Ensemble Learning Optimization for Diabetic Retinopathy Image Analysis

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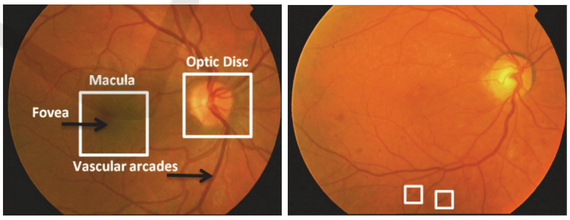
Abstract: Ensemble Learning has been proved to be an effective solution to learning problems. Its success is mainly dependent on diversity. However, diversity is rarely evaluated and explicitly used to enhance the ensemble performance. Diabetic Retinopathy (DR) automatic detection is one of the important applications to support the health care services. In this research, some existing statistical diversity measures were utilized to optimize ensembles used to detect DR related signs. Ant Colony Optimization (ACO) algorithm is adopted to select the ensemble base models using various criteria. This paper evaluates several optimized and non-optimized ensemble structures used for vessel segmentation. The results demonstrate the necessity of adopting the ensemble learning and the advantage of ensemble optimization to support the DR related signs detection.

1 INTRODUCTION

Diabetic retinopathy (DR) is one of the common eye diseases associated with diabetes. As the rising prevalence of diabetes worldwide, DR will become a more important problem. Early detection of DR is very essential for effective treatment. Given the increasing number of DR patients worldwide and the need of regular eye examination, the development of automated screening of DR has received a lot of attention from many research communities. The main goals are to reduce the ophthalmologists' workload and to improve the health care services. DR computer-aided-diagnosis (DR-CAD) systems are designed to distinguish between normal and abnormal retinal images, in which DR symptoms appear. Figure 1 shows two samples of retinal fundus images; normal and image with DR lesion called haemorrhages. Vessel segmentation is a vital component of DR-CAD systems. Retinal blood vessels must be excluded to reduce the false positives in the detection of pathological lesions such as haemorrhages shown in Figure 1-b. The automatic detection of vessels can also be useful in in locating other anatomical structures such as optic disc and fovea. Furthermore, vessel segmentation is an important diagnosis key for several retinal pathologies leading to vascular anomalies. Many vessel segmentation techniques and algorithms have



a) Normal Retina

b) Retina with DR Lesions (haemorrhages)

Figure 1: Retinal Fundus Images Samples.

been developed in the literature. However, the presence of noise, the variability of image acquisition equipment, and the presence of some pathological lesion make the vessel segmentation process more and more challenging. This emphasizes the need for developing more accurate automated techniques (Preethi and Vanithamani, 2012) (Khan, Shaikh, and Mansuri, 2011) (Fraz et al., 2012). Vessel segmentation studies can be classified into two main groups, rule-based approaches and machine learning approaches (Marin, Aquino, Gegundez-Arias, and Bravo, 2011). Adaptive thresholding (Xu and Luo, 2010) (Jiang, Society, and Mojon, 2003), vessel tracking (Liu and Sun, 1993) (Vlachos and Dermatas, 2010) (Delibasis, Kechriniotis, Tsonos, and Assimakis, 2010), mathematical morphology (Zana and Klein, 1999) (Zana and Klein, 2001), and matched filtering

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(Zhang, Zhang, Zhang, and Karray, 2010) (Chaudhuri, Chatterjee, Katz, Nelson, and Goldbaum, 1989), are all examples of the rule based approach. On the other hand, machine learning approach which can be supervised or unsupervised learning, is used to classify all pixels in an image into vessel or non-vessel classes. Supervised learning, such as work presented in (Becker and Rigamonti, 2013) and (Ricci and Perfetti, 2007) is based on training a classifier on a set of manually labelled reference images known as gold standard or ground truth data. By contrast, unsupervised learning performs the vessel segmentation without any prior labelling information. Examples of such approaches were suggested in (Ricci and Perfetti, 2007) and (Tolias and Panas, 1998). In this research we adopt heterogeneous ensemble learning for pixel classification.

