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Automated Computer Aided Detection of Diabetic Retinopathy using Machine Learning Hybrid Model

Aishwarya Kubde[1] and Sharad W. Mohod[2]
[1]Research Scholar, Dept. of Electronic Engineering, Prof. Ram Meghe Institute of Technolgy & research Badnera, Amravati
Email: kubdeaishwarya@gmail.com
[2]Professor and Dean, Dept. of Electronic Engineering, Prof. Ram Meghe Institute of Technology & research Badnera, Amravati
Email: sharadmohod@rediffmail.com

***Abstract*—Diabetic retinopathy is spreading dangerously worldwide among people with diabetes, leading to reduced vision and completely blindness. In this paper, a technique is proposed to identify diabetic retinopathy using the fundus image obtained from the patient's retina. The method involves processing the digital image on the fundus image, which help the ophthalmologist in examine DR. Micro-aneurysm, which is considered as first stage of diabetic retinopathy has been diagnosed using Neural Network. The proposed Support Vector Machine has been compared to existing methods - Naive Bayes classifier. Experimental validation is done with MATLAB/SIMULINK software. The preprocess image has been applied as input data for neural network pattern recognition. A significant improvement has been observed in terms of Sensitivity, Specificity and Accuracy compared to the aforementioned existing methods.**

***Index Terms*— Diabetic retinopathy (DR), SVM, Neural network.**

I. INTRODUCTION

Diabetic retinopathy is a very complex problem that affects the eye due to high level of glucose in blood. This can lead to reduced vision and severe blindness in severe cases. Symptoms of retinopathy in the early stages include loss of vision, dark areas of vision, floaters of the eyes, and difficult to understand colors. Complete blindness can be prevented by early detection of diabetic retinopathy. Diabetes is generally understood by physicians to be one of two types-Type 1 diabetes, sometimes referred to as insulin-dependent diabetes, is defined as an autoimmune condition that destroys insulin-producing cells in the pancreas. The much more common form of the disease is type 2 diabetes. Unlike type 1, which appears to be autoimmune related, type 2 is arguably a lifestyle disease. While there are unavoidable risk factors such as age and genetics, lifestyle choices play the largest role. In the development of type 2 diabetes, key among these is a low activity levels, smoking, and a diet high in refined starches, saturated and Trans fats, and sugar.

Type 2 diabetes can be a bit trickier, as there are often few symptoms until the disease has progressed. Given this, there are two ways many people with type – 2 diabetes learn they have the disease: (i) a high-fasting blood glucose test with a reading of 150 mg/dL or higher or (ii) an eye exam. During an eye exam, doctor can examine the optic nerve, the retinal blood vessels, and the back of the eye. During such exam, the physician may notice

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leakages in the small capillaries in the retina, which often indicate diabetic retinopathy. Diabetic retinopathy is an early stage of the disease in which a small red spot is found in the retina of the human eye. These small spots represent hemorrhage and abnormal poaching of blood vessels. The lining of the blood vessels in the human eye can be damaged and fluid and fatty substances called exudates can come out. Different types of tests need to be performed to identify diabetic retinopathy, including pupil proliferation, visual acuity test, optical coherent tomography, and more. All these tests take a lot of time and patients have to face a lot of problem [1]-[2].

Untreated diabetes can lead to a number of horrific consequences, including neuropathy, amputation, blindness, and even death. In the case of vision, diabetics are at risk for a number of issues, including glaucoma and cataracts, as well as a blinding condition. Diabetic retinopathy occurs when the amount of glucose in the blood is poorly controlled, causing tiny blood vessels in the retina to break, swell, leak, or grow abnormally. The new blood vessels are more fragile, and can leak fluid or blood, causing patients to experience blurred vision, vision loss, and even blindness. These same changes may also occur in patients with poorly controlled blood pressure, in which case the condition is referred to as hypertensive retinopathy. Thus, early detection and treatment can reduce the risk of blindness from the disease by 95 percent.

Among them, the severity scale proposed by Wilkinson ET. al. [3] is the most widely used and therefore followed in this work. They have proposed severity levels of DR as a) No apparent retinopathy b) Mild non-proliferative DRc) Moderate non-proliferative DR d) Severe non-proliferative DR e) Proliferative DR. and shown in Fig. 1.

