• Intelligent Ophthalmology •

Prediction of postoperative vault after implantable collamer lens implantation with deep learning

Dong-Qing Yuan[1], Fu-Nan Tang[2], Ying Wang[2], Hui Zhang[2], Wei-Wei Zhang[1], Liu-Wei Gu[1], Qing-Huai Liu[1]

[1]Department of Ophthalmology, Jiangsu Province Hospital, the First Affiliated Hospital with Nanjing Medical University, Jiangsu Women and Children Health Hospital, Nanjing 210029, Jiangsu Province, China
[2]Clinical Medical Engineering Department, Jiangsu Province Hospital (the First Affiliated Hospital with Nanjing Medical University), Nanjing 210029, Jiangsu Province, China
Co-first Authors: Dong-Qing Yuan and Fu-Nan Tang
Correspondence to: Qing-Huai Liu. Department of Ophthalmology, Jiangsu Province Hospital, the First Affiliated Hospital with Nanjing Medical University, Jiangsu Women and Children Health Hospital, 300 Guangzhou Road, Nanjing 210029, Jiangsu Province, China. liuqh@njmu.edu.cn
Received: 2024-05-14 Accepted: 2025-01-15

Abstract
● **AIM:** To predict the post-operative vault and the suitable size of the implantable collamer lens (ICL) by comparing the performance of multiple artificial intelligence (AI) algorithms.
● **METHODS:** A retrospective analysis of 83 patients with 132 eyes was conducted from 2020 to 2023. All patients underwent implantation of EVO-V4C ICLs. ICLs were selected based on STAAR's recommended formula. Postoperative vault values were measured using anterior segment optical coherence tomography (ASOCT). First, feature selection was performed on patients' preoperative examination parameters to identify those most closely related to postoperative vault and incorporate them into the machine learning model. Subsequently, four regression models, namely MLP, XGBoost, RFR, and KNN, were employed to predict the vault, and their predictive performances were compared. The ICL size was set as the prediction target, with the vault and other input features serving as new inputs for predicting the ICL size.
● **RESULTS:** Among all preoperative parameters, 16 parameters were most closely related to postoperative vault and were included in the prediction model. In vault prediction, XGBoost performed the best in the regression model (R^2=0.9999), followed by MLP (R^2=0.9987) and RFR (R^2=0.8982), while the KNN model had the lowest predictive performance (R^2=0.3852). XGBoost achieved a prediction accuracy of 99.8%, MLP had a prediction accuracy of 98.9%, while RFR and KNN had accuracies of 87.1% and 57.4%, respectively.
● **CONCLUSION:** AI effectively predicts postoperative vault and determines ICL size. XGBoost outperforms other machine-learning algorithms tested. Its accurate predictions help ophthalmologists choose the right ICL size, ensuring proper vaulting.
● **KEYWORDS:** vault prediction; implantable collamer lens; size selection; machine learning; artificial intelligence
DOI:10.18240/ijo.2025.07.02

Citation: Yuan DQ, Tang FN, Wang Y, Zhang H, Zhang WW, Gu LW, Liu QH. Prediction of postoperative vault after implantable collamer lens implantation with deep learning. *Int J Ophthalmol* 2025;18(7):1197-1204

