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Detection of Diabetic Eye Disease from Retinal Images using a CNN model

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Abstract

Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME) are the two major complications of diabetes and have a significant impact on working individuals of the world population. DR doesn't give any early symptoms. Therefore, it is important to diagnose DR at an early stage. The two above mentioned diseases usually depend on the presence and areas of lesions in fundus images. The four main related lesions include soft exudates, hard exudates, microaneurysms, and haemorrhages. Since lesions in retinal fundus images are a pivotal indicator of DR, analyzing retinal fundus images is the most popular method for DR screening. The examination of fundus images is time-consuming and small lesions are hard to observe. Therefore, adopting deep learning techniques for lesion segmentation is of great importance. In this project, we use one of the deep learning techniques called U-Net, which is a variant of Convolutional Neural Networks (CNN) for multiple lesion segmentation.

Keywords: UNet architecture, Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME), rectified linear unit (ReLU).

1. Introduction

In recent times, India and other parts of the world have been faced with an increase in age and society related diseases like diabetes. According to recent survey, 24% of the country population has been diagnosed of diabetes disease alone and it have been recognized and accepted as one of the main causes of blindness in the country if not properly treated and managed. Early detection and diagnosis have been identified as one of the ways to achieve a reduction in the percentage of visual impairment caused by diabetes with more emphasis

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on routine medical check which the use of special facilities for detection and monitoring of the diabetes.

Diabetic related eye diseases are the most common cause of blindness in the world. Diabetic Retinopathy is severer and widely spread eye disease, which can be regarded as manifestation of diabetes on retina. Diabetic Retinopathy is a specific micro vascular complication of both insulin dependent (type 1) and non-insulin dependent (type 2) diabetes. The prevalence of retinopathy s strongly linked to the duration of diabetes. After20 years of diabetes nearly all patients with type one diabetes and over 60% of patients with type 2 diabetes have some degree of retinopathy.

Vision losses often, late symptoms of advanced diabetic retinopathy, many patients remain undiagnosed even as their disease is causing severe retinal damage. Hence there is an urgent need for mass screening retinal examination for the early detection and treatment of diabetic retinopathy.

A convolution is a mathematical calculation on two functions named f and g that gives a third function (f * g). This third function reveals how the shape of one is modified by the other. Convolution is very important. It can manipulate Blurred, Sharped, Edge detection, Noise reduction images.

A mask (g)- a small matrix whose values are called weight. A two-dimensional matrix represents it. It is also known as filtering. Its interesting point is that it should be in odd numbers. Otherwise, it is difficult to find the mid of the mask.

2. Related work

This paper presents a new unsupervised fuzzy algorithm for vessel tracking that is applied to the detection of the ocular fundus vessels. This method overcomes the problems of initialization and vessel profile modeling that are encountered in the literature and automatically tracks fundus vessels using linguistic descriptions like “vessel” and “non-vessel.” The main tool for determining vessel and non-vessel regions along a vessel profile is the fuzzy C-means clustering algorithm [1] that is fed with properly preprocessed data. Additional procedures for checking the validity of the detected vessels and handling junctions and forks are also presented. This paper presented a novel scheme that automatically tracks vessels in fundus images without the need of user intervention.

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In this paper a semi-automatic method to measure and quantify geometrical and topological properties of continuous vascular trees in clinical fundus images is described. Measurements are made from binary images obtained from segmentation process [2]. The skeletons of the segmented trees are produced by thinning off branch and crossing points are identified and segments of the trees are labeled and stored as a chain code. The operator selects a tree to be measured and decides if it is an arterial or venous tree. An automatic process then measures the lengths, areas and angles of the individual segments of the tree. Geometrical data and the connectivity information between branches from continuous retinal vessel trees are tabulated. A number of geometrical properties and topological indexes are derived.

