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Feature Selection for Simple Color Histogram Filter based on Retinal Fundus Images for Diabetic Retinopathy Recognition

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ABSTRACT
Applications of learning models for text-based datasets as well as image pixels-based datasets grow rapidly for prediction purposes. Pre-processing becomes challenging in carrying out image filtering and classifying. Retinal Fundus images plays important role in Diabetic Retinopathy (DR) diagnosis and treatment planning in various stages. Diabetic Retinopathy is diagnosed by observing the variation in retinal blood vessel, exudates, micro aneurysm, hemorrhages, and the new blood vessel growth inside the retina. The objective of this study is to enrich the diagnosis for the Diabetic Retinopathy from the retinal fundus images by applying machine learning algorithms. The proposed work implements normalization, parameter tuning, and optimal feature selection method to improve the classification accuracy offered by selected algorithms like decision tree algorithm and K-nearest neighborhood classifiers. The highest accuracy of 81.99%, Weighted Average of Receiver Operating Characteristics (ROC) 0.907 are obtained by k-Nearest Neighbor (KNN) classifier due to its best performance.

KEYWORDS
Attribute selection; Diabetic Retinopathy; J48; KNN; Simple color histogram filter; WEKA

1. INTRODUCTION

Diabetic Retinopathy (DR) is one of the commonest kinds of diabetic consequent diseases. Diabetic Retinopathy usually affects only the people having diabetes (diagnosed or undiagnosed) for many years [1]. Diabetic Retinopathy occurs when changes in blood sugar levels cause changes in retinal blood vessels that cause hemorrhages, exudates, swelling in vessels (macular edema) and leakage of fluid into the rear part of the eyes [2–5]. In other cases, due to the starving of retina for oxygen, abnormal blood vessels will grow on the surface of the retina. Unless treated, Diabetic Retinopathy can gradually become more serious and progress from “background retinopathy” to significantly affecting vision and may cause blindness. In fact, Diabetic Retinopathy is categorized into three different types: (a) Background retinopathy, (b) Diabetic maculopathy, and (c) Proliferative retinopathy [6–11].

Diabetic Retinopathy is best diagnosed with a comprehensive dilated eye exam and fundus photography. Fluorescein angiography and Optical Coherence Tomography (OCT) are also performed for better decision making especially for Diabetic maculopathy and proliferative retinopathy. Decisions taken by a comprehensive dilated eye exam and fundus photography are subjective and the sensitivity and specificity are varying from one another.

The practice of e-maintenance of health data and the evolution of artificial intelligence and deep learning algorithms [12–15] are supporting physicians to improve the decision making in this context. In recent years, the research community has developed different techniques and applied several deep learning frameworks to address this problem. The input images for learning models are fundus images with labels indicating the presence or the level of severity of Diabetic Retinopathy identified by professional graders. We apply supervised learning models like decision trees and k-nearest neighborhood for this purpose.

The authors C. Mahiba et al. (2019) [16] proposed hybrid structure descriptor and modified Convolutional Neural Networks (CNN) classifiers, attain high accuracy level for Severity Analysis of Diabetic Retinopathy. Rahul Kumar Chaurasiya et al. (2019) [17] applied a method based on Binary particle swarm optimization (BPSO) with feature selection that improves the classification accuracy offered by an SVM classifier to detect once again the severity. R. Karthikeya and P. Alli et al. (2018) [18] applied Support Vector Machine (SVM) parameters optimized with Glow-worm Swarm Optimization (GSO) with Genetic Algorithm (GA) for searching the efficient features. Valarmathi S et al (2019) [19] presented a generalized method of “semi-automatic exudates characterization” to

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diagnose Diabetic Retinopathy with exudates screening system of retinal image.

The objective of this proposed work is to use some of the familiar machine learning algorithms for identifying the Diabetic Retinopathy condition from the fundus digital images. It gives a variation from the previous works by suggesting yet another novel framework. The proposed work with shallow learning requires less computational power and less time to produce comparable results with deep learning models using the features extracted from the fundus image. The proposed work uses specialized filter on the specific image set for feature extraction and attribute selection and selected attributes are given for both J48 and KNN classifiers for performing multi classifications corresponding to the various levels of the DR symptom.

