Detection of Subclinical Keratoconus Using a Novel Combined Tomographic and Biomechanical Model Based on an Automated Decision Tree

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Abstract

The aim of this study was to develop a predictive model for subclinical keratoconus (SKC) based on decision tree (DT) algorithms. A total of 194 eyes (including 105 normal eyes and 89 SKC) were included in the double-center retrospective study. Data were separately used for training and validation databases. The baseline variables were derived from tomography and biomechanical imaging. DT models were generated in the training database using Chi-square automatic interaction detection (CHAID) and classification and regression tree (CART) algorithms. The discriminating rules of the CART model selected variables of the Belin/Ambrósio deviation (BAD-D), stiffness parameter at first applanation (SPA1), back eccentricity (Becc), and maximum pachymetric progression index in order, while the CHAID model selected BAD-D, deformation amplitude ratio, SPA1, and Becc. The CART model allowed discrimination between normal and SKC eyes with 92.2% accuracy, which was higher than that of the CHAID model (88.3%), BAD-D (82.0%), Corvis biomechanical index (CBI, 77.3%), and tomographic and biomechanical index (TBI, 78.1%). The discriminating performance of the CART model was validated with 92.4% accuracy, while the CHAID model was validated with 86.4% accuracy in the validation database. Thus, the CART model using tomography and biomechanical imaging was an excellent model for SKC screening and provided easy-to-understand discriminating rules.

Introduction

Keratoconus (KC) is a progressive sight-threatening ectatic corneal disease that is one of the most common causes of corneal blindness in adolescents.¹ Due to the overlap in most parameters derived from topography and tomography imaging between subclinical keratoconus (SKC) and normal eyes (NE), identifying SKC remains one of the most challenging situations before making the decision to perform refractive surgery.^{2,3} In the field of SKC screening, establishing combinations or models based on different algorithms has attracted increasing attention.

Currently, the strict criteria that define SKC are not well established. The inclusion criteria of subjects influence the outcomes of predictors' discriminatory power in diagnosis studies. Previously, most studies only adopted topographic criteria to define the SKC, which may result in overestimation of the model's performance.^{4,5} Hwang reported that a logistic regression model achieved amazing high accuracy (AUC=1.0) in detecting the SKC with a normal topographic aspect.⁴ Ambrósio et al. introduced a new combined index, the tomographic and biomechanical index (TBI)⁶, which was shown to exhibit a high AUC value of 0.985 in detecting SKC with a topography-based KISA% index⁷ of less than 60%. However, Steinberg et al.⁸ demonstrated that the discriminatory power of TBI decreased with an AUC of 0.825 in a validation research using the same inclusion and exclusion criteria as Ambrósio's study⁶. The results of the aforementioned studies appear to be encouraging; however, when evaluating the performance of a model, the distribution of variables within the studied population should be considered seriously. Although the first detectable sign of KC has not been defined definitively, previous studies highlight the importance of posterior surface abnormalities in SKC diagnosis.^{9,10} Bae suggested that the back elevation difference (BED) should be included in the criteria of SKC for the future.³ Therefore, further study should be performed to detect SKC defined by stricter criteria considering topography and posterior surface elevation.

Clinically, another troublesome situation in SKC diagnosis is choosing the most useful variables from vast amounts of data and interpreting the complex variables. In practice, the final decision before refractive surgery is often based on personal experience or proposed cutoffs of summary metrics in previous studies. Generally, an ideal model is easily interpretable, clinically credible, and statistically valid. A decision tree (DT) model represents a symbolic classification with "if-then rules", which could provide easier interpretation than that of purely quantitative models, such as neural networks and logistic regression. Based on the DT algorithm, Smadja analyzed the metrics only from the GALILEI Dual-Scheimpflug Analyzer and reported an easy-to-understand discriminating rule and its desired accuracy for SKC screening.⁵

The purpose of the present study was to develop easy-to-understand discriminating rules based on DT algorithms by overall analysis of the metrics from tomography and biomechanical imaging and evaluate the performance of DT models in detecting SKC defined with normal topography and BED.

Materials And Methods

This retrospective study was performed through a cooperative effort between the Wuhan Aier Hankou Eye Hospital (Wuhan, China) and Henan Eye Hospital (Zhengzhou, China). Our study adhered to the tenets of the Declaration of Helsinki and was separately approved by Institutional Review Boards from the Wuhan Aier Hankou Eye Hospital and the Henan Eye Hospital. Written informed consent was obtained from each participant.

