Application of Artificial Intelligence for prediction of congenital ophthalmologic malformations using perinatal data

Aplicação da Inteligência Artificial na predição de malformações oftalmológicas congênitas a partir de dados perinatais

Helvécio Neves Feitosa Filho[1], Rian Vilar Lima[1], Lucas Macêdo Aurélio Paiva[1], João Filipe Cavalcante Uchoa Furtado[1], Pedro Vianna Caldas Ribeiro[1], Felipe Cavalcanti Dias[1], Isabela Diógenes Feitosa[1]

[1] School of Medicine, Universidade de Fortaleza, Fortaleza, Ceará, Brazil.

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Corresponding author:
Helvécio Neves Feitosa Filho
E-mail: helvecionff@gmail.com

Institution:
Universidade de Fortaleza, Fortaleza, Ceará, Brazil.

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Universidade Federal de Juiz de Fora, Juiz de Fora, MG, Brazil
https://orcid.org/0000-0002-9451-738X

ABSTRACT

Objective: To evaluate whether an Artificial Intelligence model based on easily accessible perinatal variables can predict congenital ophthalmologic malformations, particularly those whose late detection may lead to preventable blindness.

Methods: Retrospective diagnostic accuracy study using the DATASUS database. A total of 6,633 newborns in Brazil (2014 to 2022) were included, with 2,211 congenital ophthalmologic malformations (ICD-10 Q100-Q159) and 4,422 controls. Predictors comprised 14 maternal, obstetric, and neonatal factors; records with missing data were excluded. Logistic regression and support vector machine models were applied, assessing accuracy, sensitivity, specificity, and AUC. Subanalyses targeted clinically challenging congenital ophthalmologic malformations and those requiring early screening.

Results: Logistic regression achieved 55.05% sensitivity, 91.32% specificity, and AUC 0.833; support vector machine yielded 47.82%, 93.01%, and 0.834, respectively. For hard-to-detect congenital ophthalmologic malformations, logistic regression obtained AUC 0.795, support vector machine 0.842. For screenable conditions, logistic regression reached AUC 0.790, support vector machine 0.761.

Conclusion: AI models using perinatal data demonstrated good accuracy for congenital ophthalmologic malformation identification, supporting early screening in resource-limited settings.

RESUMO

Objetivo: Avaliar se um modelo de Inteligência Artificial baseado em variáveis perinatais de fácil acesso é capaz de prever malformações oftalmológicas congênitas, sobretudo aquelas cuja detecção tardia pode levar à cegueira evitável.

Métodos: Estudo retrospectivo de acurácia diagnóstica utilizando o banco de dados do DATASUS. Foram incluídos 6.633 recém-nascidos no Brasil entre 2014 e 2022, sendo 2.211 com malformações oftalmológicas congênitas (CID-10 Q100-Q159) e 4.422 controles. Analisaram-se 14 variáveis maternas, obstétricas e neonatais, excluindo-se registros com dados faltantes. Aplicaram-se modelos de regressão logística e máquina de vetor de suporte, avaliando acurácia, sensibilidade, especificidade e AUC. Subanálises consideraram malformações oftalmológicas congênitas de difícil diagnóstico clínico e condições rastreáveis com impacto terapêutico.

Resultados: A regressão logística apresentou sensibilidade de 55,05%, especificidade de 91,32% e AUC 0,833; a máquina de vetor de suporte obteve 47,82%, 93,01% e 0,834. Para malformações oftalmológicas congênitas de difícil diagnóstico, a regressão logística alcançou AUC 0,795 e a máquina de vetor de suporte 0,842. Para condições rastreáveis, a regressão logística obteve AUC 0,790 e a máquina de vetor de suporte 0,761.

Conclusão: Modelos de Inteligência Artificial baseados em dados perinatais mostraram boa acurácia para identificar malformações oftalmológicas congênitas, auxiliando no rastreio inicial em cenários com recursos limitados.

INTRODUCTION

Congenital ophthalmologic malformations (COMs) encompass a variety of anomalies that can severely compromise patients' quality of life and still relevant causes of evitable childhood blindness.[1] These malformations include congenital cataracts, congenital glaucoma, and colobomas, which often have genetic origins or result from teratogenic exposures during embryonic development.[2] These conditions pose significant diagnostic and therapeutic challenges, especially in regions with limited access to specialized services.