INTRODUCTION

Myopia is one of the common ocular diseases globally, with approximately 10%–30% of the global adult population being myopic[1]. About 80%–90% of young people in East and Southeast Asia suffer from myopia[2]. An estimated 277 million people worldwide suffer from extreme myopia, making up 4.0% of the total population[3]. Current therapies are unable to totally cure myopia; they can only halt its growth. For people who are extremely myopic, the most effective way to enhance visual function at this time is refractive surgery. Presently available therapies are only able to partially reverse the effects of myopia; they cannot reverse its course entirely. For people who are extremely myopic, the most effective way to enhance visual function at this time is refractive surgery. At this point, intraocular lens implantation and corneal refractive surgery are examples of refractive operations[4-5]. Low to moderate myopia is the primary target population for corneal refractive surgery. Nevertheless, the function and structure of the cornea are altered by this operation, and the risk of problems including corneal ectasia and postoperative myopia regression increases with full correction of severe myopia[6]. By implanting an artificial lens into the patient's eye, intraocular implanted collamer lenses (ICLs, STAAR Surgical, Nidau, Switzerland) implantation, on the other hand, has a negligible effect on the cornea[7]. It also makes it possible to modify the surgical result through follow-up surgery. Furthermore, ICL implantation is the recommended surgical procedure for very myopic individuals because it can treat a wider spectrum of refractive defects than corneal refractive surgery. Concurrent cataracts and secondary glaucoma are two of the problems associated with ICL implantation, albeit[8]. The vault is the distance measured between the anterior surface of the crystalline lens and the highest point on the posterior surface of the implanted ICL. The ICL pulls the iris forward when the vault is too high, which lowers the anterior chamber's depth and volume, modifies the anterior chamber's angle morphology, and increases the risk of subsequent glaucoma. The risk of cataracts increases if the vault is too low because there is less space between the crystalline lens and the posterior surface of the ICL. As a result, choosing the right lens size and anticipating the postoperative vault are essential. Preoperative evaluation criteria are now the basis for predictions, and the STAAR-recommended formula is the one that is most frequently applied in clinical practice[9-11]. In practical practice, there are disparities between the predicted and actual vault, though. Some individuals develop aberrant vaults following surgery, necessitating further treatments, causing severe discomfort, and presenting a serious problem for ICL implantation procedures because to the limitations of prognostic accuracy.

Big data analysis and artificial intelligence learning techniques have been used to forecast postoperative vaults as science and technology have advanced[12]. According to the most recent study, in terms of average absolute error in postoperative vault prediction, an ensemble model utilizing eXtreme Gradient Boosting (XGBoost) and lightGBM performs better than other machine learning approaches, the NK formula, and conventional formulae[13]. However, the results of the measurements may vary because various hospitals use different types of measurement equipment, even within the same device category, and because different clinicians measure different things with the same instrument[14]. Furthermore, extensive clinical sample data are required to validate the efficacy and practicality of the prognostic formulae for postoperative vaults and the selection of ICL sizes[15]. In addition, different size formulas cannot be simply compared. For the aforementioned reasons, we thus want to improve the prediction model's accuracy by integrating objective clinical indicators acquired from different ophthalmic equipment in order to forecast postoperative vaults and assist surgeons in choosing the ideal ICL size. Selecting the right ICL size, establishing a fair postoperative vault, and lowering the risk of surgical complications can all be aided by this research.

PARTICIPANTS AND METHODS

Ethical Approval The First Affiliated Hospital with Nanjing Medical University granted ethical permission for the study, which was conducted in accordance with the Declaration of Helsinki's tenets. Informed consent was waived due to the retrospective nature of the study.

Participants In this retrospective study, 83 patients (45 men and 38 women, totaling 132 eyes) who had ICL V4c implantations between January 2020 and December 2023 were recruited from the Department of Ophthalmology, the First Affiliated Hospital with Nanjing Medical University. Those between the ages of 18 and 45 were eligible if they met the following requirements: anterior chamber depth (ACD) of at least 2.80 mm, endothelial cell density (CD) of at least 2000 cells/mm^2, spherical myopia of up to −18.00 D, astigmatism of up to −6.00 D, stable refraction for more than two years, ICL V4c positioned at a 10° horizontal angle, and vault size measured one month after ICL V4c implantation. The following conditions were excluded: ciliary body cysts; zonule abnormalities; severe systemic diseases; loss of preoperative examination data; ocular diseases affecting vision (*e.g.*, keratoconus, severe dry eye, active ocular infection, cataract, glaucoma, and fundus diseases significantly affecting vision). The traditional manufacturer's nomogram was followed in choosing the ICL V4c size (12.1, 12.6, 13.2, or 13.7 mm) based on white-to-white (WTW) distance and ACD.

Surgical Procedures The skilled surgeon (Yuan DQ) carried out each and every surgery. The temporal corneoscleral limbus was cut 2.8 mm in the temporal cornea, and the anterior chamber was then filled with an injection of hyaluronic acid. The ICL V4c was then placed into the anterior chamber using an injector cartridge, and the four ICL haptics were swept under the iris using a placement tool. Following the surgery, a watertight surgical incision was formed, the residual viscoelastic agent was removed, and balanced salt solution (BSS) was substituted. Once proper intraocular pressure (IOP) was confirmed, patients were given ofloxacin eye ointment and sterile gauze was placed over their eyes. For three days, six doses of antibiotics and steroidal drugs were given daily; the dosage was then gradually tapered off.

