Multi-Index Optic Disc Quantification via MultiTask Ensemble Learning

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Abstract. Accurate quantification of optic disc (OD) is clinically significant for the assessment and diagnosis of ophthalmic disease. Multi-index OD quantification, i.e., to simultaneously quantify a set of clinical indices including 2 vertical diameters (cup and disc), 2 whole areas (disc and rim), and 16 regional areas, is an untouched challenge due to its complexity of the multi-dimensional nonlinear mapping and various visual appearance across patients. In this paper, we propose a novel multitask ensemble learning framework (DMTFs) to automatically achieve accurate multi-types multi-index OD quantification. DMTFs creates an ensemble of multiple OD quantification tasks (OD segmentation and indices estimation) that are individually accurate and mutually complementary, and then learns the ensemble under a multi-task learning framework which is formed as a tree structure with a root network for shared feature representation, two branches for task-specific prediction, and a multitask ensemble module for aggregation of multi-index OD quantification. DMTFs models the consistency correlation between OD segmentation and indices estimation tasks to conform to the accurate multi-index OD quantification. Experiments on the ORIGA datasets show that the proposed method achieves impressive performance with the average mean absolute error on 20 indices of 0.99 ± 0.20, 0.73 ± 0.14 and 1.23 ± 0.24 for diameters, whole areas and regional area, respectively. Besides, the obtained quantitative indices achieve competitive performance (AUC=0.8623) on glaucoma diagnosis. As the first multi-index OD quantification, the proposed DMTFs demonstrates great potential in clinical application.

1 Introduction

Accurate quantification of optic disc (OD) from fundus images is the most clinically important for the comprehensive assessment of ophthalmic disease. According to [7], multi-index OD quantification is defined as simultaneously quantifying a set of clinical indices, i.e., 2 vertical diameters (cup and disc), 2 whole areas (disc and rim), and 16 regional areas (as shown in Fig.1), to characterize the global and focal appearance of OD. Clinically, accurate quantification provides effective assessment tools and detailed information for diagnosis, treatment, and follow-up of many ophthalmic diseases, especially chronic glaucoma [8, 12, 14].

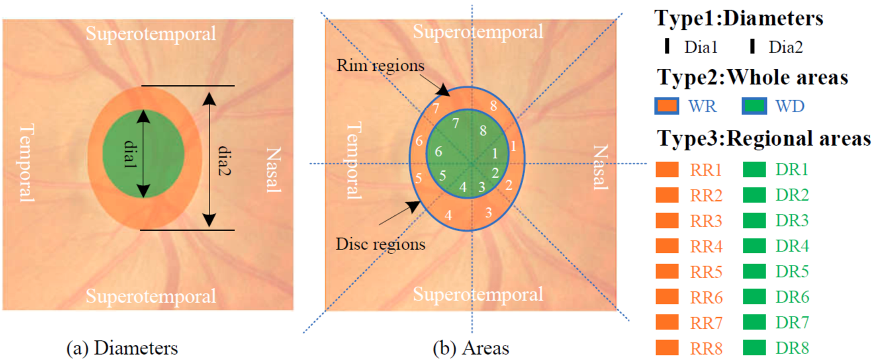

Fig. 1. Multi-index OD quantification includes three type of indices: diameters, whole areas and regional areas. (a) diameters of optic disc and cup. (b) areas of optic disc and neuroretinal rim for the whole disc and for individual 45 degree regions followed as [7] to characterize the global and local appearance. RR: rim regions; DR: disc regions; WR: whole rim; WD: whole disc.

Existing methods address only single index OD quantification by either learning a nonlinear mapping between fundus image and quantitative index, such as CDR [16], or measuring on the segmented OD mask [2, 4, 9]. However, those methods are still open challenging to achieve multi-index OD quantification because the former approach (direct estimation) always implements a complex nonlinear regression which is hard to train individually [5, 17]; the latter is a common segmentation-based approach, but the great variability of shape and inhomogeneity in OD appearance, especially the ambiguity optic cup borders, easily cause critical inconsistency of OD indices compared to actual ones.