This paper is organized with four sections as follows: The second section covers superficial descriptions towards required materials and methods for the sake of completion. The third section contains data description and preparation, and the final section demonstrates the experimental results followed by the conclusions.

2. MATERIALS AND METHODS

The terms/materials used for this experiment are described for the sake of improving the readability for proposed framework with clarity. Moreover, the rationale behind the classifiers and their representation models are discussed in this section.

2.1 Simple Color Histogram Filter and Other Pre-processing Filters

This is a batch filter for extracting color histogram feature from images and has the most basic color features that can be computed; essentially, it three histograms (one for red, one for green, one for blue) each of which has 32 bins. Each bin contains a count of the pixels in the image that fall into that bin category. Using this filter, the image data set is transformed from pixels to numerical features.

2.1.1 Normalization

Normalization is one of the essential steps in data preprocessing. This step is important when dealing with parameters of different units and scales. Normalization is the process of normalizing all numeric values in the given dataset except the categorical and class attributes. By default, interval range of output is [0, 1]. Moreover, with the scale $= 2.0$ and translation $= -1.0$, we get values in the range $[-1, +1]$ to include the bipolarity.

2.1.2 Parameter Training

Parameter training is for improving the performance of machine learning models. Here KNN classifier with varying number of neighbors (k) values predicts the accuracy level and yields the ROC values.

2.1.3 Attribute Selection

Feature Selection is an important step after feature extraction to look for the possibility to improve accuracy and to decrease training and testing errors [17]. Removing unwanted attributes from the database is very essential to produce a good machine learning model. There exist automated tools for feature selection. Since we consider with Waikato Environment for Knowledge Analysis (WEKA) an open tool, we select its attribute selection routines like Correlation Attribute Eval /Ranker Method found in this tool to evaluate attribute ranking order. We always remove attributes in lower-ranking order to produce better result performance. We perform iteration over the list of ordered lists of attributes with respect to the preferred threshold to limit the number of iterations.

2.2 Selected Classifiers (Supervised Learning Algorithms)

The following two classifiers are selected from the set of supervised learning algorithms as our base models due to their familiarity and simple implementation leading to easier interpretations.

2.2.1 J48

The algorithm is meant for constructing decision trees based on information entropy gain and "divide and conquer" principle. Interpolation of results due to J48 implementation is very simple and readable in nature and the complexity of the algorithm is determined by construction of the tree which in turn depending on the significant attributes.

2.2.2 KNN

One of the simple algorithms is nearest neighborhood algorithm, where the data are distributed in the hyperdimensional space and the computation taking place depending on the "k" nearest neighbors by simply copying the labels of the weight without any specific effects on computation for prediction. Even though it is computationally intensive, it is very simple for implementation.

2.3 Performance Analysis

The performance metrics are obtained through the prediction patterns generated by the applied classifiers reflected by the entries available in the confusion matrices, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [20–23].

Eventually the performance metric namely the Receiver Operating Characteristic (ROC) area is also calculated in terms of the following expressions.

(i) Sensitivity is defined as the algorithm's capability to detect the disease correctly.
Sensitivity = TP/(TP + FN)
(ii) Specificity denotes the algorithm's ability to detect the disease correctly.
Specificity = TN/(TN + FP)
(iii) Accuracy is the ratio of the total number of correctly classified pixels to the number of pixels in the image field of view.
Accuracy = (TP + TN)/(TP + FN + TN + FP)
(iv) True Positive Rate (TPR) = Sensitivity
(v) False Positive Rate (FPR) = 1 −Specificity

3. DATA DESCRIPTION AND PREPARATION

Kaggle [24–25] public dataset is used for our experiment to make analysis and identification of Diabetic Retinopathy. Kaggle dataset is provided with a large set of high-resolution retina images taken under a variety of spatial conditions. A left and right field with two different angles of projection is provided for every subject. Images are labeled with a subject id as well as either left or right indication (*e.g.* 1_left.jpeg is the left eye of patient id 1). These images are labeled by an experienced pathologist according to a scale from 0 to 4 representing "No_DR", "Mild", "Moderate", "Proliferative DR", and "Severe" as the class labels for the image data records and their distribution is shown in the Table 1.