Preoperative and Postoperative Measurements Prior to the operation, every patient received comprehensive optical exams, which included measurements of IOP, anterior segment *via* slit-lamp examination, fundus examination, and cycloplegic refraction. Optical biometric instrument (Optical Biometric Instrument, Japan) measured WTW, ACD, flat keratometry (K1), steep keratometry (K2), dark pupil diameter (PD), and central corneal thickness (CT), while Pentacam HR (Oculus Optikerate, Carl Zeiss, Germany) measured horizontal WTW, central ACD, anterior chamber angle, K1, and K2. Ultrasound biomicroscopy (UBM SW-3200, KINSCAN, SUOER) measured ACD, horizontal sulcus-to-sulcus diameter (STS-H), and vertical STS diameter (STS-V). Partial coherence interferometry (IOL Master 700; Carl Zeiss Meditec, Jena, Germany) was also used to assess other characteristics, including lens thickness (LT; mm), WTW, and axial length (AL; mm). Additionally, measurements such as ACD (mm), anterior chamber width (ACW; mm), angle-to-angle (ATA) distance (mm), crystalline lens rise (CLR; μm), PD (mm), and angle opening distance (AOD; 500 and 700 μm) were obtained in large part thanks to anterior segment optical coherence tomography (ASOCT, Visante; Carl Zeiss Meditec). Using the same ASOCT, the central vault was measured one month after the surgical procedure. The same skilled doctor performed these examinations in a naturally lit indoor environment every time. Three measurements were taken to verify accuracy, and the average value was taken into consideration for analysis.

Machine Learning Models for Preoperative Parameters We employed the Chi-square filter selection method to choose the most relevant feature parameters for postoperative vaulting. Considering the nonlinearity of surgical parameters, we mainly applied the XGBoost technique for precise prediction. We contrasted our method with three other modeling approaches, namely Multilayer Perceptron (MLP), Random Forest (RF), and K-Nearest Neighbor (KNN) neural network, in order to further confirm its prediction effectiveness. Creating a powerful classifier by combining several weak classifiers (decision trees) is the fundamental concept of the XGBoost regression model[16]. By iteratively optimizing the loss function, each decision tree is trained using the residuals from the preceding tree, thereby lowering the residuals. By employing regularization terms and limiting the complexity of the trees, the model lowers the danger of overfitting in the interim. XGBoost uses the gradient boosting technique in its implementation, fitting the negative gradient to gradually optimize the loss function. The input, hidden, and output layers make up the MLP class of feedforward neural network[17]. On generate output results, it applies a number of nonlinear changes on the input data. Strong expressive capability is demonstrated by MLP, which can recognize and learn intricate patterns. The MLP's operating concept may be summed up as follows: by continually modifying the network's weights and biases, the output of the network becomes as close as feasible to the real values. In particular, MLP minimizes the loss function (also known as the cost function) by iteratively optimizing the weights and biases using the backpropagation technique. On the other hand, the Random Forest technique makes use of a group of decision trees to carry out tasks related to regression or classification[18]. Multiple decision trees are trained on randomly chosen subsets of the original data and features during the training and prediction stages of the building process. Next, a prediction is created by adding up the outcomes of every tree. Furthermore, the K Neighbors Regressor class is used with the KNN regression model, which is a fundamental machine learning model[19]. We have employed k-fold cross-validation, where the dataset is divided into k subsets. The model is trained on k-1 subsets and validated on the remaining subset. This process is repeated k times, with each subset used exactly once as the validation set. The final performance metrics are averaged over all k iterations, providing a robust evaluation of the model's generalization capability.

Model Evaluation In order to evaluate the predictive performance of the regression models quantitatively, the following metrics are used: mean absolute error (MAE), mean square error (MSE), and R^2-score (the percentage of the dependent variable's variance that can be accounted for by the independent variables in the model). Scatter plots are produced after training to see how well the expected and actual values match together. Higher fitting is indicated by closer closeness to the center diagonal line, which is consistent with R^2. Moreover, following model training, Bland-Altman plots are generated for predictions on scaled original data.

