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Enhanced Detection of retinopathy affected blood vessels using deep convolutional neural networks

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Abstract

In human body, one of the complete sensory organ is eye. For getting the human vision perfectly, blood vessels in retina and neurons in eye plays a key role. Some of the diseases like hypertension, arteriosclerosis and diabetes retinopathy are causing the branch pattern change and also retinal blood vessels diameter leads to blindness. By segmenting the retinal blood vessels, we can analyze these changes. In this research work, we have proposed two types of neural network architecture based on deep learning technique which will segment the retina blood vessels. By pixel classification, the features map of different fundus images are retrieved by the multiple hidden layers. By the support of loss function, we are avoiding the losses due to the variation between the vessel and non-vessel. Proposed work will be examined for both of the architectures with database DRIVE.

Keywords: *Retinal Color fundus images, deep convolutional neural network, Loss function*

1. INTRODUCTION

Fundamental requirement for screening and analysis of retinal sicknesses includes division of retinal veins. Two dimensional or three dimensional shading fundus pictures are utilized for fragmenting retinal vessel. In early days investigator or specialists physically portion the retinal vessel from the fundus pictures which is a tedious advancement and it lead to mistake. Programmed division of retinal veins lessens time and it helps in early location and analysis of infections. A few administered or solo techniques have just been proposed for retinal vessel division. Supervised methods rely on manual annotation groundtruth for segmentation of retinal vessel whereas unsupervised method does not depend on manual annotationIn [1], Salem et al. proposed a calculation that map the dispersions of the information by utilizing separation guideline. Also, the proposed grouping calculation is improved with a fractional supervision procedure and it is exhibited that it can fragment veins of little breadths and low differences. The highlights utilized right now the green channel power, the neighborhood maxima of the slope extent and enormous Eigen esteem. RACAL characterizes a standardized separation parameter, which goes about as the determinant of the bunch. The creator asserted that RACAL as a classifier performs superior to the KNN classifier. Affectability accomplished for RACAL is 85.47% and for KNN is 83.14%.

In [2], Marin et al. proposed a strategy for vessel division utilizing neural system (NN) for pixel arrangement and figures a seven dimensional vector which are made out of minute invariants based highlights for pixel portrayal and dim level. The info pictures are standardized with foundation utilizing foundation homogenisation, focal light reflex is expelled and vessel is improved. Dark level based highlights, Moment invariants based highlights are the two arrangements of highlight separated in the proposed work. The neural system comprises of three shrouded layers, each concealed layer contains 15 neurons that are given an ideal NN setup. The yield layers are associated by the shrouded layer neurons through a nonlinear calculated sigmoid enactment capacity to a solitary neuron, so its yield goes somewhere in the range of 0 and 1. Classifier execution is improved by the incorporation of a two stage post handling stage: the initial step is planned for filling pixel holes in distinguished veins, while the subsequent advance is planned for evacuating erroneously recognized disengaged vessel pixels. The proposed technique is assessed for two dataset and exactness accomplished for

DRIVE is 94.52% and for STARE is 95.26%.

The combination of two supervisor classifier is proposed in [3] by Wang et al. Hierarchical features are extracted by CNN and the extracted features are classified using Random Forest classifier which is able to predict patterns and learn features by integrating the feature leaarning. CNN removes include by utilizing Convolution layer, subsampling layer and Fully associated layer (FC). Subsampling layer go about as highlight choice layer, by playing out a nearby averaging and a subsampling as the spatial goals of each component map is decreased by the subsampling layers. Arbitrary woodland comprises of tree indicators, where each tree in the tree indicators of Random timberland with a similar conveyance for all trees in the backwoods relies upon the estimations of an irregular vector which are inspected autonomously. The green channel of the RGB shading retinal picture is extricated and is preprocessed for making the force progressively uniform and improving the complexity of the vessels. The green channel picture is preprocessed with histogram leveling and Gaussian sifting, to decrease commotion. Exactness and affectability esteem acquired for DRIVE dataset are 94.67% and 87.71% individually.

