An interpretable model predicts visual outcomes of no light perception eyes after open globe injury

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ABSTRACT

Background The visual outcome of open globe injury (OGI)-no light perception (NLP) eyes is unpredictable traditionally. This study aimed to develop a model to predict the visual outcomes of vitrectomy surgery in OGI-NLP eyes using a machine learning algorithm and to provide an interpretable system for the prediction results.

Methods Clinical data of 459 OGI-NLP eyes were retrospectively collected from 19 medical centres across China to establish a training data set for developing a model, called 'VisionGo', which can predict the visual outcome of the patients involved and compare with the Ocular Trauma Score (OTS). Another 72 cases were retrospectively collected and used for human–machine comparison, and an additional 27 cases were prospectively collected for real-world validation of the model. The SHapley Additive exPlanations method was applied to analyse feature contribution to the model. An online platform was built for real-world application.

Results The area under the receiver operating characteristic curve (AUC) of VisionGo was 0.75 and 0.90 in previtrectomy and intravitrectomy application scenarios, which was much higher than the OTS (AUC=0.49). VisionGo showed better performance than ophthalmologists in both previtrectomy and intravitrectomy application scenarios (AUC=0.73 vs 0.57 and 0.87 vs 0.64). In real-world validation, VisionGo achieved an AUC of 0.60 and 0.91 in previtrectomy and intravitrectomy application scenarios. Feature contribution analysis indicated that wound length-related indicators, vitreous status and retina-related indicators contributed highly to visual outcomes.

Conclusions VisionGo has achieved an accurate and reliable prediction in visual outcome after vitrectomy for OGI-NLP eyes.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ There is currently no effective method to predict the visual outcomes of no light perception eyes caused by open globe injury (OGI-NLP eyes). The Ocular Trauma Score (OTS) and doctor's experience can help to predict but with certain limitations and low accuracy.

WHAT THIS STUDY ADDS

⇒ Multicentre research was performed and an explainable model named 'VisionGo' was developed based on a machine learning algorithm and enabled the accurate prediction of visual outcomes of vitrectomy for OGI-NLP eyes and provided an explanation system for the predicting results.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ 'VisionGo' provides a reliable and interpretable method for predicting visual outcomes of OGI-NLP eyes, which overcomes the limitations of OTS and doctors' experience, and helps doctors and patients in making clinical decisions.

INTRODUCTION

The light perception function of the eye needs to be maintained under the protection of a stable eye microenvironment. Any changes in external forces, inflammation, intraocular pressure or the structural integrity of the eyeball will affect the maintenance of photosensitivity, and the effect can be irreversible. In the case of severe ocular trauma, the microenvironment of the eye suffers drastic changes, the integrity of the eyeball is destroyed, the eye loses its ability to perceive light, and the vision plummets to no light perception (NLP). Ocular trauma, especially open globe injury (OGI), causes many cases of vision loss worldwide. Approximately half a million people worldwide are blind due to ocular trauma,[1] and the number keeps rising.[2] As reported, ocular trauma is most common in young adults,[3] who are the main source of family income. Hence, vision loss caused by severe ocular trauma has many severe consequences for both families and society.[4]

NLP vision caused by severe ocular trauma, especially OGI, usually suggests severe ocular damage and very poor visual outcome.[5 6] In the past, such eyeballs would have been removed. However, with the continuous development of ophthalmologic microscopic surgery, the current view is that the eyeball should be preserved as much as possible to provide an opportunity for ocular reconstructive vitrectomy surgery.[7 8] Vitrectomy has become the best treatment for OGI-NLP eyes. According to the literature, 3%–33% of OGI-NLP eyes acquire light perception or better vision after vitrectomy, which has become the best treatment for OGI-NLP eyes.[9–11] Currently, there is no effective manner to help clinicians and patients predict which OGI-NLP eyes can regain the ability to perceive light after vitrectomy. Although a few experts in the field of ocular trauma can make predictions of visual outcomes of injured eyes based on their rich experience, those predictions are inexact, and can not be applied widely. Therefore, it is necessary to seek more accurate and effective techniques to help ophthalmologists predict the possibility of restoring light perception ability on OGI-NLP eyes following severe ocular trauma.

Machine learning (ML) is an aspect of artificial intelligence (AI) that shows great potential in predictive analytics. Personalised predictions by ML have been verified to have high accuracy in the prediction of prognosis of many diseases like autism,[12] myopia development,[13] glaucoma[14] and age-related macular degeneration.[15] However, its application in the prediction of the visual outcomes of ocular trauma has not been reported. In this study, we designed multicentre research and constructed an explainable ML model, named 'VisionGo', to predict the visual outcomes of vitrectomy for OGI-NLP eyes, and provide an interpretive system for the results of the prediction. We aimed to achieve a breakthrough in the prediction of visual outcome of OGI-NLP eyes via an ML algorithm and to provide an accurate and effective method for ophthalmologists in terms of clinical decision-making.