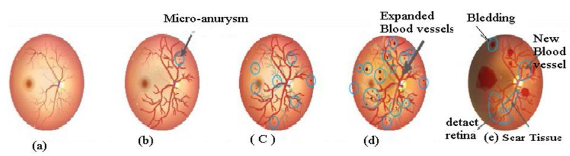

Fig. 1. a) Normal DR b) Mild DR c) Moderate DR
d) Severe DR d) Proliferative DR

The paper focuses on automated computer aided detection of diabetic retinopathy using machine learning hybrid model by extracting the features hemorrhage, microaneurysms and exudates. The Support Vectors machines most popular for generating classifier is used in the proposed model.

The Deep learning (DL) novel approach to proposed model of machine learning is applied in a diverse range of computer vision and biomedical imaging analysis. It can be of as a multilayered hierarchical architecture that attempts to learn high level abstractions in the data. Moreover, deep learning methods contain a significant number of advantages, such as they can learn low level features from data using minimal processing, ability to work with unlabeled data, high cardinality with class memberships, ability to identify interactions among features, and can jointly learn feature extraction with discriminative power. The learning mechanism of deep learning models is usually operated in a multilayered fashion. It uses multiple techniques to process input data and automatically convert it into decent representations. Initially, the first layer extracts pixels from the input image. Next, these pixels are grouped into the second layer to identify edges within an image. These edges are then divided by the third layer into small segments. Finally, some other layers convert these segments into the classification/recognition of images. All these layers learn feature from the input data using learning procedures and without expert intervention. Recently, deep learning method, i.e., convolutional neural network (CNN) most commonly applied to analyze the images. It uses a feed forward neural network type and has been found effective in the classification of DR stages using fundus images e.g., cancer, brain tumor and retinopathy detection. DR have proven to be effective way in early DR assessment. Thus, it supports the ophthalmologist to examine DR correctly. Automatic computer detection provides good performance in image analysis in DR and gives satisfactory results.

II. Data base in Diabetic Retinopathy

The source of database consists of color image of patient’s eye. The images of retina are taken by a device named fundus camera. This device takes images of the internal surface of retina, posterior pole, macula, optic disc, and blood vessels. Some benchmark databases are openly available for the assessment of algorithms introduced for the computerized screening and analysis of DR. The purpose of databases is to check the strength of automatic screening of DR and then compare the results with current techniques. The available datasets include DRIVE, STARE, DIARETDB, e-ophtha, HEIMED, Retinopathy Online Challenge (ROC), and Messidor. [ ]

III. DETECTION METHODS OF DR

The computational segmentation and classification algorithms implemented for the detection of retinal anatomic landmarks with DR lesions using fundus images. The optic disc (OD) is a clinical intense fundus feature and is considered as a preliminary indicator of retinal vessel, optic cup (OC), macula, and fovea detection in fundus photographs. Most OD extraction approaches in the literature are based on morphological and geometrical-based methods. Considering the significance of optic disc segmentation for reliable glaucoma and DR screening, considered morphological features to segment the OD boundary [23]. The finite impulse response (FIR) filter is applied to remove retinal vessels and to extract morphological features for disc extraction. However, the algorithm was unsuccessful on low bright disc color images. Similarly, Alshayeji et al. in [24] applied an edge detection algorithm based on a gravitational law followed by pre-and post-processing steps for OD segmentation. They showed an accuracy of 95.91% with a cost of high running time. A real-time approach is developed for OD segmentation, in which the disc boundary was extracted after the removal of vessels using a region growing adaptive threshold and ellipse fitting methods, which gives an accuracy of 91%.

IV. SCREENING OF DIABETIC RETINOPATHY

A systematic diabetic retinopathy screening is to reduce the risk of vision impairment and blindness among asymptomatic people with diabetes through the prompt identification and effective treatment of sight threatening diabetic retinopathy. Early discovery and treatment of DR and diabetic macular edema (DME) play a major role in preventing adverse effects such as blindness. Optical Coherence Tomography (OCT) imaging is ideal for uncovering DME on account of its extended axial resolution and extended retinal scan coverage, spatial domain optical coherence tomography (SD-OCT), revealed DME-related changes of the photoreceptors, external restricting film, Bruch’s layer, and retinal pigment epithelium layer. Moreover, SD-OCT perceived related epiretinal layers, changes in the retinal decay, and vitreoretinal interface. The issues of automatic classification of SD-OCT information for automatically recognizable proof of patients with DME versus ordinary subjects are tended as well. The proposed technique depends on Local Binary Pattern (LBP) features to portray the texture of OCT pictures and contrast diverse LBP features extraction approaches with the process of single signature for the entire OCT volume.

