MULTI-MODAL LEARNING USING PHYSICIANS DIAGNOSTICS FOR OPTICAL COHERENCE TOMOGRAPHY CLASSIFICATION

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ABSTRACT

In this paper, we propose a framework that incorporates experts diagnostics and insights into the analysis of Optical Coherence Tomography (OCT) using multi-modal learning. To demonstrate the effectiveness of this approach, we create a medical diagnostic attribute dataset to improve disease classification using OCT. Although there have been successful attempts to deploy machine learning for disease classification in OCT, such methodologies lack the experts insights. We argue that injecting ophthalmological assessments as another supervision in a learning framework is of great importance for the machine learning process to perform accurate and interpretable classification. We demonstrate the proposed framework through comprehensive experiments that compare the effectiveness of combining diagnostic attribute features with latent visual representations and show that they surpass the state-of-the-art approach. Finally, we analyze the proposed dual-stream architecture and provide an insight that determines the components that contribute most to classification performance.

Index Terms— Multi-modal Learning, Diagnostic Attributes, Latent Representation, Autoencoder, OCT

1. INTRODUCTION

Optical coherence tomography (OCT) is a non-invasive imaging technique that provides high-resolution cross-sectional images of the retina. Eye care professionals use it to evaluate the health of the posterior segment of the eye and to detect signs of various vitreoretinal pathologies. The physician’s assessment when interpreting an ophthalmic image, provides valuable information that can be a source of knowledge to a model while training. However, current methods are not using this information. Existing approaches for OCT classification typically entail transfer learning with pretrained models [1, 2], as shown in Fig. 1. Though transfer learning often yields better performance than medical experts, very rarely does this transition from research to real clinical settings. This is because transfer learning models make decisions based on unrelated, non-medical, internal weights that are not directly optimised for OCT. This lack of medical intuition behind the decision-making process inspires a lack of trust from the medical community.

In this paper, we aim to mitigate these concerns by considering a physician’s assessment as another modality to incorporate with OCT for richer feature representations and improve retinal diagnosis performance. A modality, in this context, is an information channel such as OCT. A multi-modal machine learning problem uses information sourced from multiple communication channels to train models [3]. Existing multi-modal research with OCT combine it with other medical imaging technologies [4]. However, combining OCT with diagnostic information is largely unexplored. Diagnostic attributes are text-based and they characterize diseased OCT on patterns a physician would recognize. Combining OCT with diagnostic attributes adds medical context to a model from a multi-modal machine learning perspective. To the best of our knowledge, this is the first attempt to combine ophthalmic imagery with diagnostic attributes for OCT classification.

Fig. 1: High-level overview of proposed multi-modal learning framework using Physicians diagnostics as an attribute.
We highlight the difference between existing and proposed methods for OCT classification in Fig. 1. Our approach involves fusion of heterogeneous modalities trained from the outset with random weights. The challenge is to transform the data into a meaningful format for the model to join these modalities. Combining the uni-modal information into the same representation space with a dual-stream autoencoder accomplishes this. The dissimilar nature of data makes it challenging to optimally exploit any complementarity and redundancies present. Additionally, there is no closed-form relationship between each data type so the ideal mapping of the modalities may not exist [3]. However, multi-modal learning with diagnostic attributes adds robustness to the feature space as they are not susceptible to variations in image quality like OCT. Also, in practice, networks trained from random initialization improve generalization as they avert rote memorization and emphasize learning over time.

The diagnostic attributes dataset was acquired by mining a plethora of medical documentation describing attributes indicative of retinal pathologies. During data collection, each attribute noted was chronicled in multiple medical publications. These attributes allow integration of medical insight in the framework to improve OCT classification.

In this paper, we create a diagnostic attribute dataset consisting of features highly representative of three retinal pathologies. We also demonstrate how these attributes are created. We then propose to characterize these diseases among healthy ophthalmic images through use of this dataset along with OCT. We create a dual-stream architecture and compare it to other architectures trained without diagnostic attributes to show the generalizability of diagnostic attributes for pathology classification. More specifically, we fuse diagnostic attributes with spectral-domain OCT images in order to improve disease classification performance. The contributions of this paper are three fold:

i We create an ophthalmic imagery diagnostic attribute dataset with features indicative of three retinal pathologies.

ii We propose a dual-stream autoencoder to learn joint representations for diagnostic attributes and OCT.

iii We show that combining diagnostic attribute features with latent visual representations surpasses the state-of-the-art approach.

