

Artificial Intelligence in Refractive Surgery: Prediction, Simulation, and Explainability

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ABSTRACT:

Deep learning and machine learning are among the core areas of artificial intelligence, which is changing many fields, including healthcare. In ophthalmology, these methods can be considered essentially important because eye disease and surgical choices depend on the detailed images and biometric analysis. This review focuses on four main aspects such as utilizing AI to predicting refractive errors and simulating post-surgery outcomes, generating images and explainability AI (XAI). Deep learning models, particularly convolutional neural networks, have shown high accuracy than other models. Generative models, such as GANs, create realistic eye images for training. Integration of XAI helps to make predictions clearer for clinicians. However, many studies use small datasets and lack validation. A future framework is suggested that combines multimodal learning, XAI, and image simulation to make more personalized, transparent, and reliable.

Keywords : *Artificial Intelligence, Refractive Surgery, Corneal Topography, Deep Learning Model, Explainable AI, Simulated Outcomes, CNN.*

1) Introduction:

Refractive surgery is a type of surgery which is used to improve the eye's vision by modifying the cornea or replacing the eye's natural lens. Refractive surgery addresses refractive errors such as hyperopia, myopia and astigmatism that are anticipated when the eye doesn't follow the light correctly on the retina, which will lead to blurry vision. The most common types of refractive surgeries are LASIK, PRK and SMILE. The main goal of these surgery is to improve the acuity of vision and eradicating the usage of corrective glasses. Near-sightedness, farsightedness and astigmatism are common refractive errors that affect millions worldwide, resulting in reducing their quality of life and productivity. [1] Although refractive surgery is considered a safe and effective method to improve visual acuity, it still has a few complications, such as night vision disturbance [2], Dry eye [3], Corneal Ectasia [4] a rare but serious complication. Current surgery planning mainly depends on clinical expertise and has generalized decision making criteria, which enables only a limited amount of patient personalisation.

The blooming of cognitive computing (AI), particularly deep learning, has brought many options for refractive surgery planning. The DL model can analyse the massive image dataset (pre-operative topography) to provide valuable insights such as outcome prediction, risk assessment and even simulation of predicted outcome. Additionally, the integration of Explainable AI (XAI) framework can provide a better understanding of model for the clinicians, which enables transparency and trust in the model decision.

To give a clear overview of the latest research setting, this review organize the pervious existing work into four main themes: **(1) Artificial Intelligence in refractive error prediction and surgical planning, (2) AI-based post-surgery outcome prediction in ophthalmology, (3) generative models for image simulation and data augmentation (4) explainable AI approaches for transparency and clinical trust.** By aggregating the outcomes from all these themes, this study highlights the results achieved so far, challenges and suggestion for future research on where and how to integrates AI in routine surgery practice.

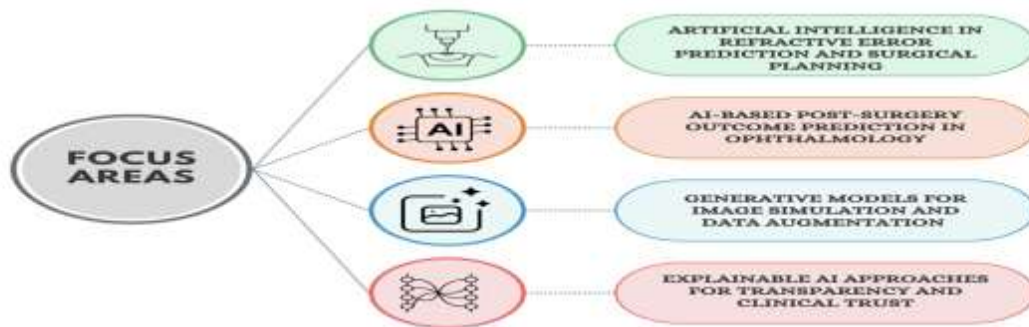


Fig 1.1 Thematic Categorization of studies included in this review.

2) Related Studies

Artificial intelligence has turned out a very powerful tool in refractive surgery, offering various new avenues for patient selection, surgery planning, postoperative risk prediction and even simulated postoperative outcomes. Many studies have been done in machine learning and deep learning in this particular domain, which has very promising results. For instance, [5] this study has used ResNet 50, PCA, and XGBoost to predict early visual outcomes after smile surgery using 3 cohorts (159 patients, 318 eyes), SMILE surgical videos, and 10,176 femtosecond laser images extracted from the video. The DL model achieved high accuracy of 96% with AUC values (~0.93–0.99), XGBoost with AUC up to 1.0, and also DL detected complications such as black spots, OBL, and suction loss. But the study had a small sample & short follow-up, which affects the generalisability and robustness of the result. Likewise, in this study [6], researchers have used 6,465 corneal tomographic images (Pentacam HR) from 1,385 patients to build a CNN model to predict the candidates who are all suitable for the refractive surgery. The DL model achieved 95% accuracy and an AUC :0.98 in finding the eligible candidates for surgery using a corneal map. The limitation of this study is generalizability. It requires the expertise of labelling the data as what is what, which will result in subjectiveness and bias in the training model. The model's ability to find post-op risks such as ectasia remains unproved. The study focuses on cross-sectional data and doesn't keep track of post-surgical changes.

Some research also focused on making AI more of a white box by using explainable AI in the research. In this study [7], authors has created the model to recommend suitable refractive surgery for the patients using SHAP technique, XGBoost, and data from 18,480 healthy Korean patients undergoing refractive surgery along with demographics, ophthalmic measurements, patient questionnaires, and other 142 variables. A higher accuracy of 78.9% and 81% in both validations (external, Internal) were achieved by XGBoost. The SHAP model decision was closely matched with the expertise, with a 92.7% agreement rate. However, the limitation of this research was conducted in a single place, so the result will not apply everywhere. The model relies on patient choice, which may not match the doctor's decision and has a risk of multicollinearity.