Identification and measurement of blood vessels in retinal images could allow quantitative evaluation of clinical features, which may allow early diagnosis and effective monitoring of therapies in retinopathy. A new system is proposed for the automatic extraction of the vascular structure in retinal images, based on a sparse tracking technique. After processing pixels on a grid of rows and columns to determine a set of starting points (seeds), the tracking procedure starts. It moves along the vessel by analyzing subsequent vessel cross sections (lines perpendicular to the vessel direction), and extracting the vessel center, caliber and direction. Vessel points in a cross section are found by means of a fuzzy c-means classifier. The system proposed here is the first that integrates a reliable tracking technique with bifurcations and crossing identification, showing the possibility of devising a fully automatic system for vascular morphology and lesion analysis in retinal images.

Vessel detection is an important process in many medical imaging applications. In this paper, an edge tracking scheme is proposed for the detection of blood vessels in retinal images [3-4]. This method detects edge points iteratively based on a Bayesian approach using local grey levels statistics and continuity properties of blood vessels. Combining the grey level profile and vessel geometric properties improves the accuracy and robustness of the tracking process. Experiments on both synthetic and real retinal images show promising results. The difficulty in this method is to calculate the a priori probability of different configurations. So, a more advanced a priori model should be adopted to improve the performance of this method. Besides, a deeper evaluation on retinal images is needed to make the proposed method widely usable for vessel detection technique.

Exudates are the primary signs of diabetic retinopathy which are mainly cause of blindness and could be prevented with an early screening process. Pupil dilation is required in the

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normal screening process but this affects patients' vision. This paper investigated and proposed automatic methods of exudates detection on low-contrast images taken from non-dilated pupils. The process has two main segmentation steps which are coarse segmentation using Fuzzy C- Means clustering and fine segmentation using morphological reconstruction [5]. Four features, namely intensity, standard deviation on intensity, hue and adapted edge, were selected for coarse segmentation. The detection results are validated by comparing with expert ophthalmologists' hand-drawn ground-truth.

3. Methodology

U-Net is a convolutional neural network originally developed for segmenting biomedical images. When visualized its architecture looks like the letter 'U' and hence the name U-Net. Its architecture is made up of two parts, the left part – the contracting path and the right part – the expansive path.

The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions [6-7] (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for down sampling. At each down sampling step, we double the number of feature channels.

The expansive path consists of an up sampling of the feature map followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers.

3.1. Advantages of UNet

- Fitted for segmentation: it computes a pixel-wise output (minus the validity margins of the convolutions). Since we want to tackle segmentation tasks here, then it should work withoutmodifications.
- It has a simple structure. It's a repetition of basic building
- Up sampling, convolutions, reLu for the up sampling/decoding path. Hence, it should not betoo complicated to implement.
- It exhibits good performance. It won various benchmarks when introduced, and it still

allowsto get decent rankings in segmentation challenges[8-13].

- It works with little amount of training data. While the original authors don't really providean explanation about that point, they achieved these good results with only 30 training images.

3.2. Filter-bank like structure

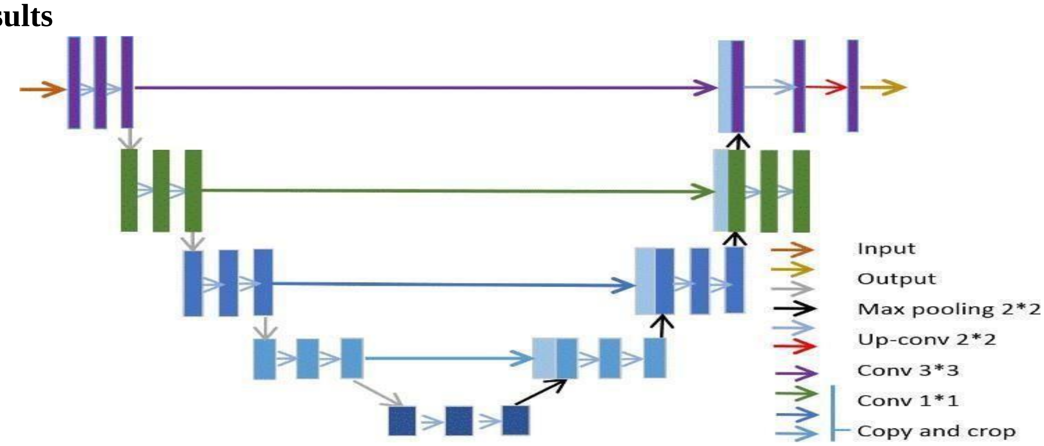
Most importantly, when analyzing the structure of the U-Net I've been struck by its proximity with well-known Signal Processing tools: scale-spaces or multi-resolution analysis. While it's still hard to explain why the network works so well, it's tempting to analyze its structure as:

