

Diabetic Retinopathy Detection Using Tensor Flow Based on Machine Learning

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ABSTRACT: Diabetic retinopathy is a main source of visual impairment among working-age grown-ups. It affects the blood vessels of the light-sensitive tissue at the back of the eye (retina). Early screening and treatment of DR prevents vision deterioration, however the recommendation of yearly screening is often not being met. Hemorrhages, hard Exudates, and Micro-aneurysms (HEM) that appear in the retina are the early signs of DR. Early diagnosis of HEM is crucial to prevent blindness. Textures features such as Local Binary pattern (LBP), Local Ternary Pattern (LTP) and Local Energy-based Shape Histogram (LESH) have been widely used in the past as a technique for DR detection. This paper focuses on a machine learning solution that identifies vascular diseases of the retina affected with diabetes mellitus using TensorFlow. So we use A histogram binning scheme along with K-Means algorithm for features representation is proposed. KNN and SVM for classification. The experimental results show that K-Means, KNN and SVM is the best performing algorithm with an obtained accuracy of 97.608 % for extraction of features and in detection of diabetic retinopathy which makes the diagnosis and screening of retinal images

KEYWORDS: SVM (support vector machine), K-means algorithm, diabetic retinopathy, Machine learning, K-nearest neighbors algorithm.

I. INTRODUCTION

The eye is one of the most important and sensitive part of the human body. The inner part of the eye, facing the lens, includes retina, optic disc, macula, and fovea. It can be seen during an eye exam by looking through the pupil. The retina is sensitive to light. Ophthalmologists examine retinal images manually. These images, known as retinal fundus images are captured by specialized cameras and are used in medical diagnosis.

Diabetic Retinopathy (DR) is an eye disease, which is caused by the damage occurs in the retina due to diabetes. Typically, DR is asymptomatic until it becomes a serious threat for vision; therefore, diagnosing DR at early stages can be crucial to increase the chances of early treatment. By automatic screening, DR can be detected in early stages, while minimizing subjectivity and human errors in the manual approach [1]. Diabetic Retinopathy is described by the nearness of hemorrhages on the retina and level of seriousness is chosen by the degree to which harm has been caused to the veins in the retina. Generally, Fundoscopic shots of the retina are screened by ophthalmologists to detect the disease [2]. Many researchers have devoted their effort to develop an automatic Computer-Aided Detection (CAD) system for DR. Various approaches have been proposed [1-4], but HEM detection in the retinal fundus images and its accuracy are still a big challenge. Non-uniform lighting, low contrast, small lesions, and the presence of objects in a normal retina that have similar attributes to HEM [1] such as optic disc, blood vessels, etc. make it difficult to accurately identify HEM.

The thought is to utilize Machine Learning to recognize and analyse DR in a subject to quicken the procedure so as to handle the issue of specialist to diabetic patient proportions in India. To implement this idea, we are using a TensorFlow. It is an open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library and is also used for Machine Learning. With the help of TensorFlow, we can use the necessary functions required to construct a K-Means algorithm for extraction of Features (HEM) and Support Vector Machine

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and KNN for image classification. In the result of diabetic retinopathy automatic detection using Support Vector Machines (SVM) algorithm and it has an accuracy of 97.608 %.

II. RELATED WORK

Some work has been proposed to detect DR using texture features to preserve the HEM structure. In [2], the authors use Local Binary Patterns (LBP) for the detection of hemorrhages and exudates (HMA). The tests were performed on a database of 89 images. They obtained an average accuracy of 86.15% and an AUC of 0.87. In [3], the authors used fluorescein angiography (FA) fundus images to detect micro-aneurysms (MA). They used Radon transform (RT) and multi-overlapping windows. Tests were conducted on three databases of respectively 120, 50, and 22 images. The authors report the obtained best results for the two first databases with respectively sensitivity and specificity of 94% and 75% for the first database and 100% and 70% for the second one. MA can be easily detected using this imaging modality, but the procedure needs the administration of some injections to the patient, making this approach less interesting as it can cause non-desirable health effects. The best way to examine the retinal fundus is still to use standard retinal fundus imaging technologies. In [4], discrete wavelet transforms are used. The wavelet decomposition was performed up to the second level. Eight energy features were extracted. Two features from the coefficients of two levels and six energy values in three orientations (horizontal, vertical, and diagonal). Classification was performed using Support Vector Machines (SVM) with different kernels. The authors collected 240 retinal fundus images (120 normal and the remaining with different degrees of DR). They reported a result for accuracy, sensitivity, and specificity of 99% using SVM with polynomial kernel of order 3. The results of these research works are interesting, however the number of images used for experimental tests is small. In recent years, deep learning techniques were proposed for DR detection. Gulshan et al. [5] trained an Inception-v3 Convolutional Neural Networks (CNN) using a dataset of 128,175 retinal images, they report an AUC performance of 0.991. Ting et al. [6] trained a deep convolutional network in 71,896 retinal images and obtained an AUC of 0.936. They experimented using 10 additional datasets, and obtained an AUC ranging from 0.889 to 0.983. Deep learning techniques are data hungry and need large image numbers for training. In this work we use an available public dataset that has a limited number of images. Past work dealing with DR using texture features, has mainly focuses on Local Ternary Patterns (LTP) and Local Energy-based Shape Histogram (LESH) with obtained accuracy 0.904 using SVM.

