

Classification of glaucomatous patients from normal subjects using the portable RETeval device and machine learning algorithms.

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1. Background-Aim

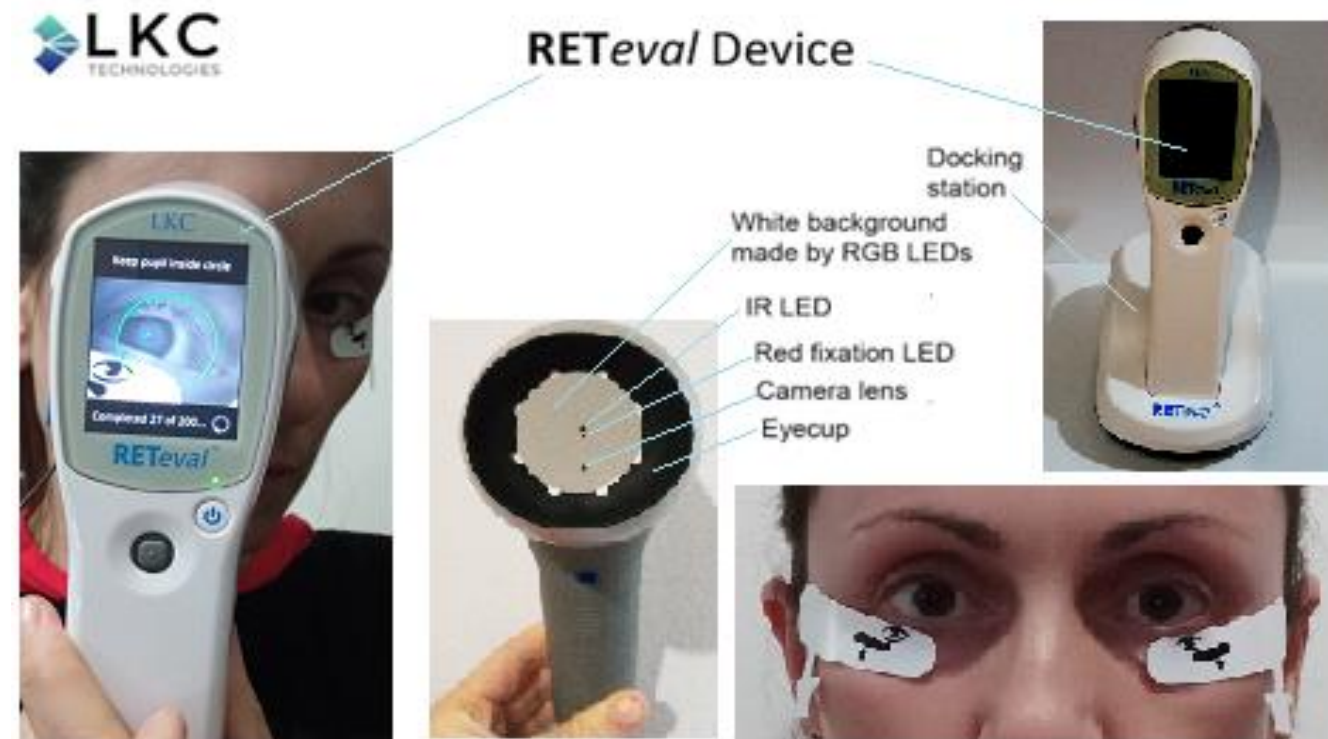
- Glaucoma is a progressive neuropathy that cause irreversible damage on the optic nerve, vision loss and blindness. Because of its asymptomatic characteristics, it is crucial to have early detection in order to manage and prevent the progression of the disease.
- In this study, we classify patients with glaucoma (case group) related to normal individual (control group) using Artificial Intelligence (AI) based on machine learning (ML) and deep learning techniques (DL). We apply computational algorithms that proceed various input data in order to have the final result which is the above classification.
- We examined 172 eyes at the Ophthalmology Clinic of the “Elpis” General Hospital of Athens between October 2022 and September 2023, using diagnostics systems in order to determine the characteristics of the disease.
- Also, there was glaucoma classification regarding
 - (a) eye selection and
 - (b) gender of the patient