Recent studies have explored the application of Artificial Intelligence (AI) in the diagnosis of ophthalmological congenital malformations, demonstrating great potential in the analysis of medical images and early identification of structural anomalies.[3-5] Deep learning models, such as convolutional neural networks, have been used to diagnose congenital cataracts with levels of accuracy comparable to that of human experts.[5] Other applications include the automated detection of retinopathy of prematurity[1] and the use of supervised learning algorithms to classify pediatric conditions such as strabismus and refractive errors.[6] Despite these advances, the proposed methods until now depend on the acquisition of high-quality images and/or the availability of high computing power, making them difficult to use in scenarios with fewer resources.

Reviews reinforce AI's transformative potential in ophthalmology, particularly for early detection of sight-threatening diseases such as cataract, glaucoma, and retinopathy of prematurity. AI has been shown to deliver diagnostic accuracy comparable – or even superior – to experienced ophthalmologists, with the added advantage of scalability to underserved populations.[7,8] A recent meta-analysis confirmed that AI significantly improves diagnostic accuracy across ophthalmic diseases.[9] Furthermore, novel implementations, such as real-time AI systems integrated into ultrasonography, have shown efficacy in detecting fetal intracranial malformations, expanding the potential of AI in prenatal screening.[10]

Most recently, AI-driven cloud-based collaborative platforms have been validated in multicenter trials for congenital cataracts, showing comparable diagnostic and treatment decision performance to expert ophthalmologists while facilitating wider access to care.[5] Reviews and prospective analyses highlight the critical role AI can play in expanding access to early ophthalmic diagnosis, optimizing treatment strategies, and supporting ophthalmic care in low-resource environments.[11,12]

Therefore, this study aims to evaluate whether an AI model based on easily accessible perinatal variables can predict COMs, particularly those whose late detection may lead to preventable blindness.

METHODS

Study design

We conducted a quantitative retrospective diagnostic accuracy study using the DATASUS database, a unified system of the Brazilian public health system. We analyzed all records of children born with COMs (ICD Q100 to Q159) in Brazil from 2014 to 2022. The case group consisted of 2,211 children with COMs, diagnosed according to the International Classification of Diseases, 10th Revision (ICD-10) code Q100 to Q159. The control group comprised 4,422 children without any congenital anomaly.

Dataset establishment

We used data from *Informações de Saúde* (TABNET) and the *Sistema de Informação sobre Nascidos Vivos* (SINASC), provided by the Departamento de Informação e Informática do SUS (DATASUS) and the Secretaria de Saúde of Brazil. Certificate of Live Birth number was used as the univocal term. Our variable for prediction was presence or absence of COMs at birth, and our predictors were maternal socioeconomic (age, mother's marital status, mother's education, number of live and death children during pregnancy), obstetric (type of pregnancy, delivery, prenatal appointments), and neonatal (gender, ethnicity, weight, Apgar 1, Apgar 5 and gestational age) factors. Patients whose register did not contain any of the 14 characteristics under investigation missing were automatically excluded from the analysis by the models.

A subgroup analysis was conducted on COMs that are challenging to identify through physical examination: (120), Congenital Aphakia (123), Congenital Corneal Opacity (133), Congenital Malformations of the Retina (141), Congenital Malformations of the Optic Disc (142), Congenital Choroidal Malformations (143), Congenital Malformations of the Vitreous Humor (140), Congenital Malformations of the Anterior Chamber of the Eye (139), and Congenital Glaucoma (150). Additionally, a separate analysis was performed on conditions for which screening would be potentially beneficial (i.e., conditions that can lead to blindness with effective and available treatment if identified): Congenital Cataract (120), Congenital Glaucoma (150), Congenital Aphakia (123), and Congenital Corneal

Opacity (133). Throughout these analyses, a 1:2 case-to-control ratio was meticulously maintained.