III. PROPOSED SYSTEM

We propose machine learning algorithms especially k-means, knn and SVM algorithm for feature extraction and detection of diabetic retinopathy. In this work, we want to detect if DR is present or not, only two classes will be considered. we use CSV dataset for image classification. The dataset is labeled as normal for all the images with no DR and as abnormal for all the images with DR, no matter the grade of the retinopathy. In recognizing anomalies related with fundus picture, the pictures must be Pre-Processed so as to address the issues of uneven brightening issue, lacking complexity between exudates, picture foundation pixels, nearness of commotion in the information fundus picture, normalizing the power of the individual molecule images, removing reflections, masking parts of pictures. Beside previously mentioned issues, this area is additionally in charge of shading space change and picture estimate institutionalization for the framework

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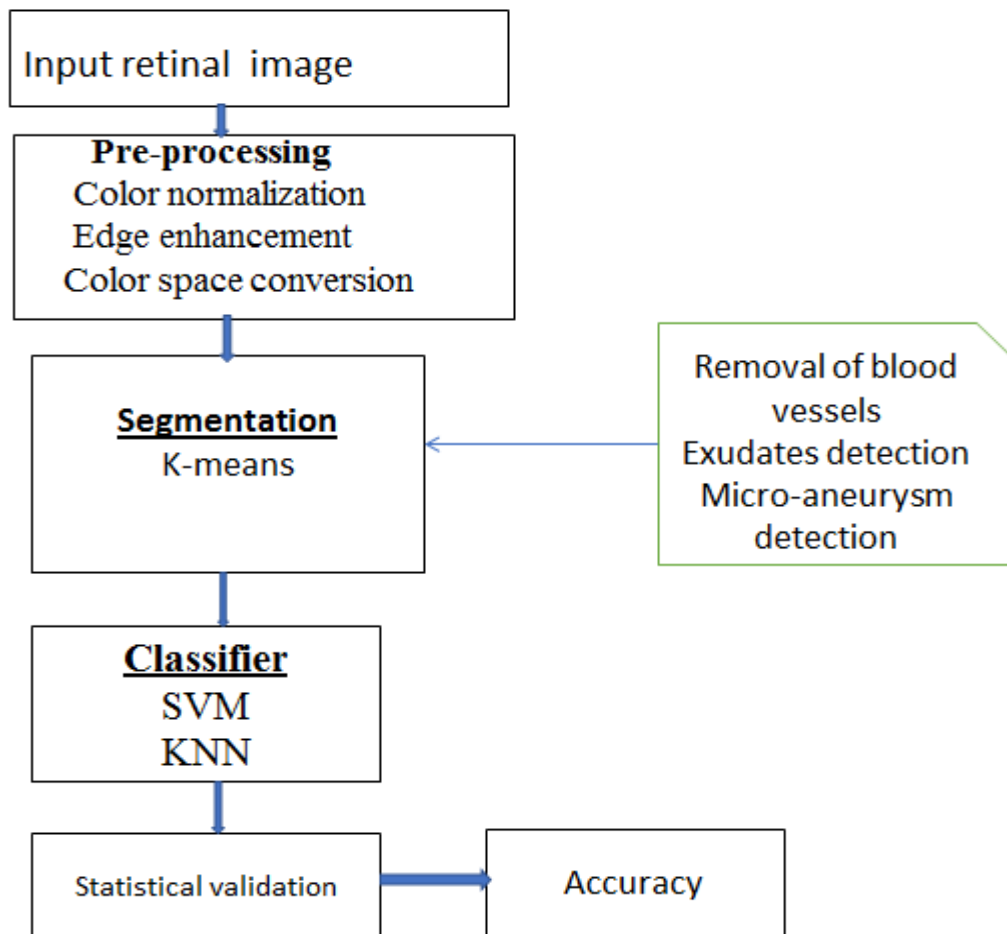