METHODS

Study design

This was a real-world evidence study involving 19 medical centres across China. We developed a predictive ML model (VisionGo) to predict the possibility of injured eyes regaining the ability to perceive light, using clinical information for 459 OGI-NLP eyes. The model performance was compared with a traditional scoring system, the Ocular Trauma Score (OTS). Then, the other recently collected 72 cases were used for external validation, and the performance was compared with predictions by ophthalmologists. VisionGo was finally tested by real-world validation using prospectively collected clinical data for 27 OGI-NLP eyes. The geographical and case distribution of the 19 medical centres is shown in online supplemental figure S1. Finally, informative clinical feature analysis was performed using SHapley Additive exPlanations (SHAP) value. Figure 1 shows the workflow of our study. The study was approved by local ethical committee of each centre. All methods were performed in accordance with the Declaration of Helsinki. Due to the retrospective nature of model building, internal and external validation and human–machine comparison parts of the study, the ethical committee waived the need for written informed consent to these patients concerned. All participating patients in real-world validation provided written informed consent.

Definition of NLP

NLP eyes were identified according to clinical diagnostic criteria, where the examination was performed in a dark room using a slit-lamp microscope (or binocular indirect ophthalmoscope or a flashlight) with the highest intensity light. An eye-shade completely covered the fellow eye. If the injured eye could not perceive light, NLP was documented.

Patients

Clinical data on patients diagnosed with OGI according to the classification of mechanical ocular trauma,[16] hospitalised in the involved medical centres from November 2009 to October 2021, with NLP, were collected from the Hospital Information System and analysed by experienced ophthalmologists. The inclusion criteria and exclusion criteria are shown in online supplemental

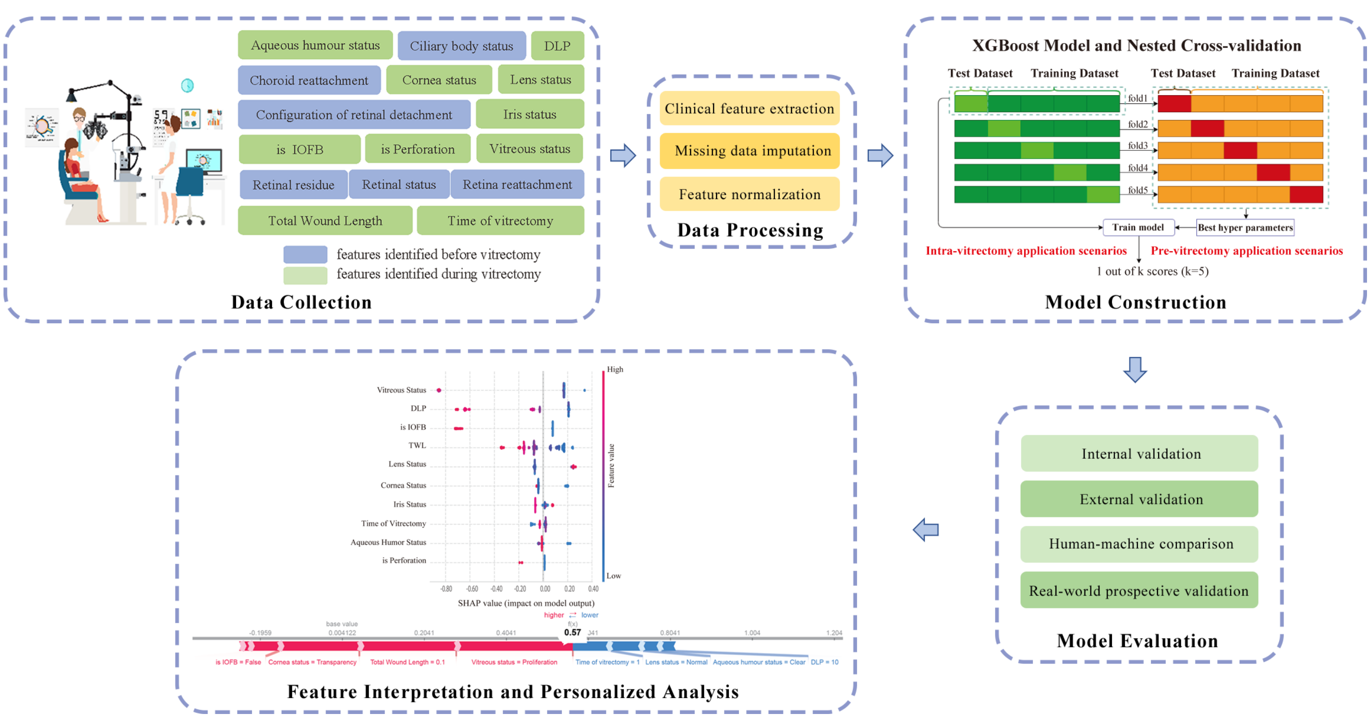

Figure 1 A flowchart showing the workflow of our study. IOFB, intraocular foreign body; SHAP, SHapley Additive exPlanation; TWL, total wound length; DLP, distance from the limbus to the most posterior of the full-thickness sclera wound.

table S1a. After systematic clinical feature extraction and filtering, a total of 531 eyes (530 patients) were included.