The down sampling path is creating something similar to a scale-space and loses gradually some locality in exchange for higher level features or a broader horizon.

The up-sampling path propagates these high-level, coarsely localized features into each original pixel.

The horizontal path (from one downward level to the corresponding upward level) re-injects the details lost in the down sampling (max pool) step. This is strangely similar to what wavelet-based algorithms do.

4. Results



"Prediction" refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome, such as whether or not a customer will churn in 30 days. The algorithm will generate

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probable values for an unknown variable for each record in the new data, allowing the model builder to identify what that value will most likely be.

The word "prediction" can be misleading. In some cases, it really does mean that you are predicting a future outcome, such as when you're using machine learning to determine the next best action in a marketing campaign. Other times, though, the "prediction" has to do with, for example, whether or not a transaction that already occurred was fraudulent. In that case, the transaction already happened, but you're making an educated guess about whether or not it was legitimate, allowing you to take the appropriate action.

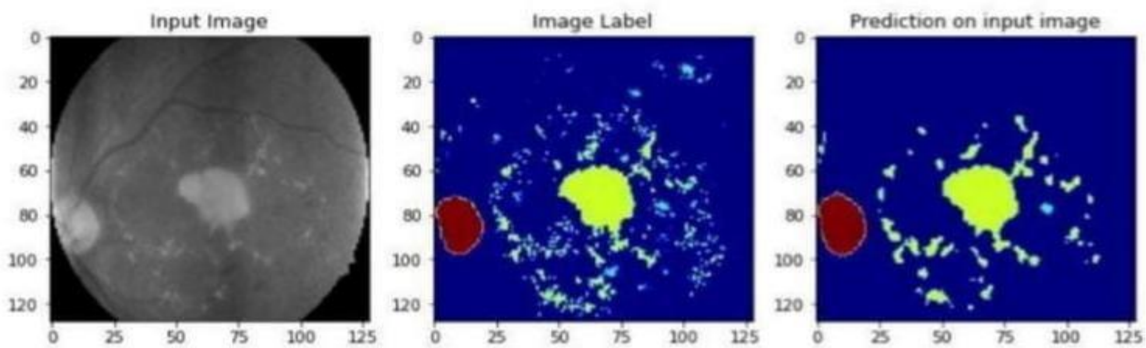

Fig. 1. Input image and corresponding prediction

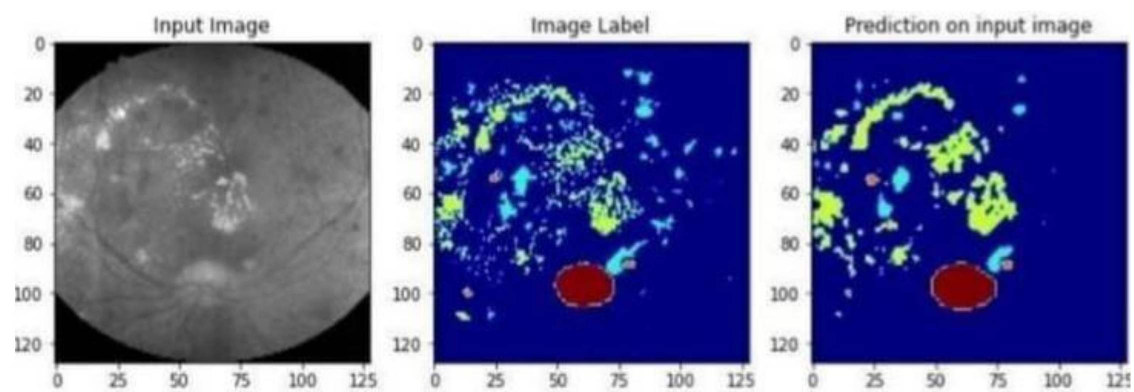

Fig. 2. Input image and corresponding prediction

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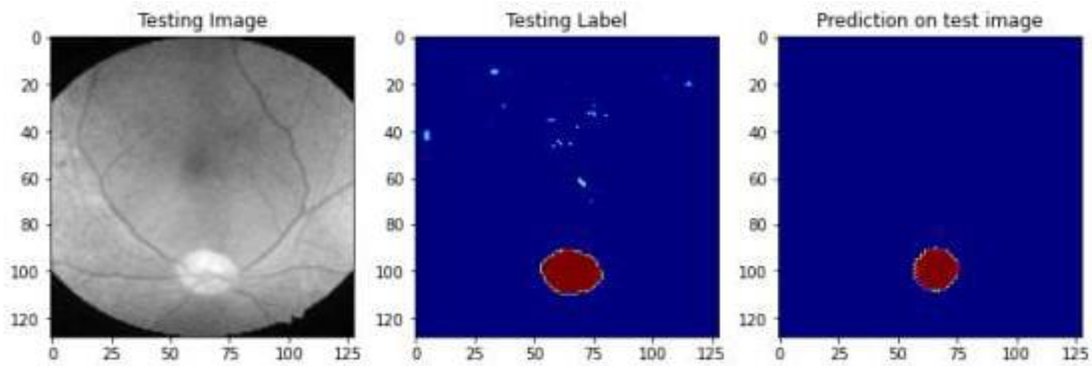
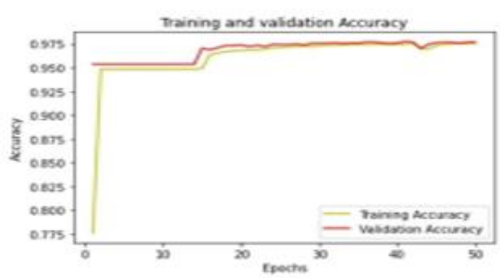


