GLCA Detection of Macular Age Affiliated Degeneration Using Ensemble Tree Classification in OCT Images Scan

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Abstract. Age-related macular degeneration (AMD) detection in OCT images is done utilizing GLCA texture features, optimized through genetic algorithms, and classified with an ensemble tree model for precise detection. Constraints include the use of texture alone, parameter sensitivity, requirement of large datasets, vulnerability to OCT noise, and lower clinical interpretability. This research introduces new algorithmic methods for improving the quality of Optical Coherence Tomography (OCT) images for the identification of age-related macular degeneration (AMD). Integrated into an automated AMD detection system, the proposed techniques enhance the identification of abnormalities in OCT scans, enabling correct classification of healthy and diseased macular tissues. The method combines texture analysis, statistical evaluation, and genetic algorithms to find the best features. A genetic algorithm is employed to feature selection through finding the most representative attributes, using in-depth texture descriptors of the Gray Level Co-occurrence Array (GLCA) as well as statistical parameters. GLCA features are derived at four orientations (0°, 45°, 90°, and 135°), and an ensemble tree model created based on optimized feature set. The model shows extreme efficacy, having an error rate of 0% with chosen features, 2.0% with all features, and 7.0%without features. Entire system has 100% model development accuracy on all cases, and evaluation accuracy of 91.358%, 96.103%, and 100% for no features, all features, and selected features, respectively.

1 Introduction

Optical coherence tomography (OCT) is an extensively applied, non-invasive imaging method in ophthalmology. Its safety, low cost, and lack of undesirable effects make it widely available to a large population [1]. Through the assistance of inexpensive, nonradioactive optical contrast agents, OCT facilitates accurate, sensitive, and safe imaging of particular areas of the eye [2]. Further advantages are portability, low-cost equipment, and minimal maintenance needs. Since its development in 1991, OCT is now the gold standard for vitreoretinal examinations [3]. In 2020, approximately 196 million people were diagnosed with age-related macular degeneration (AMD), and this is expected to increase to 288 million by 2040, accounting for approximately 8.7% of the world's population [4]. OCT provides high-resolution cross-sectional images of the retinal layers, in which difference in compactness and unevenness act as important indicators for detecting conditions such as AMD, normal retinal structure identification, and detection of drusen deposits. Outside ophthalmology, OCT has been found to uncover biological markers for conditions such as diabetic retinopathy [5], eye pressure disorder [6], neurological disorder [7], and others, broadening its diagnostic uses [11]. AMD itself is divided into two broad categories: Atrophic AMD, which is characterized by the presence of retinal deposits, and Neovascular AMD, which is characterized by the growth of abnormal choroid-associated blood vessels.

1.1 Healthy

Fig. 1(a) shows an OCT image of a normal eye, pointing out the retina, optic nerve, and surrounding structures. This high-quality visualization is useful for providing insight into ocular structures and is also a valuable tool for assessing eye health and diagnosing any irregularities. These images assist doctors in detecting aberrations in normal anatomy so that early treatment of potential eye conditions can be initiated.

1.2 Atrophic AMD

Retinal deposits, also known as Dry AMD, are solid firm tissue deposits. They are characterized by small accumulations of fluid with clearly defined boundaries. Typically considered minimal-risk changes linked to getting older, drusen can vary in type. Fuzzy drusen, composed of undifferentiated deposits, are believed to be early indicators of AMD. The presence of drusen can contribute to either atrophic or neovascular forms of AMD. Risk assessment depends on factors such as the number, size, and merging of drusen. Fig. 1(b) illustrates drusen in color using SD-OCT imaging. When drusen are present, the Retinal Pigment Epithelium (RPE) and Bruch's membrane may show noticeable corrugations.

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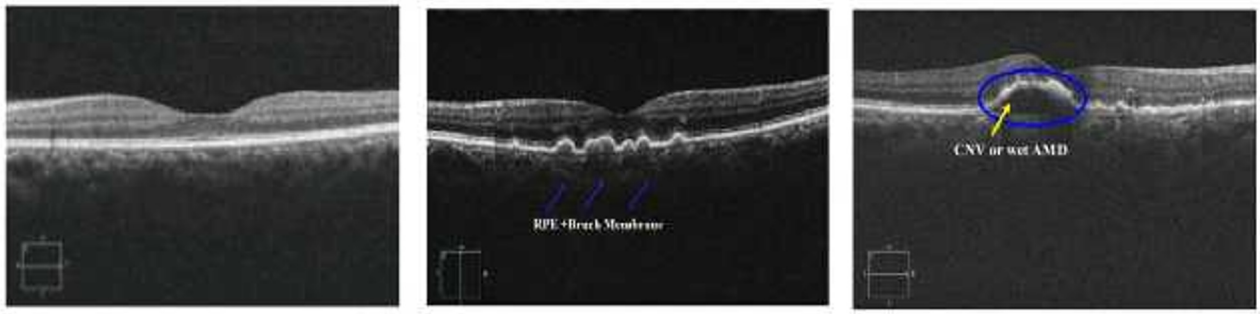

