

Original article

# Role of Artificial Intelligence in Predicting Visual Prognosis After Open Globe Trauma in Children

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## ARTICLE INFO

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## ABSTRACT

**Background and aims.** Open globe eye injuries are a frequent cause of morbidity, amblyopia, and monocular blindness in children. In our study, we propose to establish deep learning models to predict the final visual acuity (VA) prognosis and the risk of amblyopia after an open globe injury in children. **Methods.** This study involves deep learning models based on a dataset containing 146 variables of 87 patients aged  $\leq 16$  years (87 eyes) who had an open globe injury between January 1, 2015, and December 31, 2021. We used the Knime software for predicting the final visual acuity prognosis and the risk of amblyopia. The methods used were the neural network system, the support vector machine (SVM), and the decision tree. **Results.** The deep learning system was able to predict the risk of having a poor final visual acuity prognosis with good accuracy for both the neural network system and SVM (76.9% and 88.9%, respectively). The identified prognostic factors for poor VA prognosis in the decision tree were low initial visual acuity, wound size  $> 6$ mm and its shape, the presence of anterior chamber inflammation or abnormal ultrasound. Our study also accurately predicted the risk of amblyopia with good specificity (80.8% and 100%, respectively, for the neural network system and 78.4% and 74.1%, respectively, for SVM). Similarly, the decision tree identified children at high risk of subsequent amblyopia, namely initial visual acuity, presence of a limbal wound, absence of isolated corneal involvement, and presence of postoperative complications. **Conclusion.** Predicting VA prognosis and the risk of amblyopia after an open globe injury in children could play a major role in identifying high-risk groups to adjust the postoperative surveillance rate and reduce the optical disturbances caused by open globe injuries.

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## INTRODUCTION

Open globe eye injuries represent a common cause of morbidity, disability, and monocular blindness in children [1]. Their socio-economic repercussions are significant as they compromise the future educational and professional prospects of these future adults, in addition to the psychological and emotional repercussions [2]. Thus, a better understanding of prognostic factors in open globe injuries in children would improve medical, surgical, and psychological management [3].

Current formulas for predicting the outcomes of an open globe injury often heavily rely on visual acuity (VA) and the presence of an afferent pupillary defect [4]. However, elements of clinical examination are rarely used due to challenges in evaluating them in young children [5]. In our work, we aimed to establish a deep learning approach using both a neural network and a support vector machine (SVM) to predict final visual acuity and the risk of amblyopia after an open globe injury in children and analyze the characteristics of open globe injuries in children aged up to 16 years to facilitate the development of an algorithm to predict visual outcomes in this age group.

## METHODS

### *Study design and setting*

This is a deep learning study of a database containing 146 variables from 87 patients (87 eyes) who suffered an open globe trauma, collected from January 1<sup>st</sup>, 2015 to December 31<sup>st</sup>, 2021.

The study was conducted in accordance with ethical principles applicable to medical research involving human subjects (Helsinki Declaration). We obtained the consent of the parents or legal guardians of children before including them.

### *Data collection procedure*

The study included children aged  $\leq 16$  years who underwent emergency surgery for open globe trauma. We included children with an ocular wound, defined as an open globe rupture, penetrating wound, or perforating wound, according to the "Birmingham Eye Trauma Terminology system" (BETT) [6]. Children who were lost to follow-up and cases with missing data were excluded. Data were collected from patients' medical records, including anamnestic, clinical, therapeutic, and evolutionary data. Data of a complete bilateral ophthalmologic examination data were used for all children at presentation and during follow-up visits. The variables included the wound location (according to the Ocular Trauma Classification Group (OTC) in zone I, zone II, or zone III and as corneal wound, limbal wound, corneolimbic wound, corneoscleral laceration, or scleral wound) [7], presence of visual axis involvement, size and shape of the wound, state of the wound edges, and presence of foreign bodies at the wound edges and the presence of complications. A negative outcome was defined as a visual acuity worse than 2/20, and a favorable outcome as a visual acuity greater than 2/20. The presence of amblyopia was considered as a major prognostic factor studied independently.

We used the Knime software for deep learning [8]. It is a free and open-source data analysis software that includes a set of tools for machine learning and data exploration through a modular workflow interface. Three workflows were used for the deep learning: neural network [9], SVM [10] and decision trees. The steps used are schematized in Figure 1.