One hundred ninety-four participants were included in this double-center retrospective study. A total of 128 participants (70 healthy and 58 with very asymmetric ectasia) were enrolled from the Hankou Aier Eye Hospital (training database), and 66 participants (35 healthy and 31 with very asymmetric ectasia) were enrolled from the Henan Eye Hospital (validation database). All patients underwent comprehensive ophthalmic examinations, including a subjective analysis with slit-lamp biomicroscopy by an experienced anterior segment expert and objective examinations (i.e., Corvis ST and Pentacam HR examinations).

The objective definitions for normal and KC were based on the well-established topographical keratoconus classification (TKC) index from topometric display and tomography imaging in the Pentacam system.³ An eye was diagnosed as having KC if it met with (1) a TKC index of greater than 0 and (2) at least one of the following signs: Vogt striae, Fleischer ring, Munson's sign, and focal thinning. The diagnosis of KC was only used to aid the definition of SKC and was not used for further analysis. The less affected fellow eye of a very asymmetric ectasia individual was diagnosed as having SKC if it met with (1) normal slit-lamp, (2) CDVA of 20/20 or better, (3) normal topographic aspect, a TKC index of 0,¹¹ the central mean keratometry value <47.2D and I-S value <1.40D,¹² (4) BED <12 μm ¹³. The NE definition was met with the same criteria as in SKC (both eyes of normal individuals met the criteria). All normal control patients underwent refractive surgery and had a 2-year follow-up without any evidence of ectatic corneal changes. Only one eye was randomly selected for further analysis.

For all eyes included in the study, no contact lenses had been worn for at least 4 (rigid contact lenses) or 2 (soft contact lenses) weeks prior to examination; no history of other eye diseases, no previous ocular surgery, and no use of topical medications other than artificial tears.

The techniques for Pentacam and Corvis ST analyses have been described previously.^{14,15} Not only the "QS" buttons from the Corvis ST and Pentacam HR read OK but also the measured area of Belin/Ambrósio Enhanced Ectasia was no smaller than 8 mm, and the measurement was included in the study. All cases from each hospital had tomographic data masked for reevaluation by an anterior segment expert from the other center (SW and QY) to confirm recruitment.

Objectively, the variables analyzed included keratometry values, eccentricity, and astigmatism of the anterior and posterior surfaces; Kmax; the distance between any two points of the corneal apex (Apex), corneal thinnest corneal point (TCP), and pupil center point (PCP) [including the distances (D) from the TCP to the Apex, $D_{\text{TCP-Apex}}$; TCP to PCP, $D_{\text{TCP-PCP}}$; and PCP to Apex, $D_{\text{PCP-Apex}}$]; PPImax (maximum of pachymetric progression index); Belin/Ambrósio deviation index (BAD-D); BED; back eccentricity (Becc); index of surface variance (ISV); index of vertical asymmetry (IVA); index of height asymmetry (IHA); index of height decentration (IHD); keratoconus index (KI); central keratoconus index (CKI); deformation amplitude ratio (DA-ratio); integrated radius (Integ-R); stiffness parameter at first applanation (SPA1); Corvis biomechanical index (CBI); and TBI.

Description and tree-growing criteria of both the CHAID and CART decision trees

We used SPSS 22.0 software to generate DTs based on chi-square automatic interaction detection (CHAID) and classification and regression tree (CART) algorithms in the training database (schematic theory of the discriminating rule based on a DT is presented in Supplementary Figure 1). The tree-growing method of CHAID chooses the independent variable that has the strongest interaction with the dependent variable. Chi-square tests were used to determine node splitting and category merging. In the CHAID method, the most significant discriminant variable divides the entire sample into two or more subgroups, which are subsequently divided by the next selected variable. The significance level for node splitting in the CHAID model was a *P*-value less than 0.05. The CART method splits the data into segments that are as homogeneous as possible with respect to the dependent variable in the tree growing procedure. A DT generated using CART is referred to as a binary tree. The CART-growing method attempts to maximize within-node homogeneity, and the Gini was selected to measure impurity at the split. The minimum change in improvement was set as 0.0001. Furthermore, the pruning procedure was performed in the CART procedure to reduce overfitting.