Fig. 1. Examples from the OCT image dataset displaying a series of scans for Fig(a) healthy, Fig(b) atrophic, Fig(c) neovascuar AMD.

1.3 Neovascular AMD

Neovascular AMD, also referred to as choroidal neovascularization (CNV), is characterized by the abnormal development of blood vessels from the choroid. These vessels invade the Bruch's membrane, the thin barrier between the choroid and the RPE. They grow in the subretinal space, between the RPE and the neurosensory retina. CNV tends to cause sudden and severe vision impairment in AMD patients. About 11% of AMD patients develop the wet or neovascular type.
Ultra transparent, layer-view retinal and choroidal imaging with non-invasive optical coherence tomography (OCT) can identify CNV. Fig. 1(c) displays the pathological blood vessels typical of wet AMD. This paper suggests a new approach to the early detection of AMD by integrating OCT imaging with Gray Level Co-occurrence Array (GLCA) analysis, feature selection through Genetic Algorithms (GA), and classification through an Ensemble Tree (ET) algorithm.

Major highlights of this work encompasses: 1 The GLCA analyzes OCT data to find important features related to the initial stages of AMD, 2 Genetic algorithms (GA) are used for selecting the vital extracted features from GLCA for the recognition of AMD, making the system concentrate on the important elements to identify correctly, 3 An Ensemble Tree (ET) algorithm accurately identifies AMD and non-AMD OCT scans, with its combined learning style improving both the accuracy and reliability of the evaluation, 4 Systematic combining of GLCA, GA, and ET methods significantly improves the initial detection of AMD, allowing for faster treatment initiation, and 5 The framework also allows for instant AMD evaluation in clinical settings, giving eye specialists a fast and reliable tool for detecting the disease.

For people aged 50 and older, age-related macular degeneration (AMD) is one of the major causes of vision loss. It accounts for approximately 5.5% of blindness cases worldwide, thus placing it as the third most frequent cause of blindness. Typical manifestations of AMD are drusen, reticular drusen, choroidal neovascularization (CNV), and geographic atrophy.

Given that the disorder is progressive and irreversible, vision loss takes place permanently. Abnormal growth of blood vessels in neovascular AMD is responsible for visual damage, while atrophy AMD—more prevalent—results in degeneration of photoreceptor cells. Both the two types of AMD, exudative (wet) and atrophy (dry), are associated with risk factors including aging, heredity, tobacco use, and poor dietary habits. Redox imbalance also contributes to retinal cell damage, though its role is not yet thoroughly comprehended. In spite of the differences, AMD shares common risk factors and disease pathways. With the evolution in eye scanning, precise diagnosis and effective treatment are made feasible [8]. Artificial intelligence methods are revolutionizing eye care by quickly and precisely interpreting eye scans, enabling early-stage condition detection and decreasing diagnosis costs. They reduce human errors, increase the availability of sophisticated eye care in rural regions, and help investigators in understanding the progress of condition. Substantial breakthroughs in these smart systems have immensely enhanced diagnosis and treatment of eye conditions, radically revolutionizing care of the eyes. Further, adaptive equipment fosters independence for individuals with special needs, highlighting the need for further innovation and advancement [9]. Use of OCT and retinal imaging is of great importance in the detection of optic disfunction using artificial intelligence (AI) and biomedical imaging.OCT gives extremely clear planar images of the retina, facilitating detection and tracking without resorting to surgery. Preprocessing operations like visual enhancement, scaling, and denoise are performed to boost data integrity. Attribute extraction is based on statistical and textural features, whereas expert annotation helps ophthalmologists detect abnormalities. OCT images, especially, prove extremely useful for detecting eye-related afflictions.

