

# Automated Macular Pathology Diagnosis in SD-OCT Scans Based on Multi-Scale Texture and Shape Features within a Pathology-Specific Spatial Mask

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## Abstract

**Purpose:** To extend an automated method to identify the presence of healthy macula and three macular pathologies (macular hole (MH), macular edema (ME), and age-related macular degeneration (AMD)) from fovea-centered cross sections in 3D SD-OCT images.

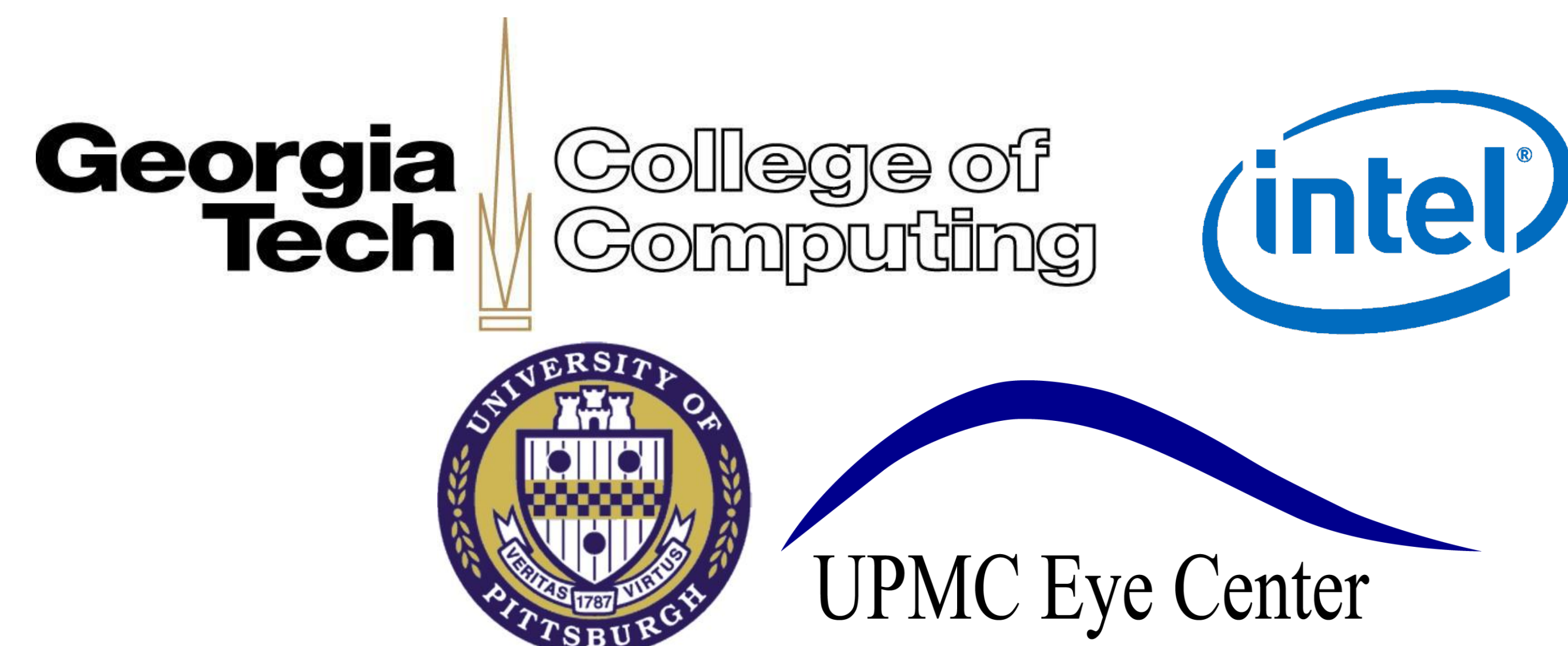
**Methods:** SD-OCT scans (Macular Cube 200x200 scan protocol; Cirrus HD-OCT; Carl Zeiss Meditec, Inc., Dublin, CA) were obtained on healthy eyes and eyes with MH and/or ME and/or AMD. For each fovea-centered frame, image characteristics within a pathology-specific mask were encoded using multi-scale texture and shape descriptors. This method augments our prior method in the use of shape features and spatial masks to capture the relevant retinal areas only. Three OCT experts labeled each fovea-centered frame independently and the majority opinion for each pathology was used as the ground truth. Machine learning algorithms were used to identify the most discriminative features automatically. Two-class Support Vector Machine classifiers were trained to identify each pathology separately using ten-fold cross validation.

**Results:** 326 SD-OCT scans from 136 subjects (193 eyes) were enrolled (65 healthy, 33 MH, 90 ME, and 26 AMD subjects). The area under the receiver operating characteristic curve (AUC) and best balanced accuracy were 0.980 and 95.7% for healthy macula, 0.935 and 87.9% for MH, 0.948 and 87.8% for ME, and 0.949 and 91.3% for AMD. It is found that the augmented method outperforms the original method in AUC by 0.011 for healthy macula, 0.135 for MH, 0.009 for ME, and 0.024 for AMD.