Growth limits

The maximum level of tree depth was set to 3 for CHAID and 5 for CART. The minimum number of cases was set to 10 for parent nodes and 5 for child nodes.

Internal- and external-validation

A 10-fold cross-validation method was used for internal validation. The training database was split into 10 approximately equal-sized folds, and trees were then produced 10 times. The final tree was selected to be the one with the smallest cross-validation estimate of error. The external validation procedure was performed based on the validation database from Henan Eye Hospital.

Statistical analyses were performed using SPSS 22.0 software and MedCalc software. The mean $\pm$ standard deviation (SD) and range were used to describe the data. All data were analyzed using the Kolmogorov-Smirnov normality test and Levene's test for equal variances to choose the appropriate method. The differences between two groups were compared using the independent t-test or Mann-Whitney U test. The DTs were generated based on the CHAID and CART methods. The receiver operating characteristic (ROC) curve was used to test the performance of the studied metrics and DT models in differentiating populations. DeLong's test was used for the pairwise comparisons of AUCs. $P < 0.05$ (two-tailed) was considered statistically significant.

Results

The predictive accuracies of the CHAID model in the training database (CHAID-T) and CART model in the training database (CART-T) were 88.3% and 92.2%, respectively (Table 1). The CART-T model had a higher sensitivity of 89.7% than the CHAID-T model (82.8% sensitivity) (Table 1). The most important predictors in the CHAID-T to discriminate NE and SKC included the BAD-D, DA-ratio, SPA1, and Becc (Figure 1 and Table 2), whereas that in CART-T included the BAD-D, SPA1, Becc, and PPImax (Figure 2 and Table 2). For both trees, the BAD-D was selected as the most discriminant variable to differentiate SKC and NE at the first split (with similar cutoff values of BAD-D: 1.53 in the CHAID-T and 1.635 in the CART-T). SPA1 was selected as the second most discriminant variable for differentiating SKC from NE (cutoff values: 92.2 in the CHAID-T and 89.25 in the CART-T). The external validation procedure revealed that the CHAID tree in the validation database (CHAID-V) had 86.4% accuracy and that the CART tree in the validation database (CART-V) had 92.4% accuracy (Table 1). The interpretation details of the discriminating rules of the CHAID-T and CART-T are summarized in Table 2, Figure 1, and Figure 2.

Table 1
The performance of CHAID and CART decision tree to discriminate SKC from NE

Model	Eye number (NE vs SKC)	Accuracy (%)	Youden	Sensitivity (%)	Specificity (%)
CHAID-T	70 vs 58	88.3	0.76	82.8	92.9
CART-T	70 vs 58	92.2	0.84	89.7	94.3
CHAID-V	35 vs 31	86.4	0.73	90.3	82.9
CART-V	35 vs 31	92.4	0.85	90.3	94.3
CHAID-T, CHAID decision tree based on training-database; CHAID-T, CART decision tree based on training-database; CHAID-V, the validation of CHAID; CART-V, the validation of CART					

Table 2
Predictions of CHAID and CART for the outcome to discriminate NE and SKC in training database

Node	Discriminating rules	Outcome	Probability(%)	Population
CHAID decision tree in the training-database				
4	If (BAD-D >1.94)	SKC	100	25
3	If (1.53 < BAD-D ≤ 1.94)	SKC	84.6	11
5	If (BAD-D ≤ 0.92) and (DA-ratio ≤ 4.5)	NE	91.1	41
7	If (0.92 < BAD-D ≤ 1.53) and (SPA1 ≤ 92.2)	SKC	88.9	8
9	If (0.92 < BAD-D ≤ 1.53), (SPA1 >92.2) and (Becc ≤0.60)	NE	95	19
CART decision tree in the training-database				
2	If (BAD-D >1.635)	SKC	100	34
3	If (BAD-D ≤1.635) and (SPA1 ≤89.25)	SKC	91.7	11
5	If (BAD-D ≤1.635), (SPA1 >89.25), and (Becc ≤0.605)	NE	91.9	57
7	If (BAD-D ≤1.635), (SPA1 >89.25), (Becc >0.605), and (PPlmax ≤1.25)	NE	90	9
8	If (BAD-D ≤1.635), (SPA1 >89.25), (Becc >0.605) and (PPlmax >1.25)	SKC	70	7
BAD-D, Belin/Ambrósio Enhanced Ectasia Display Index; DA-ratio, deformation amplitude ratio; SPA1, stiffness parameter at first applanation; Becc, back eccentricity; PPlmax, maximum of pachymetric progression index				