Model building

The model building process involved training, testing, and validating the dataset in a 70%-15%-15% split using three distinct approaches: binary logistic regression (LR) and machine learning (ML) with the support vector machine (SVM) model. LR is a well-established method for binary classification tasks and is widely applied in medical and epidemiological research due to its simplicity, interpretability, and solid statistical basis. It allows the estimation of the relationship between predictors and a binary outcome (e.g., case and control), making it a robust choice for identifying risk factors in health studies.[13] SVMs are ML algorithms known for their robustness in handling high-dimensional data and their ability to generalize well even with limited data points. This algorithm is particularly suitable for our population due to its accuracy in binary classification problems and its ability to manage complex relationships in medical datasets.[14,15]

Statistical analysis

The Statistical Package for the Social Sciences (SPSS) software version 25.0 and XLSTAT were used for statistical analysis. SPSS was used to first perform the descriptive quantitative analysis of the epidemiology of cases and controls. The XLSTAT software (Addinsoft, New York, USA) was used to apply the binary LR model and SVM. The area under the curve (AUC) Receiver Operating Characteristic (ROC), sensitivity and specificity were calculated.

To evaluate the contribution of each predictor variable to the classification task (case vs. control), we applied a variable importance analysis specific to each ML algorithm. For the LR model, normalized regression coefficients were used to quantify the relative weight of each variable. For the SVM model, variable importance was derived from the magnitude of the feature weights in the decision function. In both models, the resulting values were normalized to a 0 to 100% scale, allowing direct comparison of the relative influence of each predictor on the final classification.

Ethics approval and consent to participate

The data used in this research are publicly available and do not involve human subjects or personal information. Therefore, this study is exempt from ethical review according to the Brazilian Ministry of Health and the National Health Council Resolution n. 466/12.

RESULTS

Population

A total of 6,633 newborns were included in the study, with 2,211 having a COMs and the remaining 4,422 being healthy controls chosen at random to maintain a 2:1 ratio. Palpebral malformations had the greatest representation with 787 cases (35.59%), microphthalmia was present in 283 cases (12.79%), and congenital cataract in 124 cases (5.60%). All COMs by number of cases are arranged in table 1. Sample characteristics divided by cases and controls are available in table 2.

Table 1. Number of cases per congenital ophthalmologic malformations

COMs (ICD-10)	n
Congenital ptosis (100)	23
Congenital ectropion (101)	11
Congenital entropion (102)	4
Other congenital malformations of the eyelids (103)	787
Absence or agenesis of the lacrimal apparatus (104)	15
Congenital stenosis or narrowing of the lacrimal duct (105)	10
Other congenital malformations of the lacrimal apparatus (106)	23
Congenital malformations of the orbit (107)	27
Cystic eye (110)	6
Other forms of anophthalmia (111)	133
Microphthalmia (112)	283
Macrophthalmia (113)	16
Congenital cataract (120)	124
Congenital lens dislocation (121)	3
Coloboma of the Lens (122)	1
Congenital aphakia (123)	4
Other congenital malformations of the lens (128)	5
Unspecified congenital malformation of the lens (129)	7
Iris coloboma (130)	9
Absence of the iris (131)	4
Other congenital malformations of the iris (132)	10
Congenital corneal opacity (133)	58
Other congenital corneal malformations (134)	14
Blue sclera (135)	4
Other congenital malformations of the anterior chamber of the eye (138)	6
Unspecified congenital malformations of the anterior chamber of the eye (139)	12
Congenital malformation of the vitreous humor (140)	3
Congenital malformations of the retina (141)	6
Congenital malformations of the optic disc (142)	4
Congenital choroidal malformations (143)	19
Other congenital malformations of the posterior chamber of the eye (148)	2
Unspecified congenital malformations of the posterior chamber of the eye (149)	10
Congenital glaucoma (150)	64
Other specified congenital malformations of the eye (158)	379
Unspecified congenital malformations of the eye (159)	125

COM: congenital ophthalmologic malformation.