Though the Retinal Dataset consists of total 35,126 images, the class distribution is as follows: 25,810 (73.47%) of retinal images belong to No_DR class and the remaining instances 9316 (26.52%) images belong to the rest of the classes (Mild, Moderate, Severe, Proliferative DR). Since the ratio 3:1 between the majority class to the remaining may give rise to poor results, we transform the dataset to overcome this problem by replicating the classes Mild, Severe and Proliferative DR retinal fundus data top to bottom around three times for balancing purpose. Random selection of input images from the data set was performed through the random generators or random subsample filters available in Waikato Environment for Knowledge Analysis (WEKA) tool. The selection modes can first be "spread- sub sample" followed by resampling the normalizing the input image dataset. Eventually, we construct a subset of maximum count of 3000 with equal distribution of all classes in dataset. Now the resultant database gets a total no of instances: 15.000 and attributes: 65 (After applying the filter RGB color Histogram features 0–63 and the default output class attribute as 1).

Table 1 describes the distribution of five class values with their Instances count. The classes No_DR, Mild, and Moderate, dominate the other two classes namely Proliferative DR and severe.

Table 1: Experimental image dataset for classification

S. no	Diabetic Retinopathy types	Instances count	Class description of Diabetic Retinopathy (DR)
1	No_DR	3000	DR not present
2	Mild	3000	DR mildly present
3	Moderate	3000	DR moderately present
4	Proliferative DR	3000	Multiple rapid growth of DR
5	Severe	3000	Extremely high presence of DR

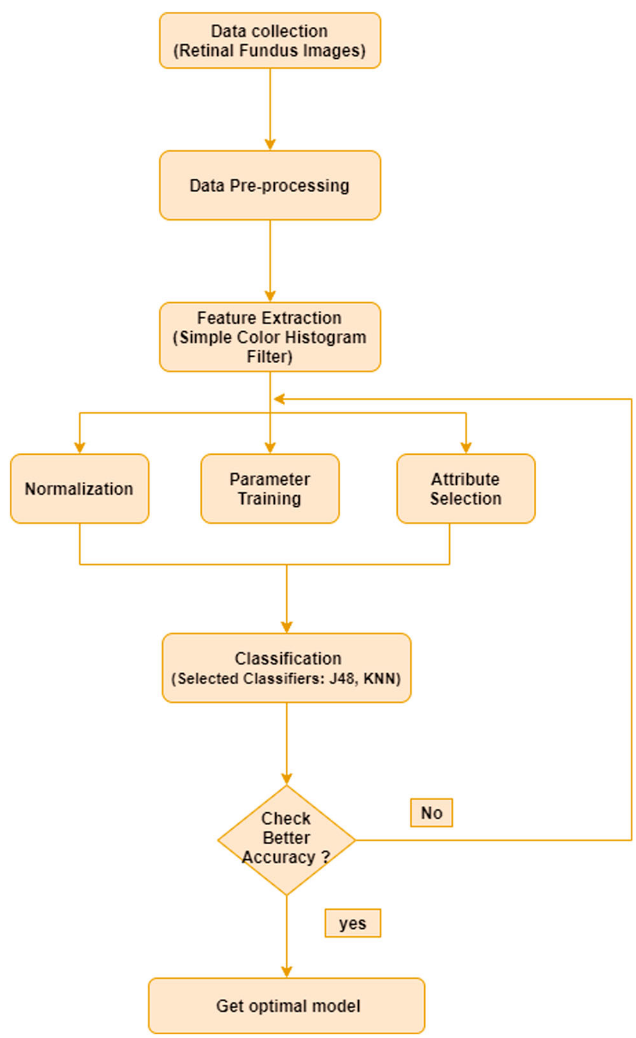

Figure 1: Flow chart for Diabetic Retinopathy detection

4. EXPERIMENT AND RESULTS

In this section, the proposed experimental setup is discussed. The proposed framework methodology is shown in Figure 1. The java implementation of decision tree classifier J48 is applied with selected features results as shown in Table 2. The classifier KNN with selected features and parameter training/tuning on neighborhood size "k" shown in Table 3. The graphical analysis of attribute level vs accuracy and attribute level vs weighted avg. ROC are shown in Figures 2 and 3, respectively.