2. Materials & Methods

Diagnostics Systems:

a) Portable Reteval Device (LKC Technologies Inc., Gaithersburg, MD, USA): offers **visual electroretinography (ERG) tests** which provide objective information on the function of the visual system. In this study we investigate the function of optic nerve which is composed by retinal ganglion cells (RGCs) and the measured parameter that is correlated with the function of RGCs is called **Photopic Negative Response (PhNr)**. It has been shown that glaucoma patients demonstrate pathologic photopic negative response (PhNR) values. The ERG data were measured with the RETeval device using self-adhering skin sensor strip electrodes.

b) Optical Coherence Tomography (OCT) imaging System: offers high-resolution, cross-sectional images and maps of optical nerve head (ONH), **retinal nerve fiber layer (RNFL)** thickness and macula. In Glaucoma it is essential to observe and detect even the smallest changes in the thickness of RNFL. In this study we measure RNFL thickness of the participants by using the Cirrus HD-OCT 4000 (Carl Zeiss Meditec Inc., Dublin, CA, USA).



2. Materials & Methods

Categories of participants (172 eyes)		
	Case Group	Control Group
All	73	78
OD- Right Eye	36	40
OS- Left Eye	37	38
Male	40	25
Female	33	53

Table 1: Categorization of participants.

Measured Parameters	
RETEVAL System	OCT System
(i) a-wave (amplitude (μV) & time response (ms))	RNFL thickness (μm)
(ii) b-wave (amplitude (μV) & time response (ms))	
(iii) the minimum PhNR- Pmin (amplitude (μV) & implicit time (ms),	
(iv) W-ratio	

Table 2: The parameters measured from the diagnostics systems.

Machine learning Classifiers
Bayesian,
Probabilistic Neural Network (PNN)
Support Vectors Machines (SVM)

Table 3: The different classifiers of the machine-learning approach.