Table-3. Descriptive statistics of the key studied variables in the training-database									
Variable	NE	SKC	P value	AUC	95% CI	Cutoff	Accuracy	Sensitivity	Specificity
BAD-D	0.79±0.4	2.04±1.00	<0.001*	0.86	0.79-0.92	1.33	82.0%	69.0%	92.9%
SPA1	111.9(103.5,121.6)	89.3(81.0,100.8)	<0.001#	0.86	0.78-0.91	101.2	81.3%	79.3%	82.9%
DA-ratio	4.3(4.0,4.4)	4.9(4.5,5.2)	<0.001#	0.84	0.77-0.90	4.5	78.9%	70.7%	85.7%
PPlmax	1.24(1.15,1.32)	1.48(1.34,1.63)	<0.001#	0.86	0.78-0.91	1.34	82.0%	74.1%	88.6%
Becc	0.49(0.43,0.56)	0.60(0.48,0.65)	0.001#	0.68	0.59-0.76	0.54	67.2%	63.8%	70.0%
CBI	0.01(0,0.04)	0.18(0.02,0.81)	<0.001#	0.80	0.72-0.87	0.05	77.3%	65.5%	87.1%
TBI	0.07(0.01,0.18)	0.35(0.20,1.00)	<0.001#	0.84	0.76-0.90	0.17	78.1%	81.0%	75.7%
BAD-D, Belin/Ambrósio Enhanced Ectasia Display Index; SPA1, stiffness parameter at first applanation; DA-ratio, deformation amplitude ratio; PPlmax, maximum of pachymetric progression index; Becc, eccentricity of back surface; CBI, corvis biomechanical index; TBI, combined tomography and biomechanical index;									
* Independent t-test. # Mann-Whitney U test									

Table-4. DeLong's Test Results of Major Predictors' AUCs for NE vs SKC				
	AUC difference	SE	95% CI	P value
BAD-D vs CBI	0.06	0.04	-0.02-0.15	0.158
BAD-D vs TBI	0.02	0.03	-0.04-0.09	0.420
TBI vs CBI	0.04	0.05	-0.06-0.13	0.422
CHAID-T vs BAD-D	0.07	0.03	0.01-0.13	0.014
CHAID-T vs CBI	0.14	0.04	0.05-0.22	0.001
CHAID-T vs TBI	0.10	0.03	0.03-0.16	0.004
CART-T vs BAD-D	0.08	0.03	0.02-0.14	0.015
CART-T vs CBI	0.14	0.05	0.05-0.23	0.002
CART-T vs TBI	0.10	0.03	0.04-0.17	0.002
CHAID-T vs CART-T	0.01	0.02	-0.03-0.05	0.781
BAD-D, Belin/Ambrósio Enhanced Ectasia Display Index; CBI, corvis biomechanical index; TBI, combined tomography and biomechanical index; CHAID-T, CHAID decision tree based on training database; CART-T, CART decision tree based on training database				

Descriptive statistics of the key studied variables are displayed in Table 3. Compared with those in NE eyes, the BAD-D, DA ratio, PPImax, Becc, CBI, and TBI were significantly higher, and the SPA1 was significantly lower in SKC eyes. The ROC results showed that the BAD-D, SPA1 and PPImax had the highest AUC values of 0.86, followed by the DA-ratio and TBI (AUC values: 0.84 and 0.84, respectively). The AUCs of the CHAID-T and CART-T were 0.94 and 0.94, respectively. The CHAID-V and CART-V demonstrated similar AUC values to those in the training database (CHAID-V, 0.92; CART-V, 0.95). DeLong's test showed that both the CHAID-T and CART-T demonstrated significantly higher AUC values than each AUC of the individual BAD-D, CBI, and TBI (Table 4). The ROC curves of the CHAID-T, CART-T, BAD-D, CBI, and TBI are presented in Figure 3A, whereas the ROC curves of the CHAID-V and CART-V are presented in Figure 3B.