Data collection

All the information were obtained from the medical records and operation video. Basic information included sex, age, occupation, details of the injury (including cause of injury, location of accident, etc) and duration between injury and admission. Clinical information included the injured eye, the type of injury, clinical features of the injured eye (including clinical classification,[16] zone of injury,[17] total wound length (TWL), distance from the limbus to the most posterior of the full-thickness sclera wound (DLP, online supplemental figure S2), iris status, cornea status, aqueous humour status, lens status, vitreous status, time of vitrectomy, retinal residue, configuration of retinal detachment, retina status, retina reattachment, choroid reattachment and ciliary body status), details of surgery, follow-up time, vision and anatomy outcome. The definitions of clinical features are given in online supplemental table S2.

Model development and internal validation

Clinical data onto 459 eyes from November 2009 to October 2020 were selected from the 531 included eyes for modelling and internal validation. Before model development, feature engineering was performed.

Accurate classification of ocular trauma is usually affected by doctors' varied understanding of the cause of injury, which can lead to inconsistent clinical classification of collected data. Therefore, we engineered this subjective factor by replacing the original classification with two simplified indicators—intraocular foreign body (IOFB) and perforating injury. Given that the injury zone is highly dependent on DLP, we eliminated the zone of injury. Finally, 16 new clinical features were employed, including 10 features detected before performing vitrectomy (IOFB or not, perforating injury or not, TWL, DLP, iris status, cornea status, aqueous humour status, lens status, vitreous status, time of vitrectomy) and six features detected during vitrectomy (retinal residue, configuration of retinal detachment, retina status, retina reattachment, choroid reattachment and ciliary body status).

All 16 clinical features were divided into categorical and numeric types. To maximise sample usage and verify the fit of the model, we performed multiple imputation by chained equations (MICE) method[18] to fill in missing data. In clinical practice, patients with zero residual retina have no photoreceptor cells; thus, the type, state and reposition of the detachment cannot be observed. To make full use of the clinical characteristics of patients to predict postvitrectomy recovery, we retained samples with a residual amount of zero and divided the patient's disengagement type, state and reduction status into one category for interpolation. The clustering and weighted mean methods implemented in the MICE package were used to impute categorical variables and continuous variables, respectively.[18] Pearson's correlation test and hierarchical clustering were used to evaluate the relationships of integrated features with our collected and imputed clinical data sets.

We used XGBoost and a nested cross-validation (CV) strategy to construct classification model for predicting visual outcomes (remained NLP or regained vision) after vitrectomy recovery. XGBoost is a scalable and end-to-end tree boosting system that has shown state-of-art performance, and the nested CV which contains inner and outer loops is used to overcome the problem of overfitting the training data set and bias in performance evaluation.[19] Briefly, in the inner loop, we first performed a grid search based on fivefold CV on each outer training set for hyperparameter optimisation and selected the best model. The outer CV was applied to assess the performance of the selected model of the inner CV on the corresponding outer testing set. We averaged the predictions of the outer CV models to improve generalisability/robustness of the predicted result over a single model. While tuning training data sets with the unbalanced positive and negative samples, we adjusted the weight of positive samples according to the ratio of the two visual outcomes. For both inner and outer CV, we used the receiver operating characteristic (ROC) curve and area under the ROC curve (AUC) as metrics to evaluate the model performance. The performance of VisionGo was compared with that of the OTS. We used SHAP to explain the contribution of individual predictions to the model. SHAP interprets the predicted value of the model as the sum of the attribution value of each input feature. The biggest advantage of the SHAP value is that it can reflect the influence of the features in each sample and show positive or negative impacts.

External validation and human–machine comparison

Clinical information on another 72 eyes from November 2020 to October 2021 was selected from the 531 included eyes for external validation and human–machine comparison. The performance was compared with six ophthalmologists with different levels of experience (two chief residents who were responsible for emergency treatment of ocular trauma, two ophthalmologists with 5–10 years of experience and two eye trauma specialists with >10 years of experience). The six ophthalmologists did not know the patients' visual outcomes nor the result of model prediction before their prediction.

Real-world validation

Data on patients that were prospectively collected after the model built was used for real-world validation. The inclusion criteria and exclusion criteria are shown in online supplemental table S1b. In total, 27 patients (27 eyes) were included from November 2021 to March 2022. Same clinical features were collected and inputted into the model for real-world validation.

RESULTS

Basic information on cases

A total of 531 OGI-NLP eyes (530 patients) were included in this study. Table 1 shows the basic information of the included cases. Information on the injured eyes is shown in table 2. After vitrectomy, 324 eyes (61.0%) remained NLP, 207 eyes (39.0%) achieved vision better than 10/200 (table 2). 95.3% of the injured eyes were preserved, and 4.7% were enucleated (table 2).