Models

In the application of LR and SVM to the general population dataset, a total of 420 cases and controls with one or more missing variables were excluded from the analysis. Consequently, in our validation, the LR model demonstrated a sensitivity of 55.05%, a specificity of 91.32%, and

Table 2. Sociodemographic characteristics of the groups included

Variables	Cases (n = 2,211)	Controls (n = 4,422)	Missing data
Mother's marital status			17 cases, 22 controls
Single	921	1,784	
Married	806	1,417	
Widowed	9	8	
Legally separated	46	43	
Consensual union	412	1,148	
Mother's education, years			17 cases, 5 controls
None	12	31	
1-3	61	80	
4-7	335	581	
8-11	1,268	3,009	
12 or more	518	716	
Type of pregnancy			2 cases, 2 controls
Single	2,164	4,373	
Gemellar	45	47	
Type of delivery			4 cases, 1 control
Vaginal	809	1,869	
Cesarean	1,398	2,552	
Prenatal appointments			27 cases, 2 controls
None	44	22	
1-3	160	135	
4-7	508	676	
7+	1,472	3,587	
Ethnicity			68 cases, 34 controls
White	844	633	
Black	144	111	
Asian	12	12	
Brown	1,117	3,614	
Amerindian	26	18	
Gender			42 cases, 0 control
Male	1,080	2,105	
Female	1,089	2,317	
Mother's age	30.01 (± 7.95)	26.83 (± 6.67)	0 case, 0 control
Number of live children	1.17 (± 1.41)	1.01 (± 1.24)	46 cases, 28 controls
Number of death children	0.35 (± 0.68)	0.22 (± 0.55)	75 cases, 19 controls
Apgar 1	6.58 (± 2.57)	8.35 (± 1.02)	41 cases, 35 controls
Apgar 5	7.93 (± 2.35)	9.37 (± 0.83)	40 cases, 33 controls
Weight (g)	2,652.03 (± 806.33)	3,239.33 (± 541.85)	2 cases, 0 control
Gestational weeks	36.82 (± 3.67)	38.41 (± 2.33)	26 cases, 26 controls

an AUC of 0.833. Conversely, the SVM model exhibited a sensitivity of 47.82%, a specificity of 93.01%, and an AUC of 0.834. The values for training, testing, and validation phases, together with ROC curves of both models are shown in table 3 and figure 1, respectively.

Proceeding to the first sub-analysis, which focused on COMs that are challenging to detect during physical examination, a total of 48 cases with incomplete data were first excluded. Subsequently, the LR model was applied, achieving a sensitivity of 50.00%, a specificity of 87.78%, and an AUC of 0.795. The SVM model exhibited a sensitivity of 43.75%, a specificity of 98.81%, and an AUC of 0.842. The data from all stages are presented in table 4.

Advancing to the second sub-analysis, which pertains to COMs whose screening would be potentially beneficial, an initial exclusion of 45 cases with missing data was conducted. Thereafter, the LR model was employed, achieving a sensitivity of 50.00%, a specificity of 90.24%, and an AUC of 0.790. The SVM model exhibited a sensitivity of 45.16%, a specificity of 92.25%, and an AUC of 0.761. The data from all stages are compiled in table 5.

The ML models employed considered variables of significant weight for discrimination between cases and controls. The LR model identified the variables with the greatest impact on classification, presented in order of normalized importance: weight (100%), Apgar 5 (75.1%), Apgar 1 (54.8%), maternal age (53.4%), and gestational weeks (36.3%). Conversely, the SVM model assigned the highest weightings to the following variables: Apgar 1 (100%), weight (55.7%), Apgar 5 (39.0%), maternal age (27.7%), and number of non-living children (27.4%). The weights of these and other variables per model are shown in figure 2.

DISCUSSION

This study stands as a proof of concept that applying AI and traditional LR analysis with the aim of predicting children with high risk for COMs that may be hard to diagnose without proper ophthalmological evaluation can yield great accuracy even with limited number of characteristics available.

The prediction models obtained considerable and similar performance when subjected to general analysis with LR AUC of 0.833 and SVM with AUC of 0.834. In the sub-analyses, the ML model obtained better performance in conditions of difficult detection in the physical examination and the traditional mathematical model in

Table 3. General performance of machine learning models in the training, testing and validation phases

Models	Training		Testing		Validation	
Logistic regression	Sensibility	54.35%	Sensibility	47.87%	Sensibility	55.05%
	Specificity	91.63%	Specificity	92.75%	Specificity	91.32%
	AUC	0.840	AUC	0.812	AUC	0.833
	Case *versus* control (n)	1321 *versus* 2902	Case *versus* control (n)	305 *versus* 690	Case *versus* control (n)	327 *versus* 668
SVM	Sensibility	48.37%	Sensibility	52.56%	Sensibility	47.82%
	Specificity	94.17%	Specificity	94.43%	Specificity	93.01%
	AUC	0.831	AUC	0.839	AUC	0.834
	Case *versus* control (n)	1321 *versus* 2902	Case *versus* control (n)	322 *versus* 673	Case *versus* control (n)	312 *versus* 683

AUC: Area Under the Curve; SVM: Support Vector Machine.

