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# Optimization of cataract IOL computational model parameters and enhancement of tele-diagnosis based on integrated learning approach

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**Abstract** Integrated learning methods have been developed so far, and there are still great challenges in automatic cataract detection and computation tasks. In order to solve the problem of low accuracy and sensitivity of cataract grading diagnosis, this paper proposes an improved integrated learning method, EasyEnsemble, for IOL calculation and cataract diagnosis by improving the Adaboost algorithm with selected generations on the basis of undersampling. The cataract ultrasound dataset is selected and compared and analyzed with other methods, and the results show that the AUC, ACC, TPR, and TNR of this paper's method are around 0.9, and its accuracy and sensitivity are much higher than that of other existing methods. And the experimental results based on the eye ultrasound image dataset show that the method integrated in this paper can adaptively focus on the abnormal region in the eye where cataract lesions occur, with better feature selection, and can more accurately characterize the cortical cataract.

**Index Terms** adaboost algorithm, integrated learning, cataract, EasyEnsemble, IOL computation

## 1. Introduction

With the increasing age of the world's population, diseases that damage visual function, mainly cataract, have become a major cause of blindness, and at the end of the last century, cataract was an important global problem that did not receive enough attention [1], [2]. Cataract is an ocular disease in which the cornea or lens of the eye becomes cloudy, resulting in poor vision. There are many causes of cataract, including gender, age, heredity, environmental factors, nutritional factors, and ocular diseases, and women are more likely to develop cataract than men. The prevalence of cataract increases gradually with age, especially in people over 40 years of age, where the prevalence of cataract is high [3]-[6].

With increasing age, the proteins in the lens will degenerate and coagulate, causing the lens to become cloudy, which in turn affects the propagation and scattering of light, making the patient's vision blurred, night vision decreased, glare increased and other symptoms, seriously affecting the patient's daily life and work [7]. Cataract surgery is one of the effective methods to treat cataract, which involves removing the cloudy lens and implanting an artificial lens (IOL) to restore the patient's vision [8]. Before the surgery, the surgeon needs to perform a series of examinations on the patient, including IOP measurement, fundus examination, corneal curvature measurement, etc., to determine the exact method of the surgery and the choice of IOL. IOL calculation, on the other hand, refers to the selection of an appropriate IOL for the patient during cataract surgery in order to restore the patient's vision. IOL calculation is a crucial step in cataract surgery, and its purpose is to select the appropriate IOL in order to achieve the effect that the patient is able to see and recognize the objects better after the surgery [9].

In the past, doctors mainly relied on experience and conventional surgical calculation formulas to select the degree of IOL, but since the shape of the eye, corneal curvature, and the severity of cataract varies from patient to patient, the error rate of the traditional formulaic calculation method increases, which affects the patient's postoperative outcome [10]-[12]. This method often fails to meet the needs of patients. With the development of digital diagnosis and treatment technology, IOL calculation also ushers in the era of digitally driven scientific computing. Computational models, such as machine learning, obtain higher predictive effects than traditional formulas by calculating eye-related parameters, but a single computational model is prone to reduced generalization ability of the model in the case of a small sample size, and the local data distribution is sensitive to the reduced adaptability of its model in other application environments outside the scope of conventional applications [13]-[15]. In order to improve postoperative outcomes, utilizing multi-model collaboration is an effective way to address the

above challenges. And integrated learning improves the generalization ability and robustness of learners by combining the prediction results of multiple learners [16]. In IOL computation, its innovative potential is unlimited.

In this study, a dataset containing ocular ultrasound images of normal eyes, cataract eyes, and eyes with other ocular diseases was collected, and multidimensional and fine-grained patient analysis data were established to provide a data base for the study. Aiming at the problems of low accuracy and sensitivity of cataract grading diagnosis, an improved integrated learning method EasyEnsemble is given to construct the IOL cataract diagnosis model based on integrated learning. With SVM as the basic classifier of EasyEnsemble method, based on Adaboost and undersampling, the number of majority class samples is contracted to the same number as the minority class samples, which can well deal with the problem of slightly unbalanced data and improve the performance on slit light source images. Five SVM classifiers are utilized to finally make a joint decision on the final classification result.

## II. IOL calculation model

Cataract is one of the major blinding eye diseases in medicine nowadays, and more than 47% of blindness in the world is caused by cataract. With the development of cataract surgical instruments, improved operator skills and the development of various types of artificial lenses (IOLs), today's patients are not only looking for improved vision after surgery, but also high quality of vision after surgery.