Correlation analysis of clinical features

For each case, 16 clinically accessible features were selected to describe critical indicators (online supplemental table S2). To visualise the underlying relationships among the 16 clinical features, we clustered them according to their pairwise relationships based on our data. We found that these features could be generally partitioned into three subsets (figure 2A). Among the three clusters, retinal residue, IOFB and perforating injury were, in general, negatively correlated with other features. For example, retinal residue was strongly negatively correlated with configuration of retinal detachment, retina status and retina reattachment, which means that the most severe retinal detachment was associated with curlier detached retina, worse retinal reattachment and a lower residual amount of retina. In addition,

Table 1 Data of patients with OGI-NLP eyes

Age, mean±SD, years	43.0±14.0
Sex, n (%)	
Male	475 (89.6)
Female	55 (10.4)
Occupations, n (%)	
Worker	272 (51.3)
Farmer	108 (20.4)
Freelance	41 (7.7)
Staff	31 (5.8)
Unemployed	28 (5.3)
Primary/middle school student	14 (2.6)
Driver	10 (1.9)
Retiree	7 (1.3)
Preschool child	5 (0.9)
College student	3 (0.6)
Fisherman/herder	3 (0.6)
Soldier	2 (0.4)
Data missing	6 (1.1)
Causes of injury, n (%)	
Violence	321 (60.5)
Blast	66 (12.4)
Accident in daily life	50 (9.4)
Road accident	33 (6.2)
Fall over	32 (6.0)
Extrusion	25 (4.7)
Fall from a height	4 (0.8)
Places of injury, n (%)	
Construction site	273 (51.4)
Home	102 (19.2)
Public buildings	67 (12.6)
Road	50 (9.4)
Agricultural environment	26 (4.9)
Outdoors	7 (1.3)
School	3 (0.6)
Sports venues	3 (0.6)

OGI-NLP, Open globe injury-no light perception.

Table 2 Information of the OGI-NLP eyes receiving combined PPV

Laterality of eyes, n (%)	
Right	257 (48.4)
Left	272 (51.2)
Bilateral	1 (0.2)
Previous history of the injured eyes, n (%)	
Myopia	5 (0.9)
LASIK surgery	1 (0.2)
RK surgery	1 (0.2)
Keratoconus	1 (0.2)
Cataract surgery	2 (0.4)
Ocular trauma	1 (0.2)
Vitrectomy	1 (0.2)
None	522 (98.3)
Time interval from injury to admission, n (%)	
≤24 hours	509 (95.9)
>24 hours	21 (4.0)
Mean±SD, hours	16.6±48.8
Type of ocular injuries, n (%)	
Rupture	290 (54.6)
Penetrating	171 (32.2)
IOFB	57 (10.7)
Perforating	13 (2.4)
Zone of injury	
Zone I	73 (13.7)
Zone II	109 (20.5)
Zone III	341 (64.2)
Data missing	8 (1.5)
Endophthalmitis, n (%)	
No	476 (89.6)
Yes	55 (10.4)
Time of vitrectomy, n (%)	
≤3 days	46 (8.7)
>3–7 days	122 (23.0)
>7–14 days	248 (46.2)
>14–21 days	73 (13.7)
>21 days	41 (7.7)
Missing	1 (0.2)
Management during vitrectomy, n (%)	
Endotamponade agent	
Silicone oil	477 (89.8)
BSS	32 (6.0)
Foldable capsular vitreous body	18 (3.4)
C_3F_8	4 (0.8)
Traumatic cataract excision	217 (40.9)
Ciliary body suturing	32 (6.0)
External sclerotomy drainage of suprachoroidal haemorrhage	24 (4.5)
Silicone oil retention suture	9 (1.7)
Choroid suturing	6 (1.1)
Scleral buckling	1 (0.2)
Mean duration of follow-up, months	8.0
Reoperation, n (%)	
No	429 (80.8)
Yes	102 (19.2)
Anatomy outcome, n (%)	
Silicone oil dependent	248 (46.7)
Atrophy	133 (25.0)
Anatomical repaired	94 (17.7)
Enucleation	25 (4.7)

Continued

a cluster denoted a strong positive correlation among configuration of retinal detachment, retina status and retinal reattachment, and these features also moderately correlated with choroid reattachment and ciliary body status. We also found that time of vitrectomy barely correlated with other clinical features, except IOFB.

Cohort and clinical features

Among the 16 features, 13 were categorical features and three were continuous features. Approximately 0.2% to 19.80% missing data rate among these features were observed (online supplemental table S3). The comparisons between raw and imputed data (supplemented by using MICE method[18]) suggested that the data distribution of the original features were maintained (online supplemental figure S3).