In the current study, ML is utilized to create a two-class classification system in ophthalmology that separates normal cases from cases of AMD. The methodology utilizes the GLCA feature extraction method and a genetic algorithm for choosing optimal features. These processes deal with issues related to the complexity and high dimensionality of retinal images, as well as the heavy numerical burden of deep learning models. GLCA assists in the extraction of high-texture details of retinal images by quantifying parameters including uniformity, energy, correlations, and contrast necessary in distinguishing normal and AMD conditions. Following the extraction of features, the genetic algorithm diminishes the dimensionality by leaving behind the most critical features, thus making the system more efficient and perfect for real-time operation, remote medical care, and low-end environments.

The refined features are then used to train an Ensemble Tree classifier, chosen for its robustness,

ability to avoid overfitting, and adaptability to variations in retinal data. This combined strategy-GLCA for feature extraction, genetic algorithm for attribute selection, and Ensemble Tree for classification-allows for precise discrimination of normal and AMD retinal images. In addition to speeding up the diagnostic process, the method also provides the potential for interventions earlier on, which can improve patient outcomes in eye care.

2 Literature Survey

Identifying AMD in OCT scans is vital in eye care. Various research has utilized artificial intelligence methods and scan analysis to support this identification, such as the research by El-Khalek et al [10]. Saleh et al presented a new key attribute extraction approach employing ocular images for optic neuropathy categorization with extracted 3D OCT attributes. Determining the most important attributes is critical for precise ocular condition identification [13]. Additionally, emphasis is placed on medical Gholami et al. (2020) present a comprehensive open-source image repository containing over 500 high-quality OCT images categorized into various medical conditions, including AMD, healthy, macular tear, diabetic retinal disorder, and central serous chorioretinopathy. Their research focused on a subset of this repository, analysing 204 OCT images from healthy individuals and 57 images exhibiting AMD-related features. Despite the unequal distribution of healthy and AMD cases, this repository enables a detailed investigation of OCT characteristics associated with both healthy eyes and AMD intelligence for the early detection of diseases, including age-related macular degeneration (AMD), as discussed by Tamim et al [14]. Genetic optimization algorithms have been effectively used for detecting diabetic retinopathy and eye pressure disorder, illustrating the value of characteristics collection and identification of disorder classification. For AMD detection in OCT scans, GLCA based descriptors along with evolutionary algorithm driven search an Ensemble Tree classifier have shown promising results. A similar approach was applied by Dildar et al.[15] for detecting skin cancer. This method was applied for dermal malignancy detection. Additionally, Umer et al. conducted a comprehensive review of deep learning techniques for diagnosing retinal disorders, including AMD. Shaukat et al conducted research [12] deep neural networks have been used for attribute derivation and screening, while advanced techniques such as PCA help in separating and segmenting diabetic eye disorder. Modern research employs machine learning techniques, such as CNN and SVM, to identify clinical conditions and classify various diseases through analysis of clinical images and biomedical information. The techniques improve accuracy by using effective feature selection and data compression. Ophthalmic AI research solves issues such as hybrid imaging, expandability, heterogeneity, model interpretability, time-dynamic patterns, individualized framework, cross-population evolution, and smooth clinical implementation. This method uniquely merges GLCA for processing OCT images, GA to select the best features, and ET to classify, creating a quick and accurate system that can detect early AMD in real-time clinical applications. Using machine learning and image processing, it improves diagnostic efficiency and accuracy, which benefits both healthcare providers and patients.

3 Proposed Methodology

This section offers an extensive description of the resources and procedures applied in constructing an ensemble tree model for genetic algorithms and AMD diagnosis. The method applied in this study is described in the "Variable Selection" section. The model begins with the obtaining of OCT images, which are then processed using image enhancement methods as shown in Fig. 2. Afterwards, the GLCA method is used to obtain texture descriptors from these images. The dataset is split, with 80% used for model development and the remaining 20% for evaluation. A genetic algorithm is next utilized for variable selection to make the model more efficient. With these optimized variables, an Ensemble Tree classifier is created and optimized to support in the detection of eye-related disorders. The efficacy of the system is then evaluated on the evaluation set. This combined process fortifies diagnostic pipelines utilizing image enhancement, descriptor extraction, and sophisticated machine learning techniques.