### II. A. IOL Spherical Mirror Computational Model

The calculation methods of IOL spherical lenses are mainly divided into: (1) based on the history or refraction principle; (2) based on linear regression analysis study; (3) based on regression study and theoretical formulas; (4) based on ray tracing principle; (5) based on artificial intelligence. Some scholars have also classified them into three types: (1) standard refractive power method; (2) clinical judgment method; and (3) formula calculation method, in which the formula calculation method is subdivided into the first generation, the second generation, the third generation, the fourth generation, the fifth generation, and the new IOL refractive power formula according to the development time [17].

The main methods represented based on historical or refractive principles are the standard refractive index method, the clinical judgment method, and the Binkhorst formula. It was derived by Binkhorst using the principles of geometric optics based on the thin lens imaging formula  $P = \frac{N(4R - L)}{(L - C)(4R - C)}$ , in which the patient's degree of

implanted IOL is denoted by P, 1,000 times the refractive index of the aqueous humor (1,336) is denoted by N, the radius of curvature of the anterior corneal surface (mm) is denoted by R, the axial length of the eye (mm) is denoted by L, and the depth of the anterior chamber (mm) is denoted by C.

The formulas based on regression studies only are mainly represented by SRK I formula, SRK II formula.

The ray tracing principle is mainly represented by the Olsen formula. The IOL position can be interpreted as the IOL constant derived from the formula, and it is usually calculated from the actual postoperative refraction back to how much this constant should be to ensure that the average prediction error is zero, and if the formula is a thin lens formula, the ELP is not an anatomical position of the IOL by definition because the thin lens formula does not take into account the IOL thickness and the optical structure, and the error that exists in the computation of the true corneal refractive power will cause the ELP to deviate, in order to allow the IOL to be implanted in a more accurate position and to eliminate errors in the ELP, the concept of the C constant was proposed, which was used to predict the postoperative ELP using ray tracing in order to correct the spherical aberration between the cornea and the IOL.

Formulas based on artificial intelligence principles, on the other hand, require the use of large databases and are mainly represented by the Hill-RBF formula, which is based on IOL data collected by cataract surgeons from all over the world, analyzing the big data using artificial intelligence and pattern recognition, and performing IOL calculations by means of a unique reliability test.

### II. B. IOL Column Mirror Computational Model

Astigmatism is a manifestation of refractive irregularity related to the curvature of the cornea. Astigmatism in the human eye may be caused by irregular curvature of the lens or cornea, and most of the astigmatism in the eye is cornea-related. According to the regularity of the refractive meridian, astigmatism can be categorized into regular astigmatism and irregular astigmatism, of which the former can be categorized into conformal astigmatism, contra-conformal astigmatism, and oblique-axis astigmatism based on the comparison of refractive strengths between the vertical and horizontal principal meridians. According to research statistics, the degree of corneal astigmatism in cataract patients before surgery ranges from 0.50D to 1.00D for 32.5% to 36.4%, from 1.00D to 1.50D for 21.3% to 22.4%, from 1.50D to 2.00D for 10.6% to 12.4%, and over 2.00D for 8.2% to 13.0%. This significantly affects the patients' vision and visual quality after surgery.

## II. C. Other IOL computational models

With the development of refractive surgery, the earliest methods of correcting refractive error appeared to be excimer laser refractive keratomileusis (PRK), on which excimer laser in situ keratomileusis (LASIK) and excimer laser subepithelial keratomileusis (LASEK) were subsequently developed. After excimer laser surgery cataract patients before and after the surface curvature ratio, refractive index, anterior chamber depth have been changed, although the biological parameters of the eye after keratoconus surgery changes, but the refractive index of the lens is not affected by the surgery, theoretically the calculation of the IOL before and after keratoconus surgery should be the same, and the difference between the two shows that the accuracy of various IOL calculation formulae Differences in the accuracy of the various IOL calculation formulas are illustrated by the differences between the two.