Model construction and evaluation

We leveraged XGBoost to construct classification model, called VisionGo, for predicting visual outcomes after vitrectomy recovery (total 459 eyes, 193 with regained vision and 266 with remained NLP collected from November 2009 to October 2020). VisionGo provides two different application scenarios to

Table 2 Continued

Partial repaired	22 (4.1)
Hypotony	12 (2.3)
Visual acuity at last follow-up, n (%)	
NLP	324 (61.0)
LP/HM/CF	169 (31.8)
2/200–10/200	12 (2.3)
>10/200	26 (4.9)
OTS category, n (%)	
1	334 (62.9)
2	197 (37.1)

BSS, balanced salt solution; C_3F_8, perfluoropropane; CF, counting fingers; HM, hand movement; IOFB, intraocular foreign body; LASIK, laser-assisted in situ keratomileusis; LP, light perception; NLP, no light perception; OGI-NLP, open globe injury-no light perception; OTS, Ocular Trauma Score; PPV, pars plana vitrectomy; RK, radial keratotomy.

predict the possibility of regaining sight: previtrectomy application scenarios, which predicts before vitrectomy is performed; and intravitrectomy application scenarios, which predicts right at the time vitrectomy was completed. The average AUC of the previtrectomy application scenarios was 0.75 on the outer training set and 0.70 on the outer testing set (figure 2B), indicating the feasibility of predicting visual outcome of vitrectomy for NLP eyes based on clinical parameters obtained from primary surgery after OGI. The performance of VisionGo in intravitrectomy application scenarios was increased, yielding an AUC of 0.90 and 0.85 on the outer training set and outer testing set, respectively (figure 2B). The performance of intravitrectomy application scenarios (AUC=0.90) using the total dataset still greatly outperformed that of the previtrectomy application scenarios (figure 2C). Unexpectedly, the conventional OTS failed to rank and predict the postoperative results when evaluating the visual outcome of vitrectomy for OGI-NLP eyes, yielding a non-effective AUC of 0.49 (figure 2C).