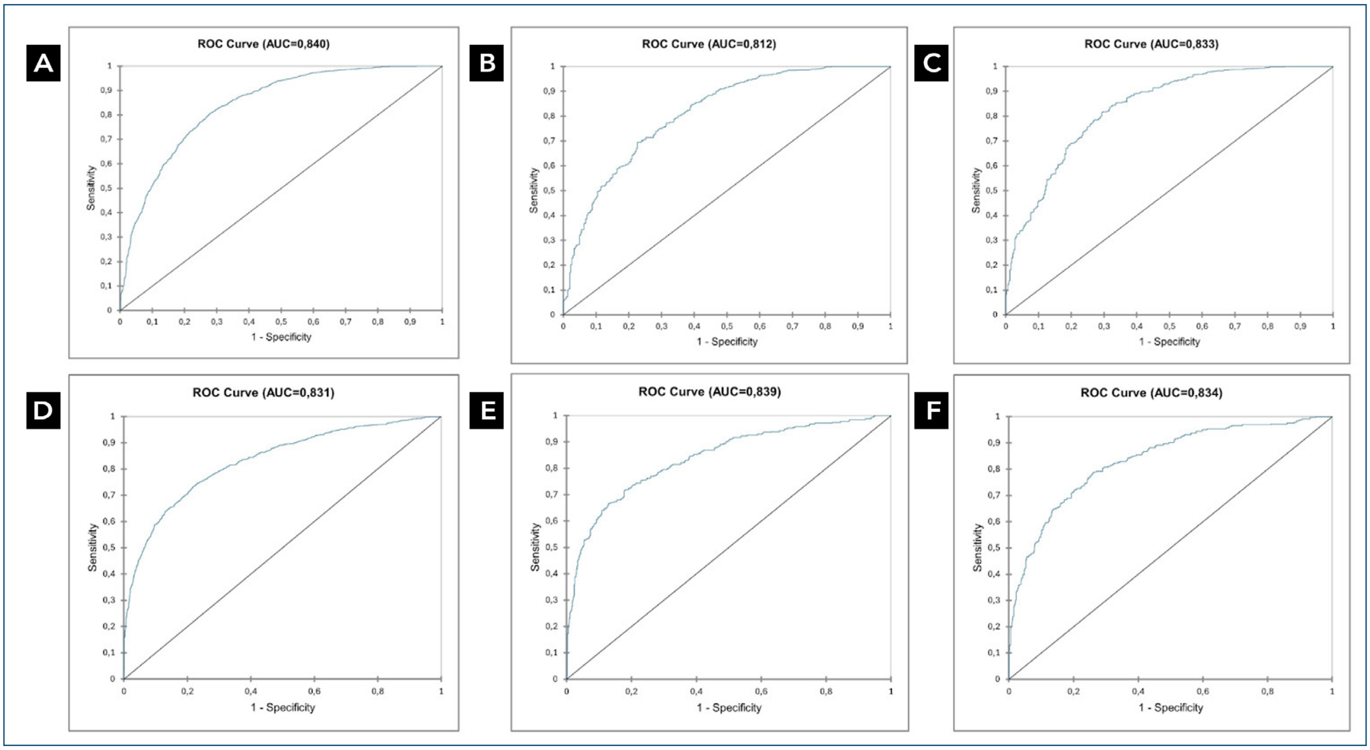

Figure 1. Receiver Operating Characteristic curves of logistic regression in training (A), test (B), and validation (C) and SVM in training (D), test (E) and validation (F) in the general population.