Discussion

We developed two DT models separately based on the CHAID and CART methods in a training database. The results showed that the CART-T model had a higher discriminating accuracy of 92.2% (89.7% sensitivity and 94.3% specificity), whereas the CHAID-T model demonstrated 88.3% accuracy with 82.8% sensitivity and 92.9% specificity. The nonparametric nature of a DT allows for the lack of requirement for a specified distribution of outcome data or a large sample size; however, this nature renders them more sensitive to overfitting than parametric models.¹⁶ To minimize the overfitting risk, we performed cross-validation in both the CHAID-T and CART-T procedures. Based on the same database, internal validation itself may still overestimate model performance; therefore, an independent database is recommended to evaluate the model for generalizability. In the external validation procedure, we found that the CART-V had a similar predictive accuracy for SKC compared to the CART-T (Table 1). Compared with that of CHAID-T, the sensitivity of CHAID-V increased, whereas the specificity and overall predictive accuracy decreased. In terms of sensitivity and specificity, the performance of the CART in the training and validation databases presented high consistency. Considering the severe outcomes of missed diagnosis of SKC, the CART-T with higher predictive sensitivity and generalizability may be an optimal tool for ophthalmologists to detect SKC.

Based on different tree-growing methods, both CHAID-T and CART-T selected BAD-D as the most discriminant variable to distinguish between the SKC and NE. Studies of SKC screening have confirmed the superior discriminatory power of the BAD-D over topographic variables and central thickness evaluation.^{17,18} The cutoff values of the BAD-D used to discriminate SKC from NE were 1.6 in Shetty's study¹⁸ and 1.09 in Steinberg's study⁸, whereas the cutoff value of the individual BAD-D was 1.33 in our study. When selecting an optimal cutoff value, special attention should be given to the generalizability of it found within the studied population. In the present study, both the CHAID-T and CART-T selected similar cutoff values (1.53 in CHAID-T and 1.635 in CART-T) of BAD-D to

generate the first split, which were nearly equal to the reference value of 1.6 between normal and suspected patients provided by the Pentacam system. Selecting a higher cutoff value of the BAD-D resulted in high screening specificity for SKC while decreasing the false-positive rate in the first split of the DTs. Accumulating these findings, BAD-D should be most considered in the clinical diagnostic rule of SKC.

Both DTs selected biomechanical variables as the second most discriminant variable for differentiating SKC from NE (CHAID with DA-ratio and SPA1; CART with SPA1). Compared with the CHAID-T with multiple branches, the CART-T with a binary split nature incorporated a lower cutoff value of the SPA1 with 89.25 (SPA1 cutoff of 92.2 in CHAID-T). Generally, the CART tree-growing method attempts to maximize within-node homogeneity. Zhou reported that the SPA1 index, which reflects corneal stiffness, decreased and had a significant correlation with the thinnest corneal thickness in moderate-to-severe KC but not in NE.¹⁹ The DA ratio reflects the corneal deformation level under specific air impulses; a weaker cornea is more prone to deformation. Previous studies have demonstrated that the individual DA ratio and SPA1 can effectively discriminate KC from NE but performed worse in discriminating SKC from NE.^{20,21} In our study, both the individual DA ratio and SPA1 demonstrated the same AUC of 0.84 when comparing SKC and NE. However, the results in this study highlighted the importance of biomechanical variables in SKC diagnosis.

According to our findings, PPI_{max} and Becc were not selected in the upper part of either the CHAID-T or CART-T. The PPI_{max} represents the corneal thickness distribution from the thinnest point to the periphery, and the PPI_{max} increases if the central cornea becomes thinner. It has been validated with higher accuracy for discriminating KC from NE than that of the single pachymetric index.²² We found that the PPI_{max} had an AUC value of 0.86 for discriminating SKC from NE. Eccentricity is an important index for describing changes in corneal shape, and the normal value ranges from 0.4-0.6.²³ A previous study reported that eccentricity increases in keratoconus, even in its primary stages, with normal visual acuity of 1.0 and normal slit-lamp findings.²⁴ Although the AUC of individual Becc was low for differentiating SKC from NE in our study, collaboration with other variables in the DTs strengthened its function in SKC screening.

When comparing the performance of the DTs with other models, a major problem that arises is the inconformity of studied populations among different studies. Smadja reported that a DT based on Scheimpflug imaging parameters had a higher accuracy of 96.4% than that of our discriminating rules for detecting SKC.⁵ In fact, stricter criteria (normal topography and BED) were used for SKC patient selection in our study. Atalay et al. developed a logistic regression model that combined metrics from tomography and ocular response analyzer imaging and reported that the model could detect SKC with 87.1% sensitivity and 91.4% specificity²⁵. In their study, the inclusion criterion for SKC considered BED; however, they included individuals who fell into the suspected category ($BED \leq 16 \mu m$). Regardless of the difference in inclusion criteria, the predictive accuracy of DT models in our study was higher than that of the logistic-regression model in Atalay's study.