Statistical Analysis The statistical analyses were performed with IBM, Chicago, IL's SPSS Statistics 23.0. The Friedman test was used to determine variations in MAE, MSE, and R^2 among different machine learning techniques. Multiple comparisons were then carried out using the Bonferroni test. For all analyses, a two-tailed *P*-value of less than 0.05 was deemed suggestive of statistical significance.

RESULTS

Demographics of Patients The mean age of the 83 patients (132 eyes) was 25.32±6.49y. Sixty-four eyes (48.87%) had a toric ICL V4c implanted, whereas 68 eyes (51.13%) had a non-toric ICL V4c implanted. In 6 eyes (5.26%), 85 eyes (63.91%), 39 eyes (29.32%), and 2 eyes (1.50%), the implanted ICL V4c measured 12.1, 12.6, and 13.2 mm in size. The patients' postoperative vaults and preoperative demographics were listed in Table 1.

Preoperative Parameters Feature Selection in Data Initially, we considered the inclusion of the following input parameters: K1 value, K1 axis, K2 value, K2 axis, ACD, WTW of Pentacam, WTW of IOL Master, AL, IOP, CT, STS-H, STS-V, sphere diameter (sphere), cylinder diameter (cylinder), cylinder axis, spherical power of ICL, cylindrical power of ICL, cylinder axis of ICL, corneal endothelial CD, and ICL size, totaling 20 input parameters. Additionally, ICL size are replaced with numeric values for ease of processing, where ICL121, ICL127, ICL131, and ICL132 correspond to 0 to 3, respectively. Subsequently, we conducted feature selection, where R^2 is commonly used to measure the degree of association between each feature and the target variable, *i.e.*, the explanatory power of the features on the target variable. The range of R^2 values is between 0 and 1, with values closer to 1 indicating a better ability of the model to explain the variance of the target variable. We calculated the R^2 score for each feature with the target variable and selected the influencing factors on postoperative vaulting based on the feature's R^2 score, automatically selecting factors with scores ranking in the top 80%. Consequently, 16 effective input parameters were determined, namely ACD, ICL size, STS-H, AL, CD, WTW, K1 axis, spherical power of ICL, sphere, CT, STS-V, K2 axis, cylindrical power of ICL, WTW of Pentacam, IOP, cylinder, K1 value, K2 value, cylinder axis of ICL, and cylinder axis (Figure 1).

Prediction of the Vault In all predicted patients, the XGBoost model has the best results in the regression model (R^2=0.999989, MAE=0.000530, MSE=6.19×10^{-7}), then follows the MLP model (R^2=0.998676, MAE=0.005186, MSE=7.74×10^{-5}) and RFR model (R^2=0.898150, MAE=0.058162, MSE=5.96×10^{-3}). Compared to the preceding three models, the predictive performance of the KNN model is the lowest (R^2=0.385172, MAE=0.147560, MSE=3.59×10^{-2}). The performance of the regression models for vault prediction was listed in Table 2. The results showed that the XGBoost and MLP outperformed other classification methods. Figure 2A depicted the density curves of predicted vaulting values versus actual vaulting values for the four predictive models. From the results, it was evident that the XGBoost model's predicted vaulting closely aligns with the actual results, with a predictive efficiency exceeding 0.9999. Figure 2B illustrated the distribution of differences between predicted and actual values generated by the four computational models. Figure 2C presented statistical summaries of the discrepancies between predicted parameters and actual values, indicating that the XGBoost model's predictions were closest to the actual values. Figure 2D displayed a scatter plot of actual vaulting values against predicted values, showcasing the relationship between them. Each point represents a sample, with the horizontal axis representing the actual values and the vertical axis representing the predicted values. Ideally, all points should lie on the y=x line, indicating perfect alignment between actual and predicted values. A concentrated and linear distribution of points suggests good predictive performance, while a scattered or distant distribution indicates poorer predictive accuracy. This scatter plot provides a visual assessment of the model's predictive accuracy and bias.

