

Automatic Retinoblastoma Screening and Surveillance

Using Deep Learning

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ABSTRACT

Retinoblastoma is the most common intraocular malignancy in childhood. With the
advanced management strategy, the global salvage and overall survival have
significantly improved, which proposes subsequent challenges regarding long-term
surveillance and offspring screening. Here, we developed deep learning algorithm,
called Deep Learning Assistant for Retinoblastoma (DLA-RB) training on A total of
36623 images from 713 patients. We validated it in the prospectively collected dataset,
comprised of 1366 images form 139 eyes of 103 patients. In identifying active
retinoblastoma tumors (treatment required) from all clinical-suspected patients, the
area under the receiver operating characteristic curve (AUC) of DLA-RB reached
0.991 (95% CI 0.970-1.000). In identifying active retinoblastoma from stable
retinoblastoma patients (treatment is not required), AUC of DLA-RB reached 0.962
(95% CI 0.915-1.000), respectively. Cost-utility analysis revealed that DLA-RB based
diagnosis mode is more cost-effective in both retinoblastoma diagnosis and
retinoblastoma activity surveillance. The DLA-RB achieved high accuracy and
sensitivity in identifying active retinoblastoma from the normal and stable
retinoblastoma fundus. It can be incorporated within telemedicine programs in the
future.

41 Introduction

42 Retinoblastoma is the most common intraocular malignancy in childhood. It is
 43 estimated to affect one case per 16,000–18,000 live births worldwide.¹ China, India,
 44 and other populous countries in Asia and Africa have the largest amount of newly
 45 diagnosed retinoblastoma patients. With advanced screening techniques and
 46 multidisciplinary management, most retinoblastoma patients achieve life-saving,
 47 globe salvage, and even useful vision.² In a recent national cohort study in China, the
 48 overall survival rates of RB patients were 81%, 83%, and 91% in patients diagnosed
 49 in 1989-2008, 2009-2013, 2014-2017, respectively.³ For globe salvage, almost all
 50 retinoblastoma classified by the International Intraocular Retinoblastoma
 51 Classification (IIRC)⁴ as group A-C can achieve globe salvage through systemic
 52 chemotherapy with adjuvant laser therapy and cryotherapy.⁵ Group D retinoblastoma
 53 can also achieve 40% (95%CI:31–51%) globe salvage rate through chemotherapy
 54 alone ⁶ and a significantly higher globe salvage rate when receiving intra-ophthalmic
 55 artery chemotherapy.⁷

56 Improved overall survival and successful local control propose subsequent challenges
 57 regarding long-term surveillance after tumor control and screening for the offspring
 58 and relatives of retinoblastoma survivors. The current expert consensus recommends
 59 every 2–6 months for 4 years after tumor control.¹ In real-world practice, group D
 60 retinoblastoma received an average of 21 examinations under anesthesia (EUAs)
 61 during 5-year follow-up.⁸ Furthermore, offspring of retinoblastoma survivors have 50%

chance of inheriting the mutant RB1 from the affected parent, which would result in a 97% risk of developing retinoblastoma.⁹ Global preserving approach thus leads to additional disease burden comprised of health care, socioeconomic, and mental aspects. Furthermore, in most developing countries, only experienced medical ophthalmologists at tertiary eye centers can perform EUAs. This unbalanced distribution of health care resources may delay the diagnosis and proper management during the referring process.

The application of deep learning (DL) techniques proposes reliable and low-cost methods for screening and diagnosing retinal diseases. Previous studies showed that the DL algorithm based on fundus images achieves close-to-expert performance for the automatic detection of retinal diseases, including diabetic retinopathy¹⁰, age-related macular degeneration (AMD),¹¹ glaucoma,¹² myopic maculopathy,¹³ and papilledema.¹⁴ Recently, researchers have applied DL in detecting plus diseases in retinopathy of prematurity.^{15,16} The DL algorithm exceeds 6 of 8 experts in identifying plus diseases, which indicates it can reach robust performance in images obtained by EUAs.

Thus, in the current study, we developed Deep Learning Assistant for Retinoblastoma (DLA-RB) and validated it in the prospectively collected dataset. The DLA-RB aims to assist the fundus surveillance after local control and provide referral advice. The DLA-RB also provides automatic surveillance of the contralateral eye of retinoblastoma patients and the offspring of retinoblastoma survivors.