4.1 Proposed Method

The proposed method uses the Kaggle dataset for training the model and this reliable dataset is widely used by the research community for Diabetic Retinopathy detection applications.

The pre-processing techniques like data cleaning and labeling by professional graders were already performed on this dataset. The labeled images are not evenly distributed among the multinomial classes and images with labels "No DR" and "moderate DR" dominate the rest of the classes. Since this implies a high degree of imbalanced distribution of images, training this image data set will bias the result and reduces the accuracy in classification. To avoid this bias, the count of the images in the remaining classes was increased through data replication techniques. This pre-processed data undergoes a feature extraction process using simple color histogram filters and then features were extracted. In the process of getting the optimal model, the data pre-processing operations like Data Normalization, Parameter Tuning, and Attribute Selection process were carried out on both J48 and K-Nearest Neighbor classifiers. The performance of both the classifiers is compared for different configurations and the better model is obtained based on the accuracy. The flow chart shown in Figure 1 graphically explains the above-framework with its components.

4.2 Performance Results

In this section, performance results are discussed on feature selection and parameter training/tuning tested through J48 and KNN classifiers. Available common technique by iteration for improving the performance of machine learning models and reduce the training time is follow. The attribute selection is done by Correlation Attribute Eval/Ranker available in WEKA. Parameter tuning is done by KNN classifier varying nearest neighborhood (k).

Decision trees or rules are not suitable models to classify the DR as we see from the above table for iteration over the lists of attributes dictated by the Attribute Evaluator/Search Methods for selecting the given set of attributes. However, the instance-based classifiers are observed to give higher performance as seen in the table. Encouraged by this instance-based classifier we further iterate over the parameter of this classifier namely, the number of neighbors (k).

Table 2: Performance of J48 with feature selection module

S. No	Removed attribute list	Attribute selection method (Attribute evaluator/Search method)	J48 Classifier accuracy (%)	J48 Classifier weighted Avg. ROC
1	No removal (All 65 attributes are retained)	Correlation attribute eval /Ranker	74.5933%	0.882
2	RGB Color Histogram 35,24,9,7,55,3,2,51,8,34,19,28,18,11,29,15,14,13,12& 50 (45 attributes retained; 20 attributes removed)	Correlation attribute Eval /Ranker	74.5933%	0.882
3	RGB Color Histogram 17,25,57,10,44,31,37,35,24,9,7,55,3,2,51,8,34,19,28, 18,11,29,15,14,13,12& 50 (38 attributes retained; 27 attributes removed)	Correlation attribute eval /Ranker	74.4133%	0.882
4	RGB Color Histogram 30,26,45,61,33,17,25,57,10,44,31,37,35,24,9,7,55,3,2, 51,8,34,19,28,18,11,29,15,14,13,12& 50 (33 attributes retained, 32 attributes removed)	Correlation attribute eval /Ranker	73.5333%	0.880
5	RGB Color Histogram 60,38,32,58,36,30,26,45,61,33,17,25,57,10,44,31,37,35, 24,9,7,55,3,2,51,8,34,19,28,18,11,29,15,14,13,12& 50 (28 attributes retained; 37 attributes removed)	Correlation attribute eval /Ranker	73.6%	0.881
6	RGB Color Histogram Features 54,52,4,6,47,60,38,32,58,36,30,26,45,61,33,17,25,57, 10,44,31,37,35,24,9,7,55,3,2,51,8,34,19,28,18,11,29,15,14,13, 12& 50 (23 attributes retained; 42 attributes removed)	Correlation attribute eval /Ranker	73.6733%	0.881
7	RGB Color Histogram 23,5,49,56,48,27,54,52,4,6,47,60,38,32,58,36,30,26,45, 61,33,17,25,57,10,44,31,37,35,24,9,7,55,3,2,51,8,34,19,28, 18,11,29,15,14,13,12& 50 (17 attributes retained; 48 attributes removed)	Correlation attribute eval /Ranker	72.64%	0.879
8	RGB Color Histogram 59,0,62,53,40,23,5,49,56,48,27,54,52,4,6,47,60,38,32,58, 36,30,26,45,61,33,17,25,57,10,44,31,37,35,24,9,7,55,3,2,51, 8,34,19,28,18,11,29,15,14,13,12& 50 (12 attributes retained, 53attribute removed)	Correlation attribute eval /Ranker	69.7267%	0.873