## III. Integrated Learning Based Cataract Diagnostic Model for IOL

### III. A. Cataract diagnosis

#### III. A. 1) Cataract pathology and characteristics

Cataracts occur in the lens in the anterior chamber of the eye, which is positioned between the iris, pupil and vitreous. The main component of the lens is protein, which is originally a transparent and light-transmitting structure. However, as we age, most people experience some degree of metabolic disruption of the lens, causing the protein to oxidize and become cloudy. The light that should pass through the transparent lens and fall on the retina is blocked by the cloudy, light yellow or milky white lens, resulting in blurred vision and vision loss. This clouding of the lens affecting vision is diagnosed as cataract. As the clouding worsens, the patient's vision deteriorates and eventually becomes blind. Most cataracts occur due to natural aging of the lens, a characteristic that makes cataracts the most prevalent eye disease in the elderly population, and the rate of blindness is far ahead of others, which can be considered as a health killer for the elderly [18].

#### III. A. 2) Ultrasound images of the eye

Compared with slit lamp and fundus examination, eye ultrasound not only does not have the limitation of examination scope, but also can observe the complete eyeball and clear lens. It is also painless, non-invasive, easy to operate and highly accurate. Ultrasound is already a routine examination that must be performed in the eye examination before cataract surgery. In addition, for some cataract eyes with extremely cloudy lens, the light from slit lamp and funduscope can not pass through the lens, and it is difficult to examine some tissue structures in the eye including the lens, and then these two examinations are completely impossible. Ultrasound, on the other hand, is able to clearly visualize the posterior segment of the eye and deeper lesions without being affected by the degree of lens clouding, making it a more comprehensive, accurate, and reliable examination method. A normal eye in an ocular ultrasound image. A cataract-free lens appears as a hyperbolic band of light with a thin periphery and thin, smooth edges in the eye ultrasound image. Internal sound transmission is good and there is no echo.

### III. B. Integrated Learning Algorithm

#### III. B. 1) AdaBoost Algorithm

Adaboost algorithm is an improved iterative method of Boosting algorithm [19], the overall flow of the algorithm is as follows:

(1) In the initial stage, each training sample is given the same weight. After initialization, the initial weight distribution  $D_1(i)$  of the training set can be expressed as equation (1):

$$D_1(i) = (w_1, w_2, \dots, w_n) = \left(\frac{1}{n}, \dots, \frac{1}{n}\right) \quad (1)$$

The initial distribution of weights ensures that each sample has the same importance for the training process initially.

(2) Perform iterations

A particular weak classifier with a low current error is selected as the next iteration base classifier and used as the weak classifier  $h_t : X \rightarrow \{-1, 1\}$ , which has the formula for the variance in the distribution  $D_t$ :

$$e_t = P(H_t(x_i) \neq y_i) = \sum_{i=1}^N w_{it} I(H_t(x_i) \neq y_i) \quad (2)$$

The formula for estimating the weight of weak classifiers in the final classifier (the weight taken is denoted by  $\alpha$ ) is (3):

$$a_t = \frac{1}{2} \ln\left(\frac{1-e_t}{e_t}\right) \tag{3}$$

The formula for updating the weight distribution  $D_{t+1}$  of the training samples is (4):

$$D_{t+1} = \frac{D_t(i) \exp(-a_t y_i H_t(x_i))}{Z_t} \tag{4}$$

where  $Z_t$  is the normalization constant  $Z_t = 2\sqrt{e_t(1-e_t)}$ .

Combine each if the classifiers by the weak classifier weights  $a_t$  with the formula:

$$f(x) = \sum_{t=1}^T a_t H_t(x) \tag{5}$$

The sign function is introduced to obtain the strong classifier result, which is given by Eq:

$$H_{final} = \text{sign}(f(x)) = \text{sign}\left(\sum_{t=1}^T a_t H_t(x)\right) \tag{6}$$

### III. B. 2) Improved Integration Learning Algorithm-EasyEnsemble

In order to fully validate the effectiveness of DCNN-Ensemble on slit light source images and the low diagnostic accuracy and sensitivity of cataract grading, four classical feature methods as well as the EasyEnsemble integrated learning method were used for the comparison experiments, and the EasyEnsemble integrated learning method is briefly described below [20]. Based on Adaboost and undersampling, an improved integrated learning method EasyEnsemble is proposed, which can effectively improve the performance of classical features on slit light source images. In addition, there are related literatures verifying that integrated learning can not only substantially improve the performance of weak classifiers, but also be effective for strong classifiers (e.g., SVM), therefore, SVM is chosen as the basic classifier of EasyEnsemble in this study. First, the number of majority class samples is scaled to the same number as the minority class samples based on the undersampling method to deal with the problem of slightly unbalanced data in slit light source images, and a total of 10 undersampling treatments are performed. Then, five SVM classifiers are trained based on the Adaboost algorithm for each undersampling processed data, thus, the whole algorithm contains a total of 50 classifiers, which are jointly used to make a decision on the final classification result. The flow of the EasyEnsemble algorithm is shown below:

Step 1: Set the parameters of EasyEnsemble algorithm. Let P and N represent the training sets of the minority and majority classes, respectively, and  $|P| < |N|$ , i.e., the number of samples of the minority class is smaller than the number of samples of the majority class. The total number of undersampling  $m = 10$ , in each undersampling, train  $S_i = 5$  classifiers based on Adaboost method.