83

84 **Results**

85 Between March 2018 and January 2022, 47503 images from 713 patients were
 86 retrospectively collected from the anonymous data center in Beijing Tongren hospital
 87 (**Figure 1**). After manually excluding low-quality images due to non-fundus image,
 88 halation, blurs, and defocus (**Supplementary Figure S1**), a total of 36623 images
 89 from 713 patients were finally included for DLA-RB development, with 19045
 90 (52.0%), 2918 (8.0%), and 14660 (40.0%) images were normal, stable and active
 91 retinoblastoma (**Supplementary Table S1**). At patient levels, 713 patients were
 92 randomly allocated for DLA-RB development and five-fold cross-validation.
 93 Considering that it is more complicated to distinguish between stable and active
 94 retinoblastoma, we first trained ResNet-50 and InceptionResnetV3 for this two-class
 95 task to compare the performance of these two architectures. ROC indicated slight
 96 better performance of ResNet-50 in five-fold cross-validation (0.940 [95%CI
 97 0.851-0.996] vs. 0.934 [95%CI 0.735-0.946], **Supplementary Figure S2**). Thus,
 98 ResNet-50 was used to establish DLA-RB. To distinguish between the normal fundus
 99 and active lesion, DLA-RB achieved an AUC of 0.9982 (95%CI 0.986-1.000) in the
 100 development dataset (**Supplementary Figure S3**).

101 From February 2022 to June 2022, 103 patients with clinical-suspected
 102 retinoblastoma and treated retinoblastoma patients first visited Beijing Tongren
 103 hospitals. Fundus images of these patients were not used in developing DLA-RB. If

more than one time of EUA, only the first EUA images were collected. In total, 139 eyes of 103 patients were included for prospective validation (**Table 1**). 69 eyes were clinically diagnosed with retinoblastoma. According to international intraocular retinoblastoma classification (IIRC),¹⁷ 3 (4.3%), 7 (10.1%), 8 (11.6%), 40 (58.0%), and 11 (15.9%) eye was classified as A-E stage, respectively. 43.5% of retinoblastoma was endophytic, while 56.5% were exophytic. For each EUA, the highest probability among all images was assigned as an eye-level probability.

DLA-RB could accurately identify active retinoblastoma tumors from all clinical-suspected retinoblastoma (**Figure 2A-B, Table 2**). The AUC, sensitivity, and specificity reached 0.991 (95%CI 0.970-1.000), 0.979 (95%CI 0.927-1.000), and 1.000 (95%CI 1.000-1.000), respectively. Compared with the human ophthalmologists, the DLA-RB reached significantly higher sensitivity and specificity in identifying new retinoblastoma tumors (**Figure 2A-B, Supplementary Table S2-3**). The only misclassified case of DLA-RB was a Group A retinoblastoma located at superior-nasal ora Serrata (**Supplementary Figure S1**).

DLA-RB could also accurately distinguish active retinoblastoma from stable retinoblastoma (**Figure 2C-D, Table 2**). Among all referred and treated retinoblastoma patients, the AUC, sensitivity, and specificity reached 0.962 (95%CI 0.915-1.000), 0.978 (95%CI 0.932-1.000), and 0.800 (95%CI 0.556-1.000) respectively. Compared with competent ophthalmologists, the DLA-RB reached superior sensitivity yet inferior specificity in identifying active retinoblastoma from

125 stable retinoblastoma (**Figure 2C-D, Supplementary Table S2-3**). Of all 4
126 misclassified cases in this task, 3 cases were false-positive, whereas only 1 case was
127 false-negative (**Table 4**).

128 Heatmap visualization revealed that the DLA-RB mainly focused on the tumor of the
129 newly-diagnosed retinoblastoma (**Figure 3A**). The DLA-RB focused on the relapse
130 site of retinoblastoma on fundus images (**Figure 3B**).

131 DLA-DR has proven to be sensitive and accuracy in identifying active retinoblastoma
132 from the normal fundus and stable retinoblastoma fundus. Yet, the cost-effectiveness
133 of a DLA-RB based approach to screen and surveillance retinoblastoma is unknown.