V. COMPUTER AIDED DIAGNOSTIC SYSTEM OF RETINAL IMAGING

In retinal imaging fundus photography is widely used for population-based, large scale detection of diabetic retinopathy, glaucoma, and age-related macular degeneration. Optical coherence tomography (OCT) and fluorescein angiography are widely used in the diagnosis and management of patients with diabetic retinopathy, macular degeneration, and inflammatory retinal diseases. OCT is also widely used in preparation for and follow-up in vitriol-retinal surgery. With the help of retinal imaging, the inflammatory diseases are monitored for the posterior segment of fundus photography. Fundus fluoresces in angiography (FA) and OCT are the most commonly used techniques for retinal imaging. These imaging modalities are helpful in the therapy of patients with inflammatory conditions for the correct diagnosis of posterior pole [14]. FA is an invasive technique which utilizes fluoresces in color and OCT is a costly imaging strategy contrasted with fundus photos. The arrangement of automated computer aided diagnosis of DR from fundus images is shown in Fig. 2.

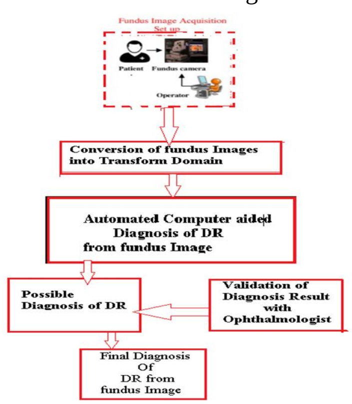

Fig.: 2. Automated computer aided diagnosis of DR

The computer vision approach can process the information which is stored in the form of pixels. The machine learning method which can classify the data into certain classes based on the training set. The diabetic retinopathy detection has various steps which are preprocessing, feature extraction, segmentation and classification. The technique of SVM is the best classification algorithm which can classify diabetic and non-diabetic spots from the input image. The objective of computer-aided diagnosis is to recognize DR and normal images in utilizing features like area of EXs, MAs, veins, texture, HMs, node points, and so forth [18]-[19]. Dark lesions were segmented out using moat operator and EXs were extricated using recursive region growing (RRGT) and adaptive intensity thresholding (AIT) [20]. Support vector machine (SVM) kernel classifiers are employed in CAD framework to discover the absence or presence of DR. The anticipated CAD framework has managed the classification issues in DR. To recognize DME, DR, and essential injury, an algorithm in view of examination of mechanized fundus photo was proposed. While screening for DR, algorithm is an enhanced substitution for the fundus photo manual examination which expends a considerable measure of time. In medicinal imaging, contextual information performs an important role. Bright lesions detection and discrimination has been performed through contextual information in fundus image modalities. Diagnosis of coronary calcifications and hard EXs in CT scan is performed through this contextual information. In the spatial relation, high-level contextual features are used to explain the context.

VI. Propose Framework of Automated Computer Diagnosis

In the propose framework of automated computer diagnosis, the DR detection was performed by utilizing the characteristics of the DR features, such as intensity value, shape and size. The DR features that need to be detected are new vessels, hemorrhages and exudates. The stages used in the proposed automated computer diagnosis of DR are image pre-processing, blood vessels and hemorrhages detection, optic disc removal and exudates detection, as shown in Fig. 3.