**Conclusions:** The proposed method successfully identified various macular pathologies (all AUC > 0.930). The added shape features and spatial masks enhanced the performance in all categories, particularly for MH.

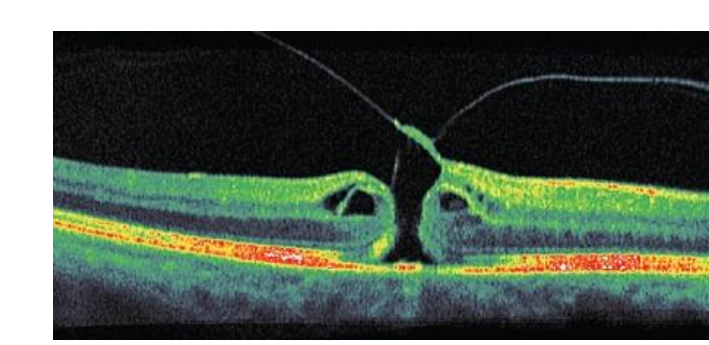
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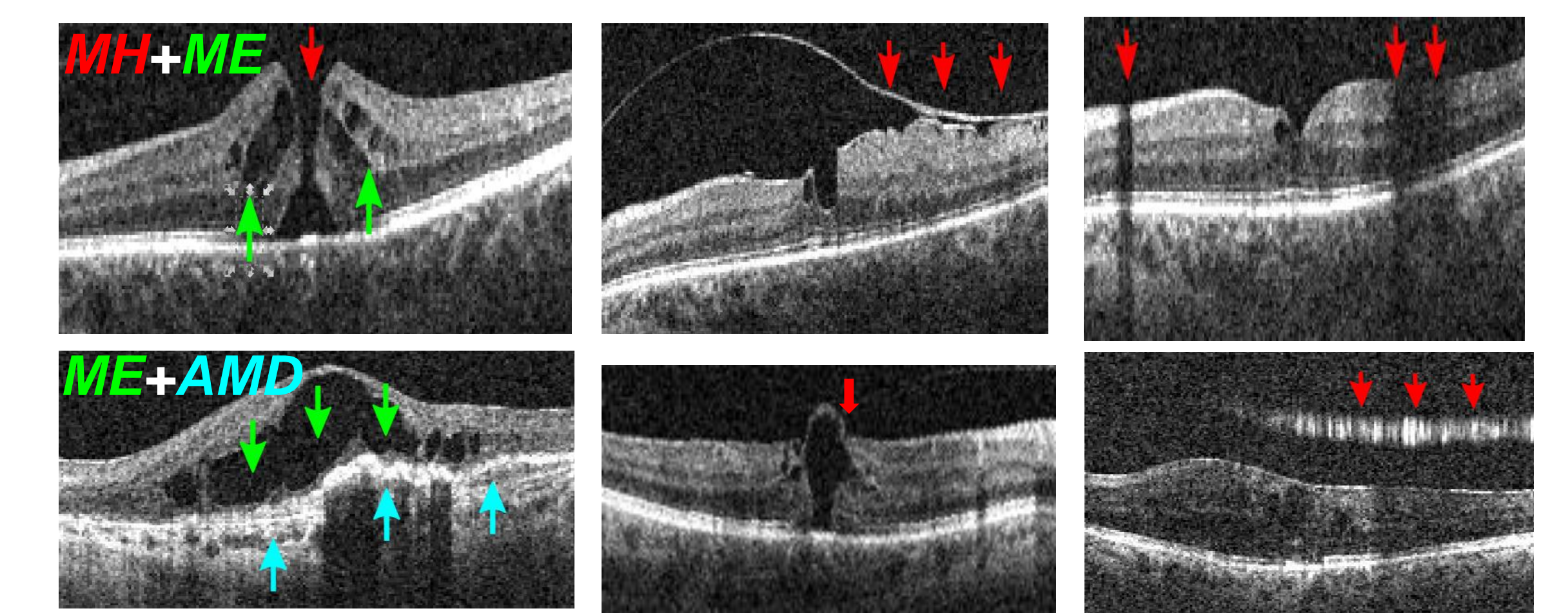
**Purpose :** develop a general slice-based approach for diagnosing every slice in the OCT volume

➤ **Focus on foveal slice diagnosis for this study: identify the presence of normal macula (NM) and three macular pathologies (MH, ME, AMD)**