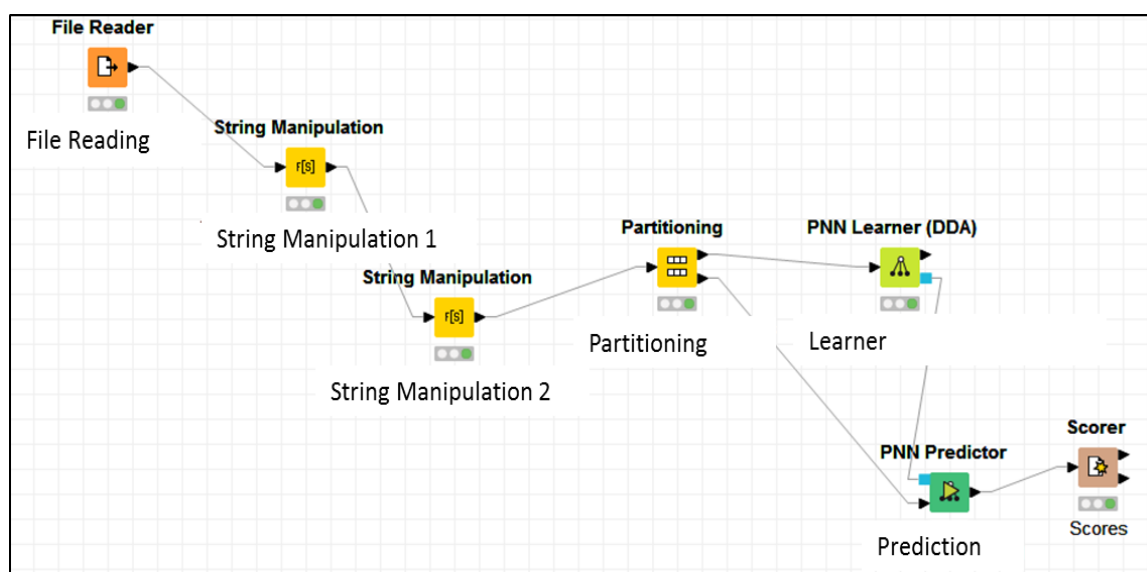


Figure 1. Workflow of the probabilistic neural network. Same steps were used for the support vector machine and tree decision.

### *Data analysis*

The data was modified and processed to remove confounding factors and adapt variables to the requirements of the software for both factors studied (FVA and risk of amblyopia). The prediction using both neural network and SVM systems to choose the best model with the highest accuracy and specificity. Performance evaluation was done through metrics such as accuracy, true positives (TP), false positives (FP), true negatives (TN), false negatives (FN), sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), recall, and F-measure.

## RESULTS

### *Results of the final visual acuity study*

For the neural network, after completing the learning process, the system was tested on 52 eyes of 52 patients. The

prognosis was good in 37 eyes (TN=30 and FN=7) and bad in 15 eyes (TP=10 and FP=5). The system was able to predict the outcome in 76.9% of cases (Table I). For the SVM, the deep learning system established for final visual prognosis was tested on 36 eyes of 36 patients. The prognosis was good in 18 eyes (TN=16 and FN=2) and poor in 18 eyes (TP=16 and FP=2). The system was able to predict the outcome in 88.9% of cases (Table I).

**Table 1. Summary of deep learning results for final visual acuity and amblyopia risk using neural network and support vector machine**

Variables	Neural network	Support vector machine
<b>Final visual acuity</b>		
Accuracy	76.9%	88.9%
Sensitivity	85.7%	88.9%
Specificity	58.8%	88.9%
PPV	66.7%	88.9%
NPV	81.1%	88.9%
Recall	85.7%	88.9%
F-measure	83.3%	88.9%
<b>Amblyopia</b>		
Accuracy	80.8%	78.4%
Sensitivity	16.7%	90%
Specificity	100%	74.1%
PPV	100%	56.2%
NPV	80%	95.2%
Recall	16.7%	90%
F-measure	28.6%	69.2%

PPV: Positive predictive value, NPV: Negative predictive value

The decision tree allowed predicting the final visual prognosis based on initial clinical and paraclinical examination results as well as early management data. The major parameters influencing the prognosis were initial visual acuity, wound size, wound shape, presence of anterior chamber inflammation, and B-mode ultrasound results (Figure 2). This decision tree had an accuracy of 85.7% and a specificity of 82.6%.

#### **Results of the amblyopia risk study**

The neural network was tested on 52 eyes of 52 patients. Amblyopia was found in 40 eyes (TP=40 and FP=0) and absent in 12 eyes (TN=10 and FN=2). The system was able to detect amblyopia in 80.8% of cases (Table 1).

The SVM established for amblyopia risk was tested on 37 eyes of 37 patients. Amblyopia was found in 27 eyes (TP=20 and FP=7) and absent in 10 eyes (TN=9 and FN=1). The system was able to predict the result in 78.4% of cases. The decision tree was used to predict the risk of amblyopia based on the results of the initial clinical and paraclinical examination as well as early management data. Major risk factors for amblyopia were initial visual acuity, absence of isolated corneal involvement, presence of a limbal wound, and postoperative complications (Figure 2). This decision tree had an accuracy of 77.6% and a specificity of 83.8%.

