Automating Diabetic Retinopathy Detection for Enhanced patient Care

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***Abstract*—Diabetic Retinopathy (DR) is a critical eye condition associated with diabetes, potentially resulting in blindness if not diagnosed and treated promptly. This project aims to detect the various stages of DR using advanced machine learning techniques. Utilizing the APTOS 2019 Blindness Detection Challenge dataset, which comprises retinal images categorized into five classes (No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR), we applied a combination of feature extraction methods, including Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT). Several classification algorithms were employed, namely Random Forest, Logistic Regression, k- Nearest Neighbors, Support Vector Machine, and Naive Bayes. Additionally, a VGG16 convolutional neural network was implemented to compare its performance with traditional approaches. The results demonstrated significant accuracy improvements with feature extraction, particularly with HOG and LBP, and highlighted the superior performance of the VGG16 model, achieving an accuracy of 99%.**

This study underscores the potential of integrating machine learning and deep learning techniques in the early detection and classification of diabetic retinopathy, facilitating timely and effective treatment to prevent vision loss.

***Index Terms*—Feature Extraction,Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), Convolutional Neural Network (CNN), VGG16, Random Forest, Logistic Regression, k-Nearest Neighbors, Support Vector Machine (SVM), Naive Bayes, Early Detection, Vision Loss Prevention.**

I. Introduction

Diabetic Retinopathy (DR) is a severe eye disease resulting from prolonged diabetes, which can lead to irreversible blindness if not diagnosed and treated promptly. The condition damages the blood vessels in the retina, causing them to leak or become blocked, ultimately impairing vision. As the prevalence of diabetes continues to rise globally, the incidence of DR is also increasing, making it a significant public health concern. Early detection and timely intervention are essential for preventing vision loss in patients with diabetic retinopathy. Traditional methods of diagnosing DR involve manual examination of retinal images by ophthalmologists, which is time-consuming and subject to human error. Hence, there is a growing need for automated and accurate diagnostic tools to assist healthcare professionals in identifying DR at its earliest stages. This project aims to leverage machine learning techniques to develop an automated system for detecting various stages of diabetic retinopathy. The dataset employed is from the APTOS 2019 Blindness Detection Challenge, which contains 3296 retinal images categorized into five classes: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. These images are divided into training and testing sets, with 2930 images used for training and 366 images for testing. To enhance the performance of our machine learning models, we implemented several feature extraction techniques, including Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT). These methods help in capturing essential patterns and features from the retinal images, making them more suitable for classification. We then applied various classification algorithms such as Random Forest, Logistic Regression, k-Nearest Neighbors, Support Vector Machine, and Naive Bayes to evaluate their effectiveness in detecting DR. Furthermore, we explored the use of a deep learning approach with the VGG16 convolutional neural network to compare its performance with traditional machine learning methods. The results of our study highlight the potential of integrating feature extraction techniques and advanced machine learning algorithms in developing a robust system for early detection of diabetic retinopathy, ultimately aiding in the prevention of vision loss and improving patient outcomes.

II. Dataset Overview

A. Dataset Description and Classification Categories

The dataset utilized for this project is sourced from the APTOS 2019 Blindness Detection Challenge and comprises a total of 3296 retinal images. These images are divided into two sets: 2930 images for training and 366 images for testing. The images are categorized into five distinct classes based on the severity of diabetic retinopathy: No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. This

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classification provides a comprehensive representation of the disease's progression, facilitating the development and evaluation of machine learning models aimed at accurately detecting and diagnosing the various stages of diabetic retinopathy.