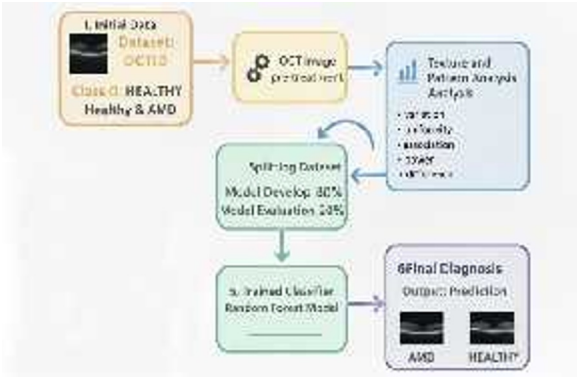

Fig. 2. Developed approach

3.1 Data Collection

Gholami et al provide a well-rounded open-source image database consisting of more than 550 high-resolution OCT scans grouped into different medical conditions, such as AMD, healthy, macular tear, diabetic retinal disorder, and central serous chorioretinopathy. They worked on a subset of this database, examining 204 OCT images of healthy subjects and 57 images showing AMD-related characteristics. Although the numbers of healthy and AMD patients, this archive allows for in-depth examination of OCT features seen in healthy eyes and AMD. Collection of data, development, and evaluation of models for healthy and AMD OCT scans are represented in Table 1.

Table 1. OCT scan Dataset for Training and Validation data

Category	Number	Training data	Validation data
Healthy	216	170	46
Age-related Macular Degeneration	60	50	10
Overall	276	220	56

3.2 Characteristic identification

This paper examines speckle, a phenomenon that happens when reflected waves of varying phases interfere with one another, giving rise to alternating low-intensity and bright areas. These speckle patterns have textural properties, which serve to enhance visual features in images. The purpose of this paper is to extract different features from grayscale OCT images based on texture analysis. Intensity Profile Lines (IPLs) OCT images are used to measure textural attributes like uniformity, orientation, pattern consistency, and homogeneity.

3.3 Variable Extraction

3.3.1 GLCA

Gray-Level Co-occurrence Array (GLCA) is a powerful Technique for interpreting visual data in fine detail and for deriving relational information. This method produces an array that describes how frequently pairs of image points of specified intensity degrees are found together, taking into account the angle and relative positions. The building of this array primarily relies on two parameters : the distance between image points (d) and the angle-dependent direction (ψ), generally expressed in degrees. Texture description is finalized with four typical angles 0°, 45°, 90°, and 135°. GLCA analysis provides five major pattern features : Difference (M) given in Equation (1), as a measure of the mean gray-level differences between neighboring visual points, also aids in the characterization of patterns. These pattern informations are extensively applied to diverse visual data processing and interpretation operations. Attribute derivation in the OCTID case begins with visual point resizing and standardization. Through the use of the GLCA to extract features and estimate a probability model, the best-fit parameters can be established. Variation (N) in Equation (2) , which measures the immediate relations between visual point values ; Uniformity (Hom) in Equation (3), which determines the closeness of array entries clustering ; Power (W_{ASM}) given in Equation (4) ,measure indicates the uniformity of visual point pair appearances by summing the squared values of the GLCA entries and Association (ρ) in Equation (5), which measures gray-level variations. The GLCA numerically represents visual point position relationships in visual analysis, tracking pairs of visual point gray-level values at particular angles and offsets to enable texture segmentation and pattern classification. The method allows for the derivation of features like uniformity measure, intensity variation, uniformity, and association.

The GLCA technique is utilized to extract pattern attributes and positional relations from images. These calculations depend only on the intensities stored within the GLCA. Take (a, b) to be an image of size $Z_a \times Z_b$ with each pixel having Z gray-level intensities. The direction of the positional displacement is indicated by c. The GLCA function, P (k, l), is the number of occurrences of visual point l relative to visual point k at displacement c, with k and l ranging from 1 to Z. The displacement c can be defined in terms of either orientation or spacing.

$$\text{Difference } (M) = \sum_{k=0}^{Q} \sum_{l=0}^{Q} P(k,l)|k-l| \quad (1)$$

$$\text{Variation } (N) = \sum_{k=0}^{Q} \sum_{l=0}^{Q} P(k,l)(k-l)^2 \quad (2)$$

$$\text{Uniformity } (Hom) = \sum_{k=0}^{Q} \sum_{l=0}^{Q} \frac{P(k,l)}{1+|k-l|} \quad (3)$$

$$\text{Power } (W_{ASM}) = \sum_{k=0}^{Q} \sum_{l=0}^{Q} P(k,l)^2 \quad (4)$$

$$\text{Association } (\rho) = \sum_{k=0}^{Q} \sum_{l=0}^{Q} \frac{P(k,l)(k-\mu)(l-\mu)}{\sigma^2} \quad (5)$$

3.3.2 Attribute screening

In attribute screening, the steady state evolutionary strategy is known to effectively shield optimal feature sets from generation to generation. It does not modify the whole population as in classical GA but instead modifies only the chosen individuals per generation, keeping the optimal combinations intact. Using an ensemble tree classifier for fitness evaluation, the technique chooses the most effective feature sets for AMD diagnosis. This strategy at the same time retains valuable information and examines a range of feature subsets and thus enhances diagnostic accuracy in OCT visual assessment. The GA optimizes model performance by searching for optimal feature subsets in the fitness evaluation, crossover, mutation, and competitive selection. Fitness values ranged from 660.25 to 744.09 for different rates of mutation variability. The features finally selected were association_0, uniformity_0, gray-level difference_0, power_135, and variation_0, identifying 5 primary textural characteristics at certain angles to aid effective AMD detection.