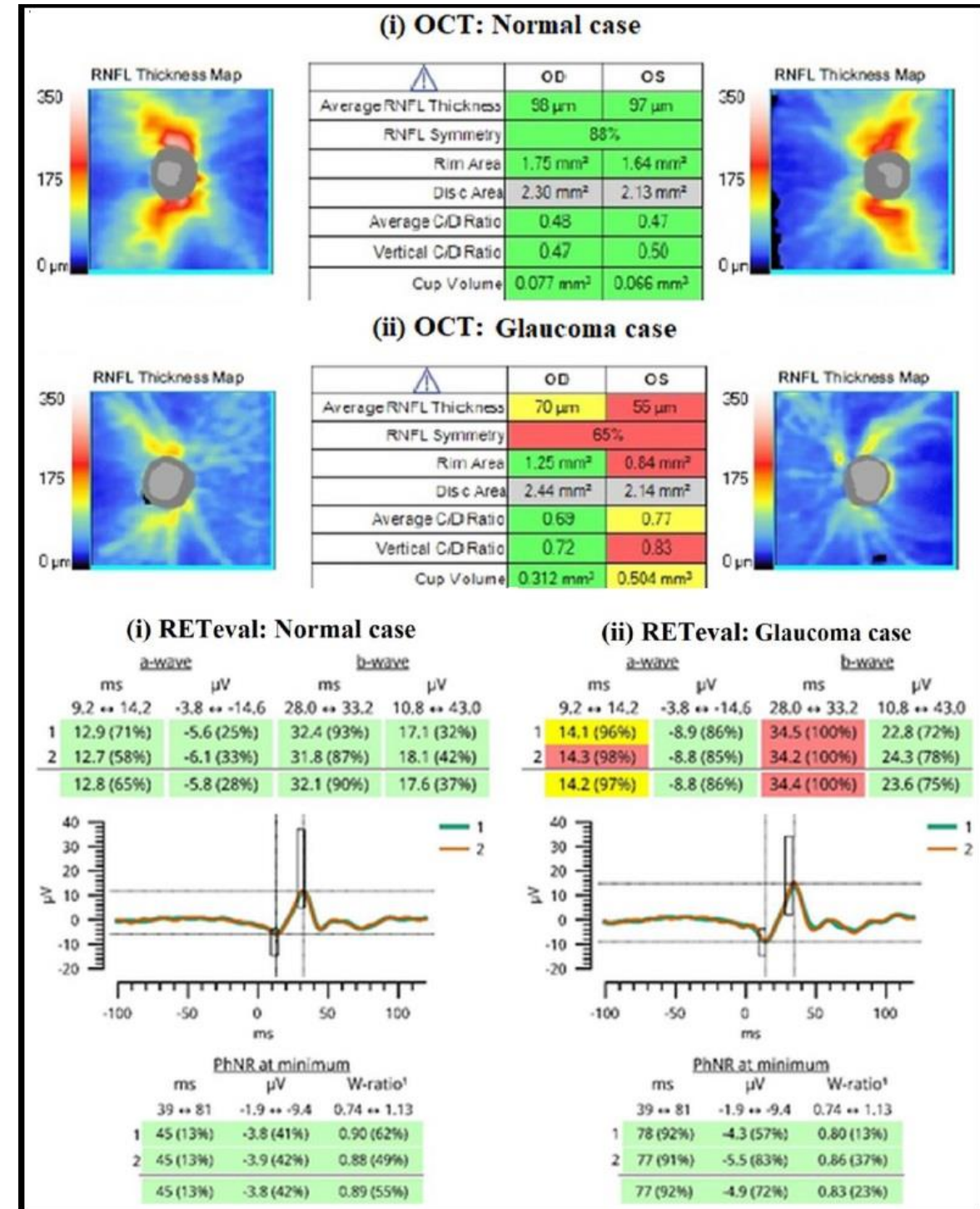
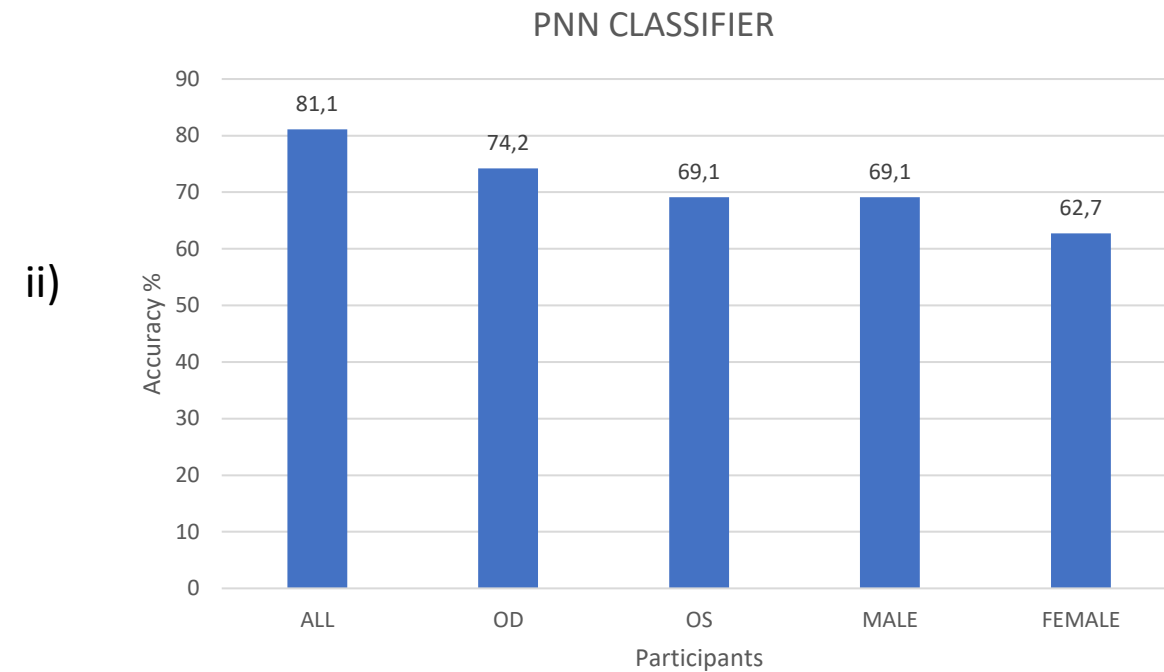