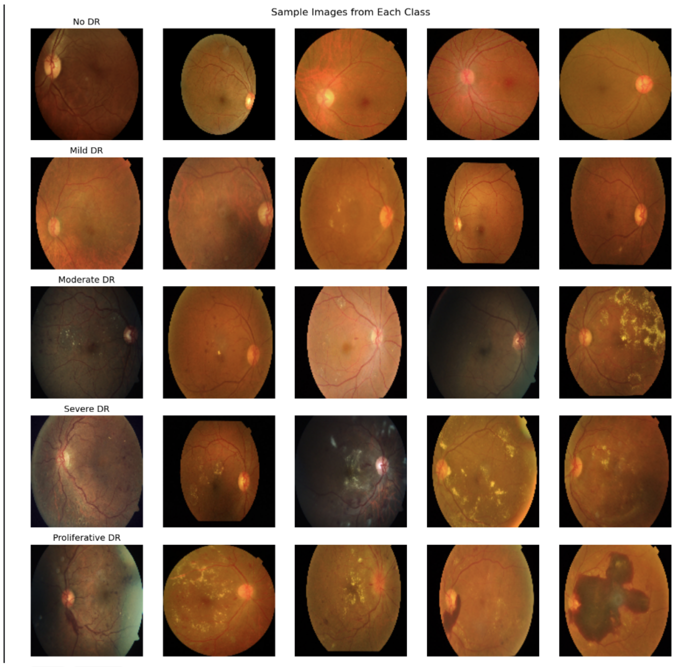

Fig. 1. Different stages of Diabetic Retinopathy

III. Methodology

A. *Feature Extraction techniques*

Feature extraction is a crucial step in the machine learning pipeline, especially in image classification tasks. It involves transforming raw image data into a set of meaningful features that can be used to improve the performance of classification algorithms. In this project, we employed three prominent feature extraction techniques: Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Scale-Invariant Feature Transform (SIFT). Each of these methods captures different aspects of the image, providing a diverse set of features for the classification task. To enhance the performance of classification algorithms, the following feature extraction techniques were applied:
1. Histogram of Oriented Gradients (HOG)
2. Local Binary Patterns (LBP)
3. Scale-Invariant Feature Transform (SIFT)
4. Generalized Iterative Scaling Technique (GIST)
5. Speeded-Up Robust Fea (SURF)

B. *Classification Algorithms*

The effectiveness of the feature extraction methods was evaluated using a range of classification algorithms, each offering unique strengths for the task of diabetic retinopathy detection. These algorithms were chosen for their diverse approaches to classification and their ability to handle different types of data distributions and feature spaces.

1) ***Random Forest Classifier****:* The Random Forest Classifier is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification tasks. This method is robust to overfitting due to its averaging of multiple decision trees. It can handle large datasets with higher dimensionality, making it suitable for the complex features extracted from retinal images. Random Forest also provides feature importance scores, which can offer insights into the most relevant features for classification.

2) ***Logistic Regression****:* Logistic Regression is a linear model for binary classification that can be extended to multiclass classification through methods such as one-vs-rest or softmax regression. It is particularly effective for problems where the classes are linearly separable. Logistic Regression provides probabilistic outputs, allowing for the estimation of class probabilities, which can be valuable in medical diagnosis for assessing the confidence of predictions.

3) ***k-Nearest Neighbors (k-NN)****:* k-NN is a non-parametric, instance-based learning algorithm that classifies a data point based on the majority class of its k nearest neighbors in the feature space. It is simple and effective, especially in cases where the decision boundary is complex. However, k-NN can be computationally intensive during prediction since it requires computing distances to all training samples. It also relies heavily on the choice of k and the distance metric used.

4) ***Support Vector Machine (SVM)****:* SVM is a powerful classification algorithm that seeks to find the optimal hyperplane that maximizes the margin between different classes. It is effective in high-dimensional spaces and is particularly robust against overfitting in scenarios where the number of dimensions exceeds the number of samples. SVM can also be extended to non-linear classification using kernel functions, which map the input features into higher-dimensional spaces where a linear separator may exist.

5) ***Naive Bayes****:* Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming strong (naive) independence between features. Despite its simplicity, Naive Bayes can perform surprisingly well on certain datasets, especially when the independence assumption roughly holds. It is efficient in terms of both computational complexity and storage, making it a practical choice for large datasets with numerous features.