134 **Table 4** shows the base-case results of the cost-utility analysis. For identifying active
135 retinoblastoma tumors from all clinical-suspected retinoblastoma, the cumulative
136 costs for traditional ophthalmologic centers-based diagnosis mode and DLA-RB
137 based diagnosis mode were \$4882 and \$3519, respectively, and cumulative
138 quality-adjusted life-year (QALYs) for both diagnosis modes were 2.87769 and
139 2.8724 respectively. Compared with DLA-RB based diagnosis mode, the traditional

140 ophthalmologic centers-based diagnosis mode was not cost-effective since it resulted
141 in a gain of 1 QALY at the cost of \$257645. For distinguishing active retinoblastoma
142 from stable retinoblastoma patients, the cumulative costs and QALYs for traditional
143 ophthalmologic centers-based diagnosis mode were \$7614 and 5.46436, and the
144 figures for DLA-RB-based diagnosis mode were \$6981 and 5.46345. Traditional
145 ophthalmologic centers-based diagnosis mode was still unsatisfied with the

146 cost-effectiveness threshold since it produced an ICUR of \$694323. Therefore,
147 DLA-RB based diagnosis mode is cost-effective option in both RB diagnosis and
148 active lesion identification progress.

149 The tornado diagram shows the parameters that had the greatest impacts on base-case
150 outcomes and how much they influenced the outcomes (**Supplementary Figure S5**).

151 Probabilistic sensitivity analyses were conducted by taking 10000 random draws
152 surrounding the basic values (**Supplementary Figure S6**). According to
153 cost-effectiveness acceptability curves, at the current cost-effectiveness threshold,
154 DLA-RB based diagnosis mode had a 100% probability of being the more
155 cost-effective option in the process of RB diagnosis from all clinical-suspected
156 retinoblastoma, and it had a 59% probability to be cost-effective for identification of
157 active retinoblastoma from all treated retinoblastoma patients.

158

159 **Discussion**

160 In the current study, we developed Deep Learning Assistant for Retinoblastoma
161 (DLA-RB) that could accurately identify active retinoblastoma from the normal
162 fundus and stable retinoblastoma fundus. The DLA-RB further exhibited superior
163 sensitivity in identifying newly onset retinoblastoma and similar sensitivity in
164 identifying relapse retinoblastoma. The diagnosis accuracy and sensitivity were
165 superior/non-inferior than competent with about 2-5 years of experience in EUAs

166 examination. Compared with referral procedures to ophthalmologic centers, DLR-RB
167 based approach is cost-effective and readily implemented in the regional hospital.
168 According to the consensus from the American Association of Ophthalmic
169 Oncologists and Pathologists, children with a family history of the retinoblastoma are
170 highly recommended to take sufficient retina examination until the age of 7.¹⁸ Among
171 all family members of retinoblastoma patients, offspring of bilateral have near 50%
172 risk. In contrast, other siblings and nieces/nephews have less than 2.5% risk of
173 harboring RB1 mutation. EUA is strongly recommended for any child unable to
174 participate in an office examination sufficiently to allow a thorough examination of
175 the retina.¹⁸ However, the frequent screening schedule is often limited by the scarcity
176 of ophthalmological resources, especially in underdeveloped regions.¹⁹ Here, we
177 proposed a novel screening solution for offspring and family members of patients.
178 DLA-RB showed high efficiency with 0.991 of AUC and 0.979 sensitivity in the
179 prospective validation dataset. The diagnostic accuracy and sensitivity of DLA-RB
180 surpassed competent ophthalmologists. In real-world practice, the DLA-RB could
181 provide automatic and real-time feedback on retinoblastoma screening, especially
182 among the high-risk population.
183 Nowadays, although advanced multidisciplinary management concepts have been
184 adopted in developed countries, less significant improvement in globe salvage rate
185 was seen in the lower-middle-income country.²⁰ DLA-RB could also be used as a
186 screening technique for the contralateral eye of unilateral retinoblastoma patients who

received primary enucleation. In a retrospective analysis comprising unilateral-presenting Group D retinoblastoma patients, during a median time of approximately 5 years follow-up, only 1 out of 55 developed a new tumor in the contralateral eye.⁸ Using DLA-RB at the local hospital could save time and financial burden when ophthalmologic centers are not near at hand.