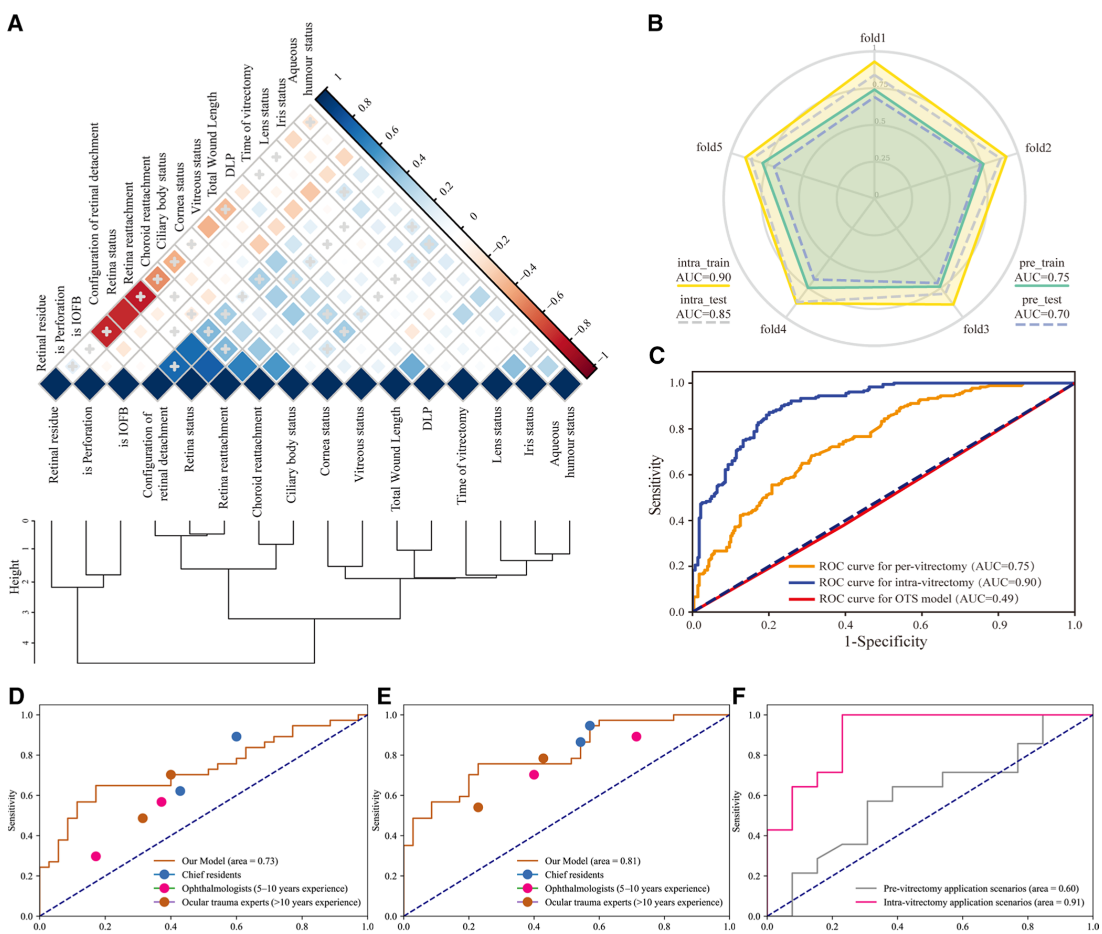

Figure 2 Correlation analysis of clinical features and performance analysis of trained model. (A) Pearson correlation and hierarchical clustering of 16 clinical features. Positive correlations are displayed in blue and negative correlations in red colour. Colour intensity and the size of the square are proportional to the correlation coefficients. Non-significant result (p>0.05) is marked with a cross. (B) Nested cross-validation evaluation of pre-vitrectomy and intra-vitrectomy application scenarios using XGBoost. pre_train and pre_test: the average AUC in pre-vitrectomy application scenarios on the outer-training and outer testing set; intra_train and intra_test: the average AUC in intra-vitrectomy application scenarios on the outer-training and outer-testing set. (C) The ROC curve and AUC of VisionGo in pre-vitrectomy and intra-vitrectomy application scenarios and OTS using the total dataset for. (D) and (E) Comparisons of model performance with ophthalmologists of various experience in pre- and intra-vitrectomy application scenarios. (F) The ROC curve and AUC of VisionGo in real-world prospective verification. AUC, area under the receiver operating characteristic curve; IOFB, intraocular foreign body; OTS, Ocular Trauma Score; ROC, receiver operating characteristic; DLP, distance from the limbus to the most posterior of the full-thickness sclera wound.

Human–machine comparison tests for additional 72 eyes (37 with regained vision and 35 with remained NLP collected from November 2020 to October 2021) were performed between the performance of ophthalmologists and that of VisionGo. VisionGo showed better performance than the ophthalmologists in both previtrectomy and intravitrectomy application scenarios (AUC=0.73 vs 0.57, and 0.87 vs 0.64) (figure 2D,E). The performance of ophthalmologists with different levels of experience showed large variations (sensitivity ranges from 0.30 to 0.89 in previtrectomy application scenarios (figure 2D), and 0.54 to 0.95 in intravitrectomy application scenarios (figure 2E)). Chief residents had the highest predictive sensitivity among the ophthalmologists. During 5 months of real-world prospective verification for 27 eyes (14 with regained vision and 13 with remained NLP), VisionGo still demonstrated good performance, yielding an AUC of 0.60 and 0.91 in previtrectomy and intravitrectomy application scenarios, respectively (figure 2F). In order to facilitate ophthalmologists and other clinicians to quickly evaluate the potential recovery opportunity of an OGI-NLP eye, we also provided a web-based auxiliary diagnosis tool, which is freely available at http://yanhlab.tmu.edu.cn.

Informative clinical feature analysis

We used the SHAP method to analyse the feature contribution to the model and provide transparent interpretability of individual predictors. According to the feature weight and the SHAP values for the previtrectomy application scenarios (figure 3A,B), vitreous status, DLP, IOFB, TWL made a relatively large contribution to the prediction of visual outcome. Eyes with a TWL value of >12 mm or a DLP value of >8 mm tend to have NLP after vitrectomy (online supplemental figure S4A,B). Purulent or prolapsed vitreous body and IOFB usually indicate a persistent NLP vision (online supplemental figure S4C,D).

In addition, we analysed the interpretability of the intravitrectomy application scenarios. As expected, retinal reattachment and retinal residue are the two most important features (figure 3C). SHAP analysis indicated that the more retinal reservation, the higher the chance of light perception gained after surgery (figure 3D). An in-depth subclass plot for single features revealed that retinal reattachment is conducive to recovery of light perception, and >60% retinal residue could be a valid predictor of good vision (online supplemental figure S4e and S4f).