No work has successfully achieved multi-index OD quantification due to three challenges: 1) estimating multiple indices from fundus image is complicated and difficult due to the complexity of nonlinear mapping from fundus image to multivariate vector. 2) Large variation of fundus appearance cross patients increases the difficulty of feature representation for comprehensive OD quantification. OD appearance changes in different ways with different pathology, e.g., cupping caused by thinning of rim and notch caused by focal enlargement of the cup [1]. 3) Combining OD segmentation and direct index estimation for accurate quantification is challenging due to the modeling difficulty of correlations between the two approaches.

Multi-task learning (MTL) [6, 10, 15, 16] has great potential since it improves the performance of the individual task by joint learning of the two OD quantification approaches (OD segmentation and indices estimation). However, traditional MTL methods can not formulate the two approaches into an ensemble model to aggregate their quantitative indices effectively. Our work constructs a particular case of multi-task learning when OD quantification is divided into an ensemble of multiple correlated but diverse tasks by modeling the consistency correlation between those tasks. The multi-task learning structure is encoded as a tree, where the root indicates task-shared representation, and branches implement a set of decision trees which obtain the confident task-specific predictions that can be aggregated into a consistent OD quantification in multiple granularities [11].

In this paper, we propose a novel multitask ensemble learning framework (DMTFs) to automatically quantify optic disc (OD) by obtaining multi-type quantitative indices. DMTFs is capable of achieving accurate OD quantification by: 1) creatively formulating multi-index OD quantification as multitask ensemble learning to learn OD segmentation and indices estimation tasks jointly; 2) modeling consistency correlations between two quantification tasks based on the advantages integration of multi-task and ensemble learning frameworks; and 3) addressing the multitask ensemble learning with multi-objective optimization to find the effective solution. Benefit from the multitask ensemble learning, DMTFs enables high-efficiency solution on accurate multi-index OD quantification.

Our main contributions are three-folds: 1) For the first time, multi-index OD quantification is achieved to help the clinician to assess global and focal changes of optic disc for diagnosis, treatment, and follow-up of many ophthalmic diseases. 2) The proposed distribution regression forest provides an effective approach for task-specific feature selection and distribution regression to handle the task-specific prediction problem in each individual task. 3) Multitask ensemble learning framework (DMTFs) is innovatively proposed to create an ensemble of multiple OD quantification tasks (OD segmentation and indices estimation) to effectively achieve accurate multi-index OD quantification.

2 Deep Multi-Task Forests (DMTFs)

DMTFs (Fig.2) creates an ensemble of multiple OD quantification tasks (OD segmentation and indices estimation), and learns the ensemble under a multi-task learning framework by modeling the consistency correlations between the two quantification tasks. Taking advantages of multi-task learning and ensemble learning, DMTFs promotes performance improvement on each individual task and achieves accurate multi-index OD quantification by multitask ensemble.

2.1 Architectures of DMTFs

The proposed DMTFs consists of a root network for shared feature representation, followed with two branches for task-specific prediction (OD segmentation and indices estimation) by implementing a set of distribution regression forests,