Through multidisciplinary management, the globe salvage rate in the high-income country has tremendously improved from 34% in 1980–89 to 70% in 2010–20.²⁰ Based on a meta-analysis, retinoblastoma recurrence occurs in about 15% of patients.⁷ Advanced retinoblastoma (IIRC Group D-E) has a significantly higher risk of recurrence.²¹ Extensive recurrence of subretinal or vitreous seeds was the most common cause of treatment failure and final enucleation. Thus, there are increasing burden of tumor surveillance after intraocular local control. Here, DLA-RB showed high sensitivity to detect active retinoblastoma in the background of stable retinoblastoma appearance (calcification, atrophy, laser and cryotherapy scar, and fibrosis). In real-world practice, DLA-RB can provide automatic assistance in treatment decision-making.

In the past two decades, telemedicine technology has enabled the centralization of care at a single center in developing countries to achieve patient outcomes comparable to those of developed countries.²² Within the domain of telemedicine, the DLA-RB can largely contribute to lowering the burden in diagnosis and follow-up and concentrate the limited healthcare resource in making multidisciplinary management.

DLA-RB can also help to promote the availability of retinoblastoma screening and surveillance by improving the early diagnosis of population at-risk and long-term follow-up for retinoblastoma patients. Such an approach has successfully managed retinopathy of prematurity, a leading cause of childhood blindness worldwide.^{15,16,23} Despite these remarkable results, some inherent limitations of DLA-RB are worth highlighting. First, the development and prospective validation of DLA-RB were conducted in a single institution (Beijing Tongren Hospital). The generalizability of diagnostic performance needs further validation. Yet, in the current study, fundus images in the present study were captured by five ophthalmological experts and two different commercially available cameras, which fully reflected the variability in operators' experience, image quality, resolution, different camera systems, illumination, and field of view. Thus, the result from the perspective validation dataset can represent the performance of DLA-RB in real-world practice. Secondly, retinoblastoma begins as a round, translucent, gray to white tumor in the retina, similar to the halation caused by microbubble in couplant. Careful image quality control was required for ophthalmologists. An artificial intelligence-based quality control module is needed to incorporate with DLA-RB, which warrants further development. Third, accurately identifying active retinoblastoma also rely on a thorough examination of the posterior pole and peripheral retina, which depends on the experience of the operator. A deep-learning-based operation indicator may need to cooperate with DLA-RB to lower the risk of false-negative chance. Fourth, because of

the low incidence of retinoblastoma, only 103 patients were included in prospective validation, which limited subgroup analysis. It warrants further study to explore the diagnosis accuracy of DLA-RB in different IIRC group retinoblastoma.

In conclusion, DLA-RB achieved high accuracy and sensitivity in identifying active retinoblastoma from the normal fundus and stable retinoblastoma fundus. Compared with referral procedures to ophthalmologic centers, DLA-RB based automatic screening and activity surveillance is also cost-effective. In the future, DLA-RB can incorporate telemedicine programs to reduce the burden in diagnosis and follow-up and concentrate the limited health-care resource in making multidisciplinary management.

Methods

Clinical trial registration and ethics approval

This single-center diagnostic study was done in Beijing Tongren hospitals in China. The methods were performed in accordance with relevant guidelines and regulations and approved by the Medical Ethics Committee of Beijing Tongren Hospital. Because individually identifiable information was removed during retrospective collection, written informed consent was exempted in the retrospective collected dataset. In the prospectively collected validation dataset, written informed consent was obtained from all caregivers prior to their inclusion. This study was registered on ClinicalTrials.gov (NCT05308043) on February 2022. Because this study was a

250 diagnostic study that did not assign designative interventions to participants, clinical
251 trial protocol is not applicable.

252 **Dataset collection**

253 Training and internal test dataset were retrospectively collected between March 2018
254 and January 2022. All EUAs were performed for screening or pretreatment
255 examination in daily clinical practice. Five ophthalmological experts (HS Zhao, X Ge,
256 XL Xu, LB Jiang, JS, and JM Ma) obtained images using a commercially available
257 camera (RetCam3; Natus Medical Incorporated) and the standard imaging protocol. In
258 brief, posterior pole and 12 clocks of peripheral retina images were obtained during
259 EUAs. Repeatedly images were taken if necessary. We collected all EUAs images
260 from patients clinically diagnosed with retinoblastoma. For patients with several
261 EUAs, we included all images in the retrospective dataset. Patients who were
262 considered with Coats' disease, persistent fetal vasculature and other retinal diseases
263 were excluded.