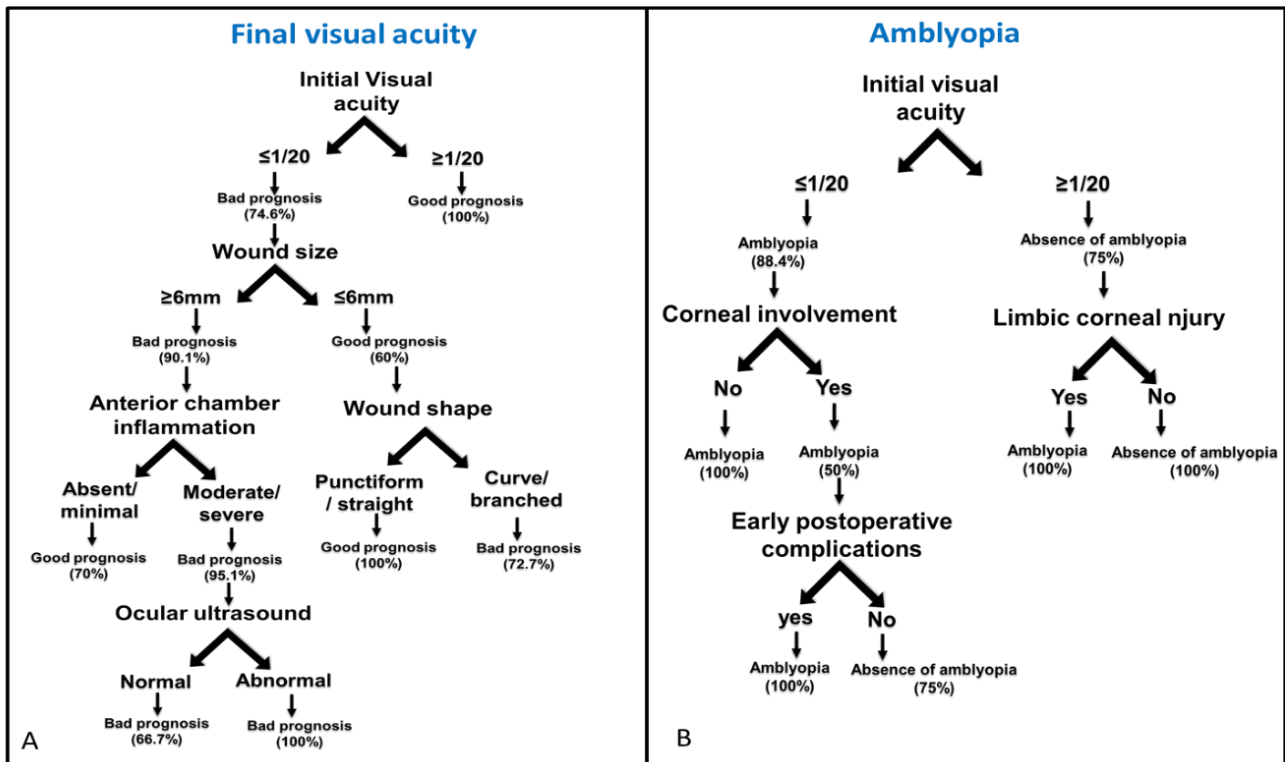


Figure 2. Decision trees. A. For the risk of poor final visual acuity. B. For the amblyopia risk

**DISCUSSION**

The simultaneous maturation of multiple digital and telecommunications technologies, especially since 2020 due to the difficulties in accessing healthcare caused by the global COVID-19 pandemic, has created an unprecedented opportunity for ophthalmology to adapt to new care models using digital innovations [12]. Artificial intelligence has provided synchronous solutions to the challenges faced by ophthalmologists and healthcare providers around the world, especially in diabetic retinopathy [13], retinopathy of prematurity [14], age-related macular degeneration [15], and glaucoma [16]. Despite the widespread use of artificial intelligence in predicting visual acuity after various medical and surgical interventions [17-19], to our knowledge and as of today, artificial intelligence has not been used to predict final visual acuity in eye injuries, especially in children. This is mainly due to the difficulty of collecting comprehensive data in an emergency context and the difficulty of clinical examination in children. However, our study was able to predict the final visual prognosis and the risk of amblyopia and create a decision tree.

