

Proceeding Paper

Feature Extraction of Ophthalmic Images using Deep Learning and Machine Learning Algorithms. †

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Abstract: Deep learning and Machine Learning Algorithms has become the most popular way for analyzing and extracting features especially in medical images. And feature extraction made the task much easier. Our aim is to check which feature extraction technique works best for a classifier. We used Ophthalmic Images and applied feature extraction techniques such as Gabor, LBP (Local Binary Pattern), HOG (Histograms of Oriented Gradients), and SIFT (Scale-Invariant Feature Transform), where the obtained feature extraction techniques are passed through classifiers such as RFC (Random Forest classifier), CNN (Convolutional neural network), SVM (Support vector machine), and KNN (K-Nearest Neighbors). Then we compared the performance of each technique and selected which feature extraction technique gives the best performance for a specified classifier. We achieved 94% accuracy for Gabor Feature Extraction technique using CNN Classifier, 92% accuracy for HOG Feature Extraction technique using RFC Classifier, 90% accuracy for LBP Feature Extraction technique using RFC Classifier and we achieved 92% accuracy for SIFT Feature Extraction technique using RFC Classifier.

Keywords: Ophthalmic images; Diabetic Retinopathy; Feature Extraction; CNN; SVM; KNN; RFC; LBP; GABOR; HOG; SIFT

1. Introduction

Deep learning and Machine Learning has transformed the field of ophthalmology by providing powerful tools for analyzing and extracting meaningful information from ophthalmic images. Ophthalmic images, such as retinal fundus images, optical coherence tomography (OCT) scans, or fluorescein angiography images, are used for diagnosing and monitoring various eye diseases and conditions. Feature Extraction plays a huge role when it comes to machine learning and deep learning. It transforms raw data into a set of meaningful and easily understandable features. These features are then used as input for the algorithms. Feature extraction is used for dimensionality reduction, noise reduction, enhancing model performance.

In this paper, we did a survey on which feature extraction technique worked the best when it comes to a specific algorithm and for this model. We used extraction techniques such as LBP, SIFT, HOG & Gabor and different algorithms such as SVM, CNN, KNN & RNN on this model. We were able to tell that Gabor as a feature extraction technique and RNN as an algorithm worked the best and gave good results for this specific model.

2. Proposed Methodology

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In this, we are using feature extraction techniques and applying them to fundus/ophthalmic image datasets that we have, with the goal of implementing the concept of using classification algorithms to build the model, reconstruct those images, and obtain performance metrics. We are using various feature extraction techniques such as LBP, HOG, SIFT, and Gabor, and we are checking the performance metrics for each technique by applying various classification algorithms such as SVM, CNN, RFC and KNN, and comparing the techniques and deciding on the best classifier based on the metrics.

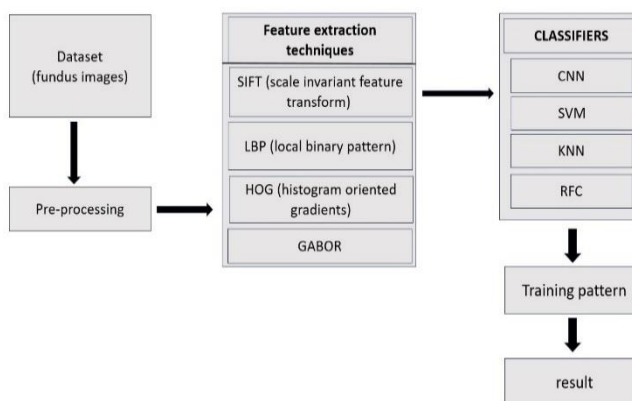
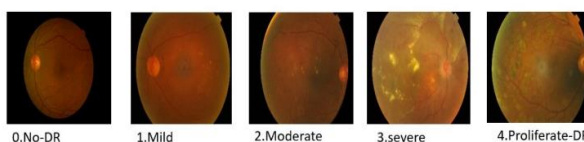


Figure 1. Architecture.

2.1. STEP-1

Data Preparation- when it comes to the dataset there are multiple diseases related to the fundus of the eye. For our model, we are taking a dataset consisting of fundus images related to Diabetic Retinopathy (DR). There are five stages in DR i.e., No DR, Mild DR, Moderate DR, Severe non- proliferative DR, Proliferative DR. After collecting the dataset, the images are resized into the desired pixels (i.e., 224x224) for them to be used with any of the pre-trained deep-learning classifiers.



2.2. STEP-2

Image Preprocessing- There are various preprocessing techniques that we used on the dataset such as Resizing, Cropping, Denoising.

Resizing: Involves adjusting the dimensions of the image while maintaining its proportions into a desired size.

Denoising: It is the removal of noise from an image so that it can be reproduced in its original form. In contemporary image processing systems, picture denoising is crucial.

Cropping: Involves removing of any unwanted parts of an image to focus on a particular region. It helps in improving composition, removing distractions, and reducing the image size while maintaining the desired proportions.