Fig. 3. Testing image and corresponding prediction

In the above fig 1 and fig 2 represents input image and corresponding prediction image & fig 3 represents testing image and corresponding prediction image. The graphs of training & validation losses vs the number of epochs and training & validation accuracyvs the number of epochs is quite opposite to each other. The increase in the value of training and validation loss after a certain number of epochs is due to numerical instability of some weights or gradients. The below figure shows the graphs of training and validation loss with respect to the number of epochs.



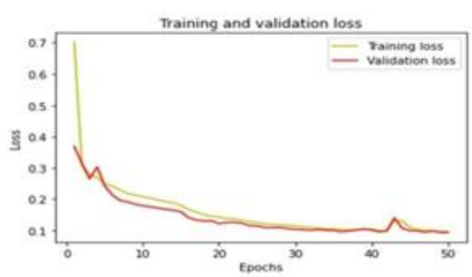


Fig. 4. Training and validation accuracy
Fig. 5. Training and validation loss

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In the above fig 4 represents Training and validation accuracy and fig 5 represents training and validation loss respectively.

5. Conclusion and Future enhancement

In this algorithm investigated and proposed a method based on anatomical structural details and retinal image information. This system intends to help the ophthalmologists not only in DR screening process but any other eye related abnormality which is based on retinal photography. It is not a final result application but it can be a preliminary diagnosis tool or a decision support system for ophthalmologists. Human ophthalmologists are still needed for the cases where detection results are not very obvious. This type of presentation will enable clinicians to identify retinal landmarks more quickly and will also help to take decision while treating the abnormality, particularly retinopathy.