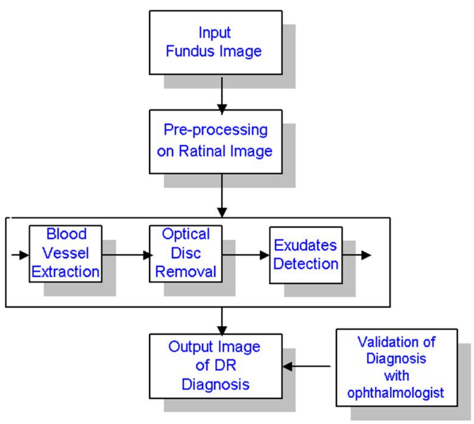

Fig. 3: Proposed framework of Automated Computer Diagnosis

A. Image pre-processing

Image pre-processing is performed with the aim to decrease noises and to improve image contrast. The first step in the pre-processing is to extract image's green component to be used in the following process. The reason of using green component is due to the highest contrast between blood vessels, optic disc, exudates and the background compared to the red and blue components. In addition, the red lesions (blood vessels and hemorrhages) appear dark and for the white lesions (exudates and optic disc), the features appear bright in the green plane image. Then, the second step is to perform noise reduction using median filter. Median filter is a nonlinear filter that is widely used for smoothing the image as it preserves edges while removing noise under certain condition [6]. In this work, the median filter was applied on the green channel image with 5x5 kernel and shown in (1)

$$I_{med}(x,y) = \underset{(s,t)\in W_{xy}}{medium}\{IG(s,t)\} \quad (1)$$

Where I_{med} represents median filtered image, W represents a neighborhood centered on location (x, y) in the image and IG represents the green plane image. After noise reduction, the next step is to invert the image so that the color of the blood vessels and hemorrhages is clearly seen. Then, the image contrast was improved using

Contrast Limited Adaptive Histogram Equalization (CLAHE). This is in order to highlight the DR features. The example of the result obtained for each stage is shown in Fig. 4.

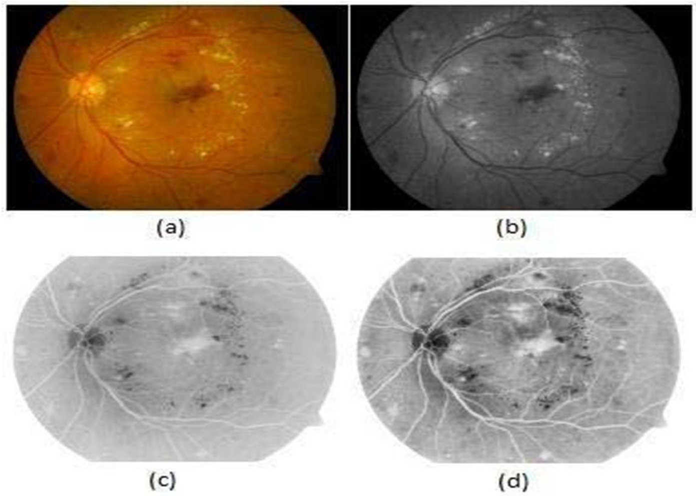

Fig 4. The processing results; (a) Original image, (b) The result of applying median filter on the green plane image, IG, (c) Inverted green plane image, (d) Contrast enhanced image using CLAHE

B. Blood Vessels and Hemorrhages Detection

In order to successfully segregate blood vessel information from the rest of the eye image, SVM algorithm creates support vectors that separate the blood vessel pixel from the rest of the image through a supervised environment. Detecting blood vessel from new images can be done through similar manner using support vectors. The detection of blood vessels and hemorrhages are very crucial in the identification of DR stages. Based on our observation, the color of hemorrhages is almost the same as blood vessels. Therefore, due to this reason, vessels and hemorrhages were detected together. The detection of vessels and hemorrhages was performed by filtering the features using a 5x5 median filter, with the reason of creating the background, IBK that is darker in intensity than the DR features. The background was used to produce a normalized image, INR, which was obtained by subtracting IBK from the enhanced image, ICL. The equation to produce normalized image as shown in (2)

$$INR = ICL - IBK \qquad (2)$$

The normalized image was further processed using morphological operations, which is a set of operations that process images based on the shape using structuring element (SE) The operations used in this work are top-hat and closing operations with disc SE. The shape and size of SE were determined through visually examining the DR features that need to be extracted. Top-hat operation involves the subtraction of the image produced by the opening operation from the original image. Meanwhile, closing operation consists of dilation and erosion. The function of closing operation is to smooth the object’s contour, eliminates small holes and fuses gaps between objects.