Interestingly, using the same SKC criteria of (KISA% <60%) and (I-S value <1.45D), the AUCs of individual BAD-D, CBI, and TBI were variant between Ambrósio's study (AUCs for BAD-D, 0.84; CBI, 0.82; TBI, 0.99)⁶ and Steinberg's study (AUCs for BAD-D, 0.75; CBI, 0.79; TBI, 0.83)⁸ when comparing SKC and NE. According to the correlation between the KISA% index and BAD-D reported by Steinberg²⁶, we robustly converted the BAD-D value of each individual in our study to KISA% and found that all included patients met the criteria of KISA% <60%. Both Steinberg's study⁸ and our study found that there were no significant differences between any two AUCs among those of the individual BAD-D, CBI, and TBI for differentiating SKC and NE. Furthermore, DeLong's test showed that both the CHAID-T and CART-T had significantly higher AUCs than those of the individual BAD-D, CBI, and TBI. These findings confirmed that the performance of DT models in detecting SKC was superior to that of the summary combined metrics. However, to identify the superiority of the DT, further studies based on different methodologies using our training and validation databases are required.

To investigate earlier changes in SKC, previous studies considered BAD-D analysis in the selection of SKC patients, which resulted in lower cutoffs with consuming sensitivity and specificity.^{8,12} In our study, we did not consider BAD-D analysis when selecting SKC patients. First, the BAD-D has been reported to have good performance in SKC screening, and we desired that the studied model include the efficient parameter BAD-D. Second, the strictest criteria with a normal BAD-D may result in a lower cutoff in the DT discriminating rules and diminish the generalizability of the screening model in the whole population.

In conclusion, the DT models combined with metrics from tomography and biomechanical imaging showed excellent performance for discriminating SKC with normal topography and BED from NE, which highlighted the importance of overall analysis from

broader features of the cornea. Moreover, the DT models generated visualized and easy-to-understand discriminating rules to help ophthalmologists screen for SKC. The BAD-D variable was the most critical determinant in classifying and identifying SKC, followed by SPA1.

Declarations

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Informed Consent Statement: Written informed consent was obtained from all individual participants.

included in the study.

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Figures

Figure 1

The CHAID decision tree to discriminate between NE and SKC in the training database (CHAID-T). This discriminating rule achieved 82.8% sensitivity and 92.9% specificity. When generating a split, the cutoff values were as follows: BAD-D: 0.92, 1.53, and 1.94; DA-ratio, 4.5; SPA1, 92.2; and Becc, 0.6. Details of the splitting between categories of eyes are specified in the boxes at each node. The category with the gray background was the targeted category. CHAID, Chi-square automatic interaction detection; NE, normal eye; SKC, subclinical keratoconus; CHAID-T, CHAID tree in the training database; BAD-D, Belin/Ambrósio deviation index; DA ratio, deformation amplitude ratio; SPA1, stiffness parameter at first applanation; Becc, back eccentricity

Figure 2

The CART decision tree for discriminating between NE and SKC in the training database (CART-T). This discriminating rule achieved 89.7% sensitivity and 94.3% specificity. When generating a split, the cutoff values were as follows: BAD-D, 1.635; SPA1, 89.25; Becc, 0.605; and PPImax, 1.25. Details of the splitting between categories of eyes are specified in the boxes at each node. The category with the gray background was the targeted category. CART, classification and regression tree; NE, normal eye; SKC, subclinical keratoconus; CART-T, CART tree in the training database; BAD-D, Belin/Ambrósio deviation index; SPA1, stiffness parameter at first applanation; Becc, back eccentricity; PPImax, maximum pachymetric progression index

Figure 3

The ROC curves of the CHAID-T, CART-T, BAD-D, CBI, and TBI are presented in (A), whereas the ROC curves of decision trees in the validation database are presented in (B). ROC, receiver operating characteristic; CHAID-T, CHAID tree in the validation database; CART-T, CART tree in the validation database; BAD-D, Belin/Ambrósio deviation index; CBI, Corvis biomechanical index; TBI, tomographic and biomechanical index

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