Medical image segmentation has an essential role in computer-aided diagnosis systems in different applications. It divides an image into areas based on a specified description, such as segmenting body organs/tissues in the medical applications for border detection, tumor detection/segmentation, and mass detection. The UNet architecture was introduced for Biomedical Image segmentation to extract the factors in the image. The second part decoder uses transposed convolution to permit localization. It is again a Fully Convolutional connected layers network. The IDRiD dataset contains only a limited number of samples and U-Net architecture requires large data in order to perform image segmentation tasks efficiently. Therefore, data augmentation is performed on the IDRiD dataset, and 960 samples were generated. These samples are further processed and trained using the U-Net architecture. The data took 50 minutes to train and yield the result of the segmented mask using U- Net. U-Net architecture achieved very good performance on fundus image segmentation tasks. Though we studied and applied U-Net for multi lesion segmentation on fundus images, we believe that U-Net can be applied to other image segmentation tasks.

Diabetes affects slowly the circulatory system including that of the retina. Soothe vision of a patient may start to deteriorate and lead to diabetic retinopathy. This work proposes an algorithm for the detection of various stages of diabetic retinopathy and the degree of blindness from diabetic retinopathy (DR) images of both left and right eye. This algorithm uses color fundus images obtained from mydriatic camera. The quantitative performance is evaluated by calculating sensitivity, specificity and predictive value. Overall sensitivity

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(Se), specificity (Sp) and predictive value (PV) obtained in detecting optic nerve head from normal images and from abnormal images.

References

[1] Y. Zhou, Y. Zhu, Q. Ye, Q. Qiu, and J. Jiao, "Weakly supervised instance segmentation using class peak response," in CVPR, 2018.

[2] Z. Gu, J. Cheng, H. Fu, K. Zhou, H. Hao, Y. Zhao, T. Zhang, S. Gao, and J. Liu, "CE-Net: Context encodernetwork for 2d medical image segmentation," IEEE transactions on medical imaging, 2019.

[3] V. Gulshan, L. Peng, M. Coram, M. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, T.Madams, J. Cuadros et al., "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," JAMA, vol. 316, no. 22, pp. 2402– 2410, 2016.

[4] S. D. Solomon, E. Chew, E. J. Duh, L. Sobrin, J. K. Sun, B. L. VanderBeek, C. C. Wykoff, and T. W. Gardner, "Diabetic retinopathy: A position statement by the American Diabetes Association," Diabetes Care,vol. 40, no. 3, pp. 412–418, 2017.

[5] T. Laibacher, T. Weyde, and S. Jalali, "M2U-Net: Effective and efficient retinal vessel segmentation for real-world applications," in CVPRW, 2019.

[6] W. Wang, Z. Xu, W. Yu, J. Zhao, J. Yang, F. He, Z. Yang, D. Chen, D. Ding, Y. Chen, and X. Li, "Two-stream CNN with loose pair training for multi-modal AMD categorization," in MICCAI, 2019.

[7] T. Durand, T. Mordan, N. Thome, and M. Cord, "WILDCAT: Weakly supervised learning of deep convnetsfor image classification, pointwise localization and segmentation," in CVPR, 2017.

[8] W. Ge, S. Yang, and Y. Yu, "Multi-evidence filtering and fusion for multi-label classification, object detection and semantic segmentation based on weakly supervised learning," in CVPR, 2018.

[9] J. Fu, J. Liu, H. Tian, Y. Li, Y. Bao, Z. Fang, and H. Lu, "Dual attention network for scene segmentation,"in CVPR, 2019.

[10] H. Fu, J. Cheng, Y. Xu, D. Wong, J. Liu, and X. Cao, "Joint optic disc and cup segmentation based on multi-label deep network and polar transformation," IEEE transactions on medical imaging, vol. 37, no. 7, pp.1597–1605, 2018.

[11] J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in CVPR, 2015.

[12] V. Badrinarayanan, A. Kendall, and R. Cipolla, "SegNet: A deep convolutional encoder-decoder architecture for image segmentation," TPAMI, vol. 39, no. 12, pp. 2481–2495, 2017.

[13] L. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder decoder with atrous separable convolution for semantic image segmentation," in ECCV, 2018.