In [4] [5], They proposed a technique for retinal vessel division utilizing a restrictive irregular field model. Parameters is generally utilized for organized expectation. The proposed strategy utilizes a completely associated CRF, where every hub is thought to be connected to each other pixel of the picture. Utilizing these higher request possibilities, the strategy can consider neighboring data as well as long range associations between pixels. This property improves the division exactness, yet makes usage of the deduction procedure computationally costly. The affectability calculated by this strategy for DRIVE dataset is 79.80%.

Dasgupta et al. [6] proposed a method for segmentation of retinal vessel in which input images are preprocessed by extracting green channel of fundus image to remove non uniform illumination and then the image is divided into patches and trained using fully convolved neural network. The images are then classified using probability map by setting threshold. In [7] sumathi et al. proposed a robust algorithm for segmentation of retinal vessels. The input images are preprocessed to normalize the illumination and contrast problem and thirteen dimension feature vectors are extracted

In [8], Kai et al. proposed a novel retinal vessel division strategy for the fundus pictures dependent on convolutional neural system (CNN) and completely associated contingent arbitrary fields (CRFs). The information picture is information enlarged (irregular flipping and revolution) is done inorder to build the quantity of info picture to the convolutional neural system. A multiscale CNN design is developed by joining the component guide of each center layer to learn more detail data of the retinal vessels. A cross entropy misfortune work is performed which overlooks the loss of vessels and furthermore to distinguish hard examples (edge vessels). Reasonable parameters for the improved misfortune work is discovered utilizing a likelihood dissemination of the base convolutional neural system. The proportion of misclassified pixels at every likelihood esteem for vessels and non vessels are determined. CRFs is applied to get the last parallel division result which utilizes increasingly spatial setting data by considering the connections among the entirety of the pixels in the fundus pictures. The precision accomplished is 95.33% and affectability is 77.72% for DRIVE and for STARE the exactness is 96.32% and affectability is 75.54%.

In [9], Americo Oliveira, Sergio Pereira Carlos A. Silva proposed a novel strategy for retinal vessel division by the multiscale examination. During preparing, 2750, 3250, and 3750 patches are separated from every retinal fundus picture of the DRIVE, STARE, and CHASE_DB1 databases. CNN engineering contains many number of actuation, pooling, up testing, dropout and regularization layers. Completely associated layers are supplanted by convolution so as to take a picture, of any size, as info, and straightforwardly yield a lot of likelihood maps with similar measurements. The proposed system can portion a lot of pixels on the double, rather than treating every pixel. To investigate the data mastered during preparing and to refine the division, information augmenation is performed by revolution activity. The exactness acquired by this technique for DRIVE database is 95.70%.

In [10], Zengqiang et al proposed a method for segmenting retinal blood vessel by considering segment level loss which emphasizes more on thin vessels because the thickness of fine vessel is less compared to main vessel. The pixel insightful misfortune is taken in to thought as it for the most part centers around thickness of vessels. The section level misfortune is performed by skeletonizing the vessel and afterward estimating the thickness irregularity of every vessel portion as opposed to every vessel pixel by isolating the whole skeletons into fragments, for any portion longer than a predefined greatest length it is additionally partitioned in to littler portion. In the preparation stage division is actualized as two branches containing the section level misfortune and the pixel wiseloss to dispense with the thickness irregularity of both slim vessels and thick vessels. In the test stage the likelihood maps produced by the two branches are consolidated by pixelwise duplication for conclusive division. The proposed technique assessed utilizing DRIVE database and precision accomplished is 95.44% and affectability is 76.68%

In [11], Vijay Badrinarayanan et al proposed a deep convolutional neural network named 'segnet' for semantic image segmentation. The network consists of encoder and decoder stages. The encoder stage consists of thirteen layers similar to VGG16. The VGG 16 is a pretrained module and it is trained for RGB images. The decoder upsamples the lower feature maps of the encoder. It uses the pooling index of the unpooling layer in the encoder to perform upsampling. The proposed architecture is widely compared with fully convolutional net and DeepLab_Large. The semantic images are classified based on pixel values. The last three layers of the network consist of 1x1 convolution, softmax and pixel classification layer.