Table 3: Performance of IBK ($K = 1,2,3$) with feature selection module

S. No	Removed attribute list	Attribute selection method (Attribute evaluator/Search method)	Classifier IBK ($k = 1$) Accuracy (%)	Classifier IBK ($k = 1$) Weighted avg. ROC	Classifier IBK ($k = 2$) Accuracy (%)	Classifier IBK ($k = 2$) Weighted avg. ROC	Classifier IBK ($k = 3$) Accuracy (%)	Classifier IBK ($k = 3$) Weighted avg. ROC
1	No removal (All 65 attributes are retained)	Correlation attribute eval/Ranker	81.9933%	0.907	67.38%	0.889	59.2933%	0.867
2	RGB Color Histogram 35,24,9,7,55,3,2,51, 8,34,19,28,18,11, 29,15,14,13,12& 50 (45 attributes retained; 20 attributes removed)	Correlation attribute eval/Ranker	81.9933%	0.907	67.38%	0.889	59.2933%	0.867
3	RGB Color Histogram 17,25,57,10,44, 31,37,35,24,9, 7,55,3,2,51,8, 34,19,28,18,11,29, 15,14,13,12& 50 (38 attributes retained; 27 attributes removed)	Correlation attribute eval/Ranker	81.96%	0.906	67.2933%	0.888	58.12%	0.865
4	RGB Color Histogram 30,26,45,61,33,17, 25,57,10,44, 31,37,35,24,9,7, 55,3,2,51,8,34, 19,28, 18,11,29,15, 14,13,12& 50 (33 attributes retained, 32attribute removed)	Correlation attribute eval/Ranker	81.9667%	0.906	67.2267%	0.888	57.96%	0.864
5	RGB Color Histogram 60,38,32,58,36, 30,26,45,61, 33,17,25,57, 10,44,31, 37,35, 24,9,7,55,3,2,51,8, 34,19,28,18,11, 29,15, 14,13,12& 50 (28 attributes retained; 37 attributes removed)	Correlation attributeeval /Ranker	81.7867%	0.906	66.6733%	0.886	57.6467%	0.862
6	RGB Color Histogram 54,52,4,6,47, 60,38,32,58, 36,30,26,45, 61,33,17, 25,57,10,44, 31,37,35,24, 9,7,55,3,2, 51,8,34,19,28, 18,11, 29,15,14, 13,12& 50 (# 23 attributes retained; 42 attributes removed)	Correlation attribute eval/Ranker	81.7%	0.905	66.54%	0.885	57.52%	0.861
7	RGB Color Histogram 23,5,49,56,48, 27,54,52,4,6,47, 60,38,32,58,36, 30,26,45, 61,33,17,25, 57,10,44,31,37, 35,24,9,7,55,3, 2,51,8,34,19,28, 18,11,29,15,14, 13,12& 50 (# 17 attributes retained; 48 attributes removed)	Correlation attribute eval/Ranker	81.5067%	0.905	66.7933%	0.885	57.6733%	0.862
8	RGB Color Histogram 59,0,62,53,40, 23,5,49, 56,48,27, 54,52,4,6,47, 60,38, 32,58,36,30, 26,45,61,33, 17,25,57,10, 44,31,37, 35,24,9,7,55, 3,2,51,8,34,19, 28,18,11, 29,15,14, 13,12& 50 (# 12 attributes retained; 53 attributes removed)	Correlation attribute eval/Ranker	78.6333%	0.902	64.82%	0.880	56.1333%	0.856