264 The validation dataset was prospectively collected from February 2022 to June 2022.
265 Clinically suspected retinoblastoma and treated retinoblastoma patients that first
266 visited Beijing Tongren hospitals were standard EUAs. Patients involved in algorithm
267 development and considered to have other retinal diseases were excluded. During
268 prospective collection, a new generation of a commercially available camera
269 (RetCam3) was deployed in Beijing Tongren hospital with updated illumination and

270 imaging capture system. Thus, the prospective validation dataset was further divided
271 into two subsets (Equipment 1 and 2) to examine the reliability of new equipment.

272 **Image quality control and labeling**

273 All EUAs images were stored in jpeg format in the imaging databases. Poor-quality
274 images resulting from halation, blur, and defocus, as well as non-EUAs images, were
275 excluded manually. In addition, blurred images due to leukoplakia and secondary
276 cataract in advanced retinoblastoma were also excluded. A multidisciplinary
277 management team consisting of ophthalmology, pediatric and radiologist experts
278 made personal treatment strategies after EUAs. The personal treatment strategies
279 comprised a combination of a systemic chemotherapy regimen of carboplatin,
280 vincristine, etoposide, and focal consolidation therapy. Each chemotherapy cycle was
281 repeated every 3 to 4 weeks for 6 to 8 cycles, according to condition and tumor status.
282 Follow-up by EUAs was undertaken before each cycle of chemotherapy and every 3
283 to 4 weeks thereafter, during which the adjuvant laser therapy and cryotherapy were
284 applied as needed. In accordance with treatment strategies, five ophthalmological
285 experts (HS Zhao, X Ge, XL Xu, LB Jiang, JS, and JM Ma) with a minimum of 15
286 years of experience labeled all images as “normal fundus”, “stable retinoblastoma”
287 that specific treatment is not required, and “active retinoblastoma” that specific
288 treatment is required.

289 **Development of DLA-RB**

290 The patients from the retrospective dataset were randomly split into training and the
 291 internal validation dataset as five-fold cross-validation for developing and evaluating
 292 the performance of DLA-RB, respectively. To automatically distinguish “normal
 293 fundus”, “stable retinoblastoma”, and “active retinoblastoma”, we first compared the
 294 performance of some architectures including ResNet-50 and InceptionV3.²⁴⁻²⁶
 295 ResNet-50 which did not occupy much computational resource achieved better
 296 performance and was chosen to complete the task. The input of the model was an
 297 image from EUAs. The output of the first model is a binary output determined
 298 whether the input image contained active retinoblastoma was among normal fundus
 299 and active retinoblastoma. The second binary classification task for determining
 300 among stable retinoblastoma and active retinoblastoma, whether the input image
 301 contained active retinoblastoma. In addition, the training dataset is imbalanced, so we
 302 adopted a class weight policy in the training process. All models were developed with
 303 Tensorflow 1.10.0 and Keras 2.2.4 on the server with three NVIDIA 1080 GPUs
 304 (Graphical Processing Units).²⁷ All images were resized to 256×256 and then fed into
 305 models to train or test. The optimization algorithm was SGD (Stochastic Gradient
 306 Descent)²⁸, the default hyperparameters in Keras 2.2.4 were used, and at the same
 307 time, the batch size was 32. Besides, class weight was used for trading off the effect
 308 of the imbalanced distribution of two classes. Based on the repeated experiments,
 309 different epochs were also applied to train the models without underfitting. Moreover,
 310 the best models in terms of validation accuracy is saved as the final deployed model.

311 **Validation of DLA-RB**

312 We first validated the performance of DLA-RB in identifying retinoblastoma activity
313 in patients using an internal validation dataset and a prospective validation dataset
314 from Beijing Tongren Hospital. For further performance evaluation, two varying
315 degrees of expertise (competent and trainee), masked to the patients' demographics
316 and final multidisciplinary management strategy, were asked to classify every patient
317 in the prospective dataset independently, and their results were compared with those
318 of DLA-RB. The competent ophthalmologists attended doctors with about 2-5 years
319 of experience in general ophthalmology and EUAs examination. The trainee was a
320 resident who had finished EUAs training.