C. Optic Disc Removal

Optic disc is a retinal feature, which is more or less circular in shape, high intensity and appears in same size. Optic disc removal is required because it has a similar intensity as exudates. In this paper, the method used to locate the optic disc is contour detection, which works based on shape and size. Contour is a curve that connects all the continuous point with same intensity. Typically, contour is detected using build in function available simulation tool. However, in some cases, optic disc was detected along with exudates and this is due to similar intensity value. In order to ensure that only optic disc is removed, a threshold value is introduced. Based on our observation, optic disc is larger than exudates in most cases, and therefore, the largest detected contour is claimed as the contour of optic disc. Due to this reason, the detection is based on the radius of the detected contour, where it is observed in the training that the radius of the optic disc is greater than 30 pixels. Hence, the threshold used to select the contour is set at 30.

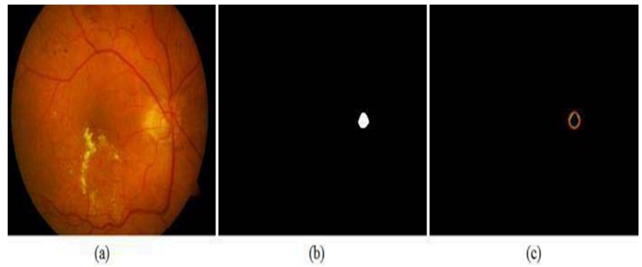

Fig 5. Optic disc contour detection. (a) Original image, (a) the detected optic disc, (b) The contour of optic disc

D. Exudates Detection

Exudates are bright features that appear in different sizes and shapes. In this work, exudates were detected using morphological closing operation on green plane image, IG where the disc SE in the closing operation helps to eliminate the vessels. In addition, top-hat operation was applied to smooth the background. Fig. 6 illustrates the example of result obtained at each stage for exudates detection.

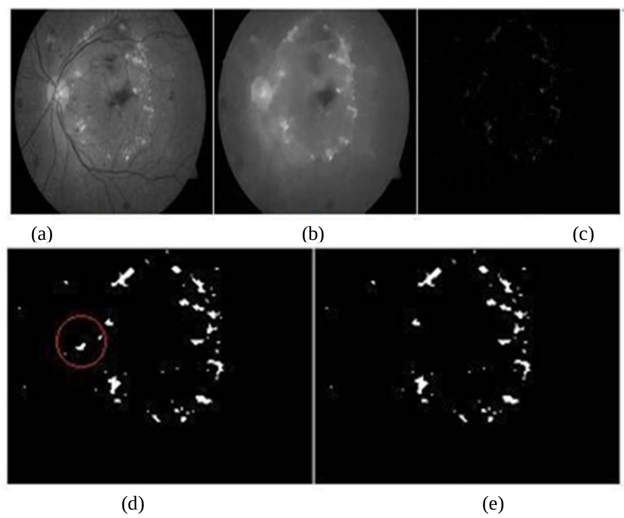

Fig 6. Result of Exudates detection; (a) Green plane image, IG, (b) The result of morphology closing, (c) The result of morphological top-hat, (d) The detected exudates with optic disc, IEX, and (e) The detected exudates after optic disc removal

VII. EXPERIMENTAL RESULT IN DR

Chosen image pixel for the proposed method is 250 x 250. Preprocessed image has been applied as input data for neural network pattern recognition tool. Using MATLAB (3x268) input data has been applied and (2x268) data has been obtained as target data. Target data is binary number combination data. Here '1' means healthy and "0" mean unhealthy. Formula used to calculate sensitivity, specificity, accuracy is as follows-

$$Sensitivity = \frac{TP}{TP + FN} \quad (3)$$

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

$$Diagnostic\ Accuracy = \frac{TP + TN}{TP + TN\ FP + FN} \quad (5)$$

TP and TN are the true positives and true negatives respectively, which specify the correctly classified (CC) cases. In this study, TP indicates whether the input scan was macular edema and it was classified as macular edema too, while TN represents the cases where actual input scan was of healthy eye and the classification also showed it as healthy. FP and FN stand for false positive and false negative, respectively, these are false classification indicators. FP cases are those in which actual input scan was of healthy eye and classifier classified it as ME, while FN is the reverse of FP.

Fig. 5(a), shows a confusion matrix chart of our input and training data. The green boxes in Confusion matrix represents correct classification whereas red ones indicate incorrect.