Step 2: For  $i = 1, \dots, m$  in each  $i$ , train the classifier according to the following method.

Based on the undersampling method, a number of samples are randomly selected from the majority class training set N, constituting the sample set  $N_i$  and  $|N_i| = |P|$ . On the P and  $iN$  datasets, five SVM classifiers are trained based on the Adaboost method, and each SVM classifier and the corresponding weights are  $h_{i,j}$ ,  $a_{i,j}$ , and the threshold of Adaboost is  $\theta_i$ . Then for any sample  $x$ , the classification output of Adaboost  $H_i(x)$  is shown in Equation (7), where  $\text{sign}(s)$  is the sign function, which has the value of 1 when  $s \geq 0$ , and -1 otherwise:

$$H_i(x) = \text{sign}\left(\sum_{j=1}^{S_i} a_{i,j} h_{i,j}(x) - \theta_i\right) \tag{7}$$

Step 3: After performing m undersampling and Adaboost training, the final output of EasyEnsemble integrated learning is shown in Equation (8):

$$H_i(x) = \text{sign}\left(\sum_{i=1}^m \sum_{j=1}^{S_i} a_{i,j} h_{i,j}(x) - \sum_{i=1}^m \theta_i\right) \tag{8}$$

### III. C. Algorithm performance evaluation criteria

In this paper, the model is evaluated based on four metrics, which are accuracy, precision, recall and F1 score, as shown in Eq. (9-12). Among them, the F1 score is calculated from the values of precision and recall, which is more comprehensive and integrated:

$$Accuracy : A = \frac{TP + TN}{TP + TN + FN + FP} \quad (9)$$

$$Precision : P = \frac{TP}{TP + FP} \quad (10)$$

$$Recall : R = \frac{TP}{TP + FN} \quad (11)$$

$$\begin{aligned} F1Score : F1 &= \frac{2 \times Precision \times Recall}{Precision + Recall} \\ &= \frac{2 \times TP}{2 \times TP + FP + FN} \end{aligned} \quad (12)$$

The T in the formula stands for True, which means that the model's predictions are correct. F stands for False, i.e., the model's prediction is wrong. P stands for Positive, i.e., positive sample, meaning that the model predicts a category of 0. N stands for Negative, which is a negative sample, meaning that the model predicts a category of 1. Therefore, TP, i.e., the category 0 predicted by the representative model, is correct. FP means that the model predicted category 0 is wrong, i.e., this sample actually has category 1. Similarly, TN means that the model predicted category 1 is correct. FN represents that the model predicted category 1 incorrectly, i.e., this sample actually has category 0. In addition, the diagnostic models in this paper were further evaluated using ROC (receiver operating characteristic) curves. ROC curves are commonly used to evaluate the effectiveness of binary classification models:

$$ROC \quad X-axis : FPR = \frac{FP}{TP + FN} \quad (13)$$

$$ROC \quad Y-axis : TPR = \frac{TP}{TP + FN} = Recall \quad (14)$$

The horizontal coordinate of the ROC curve is the FPR (False Positive Rate), calculated as shown in equation (13). The vertical coordinate is the TPR (True Positive Rate), which is the recall rate, calculated as shown in equation (14). AUC refers to the area under the ROC curve. The larger the value of the AUC corresponding to the ROC curve, the better it represents the effectiveness of the model.

## IV. Experimental results and analysis

### IV. A. Experimental data set

#### IV. A. 1) Ultrasound eye images

An interactive dataset of eye ultrasound images in DICOM format was collected with the help of ophthalmologists. The collected dataset contains ocular ultrasound images of normal, cataracted and other ocular disease eyes along with the relevant diagnostic rationale of the ophthalmologist. Under the guidance of experts, we have also created multi-dimensional fine-grained patient analysis data. Among them, we know that the mainstream scholars at home and abroad are researching the following six types of medical images for classification and recognition, segmentation and localization detection tasks: CT images, ultrasound images, X-ray images, PET images, MRI images, and pathological optical images, which all have the following properties.