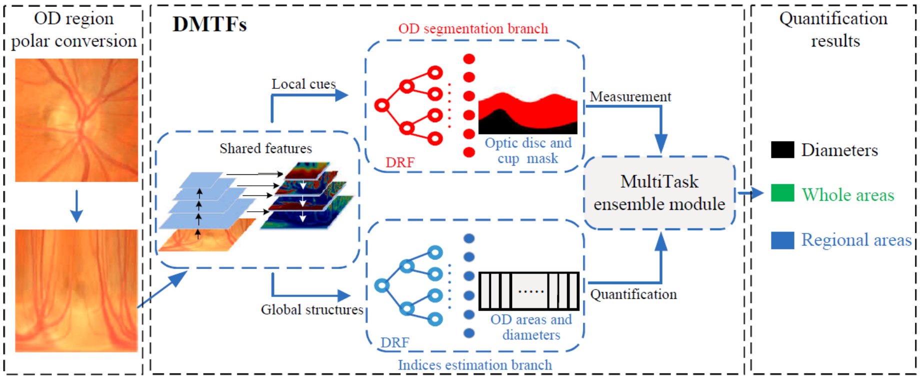

Fig. 2. Overview of DMTFs, which is a multitask ensemble learning framework consisting of a root CNN for task-shared feature representation, two task-specific branches for OD segmentation and indices estimation tasks, and a multitask ensemble module for joint optimization and final OD quantification. Each branch implements a distribution regression forest, randomly linked with the shared root network. The DMTFs is trained by the multi-objective optimization algorithm with the end-to-end manner.

and a multitask ensemble module for final OD quantification. The DMTFs allows for learning of the inter-task correlation by shared feature representation and consistency regularization, whilst simultaneously allows for modeling of task-specific correlation by task-specific feature selection and ensemble learning. To learn those correlations, the objective of DMTFs is formulated as

$$\arg\min_{\mathbf{w},\mathbf{p_{seg}},\mathbf{p_{est}}} (\underbrace{\mathbf{L}_{seg}(\mathbf{w},\mathbf{p}_{seg})}_{segmentation\ task\ loss}, \underbrace{\mathbf{L}_{est}(\mathbf{w},\mathbf{p}_{est})}_{estimation\ task\ loss}, \underbrace{\mathbf{L}_{cons}(\mathbf{w},\mathbf{p}_{est},\mathbf{p}_{seg})}_{consistency\ loss})^{\intercal} \quad (1)$$

where L_{seg} is the loss to ensure the precise of OD segmentation task, L_{est} is the estimation loss to ensure the accuracy of the indices regression task, and L_{cons} denotes the consistency regularization to impose a penalty for the consistent OD quantification from segmentation and estimation tasks. $\mathbf{w}$ is the parameters, $\mathbf{p}_{seg}, \mathbf{p}_{est}$ are predicted indices vectors by the segmentation and estimation tasks, respectively. Notes $\mathbf{p} = (Dia1, Dia2, WR, WD, RR1 : RR8, DR1 : DR8)$.

Multi-task learning often requires modeling of the trade-off between OD segmentation and indices estimation tasks, for example, the direct estimated area of the regional rim is conflicting with the segmented rim region. To find the solutions that are not dominated by any tasks, DMTFs is formulated as multi-objective optimization and the loss function is defined as a vector-valued loss as shown in Eq.1 with the overall objective of finding a Pareto optimal solution.

2.2 Task-Specific Branches with Distribution Regression Forest

Task-specific branches employ distribution regression forests (DRF) to individually achieve OD segmentation and indices estimation tasks by constructing a multitude of differentiable decision trees [13] linked with the root network. Each task-specific branch extracts task-related features and obtains task-specific prediction based on the feature selection and distribution regression of DRF module.

Each DRF module is consisted of a set of split nodes $\mathcal{N}$ and leaf nodes $\mathcal{L}$. Split and leaf nodes construct a multitude of decision trees at training time and output the prediction of the individual branch. To enable the tree with task-related feature selection, a routing function $\mu_l(\mathbf{x}|\mathbf{w})$ is defined to provide the probability that input $\mathbf{x}$ will reach leaf node l as

$$\mu_l(\mathbf{x}|\mathbf{w}) = \prod_{n\in\mathcal{N}} h_n(\mathbf{x};\mathbf{w})^{\mathbb{1}(l\in\mathcal{L}_n^{left})}(1-h_n(\mathbf{x};\mathbf{w}))^{\mathbb{1}(l\in\mathcal{L}_n^{right})} \tag{2}$$

where $\mathbb{1}(\cdot)$ is an indicator function, $\mathcal{L}_n^{left}$ and $\mathcal{L}_n^{right}$ denote the sets of leaf nodes held by the subtrees rooted at the left and right children $left$, $right$ of node n, $h_n(\mathbf{x};\mathbf{w})$ indicates the probability that split node $n\in\mathcal{N}$ selects input feature $\mathbf{x}$ as its task-specific feature.