One of the most significant utilization of Ai in refractive surgery is to simulating the postoperative outcome. This study [8] introduced MCSTransWnet, a novel multimodal fusion GAN to predict the postoperative topography of cornea. In this study the researchers used 115 patient's corneal topographic curvature data (pre- and post-operative), 100 for training, and 15 for testing, along with FLAK surgical parameters and parameter space encoders to develop a MCSTransWnet (a new multimodal fusion GAN), which has a generator made of two U-Nets, vision transformers(ViT and Swin ViT) , and a module to add surgical data with Pix2Pix pixel discriminator. The MSCTransWnet successfully predicted postoperative corneal topography with 0.765% of structural similarity, 16.012 of peak signal-to-noise ratio along with 9.264 of FID(Fréchet inception distance). However, the model's ability was only to provide a rough estimate about the effect of surgical parameters, and it cannot suggest the best surgical option. The model was limited to simulating the post-op corneal image with a single size and has issues converting corneal shape to refraction data.

Risk prediction studies also showered the necessity of Ai in refractive surgery. For example, this study [9] has used random forest to develop a model to predict the complications in patients who have done a surgery for refractive error.

The model was developed using clinical record of 2667 myopic patients between January 2021 and December 2023, achieving a validation set accuracy of 96.0% and test set accuracy of 95.7%.

The study was retrospective, which is prone to selection bias and also it lacks the external validation, so it affects the robustness of the result. In this study [10], the author has combined deep learning (Resnet50) with XGBoost to develop a model to predict myopia regression after refractive surgery. The data used here to develop a model was a retrospective dataset of corneal refractive surgery patients in which 1606 eye's data was for training set and 403 eye's data was for the validation set. The combined model predicted the myopic regression for 4-year fair accuracy of ROC-AUC = 0.753 (95% CI: 0.710–0.793).

2.1 Artificial Intelligence in refractive error prediction and surgical planning

Table 2.1A Study Details for AI-based refractive error prediction and surgical planning.

Author	Year	Technique/methodology	Data source
Lin H. et al. [6]	2020	Convolutional Neural Network (CNN).	6,465 corneal tomographic images (Pentacam).
T. Yoo et al. [11]	2019	Ensemble Machine Learning(5 base classifier combined).	18480 subjects data (preop clinical measurements, corneal tomography, pachymetry, pupil size, tear break-up time, and patient questionnaires).
Shi, C., Wang, M., Zhu, T. et al. [12]	2020	Neural Network-based classifier, Fisher's score.	Scheimpflug (Pentacam HR) and UHR-OCT images of 121 eyes.
R. Stulting et al. [13]	2022	Phorides Analytical Engine, Contoura vision (Topography guided LASIK).	65 patients with the condition of myopic astigmatism and myopia in a total of 130 eyes.
Syauqie Muhammad et al. [14]	2025	Multi branch Convolutional Neural Network , Grad – CAM.	2139 photorefractive images captured using smartphone.
Varadarajan, AV.et al. [15]	2018	Attention based CNN model.	UK biobank fundus dataset (45° FOV) and AREDS study fundus dataset(30° FOV).
Eugene Yujun Fu et al. [16]	2020	Active learning and CNN features from pre trained gaze estimation model.	Smartphone photorefractive images.
Yoo, T.K., Ryu, I.H., Kim, J.K. et al. [17]	2022	ResNet50 and Grad-CAM.	936 OCT images (Posterior OCT)
Park S., et al. [18]	2021	AdaBoost (Contrast with MLR, Decision Tree, XGBoost, MLP).	3034 eyes of retrospective dataset and pre operative clinical parameters.
Yang, S H et al. [19]	1998	Commercial Neural Network based nomogram calculator	44 PRK/LASIK patients

Qi Z, Li T, Chen J, et al. [20]	2024	DL (CNN – based AI: DeepMyopia)	Retinal fundus images - Internal (n=1,638,315) + External (n=22,060) from 7 centers in China
Tan, Tien-En et al. [21]	2021	Deep learning algorithms + blockchain based deployment	226686 retinal images from Singapore(training /validation) and external dataset from China, India, Taiwan, Russia, UK.
Ye, Xin et al. [22]	2021	ResNeSt101 CNN + Focal Loss.	2342 OCT images for training and 450 OCT image for testing.
Li, Yonghao et al. [23]	2022	InceptionResNetV2 – based CNN (4models), focal loss and Grad-CAM.	5505 OCT macular images (development) and 412 images for test from high myopia patients.
Kundu, Gairik et al. [24]	2023	Logistic Regression, Decision Tree, Random Forest Classifier.	Electronic Health records of 423 refractive surgery clinic patients
Li, J., Dai, Y., Mu, Z. et al. [25]	2023	RF, AdaBoost, XGBoost, BP-NN, DBN(10-fold CV) and SMOTE	7081 refractive surgery cases (2000 – 2007).

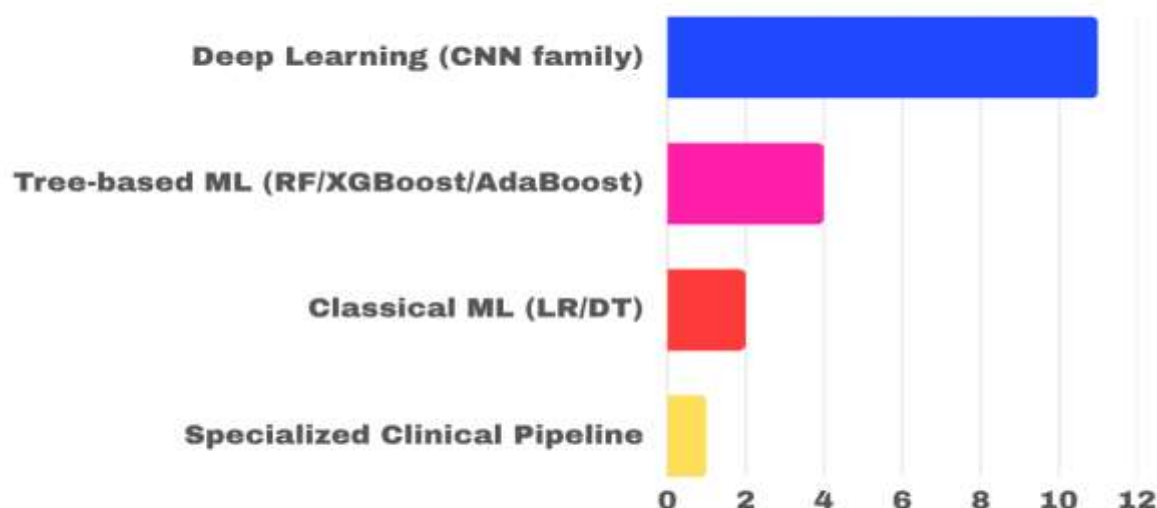


Fig 2.1A Frequency of AI models used in refractive surgery studies.