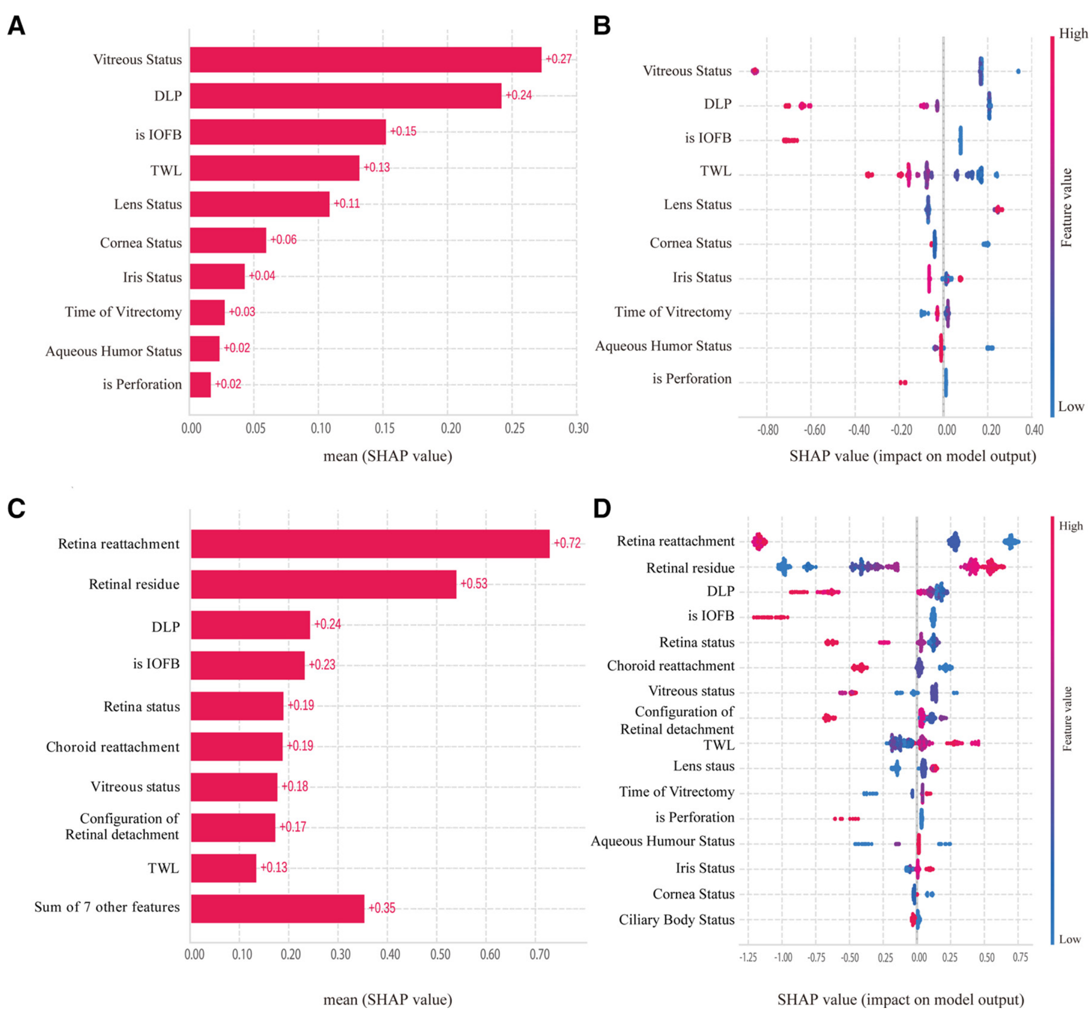

Figure 3 Feature importance and critical feature analysis using SHAP. (A) and (B) shows the influence of features on the samples of VisionGo in pre-vitrectomy application scenarios. (C) and (D) show the influence of features on the samples of VisionGo in intra-vitrectomy application scenarios. IOFB, intraocular foreign body; SHAP, SHapley Additive exPlanation; TWL, total wound length; DLP, distance from the limbus to the most posterior of the full-thickness sclera wound.

DISCUSSION

In the past, NLP eyes caused by OGI have been surgically enucleated. With the technical development of ocular trauma treatment, preserving the eyeball followed by vitrectomy surgery brings hope of vision restoration. Hence, it is urgent to invent an effective way to assess which OGI-NLP eyes can regain light perception through surgical treatment. Recently, AI has been widely studied and applied in screening and diagnosis of diseases in ophthalmology. The acquisition of clinical data for these diseases depends on image capturing, which has a strong objectivity that makes them well suited to the use of AI algorithms and easy-to-make AI models. However, there are relatively few objective indicators in clinical data on eye injury, which makes it is more difficult to build an AI model for ocular trauma. In general, the damage of ocular trauma is much greater than that of other eye diseases, so curative effect prediction is more important and valuable. To the best of our knowledge, this is the first application of ML in the field of predicting the visual outcome of OGI-NLP eyes. An ML algorithm with high performance usually needs a large number of representative samples to be trained and validated. Our study included 19 medical centres in China, covering the eastern, southern, western and northern regions of the country (online supplemental figure S1). These 19 medical centres are all members of the Chinese Ophthalmological Society Group of Eye Trauma, and the clinical data they provided were representative and reliable. Furthermore, our study includes the largest cohort of OGI-NLP eyes so far (previous studies had sample sizes of <100 cases). Therefore, the establishment of VisionGo is supported by reliable data with the largest sample size in the world, which ensures its good performance.

Performance of the predictive model

After verification, VisionGo achieved higher accuracy in comparison with the OTS and with experienced ophthalmologists and performed well in real-world application. The failure of OTS in comparison with VisionGo indicates that predicting visual outcomes of vitrectomy for OGI-NLP eyes is a totally different task from using the conventional score to predict the final visual outcome of an injured eye. Although the OTS is acknowledged as a scoring system to predict the visual outcomes of ocular trauma, showing good predictive effects in different cohort studies,[20] it has certain limitations in application to NLP eyes with severe ocular trauma due to less clinical features collected. The OTS predicts visual acuity by collecting six clinical features, including initial vision, perforating injury, retinal detachment, relative afferent papillary defect, globe rupture and endophthalmitis.[20] In view of the diversity of eye damage caused by OGI, there are many factors affect the visual outcome (such as length and location of the wound, retina residue, *et al*), and the interactions of each factor are not clear. The use of ML methods to integrate the influence of multiple factors can improve the prediction of visual outcome. In VisionGo, we used 16 clinical features to describe the injured eye which is far more than indicators used in the OTS. In addition, the OTS cannot obtain scores when clinical feature data are missing. However, VisionGo can impute missing values via the MICE method to overcome the problem of algorithm failure caused by incomplete clinical data. Furthermore, VisionGo can calculate which clinical feature(s) contribute most to the injured eye regaining light sensation compared with the OTS, thus reminding clinicians and patients to pay more attention to these clinical features in postoperative treatment and follow-up, so as to facilitate timely and accurate clinical decisions.