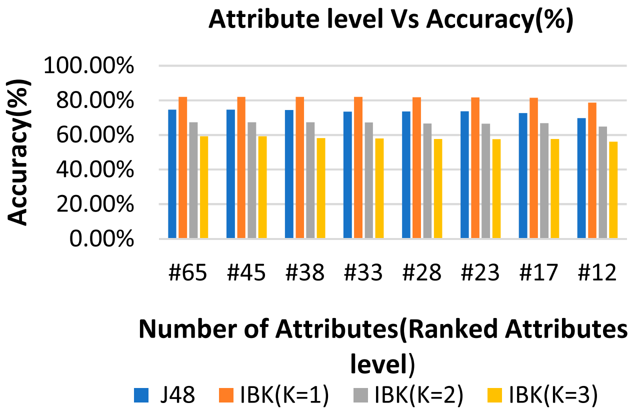

Figure 2: Performance of J48 & KNN ($K = 1,2,3$) attribute level vs accuracy

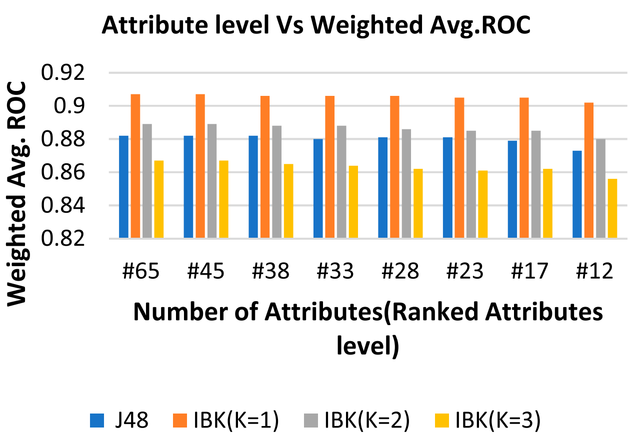

Figure 3: Performance of J48 & KNN ($K = 1,2,3$) attribute level vs weighted Avg. ROC

We observe that the J48's accuracy obtained vary from 69.73% to 74.59% based on attribute selection methods. J48 classification algorithm has obtained 74.59% as the highest accuracy rate when comparing 65 and 45 features, respectively.

The above graph describes the comparison of J48 & KNN algorithm with multi k values. Bars show accuracies obtained from neighborhood of size $k = 1,2.3$, respectively. We observe that 81.99% as the highest accuracy obtained by KNN with $k = 1$ value.

We observe that the Weight Avg. ROC obtained vary from 0.873 to 0.882 based on the feature selection method. J48 classification algorithm has obtained 0.882 high ROC value when trained with 65, 45, and 38 selected features as shown in Table 3.

KNN algorithm is iterated with various k values. The orange line indicates standard k value in WEKA tool, base line indicates nearest neighborhood $k = 2$, yellow line indicates nearest neighborhood $k = 3$. We observe that the 0.907 highest weighted Avg. ROC obtained by KNN with standard k values. We conclude that KNN algorithm shows better classification performance for ($K = 1$) when compared to J48. The tree-based J48 classifier is unable to produce higher classification accuracy due to the nature of the used dataset and its extracted features. KNN classifier does not improve the results when increasing its neighborhood size or K values.

5. CONCLUSION

The proposed framework consists of two main components with filters and classifications; Attribute selection among filtered features followed by normalization as the first component and iterations with instance-based nearest neighborhood models in the second component. The optimal accuracy with maximum performance finally found to be 74.59% in the first component and the same happened to be 81.99% in the second component. These results in this work are first of its kind in this framework based on simple color histogram filter for Diabetic Retinopathy image processing.

6. FUTURE REMARKS

The Image filters especially simple color Histogram filter enable us to classify the image set of DR in an enhanced way. These types of filters and extended classifiers further be explored and estimated for more performance and accuracy levels.

COMPLIANCE WITH ETHICAL STANDARDS

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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