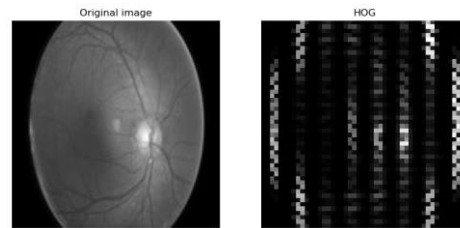
2.3. STEP-3

Feature extraction methods –

HOG:

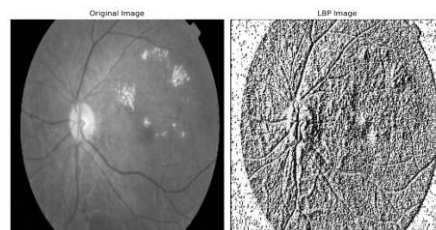
The image is broken into tiny groups and these groups are linked to one other to form cells. For each cell, gradient and orientations are calculated as part of the object recognition

process using HOG. Local object appearance and shape inside an image may be defined.



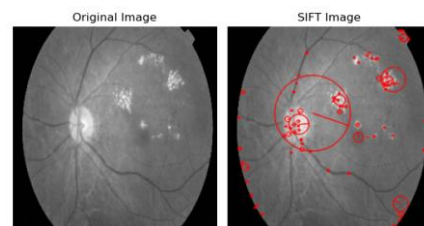
LBP:

LBP stores local texture information in order to accomplish tasks such as classification, detection, and identification. It is commonly used in image processing applications. The LBP works in 33-pixel groups. Each pixel is compared to the pixels of its immediate neighbourhood to get their local representation. LBP evaluates points near a central point and decides whether they are more than or less than the centre point (i.e., it generates a binary response). Any pixels with values less than the centre pixel are recorded as 0, while all other pixels are encoded as 1, in binary encoding.



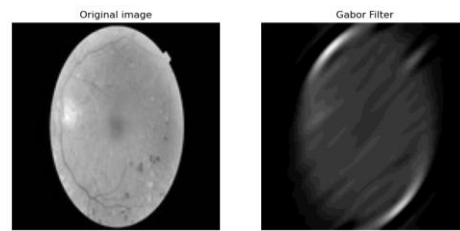
SIFT:

SIFT converts an image's information to a collection of points that may be used to discover recurrent patterns in other images. This method is typically associated with computer vision applications such as object identification and picture matching. SIFT is a strong feature extraction technique that is both easy and effective. By removing redundant features, the size of the feature space is reduced, which has a substantial impact on machine learning training, which is frequently used in large-scale applications.



Gabor:

In computer vision and image processing, Gabor feature extraction is a common method for examining the texture information of pictures. It is built on the use of Gabor filters, which are mathematical operations that may store details about the direction, frequency, and phase of texture patterns. The fundamental idea underlying the extraction of Gabor features is to convolve an image with a number of Gabor filters, each of which is intended to find distinct textures at various orientations and frequencies. After that, the filter responses are used as features in additional analysis, including object recognition or image segmentation.



2.4. STEP-4

Classification –

CNN:

CNN models, one of the earliest deep neural network hierarchies, it has hidden layers introduced between the general layers to enable the system's weights to learn more about the qualities included in the input image. The convolutional layer generates the output feature map by adding an array of weights to each input region of the picture. The output of the convolutional layer is compressed by the pooling layers. The completely linked layer, which comes last, manages the accumulation of findings from earlier layers and creates an N-dimensional vector, where N is the overall number of classes.

KNN:

KNN is a supervised machine learning method that gains knowledge from a labelled training set by learning to map the training data (X) and labels (Y) to the intended output (Y). The model solely uses training data; that is, it learns the whole training set and outputs the class where the majority of its closest 'k' neighbours, as determined by some distance measure, are located. In KNN classification, the class labels of a test sample's closest neighbours in the feature space determine the test sample's class label.

SVM:

In supervised learning, SVM is frequently used for tasks like image classification and regression analysis. It can locate the closest features and works best on challenging courses due to its memory efficiency. In order to quickly classify fresh data points in the future, the SVM approach creates a boundary or line that splits n-dimensional space into classes. The hyperplane is created using SVM by selecting the extreme points. Support vectors, from which the SVM method derives its name, are these extreme instances or spots.

RFC:

RF approach is included in the category of Supervised classification methods. RFs extend on the prior session's introduction of Decision tree learning. Random Forest Classifier is based on a large number of self-learning decision trees that, when placed together, form a "Forest." Rather than using a single decision tree, the argument for using many decision trees i.e., an ensemble is that various base learners can arrive at a single strong and robust result. By attempting to reduce the heterogeneity of the two ensuing sets of data, the optimal split might be determined given a set of input qualities and training points.

2.5. STEP-5

Training - Before testing we train the data. Here, we took 80% of data for training and 20% for testing. Each image is passed under individual feature extraction technique and then it is passed through individual classifier. The final step is to train and test the data, and the output is noted and accuracies are compared to decide which technique works the best for a classifier.