In [12], Olaf Ronneberger et al proposed deep network for biomedical image segmentation. The architecture consists of five stages of encoder and decoder with multiple hidden layers. The last stage and the previous stage consists of dropout of 0.5. The output of each hidden stage is up sampled and concatenated to previous layer output before upsampling. The upsampling is performed by transposed convolution layer which is also called as up convolution. The lower feature maps are upsampled and are concatenated to lower features of previous stage. The proposed architecture is based on fully convolution network; therefore the network replaces the fully connected layer with 1x1 convolution.

In the proposed work retinal vessels are segmented by convolutional neural network architectures. The retinal fundus images are preprocessed and the proposed architectures are trained to detect the vasculature in a supervised manner.

2. PROPOSED METHODOLOGY

2.1 Outline

The input images are split into patches and trained using Convolutional neural network. The imbalance of pixel count between vessel and non vessel are eliminated by loss function. The images are then classified as vessels and non vessels using pixel classification. The proposed model is shown in figure1.

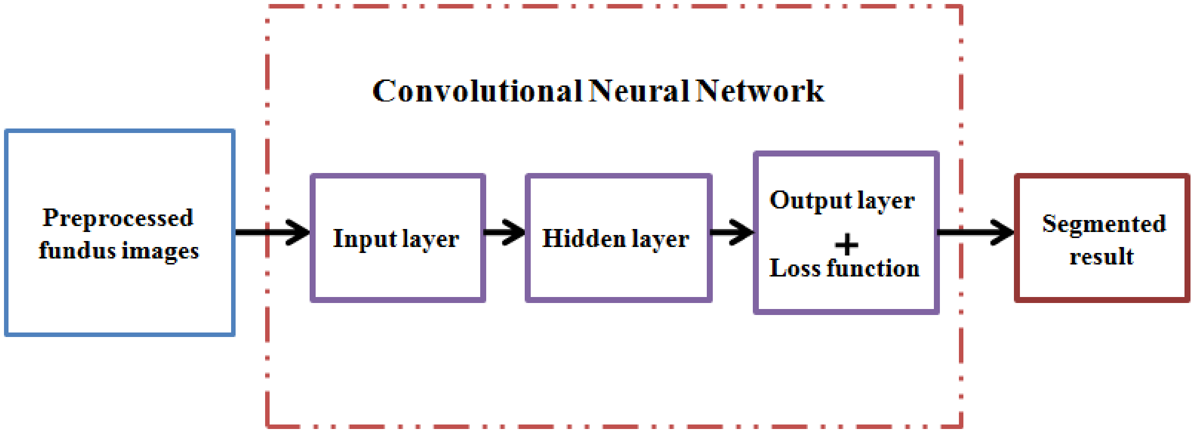

Fig. 1. Proposed methodology

2.2. Preprocessing

Non uniform enlightenment and low complexity contrast among vessels and non vessels lead to ill-advised division of vessel. Retinal shading fundus pictures are preprocessed to kill complexity and brightening issue. The green channel of the fundus picture gives better differentiation and can lessen brightening issue so the green channel of fundus pictures are removed [13-20]. The removed green channel fundus pictures are further preprocessed for vessel upgrade. In the proposed work Contrast constrained versatile histogram adjustment (CLAHE) is applied for vessel upgrade. CLAHE is a neighborhood improvement method that restrains the intensification of histogram by cutting at a predefined esteem. To empower the standard part increasingly noticeable, CLAHE is the most usually utilized method in clinical pictures. The preprocessed fundus picture is appeared in figure 1.

2.3. Neural network

The neural network consists of input layer, hidden layer for feature extraction and output layer for classification. The proposed architecture consists of five stages of encoder and decoder layer. The input images are fed into the input layer and it is processed by hidden layer. The input images are trained with two different architecture named as fully convolved convolutional neural network (FCCN), depth concatenated neural network (DCN) and the comparison of their results are made[21-28].

