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Clinical decision support system based on deep learning for evaluating implantable collamer lens size and vault after implantable collamer lens surgery: a retrospective study

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ABSTRACT

Objectives To aid doctors in selecting the optimal preoperative implantable collamer lens (ICL) size and to enhance the safety and surgical outcomes of ICL procedures, a clinical decision support system (CDSS) is proposed in our study.
Design A retrospective study of patients after ICL surgery.
Setting China Tertiary Myopia Prevention and Control Center.
Participants 2772 eyes belonging to 1512 patients after ICL surgery. Data were collected between 2018 and 2022.
Outcome measures A CDSS is constructed and used to predict vault at 1 month postoperatively and preoperative ICL dimensions using various artificial intelligence methods. Accuracy metrics as well as area under curve (AUC) parameters are used to determine the CDSS prediction methods.
Results Among the ICL size prediction models, conventional neural networks (CNNs) achieve the best prediction accuracy at 91.37% and exhibit the highest AUC of 0.842. Regarding the prediction model for vault values 1 month after surgery, CNN surpasses the other methods with an accuracy of 85.27%, which has the uppermost AUC of 0.815. Thus, we select CNN as the prediction algorithm for the CDSS.
Conclusions This study introduces a CDSS to assist doctors in selecting the optimal ICL size for patients while improving the safety and postoperative outcomes of ICL surgery.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This study combines deep learning technology with big data to predict postoperative vault and thus select preoperative implantable collamer lens (ICL) size, which will assist doctors in selecting the optimal ICL size for patients and improve the safety and postoperative outcomes of the ICL surgery.
⇒ A conventional neural network is selected to construct the expert system by combining big data and artificial intelligence, which performs better than the traditional random forest algorithm.
⇒ As a retrospective study, it does not account for variations in vaults over time, providing only postoperative vaults at 1 month for reference by clinicians.
⇒ This study is a single-centre study with a single source of data, so there are limitations to the widespread use of the system.

BACKGROUND

Intraocular refractive surgery, particularly implantable collamer lens (ICL V.4c, STAAR Surgical, Monrovia, CA, USA), has gained widespread popularity among the various methods for myopia correction. Numerous clinical studies[1 2] have consistently demonstrated that after the ICL implantation, the quality of both visual and life of patients has significantly improved. Furthermore, the procedure has been established as safe, effective, predictable and capable of providing long-term stability regarding myopia correction results during postoperative follow-up.

Numerous scholars have conducted research on the selection of ICL size.[3 4] Shen *et al*[5] show that the postoperative ICL vault (the vertical distance from the posterior surface of the ICL to the anterior surface of the lens) is strongly correlated with the ICL size. Besides, Kim *et al*[6] establish a new ICL size calculation method and a predictive model for postoperative vault, and demonstrate that ICL size plays an important role in preventing postoperative complications. Therefore, accurate ICL size is the key to maintaining postoperative vault safety and surgical success. Currently, ICL sizes are selected by manufacturers primarily by white-to-white (WTW) and anterior chamber depth. However, due to the indirect measurement of eye parameters, differences in the anatomical structure of the anterior segment, and the fact that only four ICL sizes are available for implantation in the market, the patient's postoperative vaults may be too high or too low.[7,8] Nowadays, some studies have used formula regression methods to analyse the size of ICL.[9–14] These studies have incorporated a few parameters, leading to a poor fit in multiple parameter regressions, which does not adequately consider various aspects for predicting the ICL size. Thus, it is necessary to build an accurate ICL selection system. Simultaneously, a clinical decision support system (CDSS) is widely used in the medical industry because it can summarise patient-specific information and filter knowledge according to disease-specific algorithms.[15] Therefore, constructing a machine learning-aided CDSS to help physicians make optimal ICL sizing choices is necessary. With the development of technology and the gradual maturation of deep learning technology, it has been used in the field of ophthalmology for age-related macular degeneration,[16] diabetic retinopathy[17] and glaucoma[18].

To the best of the authors' knowledge, the research of combining deep learning technology with big data to predict postoperative vault and select preoperative ICL size has not yet been reported. In this study, we propose the development of a CDSS that leverages big data and deep learning technology to establish a classification prediction model. The proposed model is designed to guide the ICL size selection by predicting the vault 1 month postoperatively.

METHODS

Data collection

Patients

This retrospective study enrols myopic patients who underwent ICL implantation in the crystalline lens eye at the Department of Ophthalmology of the Army Specialty Medical Center between April 2018 and May 2022. These patients underwent preoperative examinations and surgery following standardised procedures and completed a postoperative follow-up period of 1 month.

Inclusion criteria:

- Age ≥18 years old.
- Stable refractive state (annual refractive state change ≤−0.5 D).
- Spherical lens degree ≤−18.0 D.
- Astigmatism ≤6.0 D.
- Corrected distant vision ≥20/40.
- No history of eye surgery.