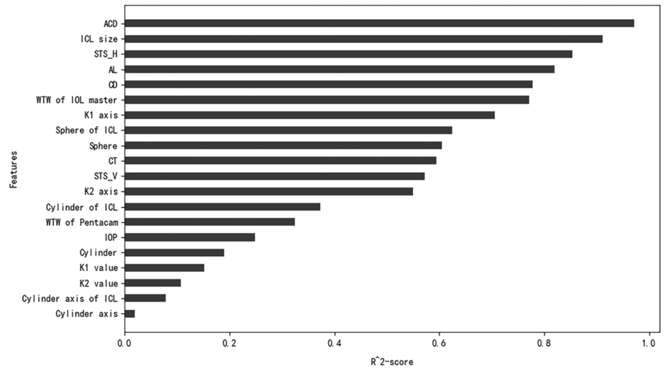

Figure 1 Using feature-based R^2 scores to screen potential factors affecting postoperative vault, automatically selecting factors with scores ranking in the top 80% ACD: Anterior chamber depth; ICL: Implantable collamer lens; STS-H: Horizontal sulcus-to-sulcus; AL: Axial length; CD: Endothelial cell density; WTW: White-to-white; K1: Flat keratometry; K2: Steep keratometry; CT: Central corneal thickness; STS-V: Vertical sulcus-to-sulcus; IOP: Intraocular pressure.

Table 1 Patient demographics, ICL characteristics, and biometric parameters of the anterior segment

Demographics	Mean±SD	Range
Patients (eyes), *n*	83 (132)	
Sex (male/female), *n*	45/38	
Age (y)	25.32±6.49	19–40
Spherical equivalent (D)	-9.75±2.10	-17.00 to -4.25
Expected spherical equivalent (D)	-0.49±0.47	-3.21–0.37
WTW (IOL Master 700, mm)	11.93±0.35	10.8–12.7
HWTW (Pentacam, mm)	11.59±0.34	10.5–12.4
K1 (Pentacam, D)	42.91±1.34	39.7–46.1
K2 (Pentacam, D)	44.59±1.51	40.5–47.8
ACD (Pentacam, mm)	3.22±0.22	2.70–3.70
ATA (ASOCT, mm)	11.82±0.38	2.83–3.81
STS-H (UBM, mm)	11.58±0.46	10.39–12.86
STS-V (UBM, mm)	12.11±0.46	10.56–13.64
LT (UBM, mm)	3.85±0.32	3.31–4.80
ICL size (mm)	12.77±0.33	12.10–13.70
Vault (mm)	0.73±0.24	0.29–1.55

ICL: Implantable collamer lens; SD: Standard deviation; WTW: White-to-white; HWTW: Horizontal white-to-white of Pentacam; K1: Flat keratometry; K2: Steep keratometry; ACD: Anterior chamber depth; ATA: Angle-to-angle; STS-H: Horizontal sulcus-to-sulcus; STS-V: Vertical sulcus-to-sulcus; LT: Lens thickness.

Table 2 Performance of the regression models for postoperative vault prediction

Model	MAE	MSE	R^2
MLP	0.005186	7.74E-05	0.998676
XGBoost	0.000530	6.19E-07	0.999989
RFR	0.058162	5.96E-03	0.898150
KNN	0.147560	3.59E-02	0.385172

MAE: Mean absolute error; MSE: Mean square error.