2.4. Fully convolutional Neural Network

The hidden layer of FCCN consists of rectified linear layer, Convolutional layer, batch normalization layer, unpooling layer & maxpooling layer. The proposed FCCN architecture is shown in figure 2

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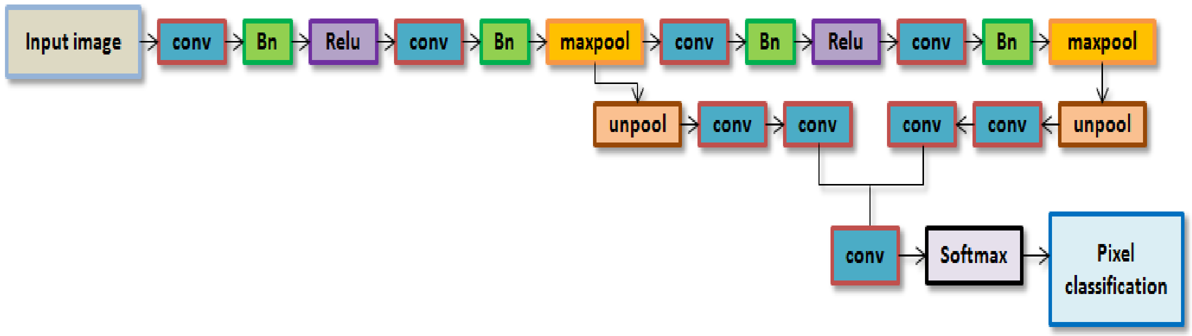

Fig 2. Fully convolved convolutional neural network

Each stage consists of two Convolution layer, each convolution layer is followed by batch normalization and rectified linear unit. Batch normalization layer and rectified linear unit layer increases the speed of training progress. The output of each hidden stage is unpooled and is convolved twice. Convolution operation performed in the proposed work involves dilated filter of 3x3 with striding and padding of one i.e. padded with zeros on all four sides. The pooling operation performed in the proposed work is 2x2 maximum pooling. The unpooling layer unpools the output of maxpooling layer of current stage and output of rectified linear unit from next stage thus performing the operation of decoder. The number of filters with which the images convolved in each stage is double that of previous stage. The number of filters in each layer remains the same. The output layer consists of softmax and pixel classification layer. The softmax layer assigns probability value for each class in image. The pixel classification layer classifies the image base on their pixel values ; 255 as vessels and 0 as non vessel region[29-40].

The hidden layer of DCN architecture consists of convolution layer, max pooling layer, ReLu layer, batch normalization layer , depth concatenation layer and up convolutional layer. The hidden layers form five encoder stages and five decoder stages. Each encoder stage consists of two convolutional layer and max pooling layer. The decoder stage consists of depth concatenation layer, two convolution layer and on up convolution layer. The last stage of decoder consists only of up convolution layer. The depth concatenation layer concatenates the two input that are of same height and width. The depth concatenation layer in the proposed work concatenates the output from the corresponding encoder stage and the output from next decoder stage. The up convolution layer performs transpose convolution operation [40-42].

2.4. Loss Function

In pixel classification layer the images are classified based on their pixel value. Vessel pixel count occupies less than one fourth of the total image pixel count this lead to misclassification of vessel as non-vessel. In order to avoid this class imbalance problem class weightage of vessel pixel are increased by taking inverse of the class weightage divided by total weight of the two classes.
The pixel count of vessels is less compared to non-vessel region leading to imbalance. In order to overcome this cross-entropy loss function is for robust segmentation of vessels.

The corresponding weights of vessels and non-vessels are denoted as $w = w^{(1)}+w^{(2)}$. The total class weight (T(CW)) is given

$$w = w^{(1)}+w^{(2)} \quad (1) \qquad\qquad T(W) = w^{(1)} + w^{(2)} \quad (2)$$

Occurrence frequency of the class is calculated by dividing the corresponding weight with total

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weight

$$F^{(i)} = \frac{cw^{(i)}}{T(w)} \quad i=1,2 \qquad (3)$$

The pixel weightage is now updated with inverse of occurrence frequency.

$$w^{(i)} = \frac{1}{F^{(i)}} \quad i=1,2 \qquad (4)$$

3. EVALUATIONS

3.1 Database

The proposed methodology is evaluated on DRIVE database. The drive database consists forty images out of which twenty images are for training and twenty images for testing. Each training images has its corresponding groundtruth and its mask image. The training images has two groundtruth and one mask image.