Table 4. Performance of machine learning models when restricted to COMs that are difficult to detect in physical examination

Models	Training		Testing		Validation	
Logistic regression	Sensibility	46.78%	Sensibility	50.00%	Sensibility	50.00%
	Specificity	93.23%	Specificity	86.73%	Specificity	87.78%
	AUC	0.806	AUC	0.757	AUC	0.795
	Case *versus* control (n)	171 *versus* 399	Case *versus* control (n)	34 *versus* 98	Case *versus* control (n)	42 *versus* 90
SVM	Sensibility	45.55%	Sensibility	37.50%	Sensibility	43.75%
	Specificity	95.64%	Specificity	94.56%	Specificity	98.81%
	AUC	0.795	AUC	0.761	AUC	0.842
	Case *versus* control (n)	180 *versus* 390	Case *versus* control (n)	42 *versus* 90	Case *versus* control (n)	48 *versus* 84

AUC: Area Under the Curve; SVM: Support Vector Machine.

Table 5. Performance of machine learning models when restricted to congenital ophthalmologic malformations that lead to blindness if left untreated and with treatment available

Models	Training		Testing		Holdout	
Logistic regression	Sensibility	41.67%	Sensibility	31.82%	Sensibility	50.00%
	Specificity	93.53%	Specificity	92.68%	Specificity	90.24%
	AUC	0.782	AUC	0.780	AUC	0.790
	Case *versus* control (n)	132 *versus* 309	Case *versus* control (n)	44 *versus* 82	Case *versus* control (n)	44 *versus* 82
SVM	Sensibility	44.44%	Sensibility	47.50%	Sensibility	45.16%
	Specificity	95.16%	Specificity	91.76%	Specificity	92.55%
	AUC	0.788	AUC	0.715	AUC	0.761
	Case *versus* control (n)	144 *versus* 310	Case *versus* control (n)	40 *versus* 85	Case *versus* control (n)	31 *versus* 94

AUC: Area Under the Curve; SVM: Support Vector Machine.

conditions where early screening is potentially beneficial. The variables that weighed most in the decision of the models were weight, Apgar, mother's age, gestational age and the number of non-living children. These data are consistent, since the association between congenital malformations and the factors mentioned is documented in the scientific literature.[16]

AI models have already been validated as an important tool to assist ophthalmologists in various diseases such as diabetic retinopathy, retinopathy of prematurity and retinoblastoma,[1-3] with most studies training prediction models on optical coherence tomography (OCT) images or fundus images. However, few studies evaluate physical examination characteristics, symptoms and

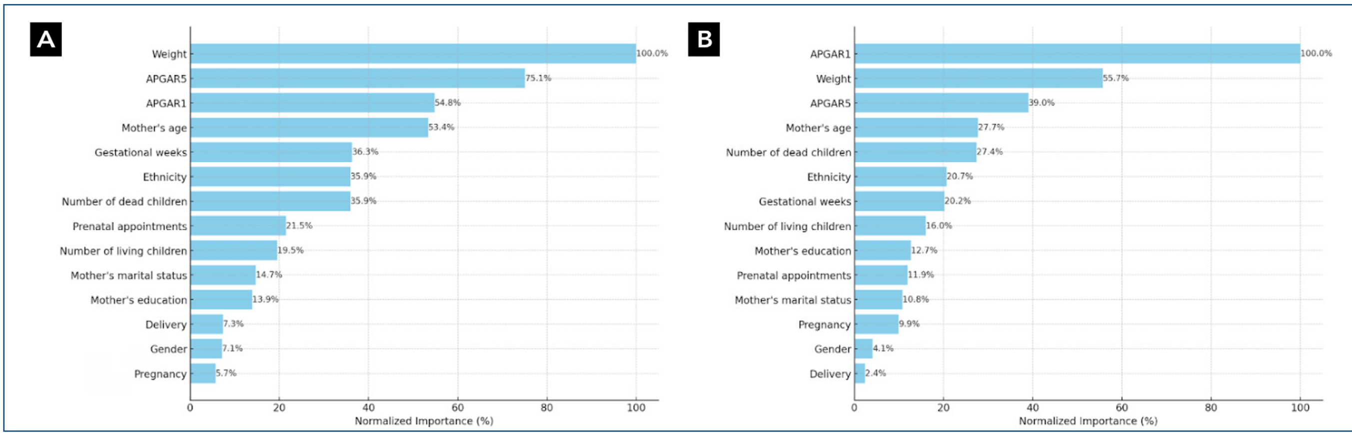

Figure 2. Variables that most influenced each model in its decision in the general population.