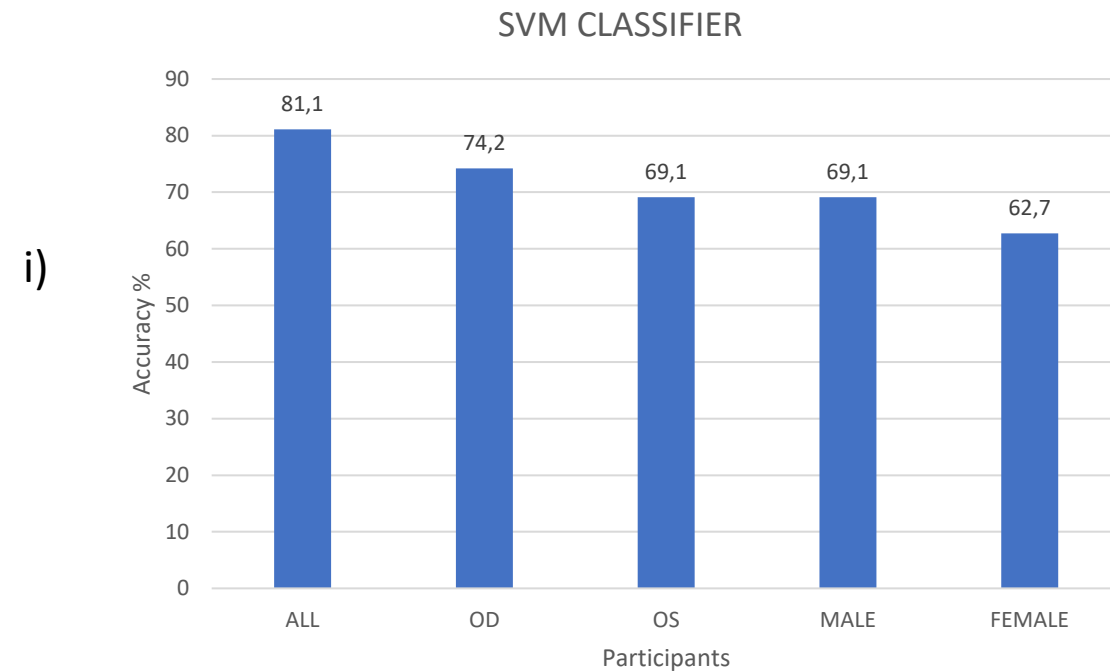