Fig. 1 Block Diagram of Proposed System

After pre-handling we perform division for highlight extraction. The consequence of picture division is a lot of sections that all in all spread the whole picture, or a lot of shapes removed from the picture. Every one of the pixels in a locale are comparative as for some trademark or processed property, for example, shading, force, or surface. For the extraction of feature (HEM) from the retinal fundus images can be done with the help of K-Means algorithm. Bunching is a technique to separate a lot of information into a particular number of gatherings. It's one of the famous technique is k-implies bunching. In k-implies bunching, it segments a gathering of information into a k number gathering of information. It arranges a given arrangement of information into k number of disjoint group. K-implies calculation comprises of two separate stages. In the primary stage it computes the k centroid and in the second stage it takes each point to the bunch which has closest centroid from the particular information point. There are distinctive techniques to characterize the separation of the closest centroid and a standout amongst the most utilized strategies is Euclidean separation. When the gathering is done it recalculate the new centroid of each bunch and dependent on that centroid, another Euclidean separation is determined between each inside and every datum point and allots the focuses in the group which have least Euclidean separation. Each group in the segment is characterized by its part protests and by its centroid. The centroid for each group is the point to which the whole of separations from every one of the articles in that bunch is limited. So K-implies is an iterative calculation in which it limits the whole of separations from each item to its group centroid, over all clusters. Let us consider a picture with goals of $x \times y$ and the picture must be bunch

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into k number of bunch. Let $p(x, y)$ be an info pixels to be group and ck be the bunch focuses. The calculation for k-means13 bunching is following as:

1. Introduce number of group k and focus.
2. For every pixel of a picture, figure the Euclidean separation d, between the middle and every pixel of a picture utilizing the connection given underneath.

$$d = \|p(x, y) - ck\|$$

3. Relegate every one of the pixels to the closest focus dependent on separation d.
4. After the sum total of what pixels have been relegated, recalculate new position of the middle.
5. Rehash the procedure until it full fills the resistance or blunder esteem.
6. Reshape the group pixels into picture.

Yield of the K-Means demonstrate the compacted picture. The compacted picture looks near the first one which implies we're ready to hold most of the qualities of the first picture.

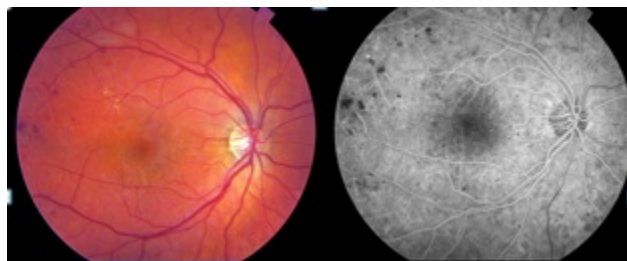


Fig. 2 Shows Difference between Orginal Picture and Compacted picture

IV. EXPERIMENTAL RESULTS

After the process of segmentation, SVM and KNN is used for learning and classification of the extracted features. The output of K-Means are fed to KNN and SVM in order to learn from the extracted vectors the patterns that best represent the retinal fundus images of a normal eye vs an eye showing signs of DR. The learned models can be used later for the classification of the images into DR or Non-DR classes. The CSV dataset is divided into two classes of normal retinal images and DR images. Using this dataset , KNN and SVM compare the given input dataset .during comparison ,it will check whether any defect occur in input image compare with normal image. if any defect occur, it will show 1 (1-means Affected) otherwise it will show 0(0-means No Affected).

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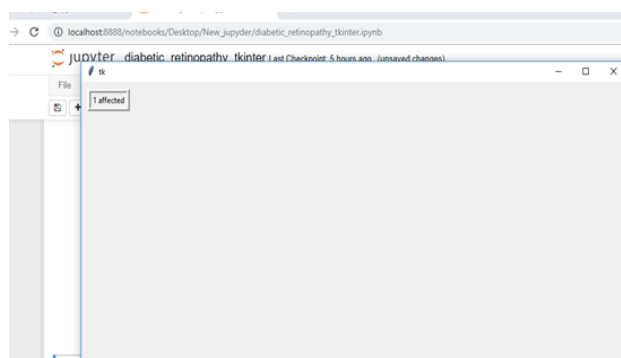


Fig. 3 Shows the output of Diabetic Retinopathy

V. CONCLUSION

The degree for this undertaking later on is to expand the exactness via preparing the model on machines with better handling force. We intend to give fast and available analysis to individuals from varying backgrounds, to keep this illness from further disintegrating to a point where it winds up untreatable. Using retinal fundus images can help automate the diagnosis. Micro hemorrhages and aneurysms, known as HEM, are the early signs of diabetic retinopathy (DR) and are difficult to identify because of their similarities with normal parts of a healthy human. Other problems such as non-uniform lighting, low contrast, etc. can lead to a bad diagnosis. Texture based techniques for DR detection were proposed in the past. Most of these techniques use LBP, LTP and LESH and wavelets for feature extraction from retinal images. In this work, we propose the use K-Means algorithm for feature extraction. These features extracted from the retinal fundus images are used to learn signs of HEM and differentiate between DR and non-DR. SVM and KNN is used to classify these features. Experimental tests with the CSV dataset show that k-mean, SVM and KNN perform well in detecting DR with an accuracy 97.608 % compared to the previous work.

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