321 **Cost-utility analysis**

322 Two Markov models were built using TreeAge Pro (TreeAge Software; Williamstown,
323 MA, USA) to compare the cost-effectiveness between traditional ophthalmologic
324 centers-based diagnosis mode and DLA-RB based diagnosis mode from a societal
325 perspective. For the first binary model, we simulated a hypothetical cohort of a
326 newborn with RB through 5 1-year Markov cycles. With the growth of age, children
327 could be found to have eye symptoms by their parents according to specific
328 probabilities and then go to the hospital. Diagnosed patients received routine
329 treatment and management, whereas undiagnosed patients could still be examined in
330 the next cycle. According to the Management Guidelines for Childhood Screening for
331 Retinoblastoma Families, we determined the screening intervals for undiagnosed
332 patients.¹⁸ For the second binary model, simulated a hypothetical cohort of
333 2-year-old RB patients who have received regular treatment and were in an inactive

stage through a total of 3 1-year Markov cycles. They were routinely reviewed every three months, and those who had active lesions received further treatment. Parameters used in Markov models were collected from our study and previous studies. Examination and treatment costs were collected in Chinese yuan from Beijing Tongren Hospital and converted to US dollars at an exchange rate of 6.45 yuan per dollar (**Supplementary Table S4**). Both direct and indirect costs were included, and the specific composition of costs and annual costs of traditional ophthalmologic centers-based diagnosis mode and DLA-RB-based diagnosis mode was shown in **Supplementary Table S5-6**. Under traditional ophthalmologic centers-based diagnosis mode, the patient and one accompanying family member spent more time in tertiary hospitals or eye hospitals, resulting in transportation, accommodation, and food costs. In DLA-RB-based diagnosis mode, we charged an additional \$15.5 for each use. Only one accompanying family member's wage loss was counted. Primary results were incremental cost-utility ratios (ICURs), which were calculated using the following formula:

$$ICURs = \text{incremental cost} / \text{quality adjusted life years gained}.$$

China's per capita gross domestic product (GDP) in 2021 was \$12551. According to the WHO definition, intervention costing between 1 to 3 times the per capita GDP was cost-effective, costing less than the per capita GDP was highly cost-effective, and costing more than three times the per capita GDP was not cost-effective.²⁴ Both 1-way deterministic and simulated probabilistic sensitivity analyses were performed to test the sensitivity and robustness of base-case values, the uncertainty ranges of parameters were presented in **Supplementary Table S7**.

Visualization and statistical analysis

To visualize the decision ways of the model used, we applied the Grad-CAM to generate heatmaps.²⁵ The performance of DLA-RB was estimated by accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F1 score for the identification of each category. We used the receiver operating characteristic (ROC) curve and precision-recall curve to show the diagnostic performance of the DLA-RB in discriminating binary classification tasks. N-out-of-N Bootstrapping with 1000 replicates was used to estimate 95% confidence intervals (95% CI) of the performance metrics at eye level. Human ophthalmologists' performance was compared with 95% CI of DLA-RB.

All statistical analysis was performed using R Statistical Software (version 4.1.1; R Foundation for Statistical Computing, Vienna, Austria), Stata (17.0, StataCorp LLC, College Station, TX).

Data availability

Python scripts enabling the main steps of the analysis are available from the corresponding author on reasonable request. The data and materials in this study are available from the corresponding author on reasonable request.

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The funders had no role in the study design, data collection, data analysis, data interpretation, or in the writing of the manuscript.

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472 **Figure legends**

473 **Figure 1.** Workflow diagram for the development and evaluation of DLA-RB.

474 RB, retinoblastoma.

475 **Figure 2.** Receiver operating characteristic curves and precision-recall curve of

476 DLA-RB performance in prospective validation dataset.

477 Receiver operating characteristic and precision-recall curve of DLA-RB in identifying

478 normal-active lesion identification (A-B), and stable-active lesion identification

479 (C-D).

480 **Figure 3.** Heatmap Visualization of DLA-RB

481 Heatmap demonstrating representative lesions, shown in original fundus image (first

482 column), general heatmap (second column) for (A) identifying active retinoblastoma

483 tumors from all clinical-suspected retinoblastoma and (B) identifying active

484 retinoblastoma from all referred and treated retinoblastoma patients.

485

486 **Table 1.** Basic characteristics of patients in prospective validation dataset.