Figure 1: Examples from the diagnostics systems.

3. Results

First we apply the classifiers on the OCT data (RNFL thickness), in order to have the accuracy classification between control and case group as illustrated below.

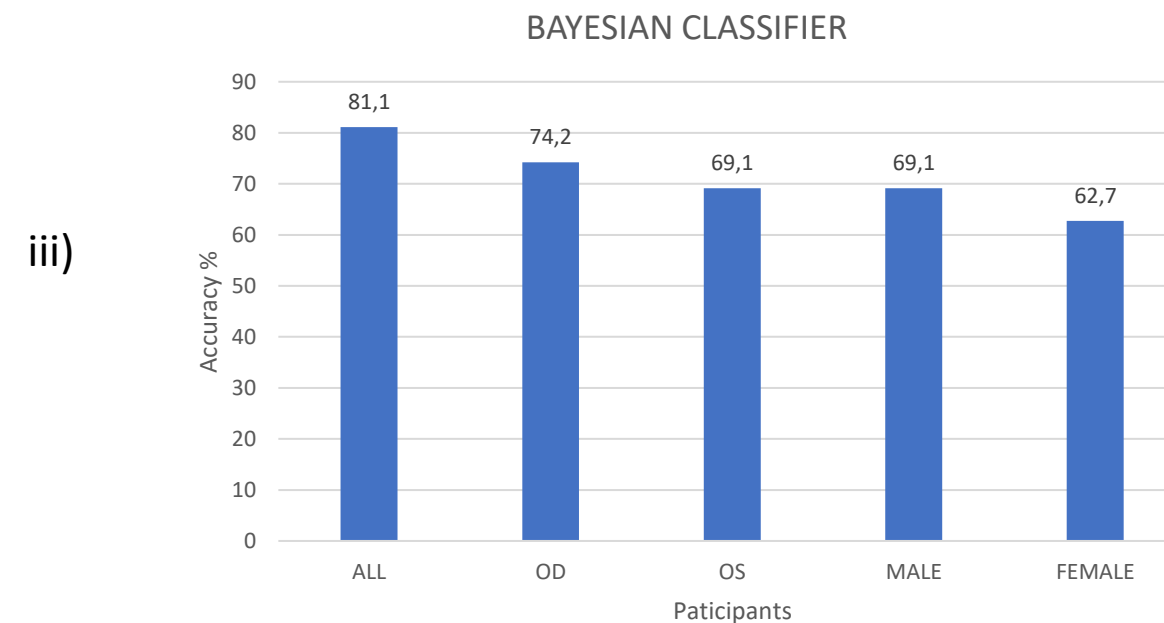


The classifiers on the OCT data (RNFL thickness):

i) SVM Classifier

ii) PNN Classifier

iii) BAYESIAN Classifier



3. Results

The classification accuracy based on the RETeval device data is shown. We test different combinations of the following parameters: (i) the a-wave amplitude (μV) and time response (ms), (ii) the b-wave amplitude (μV) and time response (ms), (iii) the minimum (Pmin) PhNR amplitude (μV) and implicit time (ms), and (iv) the W ratio.

Table 2: RETeval classification accuracy between the combination of 2 features

Classification Accuracy of RETEVAL data with 2 features			
Participants	SVM Classifier	PNN Classifier	BAYESIAN Classifier
All	91 %	91 %	84 %
Right Eye	97 %	87 %	94 %
Left Eye	93%	93 %	90 %
Male gender	96 %	91 %	96 %
Female gender	90 %	88 %	90 %

Table 3: RETeval classification accuracy between the combination of 3 features

Classification Accuracy of RETEVAL data with 3 features			
Participants	SVM Classifier	PNN Classifier	BAYESIAN Classifier
All	92 %	92 %	88 %
Right Eye	94 %	92 %	92 %
Left Eye	97 %	92 %	93 %
Male Gender	96 %	94 %	96 %
Female Gender	96 %	94 %	94 %

3. Results

Table 4: RETeval classification accuracy between the combination of 4 features.

Classification Accuracy of RETEVAL data with 4 features			
Participants	SVM Classifier	PNN Classifier	BAYESIAN Classifier
All	93 %	91 %	88 %
Right Eye	97 %	94 %	95 %
Left Eye	93 %	93 %	92 %
Male gender	93 %	94 %	93 %
Female gender	97 %	96 %	94 %

Table 5: RETeval classification accuracy between the combination of 5 features.

Classification Accuracy of RETEVAL data with 5 features			
Participants	SVM Classifier	PNN Classifier	BAYESIAN Classifier
All	92 %	91 %	87 %
Right Eye	95 %	87 %	94 %
Left Eye	95 %	92 %	93 %
Male gender	94 %	91 %	94 %
Female gender	96 %	94 %	96 %

Table 6: RETeval classification accuracy between the combination of 6 features.

Classification Accuracy of RETEVAL data with 6 features			
Participants	SVM Classifier	PNN Classifier	BAYESIAN Classifier
All	91 %	88 %	86 %
Right Eye	97 %	89 %	89 %
Left Eye	95 %	90 %	90 %
Male gender	91 %	89 %	93 %
Female gender	97 %	92 %	96 %

4. Conclusions

- Across all evaluations, we noted a significantly superior classification accuracy when utilizing the RETeval device compared to the OCT system.
- Specifically, the accuracy rates stood at approximately 15 % for all participants, 13.4% and 29.3% for eye selection (right and left, respectively), and 25.6% and 22.6% for gender (male and female, respectively).
- Our analysis revealed SVM as the most effective classifier, outperforming both PNN and Bayesian approaches.
- To sum up, our findings underscore the superiority of the RETeval device over OCT for glaucoma classification through machine learning techniques.

5. References

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