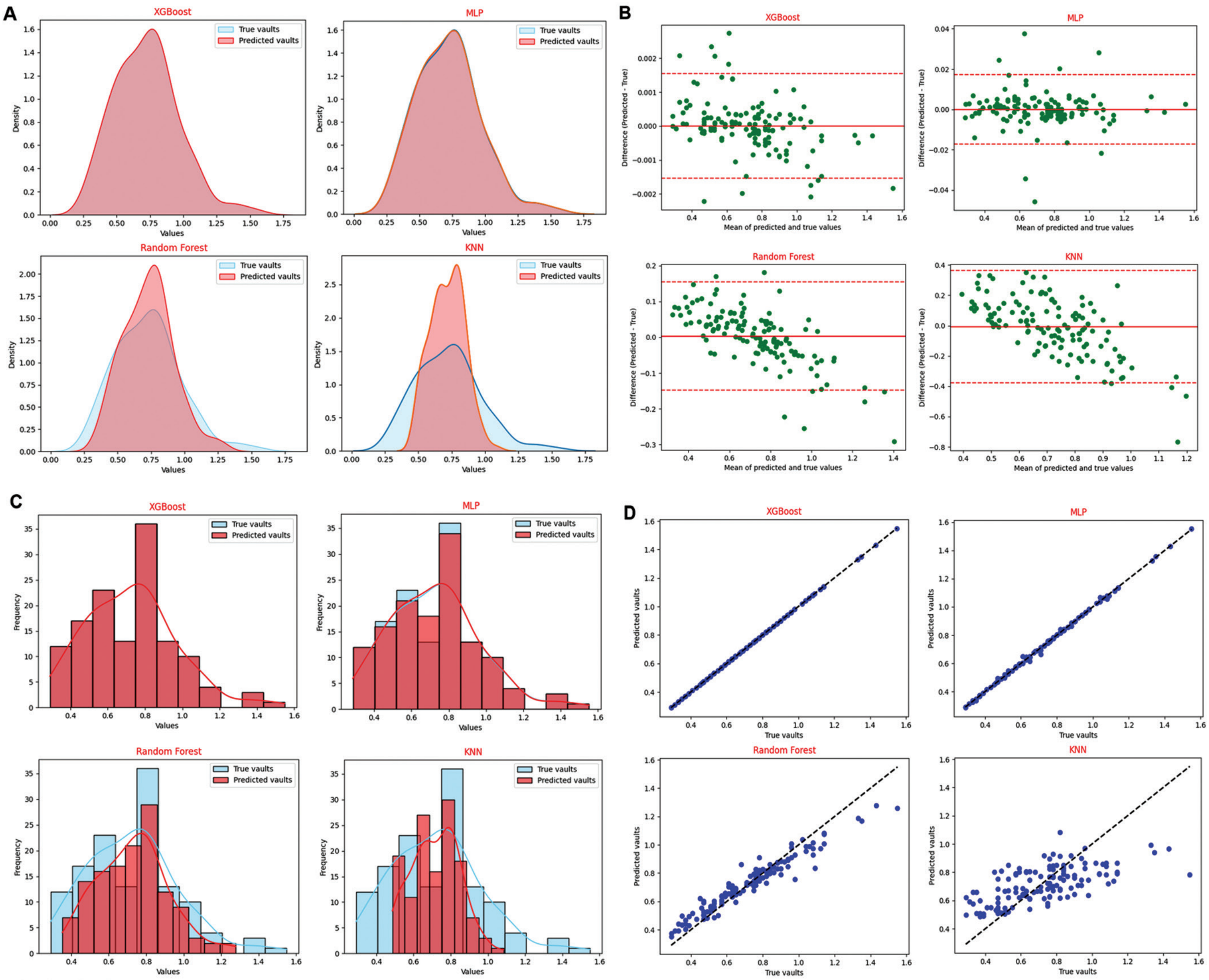

Figure 2 The results of predicting postoperative vault were compared among four regression models: XGBoost, MLP, RFR, and KNN A: The density curves of predicted vaulting values versus actual vaulting values for the four predictive models; B: The distribution of differences between predicted and actual values generated by the four computational models; C: Statistical summaries of the discrepancies between predicted parameters and actual values; D: Scatter plot of actual vaulting values against predicted values.

Prediction of ICL Size As listed in Table 3, the XGBoost predicts the ICL size with an accuracy of 99.8% and the MLP and Random Forest, which are also compatible with 98.9% and 87.1% accuracy, respectively. Compared to the preceding three models, the predictive accuracy of the KNN model is the lowest (57.4%).

Table 3 Performance of the ICL size prediction model accuracy

Model	Accuracy (95%CI)
MLP	0.989 (0.982 to 0.994)
XGBoost	0.998 (0.997 to 0.999)
RFR	0.871 (0.733 to 0.983)
KNN	0.574 (0.395 to 0.857)

ICL: Implantable collamer lens; CI: Confidence Interval.

Comparative Evaluation with and without Machine Learning We further compared whether there is a significant difference in postoperative vaulting between lens sizes selected solely based on surgeon experience and STAAR's recommended formula, without using a machine learning model, versus selecting the optimal lens size recommended after applying a machine learning model. In this comparison, we additionally assessed the postoperative vaulting of 50 eyes that did not undergo machine learning modeling and 50 eyes with lenses selected through machine learning. The comparison revealed that the proportion of postoperative vaulting within the normal range (250 to 750 μm) was 99.6% for lenses selected through machine learning, whereas for lenses not selected through machine learning, the proportion within the normal range was 92%.