Exclusion criteria:

- Unstable refractive state.
- History of other eye diseases, such as corneal abnormalities, uveitis and macular degeneration.
- Presence of abnormal angle structure or glaucoma.
- Presence of uncontrolled systemic diseases or other factors that may impact subsequent measurements, such as mental and behavioural abnormalities.

Finally, data were collected from 2936 eyes. After processing the dataset for missing and abnormal data, a total of 2772 eyes were included in this study (1365 left eyes, 1407 right eyes; 400 males (740 eyes), 1112 females (2032 eyes); mean age 28.4±5.7 years). Local ethical committee approval was obtained (ID: 2023-187) from the Ethics Committee of the Army Specialty Medical Center of the Chinese People's Liberation Army. And, all the research procedures strictly adhered to the principles outlined in the Declaration of Helsinki. Informed consent was obtained from each participant after a comprehensive explanation of the surgical procedure before the commencement of treatment. To safeguard privacy, we concealed all patients' identities in this study.

Measurements

Before the surgery, all patients underwent a comprehensive ophthalmological examination, including visual acuity (naked eye vision and best-corrected vision), atrial angle opening distance 500 (AOD500, mm), central anterior chamber depth (CACD, mm), corneal thickness (CT, mm) by anterior segment optical coherence tomography (AS-OCT, Zeiss Visant OCT), flat keratometry (K1, mm), steep keratometry (K2, mm), WTW (mm) by Pentacam corneal topography, horizontal ciliary sulcus-to-ciliary sulcus distance (STS, mm) by ultrasound biomicroscope (UBM, Tianjin Suowei SW-3200L) and the axial length (AL, mm) by non-contact optical correlation biometry. Postoperatively, the patients' vault was measured by AS-OCT. The data provided by UBM were measured by a well-trained technician, while the rest of the data were automatically measured by the instrument. The above data are averaged after every two measurements to obtain results.

Selection of the ICL size and implantation method

During the diagnostic process, a total of four sizes (12.1 mm, 12.6 mm, 13.2 mm and 13.7 mm) are available for specialists to choose from. The selection of the most suitable ICL size and implantation method is determined by experienced specialists at the Army Specialty Medical Center. These decisions are based on the parameters obtained during the preoperative examination.

Clinical decision support system

System structure

Our CDSS is a machine learning-based CDSS, thus, this study presents a CDSS developed using Python V.3.9.0 and Matlab V.2022a. Figure 1 illustrates the system's overall architecture, which comprises two primary components: (1) initial ICL size selection and (2) subsequent ICL size adjustment based on postoperative vault value predictions. The operational steps of this CDSS are as follows: In the first stage, the patient's preoperative parameters are inputted into the system, and the recommended ICL size for implantation is predicted using a deep-learning neural network. In the second stage, the doctor initially provides the selected ICL size for the implantation decision. Then, the system predicts the expected range of the patient's vault values in the postoperative 1-month period using another deep learning neural network, categorised as insufficient (0–250 µm), normal (250–750 µm) and