IV. **HOG - Histogram of Oriented Gradients**

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image.
The essential thought behind the histogram of oriented gradients descriptor is that local object appearance and shape within an image can be described by the distribution of intensity gradients or edge directions. The image is divided into small

connected regions called cells, and for the pixels within each cell, a histogram of gradient directions is compiled. The descriptor is the concatenation of these histograms.
The primary idea behind HOG is to represent an image by the distribution of gradients or edge directions. The technique involves dividing the image into small connected regions called cells, computing the gradient orientation histogram for each cell, and then combining these histograms to form the HOG descriptor.

A. *Steps in HOG Feature Extraction*

The process of HOG feature extraction can be summarized in the following steps:

1) ***Gradient Computation****:* Compute the gradient values for each pixel in the image. This can be done using filters like the Sobel filter to get the horizontal (G_x) and vertical (G_y) gradients.

$$G_x = I(x+1, y) - I(x-1, y) \tag{1}$$

$$G_y = I(x, y+1) - I(x, y-1) \tag{2}$$

2) ***Orientation and Magnitude****:* Calculate the gradient magnitude and orientation for each pixel.

$$\text{Magnitude: } M(x, y) = \sqrt{G_x^2 + G_y^2} \tag{3}$$

$$\text{Orientation: } \theta(x, y) = \arctan\left(\frac{G_y}{G_x}\right) \tag{4}$$

3) ***Histogram of Gradients****:* Divide the image into cells (e.g., 8x8 pixels each). For each cell, create a histogram of gradient directions weighted by gradient magnitudes.

4) ***Block Normalization****:* Group cells into larger blocks (e.g., 2x2 cells) to normalize the histograms, improving the invariance to illumination and contrast changes.

5) ***HOG Descriptor****:* Concatenate the normalized histograms from all blocks to form the final HOG descriptor.

6) ***Mathematical Formulation****:* The HOG descriptor H for an image can be represented as:

$$H = [H_1, H_2, ..., H_n] \tag{5}$$

$$H_i' = \frac{H_i}{\sqrt{\|H_i\|_2^2 + \epsilon^2}} \tag{6}$$

Below is a visualization example showing an image with its HOG features overlayed, depicting how the gradients are captured in various orientations. In the context of diabetic retinopathy detection:
Retinal Image Analysis: HOG features help in capturing the structural abnormalities in retinal images.
Feature Enhancement: Enhances the performance of classification algorithms by providing robust feature sets.
Integration with ML Models: Combined with machine learning classifiers, HOG features improve the accuracy of detecting various stages of diabetic retinopathy.

Accuracy of different classification methods with HOG feature extraction

Accuracy of different classification methods

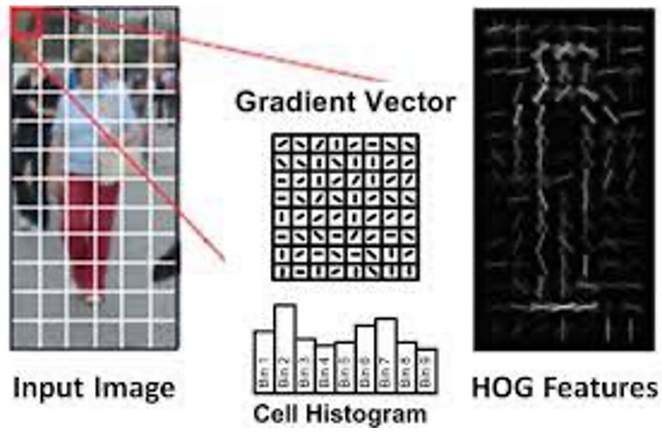

Fig. 2. HOG features

7) ***Accuracy with HOG Feature Extraction****:* The accuracies after applying HOG feature extraction were:

Method	Accuracy
Random Forest Classifier	33.79%
Logistic Regression	73.38%
k-Nearest Neighbors	68.43%
Support Vector Machine	72.18%
Naive Bayes	57.17%

TABLE I
ACCURACY OF DIFFERENT CLASSIFICATION METHODS WITH HOG FEATURE EXTRACTION

V. HOG - HISTOGRAM OF ORIENTED GRADIENTS

ACKNOWLEDGMENT

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