The use of ensemble models or ensemble classifiers has proved to provide better result than a single complex algorithm in many problems as ensembles are able to better resolve the bias-variance trade-off. However, it is well known in the literature that in order for the ensemble models to have better performance, diversity should be maintained. This diversity manifests itself as disagreement or ambiguity among the ensemble members and the performance of any ensemble models is largely dependent on diversity. Diversity is usually supposed to be enforced by the designing process such as using different training samples.

Despite of its importance, how the diversity could be utilized to enhance the performance of ensemble is rarely studied, which calls for further investigations.

In this paper, we adopt several ensemble structures used for retinal vessel segmentation. By developing ensemble models we are aiming to obtain much more accurate and robust learning model that outperforms any individual base model. An ant colony optimization algorithm is used to optimize the ensemble structures based on several criteria including the diversity and the ensemble members' performances. The results confirm the effectiveness of the ensemble learning and the advantage of ensemble optimization.

The rest of the paper is organized as follows: Section 2 presents some existing vessel detection techniques that we have used as the base models in the ensembles. Section 3 discusses some important aspects of ensemble learning and motivates the importance of ensemble optimization. Section 4 describes our ensemble optimization approach. Section 5 presents and discusses the results of the optimized ensembles. Section 6 concludes the paper and suggests further works.

2 VESSEL SEGMNATION METHODS

The large numbers of vessel segmentation approaches available in the literature makes the process of choosing base models to construct ensemble systems more complex and challenging. In spite of this fact, we evaluated several methods available from the literature found to achieve good performance. Moreover, we developed a new fast and efficient classifier model. All these methods were used in constructing different ensemble structures. In the following, we describe each type of the base models used in constructing ensembles used in this paper for vessel segmentation.

In (Soares, Leandro, Cesar Júnior, Jelinek, and Cree, 2006) Bayesian classifier is applied with class-conditional probability density distribution (PDF) defined as a linear combination of Gaussian models. The feature set consists of two-dimensional Gabor wavelet transform responses taken at different scales, augmented with pixels intensity. The method is called Gaussian Mixture Model (GMM). The number of Gaussian models k varies in each experiment. The approach was trained and tested on DRIVE and STARE publically available datasets. The training phase was performed on both datasets. The resulted classifiers were also tested on both datasets.

We also developed a simple and fast vessel segmentation algorithm based on pixel classification. Linear discriminant classifier (LDC) (Richard O. Duda , Peter E. Hart, 2000) is used with Principle Component Analysis (PCA) a classical dimension reduction method to select different number of features. The feature set consists of the output of Gaussian filters and its derivatives up to order 2 taken at multiple variances and the green channel intensity of the original image. Features were normalized to zero mean and unit variance. DRIVE training set was used for training the classifier. This approach is similar to the one used in (Niemeijer, 2006) in which kNN (k=30) is used to obtain the vessel non-vessel probability map and then thresholding is performed to get the binary segmentation. However, LDC shows extremely fast and efficient training and testing phases compared to the kNN classifier. This efficiency is crucial in constructing ensembles as many models should be trained and used for classification.

However, when using LDC for pixel classification, we have noticed that the boundary between the field of view (FOV) and the black background result in many false positives (FP) on the boundary. Thus, we enhanced the result of the LDC classifier by adopting the diffusion approach used in (Huynh, 2013). The process starts by relabeling five pixels on the boundary as background then diffuse the colour in FOV through the background by using the heat equation. After the diffusion, the features are extracted and tested using the LDC classifier in a space reduced by PCA.