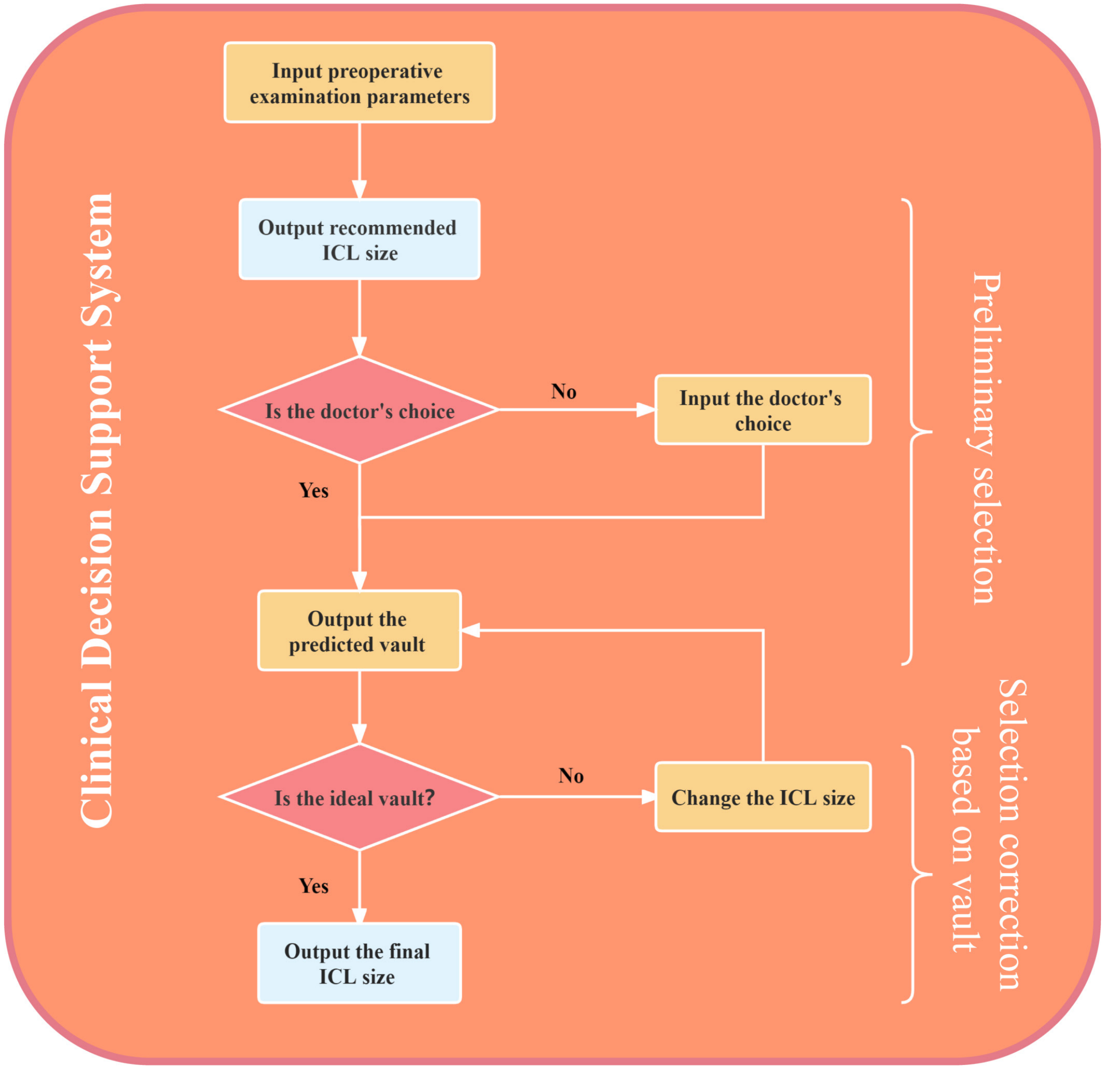

Figure 1 Structure of the prediction system. ICL, implantable collamer lens.

excessive (750 µm to +∞ µm). When the predicted vault is abnormal, the physician can adjust the ICL dimensions to modify the ICL size and get the optimal choice.

Materiality analysis

The correlation between vault and input parameters (age, pupil size, spherical lens, column lens, AOD500, AL, K1, K2, CACD, CT, WTW, STS, ICL size, ICL type and ICL implantation orientation) is investigated using the importance of alignment.

ICL size prediction

ICL size is used as a prediction target, and 14 preoperative parameters are entered by using the random forest (RF), conventional neural networks (CNNs), long short-term memory neural networks (LSTMs), backpropagation neural networks (BPNNs) and radial basis function neural networks (RBNNs) to construct a predictive model for ICL size. Fivefold cross-validation is used to reduce the uncertainty associated with data partitioning. In order to fairly compare the advantages and disadvantages of different models, the random seed is fixed at 2023. The data are randomly divided into a training set and a test set in the ratio of 80%:20%. Classification accuracy and area under curve (AUC) are used as evaluation metrics for the classification model.

Prediction of vault 1 month after ICL surgery

A classification model is employed to predict postoperative vaults (after 1 month), with patients being categorised into three postoperative vault categories: insufficient (0–250 µm), normal (250–750 µm) and excessive (750 µm to +∞ µm). The classification models used for this task include RF, CNN, LSTM, BPNN and RBNN. Incorporating the 14 preoperative parameters from the ICL size prediction, we augment the input with ICL feature parameters, resulting in a total of 15 parameters as input for the deep learning model. Simultaneously, another deep learning model sets the vaults as the prediction targets. The validation methodology mirrors that of the ICL size prediction, employing fivefold cross-validation, consistent randomised seeds, dataset division methods and evaluation metrics.

Introduction of algorithms

Deep learning neural networks offer a significant advantage over traditional machine learning algorithms when processing large-scale complex data. Therefore, in this study, we select CNN, LSTM, BPNN and RBNN deep learning neural networks to predict the ICL size and postoperative vaults. By comparing the prediction accuracy of these different methods, we aim to identify the one with the highest accuracy, which would be integrated into the final system. As Shen *et al*[5] indicate, RF algorithms have demonstrated superior accuracy for vault prediction in traditional machine learning. Thus, in order to perform a rigorous comparison and validate the advantages of deep learning neural networks, we have included the RF algorithm as a reference in this study.