Next, we will detail the eye ultrasound images and the acquired dataset showing a cross sectional ultrasound image of a normal eye and a model image of the eye at the same angle. The structure of the human eye is shaped like an elliptical sphere, with the cornea, anterior chamber, iris, anterior lens envelope, lens, posterior lens envelope, vitreous body, and spherical wall in order from top to bottom. It has an average diameter of approximately 2325 mm, and the normal lengths of the other parts are shown in Table 1. Normal ultrasound eye lens has no echoes within the ellipsoid shape, the posterior lens capsule has an incomplete curved strong echo, and there is no echo within the vitreous.

Ultrasound ophthalmoscopy has a wide range of applications for the diagnosis and differentiation of intraorbital tumors (e.g., inflammatory pseudotumors, cavernous hemangiomas, lacrimal gland tumors), intraocular tumors (e.g.,

choroidal hemangiomas, retinoblastomas, and choroidal melanoma), intraocular lesions (e.g., choroidal detachment, retinal detachment, and mechanized membranes), ocular trauma (e.g., dislocation of the crystalline lens, foreign bodies, and scleral laceration), and intraocular lesions (e.g., preexisting chorioretinal lesions, retinal detachment, and mechanized membranes). Intravitreal lesions (e.g., congenital vitreous permanence, vitreous hemorrhage, post-crystalline fibrous hyperplasia, mechanized membranes, etc.), diagnosis and differentiation of protruding eyes (e.g., Graves' disease, carotid cavernous sinus fistula, orbital tumors), and so on.

Table 1: Normal eye parameters

Region	Normal value
Length of eye	23-25
Corneal thickness	0.6-1.2
Frontal depth	2-4
Crystal thickness	3.6-5.0
Vitreous length	17-18
Ceiling thickness	2.1-3.4

**IV. A. 2) Causes and classification of cataracts**

Cataracts are caused by damage to the lens capsule due to aging, trauma, inflammation, metabolic abnormalities, and heredity, which results in a disorder of the lens metabolism or an increase in the permeability of the lens, leading to the degeneration of the crystal proteins and resulting in the clouding of the lens. Therefore, cataracts can be categorized into primary cataracts, secondary cataracts and congenital cataracts according to their causes, which correspond to aging, trauma and inflammation, and hereditary problems. In order to facilitate the ophthalmologist's clinical diagnosis, cataracts are generally categorized according to the initial clouding of the lens in the ultrasound image of the eye, into nuclear cataracts, which occur at the core of the lens, as well as cortical cataracts, which occur in the anterior and posterior layers of the cortex or under the capsule, and subcapsular cataracts.

Cataracts can be detected based on the echogenicity of various parts of the eye in the ultrasound image. In general, cataracts consist of either.

(1)Cortical and subcapsular cataract: The lens will be slightly enlarged, the echo of the curved band of the posterior capsule membrane will be enhanced and thickened, and there will be a collection of tiny strong echogenic spots in the cortical layer under the capsule membrane, but the center part of the lens will be free of echoes.

(2) Nuclear cataract: the lens is greatly enlarged, the center of the lens is annual strong echo, from the center of the lens to the anterior and posterior cortical layers of the annual strong echo gradually weakened.

**IV. A. 3) Data set description**

The collected cataract ultrasound dataset consisted of horizontal axial slices of ultrasound of the human eye as described above. Based on ophthalmic knowledge, the collected dataset was preprocessed and enhanced by cropping the ultrasound images of different sizes around the eye. Meanwhile, we continued to expand the new DICOM format data collected from the primary hospital. In the acquisition phase, the results are shown in Table 2, where we collected eight ophthalmic diseases and categorized them into 07 categories of images.

Table 2: Types of eye diseases

Type	Ophthalmia
0	Normal eye
1	Mild cataract
2	Severe cataract
3	Vitreous turbidity
4	Retinal detachment
5	Artificial lens
6	The lens dislocations

**IV. B. Experimental platform and comparison algorithms**

**IV. B. 1) Experimental platforms**

The experiments in this paper were done under Windows 7 operating system with i5 processor and 4GB RAM. convolutional neural network training and deep feature extraction used for classification were performed using CPU,

and the deep learning framework used for the experiments was Tensorflow, which is one of the widely used deep learning frameworks at present. The experiments about pupil segmentation, color recovery, reflection removal, color feature extraction, texture feature extraction and SVM training are implemented with MATLAB 2018a, and algorithm testing and evaluation are also implemented with MATLAB 2018a.