We also tested an algorithm called Multi Scale Line Tracking Algorithm (MSLTA) (Vlachos and Dermatas, 2010). The algorithm starts by extracting a set of pixels, called seeds from the image histogram. The histogram is divided into three sections by two threshold values T_low and T_high. The threshold T_low is estimated by the percentage of pixels belonging to background, while the threshold T_high is estimated by the percentage of pixels belonging to bright structure. Pixels with intensity between these two values are expected to be blood vessel and extracted as seeds for line tracking algorithm. All seed pixels are evaluated using five different scales to construct a confidence matrix used to get the initial candidate blood vessels. Then a 3×3 median filter is applied to remove FP pixels and to fill gaps in some blood vessels lines. Finally, morphological directional filtering and morphological reconstruction are applied to further enhance the result.

In (Goh, 2011), adaptive thresholding is used on the contrast-enhanced image to get candidate blood vessel objects. Then two kinds of detectors are used to make the final decision. In the first detector, the linear properties of the detected objects are evaluated to filter out non-blood vessel objects. In the second detector, features of the obtained objects are extracted and used by the classifier ensemble. The ensemble consists of an optimized set of neural networks trained using different training sets or different subsets of features. The base models are generated using different neural networks, different initial weights and different number of hidden units. This results in 270 base models. These base models are optimized by using Genetic Algorithm. The probability of each base model to be selected is proportional to its accuracy compared to the sum of all ensemble models accuracies.

3 ENSEMBLE LEARNING

We constructed five non-optimized ensemble models using the methods described previously. Ensemble A is constructed based on GMM methods trained and tested on DRIVE using different number of Gaussian models (k=1, 5, 10, 15, 20). As all of these methods are similar except in one parameter, the diversity is not expected to be high. Ensemble B is also constructed using GMM methods however, STARE dataset is used to train some of the classifiers which are then tested on DRIVE. Thus, we expect the diversity of ensemble B is higher than that of ensemble A, as different training sets are used.

Ensemble C was constructed by using different LDC-PCA methods with different number of features. Ensemble D was formed by all GMM and LDC-PCA methods. MSLTA, the adaptive thresholding approach, kNN classifier and all of the GMM and LDC-PCA methods were combined together to form ensemble E. Therefore, as different training datasets, features, methods and parameters are used in this case. Thus the diversity of this ensemble is expected to be the highest.

We evaluated the performance of all models on DRIVE testing dataset. The evaluation is performed quantitatively by comparing classification performance in terms of accuracy, sensitivity and specificity. The results are shown in Table 1.

We also estimate the diversity of the five ensembles by calculating the diversity disagreement measure (Schapire, 2003) and relate this to the improved ensembles' performances. The greater the disagreement measure, the higher the ensemble diversity. Figure 2 shows an example of the visual results of the five non-optimized ensembles compared to the gold standard and to an expert human observer.

The results in Table 1 highlight some interesting aspects of ensemble learning. First, we can see that as the diversity increases, the improvement of the ensemble performance becomes more evident. For instance, the least diverse ensemble is C which consists of the same models trained on the same features and only the number of features is different in each model. Ensemble C manifests the lowest improvement in accuracy and no improvement in specificity. On the other hand, the greatest diversity is manifested in ensemble E where different algorithms, different classifier parameters, different features and different training sets where used. This indeed accompanies with the greatest improvement in ensemble accuracy and specificity which is indeed

Table 1: Performance evaluation of non-optimized ensembles.

Ensemble	Disagreement Diversity Measure	Accuracy		Specificity		Sensitivity	
		Base Model Average	Ensemble	Base Model Average	Ensemble	Base Model Average	Ensemble
Human Observer	**-**	94.72		97.25		77.60	
A	**0.0234**	**94.00**	**94.43**	**97.08**	**96.89**	**73.13**	**77.86**
B	**0.0260**	**93.75**	**94.52**	**97.66**	**98.34**	**67.13**	**68.57**
C	**0.0094**	**91.33**	**91.44**	**98.50**	**98.21**	**41.69**	**44.55**
D	**0.0348**	**92.94**	**94.46**	**97.94**	**98.68**	**58.65**	**65.68**
E	**0.0385**	**92.58**	**94.22**	**97.97**	**99.09**	**55.53**	**60.89**