3.3.3 Evoluationary algorithm

The evolutionary algorithm (GA) is utilized for attribute selection in biomedical image classification to systematically find chosen feature subsets that improve detecting accuracy. It begins with the optimal fitness analysis, followed by the effectiveness of feature vectors being measured carefully with the use of classifier evaluation criteria. Genetic Algorithm eventually fine-tunes these feature vectors by removing weaker ones after repeated iterations involving recombination, selection, and mutation. candidates and encouraging the formation of unique, high-quality offspring. This adaptive procedure finally generates a high-fitness feature subset, i.e., specially designed for biomedical image classification purposes. With the combination of Genetic Algorithm and sophisticated image processing methods, this technique obtains high accuracy in biomedical visual detections.

The steps here show how a genetic algorithm may be used for feature extraction with an ensemble tree predictor. 1 Create an initial population [P] of randomized input vectors, 2 Evaluate the fitness of each feature vector in [P] against an ensemble tree predictive model, 3 Iterate until the stopping criterion is reached, Select parent candidate vectors according to their fitness scores, 4 Do crossover to generate progeny attribute vectors, 5 Introduce mutations to ensure

diversity among the offspring, 6 Evaluate the offspring feature vectors based on fitness, 7 Choose the fittest individuals to survive, replacing the worst-performing in [P], 8 Identify the feature vector with the highest fitness rate in the previous generation as the best feature set, and 9 Output the best feature set.

3.3.4 Ensemble Tree Classifier

The ensemble tree classifier was utilized because it is effective in the detection of AMD in OCT scans, as evidenced by previous research. Other algorithms, like AdaBoost, Decision tree, and SVM, were additionally examined and compared according to assessment measures, such as correctness, specificity, and sensitivity. The model based on trees uses an ensemble of decision trees for accurate classification and thus is appropriate for optical coherence tomography scans. In diagnosing AMD, it accurately captures complex features and relationships, learning from labeled data and testing performance. Feature vectors are optimized through evolutionary operations to discover an optimal subset, improving the accuracy and efficiency of AMD detection.

4 Result and Discussion

4.1 Methodology

This study employed a three-step procedure to categorize OCT images. An Ensemble Tree classifier was first run on the OCT images without feature selection. Subsequently, Gray-Level Co-Occurrence Array (GLCA) was employed to measure the texture information from images, and again an Ensemble Tree classifier was employed on this data without feature selection. Lastly, the genetic algorithm was utilized to find the optimal subset of features, with the performance of each case determined by its F1-score. The outcomes of these experiments show the efficiency of applying feature selection in OCT classification.

4.2 OCT based diagnosis

This part describes the implementation of an Ensemble Tree (ET) classifier in three different scenarios: without any characteristic's selection, with all the characteristics. with a limited number of characteristics selected by a genetic algorithm.

4.2.1 Without characteristic using Ensemble tree

The ensemble tree categorizer was first experimented upon with OCT scans without features. The approach fully classified model development data, but its accuracy fell to approximately 92.5% on unseen, fresh data. Although there was a minimal error rate of approximately 7.5%, the model still performed well on the whole, with a high Area Under the Curve (AUC). The F1-scores for AMD and HEALTHY classifications were 0.80, and 0.95 respectively, with a total precision of 92%.

4.2.2 With all characteristics using Ensemble tree

Then, the Ensemble tree categorizer was trained on all characteristics, including the ones extracted with the Gray-Level Co-occurrence Array (GLCA). This gave a much better performance, with the model having a model development accuracy of 100% and an evaluation accuracy of 98.13%. The AUC was also extremely high at 0.98, which suggests good diagnostic ability for AMD. The F1-scores were 0.96 for AMD and 0.99 for HEALTHY, giving a great overall 99% accuracy on Table 2.

