This method is known as transfer learning, and it involves merely training the top level of the network. The VGG16 architecture is composed of 5 blocks with a total of 16 layers. Essentially it is based on the use of 3x3 convolution with stride equal to 1 and a "Same" padding, i.e. the size of the input image matches the size of the output image. After each convolution layer, a max 2x2 pooling layer is used to reduce the size.

3.1.1 Segmentation using the Random Forest Algorithm

Our goal is to take pretrained VGG16 weights used as feature extractors and then segment the retinal images using a random drill. The images resulting from the data augmentation operation are physically stored on the hard disk of our computer, and then we have to load all the images and their associated masks. Since CNN is suitable for large images, we kept the original size of the images in our training database, which have a height of 584 and width of 565, and then they are converted from RGB to BGR because the opencv library simply reads the images as BGR. Next, we imported the VGG16 model, so now we will also import the weights corresponding to the weights in the imagenet database. The include top variable is set to false, this basically means that we have not imported the dense layers and the output layer. The size of the input images of the VGG16 model is changed as the model defaults to 244x244x3 at the size of our input images. The next step is to apply the feature extractor to our training data and see what the features look like. As shown in Figure 5, the features of the original augmented images and the preprocessed and augmented images are merged into a bag of features. The

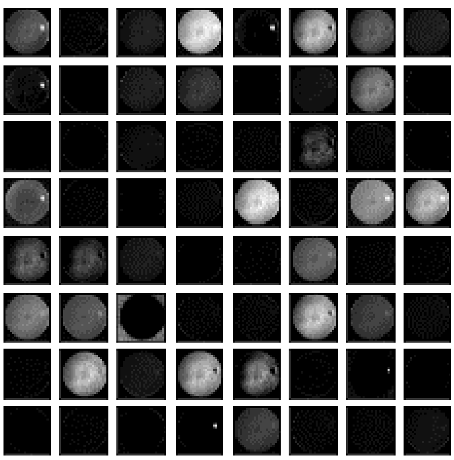

Figure 5: Displays of extracted characteristics.

number of features generated is glaring, therefore we have eliminated features such as the features that represent the background of the retinal image. These features are useless to use in training, as they will require additional training time. The pixels that represent the blood vessels are kept as features. After the feature reduction operation we feed the random forest algorithm to segment the retinal blood vessels.

4 EXPERIMENTAL RESULT

4.1 Evaluation Metrics

We examine the performance of the segmentation findings with relation to the expert's manual segmentation using the following performance measures: accuracy, sensitivity, and specificity as indicators.

Table 2: Presentation of the databases implemented in the proposed approach.

Metrics	Formule	Description
Sensitivity	$\frac{TP}{TP+FN}$	The ratio of correctly categorized vascular pixels compared to genuine vascular pixels is known as the true positive rate.
Specificity	$\frac{TN}{TN+FP}$	As compared to real non-vascular pixels, the fraction of correctly diagnosed non-vascular pixels.
Accuracy	$\frac{TN+TP}{TP+FP+TN+FN}$	As a proportion of the total number of pixels in the picture, the accuracy represents how well blood

- True positives (TP) refers to the number of accurately segmented blood vessel pixels;
- The amount of accurately divided background pixels is shown by True Negatives (TN);
- False positives (FP) are background pixels that have been segmented incorrectly into blood vessel pixels;
- False negatives (FN) are pixels in blood vessels that have been mistakenly labeled background.

4.2 Results

We used the DRIVE dataset to train the suggested models in 100 epochs. The results of our method's segmentation are more substantial. The accuracy is 98.7%, the sensitivity is 97.4%, and the specificity is 99.5 percent. Training details are depicted in the

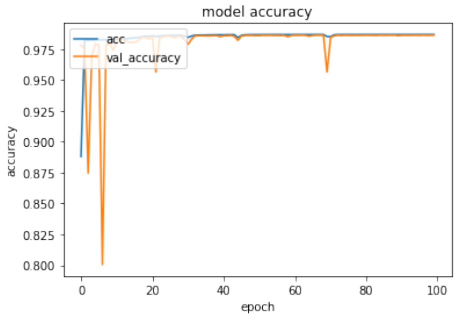

Figure 6: Model accuracy performance.