3.2 Evaluation metric

The proposed system is assessed utilizing assessment metric, for example, affectability, explicitness and precision. The vessel portioned result comprises of four cases. They are TP, TN FP, FN. TP is the result of vessel anticipated effectively as vessel and those are wrongly anticipated as non vessel pixels rather than vessels are considered FN. TN is the result of non vessel pixel accurately anticipated as non vessel and the non vessel pixel wrongly anticipated as vessel are characterized as FP. The affectability (Se), explicitness (Sp) and precision (Acc) are determined utilizing this four cases. Se, Sp, Acc are determined as follows.

$$Se = \frac{TP}{TP+FN} \qquad (5)$$

$$Sp = \frac{TN}{TN+FP} \qquad (6)$$

$$Acc = \frac{TP+TN}{TP+TN+FN+FP} \qquad (7)$$

4. RESULTS AND DISCUSSION

4.1 Results

The trained model is evaluated for twenty test images. The segmented result for database DRIVE are shown in figure 3.

The evaluation metric for twenty test images such as sensitivity, specificity and accuracy are calculated and tabulated in table 1. The average sensitivity specificity and accuracy for twenty images are 82.37, 94.74 and 92.61 respectively. The segmented result for various contrast and illuminated images are

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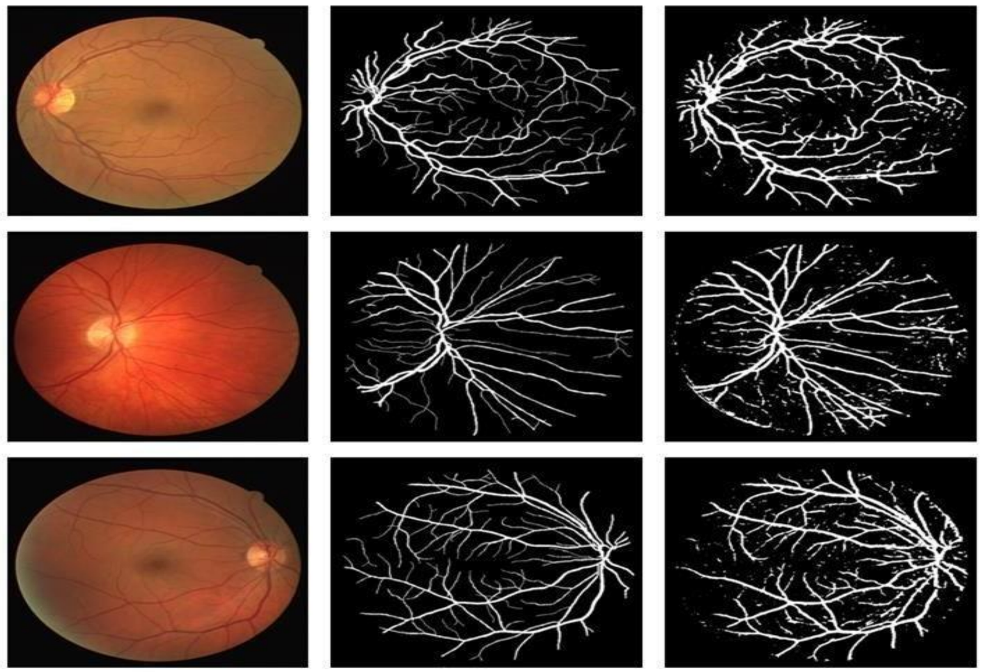
shown in figure 3.



(a) (b) (c)

Fig. 3. Segmentation result of DRIVE dataset. (a) Color fundus image. (c) Ground truth. (c) Segmentation result

Table 1. Evaluation metric for DRIVE database

Image	Drive database		
	% of Sensitivity	**% of Specificity**	**% of Accuracy**
1	83.12	95.26	92.99
2	83.31	95.53	93.01
3	86.1	92.94	91.82
4	75.57	96.81	92.78
5	87.28	93.48	92.49
6	86.74	91.9	91.09
7	83.86	94.07	92.38
8	84.35	93.5	92.17
9	85.45	93.87	92.68
10	82.39	94.65	92.7
11	77.26	95.22	91.72
12	82.49	94.79	92.76
13	84.13	93.36	91.71
14	77.86	95.99	92.81
15	82.52	94.22	92.42