2. RELATED WORKS

Using multiple modalities for different vision tasks within the medical domain is not new. In the ophthalmological space, this traditionally entails combining modalities from different imaging techniques. For example, the authors of [5] utilized information jointly between fundus images and OCT scans in order to perform segmentation of the optic disc. More recently, work in [6] takes a retinal image along with a structure map and show that two modalities are better than one. Outside OCT, multiple modalities have also been used to improve classification tasks where representations of MR and PET scans were fused for Alzheimer’s diagnosis [7]. Neither of these utilize a doctor’s assessment as an additional modality to integrate more supervision in the learning framework.

Diagnostic text-based attributes allow an ophthalmologist’s assessment to be injected into the model’s learning. However, this research task is largely unexplored. A seldom example in [8] uses clinical textual notes as a method to improve diagnosis performance. However, notes contain irrelevant and possibly inaccurate information that require pre-processing. Text-based attributes from medical reports are most commonly used with images for multi-modal document retrieval tasks [9, 10]. The work in [11] presents an argument for merging medical modalities due to the incomplete picture that a single modality can represent about a patient’s condition. However, the methods they present fail to capture direct diagnostic attributes which may offer a complete representation.

Stacked autoencoders are unsupervised neural models that
have also been used to create feature representations for each modality and share them to learn joint a representation [12]. We use a dual-stream autoencoder to learn joint representations for diagnostic attributes and OCT. In the remaining sections of this paper, we explore how diagnostic attributes impact the the learning framework for retinal disease classification and how our autoencoder architecture improves classification.

3. MULTI-MODAL REPRESENTATIONS

Autoencoders are the core elements of our proposed multi-modal OCT classification. More specifically, we employ a dual-stream autoencoder, inspired by [12], that utilizes an encoder and decoder pair for both the visual and attribute input vectors as shown in Fig. 3. When OCT, \( x \), is given to the visual encoder, \( f_v \), it generates compressed latent features \( \hat{z}_{img} = f_v(x) \) that the visual decoder, \( g_v \), uses to reconstruct its output \( \hat{x} = g_v(\hat{z}_{img}) \). When diagnostic attributes, \( a \), are fed to the attribute encoder, \( f_a \), it too creates a compact latent variable \( \hat{z}_{att} = f_a(a) \) that the attribute decoder, \( g_a \), uses to reconstruct its output \( \hat{a} = g_a(\hat{z}_{att}) \).

The visual \( \{x_1, ..., x_M\} \) and attribute \( \{a_1, ..., a_M\} \) inputs have both been projected onto the same latent space and both latent representations are fed back into their own decoder in order to reconstruct their original representation. Minimizing the reconstruction error \( L_{\text{recon}} \) allows the reconstructed image and attributes to be less differing from their input. It is defined as:

\[
L_{\text{recon}} = ||x - \hat{x}||_2 + ||a - \hat{a}||_2
\]  

(1)

Second, these representations are then fed into the decoder of the other latent vector. In other words, the visual latent representation undergoes reconstruction in the attribute decoder and vice versa. The cross-reconstruction error, \( L_{\text{cross}} \), enforces the model to learn the association between OCT and diagnostic attributes by cross-reconstructing each modality accurately. It is calculated as follows:

\[
L_{\text{cross}} = ||x - \hat{x}_a||_2 + ||a - \hat{a}_x||_2
\]  

(2)

We also impose the latent loss, \( L_{\text{dist}} \), which is the cross entropy loss of \( l_2 \) distance between latent representations of OCT and its attribute. This loss enforces alignment between the OCT latent representation and its attribute. \( L_{\text{dist}} \) is calculated as follows with \( z^k_{att} \) being the latent variable for the \( k^{th} \) class attribute:

\[
L_{\text{dist}} = -\log \left( \frac{\exp(-||\hat{z}_{img} - z^k_{att}||_2)}{\sum_{k=1}^{4} \exp(-||\hat{z}_{img} - z^k_{att}||_2)} \right)
\]  

(3)

Training of the autoencoders is optimised by minimizing the following loss function that has scale factors \( \lambda_{\text{cross}} = 1 \) and \( \lambda_{\text{dist}} = 0.005 \):

\[
L = L_{\text{recon}} + \lambda_{\text{cross}} L_{\text{cross}} - \lambda_{\text{dist}} L_{\text{dist}}
\]  

(4)