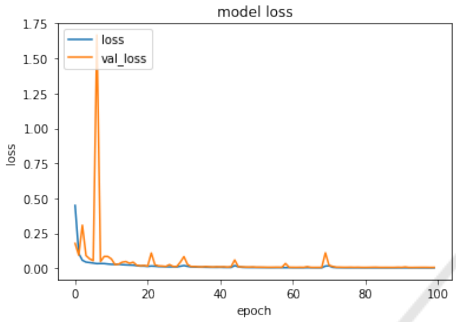

Figure 7: Model loss performance.

figures, which also show the accuracy and losses attained.

We used a subset of the DRIVE database dedicated to testing. Our primary aim is to verify the accuracy of our suggested technique. We examine the degree of similarity between the segmentations obtained using our proposed network and the ground truth.

Table 3: Comparison of segmentation performances for DRIVE.

Works	Year	Acc	Sen	Spe
(Tamim et al., 2020)	2020	0.9607	0.7542	0.9843
(Tian et al., 2020)	2020	0.958	0.8639	0.9690
(Wu et al., 2020b)	2020	0.9582	0.7996	0.9813
(Boudegga et al., 2021)	2021	0.9819	0.8448	0.99
Proposed method	2021	98.7	97.4	99.5

Acc: Accuracy **Sen**: Sensitivity **Spe**: Specificity

5 CONCLUSIONS

Early treatment of diabetic retinopathy with blood vessel segmentation helps people with diabetes avoid severe visual loss. Deep learning is one of the most sophisticated methods for segmentation challenges, as it improves accuracy. The effective convolutional neural network architecture used will help ophthalmologists to eradicate vision loss related to diabetic retinopathy. In this research, we suggest the use of a VGG16 model to extract characteristics and combine it with the random forest technique to automate blood vessel segmentation. Our technique was developed from the DRIVE dataset, which has been shown to be resilient.

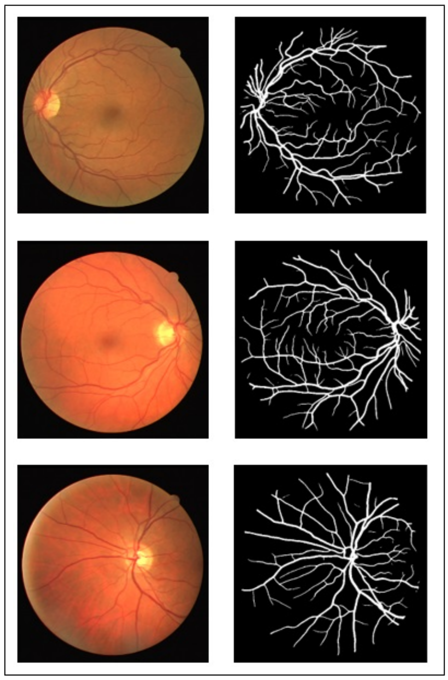

Figure 8: Comparisons of segmentation results using the test subset of the DRIVE database.

REFERENCES

Michael D Abràmoff, Mona K Garvin, and Milan Sonka. Retinal imaging and image analysis. *IEEE reviews in biomedical engineering*, 3:169–208, 2010.

Frederick A Jakobiec. *Ocular anatomy, embryology, and teratology*. Harpercollins, 1982.

Leo Breiman. Random forest, vol. 45. *Mach Learn*, 1, 2001a.

Carla Agurto, Victor Murray, Eduardo Barriga, Sergio Murillo, Marios Pattichis, Herbert Davis, Stephen Russell, Michael Abràmoff, and Peter Soliz. Multiscale am-fm methods for diabetic retinopathy lesion detection. *IEEE transactions on medical imaging*, 29 (2):502–512, 2010.

Jack J Kanski and Brad Bowling. *Clinical ophthalmology: a systematic approach*. Elsevier Health Sciences, 2011.

Sotiris B Kotsiantis, I Zaharakis, P Pintelas, et al. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1):3–24, 2007.

Andy Liaw, Matthew Wiener, et al. Classification and regression by randomforest. *R news*, 2(3):18–22, 2002.

Rahul Kapoor, Stephen P Walters, and Lama A Al-Aswad. The current state of artificial intelligence in ophthalmology. *Survey of ophthalmology*, 64(2):233–240, 2019.