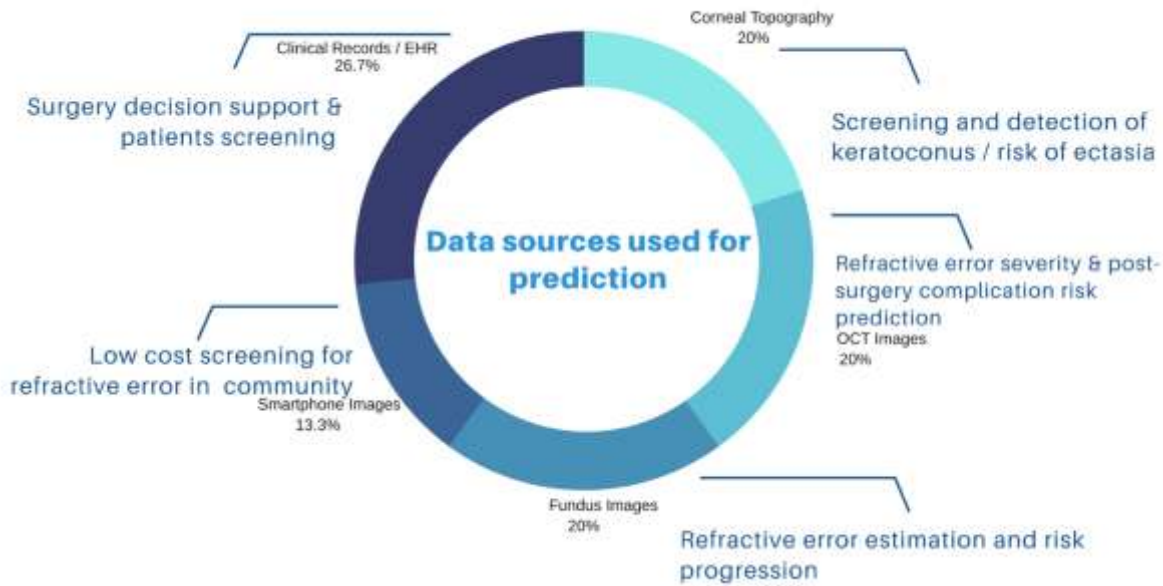


Fig 2.1B Data source distribution across included studies

Table 2.1B Study outcomes for AI-based refractive error prediction and surgical planning.

Author	Key metric(s)	Key finding	Main limitations
Lin H. et al. [6]	Accuracy $\approx$ 95%, AUC $\approx$ 0.98	CNN can screen candidates for surgery near expertise level	Cross-sectional only; Limited external validation
T. Yoo et al. [11]	Accuracy $\approx$ (94.3%, 93.4%) AUC = (0.983 , 0.972) (internal , external)	The ML outperformed Randleman ecstastic score at identify the patients at the risk of post-op ectasia.	Limited in generalizability since model was trained on single centre data
Shi, C., Wang, M., Zhu, T. et al. [12]	AUC = 0.93(Neutral Network, Subclinical KC);AUC=1.00 (KC); Accuracy $\approx$ 98%.	Combined scheimpflug and UHR-OCT features enhance the detection of subclinical keratoconus; EPV was most discriminative.	Small dataset; single-centre data.
R. Stulting et al. [13]	100 % $\geq$ 20/20 (UDVA); 92% $\geq$ pre-op CDVA; CDVA improved in 99%;	At 3 months, all eyes had UDVA 20/20 or better, CDVA was stable and visual complaints reduced	Small cohort; short follow up.
Syauqie Muhammad et al. [14]	Accuracy $\approx$ 91%;Precision = 96%;Recall=98%;AUC =0.99.	Deep learning precisely classifies refractive error using smartphone image.	Single center dataset, may not generalize across different population

			, smartphone models.
Varadarajan, AV. et al. [15]	MAE=0.56D(UKD) and 0.91D (AREDS)	The Model accurately predicted the refractive errors from fundus image and it disclose hidden information about refractive status.	Limited generalizability across different populations and imaging conditions.
Eugene Yujun Fu et al. [16]	Accuracy >80% and MAE = 0.66 by utilizing only ~18% labelled data	The Model accurately detected the refractive error, and demonstrated efficient performance with minimal annotation effort.	Limited generalizability across different phone models.
Yoo, T.K., Ryu, I.H., Kim, J.K. et al. [17]	High myopia detection Accuracy $\approx$ 71.4%; AUC = 0.813; SE MAE = 2.66D	The model could predicted the refractive error from OCT images	Limited dataset; Moderate prediction accuracy
Park S., et al. [18]	Accuracy = 96.9%, 97.6% 99.4% and RMES = 0.1378, 0.1166, and 5.17 (sphere, cylinder, and astigmatism axis, respectively)	AdaBoost achieved highest accuracy and pre-op manifest refraction was the most influential features.	Single- centre dataset; model performances may vary across different settings.
Yang, S H et al. [19]	No stable accuracy	Neural network can personalize PRK nomogram by adding patients and surgical factors	Very small dataset; Unstable prediction.
Qi Z, Li T, Chen J, et al. [20]	Internal Test AUC: 0.908, 0.813, 0.810 (1-, 2-, and 3-year respectively); External Test AUC: 0.796, 0.808, 0.767.	The AI model can predict myopia early(1-3 years before onset) and clearly points out which children have high and low risk.	Required large scale validation in real world setting.
Tan, Tien-En et al. [21]	AUC $\geq$ 0.969 (MMD), AUC $\geq$ 0.913 (High myopia); Topped 6 experts	The model can accurately detects high myopia and myopic macular degeneration.	Required validation in real world clinical setting.
Ye, Xin et al. [22]	AUC = 0.927–0.974	The model has high accuracy classification of myopia maculopathy at the specialist level.	Limited to single clinical centre.
Li, Yonghao et al. [23]	AUC = 0.961–0.999;	The model reliably identifies 4 major vision-threatening complications and performs similarly to retina specialists.	Performance may vary across different clinical settings.
Kundu, Gairik et al. [24]	ROC-AUC = 0.945, Sensitivity = 88%, Specificity = 92.5%,	The AI model successfully predicts ~93% of the likelihood of patients choosing surgery.	Prediction may vary across different healthcare system.
Li, J., Dai, Y., Mu, Z. et al. [25]	Accuracy RF =88%, Macro -F1 = 80%.	RF aligned with surgeon decision; SHAP supports clinical reasoning.	Retrospective, data loss from cleaning.