Our deep learning system was able to predict the risk of having a poor final visual prognosis with good accuracy for both the neural network system and the SVM (76.9% and 88.9%, respectively). However, between 1/10 and 1/4 of cases could not be predicted due to the heterogeneity of the sample and the relatively small number of included patients. Nevertheless, we believe that this system would be of paramount importance, especially in cases without involvement of the posterior segment and where the prognosis remains uncertain, in order to adjust surgical and medical management as well as the frequency of surveillance. In fact, several scores have tried to predict visual prognosis after open globe trauma. The two most used scores are the Ocular Trauma Score (OTS) and the Pediatric Ocular Trauma Score (POTS). In 2002, Kuhn et al. [20] developed the OTS to predict the final functional prognosis based on clinical data from the initial assessment. Most studies on OTS have found it to be a reliable score for determining the prognosis of open globe trauma. POTS was initially developed by Acar et al. [21] in 2011. It was similar to the ocular trauma score but differed in that it placed less weight on initial visual acuity, given the frequency of false initial acuity in the context of trauma or even the impossibility of obtaining it in young children. However, several studies have shown that POTS underestimated the final visual prognosis and had less reliable results [22-24]. In our learning system, initial visual acuity was a major factor since it was the first element in the decision tree. The prognostic factors for poor final visual acuity identified in our decision tree were low initial visual acuity, wound size >6mm and its shape, the presence of anterior chamber inflammation, or abnormal ultrasound. These results are consistent with those in the literature (Table 2).

In children, amblyopia is a major concern following an open globe trauma due to the prolonged duration of visual rehabilitation and therapy. Depending on the severity of the damage, the visual potential could be poor, and amblyopia could have an even more negative impact on visual prognosis. Traumatic cataracts associated with corneal laceration

were the most common cause of severe and refractory visual acuity decline in children after an open globe trauma [44]. Prevention and treatment of amblyopia have been the subject of several in-depth studies [2]. The patient should be managed by a pediatric ophthalmologist after primary repair. Bai et al. showed that occlusion therapy, combined with glasses wearing and intraocular lens implantation, was useful in treating amblyopia caused by secondary deprivation after ocular trauma or surgery in pediatric patients. Similarly, wearing optical correction with glasses in the early postoperative period could reduce the incidence of amblyopia [45]. Our study was able to predict the risk of amblyopia with good accuracy and specificity (80.8% and 100%, respectively, for the neural network and 78.4% and 74.1%, respectively, for the SVM). Thus, in this group of children at high risk of amblyopia, we strongly recommend the use of our neural network system to detect amblyopia early and reduce its incidence. Similarly, the decision tree was able to identify children at high risk of subsequent amblyopia, namely, initial visual acuity, presence of a limbal wound, absence of isolated corneal damage, and presence of postoperative complications. The presence of these risk factors should prompt closer monitoring. The strengths of our study were that, to our knowledge, it was the first deep learning attempt to predict post-open globe trauma visual prognosis in children and study the risk of amblyopia. This work was able to make predictions with good accuracy and specificity and thus create decision trees. The main limitations of this work were the relatively small number of patients included and the heterogeneity of the sample. Similarly, the difficulty in obtaining initial visual acuity in children could limit its use in practical life.

**Table 2. Summary of factors associated with poor final visual acuity found in the literature**

Identified Risk Factors for Poor Final Prognosis	Study: First author's name
Age (years)	Acar [21] (<5), Liu [25] (<6), Bunting [26] (<5), Farr [27] (<4), Gupta [28] (<5)
Low initial visual acuity	Liu [25], Gupta [28], Ihan [29], Kadappu [30], Tok [31], Guo [32], AlDahash [33]
Wound size (mm)	Bunting [26] (>6), Ihan [29], Kadappu [30] (>10), AlDahash [33] (>10), Grieshaber [34], Liu [35], Al Majed [36]
Corneoscleral wound	Grieshaber [34], Saksiriwutto [37]
Lens involvement	Kadappu [30], AlDahash [33], Grieshaber [34], Al Majed [36], Lee [38]
Posterior segment involvement	Acar [21], Liu [25], Bunting [26], Kadappu [30], Tok [31], Grieshaber [34], Liu [35], Lee [38], Dulal [39], Lesniak [40]
Globe rupture	Bunting [26], Farr [27], Kadappu [30]
Presence of vitreous hemorrhage	Wen [3], Liu [25], Guo [32], Al Majed [36]
Presence of retinal detachment	Wen [3], Liu [25], Bunting [26], Tok [31], Guo [32], AlDahash [33], Lee [38], Choovuthayakorn [41]
Presence of endophthalmitis	Wen [3], Tok [31], Guo [32], Lee [38], Narang [42], Omobolanle [43]

## CONCLUSION

The prediction of VA and the risk of amblyopia after an open globe injury in children could play a major role in identifying at-risk groups in order to adjust the frequency of postoperative surveillance and reduce the visual disorders caused by open globe injuries.

## Disclaimer

The article has not been previously presented or published and is not part of a thesis project.

## Conflict of Interest

There are no financial, personal, or professional conflicts of interest to declare.

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