

CS725-Machine Learning Project Report

Diabetic Retinopathy Identification And Severity Classification using Image Pre-Processing techniques

Suraj Singh, Prashant K. Sharma, Pratik Sanjay Wagh, Rohit Shende

1 Introduction

Diabetic Retinopathy (DR) is one of the most frequent causes of visual impairment in developed countries and is the leading cause of new cases of blindness in the working age population. Altogether, nearly 75 people go blind every day as a consequence of DR. Effective treatments for DR require early diagnosis and continuous monitoring of diabetic patients, but this is a challenging task as the disease shows few symptoms until it is too late to provide treatment. Not also the highly trained and experienced doctor can classify these images accurately even. Hence we implemented various machine learning techniques to detect the severity of DR and to classify them based on their severity in different classes, so that the diseases can be prevented from becoming more severe. Depending on the presence of abnormal vessels, exudates, microaneurysms and haemorrhage on the retina, the stage of DR can be identified in two stages. We used two approaches to solve this problem one is using bags of visual words for extracted features from images and other by locating presence of exudates and area of optical disk and blood vessels perimeter for classification.

2 Methods Used

The different machine learning techniques used for identification of severity of DR and to classify them to different classes we used bag of words with random forest, support vector classification in one method and in other the presence of exudates and area, perimeter of optical disk and blood vessels with svm, random forest. This techniques classify the dataset to class 0 (No DR), class 1 (Mild DR and Moderate DR) and class 2 (Severe DR and Proliferative DR). The figure 1 on page no 2 gives an pictorial representation of various classes.

3 DataSet Explanation

We have obtained the data from Kaggle. The data basically belongs to 5 classes class 0 (Normal), class 1 (Mild DR), class 2 (Moderate DR), class 3 (Severe DR), class 4 (Proliferative DR). We combined the data classes in the following way:

- Class 0 - It corresponds to the category of healthy eyes.
- Class 1 - It corresponds to the category of mild and moderate retinopathy.

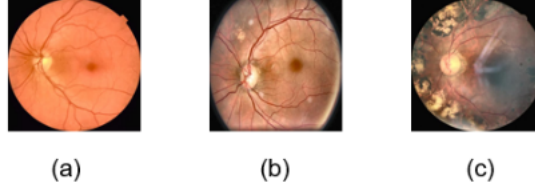


Figure 1: Example images of different stages of DR: (a) No DR (b) Mild DR (c) Severe DR. These images also show the variance in image characteristics in the dataset—the images have different dimensions, positioning of retina and color profile

- Class 2 - It corresponds to the category of severe retinopathy and thus needs medical attention.

4 Methodology

The dataset has images taken using different types of cameras, which results in differences in visual appearance and other image parameters. According to the source, there is also some noise in both the images and labels. Some of the images may contain artifacts, be out of focus, underexposed, or overexposed. Because of these factors, it is essential that we pre-process and standardize the dataset to a certain extent before extracting any information from the images for classification. Thus the methods we apply are as follows.

4.1 Green Channel Extraction

We extract green component from given image as it has been observed that the lesions are most observable show the largest contrast in the green channel and hence are most easily identifiable in this channel.

4.2 CLAHE

We apply CLAHE (Contrast-Limited Adaptive Histogram Equalization) as it is observed that contrast tends to diminish towards the edge of image. CLAHE operates on small regions of the image and improves their contrast by transforming the intensity through localised histogram equalization. After performing histogram equalization in small regions, the neighboring regions are combined using bilinear interpolation. The figure 2 on page no 4 shows the change in image after applying CLAHE.

4.2.1 Feature Extraction

After applying CLAHE (Contrast-Limited Adaptive Histogram Equalization) we extracted features from image Speeded Up Robust Features are used for feature extraction. Interest points are selected at different locations in the image, such as corners, blobs. The important property of an interest point detector is its repeatability It captures keypoints in the image and provides a “feature description” of the image using local features of these keypoints, also known as keypoint descriptors. The algorithm selects keypoints using the Hessian

blob detector and the feature descriptors are obtained using the sum of the Haar wavelet response around the interest point. For each interest point, SURF descriptor vector of length 128 is obtained. So the dimension of SURF descriptors per image is: number of interest points 128. This approach of feature extraction is only used in bags of visual words method.

4.3 Dilation

We apply Dilation is one of the two basic operators in the area of mathematical morphology, the other being erosion. It is typically applied to binary images, but there are versions that work on grayscale images. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller.

4.4 Thresholding

Fourthly we apply Threshold technique which divides the dataset to three different classes based on certain threshold. If the data is above certain constant then it will belong to one class, if between two different constant then it will belong to second class and if less than a certain constant then it will belong to third class. In this way we classified the dataset based on thresholding.