Across the studies reviewed, AI-based methods, such as CNN, ensemble models, attention networks, Grad-CAM, and classical ML, consistently demonstrate high accuracy in tasks related to refractive surgery. Deep learning approaches were used primarily in ~70% of research, which include screening and selecting the most suitable candidates before surgery and predicting post-operative outcomes such as the risk of complications and the healing responses. It also aided in detecting the refractive error and identifying conditions like subclinical keratoconus and high myopia using different data sources such as OCT, fundus images, corneal topography and even smartphone-based images. Ensemble learning models were used in about 27% of these studies. They were mainly used when structured clinical measurement were available. This supported decision-making and preoperative evaluation. These models often perform as well as or better than clinical scoring systems and human experts. They are especially good at spotting early or subtle issues, subclinical keratoconus and high-risk myopia.

However, most studies rely on single-centre datasets, small sample sizes, and retrospective designs. They often lack validation across different populations, making it hard to apply their findings broadly. Also, some models lack transparency, which is important for clinical trust. AI can help make procedures more precise and assist surgeons, but more validation and clearer understanding is needed before it can be used regularly in clinics.

2.2 AI-based post-surgery outcome prediction in ophthalmology

Table 2.2A Study details for AI-based post-surgery outcome prediction in ophthalmology.

Author	Year	Technique/methodology	Data source
Wan, Q., Yue, S., Tang, J. <i>et al.</i> [5]	2023	Resnet50, PCA, XGBoost, Grad-CAM	3 cohorts (159 patients, 318 eyes); SMILE surgical videos; 10,176 femtosecond laser images extracted
Achiron A, Gur Z, Aviv U, <i>et al.</i> [26]	2017	Decision forest (Machine learning)	17592 cases with 38 features (12-year dataset)
Kim, J., Ryu, I.H., Kim, J.K. <i>et al.</i> [27]	2022	ResNet50 and XGBoost (combined model)	2009 eyes (1606 for training and 403 for testing)
Yinjie Jiang <i>et al.</i> [28]	2023	Stacking ML models Combining SVR, LASSO, Random forest, XGBoost.	2767 eyes of 1678 patients.
Yinjie Jiang <i>et al.</i> [29]	2023	Random forest, modified holladay vergence formula.	2845 eyes (1 eye per patients), biometric parameters.
Yuancun Li <i>et al.</i> [30]	2021	Logistic Regression + IOL formulas (Kane, Barrett II, Hoffer Q, SRK/T) with prognostic nomogram.	111 eyes with PACG undergoing cataract surgery + goniosynechialysis.
Godani, K., Prabhu, V., Gandhi, P. <i>et al.</i> [31]	2025	Six ML models, Random forest (Performed Best).	158 eyes, 14652 OCT datapoint from pre-op OCT + EMR.
Bernardo T. Lopes <i>et al.</i> [32]	2018	Random forest (Pentacam Random Forest Index – PRFI)	Pentacam HR tomographic dataset (multicentre clinical data)

L. Hartmann et al. [33]	2025	Neural Network classifier	1375 eyes undergoing cataract.
Wei-Chun Lin et al. [34]	2023	Multimodal Deep learning.	Clinical record along with operative notes from trabeculectomy surgery
M. Balidis et al. [35]	2019	Learning vector quantization (Neural Network)	Retrospective Refractive surgery dataset – PRK, LASEK, Epi – LASIK, LASIK (from 2010 – 2017)
Wang, Yining et al. [36]	2023	Regression models for VR prediction (SVM = 3yrs ; Random forest = 5yrs) + Logistic regression for risk of visual impairment.	1616 eyes from 976 high – myopia patients (10 yrs clinical data, OCT+ fundus + BCVA records)
Wallerstein A., Fink J., et al. [37]	2024	Deep Neural Network (DNN)	19468 eyes; Pentacam HR.
Hui Guo et al. [38]	2024	Multimodal deep learning fusion	184 patients (retrospective)
Wen, D., Yu, Z., Yang, Z. et al. [39]	2023	DL (Inception – ResNet-v2)+ Multimodal fusion model.	Macular OCT images (5304 scan) along with clinical variable

Table 2.2B Study outcomes for AI-based post-surgery outcome prediction ophthalmology.

Author	Key metric(s)	Key finding	Main limitations
Wan, Q., Yue, S., Tang, J. <i>et al.</i> [5]	AUC = 0.962 – 0.998 (retrospective) ; AUC = 0.936 -0.959 (prospective) ; video AUC up to 1.000	AI accurately predicts early post operative visual recovery and detected complications: suction loss (100%), black spots (85%), OBL (96%)	Short term follow up ; Performance may vary across different settings
Achiron A, Gur Z, Aviv U, et al. [26]	Efficacy (≥ 0.7 in 92% , ≥ 0.8 in 84.9%) of eyes; Low efficacy (<0.4 in 1.8%)	The Model can be utilized for personalized risk assessment and surgical decision-making.	No external validation; Limited to patient <40 years.
Kim, J., Ryu, I.H., Kim, J.K. et al. [27]	ROC – AUC : 0.753 (Combined) ; 0.673 (ResNet-only)	Model predicts an long-term regression of myopia using preoperative metrics.	Require more diverse dataset.
Yinjie Jiang et al. [28]	MAE $\approx$ 0.30–0.39D	ML model equivalent / outperformed MVF, particularly in low to moderate myopia.	Limited external validation