3. RESULTS

In this model, we used different extraction methods and classifiers and trained these classifiers. As can be seen in Figure 3.a, CNN classifier is used and the following results were obtained for each feature extraction method, HOG - 93%, LBP - 34%, SIFT - 82%, Gabor - 91%. Similarly, in Figure 3.b, SVM classifier is used, yielding 50% accuracy for HOG, 50% for LBP, 34% for SIFT, and 92% accuracy for Gabor. In Figure 3.c, RFC classifier is used, HOG - 93%, LBP - 93%, SIFT - 92%, Gabor - 93%. In Fig. 3.d, KNN classifier is used, HOG - 68%, LBP - 68%, SIFT - 72%, Gabor - 72%. The accuracy we achieved allowed us to further refine the HOG feature extraction technique for our CNN classifier. Similarly, for the SVM classifier, we obtained the Gabor feature extraction method. For the RFC classifiers, HOG, LBP, and Gabor gave similar accuracies. For KNN classifiers, SIFT and Gabor gave similar results.

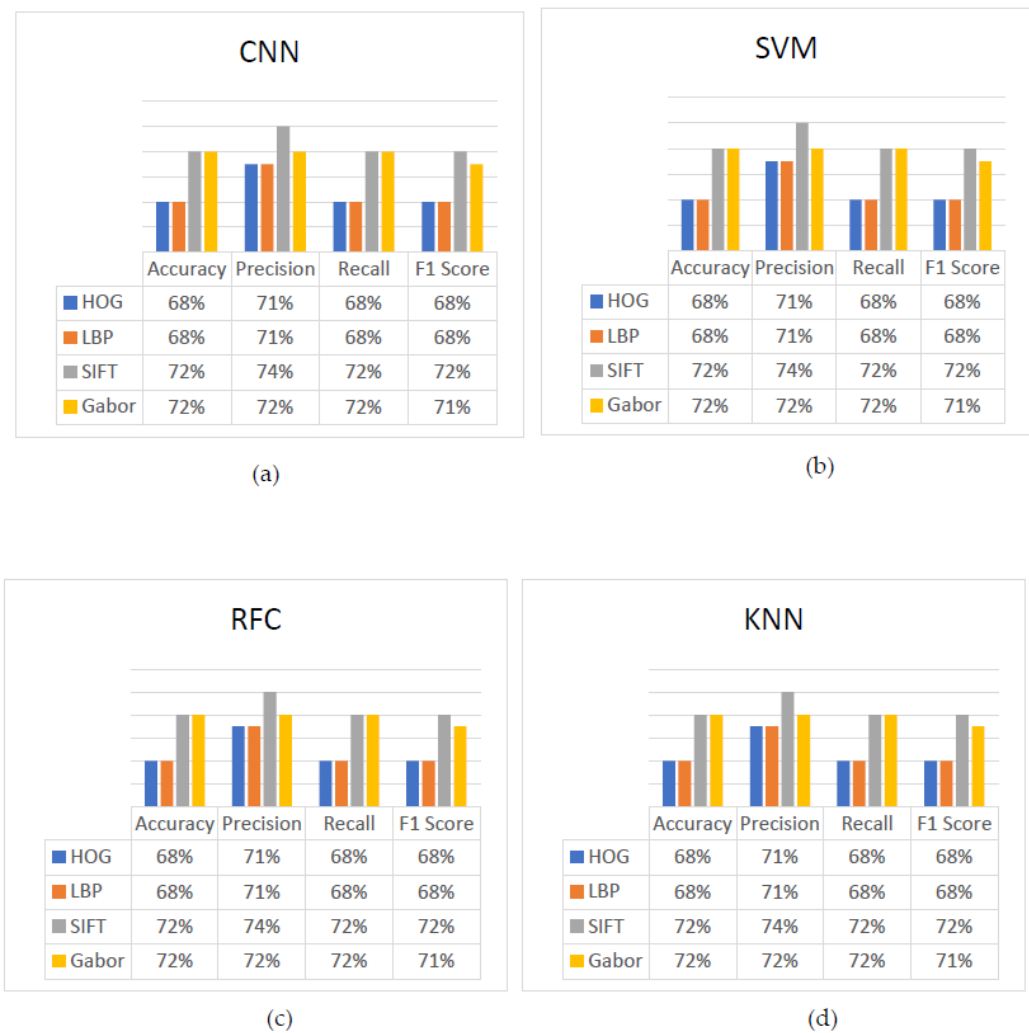


Figure 3. It shows the accuracy for the classifiers (a) CNN (b) SVM (c) RFC (d) KNN.

After analyzing the results, we found that RFC performed better as a classifier compared to other classifiers, and the Gabor feature extraction technique improved the accuracy of this model.

4. Conclusion

In this paper, we explored the efficacy of feature extraction methods such as LBP, Gabor, HOG, and SIFT in combination with various classifiers like CNN, SVM, KNN, and RFC. Our model involved applying these feature extraction techniques to ophthalmic

images for the purpose of classification. The extracted features were then applied to the training and performance testing of mentioned classifiers. The results demonstrated the efficacy of these techniques in capturing meaningful and discriminative information from the ophthalmic images. The CNN, SVM, KNN, and RFC demonstrated respectable accuracy and computing efficiency. After comparing all the classifiers and feature extraction techniques, we were able to say that Random Forest Classifier (RFC) and Gabor feature extraction technique worked best for this model.

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