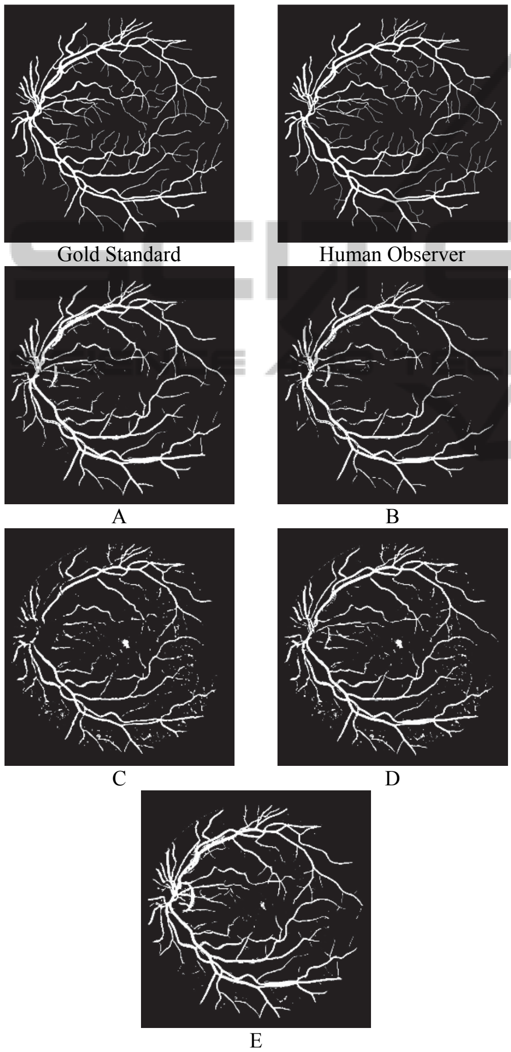

Figure 2: Example of Vessel Segmentation Results of non-optimized ensembles.

higher than the specificity achieved by the expert human observer.

Consequently, we assume that this relationship between the diversity and the improvement of the ensemble performance can be utilized to construct a better performance ensemble.

However, ensemble E achieved highest specificity but has lowest sensitivity compared to other ensembles. Thus, we assume that when increasing the number of base models, the overall performance may not be improved and the sensitivity in particular may be decreased significantly. Thus it is more desirable to construct ensemble with a small number of models not only to reduce the complexity but also to obtain an ensemble that outperforms its best models. At the same time to achieve better specificity we should maximize this number as much as possible.

4 ENSEMBLE LEARNING OPTIMIZATION

A direct approach of selecting a subset of base models to construct an ensemble is to select models which have the highest performance. This approach has several weaknesses, including over-fitting, sensitivity to the noise and possible selection of identical base models.

Since the success of ensemble learning is largely related to the base models performance as well as the diversity among these models, these aspects should all incorporated into the selection of base models process. Moreover, the performance of any base model should be evaluated based on its individual performance as well as its performance within the ensemble. In other words, selecting high performance base models is not sufficient to ensure the constructing of better ensemble. The base models should be diverse and each base model should contribute to enhance the overall ensemble performance.

Motivated by the above reasons, in this research we propose an ACO-Based algorithm to search and select the base models in an attempt to construct better performance ensemble to support DR automatic detection.

By employing the ACO algorithm in optimizing ensemble learning we aim to select the base models which perform well as individual and contribute well to the overall ensemble performance. The main advantages of this approach are to alleviate over-fitting by reducing the number of models, thus reducing the model complexity. The standard ACO algorithm is used in this research to optimize the 20 base classifier models presented in Table 1 based on different heuristics.