Automated  
Diagnosis

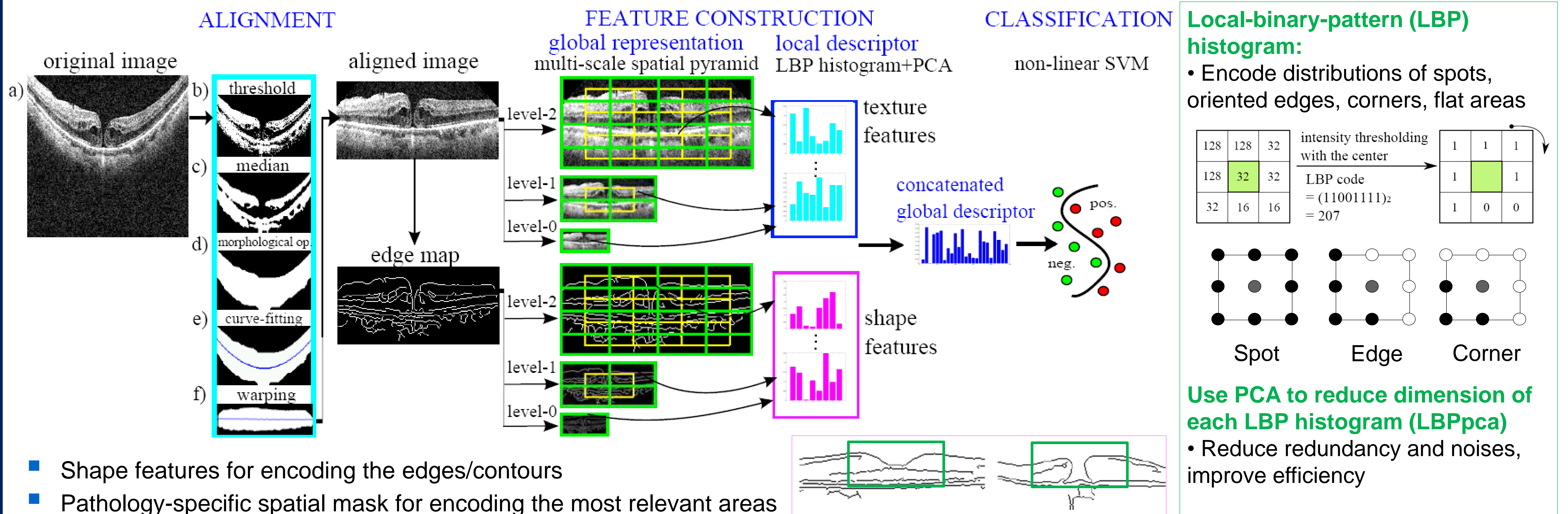
Normal macula (NM)? **NO**  
Macular hole (MH)? **YES**  
Macular edema (ME)? **YES**  
Age-related degeneration (AMD)? **NO**



➤ **Challenges in automated pathology identification**

- Multiple pathologies can co-exist, with proliferated/detached tissues
- Large appearance variations within each pathology
- Shadowing effects caused by blood vessels/opaque media

**Methods: spatially-distributed multi-scale texture and shape features with machine learning framework**



**Results: AUC > 0.930 for all three macular pathologies**

➤ **Experimental settings:**

- 326 OCT macular scans (Cirrus) from 136 subjects (193 eyes)
- Three ophthalmologists identified the pathologies from the foveal slice independently
- Complete agreement among operators is 96%, 91%, 80%, and 87% for NM, MH, ME, and AMD, respectively
- Majority opinion as ground truth

➤ **Results:**

- For ME, texture outperforms shape features (0.939 vs. 0.923)
- For MH, shape outperforms texture features (0.904 vs. 0.800)
- For NM and AMD, T+S performs the best (0.976, 0.938)
- Applying the spatial mask improves MH the most (+0.030)
- Horizontal central areas are most important for all categories

**Performance using different feature types:**

AUC	Texture (T)	Shape (S)	Texture+Shape (T+S)	Sig. Test
NM	0.969±0.002	0.971±0.002 (t=0.4)	<b>0.976±0.002</b> (t=0.4)	T < TS
MH	0.800±0.017	<b>0.904±0.006</b> (t=0.4)	0.892±0.011 (t=0.4)	T < S, T < TS
ME	<b>0.939±0.004</b>	0.923±0.005 (t=0.3)	<b>0.939±0.004</b> (t=0.4)	S < T, S < TS
AMD	0.925±0.008	0.931±0.005 (t=0.2)	<b>0.938±0.006</b> (t=0.2)	T ≈ S ≈ TS
Ave.	0.908±0.008	0.932±0.005	<b>0.936±0.006</b>	

**Performance with found best spatial masks:**

AUC	NM	MH	ME	AMD
All Area	0.976 ± 0.002	0.904 ± 0.006	0.939 ± 0.004	0.938 ± 0.006
Best Spatial Mask	<b>0.980 ± 0.002</b>	<b>0.935 ± 0.004</b>	<b>0.948 ± 0.003</b>	<b>0.949 ± 0.003</b>