To enable the forest with the capability to be optimized end-to-end together with the shared root network, the differentiable split function is defined as $h_n(\mathbf{x};\mathbf{w}) = \sigma(f_{\varphi(n)}(\mathbf{x};\mathbf{w}))$, where $\sigma(\cdot)$ is the sigmoid function, $f_{\varphi(n)}(\mathbf{x};\mathbf{w})$ is outputs of the root network, adopted as the shared feature extraction function to end-to-end learn the expressive representation of fundus image. $\varphi(\cdot)$ is an index function to assign the connection between the output of function $f(\mathbf{x};\mathbf{w})$ and split node n. In this work, the index function $\varphi(\cdot)$ is a random function to link split nodes with the shared root network randomly.

OD segmentation branch. OD segmentation branch formulates OD segmentation task as the regression segmentation problem to learn the distribution of OD and OC (optic cup) region with DRF module. To improve the segmentation for OD quantification, we develop a novel distribution-aware segmentation loss to guide the DRF to capture the smoothness priors of the OD and OC region. The segmentation loss includes a dice coefficient loss $\mathbf{L}_{dice}$ measuring the overlap between the prediction and ground truth, and a distribution loss $\mathbf{L}_{dist}$ encouraging the predictive borders of OD and OC regions to be similar to the ground truth. Therefore, the distribution-aware segmentation loss is defined as

$$\mathbf{L}_{seg}(\mathbf{w},\mathbf{p}_{seg}) = \underbrace{1-\frac{2\sum_i p_i y_i}{\sum_i p_i^2+\sum_i y_i^2}}_{\mathbf{L}_{dice}} + \underbrace{\sum_c d_c log(s_c)}_{\mathbf{L}_{dist}} \tag{3}$$

where p and y denote the predicted probability map and ground truth, respectively. s and d denote the predicted and ground truth distribution of border pixels, and c is the length of the distribution.

Indices estimation branch. Indices estimation branch handles direct indices estimation task by learning a nonlinear mapping from shared feature to the OD quantitative indices with another DRF module. In this work, the discrete distribution concatenated with the normalized OD areas and diameters acts as the ground truth to train DMTFs together with OD segmentation labels. To enable the DRF module with the ability of nonlinear regression, the Kullback-Leibler (K-L) divergence is adopted to measure the similarity between predicted distribution $\mathbf{p}_{est}$ and ground truth $\mathbf{d}$. Therefore, the learning procedure is minimizing the following cross-entropy loss as $\mathbf{L}_{est}(\mathbf{w}, \mathbf{p}_{est}) = -\frac{1}{N}\sum \mathbf{d}log(\mathbf{p}_{est})$.

2.3 MultiTask Ensemble Module for Multi-Index OD Quantification

To learn the ensemble of two OD quantification tasks and model the consistency correlation between tasks, multitask ensemble module is developed, which contains a consistency loss function to impose the penalty for the consistent OD quantification between segmentation and estimation tasks, and a two-stage aggregation for final OD quantitative indices. Consistency loss is designed to minimize the prediction difference between two branches, i.e., OD segmentation and indices estimation tasks. Ideally, indices predicted by the two branches are the same. To ensure the indices from different branches as consistent as possible, the consistency loss is defined as the difference between the indices vectors $\mathbf{L}_{cons} = \frac{1}{2}(\mathbf{p}_{est} - \mathbf{p}_{seg})^2$, $\mathbf{p}_{est}$ and $\mathbf{p}_{seg}$ denote indices vectors coming from estimation branch and OD segmentation branch, respectively.