Conventional neural networks

CNN is one of the most popular and most used deep learning networks, which is a multilayer supervised learning network with a significant advantage in processing grid-like structured data.[19] A typical CNN structure consists of a convolutional layer, a pooling layer and a fully connected layer, which has the advantage of weight sharing.

Long short-term memory neural networks

LSTM is an optimisation model modified from recurrent neural networks.[20] Through the input gate, output gate, and forgetting gate in the cell structure, the inflow and outflow, as well as the updating of information, are gradually realised, which is less prone to problems such as gradient disappearance and gradient explosion.

Backpropagation neural networks

BPNN is a multilayer feed-forward neural network trained according to the error backpropagation algorithm. It mainly consists of two processes: forward transfer of information and backward propagation of error.[21] It minimises the mean square deviation of the error between the actual and desired output values of the network by gradient descent method using the gradient search technique.

Radial basis function neural networks

RBNN has a simple topology and is a single hidden-layer feed-forward network.[21] It uses radial basis function as the hidden node activation function, which is characterised by fast convergence speed, high approximation accuracy and small network size.

Random forest

RF uses random resampling and node random splitting techniques to construct multiple decision trees and get the final result by voting. RF can analyse complex interactions to classify features, is robust to noisy data and missing values, and has a fast learning rate, which is more commonly used in machine learning algorithms.[22]

Patient and public involvement

Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

RESULTS

Statistical data analysis

The data of 2772 eyes are included in this study (1365 left eyes, 1407 right eyes; 400 males (740 eyes), 1112 females (2032 eyes); mean age 28.4±5.7 years). Patients' demographics, ICL characteristics and biometric parameters of the anterior segment are presented in online supplemental table 1. The mean vault 1 month after ICL implantation is 551.36±197.19 µm (range: 18–980 µm).

Importance analysis

To assess the influence of each preoperative parameter on both the ICL size and postoperative vault, we conduct an importance analysis of each parameter. Figure 2A illustrates the significance of each input parameter in relation to the ICL size, using WTW as the baseline with the highest importance, scaled to 1.00 for comparative purposes. Notably, WTW and STS have an exceptionally significant impact on the ICL size, with importance scores of 1.00 and 0.92, respectively.

Furthermore, figure 2B presents the importance of each parameter in predicting postoperative vault, using the same comparative method as ICL size, which is assigned the highest importance and is scaled to 1.00. In this context, ICL size, STS, CACD and orientation substantially influence postoperative vault prediction, with importance scores of 1.00, 0.74, 0.60 and 0.48, separately.

ICL size prediction

As ICL dimensions significantly influence postoperative vault, our focus is on obtaining the most accurate prediction of the ICL size while ensuring prediction correctness. Therefore, we exclude preoperative parameters of patients with abnormal postoperative vaults from the ICL size prediction datasets. Ultimately, our analysis encompasses 2051 eyes with preoperative parameters, and the ICL size serves as the predictive target. Figure 3 presents the confusion matrix for various models in the ICL size classification prediction, which displays the prediction accuracy of different models. The models include CNN, LSTM, RF, RBNN and BPNN, which achieve accuracies of 91.37%, 87.77%, 85.55%, 83.29% and 80.37%, respectively. Among all, CNN exhibits the highest accuracy. Furthermore, in figure 3A, the CNN model successfully predicted 81% of true values for ICL size of 12.1 mm, 96% for 12.6 mm, 81% for 13.2 mm and 83% for 13.7 mm.

In our datasets, 261 eyes exhibit postoperative vaults below 250 µm, 2051 eyes within the normal range, and 460 eyes exceed 750 µm. In the task of classifying and predicting postoperative vaults, CNN demonstrates the highest classification accuracy at 85.27%. LSTM achieves