Rodrigo Felipe Albuquerque Paiva de Oliveira, Carmelo Jose Albanez Bastos Filho, Ana Clara AMVF de Medeiros, Pedro Jose Buarque Lins dos Santos, and Daniela Lopes Freire. Machine learning applied in sars-cov-2 covid 19 screening using clinical analysis parameters. *IEEE Latin America Transactions*, 19 (6):978–985, 2021.

Abdelali Elmoufidi, Khalid El Fahssi, Said Jai-Andaloussi, Abderrahim Sekkaki, Quellec Gwenole, and Mathieu Lamard. Anomaly classification in digital mammography based on multiple-instance learning. *IET Image Processing*, 12(3):320–328, 2018.

Abdelali Elmoufidi, Khalid El Fahssi, Said Jai-Andaloussi, Nabil Madrane, and Abderrahim Sekkaki. Detection of regions of interest's in mammograms by using local binary pattern, dynamic k-means algorithm and gray level co-occurrence matrix. In *2014 International Conference on Next Generation Networks and Services (NGNS)*, pages 118–123. IEEE, 2014.

Abdelali Elmoufidi, Khalid El Fahssi, Said Jai-Andaloussi, and Abderrahim Sekkaki. Automatically density based breast segmentation for mammograms by using dynamic k-means algorithm and seed based region growing. In *2015 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings*, pages 533–538. IEEE, 2015.

Abdelali Elmoufidi. Pre-processing algorithms on digital x-ray mammograms. In *2019 IEEE International Smart Cities Conference (ISC2)*, pages 87–92. IEEE, 2019.

Ayoub Skouta, Abdelali Elmoufidi, Said Jai-Andaloussi, and Ouail Ochetto. Automated binary classification of diabetic retinopathy by convolutional neural networks. In *Advances on Smart and Soft Computing*, pages 177–187. Springer, 2021.

Amine El Hossi, Ayoub Skouta, Abdelali Elmoufidi, and Mourad Nachaoui. Applied cnn for automatic diabetic retinopathy assessment using fundus images. In *International Conference on Business Intelligence*, pages 425–433. Springer, 2021.

Giedrius Stabingis, Jolita Bernatavičienė, Gintautas Dzemyda, Alvydas Paunksnis, Lijana Stabingienė, Povilas Treigys, and Ramutė Vaičaitienė. Adaptive eye fundus vessel classification for automatic artery and vein diameter ratio evaluation. *Informatica*, 29(4): 757–771, 2018.

Gediminas Balkys and Gintautas Dzemyda. Segmenting the eye fundus images for identification of blood vessels. *Mathematical Modelling and Analysis*, 17(1):21–30, 2012.

Ana Salazar-Gonzalez, Djibril Kaba, Yongmin Li, and Xiaohui Liu. Segmentation of the blood vessels and optic disk in retinal images. *IEEE journal of biomedical and health informatics*, 18(6):1874–1886, 2014.

Aya F Khalaf, Inas A Yassine, and Ahmed S Fahmy. Convolutional neural networks for deep feature learning in retinal vessel segmentation. In *2016 IEEE International Conference on Image Processing (ICIP)*, pages 385–388. IEEE, 2016.

Paweł Liskowski and Krzysztof Krawiec. Segmenting retinal blood vessels with deep neural networks. *IEEE transactions on medical imaging*, 35(11):2369–2380, 2016.

Linfang Yu, Zhen Qin, Tianming Zhuang, Yi Ding, Zhiguang Qin, and Kim-Kwang Raymond Choo. A framework for hierarchical division of retinal vascular networks. *Neurocomputing*, 392:221–232, 2020.

Shuangling Wang, Yilong Yin, Guibao Cao, Benzheng Wei, Yuanjie Zheng, and Gongping Yang. Hierarchical retinal blood vessel segmentation based on feature and ensemble learning. *Neurocomputing*, 149:708–717, 2015.

Lei Zhou, Qi Yu, Xun Xu, Yun Gu, and Jie Yang. Improving dense conditional random field for retinal vessel segmentation by discriminative feature learning and thin-vessel enhancement. *Computer methods and programs in biomedicine*, 148:13–25, 2017.