To integrate predictions from each leaf node of the two task branches, two-stage aggregation is adopted. 1) Intra-task aggregation: with the prediction on each leaf nodes of DRF, the task-specific quantitative indices are obtained by aggregating those leaf nodes predictions into a single coherent output followed ensemble learning as $\sum_{l\in\mathcal{L}} \mu_l(\mathbf{x}|\mathbf{w})\mathbf{p}^l$, where $\mu_l(\mathbf{x}|\mathbf{w})$ is the probability that feature $\mathbf{x}$ be selected by leaf node l and defined in Eq.2, $\mathbf{p}^l$ is the predicted indices vector on leaf node l. Note that $\mathbf{p}^l$ is measured based on the segmented mask when node l belongs to OD segmentation branch, while directly regressed when belongs to indices estimation branch. 2) Inter-task aggregation: with the prediction of each task-specific branch, the final quantitative indices are build based on the simple yet effective adaptive weighting method. DMTFs learns to average task weighting by considering the loss for each task, and the task weighting for segmentation and estimation tasks are defined as:

$$\lambda_{seg} = \frac{\exp(\mathbf{L}^t_{seg})}{\exp(\mathbf{L}^t_{seg}) + \exp(\mathbf{L}^t_{est})}, \quad \lambda_{est} = \frac{\exp(\mathbf{L}^t_{est})}{\exp(\mathbf{L}^t_{seg}) + \exp(\mathbf{L}^t_{est})} \tag{4}$$

where $\mathbf{L}^t_{seg}$ and $\mathbf{L}^t_{est}$ are the average loss from segmentation and estimation task branches in the t-th epoch over several iterations.

3 Experiments

The effectiveness of DMTFs is validated with the open accessible dataset ORIGA [3]. Experimental results show that DMTFs accurately quantifies optic disc with multiple types of 20 indices with average mean absolute error (MAE) of 0.99 ± 0.20, 0.73 ± 0.14, 1.23 ± 0.24 for diameters, whole areas and regional areas.

Datasets and Configurations The ORIGA contains 650 images (168 glaucomatous and 482 normal eyes) with manual labeled optic disc mask, divided into 325 training and 325 testing images. To leverage the powerful representation for the circle-shaped OD appearance, the input fundus images are pixel-wisely converted into the polar coordinate system. Pixels in optic disc region are re-sampled along the angular and radius dimension, therefore resulting in the regions of OC, OD, and background in the ordered layout.

The pyramid integration structure [16] is adopted as the shared root network for shared feature representation. We apply the alternating optimization strategy to obtain the optimistic parameters and prediction on leaf nodes.

Overall Performance Results (Table 1) demonstrate that DMTFs successfully delivers accurate multi-index OD quantification with average MAE of 0.99 ± 0.20, 0.73 ± 0.14, 1.23 ± 0.24 for diameters, whole areas and regional areas, respectively. Meanwhile, the results indicate DMTFs achieves more accurate multi-index OD quantification than other single-task-based approaches with the lowest average MAE 0.98 ± 0.19 over all the 20 quantitative indices. Experimental results on glaucoma diagnosis show that the quantitative indices provide more effective assessment tools (with 0.8623 AUC) for ophthalmic diseases diagnosis.

Effectiveness of MultiTask Ensemble Learning Indices shown in the third and fourth columns are independently obtained with only one task branch (OD segmentation or estimation). The results clearly indicate that multitask ensemble improves average 3.3%, 2.2% of 20 indices compared with the single segmentation and estimation task branch, respectively. Compared with the single task, DMTFs obtains the smallest bias overall indices and lowest average MAE overall 20 indices. The average MAE and bias show multitask ensemble learning framework brings clearly improvements for all the indices quantification.