The problem of optimizing classifier ensemble can be described as an ACO problem. The base classifiers can be represented as vertices in a graph with edges representing the next classifier to be selected to construct the ensemble. Heuristic desirability and pheromone trail intensity are associated with each classifier. Each ant will select randomly the first classifier to construct its ensemble. Several measures were used to evaluate the constructed solutions as ensemble accuracy, sensitivity and specificity. Updating pheromones phase is achieved by decreasing all the pheromone values associated with all classifiers through pheromone evaporation and by increasing the pheromone values associated with best so far ensemble. For example if sensitivity is employed then that means the more sensitive the ensemble is, the more pheromone quantity will be added to classifiers used in that ensemble. The ACO-ensemble optimization algorithm proposed in this study is illustrated in

5 RESULTS AND DISCUSSIONS

Several experiments were conducted to optimize the ensemble. First, accuracy, sensitivity and specificity of the base models are used in each ensemble as heuristics to guide the ACO search. These measures are also used to evaluate the ants' constructed solutions. This results in three different optimized ensembles shown in Table 3. The results show that optimizing ensembles based on accuracy or sensitivity results in much higher sensitivity, higher accuracy and comparable specificity compared with ensembles optimized by specificity. Thus, in the subsequent experiments, accuracy and sensitivity are used to evaluate the ant's candidate solution. Diversity is incorporated into the optimization process of ensembles. ACO search is guided by seven diversity measures available from the literature (Brown, Wyatt, Harris, and Yao, 2005). Results are shown in Table 4 and Table 5.

Table 4 and Table 5, show that using disagreement diversity measures to select the base models during the ACO optimization, lead to the best accuracy compared to all other diversity measures.

The specificity and sensitivity achieved by employing disagreement and Q-static however, are

Table 2: ACO proposed algorithm for ensemble optimization.

Input: classifiers oracle outputs for some training data samples
$O = (o_1, o_2, \ldots, o_n)$
Output: base model classifiers for ensemble

1. Initialize ACO Parameters
2. Initialize Pheromone;
3. Determine the population of ants (m);
4. For each ant k do
   Repeat
      Choose in probability the classifier to include;
      Use the heuristic to adjust the probability selection;
      Append the partial solution with the candidate classifier
   Until ant k has chosen p classifiers

   Evaluate the constructed ensemble E_k;
      Use ensemble performance to evaluate the constructed ensemble

   If (termination condition not met) **do**
   For each classifier c_i used in ensemble E_k
      Update Pheromone p_i based on the solution quality, $\boldsymbol{Length_k}$
   End for
      For each classifier c_j do
         Evaporate Pheromone p_j
   End for
   Else terminate;

Table 3: Vessel segmentation optimized ensembles guided by ensemble accuracy, specificity and sensitivity.

Ensemble		Accuracy	Specificity	Sensitivity
#	ACO Heuristic			
1	Accuracy	94.72	97.75	74.10
2	Specificity	92.46	98.57	50.52
3	Sensitivity	94.27	96.46	79.48

Table 4: Vessel segmentation optimized ensembles guided by diversity and ensemble accuracy.

Experiment Settings		Accuracy	Specificity	Sensitivity
#	Diversity Measure			
1	Q-statistic	94.73	97.85	73.59
2	Disagreement	94.75	97.93	73.17
3	Double-fault	94.60	97.56	74.50
4	Kappa-statistic	94.66	98.00	71.91
5	Entropy	94.69	97.61	74.86
6	Generalized diversity	94.70	97.71	74.24
7	Coincident failure diversity	94.66	97.83	73.15

Table 5: Vessel segmentation optimized ensembles guided by diversity and ensemble sensitivity.