Table 2. Comparison of ECT performance using With all characteristics and Without any characteristics

Metrics	With all characteristics	Without any characteristics
Training Accuracy	1.0	1.0
Testing Accuracy	0.98113	0.92458
Error	0.01886	0.075472
AUC	0.98	0.97
Avg. Precision	1.0	0.99
AMD Precision	1.0	1.0
AMD Recall	0.92	0.67
AMD F1-score	0.96	0.87
Healthy Precision	0.98	0.91
Healthy Recall	1.0	1.0
Healthy F1-score	0.99	0.95
Overall Accuracy	0.99	0.92

4.2.3 Specific characteristics

Lastly, a genetic algorithm was employed in the selection of the most significant features. This technique was implemented with the purpose of optimizing the model and avoiding overlearning. This strategy turned out to be the best, as an Ensemble Tree classifier scored a perfect 100% on both the model formation and test data. This equated to a zero error rate and a perfect AUC score of 1.0. The F1-scores for both AMD and HEALTHY classes were also 1.0, proving that the model correctly classified and identified all cases. This proves that employing a genetic algorithm features significantly enhances the model's performance and generalization on Table 3.

Table 3. Evaluation summary of the ETC model for OCTID categorization with GA-optimized With all characteristics.

Parameters	AMD	Healthy
Precision	1.0	1.0
Recall	1.0	1.0
F1-score	1.0	1.0
Accuracy	1.0	1.0

4.2.4 Discussion

Ensemble Tree (ET) classifier for OCT-based diagnosis was evaluated under three scenarios : without characteristics, with all characteristics, and with specific genetic algorithm selected characteristics Fig. 3-4 . Without any characteristics, the model achieved a model development accuracy of 100% and a evaluation accuracy of 92.45%, with an error rate of 0.075472, an AUC of 0.97, and an AMD F1-score of 0.80. When trained with all characteristics, including GLCA features, the model's performance improved significantly, achieving a perfect training accuracy of 100% and a testing accuracy of 98.13%, with a much lower error rate of 0.01886, an AUC of 0.98, and an AMD F1-score of 0.96 on Table 2. Finally, when a genetic algorithm was employed to optimize feature selection, the model reached flawless results,obtaining 100% precision,

recall, F1-score, and accuracy for both AMD and HEALTHY classifications, alongside a perfect AUC of 1.0. These findings confirm that GA-based feature optimization greatly enhances the model's execution and generalization on Table 3.

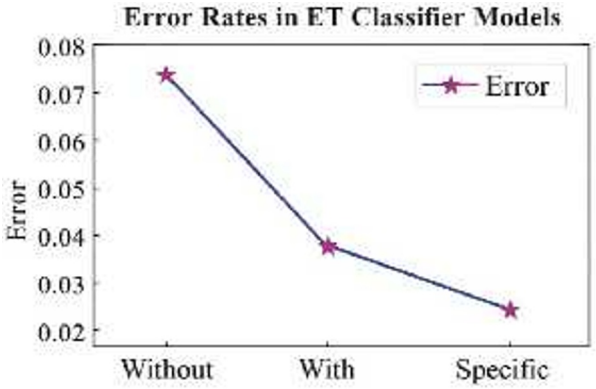

Fig. 3. ET Classifier error rate for AMD Diagnosis with without,with, and specific features.

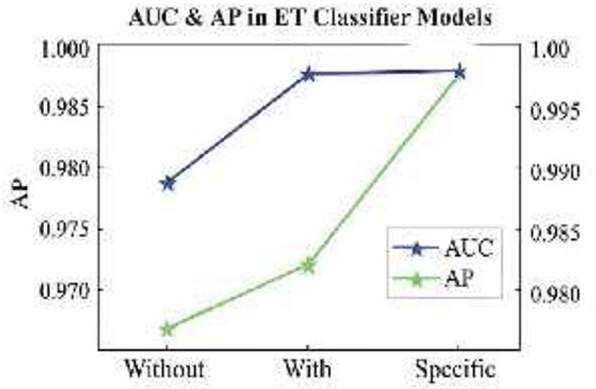

Fig. 4. ET Classifier error rate for AMD Diagnosis with without, with, specific features.

5 Conclusion

In particular, the extracted variables get perfect correctness, specificity, sensitivity, and F-measure rates of 1.0. With appropriately defined parameters, tree-based ensemble shows high efficiency and reliability in detecting OCTID cases. In total, the results highlight the pivotal role played by sophisticated variable engineering and extraction techniques in creating accurate and reliable predictive modeling systems for clinical evaluation applications such as OCTID detection.

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