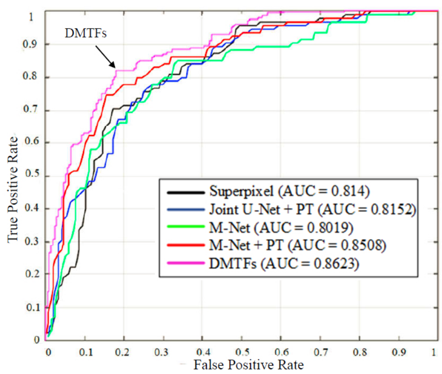

Fig. 3. The ROC curves with AUC scores for glaucoma diagnosis based on the quantitative multi-types indices for our DMTFs while only CDR for others. Source: Fu et al. [4] with our results added.

Comparison Results, compared with measured indices on the state-of-the-art segmented mask [4], show that DMTFs achieves the average improvement of 2.15% on 20 indices. Comparing column 2 and 5 of Table 1, it clearly shows DMTFs obtains more accurate multi-index OD quantification than single segmentation-based approach, which demonstrates the remarkable advantages in more detailed OD quantification.

Effectiveness of Glaucoma Diagnosis Fig.3 shows the success of the proposed DMTFs on glaucoma diagnosis based on the quantitative 20 indices. Evidenced by ROC curves and AUC value (0.8623), the glaucoma diagnosis results indicate that our multi-index OD quantification achieves a competitive performance using the 20 quantitative indices compared with the other methods only using the CDR value.

Table 1. Performance of DMTFs under different configurations and state-of-the-art method for multi-index OD quantification. Average Mean Absolute Error (MAE) is used for the quantification evaluation criterion.

Method	MNet [4]	DMTFs		
		Only Segmentation	Only Estimation	Ensemble
Diameter (10^2 pixel)				
Dia1	0.97±0.23	0.98±0.27	0.97±0.29	**0.96±0.21**
Dia2	1.09±0.28	1.08±0.21	1.05±0.25	**1.05±0.19**
Whole areas (10^4 pixel)				
WR	**0.32±0.09**	0.34±0.18	0.32±0.15	0.32±0.12
WD	1.67±0.16	1.68±0.15	1.65±0.20	**1.65±0.15**
Regional areas (10^4 pixel)				
RR1	0.74±0.21	0.74±0.25	0.75±0.23	**0.73±0.21**
RR2	0.39±0.13	0.35±0.12	0.34±0.13	**0.34±0.10**
RR3	0.11±0.08	0.12±0.12	0.12±0.10	**0.11±0.09**
RR4	**0.55±0.25**	0.57±0.33	0.55±0.32	0.55±0.29
RR5	0.70±0.31	**0.68±0.32**	0.68±0.34	0.69±0.21
RR6	0.30±0.15	0.30±0.23	0.31±0.14	**0.30±0.13**
RR7	0.15±0.26	0.14±0.32	0.15±0.25	**0.13±0.24**
RR8	0.26±0.17	0.27±0.31	0.25±0.22	**0.25±0.18**
DR1	1.28±0.19	1.29±0.14	**1.25±0.23**	1.26±0.12
DR2	**3.17±0.54**	3.21±0.57	3.29±0.53	3.21±0.46
DR3	3.80±0.38	3.79±0.42	3.78±0.39	**3.78±0.29**
DR4	3.32±0.36	3.30±0.24	3.29±0.22	**3.30±0.20**
DR5	**2.55±0.31**	2.64±0.41	2.57±0.23	2.57±0.18
DR6	1.77±0.29	1.76±0.27	1.77±0.32	**1.76±0.18**
DR7	0.68±0.24	0.66±0.23	**0.60±0.24**	0.61±0.17
DR8	0.09±0.08	0.08±0.19	0.06±0.06	**0.06±0.05**

4 Conclusion

In this paper, multitask ensemble learning framework (DMTFs) is proposed to achieve multi-index OD quantification for clinical assessment of ophthalmic disease. The DMTFs innovatively creates an ensemble of multiple OD quantification tasks (OD segmentation and indices estimation) and learns the ensemble with a multi-task learning framework by modeling the consistency correlation between the two tasks. Experimental results show that DMTFs is capable of achieving impressive performance for multi-index OD quantification. The proposed method has great potential in clinical ophthalmic disease diagnoses.

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