Huazhu Fu, Yanwu Xu, Stephen Lin, Damon Wing Kee Wong, and Jiang Liu. Deepvessel: Retinal vessel segmentation via deep learning and conditional random field. In *International conference on medical image computing and computer-assisted intervention*, pages 132–139. Springer, 2016.

Kai Hu, Zhenzhen Zhang, Xiaorui Niu, Yuan Zhang, Chunhong Cao, Fen Xiao, and Xieping Gao. Retinal vessel segmentation of color fundus images using multiscale convolutional neural network with an improved cross-entropy loss function. *Neurocomputing*, 309:179–191, 2018.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

Yishuo Zhang and Albert CS Chung. Deep supervision with additional labels for retinal vessel segmentation task. In *International conference on medical image computing and computer-assisted intervention*, pages 83–91. Springer, 2018.

Zengqiang Yan, Xin Yang, and Kwang-Ting Cheng. A three-stage deep learning model for accurate retinal vessel segmentation. *IEEE journal of Biomedical and Health Informatics*, 23(4):1427–1436, 2018.

Yehui Yang, Tao Li, Wensi Li, Haishan Wu, Wei Fan, and Wensheng Zhang. Lesion detection and grading of diabetic retinopathy via two-stages deep convolutional neural networks. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 533–540. Springer, 2017.

Yicheng Wu, Yong Xia, Yang Song, Yanning Zhang, and Weidong Cai. Multiscale network followed network model for retinal vessel segmentation. In *International Conference on Medical Image Computing* *and Computer-Assisted Intervention*, pages 119–126. Springer, 2018.

Yicheng Wu, Yong Xia, Yang Song, Yanning Zhang, and Weidong Cai. Nfn+: A novel network followed network for retinal vessel segmentation. *Neural Networks*, 126:153–162, 2020a.

Kun Wang, Xiaohong Zhang, Sheng Huang, Qiuli Wang, and Feiyu Chen. Ctf-net: Retinal vessel segmentation via deep coarse-to-fine supervision network. In *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, pages 1237–1241. IEEE, 2020.

Yicheng Wu, Yong Xia, Yang Song, Donghao Zhang, Dongnan Liu, Chaoyi Zhang, and Weidong Cai. Vessel-net: retinal vessel segmentation under multi-path supervision. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 264–272. Springer, 2019.

Bo Wang, Shuang Qiu, and Huiguang He. Dual encoding u-net for retinal vessel segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 84–92. Springer, 2019.

Wenao Ma, Shuang Yu, Kai Ma, Jiexiang Wang, Xinghao Ding, and Yefeng Zheng. Multi-task neural networks with spatial activation for retinal vessel segmentation and artery/vein classification. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 769–778. Springer, 2019.

Suraj Mishra, Danny Z Chen, and X Sharon Hu. A data-aware deep supervised method for retinal vessel segmentation. In *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, pages 1254–1257. IEEE, 2020.

Joes Staal, Michael D Abràmoff, Meindert Niemeijer, Max A Viergever, and Bram Van Ginneken. Ridge-based vessel segmentation in color images of the retina. *IEEE transactions on medical imaging*, 23(4): 501–509, 2004.

Leo Breiman. Random forest, vol. 45. *Mach Learn*, 1, 2001b.

Nasser Tamim, Mohamed Elshrkawey, Gamil Abdel Azim, and Hamed Nassar. Retinal blood vessel segmentation using hybrid features and multi-layer perceptron neural networks. *Symmetry*, 12(6):894, 2020.

Chun Tian, Tao Fang, Yingle Fan, and Wei Wu. Multi-path convolutional neural network in fundus segmentation of blood vessels. *Biocybernetics and Biomedical Engineering*, 40(2):583–595, 2020.

Yicheng Wu, Yong Xia, Yang Song, Yanning Zhang, and Weidong Cai. Nfn+: A novel network followed network for retinal vessel segmentation. *Neural Networks*, 126:153–162, 2020b.

Henda Boudegga, Yaroub Elloumi, Mohamed Akil, Mohamed Hedi Bedoui, Rostom Kachouri, and Asma Ben Abdallah. Fast and efficient retinal blood vessel segmentation method based on deep learning network. *Computerized Medical Imaging and Graphics*, 90:101902, 2021.