**IV. B. 2) Introduction to the Contrast Algorithm**

In order to verify the feasibility of the auxiliary diagnostic method of cortical cataract proposed in this paper, the method of this paper is illustrated in comparison with the classical method. There are a number of existing studies that have investigated the diagnosis of cortical cataract, but the type of data studied varies, with the use of fundus maps and slit lamp diffuse light source image maps, and in order to make the experimental analysis persuasive, the comparative experiments in this section are also all using slit lamp diffuse light source image maps. In the paper, eight cataract automatic diagnosis methods were studied and compared, and a detailed analysis was given, and these eight methods will be briefly introduced next, and the relevant parameters are shown in Table 3. All of these methods use traditional classification learning methods and do not use end-to-end integrated learning methods, so the main comparison is between the excellence of the extracted features and the goodness of the classifiers. The features used in the comparison experiments are color features, gray space dependency matrix, gray gradient covariance matrix (GGCM), transform domain features, LBP features and sparse representation totaling six features. Five types of classifiers, Extreme Learning Machine (EM), SVM, Genetic Algorithm (GA), k Nearest Neighbor Algorithm (kNN), and Differential Evolutionary Algorithm (DE), were studied.

Table 3: 8 compared to the experimental parameters

Method	Feature extraction	Classifier
1	Color characteristics; Grayscale space dependent matrix; Grayscale gradient symbiotic matrix	EM
2		SVM
3		SVM and GA
4		kNN
5	Wavelet transform	SVM
6	LBP	SVM
7	Sparse representation Color characteristics; Grayscale space dependent matrix; Grayscale gradient symbiotic matrix; Sparse representation	DE

**IV. C. Analysis of remote diagnosis results**

The specific ways of feature extraction and the parameters of the classifiers for the eight comparison experiments are not published, so the evaluation metrics used in this section for method comparison are from the published data of the paper. Evaluation metrics such as AUC of the ROC curve, classification accuracy, sensitivity, specificity, precision, and F-score are also used for the experimental comparisons in this section. Comparison experiments 5, 6 of the SVM respectively used a linear kernel and polynomial kernel, the text also compares the effect of the two kernel function, comparison experiment 7 sparse representation of the image for two different downsampling, downsampling image size of 15 × 20, 5 × 10, the dictionary were also used a different number of training samples, experiment 8 is also a comparison between the different dictionaries. Therefore, the experimental comparison is carried out in three times, respectively, as shown in Table 4.

From the table, it can be seen that all the indexes of method 1 are much lower than other methods, and the features used in methods 1, 2 and 3 are the same, and the difference is in the selected classifiers, so it shows that EM basically has no role in the classification of cortical cataracts, and nowadays, the image classification mainly adopts the structure of convolutional neural network, but not the deep neural network structure, which also shows that the effect of EM is not significant in the classification of images from another point of view. The difference between Method 2 and Method 3 is that Method 3 still uses the GA algorithm, which makes the classification accuracy and sensitivity of Method 3 much higher than that of Method 2, which indicates that the synergistic effect of GA and SVM can greatly improve the classification effect of cortical cataracts, and it can be seen that the TPR is improved plus more, which indicates that the GA algorithm makes the classifier more capable of recognizing the image of the patient who needs surgery. The kNN algorithm classification is much less effective than that of SVM, and the different choices of k do not improve the accuracy of classification much, but instead make the TPR decrease as k increases. The method in this paper also uses SVM classifier, but the accuracy and sensitivity of the proposed method in this paper is much higher than that of method 2 and method 3, which indicates that the feature

selection in this paper is better and can more accurately describe the cortical cataract features. In the experimental analysis, it is clearly stated that the color features and the features extracted by GCLM do not play a major role, which also explains why the classification effect of Method 2 and Method 3 is not as effective as the effect of this paper's method.