	Equipment 1	Equipment 2
Number of patients	64	39
Age at diagnosis		
<12month	14 (21.9%)	11 (28.2%)
12-23 month	19 (29.7%)	15 (38.5%)
24-35 month	14 (21.9%)	6 (15.4%)
≥36 month	17 (26.6%)	7 (17.9%)
Gender		
male	36 (56.3%)	23 (59.0%)
female	28 (43.8%)	16 (41.0%)
Laterality		
unilateral	44 (68.7%)	22 (56.4%)
bilateral	19 (29.7%)	16 (41.0%)
Number of eyes	88	51
IIRC Grade		
normal fundus	46 (52.3%)	24 (47.1%)
A	3 (3.4%)	0 (0.0%)
B	5 (5.7%)	2 (3.9%)
C	6 (6.8%)	2 (3.9%)
D	22 (25.0%)	18 (35.3%)
E	6 (6.8%)	5 (9.8%)
Number of eyes with retinoblastoma	42	27
Tumor focality		
unifocal	16 (38.1%)	4 (14.8%)
multifocal	26 (61.9%)	23 (85.2%)
Retinoblastoma growth pattern		
endophytic	24 (57.1%)	15 (55.6%)

exophytic	18 (42.9%)	12 (44.4%)
Fovea involvement		
not involved	14 (33.3%)	6 (22.2%)
subfoveal fluid	2 (4.8%)	4 (14.8%)
foveal tumor	26 (61.9%)	17 (63.0%)
Retinoblastoma seeds		
not seeds	17 (40.5%)	7 (25.9%)
subretinal	16 (38.1%)	10 (37.0%)
vitreous	9 (21.4%)	10 (37.0%)

487 IIRC, international intraocular retinoblastoma classification.

488

489 **Table 2.** Performance of DLA-RB in prospective validation dataset,

	Accuracy	Sensitivity	Specificity	Positive	Negative	F1 score
	(95% CI)	(95% CI)	(95% CI)	predictive	predictive	(95% CI)
				value (95%	value (95%	
				CI)	CI)	
Normal-active	0.992	0.979	1.000	1.000	0.988	0.989
retinoblastoma	[0.977-1.000]	[0.927-1.000]	[1.000-1.000]	[1.000-1.000]	[0.961-1.000]	[0.932-1.000]
identification						
Stable-active	0.934	0.978	0.800	0.937	0.923	0.957
retinoblastoma	[0.869-0.984]	[0.932-1.000]	[0.556-1.000]	[0.868-1.000]	[0.727-1.000]	[0.930-1.000]
identification						

490

491

492 **Table 3.** Confusion matrix of DLA-RB in identifying active retinoblastoma among
493 treated patients.

		DLA-RB		
		stable	active	total
Gold standard	stable	12	3	15
	active	1	45	46
	total	13	48	61

494

495

Table 4. Base-case cost-utility results.

	Costs per person, \$	QALYs per person	Incremental costs per person, \$	Incremental QALYs per person	ICURs, \$
Diagnosis of RB					
DLA-RB-based diagnosis mode	3519	2.87240
Traditional ophthalmologic centers-based diagnosis mode	4882	2.87769	1363	0.00529	257645
Identification of active lesion in treated retinoblastoma patients					
DLA-RB-based diagnosis mode	6981	5.46345
Traditional ophthalmologic centers-based diagnosis mode	7614	5.46436	633	0.00091	694323

DLA-RB, Deep Learning Assistant for retinoblastoma; ICUR, incremental cost-utility ratio; QALY,

quality-adjusted life-year.

Costs are given in US dollars. Negative ICURs are regarded as dominating.

Development dataset

47503 images from 713 patients were retrospectively collected between March, 2018 and January, 2022

666 pictures were removed
because of poor quality

10880 pictures were removed
because of poor quality

36623 images from 713 patients
19045 images were normal
2918 images were stable RB
14660 images were active RB

Prospective validation dataset

2032 images from 103 patients (139 eyes) were prospectively collected from February, 2022 to June, 2022

Equipment 1
833 images from
64 patients (88 eyes)

Equipment 2
533 images from
39 patients (51 eyes)

1366 images from 103 patients
751 images were normal
132 images were stable RB
516 images were active RB

Deep Learning Assistant for Retinoblastoma Monitoring (DLA-RB) System