Disease characterization is performed with a classifier that uses latent visual features \( \hat{z}_{img} \) to classify a total of four classes: healthy and three OCT patterns indicative of specific disease states. Its loss is weighted categorical cross entropy, \( L_{\text{class}} \). It is calculated as follows with \( \hat{y}_{[\text{class}]} \) being the classifier’s predicted output for the target class, \( y_{[\text{class}]} \) being its predicted output for the \( k^{th} \) class and \( w_{[\text{class}]} \) is the inverse frequency weight for the target class:

\[
L_{\text{class}} = w_{[\text{class}]} \left[ -\log \left( \frac{\exp(\hat{y}_{[\text{class}]}))}{\sum_{k=1}^{4} \exp(\hat{y}_{[k]})} \right) \right]
\]  

(5)

\[
w_{[\text{class}]} = \frac{\text{Number of images in largest class}}{\text{Number of images in class}}
\]  

(6)

4. ATTRIBUTE DATASET COLLECTION

The diagnostic attributes dataset is intended to improve the task of OCT classification. Therefore, all attributes considered were documented in multiple medical publications [13–16] as highly expressive of the three pathologies. For example, by OCT, drusen are visualized as uniform, typically dome-shaped hyporeflective collections beneath the retinal pigment epithelium (RPE). We identified 26 visual indicators used by physicians when making diagnoses based on review of OCT images. A subset of these are shown in Table 1.

The dataset consists of diagnostic attributes for four classes: healthy, drusen, choroidal neovascularization (CNV) and DME. Each class is associated with an attribute vector with a length equivalent to the number of attributes. For each position within the vector, a 1 represents the presence of that attribute and a 0 represented its absence. The attribute for healthy OCT had 0 for all disease attributes and 1 indicating healthy. These vectors were then associated with each image based on their class and used within the architecture described in Section 3.

| Pathology | Manifestation in OCT |
|-----------|----------------------|
| DME       | • Reduced intraretinal reflectivity  
|           | • Hard exudates        |
| CNV       | • RPE detachment       
|           | • Vitreous hemorrhage  |
| Drusen    | • Deposits underneath retina 
|           | • Bumpy surface       |

Table 1: A subset of the diagnostic attributes from each retinal disease.

5. EXPERIMENTS

To evaluate the effectiveness of diagnostic attributes for disease classification, we compare the proposed dual-stream autoencoder with two different models. First, we train a classifier directly on OCT as a baseline. The classifier contains two linear layers with relu activation, batch normalization and dropout between. For the second comparison model, we
### Table 2: Metrics comparing model performances.

| Metric           | Classifier | Single-Stream | Dual-Stream |
|------------------|------------|---------------|-------------|
| Average Precision| 0.513      | 0.664         | 0.703       |
| Average Recall   | 0.499      | 0.672         | 0.690       |
| Average F1 Score | 0.445      | 0.643         | 0.669       |

### Table 3: Impact of diagnostic attributes combined with existing pretrained Inception V3 state-of-the-art approach in [17].

| Metric          | Δ Performance |
|-----------------|---------------|
| Avg Precision   | +2.10%        |
| Avg Recall      | +0.85%        |
| Avg F1 Score    | +1.75%        |

### Table 4: Ablation study on regularization terms for the dual-stream model

| Ablation        | Recall  |
|-----------------|---------|
| No regularization| 0.665   |
| Dropout          | 0.675   |
| Batch normalization | 0.641  |
| Batch normalization and dropout | 0.690 |

### Fig. 4: Confusion matrices showing performance of the baseline (left) and dual-stream (right) classification models.

### 6. RESULTS AND DISCUSSION

We report average precision, recall and f1 scores. The positive impact of combining diagnostic attributes with the SOTA method [17] is illustrated in Table 3. The results of all other models are in Table 2. The classifier trained on visual features from the dual-stream autoencoder outperforms both baseline and single-stream models in all metrics. This means there is value in incorporating meaningful knowledge from a doctor’s view in incorporating meaningful knowledge from a doctor’s perspective.

### 7. CONCLUSION

In this paper, we propose a framework that integrates supervision from medical insights through multi-modal learning. We created a diagnostic attribute dataset to intermix the diagnostic knowledge from ophthalmologists into the machine learning framework. Our experiments validate the effectiveness of diagnostic attributes for OCT classification. In addition, we perform an ablation study to appreciate regularization terms that support learning descriptive joint representations for OCT and diagnostic attributes. Finally, we demonstrate that attributes combined with existing methods surpass SOTA. Encouraged by these results, we will further investigate learning methods to fully utilize diagnostic attributes for the characterization of pathologies.
8. ACKNOWLEDGMENTS
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9. COMPLIANCE WITH ETHICAL STANDARDS
This is a numerical simulation study for which no ethical approval was required.

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