4.5 Median filter

Finally, we subtract out the background image estimated by a median filter. This step ensures that common prominent features present in all eye images that are not indicative of DR, are subdued and only the relevant differentiating features are accentuated. After we apply all the

process we find firstly the euclidean distance of the center of the macula and the center of the optic disc to provide important information regarding the patient's condition. This feature is also normalized with the diameter of the ROI and secondly, the diameter of the optic disc.

4.6 Codebook generation

The final step for the BoW model is to convert vector-represented patches to "codewords" (analogous to words in text documents), which also produces a "codebook" (analogy to a word dictionary). A codeword can be considered as a representative of several similar patches. One simple method is performing k-means clustering over all the vectors.[5] Codewords are then defined as the centers of the learned clusters. The number of the clusters is the codebook size (analogous to the size of the word dictionary).

Thus, each patch in an image is mapped to a certain codeword through the clustering process and the image can be represented by the histogram of the codewords.

A codebook can be thought of as a dictionary that registers corresponding mappings between features and their definition in the object. We need to define set of words (essentially the features marked by words) that provides an analogous relation of an object (being trained) w.r.t. a set of features.

After feature extraction using SURF we apply codebook generation and create a dictionary out of it and feed it to our classifiers for classification

4.6.1 Bag of visual words

It is an extension to the NLP algorithm Bag of words used for image classification, other than cnn. It is quite widely used. In computer vision,

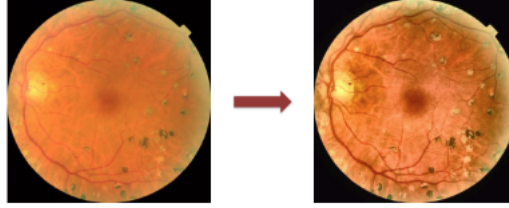


Figure 2: CLAHE applied to a image.

the bag-of-words model (BoW model) can be applied to image classification, by treating image features as words.

The figure 4 on pageno 6 shows the entire methodology pipeline described above.

5 Classification

Once we extracted the features and dictionary is created , we have come to stage where we can apply various classification method to classify the data to different classes. Thus different classification method we applied are:-

- Logistic Regression:- The first model we used is multinomial logistic regression,a natural extensiion of logistic regression uses a softmax function for prediction.implemented in sklearn library for python as LogisticRegression().
- Support Vector Classification:- This classification method used L1 regularization, in this we tune the error value using cross validation

$$\frac{1}{2}||w||^2 + C \sum_{i=1}^{\infty} \xi_i$$
- Random Forest :- This is an ensemble learning method which uses decision trees. Ran-

dom Forests build a number of decision trees from new datasets that were sampled with replacement from the original one and predict a class by taking the trees majority vote. They also restrict the features considered in every split to a random subset of a certain size.

6 Results

The results we achieved from three different classification techniques for two mentioned methods

6.1 Using bags of visual words

- Support Vector Classification achieved an accuracy of 70%
- Random Forest technique achieved an accuracy of 68%
- Multinomial Logistic Regression technique achieved an accuracy of 65%