16	83.51	95.32	93.25
17	82.93	94.08	92.44
18	79.64	95.94	93.3
19	80.56	97.17	94.04
20	78.26	96.65	93.73
Average	**82.37**	**94.74**	**92.61**

From the table it is analyzed that the sensitivity, specificity and accuracy for 20 images are more or less equal, due to enhancement of the retinal image

5. CONCLUSION

Retrieval of fine vessels from the retinal fundus images are still a challenging task. The proposed method has segmented fine vessels and also has avoided mis segmentation of non vessel as vessels. İt is also inferred that for the pixel level classification, unpooling of pooling layer has retained the information in image The proposed architectures are observed to be the optimum performing architectures due to the inclusion of class balanced cross entropy loss function.

REFERENCES

[1] S.A. Salem, N.M. Salem, A.K. Nandi, “Segmentation of retinal blood vessel using a novel clustering algorithm (RACAL) with a partial supervision strategy”, Med. Biol. Eng. Comput, vol. 45, no. 3, pp. 261–273, 2007.

[2] D. Marín, A. Aquino, M.E. Gegúndez-Arias, J.M. Bravo, “A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features”, IEEE Trans. Med. Imag, vol. 30, no. 1, pp. 146–158, 2015.

[3] S.Palanivel Rajan, T.Dinesh, “Analysis of Human Brain Disorders for Effectual Hippocampus Surveillance”, International Journal of Modern Sciences and Engineering Technology, Vol. 2, Issue 2, pp.38-45, 2015.

[4] M.Annakamatchi, V.Keralshalini," Design of Spiral Shaped Patch Antenna for Bio-Medical Applications", International Journal of Pure and Applied Mathematics , Online ISSN No.: 1314-3395,Print ISSN No.:1311-8080 ,Vol. No.:118, Issue No.:11,pp.131-135,2018.

[5] S.Palanivel Rajan, “A Significant and Vital Glance on “Stress and Fitness Monitoring Embedded on a Modern Telematics Platform”, Telemedicine and e-Health Journal, Vol.20, Issue 8, pp.757-758, 2014.

[6] S. Wang, Y. Yin, G. Cao, B. Wei, Y. Zheng, G. Yang, “ Hierarchical retinal blood vessel segmentation based on feature and ensemble learning”, Neurocomputing, vol. 149, pp. 708–717, 2015.

[7] Paweł Liskowski and Krzysztof Krawiec, “Segmenting Retinal Blood Vessels With Deep Neural Networks”, IEEE TRANSACTIONS ON MEDICAL IMAGING, 2016,VOL. 35, NO. 11, NOVEMBER

[8] Singamaneni Kranthi Kumar, Pallela Dileep Kumar Reddy, Ramesh G, Venkata Rao Maddumala (2019). Image transformation technique using steganography methods using LWT technique. Traitement du Signal, Vol. 36, No. 3, pp. 233-237. June 2019, https://doi.org/10.18280/ts.360305.

[9] S.Palanivel Rajan, C.Vivek, M.Paranthaman, "Feasibility Analysis of Portable Electroencephalography Based Abnormal Fatigue Detection and Tele-Surveillance System", International Journal of Computer Science and Information Security, ISSN No.: 1947-5500, Vol. No.: 14, Issue : 8, pp. 711-722, 2016.

[10] Ribana.K, Pradeep.S, "Contrast Enhancement Techniques for Medical Images", International Journal of Pure and Applied Mathematics, International Journal of Pure and Applied Mathematics, Online ISSN No.: 1314-3395, Print ISSN No.: 1311-8080, Vol. No.: 118, Special Issue No, pp. 695-700, 2018.

[11] S Mohanapriya, M Vadivel, "Automatic retrival of MRI brain image using multiqueries system", 2013 International Conference on Information Communication and Embedded Systems (ICICES), INSPEC Accession Number: 13485254, Electronic ISBN: 978-1-4673-5788-3, DOI: 10.1109/ICICES.2013.6508214, pp. 1099-1103, 2013.

[12] S.Palanivel Rajan, "Review and Investigations on Future Research Directions of Mobile Based Tele care System for Cardiac Surveillance", Journal of Applied Research and Technology, Vol.13, Issue 4, pp.454-460, 2015.