To further validate the generalisability of our ML model, we compared the performance of VisionGo with ophthalmologists. The results showed that the prediction results of ophthalmologists were related to their seniority and clinical experience in ocular trauma, but the overall sensitivity was lower than that of VisionGo, indicating that ML can complete prediction tasks more stably and efficiently than doctors. In prospective real-world applications, VisionGo can well predict visual outcome before vitrectomy is performed, which proves that VisionGo can provide accurate predictions in clinical applications.

Clinical interpretation of feature contribution

Only a few studies have reported the prognostic factors of visual outcome in OGI-NLP eyes. Feng *et al* found that zone 3 injury and scleral wound ≥10 mm were two predictors of poor vision after vitrectomy.[9] In our study, using SHAP values, we found that before vitrectomy, characteristics of the wound (consistent with the results of Feng *et al*[9]) and vitreous status contributed significantly to visual outcome. The location of the wound represents the conduction of external forces. A wound located closer to the posterior pole represents a further force transmission, which is easier to cause damage to the retina, choroid and optic nerve. In addition, doctors pull the eyeball during the repair surgery to obtain a good exposure, which may deform the eyeball, causing the loss of eye contents. A long wound is easy to cause the loss of eye contents, increasing the chance of failed light reconstruction. As the vitreous body is the structure most closely in contact with retina, inflammatory factors, toxins and other substances in purulent vitreous damage the retina; a prolapsed vitreous body drags the retina and choroid, which causes vitreous haemorrhage, retinal detachment and suprachoroidal haemorrhage,[21] leading to a poor visual outcome. Consistent with the study of Ahmadieh *et al*,[22] IOFB was an important contributor, leading to the failure of light reconstruction in our study due to infection, mechanical injury and harmful components of the IOFB.

After vitrectomy, the retina is a main factor contributing to visual outcome rather than the wound. Feng *et al* showed that closed funnel retinal detachment or retinal prolapse is one of the predictors of poor visual outcome.[9] Nonetheless, in our study, the configuration of retinal detachment was not a significant contributor. Retinal reattachment and retinal residue were the first two contributors and their SHAP values were far ahead of other indicators, suggesting that regardless of the severity of eye injury caused by OGI, the key to regaining vision is to retain as much retina as possible and ensure good retinal reattachment during vitrectomy.

In addition, VisionGo can compute the prognostic factors affecting OGI-NLP eyes on an individual basis. It enables the analysis of key clinical features that affect the visual outcome in the way of individualisation, which helps ophthalmologists to provide personalised therapeutic schedule. Nevertheless, it should be noted that the ranking of contributing features obtained in our study is based only on the cohort of a Chinese population and cannot, therefore, represent all OGI-NLP eyes. An open, worldwide public data set for OGI-NLP eyes is needed.

Time of vitrectomy

It is accepted that the repair surgery should be performed as soon as possible to prevent the onset of endophthalmitis and expulsive haemorrhage[23] and rescue visual acuity,[24] but the timing of vitrectomy is still controversial. Several scholars prefer to perform vitrectomy from 4 to 14 days after injury.[25 26] Kuhn *et al* pointed out that early vitrectomy (within 4 days) is more advantageous than late vitrectomy (past 4 days) in reconstruction of the intraocular structure after OGI provided, there is sufficient surgical and infrastructure-related preparedness.[23 27] A randomised controlled trial showed that early vitrectomy led to better visual outcomes than late vitrectomy, both anatomically and functionally.[28] Another study showed that vitrectomy performed >28 days after injury may have a poor visual outcome.[29] In our study, the time of vitrectomy did not contribute a lot to visual outcomes which may be because vitrectomy was performed within 14 days in most of our cases.

Limitations and future work

Our study has some limitations. First, although our study includes the largest cohort of OGI-NLP eyes that have undergone two rounds of surgery, the sample size could be insufficient for training powerful ML models. In addition, because of the diversity of injuries caused by OGI, our collected samples may not be representative of all situations. More studies with larger sample sizes should be systematically undertaken to further optimise the prediction model. Second, setting and standardising the real value of each clinical indicator mostly depend on the clinical experience of the research group, and it is easy to introduce errors owing to different judgements on the indicators in practical application. In our subsequent research work, we plan to add objective indicators such as imaging data.

In summary, using multicentre sample collection and ML methods, this study constructed a model to predict the visual outcomes of vitrectomy for OGI-NLP eyes, which shows good performances in real-world verification and in comparison with traditional scoring prediction methods and ophthalmologists, breaking through the problem of the unpredictable results of ocular reconstructive vitrectomy. The contribution analysis function of the model can help clinicians focus on the key features in clinical work and deal with changes in them in a timely manner, so as to facilitate more accurate clinical decisions.

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