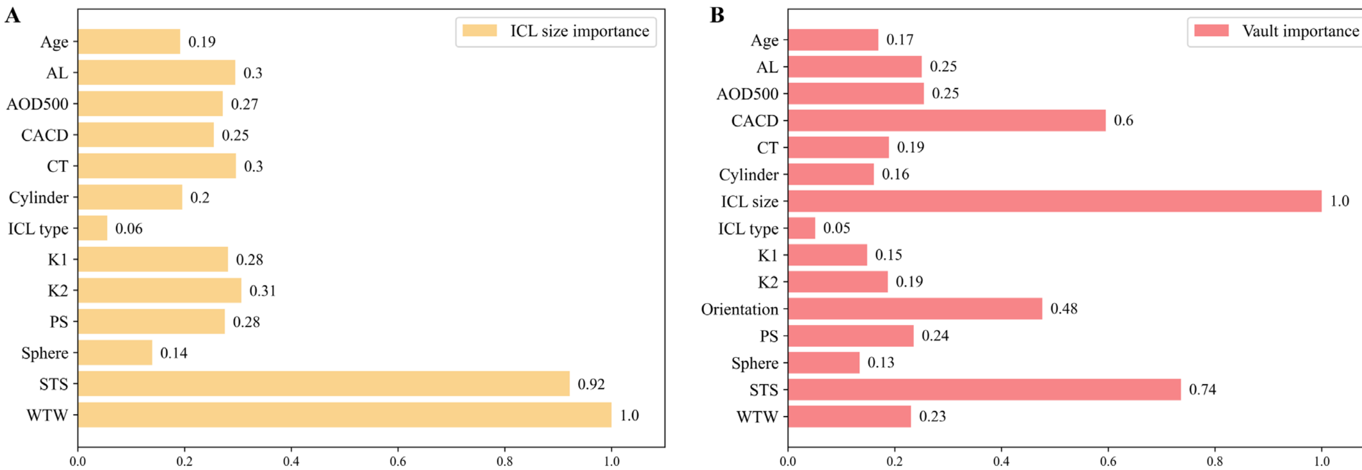

Figure 2 Importance analysis of implantable collamer lens (ICL) size prediction. (A) Importance of 13 preoperative parameters with a maximum importance of 1. Parameters included age, AL, AOD500, CACD, CT, columnar lenses, type of ICL, K1, K2, PS, spherical lens, STS and WTW. The maximum importance of the vault prediction importance analysis at 1 month postoperatively (B) is 1, and the parameters are added to (A) with the addition of the ICL size and implantation direction. AL, axial length; AOD500, atrial angle opening distance 500; CACD, central anterior chamber depth; CT, corneal thickness; K1, flat keratometry; K2, steep keratometry; PS, pupil size; STS, horizontal ciliary sulcus-to-ciliary sulcus distance; WTW, white-to-white.