[13] Dasgupta, and S. Singh, "A fully convolutional neural network basedstructured prediction approach towards the retinal vessel segmentation,"in Proc. ISBI, 2017, pp. 18-21.

[14] Sumathi T Vivekanandan P Ravikanth Balaji, " Retinal Vessel Segmentation using Neural Network (RVSNN)," Volume 12, Issue 5, May 2018, p. 669 – 678

[15] S.Palanivel Rajan, R.Sukanesh, "Viable Investigations and Real Time Recitation of Enhanced ECG Based Cardiac Tele-Monitoring System for Home-Care Applications: A Systematic Evaluation", Telemedicine and e-Health Journal, ISSN: 1530-5627, Online ISSN: 1556-3669, Vol. No.: 19, Issue No.: 4, pp. 278-286, 2013.

[16] S.Palanivel Rajan, et.al., "Intelligent Wireless Mobile Patient Monitoring System", IEEE Digital Library Xplore, ISBN No. 978-1-4244-7769-2, INSPEC Accession Number: 11745297, IEEE Catalog Number: CFP1044K-ART, pp. 540-543, 2010.

[17] S.Palanivel Rajan, et.al., "Cellular Phone based Biomedical System for Health Care", IEEE Digital Library Xplore, ISBN No. 978-1-4244-7769-2, INSPEC Accession Number: 11745436, IEEE Catalog Number: CFP1044K-ART, pp.550-553, 2010.

[18] J. Somasekar a, , G. Ramesh , Gandikota Ramu, P. Dileep Kumar Reddy, B. Eswara Reddy e, Ching-Hao Lai, "A dataset for automatic contrast enhancement of microscopic malaria infected blood RGB images", Data in brief, Elsevier, https://doi.org/10.1016/j.dib.2019.104643,2352-3409/© 2019.

[19] Kai et al., "Retinal vessel segmentation of color fundus images using multiscale convolutional neural network with an improved cross-entropy loss function", Elsevier Neurocomputing, vol. 309, pp. 179–191, 2018.

[20] Americo Oliveira, Sergio Pereira, Carlos A. Silva, "Retinal vessel segmentation based on Fully

Convolutional Neural Networks", Elsevier Expert Systems With Applications, vol. 112, pp. 229–242,2018.

[21] Zengqiang Yan, Xin Yang, and Kwang-Ting (Tim) Cheng, "Joint Segment-level and Pixel-wise Losses for Deep Learning based Retinal Vessel Segmentation" IEEE Transactions on Biomedical Engineering, 2018.

[22] M. Paranthaman, "T-shape polarization reconfigurable patch antenna for cognitive radio," 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM), Chennai, 2017, pp. 927-929. doi: 10.1109/ICONSTEM.2017.8261338

[23] M Paranthaman, G.Shanmugavadivel "Design of Frequency Reconfigurable E-Shaped Patch Antenna for Cognitive Radio" International Journal of Applied Engineering Research, ISSN 0973-4562 Vol. 10 No.20 (2015) pp.16546-16548

[24] G. Ramu, P. Dileep Kumar Reddy, Appawala Jayanthi "A Survey of Precision Medicine Strategy Using Cognitive Computing" International Journal of Machine Learning and Computing, Vol. 8, No. 6, December 2018 DOI: 10.18178/IJMLC2018.8.6.741 (Scopus) (UGC Approved) Journal No: 48748, pp 530 to 535

[25] Ramu, G. A secure cloud framework to share EHRs using modified CP-ABE and the attribute bloom filter. Educ Inf Technol 23, 2213–2233 (2018). DOI https://doi.org/10.1007/s10639-018-9713-7

[26] Ramu, G., Reddy, B.E., Jayanthi, A. et al. Fine-grained access control of EHRs in cloud using CP-ABE with user revocation. Health Technol. 9, 487–496 (2019). http://dx.doi.org/10.1007/s12553-019-00304-9

[27] P. Dileep Kumar Reddy, R. Praveen Sam, C. Shoba Bindu "Optimal Blowfish Algorithm based Technique for Data Security in Cloud"Int. J. Business Intelligence and Data Mining, ISSN online 1743-8195, ISSN print 1743-8187, Vol. 11, No. 2, 2016.Pp.171–189.DOI: 10.1504/IJBIDM.2016.10001484. (Inder Science)(UGC Approved). Journal No: 16481