Yinjie Jiang et al. [29]	Improved R-values(ideal vault $R \approx 0.60$; extreme vault $R \approx 0.86$)	ML model effectively outperformed standard ICL calculator.	Performance depends on vault estimation.
Yuancun Li et al. [30]	Nomogram AUC: 0.69 – 0.71.	Nomogram aid in pre-operative risk prediction	Small dataset; limited follow-up.
Godani, K., Prabhu, V., Gandhi, P. et al. [31]	MSE=0.038; VA prediction within 61% (± 0.1), 78% (± 0.2), 87% (± 0.3) logMAR	Post operative visual acuity can be precisely predicted pre operatively.	Retrospective; limits generalizability.
Bernardo T. Lopes et al. [32]	AUC = 0.992, Sensitivity = 94.2%, Spec = 98.8%.	PRFI outperformed BAD-D, with ~80% sensitivity for detecting post-LASIK ectasia.	It needs integration with biomechanical data
L. Hartmann et al. [33]	Accuracy = 83%.	The neural network models predict post-op refractive error accurately and aid in identifying patients at risk pre-operatively.	The system requires external validation.
Wei-Chun Lin et al. [34]	Macro AUROC=0.75,F1=0.58.	The model can be used to identify hypotony failure risk.	Single centre; complex model.
M. Balidis et al. [35]	Sensitivity = 0.88; Specificity 0.93, Cohen's kappa=0.76.	Neural network can predicts need for refractive surgery retreatment.	Retrospective single centre dataset.
Wang, Yining et al. [36]	R^2 : 0.68 (3-yrs) & 0.66 (5-yrs); AUC: 0.87.	ML models accurately predicted long-term visual outcome.	Population largely older;
Wallerstein A., Fink J., et al. [37]	TCA predicted accuracy = R^2 :0.97 (RMSE 0.10D); Formula = R^2 :0.86 (RMSE 0.23D).	DNN enhanced TCA predicted which aid in better IOL selection and more accurate postoperative outcomes	Retrospective single centre.
Hui Guo et al. [38]	AUC: 0.91; Accuracy = 0.86; Sensitivity = 0.94; Spec = 0.80.	The model accurately predicts post-surgical BCVA.	Small sample.
Wen, D., Yu, Z., Yang, Z. et al. [39]	MAE = 0.07 logMAR, R^2 : 0.80	DL model precisely predicted 6-month BCVA.	Limited generalizability.

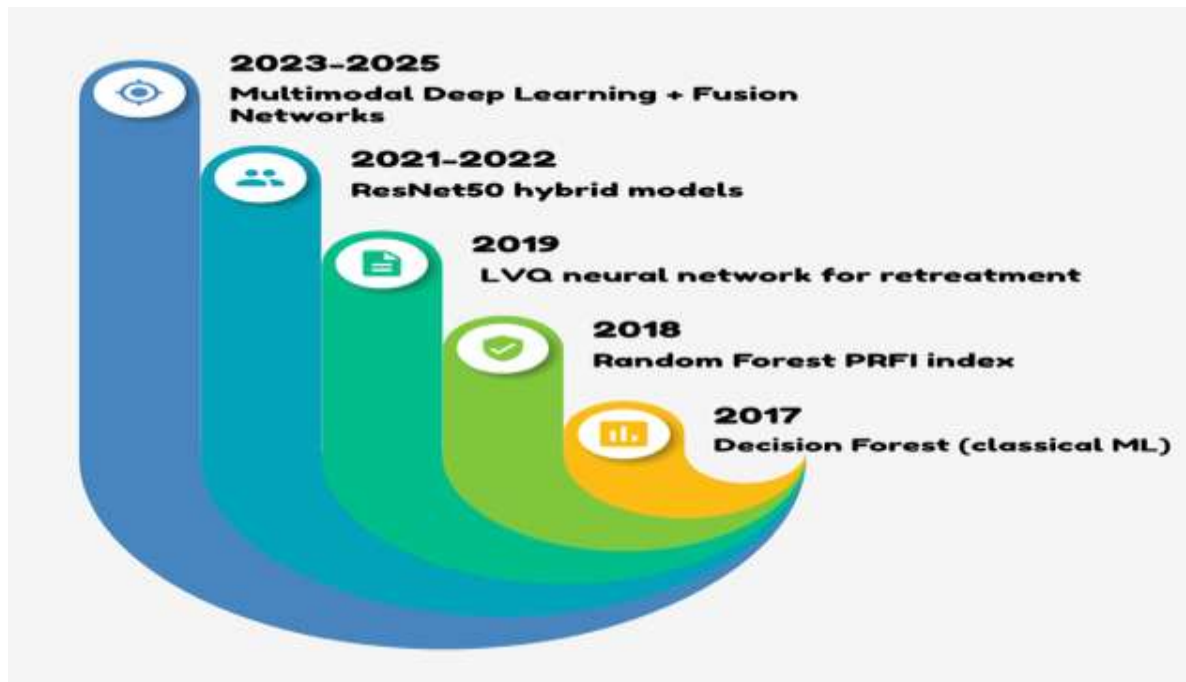


Fig 2.2A Evolution of model complexity

These studies listed show that there is a strong move towards using AI for preoperative planning and also predicting post-surgery results. Researchers commonly used machine methods like random forest, XGBoost, stacking model, neural networks, and deep learning fusion frameworks on biometrics measurements, clinical records, corneal topography, OCT scans, and surgical imaging. These models are capable of predicting different types of post-surgical results, such as visual acuity recovery, refractive stability, post-operative vault height in ICL patients, long-term risk of myopia progression, and the chances of other complications. In many cases, AI predictions were more accurate than traditional formulas. Some models even offered clinical decision-support tools, such as nomograms, to personalize risk assessment.

2.3 Generative models for image simulation and data augmentation.

Table 2.3A Generative Model Types and Data Source.

Author	Year	Generative Model Type	Data source
Jameel, Samer Kais et al. [40]	2022	Conditional GAN (cGAN)	Pentacam corneal topography images (n = 3448)
Robert Doorly et al. [41]	2025	Various GAN architecture including conditional GANs.	Various ophthalmic image dataset.