Easy and Quick Software Development for ICL Surgery Post-operative Vault Calculation We created software that instantly computes post-operative vault using our prior machine learning models, making it easier for surgeons to quickly and easily choose the right ICL sizes (Figure 3). Surgeons just need to choose a lens size and provide a few preoperative examination criteria onto this program; it will then compute the expected post-operative vault automatically. By using this criterion, surgeons may select the lens size that is safest and most appropriate for the patient, preventing issues like an excessive or inadequate post-operative vault.

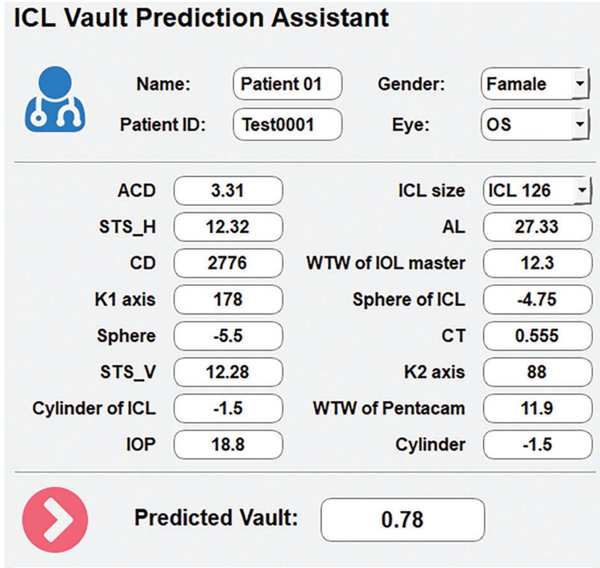

Figure 3 ICL size selection and vault prediction software interface presentation The anticipated post-operative vault may be obtained by surgeons by simply entering different examination characteristics of the patient into the correct modules, choosing the right size from the "ICL Size" dropdown menu, and clicking the red button located in the bottom left corner of the screen. By choosing several alternatives from the ICL size menu, surgeons may choose the most suitable post-operative vault. ACD: Anterior chamber depth; ICL: Implantable collamer lens; STS-H: Horizontal sulcus-to-sulcus; AL: Axial length; CD: Endothelial cell density; WTW: White-to-white; K1: Flat keratometry; K2: Steep keratometry; CT: Central corneal thickness; STS-V: Vertical sulcus-to-sulcus; IOP: Intraocular pressure.

DISCUSSION

Predicting postoperative vaulting has become more and more dependent on the use of big data analysis and artificial intelligence learning techniques in recent years[20-22]. In this study, we utilized various algorithm comparisons, stacked ensemble learning, and data from different ophthalmic devices to predict postoperative vaulting and appropriate ICL size. Initially, we conducted feature selection using preoperative examination parameters and identified 16 parameters most closely associated with postoperative vaulting. Among these ACD emerged as the most significant factor influencing postoperative vaulting, corroborating previous findings indicating a tendency for higher postoperative vaulting in myopic eyes with larger preoperative ACD. Subsequently, we employed four regression models MLP, XGBoost, RFR, and KNN for predictive modeling and compared their performance. Our results demonstrated that XGBoost and MLP achieved superior predictive performance, followed by Random Forest Regression, with KNN exhibiting the lowest performance. Compared to prior studies, our approach exhibited improved predictive accuracy on validation and test sets, and our models demonstrated good interpretability.