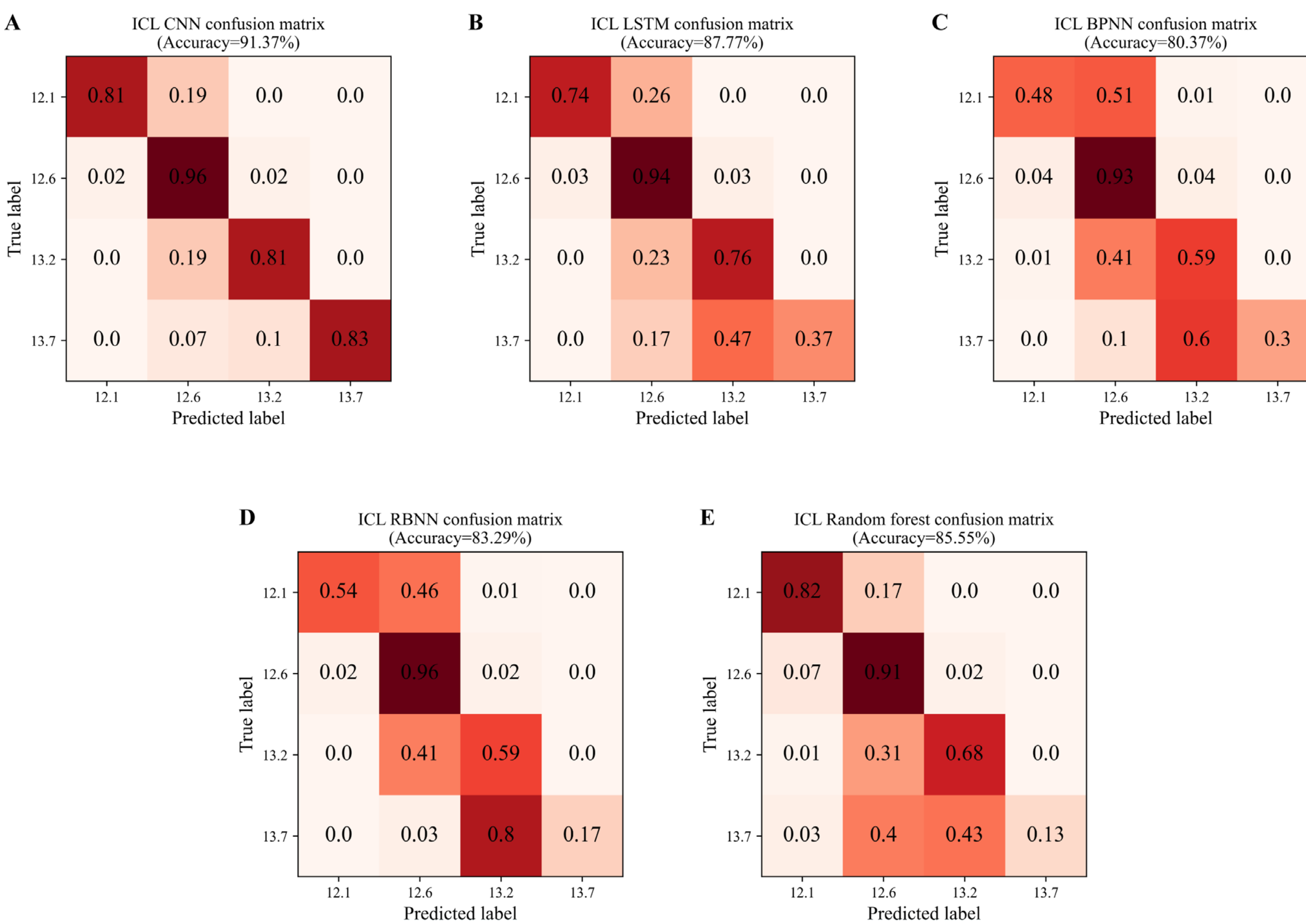

Figure 3 Confusion matrix for the classification model used for implantable collamer lens size prediction of vault values. BPNN, backpropagation neural network; CNN, conventional neural network; ICL, implantable collamer lens; LSTM, long short-term memory neural network; RBNN, radial basis function neural network.

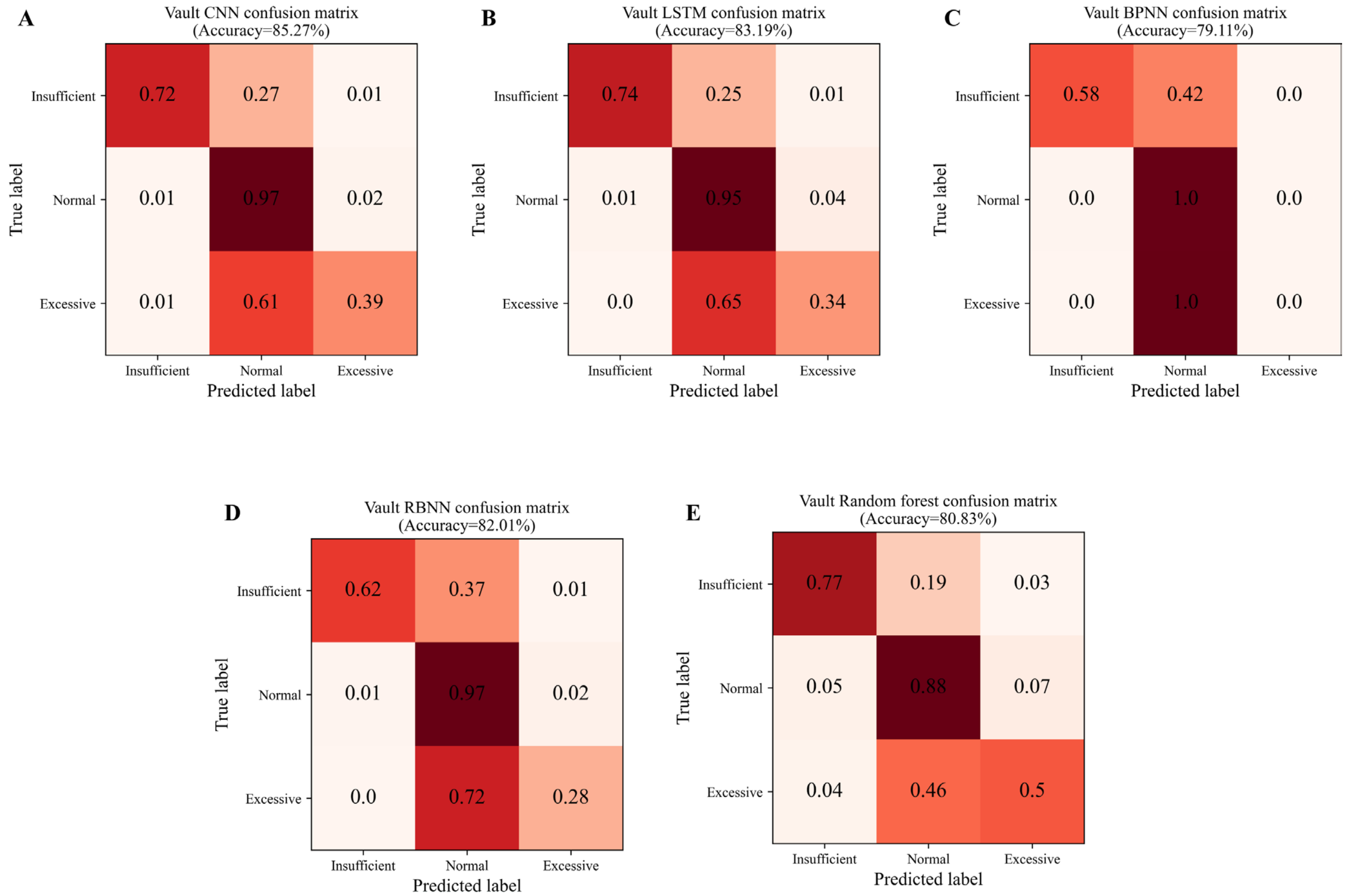

Figure 4 Confusion matrix for vault prediction classification models. BPNN, backpropagation neural network; CNN, conventional neural network; LSTM, long short-term memory neural network; RBNN, radial basis function neural network.