Agharezaei, Z., et al. [42]	2023	Variational Autoencoder (VAE) + CNN classifier	1758 corneal topography images increased to 4000 VAE synthesis.
Masalkhi, M., et al. [43]	2025	GANs (including Pix2Pix, DR-GAN, cGAN, CycleGAN).	Retinal & OCT image dataset from prior studies.
Jia, Y., et al. [44]	2024	Improved Real-ESRGAN + U-Net structural prior.	Retinal fundus images dataset.
C. Zheng et al. [45]	2019	GAN	Public OCT dataset (CNV,DME,Drusen,Normal)+clinical validation set.
Ashish Jith Sreejith Kumar et al. [46]	2022	Progressive Growing GAN	OCT scan (Normal: 990, Glaucoma: 862).
Yu Chen et al. [47]	2021	GAN (Domain – Translation + Mask – conditioned GAN)	EyePACS + segmentation data
Andrew L Beers et al. [48]	2018	Progressive GAN	Fundus Images + Brain MRI
Jimmy S Chen et al. [49]	2021	Pix2PixHD GAN	4282fundus-vessel map pair.
Skandarani Y et al. [50]	2023	Various GAN architectures (DCGAN, StyleGAN etc)	Cardiac MRI, Liver CT, Retinal Fundus
Ahmad, W., Ali, H., Shah, Z. et al. [51]	2022	GAN based super resolution (Multi-path + ResNet34 + Progressive Upscaling)	Retinal fundus, Brain MRI, Dermoscopy, Cardiac Ultrasound.
Zhang, Kuan et al. [52]	2022	SOUP – GAN (3D Super resolution GAN)	MRI Scan
Zhang, Q., Hang, Y., Wu, F. [53]	2025	LSTM + Attention based GAN	LUNA16, BraTS2021
J. Zhu, G. Yang and P. Lio. [54]	2019	LFSR + Multi-Scale GAN (MS GAN); Compared with WGAN & WGAN-GP.	Brain tumour MRI

Table 2.3A Task Objectives, Metrics, and Key Findings.

Author	Task	Evaluation Metrics	Key finding
Jameel, Samer Kais et al. [40]	To generate synthetic corneal images for dataset training.	Accuracy, Precision, F1 score, expert evaluation.	Generated images improve classifier performance and are considered realistic by the clinical experts.

Robert Doorly et al. [41]	Image synthesis, feature extraction, quality enhancement, support diagnose & prognosis.	Expert evaluation; enhanced performances in image analysis.	GANs can generate realistic eye images and help to increase diagnostic model performances.
Agharezaei, Z., et al [42]	For keratoconus detection and data augmentation	Accuracy, Sensitivity, Specificity, AUC	VAE synthesis improved model performances; VGG16 achieved accuracy of ~99%.
Masalkhi, M., et al. [43]	Synthesis ophthalmic images generation for data augmentation.	Qualitative realism	Synthesis images enhance the model training when original data is limited.
Jia, Y., et al. [44]	Super resolution (enhancing image clarity)	Peak Signal-to-Noise Ratio along with Structural Similarity Index Measure.	System enhanced the retinal image and helps in diagnostic purposes.
C. Zheng et al. [45]	To generate synthetic OCT images for training.	AUC	Local AUC: (Real: 0.99) vs (synthetic: 0.98), Clinical AUC: (Real: 0.99) vs (synthetic: 0.98)
Ashish Jith Sreejith Kumar et al. [46]	To generate synthetic OCT image to training DL model for glaucoma classification	AUC	Synthetic data worked as well as real data.
Yu Chen et al. [47]	To generate synthetic retinal fundus images to aid in class imbalance.	Accuracy, kappa.	Enhanced DR grading performance.
Andrew L Beers et al. [48]	High resolution medical synthesis image	Qualitative realism	Generated realistic images with provided disease details.
Jimmy S Chen et al. [49]	To generate synthetic retinal fundus images	Qualitative realism	Synthetic images were visually alike as real image (experts were ~59% accurate).
Skandarani Y et al. [50]	Synthetic image generation along with evaluation	FID score, accuracy.	Generated visually realistic images.
Ahmad, W., Ali, H., Shah, Z. <i>et al.</i> [51]	Convention of low resolution images into high resolution.	PSNR, SSIM, Visual comparison.	Realistic appearance with better retention of medical details

Zhang, Kuan et al. [52]	To generate thinner slice images (higher in res in z-plane)	PSNR, SSIM, Radiologist comparison.	Improved resolution. MRI
Zhang, Q., Hang, Y., Wu, F. [53]	To produce high resolution 3D scan from low.	PSNR, SSIM	Improved 3D quality and noise reduction.
J. Zhu, G. Yang and P. Lio. [54]	Super resolution of medical images	PSNR, SSIM, MOS	More realistic; improved stability; reduces artifacts.

Many studies showed that images generated by the GAN and other diffuse models were realistic, so that even experts find it difficult to distinguish them from real images. [49] [42] [45] [50] Despite all progress, there are some limitations in generative models, which is that the generation of artifact [55] [43] and the need for expert validation. [42] [43] Lack of clinical validation and generalizability, expresses worries about potential bias. [55] [41]

Generative models have been used mainly to address data scarcity and image enhancement in various ophthalmic tasks. The majority of studies have used GANs and VAEs for data augmentation. This approach helped in improving the classification of diseases and detection of keratoconus by expanding training datasets with synthetic images. Around one third of studies concentrate on super resolution reconstruction. They used GAN based architecture to improve the clarity of retinal and OCT scan, which support more accurate diagnose.

Table 2.3C Study grouped by purpose

Purpose of Generative Model	Studies
Data Augmentation for Training	[40] [42] [43] [49] [50]
Super-Resolution / Image Enhancement	[44] [51] [52] [53] [54]
Disease Feature Simulation for Training	[45] [46] [47] [48]

A smaller but important portion used domain translation and disease feature simulation to replicate diseases patterns for training classifiers in glaucoma, diabetic retinopathy and detection of macular diseases. Overall, these methods showered how synthetic images and improved images are similar to real images, which results in model generalization and diagnosis accuracy while reducing the need for large labelled datasets.