Table 4: The method and the comparison method 1-4 classification effect

Method	AUC	ACC	TPR	TNR
1	0.6845	0.6274	0.4015	0.8479
2	0.8354	0.8225	0.6225	0.9963
3	0.9257	0.9137	0.8022	0.9847
4,k=5	/	0.7248	0.6347	0.8542
4,k=10	0.722	0.7345	0.6078	0.8756
4,k=20	/	0.7415	0.5428	0.9018
This article	0.9689	0.9627	0.96	0.9728

The results of Method 5 are shown in Table 5, the best results of these three wavelet features are the haar feature and the db1 feature, the AUC and the accuracy of classification using only any of these two features is around 0.9, and the classification of these two features is the same, which indicates that these two features describe the cortical cataract images to a similar extent. Method 5 illustrates that the accuracy of wavelet feature classification using linear and polynomial kernels is similar, but it can be seen that the linear kernel is less sensitive than the polynomial kernel, indicating that the classifier with the linear kernel is not sensitive enough to accurately find out the images that require surgery. Regardless of the kernel function, the specificity of the classifiers trained using signal processing methods including the MR8 filter bank extracted features which are used in this paper are very high, indicating that this class of features can accurately describe the cataract images of non-surgical patients, and at the same time the sensitivities are not high indicating that other features are needed for the classification and that a single signal processing feature is unreliable, and from the final method in this paper, it can be seen that multi-features significantly improve the sensitivities, and consequently The results of LBP features using either linear or polynomial kernel are similar, which may represent that both kernels are not the optimal kernel function, the sensitivity and specificity values of these two sets of evaluation data are similar, which indicates that the LBP features describe the two types of images to about the same extent, and proves why the LBP features are so widely used. The polynomial kernel has a very large number of parameters, which makes it difficult to make a choice, so in this paper we use a Gaussian kernel, which also maps the features to a high-dimensional space with fewer parameters.

Table 5: The method and comparison method 5-6 classification effect

Method	Feature	Nuclear function	AUC	ACC	TPR	TNR
5	haar	Linear nucleus	0.9512	0.9036	0.7584	0.9622
		Polynomial nucleus	0.9122	0.9052	0.8225	0.9836
	db1	Linear nucleus	0.9526	0.9085	0.7586	0.9627
		Polynomial nucleus	0.9058	0.9024	0.8127	0.9835
	sym4	Linear nucleus	0.9287	0.9081	0.8597	0.9563
		Polynomial nucleus	0.9064	0.8824	0.728	0.9778
6	LPB	Linear nucleus	0.9536	0.8894	0.8778	0.9184
		Polynomial nucleus	0.9389	0.9125	0.8769	0.9186
This article	MR8	Gaussian nucleus	0.8749	0.9284	0.8352	0.9978
This article	This article	Gaussian nucleus	0.9785	0.9722	0.9584	0.9784

Comparison experiments 7-8 classification effect evaluation is shown in Table 6, comparison experiments 7-8 need to construct a dictionary, constructed a dictionary of different sizes to analyze and compare to derive the range of variation of evaluation indexes, and found that the accuracy of this method are very low or even worse than the random classification, which indicates that it is likely that the classifier is not appropriate. This type of method carries out a downsampling operation, and the image size is too small, which is likely to mistake the lesions for noise, making the positive and negative samples basically no difference, leading to bad results.

Table 6: Comparison experiment 7-8 classification effect evaluation table

Method	Sampling size	AUC	ACC	TPR	TNR
7	6±12	0.5684	0.5685±0.0258	0.5548±0.3849	0.5078±0.3684
	16±22	/	0.4785±0.0022	1±0.31	0.1±0.005
8	/	0.5412	0.4829±0.0063	0.8914±0.0879	0.0987±0.1124

## V. Conclusion

In this study, SVM is used as the basic classifier of EasyEnsemble, and the EasyEnsemble method is proposed based on Adaboost and undersampling, so as to build an integrated learning-based cataract diagnosis model for IOL. Experimental validation is performed with an interactive dataset of ocular ultrasound images in DICOM format, and the study shows that the accuracy of methods 7 and 8 is not as good as randomized classification, indicating that the other classifiers are not appropriate. The method in this paper uses SVM classifier, which provides higher accuracy and sensitivity compared to methods 2 and 3. Multi-features can significantly improve the sensitivity and consequently make the accuracy higher.

Therefore, the integrated learning model constructed in this study is excellent in characterizing cortical cataracts, and can be applied to early identification of cataracts, accurately screening abnormal fundus, assisting doctors to achieve efficient diagnosis, and providing scientific advice for its precise prevention and treatment.

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