a prediction accuracy of 83.19%, RBNN achieves 82.01%, RF achieves 80.83% and BPNN achieves 79.11%. Figure 4A illustrates the CNN classification prediction model. In this representation, the CNN model successfully predicts the true value for low vault data with an accuracy of 0.72 and for normal vault data with an accuracy of 0.97.

DISCUSSIONS

This study involves the screening and analysis of 12 feature parameters using 5 classical artificial intelligence (AI) algorithms (CNN, LSTM, BPNN, RBNN and RF) to predict the recommended ICL size selection in the preoperative phase. Building on this foundation, we further predicted the vault values at 1 month postoperatively by incorporating the parameters related to the ICL size and implantation method.

An analysis of parameter importance regarding the ICL size indicates that both STS and WTW exhibit significant importance relative to other parameters. Although existing studies continue to debate the preference between STS and WTW as the primary index for ICL size selection, they collectively acknowledge the substantial influence of both the parameters on the selection of the ICL size. This conclusion aligns with the findings of our study.[23]

In our analysis of postoperative vault importance, we observe a strong correlation between vault measurements 1 month after surgery and the selected ICL size, consistent with previous research findings.[5 24] Therefore, the CDSS proposed in this study offers an innovative approach by predicting the postoperative vault and providing feedback to optimise the selection of the ICL size. Through an iterative process, the CDSS aims to determine the most suitable ICL size for each patient, ultimately enhancing surgical success rates and outcomes. Beyond the ICL size, our analysis identifies several other influential factors affecting postoperative vault, including STS, CACD, ICL implantation orientation, AL and AOD500. These factors carry substantial weight in vault prediction and should not be overlooked. Notably, while both STS and WTW display significant importance in the analysis of the ICL size, STS seems to be more critical than WTW in postoperative vault prediction. Consequently, this study suggests that clinicians may benefit from paying closer attention to STS values in challenging clinical decision-making scenarios, which is consistent with the findings of Chen *et al*.[25]

In ICL prediction, the CNN model consistently outperforms other models across all sizes, achieving a remarkable 5.82% increase in prediction accuracy and a 6.80%

boost in prediction performance compared with the previously used RF model. Consequently, for the initial selection of the ICL size in this system, we have opted for the CNN model for analysis and prediction. To enhance the accuracy of the ICL size prediction, we exclude data from abnormal vault measurements, encompassing 261 eyes with low postoperative vaults and 460 eyes with high postoperative vaults. Thus, we can firmly focus on training and prediction solely with data featuring normal postoperative vaults. To validate the applicability of the predictive model, we use it to predict and analyse the ICL sizes that should be implanted based on preoperative examination results of the excluded data with abnormal vaults. Given the close relationship between the ICL size and postoperative vault, we aim to tailor the ICL size recommendations to individual patient needs. For patients with low postoperative vaults, we aim for the system to suggest larger ICL sizes. Conversely, for those with high postoperative vault, we expect smaller ICL size recommendations from the system. Our prediction results demonstrate that for data associated with low postoperative vault, the system recommends sizes equal to or greater than the actual implanted size in 95.02% of the cases. For data linked to high postoperative vaults, the system recommends sizes equal to or smaller than the actual implanted size in 89.57% of the cases. These outcomes underscore the practical utility of our predictive model, which surpasses decisions made by physicians based solely on clinical experience.

Given the limited availability of only four ICL sizes, the potential for substantial variations in vault measurements post-ICL implantation across the patient population is significant. Since vaults hold paramount importance for the surgical safety and overall outcomes of patients undergoing ICL implantation, we have opted to employ postoperative vault predictions to evaluate and fine-tune the selected ICL size in a clinical setting. Regarding using postoperative vault prediction to inform ICL selection, we have consistently observed superior predictive performance, especially with CNN, at each vault measurement level. Consequently, this system continues to leverage the CNN model for the analysis and prediction of postoperative vault in the initial ICL size-selection process.