F1 Score table is provided

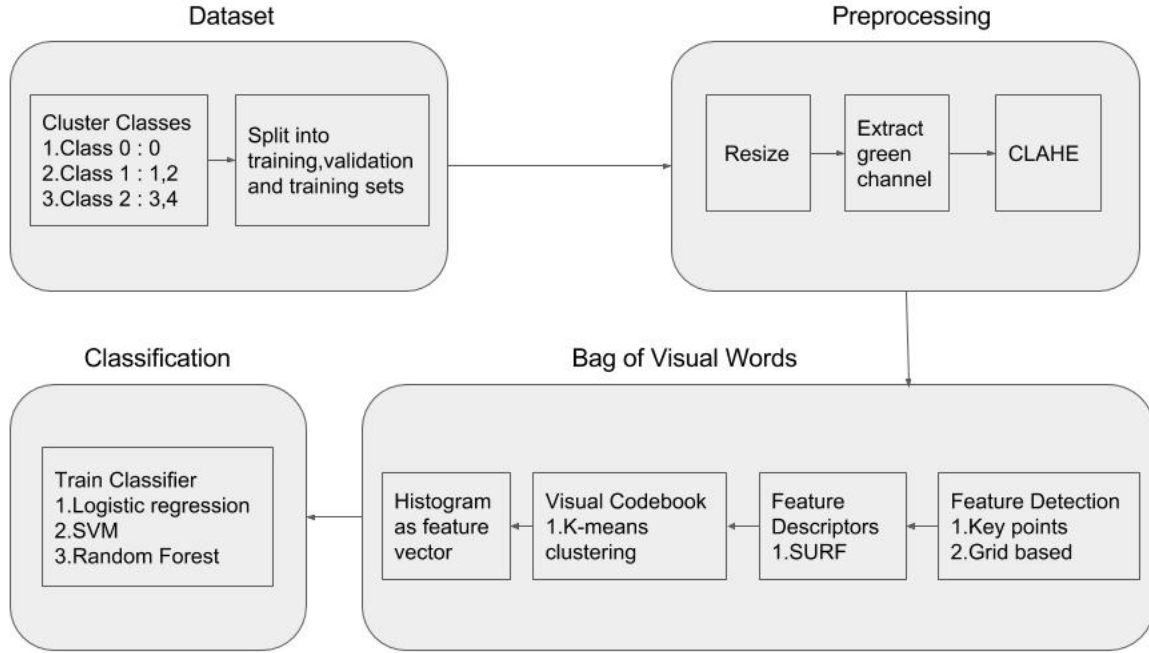


Figure 3: Entire methodology pipeline using bag of words

6.2 Using exudates locations and 7 Tables area,perimeter

- Support Vector Classification achieved an accuracy of 55%
- Random Forest technique achieved an accuracy of 67%

F1-Score-Techniques		SVM	Random Forest	Logistic Regression
0	Micro	0.70	0.68	0.650
1	Macro	0.50	0.48	0.450
2	Weighted	0.63	0.60	0.599

Table 1: F1 Score Table for bags of visual words

F1-Score-Techniques		SVM	Random Forest	Logistic Regression
0	Micro	0.643	0.65	0.611
1	Macro	0.620	0.58	0.450
2	Weighted	0.630	0.60	0.599

Table 2: F1 Score Table for exudates location

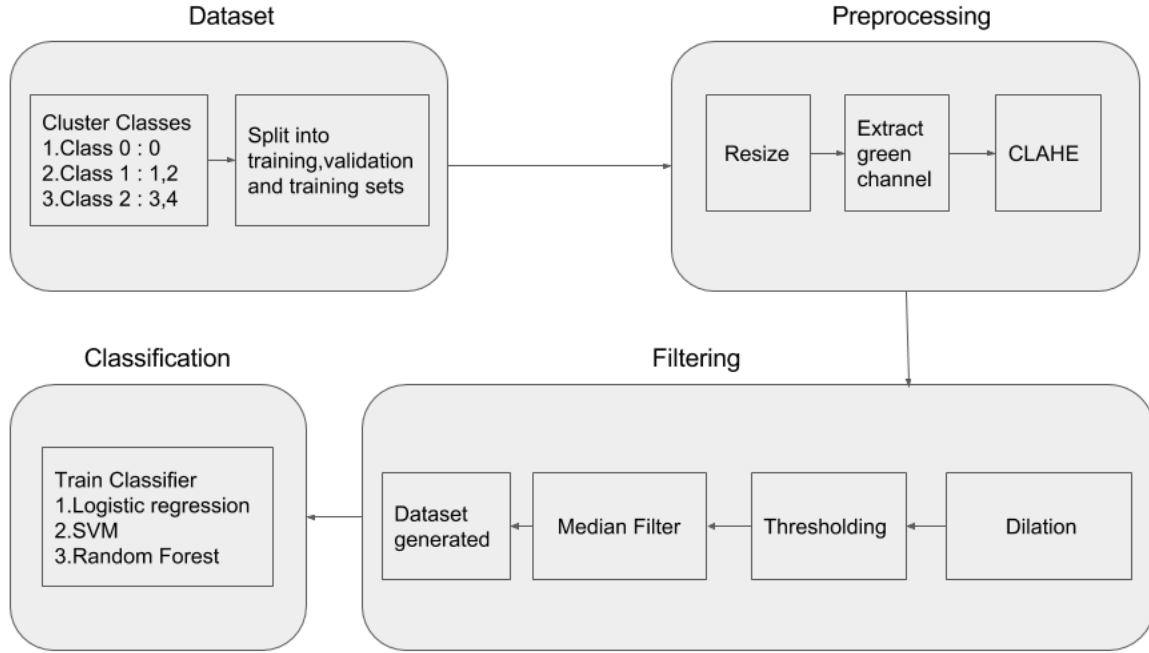


Figure 4: Entire methodology pipeline using filtering technique

8 Conclusion

Thus we have achieved better accuracy using both the techniques. We can improve the accuracy in bag of words method using better feature selection technique and filtering method using extra features and their parameters.

References

- [1] Diabetic Retinopathy Identification and Severity Classification
<http://cs229.stanford.edu/proj2016/report/HonnungarMehraJoseph-DRISC-report.pdf>
- [2] Diabetic Retinopathy Stages Identification Using Retinal Images
- [3] International Journal of Emerging Technology and Advanced Engineering
- [4] Automatic screening and classification of diabetic retinopathy and maculopathy using fuzzy image processing
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5106407/>
- [5] Random Forests in python using scikit-learn
<http://benalexkeen.com/random-forests-in-python-using-scikit-learn/>
- [6] Automated Diabetic Retinopathy Detection Using Bag of Words Approach
https://file.scirp.org/pdf/JBiSE_2017061909165753.pdf
- [7] Bag of Visual Words Model for Image Classification and Recognition
<https://kushalvyas.github.io/BOV.html>