other clinical and perinatal characteristics in COMs, such as our study that evaluated the latter cluster. Another example would be the study by Long et al., 2017, one of the largest multicenter pilot studies that applied AI to differentiate congenital cataracts from normal eyes from ocular images with a sensitivity of 100% and 97.67% specificity.[5] Another large case-control study on congenital cataract that used the Random Forest prediction model and other models assessing clinical characteristics also evaluated in our study, such as gender of the newborn and preterm births, demonstrates a similar sensitivity of 80% and a high specificity of 90%, highlighting important factors such as parental education, family history, and the presence of comorbidities.[17]

In addition to congenital cataract, the study by Marouf et al. evaluated a set of eye diseases, including primary congenital glaucoma through symptoms and changes in the physical examination, also demonstrating a high accuracy of the SVM model with 99.11% and LR of 98.58% and highlighted the clinical variables cloudy, blurry or foggy vision, double vision, and problem in identifying color.[18] Comparable advances have been reported in congenital systemic conditions. For example, AI models integrating perinatal data have successfully predicted neonatal outcomes, congenital abnormalities, and other risks, further validating the importance of easily accessible predictors in precision medicine.[19,20]

The extension of these predictive approaches to ophthalmology has the potential to reshape neonatal screening paradigms by complementing, rather than replacing, existing diagnostic workflows. A fundamental implication lies in the opportunity to transform perinatal and early-life health data – routinely collected and readily available – into actionable insights for ophthalmic risk stratification. Unlike imaging-based models, which demand expensive infrastructure, skilled personnel, and high-quality data acquisition, perinatal-based models leverage universally recorded variables such as birth weight, gestational age, and Apgar scores. This accessibility provides a foundation for democratizing ophthalmic prediction and ensuring that early risk identification is not limited to highly resourced centers.

Moreover, the integration of such AI-driven tools into routine neonatal care has significant potential to enhance healthcare equity. In many countries, ophthalmologic care is disproportionately centralized, with specialized pediatric ophthalmologists clustered in major urban areas. These results occur in delayed diagnosis for infants in remote or underserved settings, where congenital malformations may remain undetected until irreversible visual impairment. By embedding AI-supported screening algorithms into primary care settings, maternity wards, or even mobile health applications, frontline healthcare providers could be empowered to recognize high-risk newborns and initiate timely referrals. Such decentralization of risk detection aligns with global health priorities aimed at reducing preventable childhood blindness and addressing disparities in access to care.[12]

From a clinical management perspective, predictive models could also support the personalization of follow-up protocols. High-risk neonates identified by AI-based tools could be placed under intensified surveillance, ensuring earlier diagnostic imaging and specialist evaluation, while low-risk infants could continue under standard follow-up schedules. This stratified approach would optimize the use of limited ophthalmological resources, reducing unnecessary specialist consultations while simultaneously minimizing the risk of delayed detection in vulnerable groups. Additionally, by highlighting the relative importance of perinatal variables in prediction, these models provide clinicians with a more nuanced understanding of systemic risk factors that may be overlooked in routine practice, thus bridging epidemiological evidence with individualized patient care.

Another important implication is the integration of AI models into telemedicine platforms. Teleophthalmology has already been promising in expanding access to eye care, particularly for conditions such as diabetic retinopathy and retinopathy of prematurity. When combined with AI-driven perinatal risk prediction, telemedicine could create a two-tiered system: infants flagged as high risk could undergo remote consultations supported by image sharing and cloud-based AI diagnostics, ensuring rapid triage and management even in geographically isolated regions. Such synergy between predictive modeling and telehealth infrastructures would be particularly valuable in low- and middle-income countries, where both technological constraints and specialist shortages remain pressing barriers.[21]

At the public health level, predictive AI models could inform population-based screening policies. For example, risk scores derived from perinatal data could be used by ministries of health to guide resource allocation, directing screening campaigns or mobile ophthalmology units to regions with higher predicted prevalence of COMs. Furthermore, predictive analytics could be integrated into maternal and child health registries, providing policymakers with real-time epidemiological insights into the burden of congenital ocular disease and enabling evidence-based planning of preventive strategies.