Fig. 5 (a). Training Confusion Matrix

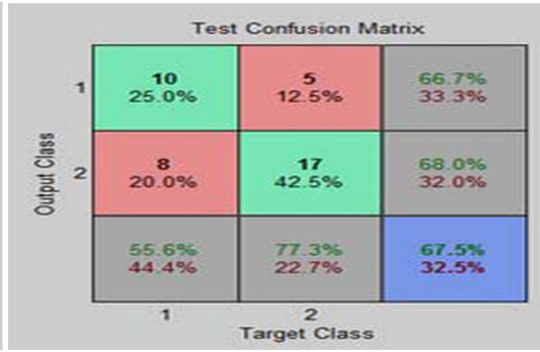

Fig. 5(b). Test Confusion Matrix

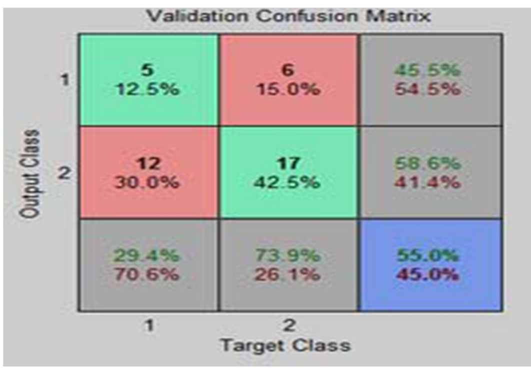

Fig. 5 (c). Validation Confusion Matrix

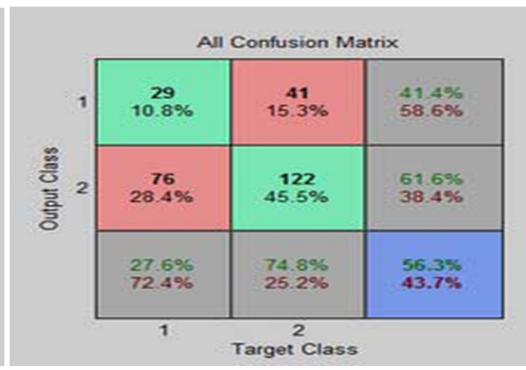

Fig. 5 (d). All Confusion Matrix

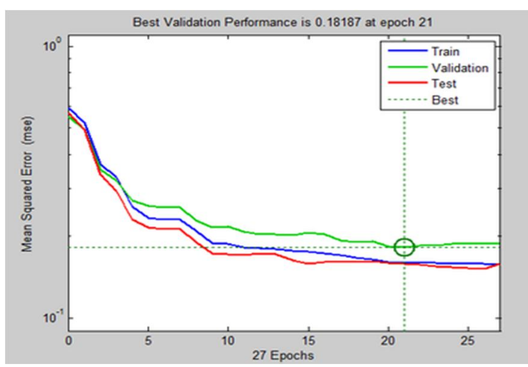

Fig.6. Mean Squared Error curve representing performance

The sensitivity, specificity rate has been calculated and compared to SVM-classifier and Naive-Bayes method, as shown in Table I.

TABLE I: COMPARATIVE ANALYSIS

Methods	SVM Classifier	Naive-Bayes Method
Sensitivity	58%	54%
Specificity	42%	44%
Accuracy	53%	50%

VIII. CONCLUSION

Digital fundus photography screening tool used for diabetic retinopathy. However, computerized screening programs have the ability to perform fast classification of DR stages using fundus images. The paper presents the significance of various computational deep learning, image processing, and machine learning algorithms in CAD systems to identify DR stages using fundus images. Those CAD systems are based on the correct segmentation of DR-related lesions, such as microaneurysms, hemorrhages, and exudates, within the fundus images. In future, the performance of the reviewed DR-CAD methods can be improved by Provide a much larger dataset of high resolution images, collected from a diverse range of ethnicities; utilize a combination of dynamic features, such as hand-engineered Symmetry 2019, 11, 749 23 of 34 and non-hand engineered, with robust classifiers to get a higher classification performance, especially in the national criteria of DR severity level; and some novel color space/appearance models need to provide better characterization of image complex patterns, overcome the four levels of the DR database issue with five DR levels; and –identify severe DR in four quadrants using a larger dataset.

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