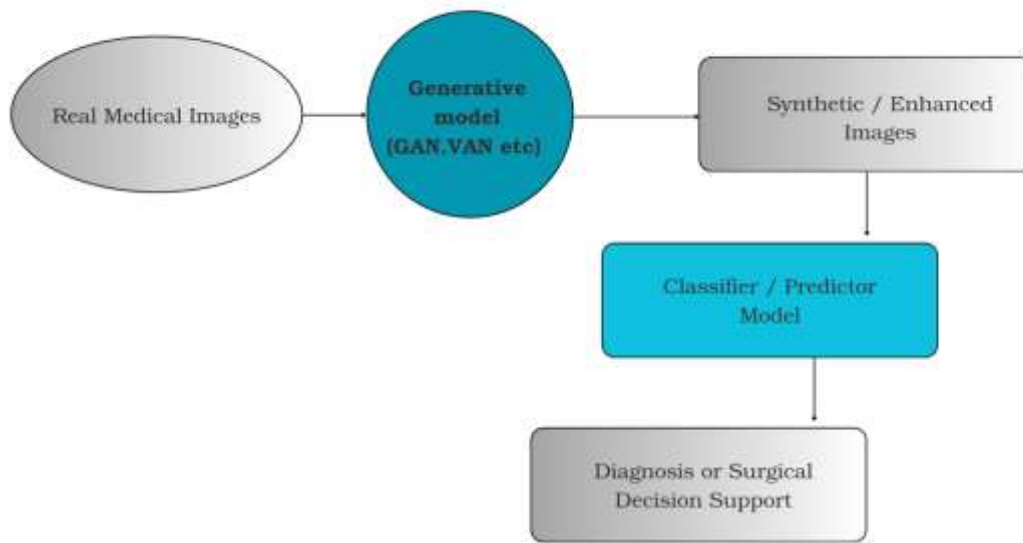


Fig 2.3A General workflow of Generative model integration in ophthalmic AI

2.4 Explainable AI approaches for transparency and clinical trust.

Table 2.4A Overview of XAI Categories, Techniques, and Explained outcomes.

Author	Year	Category	Technique	Description
Jurgita Černevičienė et al. [56]	2024	Feature based XAI.	SHAP, Feature importance	Describes how every input attribute influences the model's output fraud detection
Viswan Vimbi et al. [57]	2023	Visual & feature based XAI.	SHAP, LIME, Grad-CAM	Highlight significant features and visual region to enhance clinical trust in ai dragonise.
Rajpurkar, Pranav, et al. [58]	2017	Visual based XAI	CAM	Uses CAM to highlights chest x-ray regions influencing pneumonia prediction by CNN.
Panwar, Harsh et al. [59]	2020	Visual based XAI	Grad-CAM	Highlights infected lung regions on x-ray to interpret detection of COVID-19.
Zhang, Yunyan et al. [60]	2021	Visual based XAI	CAM, Grad – CAM, CAM++	Highlights key regions on brain to classify the diseases.

Li, X., Zhang, S., Li, X. et al. [61]	2025	Feature based XAI	SHAP	Identifies major physiological feature for behaviour prediction.
M, Mohamed Musthafa et al. [62]	2024	Visual based XAI	Grad - CAM	Highlights tumours in MRI to visually explain the prediction.
Ribeiro et al. [63]	2016	Textual based XAI	LIME	Generate human understandable explanation for the prediction.
Kim, Yoojoong et al. [64]	2023	Textual based XAI	NLP based explanation model	Highlights key medical term for guided diagnosis; provides text based explanation for recommendation.
Mullenbach et al. [65]	2018	Textual based XAI	Attention Mechanism	Highlights most relevant text for predicted medical code.
Fan Xu et al. [66]	2021	Visual based XAI	Grad - CAM	Highlights image regions for fungal keratitis diagnosis.

This table shows the various XAI methods which have been utilized to make AI predictions even more understandable. [56] [57] [64] Explainable AI (XAI) has become essential for the safe and better integration in different domains, especially in ophthalmology. Even though the rapid growth of artificial intelligences in ophthalmology has its advantage, it also has disadvantage, one of which is transparency in AI-based diagnostic. As deep learning and machine learning become more common in analysing ophthalmic images and supporting clinical decision-making, their “black box” nature raises concern for both clinician and patient regarding trust and reliability. [67] [68] [69] [70] explainable AI methods such as heatmaps, class activation mapping (Grad-CAM), LIME are now being used to visualize and justify AI decision, especially in detection and classifying diseases like glaucoma, diabetic retinopathy, cataract. [67] [68] [71] [72] These approaches not only enhance the clinician’s understandable and also enhance trust, which aids in effective integration of AI in clinical practice. [73] Although technology is improving, future work is needed make XAI methods consistent.

3) Research Gaps

Despite significant progress in using artificial intelligence for refractive surgery. Several key research limitation still holds back clinical use. Many existing studies rely on single-centre or small, homogenous dataset. This limits the model robustness and reduce their usefulness for various ethnic groups, imaging devices, and surgical techniques. [6] [26] [22] While deep learning models like CNNs and ResNet-based architectures are highly efficient in refractive error screening and predicting post-operative outcomes, [27] [36] [39] most of the studies depends on single modality of data. Although, real-world decision-making system needs to combine topography, OCT, fundus imaging, biomechanics, and clinical record. [12] [34] Generative models like GANs and VAEs have been used to argument limited datasets and improve image resolution, [40] [42] [44] but validation is mainly qualitative, with limited evaluation of whether synthetic data improves diagnostic or predictive performance in clinical practice. Also, explainable AI remains mostly post-hoc. It relies on visualization tools like CAM, Grad-CAM, and SHAP [57] [61] rather than being built into the design process, which limits the clinician trust and transparency. Finally, very few studies report on prospective clinical trials or real - time use, so they not yet used in surgical practice. [37] [31] These gap highlight the need for large-scale, multi-centre

multimodal datasets, prospective validation trails, evaluation of clinically focused generative data, and transparent model designs. This will support the safe and reliable use of AI in refractive surgery

4) Proposed Framework & Future directions

To advance AI in refractive surgery for safe and practical use, future work should focus on creating large-scale, multi-centre datasets, which will help the robustness of the model to work consistently across different populations without any device-specific biases. Progress will also require a multi-modal learning framework, which is the ability to learn different types of data, such as corneal topography, OCT, fundus images, biometrics measurements and surgical data, to have a complete view of individual cornea structure and behaviour. Additionally, prospective clinical trials are needed to evaluate how AI performs in clinical settings, not only in retrospective datasets. Furthermore, strong clinical validation is required for GenAI, to check whether the synthetic images help in prediction or just looks realistic. Also, XAI should be a core component of every model and not just post-hoc. So, the objective of the research is to develop an AI-based system to personalized refractive surgery planning.