Experiment Settings		Accuracy	Specificity	Sensitivity
#	Diversity Measure			
1	Q-statistic	94.12	96.50	77.88
2	Disagreement	94.66	97.33	76.52
3	Double-fault	94.15	96.97	74.94
4	Kappa-statistic	94.61	97.22	76.88
5	Entropy	94.56	97.26	76.29
6	Generalized diversity	94.56	97.10	77.36
7	Coincident failure diversity	94.62	97.22	76.96

comparable to the other measures. In Table 6, the best sensitivity achieved is due to incorporating the Q-statistic diversity measure into the ACO optimization. Although in this case Q-statistic results in low specificity, when looking at the visual segmentation result, we assume that these errors can be reduced by excluding the OD and FOV boundaries from the image before the segmentation.

In order to compare the performance of non-optimized and optimized ensembles, their performance is graphically illustrated in Figure 3.

The result of Q-statistic is used in this figure for the Accuracy-Diversity and Sensitivity-Diversity optimized ensembles. The reason of this is that Q-statistic gives the highest performance ensembles compared to other diversity measures. As shown in the figure, ensembles optimized by sensitivity resulting in highest sensitivity and very comparable results in specificity and accuracy compared to the best ensemble. Based on these findings, we propose to adopt the sensitivity optimized ensembles for blood vessel segmentation in the DR diagnosis system.

6 CONCLUSIONS AND FUTURE WORKS

In this paper several optimized and non-optimized ensemble structures used for vessel segmentation have been evaluated. All of the developed ensembles were evaluated with multiple performance indicators, i.e., accuracy, sensitivity and specificity as well as the diversity aspect of these ensembles. The diversity was evaluated using different statistical diversity measures. The relationship between the performance measurers and the diversity measures were analysed.

Based on the findings in this work, we aim to further study the development and evaluation of a fully optimized ensemble learning model to support the DR related signs detection. This model is expected to enhance several DR system components such as blood vessel detector, optic disc detector, red lesion detector and bright lesion detector. Moreover, as the model is of a generic form, it should also be applicable to other complex pattern recognition problems.

The optimization should be performed to learn the parameters of the base model, select the base models; optimize the number of the base models and to learn the features used for each model. Moreover, the optimization should also employ the diversity measures and the performance of base models.

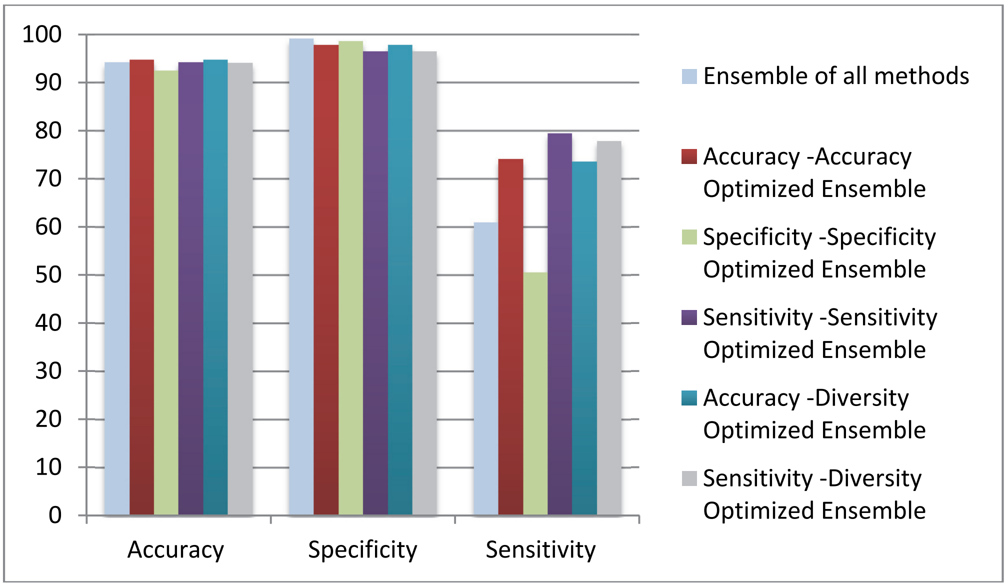

Figure 3: Comparisons of different ensembles structures performance.

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