According to a number of research, machine learning regression models are more predictable for vaulting than manufacturer nomograms[23-25]. A recent study by Russo *et al*[26] analyzed 561 eyes from 300 consecutive patients using a range of machine learning techniques, including multiple linear regression, ridge regression, random forest regression, extra trees regression, and extreme gradient boosting regression. Each model included 16 parameters (postoperative vaulting at 6mo as the goal variable) and examined readings from the MS-39 AS-OCT (CSO Italia) in addition to patient-specific characteristics including age and gender. The size of the ICL, corneal curvature, and ACD were among the coefficients that positively linked with the prediction of vaulting. In contrast, lens rise, patient age, and spherical equivalent were coefficients that inversely linked with the prediction of vaulting. Using a set of eyes, the predictive models' performance was verified. Target vaulting and preoperative characteristics were used to determine the ICL size. The regression model with additional trees showed the best capacity to predict vaulting, as 98% of vaulting fell within the desired range of ±250 μm. In a retrospective analysis using artificial intelligence on 6297 eyes, Shen *et al*[27] found that ICL size, PD, and ACD were the main factors influencing postoperative vaulting. Among these factors, RF had the highest accuracy (82.2%) in predicting ICL size, followed by Gradient Boosting and XGBoost (81.5% and 81.8%, respectively). In contrast to their findings, our study identified ACD as the most important factor influencing postoperative vaulting, with XGBoost demonstrating significantly higher predictive accuracy than RF. We speculate that the differences may be attributed to the early analysis of the correlation between preoperative examination parameters and the target variable, followed by the confirmation of 16 highly correlated preoperative examination parameters included in the model computation. Additionally, XGBoost, being a decision tree-based ensemble learning algorithm, effectively captures complex relationships between features, demonstrating robustness in handling outliers and noise in data, and exhibiting excellent performance in processing high-dimensional sparse data and large-scale data with strong generalization capabilities. Xu *et al*[28] employed neural network analysis to improve the prediction of vaulting, including data from 74 patients and 137 eyes, with ICL size, ACD, PD, ATA, posterior tear film, STS, WTW, ICL spherical power, and ICL cylindrical power as input layer neurons, and vaulting as the output layer. A model incorporating ICL size, ACD, ATA, and LT achieved an ideal prediction effect (R^2=0.90), suggesting the potential of neural networks for vaulting prediction. Kim *et al*[29] examined 892 eyes from 471 patients who had ICL surgery. They developed a number of vaulting prediction models using parameters measured by ANTERION AS-OCT (Heidelberg Engineering GmbH, Heidelberg, Germany), including classical linear regression, partial least squares, and least absolute shrinkage and selection operator (LASSO). The best prediction model was chosen by evaluating predictive capacity using the Bayesian information criterion (BIC). With characteristics such as anterior chamber angle, LT, ICL size, and ACD, the LASSO model showed the maximum prediction, with a validation dataset BIC value of 1894.9. The mean vaulting accomplished was 4.9±1.96 mm in relation to the objective. Undoubtedly, artificial intelligence holds promise for improving the postoperative vaulting dispersion in normal eyes. However, improving the safety of phakic intraocular lens (pIOL) surgery depends on identifying outliers, or eyes whose vaulting—that is, their posterior chamber size—cannot be predicted by models or formulas. Anomalies pertaining to size are what make an eye needing pIOL replacement surgery. Consequently, it makes sense to conclude that the only formulae that may completely avoid the necessity for pIOL replacement surgery are those that are derived from measurements made directly in the posterior chamber. Data about the optimization of posterior chamber pIOL size for implanted phakic contact lenses (IPCL) and other lens types, such as Eyecryl, are currently unavailable.

There still exist some limitations in this study. First, the sample size included in the study is relatively small. However, the precision of artificial intelligence computations requires a large number of samples for machine learning and validation. Therefore, in subsequent studies, we will continue to expand the sample size to further improve the preoperative prediction accuracy of ICL postoperative vaulting and guide doctors in selecting appropriate lens models. Second, the duration of observation in our study needs to be extended. Although vaulting is essentially stable one month postoperatively, some studies have indicated that there may be slight changes in vaulting with prolonged postoperative time. Therefore, extending the follow-up period and incorporating the duration of follow-up into machine learning parameters are directions for future research.

In conclusion, artificial intelligence can be used for vaulting prediction and ICL size determination. XGBoost is the most popular machine learning model, which can assist ophthalmologists in selecting the appropriate ICL size to achieve proper vaulting, reduce potential complications, and improve the safety of ICL implantation techniques.

ACKNOWLEDGEMENTS

Foundations: Supported by the National Natural Science Foundation of China (No.82271100); the Jiangsu Science and Technology Support Program (No.BE2022805); the Clinical Skills Enhancement Program of Jiangsu Province Hospital (No.JSPH-MC-2022-24).

Conflicts of Interest: Yuan DQ, None; **Tang FN,** None; **Wang Y,** None; **Zhang H,** None; **Zhang WW,** None; **Gu LW,** None; **Liu QH,** None.

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