Finally, these implications also raise ethical and governance considerations. The adoption of AI into neonatal and ophthalmic care requires robust frameworks to ensure transparency, accountability, and explainability. LR offers interpretability that can be directly communicated to clinicians and families, while more complex models such as SVM may demand additional interpretability tools to build trust and prevent the so-called “black box” dilemma. Equally important is the need to ensure that AI-based tools do not exacerbate inequities by being restricted to technologically advanced hospitals. Instead, their true transformative potential lies in being adapted to resource-limited environments, where their predictive value can have the greatest clinical and societal impact.[22]

Despite the promising findings, several limitations must be acknowledged. First, although the dataset analyzed was large and multicentric, the exclusion of newborns with missing perinatal variables reduced the effective sample size, particularly in the sub-analyses. This may have influenced the sensitivity of the models and restricted the generalizability of the results. Second, all data originated from a single-country registry, which, although diverse in terms of geography, may not fully capture variations in genetic, environmental, and healthcare factors present in other populations. External validation in different cultural and epidemiological contexts will therefore be essential before broader implementation.

Third, the reliance on routinely collected perinatal data represents both strength and limitation. While these variables are widely available and facilitate scalability, they do not replace direct ophthalmologic assessment or imaging-based diagnostics. The models should thus be seen as triage tools rather than definitive diagnostic systems. Fourth, model explainability remains a broader challenge in adoption of AI. Although LR provides interpretable outputs, the performance of SVM, while slightly superior in certain subgroups, comes with limited transparency, highlighting the tension between accuracy and interpretability in clinical AI applications.

Finally, as with most retrospective studies, the analysis is limited by potential biases inherent to the quality and completeness of registry data. The presence of unmeasured confounders—such as parental education, genetic predispositions, or prenatal exposures—may have influenced outcomes but could not be fully accounted for in our models. Prospective data collection and inclusion of broader clinical and sociodemographic variables may enhance the robustness and predictive value of future iterations of these models.

CONCLUSION

This study provides a proof of concept that Artificial Intelligence and traditional statistical approaches, when applied to perinatal and clinical variables, can effectively predict congenital ophthalmologic malformations that are otherwise difficult to detect in routine neonatal care. Both logistic regression and support vector machine models demonstrated comparable accuracy, underscoring the feasibility of using readily available, non-invasive predictors to stratify risk in newborns. The identification of birth weight, Apgar scores, maternal age, and gestational age as key determinants reinforces previously established associations between these variables and congenital anomalies, while demonstrating their utility within predictive modeling frameworks.

The broader implications of these findings suggest that Artificial Intelligence-enhanced prediction tools could complement current ophthalmic screening practices, particularly in low-resource settings where access to specialized services is limited. By enabling earlier referral of high-risk infants, such models have the potential of reducing the burden of preventable childhood blindness and optimize resource allocation. Nevertheless, limitations regarding data completeness, generalizability, and model interpretability must be addressed before clinical integration.

Future research should prioritize multicenter and cross-population validation, the incorporation of additional sociodemographic and genetic data, and the development of explainable AI systems to ensure clinical trust. With these refinements, predictive models based on perinatal features could evolve into scalable, equitable, and impactful tools for neonatal ophthalmology, bridging the gap between population-level screening and individualized risk assessment.

AUTHORS' CONTRIBUTION

Helvécio Neves Feitosa Filho contributed to the conception and design of the study, analysis, and interpretation of results, writing, and critical review of the manuscript's content. Rian Vilar Lima and Lucas Macêdo Aurélio Paiva contributed to the analysis and interpretation of data, writing, and critical review of the manuscript's content. João Filipe Cavalcante Uchoa Furtado and Pedro Vianna Caldas Ribeiro contributed to the conception and design of the study, writing, and critical review of the manuscript's content. Felipe Cavalcanti Dias and Isabela Diógenes Feitosa contributed to the writing and critical review of the manuscript's content. All authors approved the final version of the manuscript and are responsible for all aspects of the manuscript, including ensuring its accuracy and integrity.

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