[28] J. Somasekar a, , G. Ramesh , Gandikota Ramu, P. Dileep Kumar Reddy, B. Eswara Reddy e, Ching-Hao Lai, "A dataset for automatic contrast enhancement of microscopic malaria infected blood RGB images", Data in brief, Elsevier, https://doi.org/10.1016/j.dib.2019.104643,2352-3409/2019

[29] M Paranthaman, A Berlin "Design of Adaptive Changing Structures with Bandwidth Control for Wideband Applications" International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, Vol. 5, Issue 2, February 2017 pp. 26-28.

[30] M.Paranthaman, S.Palanivel Rajan" Design of Dual Band Circular Patch Antenna for Medical Imaging" International Journal of Pure and Applied Mathematics, Volume 118 No. 8 2018, pp-527-530

[31] Hoover, V. Kouznetsova and M. Goldbaum, "Locating Blood Vessels in Retinal Images by Piece-wise Threhsold Probing of a Matched Filter Response", IEEE Transactions on Medical Imaging, vol.19 no.3, pp. 203-210, March 2000.

[32] H. Fu, Y. Xu, S. Lin, D.W.K. Wong, J. Liu, "Deep vessel Retinal vessel segmentation via deep learning and conditional random field", Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 132–139, 2018.

[33] Vijay Badrinarayanan., “Segnet: A deep convolutional encoder-decoder architecture for image segmentation,” in IEEE Transaction on pattern analysis and machine learning, vol 39, No 12, December 2017.

[34] Olaf Ronneberger, Philipp Fischer, Thomas Brox, “U-net Convolutional neural networks for biomedical image segmentation”, In Proc. MICCAI, pp. 234-241, 2015.

[35] J.J. Staal, M.D. Abramoff, M. Niemeijer, M.A. Viergever, B. van Ginneken, "Ridge based vessel segmentation in color images of the retina", IEEE Transactions on Medical Imaging, 2004, vol. 23, pp. 501-509.

[36] Zhendong Zhang, Xinran Wang and Cheolkon Jung, “DCSR: Dilated convolutions for single image super-resolution,” IEEE transactions on image processing, vol 28, No 4. April 2019

[37] Xiaomeng Li, Hao Chen, Xiaojuan Qi, Qi Dou, Chi Wing Fu, “H-Dense Unet:Hybrid densely connected unet for liver and tumor segmentation from CT volumes, ” IEEE transaction on medical imaging, Vol 37, No 12 December 2018

[38] Paranthaman, M., and S. Palanivel Rajan. "Design of Triple C shaped Slot Antenna for Implantable Gadgets." Current Trends In Biomedical Communication And Tele–Medicine (2018): 40. DOI: 10.21786/bbrc/11.2/6

[39] Ruirui Li, Wenjie Liu, Lei Yang, Shihao Sun, Wei Li, “DeepUnet:A deep fully convolutional network for pixel-level sea segmentation,” IEEE journal of selected topics in applied earth observation and remote sensing Vol 11, no 11, November 2018

[40] Hoover, V. Kouznetsova and M. Goldbaum, “Locating Blood Vessels in Retinal Images by Piece-wise Threhsold Probing of a Matched Filter Response”, IEEE Transactions on Medical Imaging, vol.19 no.3, pp. 203-210, March 2000.

[41] Soares, J. V., Leandro, J. J., Cesar, R. M., Jelinek, H. F., & Cree, M. J. “Retinal vessel segmentation using the 2d gabor wavelet and supervised classification”, IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1214–1222, 2006.

[42] Li, Q., Feng, B., Xie, L., Liang, P., Zhang, H., & Wang, T. "A cross-modalityl earning approach for vessel segmentation in retinal images", IEEE Transactions on Medical Imaging, vol. 35, no. 1, pp. 109–118, 2016.

[43] Ahn, H., Lee, J. -., & Cho, H. -. (2019). Implementation of multi-object recognition algorithm using enhanced R-CNN. Test Engineering and Management, 81(11-12), 1-8. Retrieved from www.scopus.com