To assess the superior predictive performance of the selected CNN model for ICL size and postoperative vault prediction, we employ receiver operating characteristic curves and calculate the AUC as an evaluation metric in this study. As shown in figure 5, since our model is designed for multicategory prediction and the data distribution among categories is uneven, we adopt the micro-average method for data analysis and evaluation. For the four-category ICL size-selection problem, our predictive model achieves an AUC of 0.842, while for the three-category postoperative vault classification problem, the AUC reaches 0.815. These results indicate the model's effectiveness in prediction. In classification problems, four major metrics (accuracy, precision, recall and F1 score) are often used to evaluate the classification effect. However, in this paper, micro-average is used for

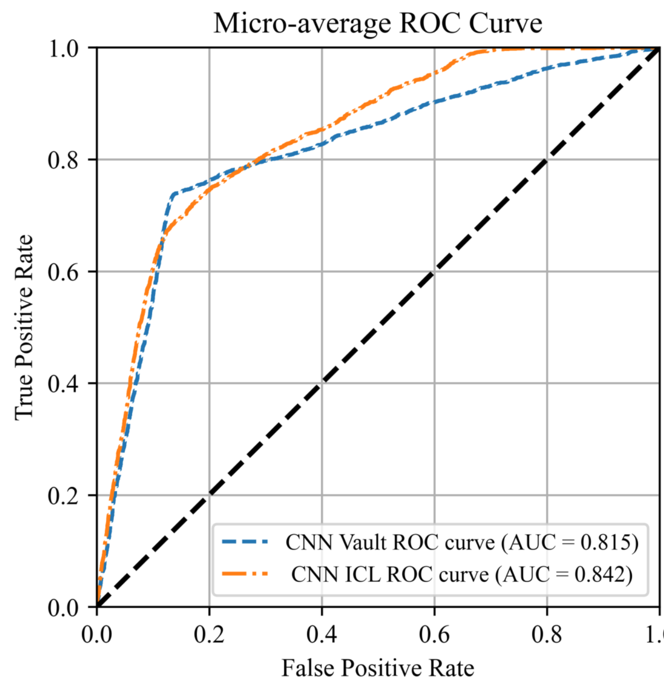

Figure 5 The ROC curve of ICL size and vault with micro-average method. AUC, area under curve; CNN, conventional neural network; ICL, implantable collamer lens; ROC, receiver operating characteristic.

the metric so that the four major metrics are numerically equal to the prediction accuracies demonstrated in figures 3 and 4. In summary, we have established this system as a CNN-based CDSS.

Nevertheless, this study does have certain limitations. First, as a retrospective study, it does not account for changes in vaults over time, providing only postoperative vaults at 1 month for reference by clinicians. Alfonso *et al*'s research[26] shows that postoperative vault tends to decrease over time, highlighting the importance of predicting patients' future vault changes. Second, this study is single-centre, drawing data from a sole source. It is essential to incorporate data from multiple sources to promote broader application, as different centres may have variations in measuring instruments and equipment, leading to distinct measurement errors. Last, while this study selects CNN as the algorithm for the system, achieving an AUC of 0.842 for ICL size prediction and 0.815 for vault prediction, there is certainly room for improvement. Future enhancements can further explore more optimised algorithms to enhance the system's predictive capabilities.

CONCLUSIONS

This study introduces an expert system leveraging AI techniques and deep learning technology to address the challenge of abnormal postoperative vault due to imprudent ICL size selection. The aim is to assist medical professionals in choosing the most appropriate ICL size for individual patients, ultimately enhancing the safety and surgical outcomes of ICL procedures.

Postoperative vault is an essential indicator for evaluating the safety of ICL surgery, whereas ICL implantation size directly influences the variation of vault parameters. Therefore, we choose to provide an auxiliary guide to preoperative implantation size by predicting postoperative vault in reverse. To predict both the ICL size and postoperative vault, we conduct a comparative analysis using five frequently employed algorithms (CNN, LSTM, BPNN, RBNN and RF). Among these algorithms, the CNN algorithm exhibits the most robust predictive performance, leading us to select CNN as the core algorithm for our CDSS.

With this system, the accuracy of the doctor's crystal selection will be dramatically improved. Future endeavours in automating the corrective prediction of ICL implant size based on postoperative vault predictions could benefit from the adoption of more optimised algorithms and the aggregation of data from multiple centres. Besides, we will consider more potential influencing factors (such as postoperative anterior chamber angle) to make the study more comprehensive. These approaches can create a more precise and comprehensive predictive model for ICL sizing decisions.

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Contributors YY had full access to all the data in the study and took responsibility for the integrity of the data and the accuracy of the data analysis. YY is the guarantor of the study. All authors meet the criteria for authorship. Data collection: YY and BL. Analysis and interpretation of the data: YY, ZL, BL, WL and JY. Writing and revising the manuscript: YY, ZL, BL, WL and JY. Supervision: WL and JY.

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Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval Local ethical committee approval was obtained (ID: 2023-187) from the Ethics Committee of the Army Specialty Medical Center of the Chinese People's Liberation Army. The study adhered to the tenets of the Declaration of Helsinki.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon reasonable request.

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