The proposed system helps the doctor and patients choose the best surgical procedure based on individual eye characteristics. It will analysis the corneal topography, ocular biometrics, and demographic data using a multimodal deep learning model to recommend whether LASIK, PRK, or SMILE is the best option for each patient. To build trust and clarity in the decision-making process, Explainable AI (XAI) techniques will be integrated to offer clear reasons for each recommendation. Additionally, a conditional GAN or diffusion model will be included to simulates post-operative corneal topography, allowing clinicians to visualize the expected outcome. This method aims to improve the accuracy of surgical planning, increase patient's understanding, and reduce reliance on general guidelines and subjective clinical judgements.

The proposed works in two phases (Ref Fig 4.1): first, it helps to identify the top two most suitable refractive surgeries for each patient. Second, it shows how the cornea should look after the surgery by simulating the corneal topography of the patient. The key components of the proposed system include:

- Personalized surgery recommendations
- Simulated post-operative corneal topography
- Integration of Explainable AI

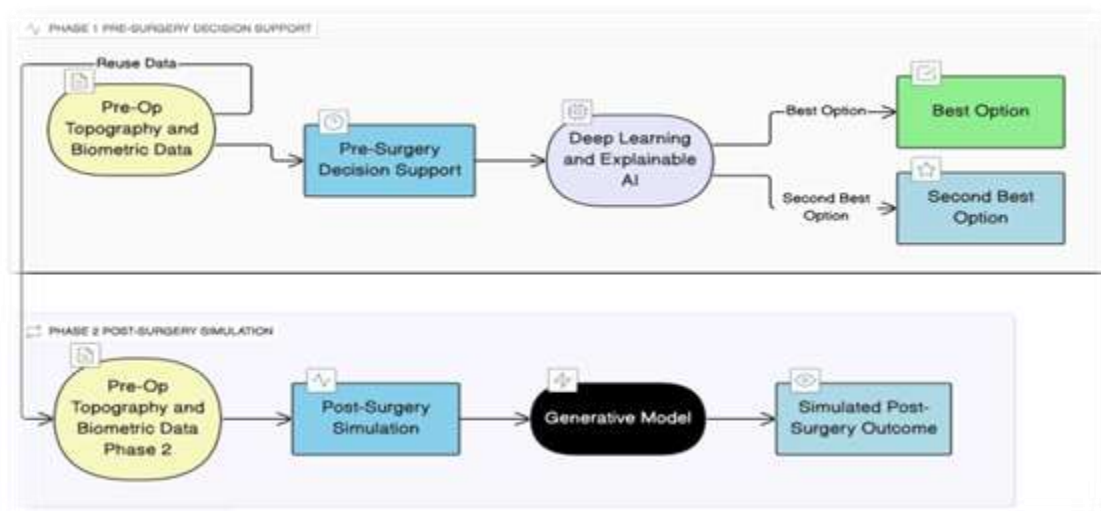


Fig : 4.1 Workflow of proposed System

5) Expected Result & Conclusions

Personalized Refractive Surgery Planning Website : An AI-powered system that recommends the most suitable surgery based on individual patients corneal data. **Simulated Post – Surgery Corneal Outcomes :** System generates predicted corneal maps showing how the eye may appear after surgery, helping patients see result before undergoing the procedure. Along with explainability report with the justification of each recommendation.

Expected outputs from phase – 1 Demonstration :

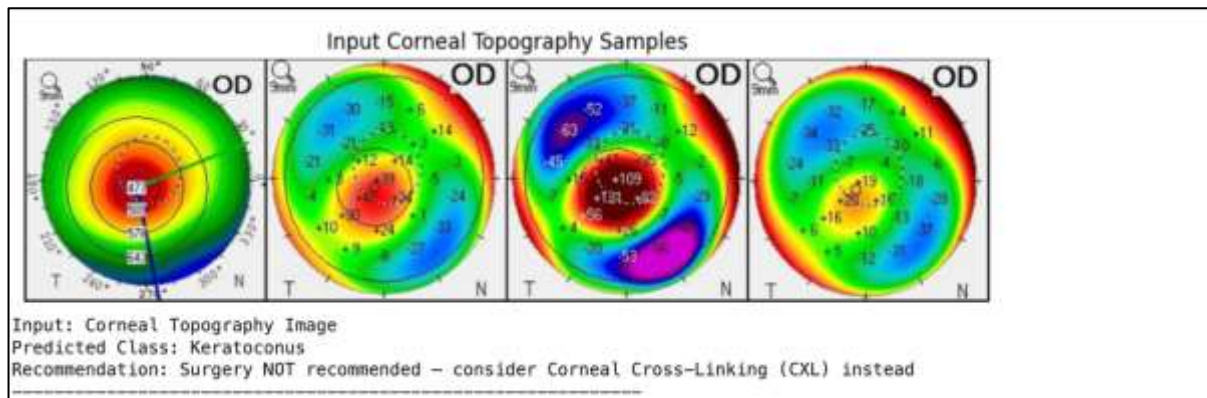


Fig 5.1A AI Detection of Keratoconus



Fig 5.1B AI Recommendation of Refractive Surgery

Existing system indicates that the development of AI in refractive surgery goes beyond improved predictive accuracy and marks a shift towards more personalized approaches to eye care. These reviewed studies show that AI is increasingly helping the ophthalmologists by analysing complex corneal and biometric patterns. The existing system support decision – making, point out subtle risk factors, and provide personalized surgical insight; this will help the surgeons to have a more informed plan. Artificial intelligence also supports treatment decisions with respect to individual corneal structure, healing response and visual need rather than general guidelines. Additionally, generative modelling and explainability are changing how outcomes are communicated, allowing patients to see what a procedure might achieve and understanding the reason behind specific recommendations. Although there are still challenges, the direction of current research shows that AI will serve as a reliable tool.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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