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Research Article

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INVESTIGATION OF THE RELATIONSHIP BETWEEN SEPTORHINOPLASTY AND FACIAL RECOGNITION SYSTEMS

SEPTORİNOPLASTİ VE YÜZ TANIMA SİSTEMLERİ ARASINDAKİ İLİŞKİNİN ARAŞTIRILMASI

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Abstract

Objectives: To investigate the temporal verification performance of the facial recognition systems after septorhinoplasty.

Material and Method: The study population included male and female patients who underwent septorhinoplasty at our institution between January 2022 and December 2023. Pre- and postoperative photographs were taken at 1, 2, and 4 weeks using the same camera, under the same distance, and under the same lighting conditions. In this technique-agnostic study, the analysis focused on the overall effect of the procedure rather than the impact of specific surgical manoeuvres. The change over time (preoperative, postoperative weeks 1, 2, 4) was compared based on the mean distance values in the face recognition systems.

Results: The evaluation was conducted on 119 patients, comprising 75 females and 44 males with a mean age of 26.9±7.34 years (range, 18-56 years). When the accuracy rates of the face recognition systems were evaluated, the highest performance rate was obtained with the Euclidean metric for the VGG-Face system (94.85%). Among the face extraction methods, the RetinaFace (99.40%) and Mtcnn (99.19%) methods had the highest accuracy rates with the Euclidean metric in the VGG-Face face recognition system. There was a significant correlation between the mean distance value (0.378) in the preoperative-postoperative 2nd week evaluation (0-2) and the mean distance value (0.279) in the 2nd–4th week evaluation (r=0.747, p=0.004).

Conclusions: The alteration of facial components and appearance following septorhinoplasty remains a challenge for postoperative biometric verification using current facial recognition technolo-

Öz

Amaç: Bu çalışmanın amacı septorinoplasti sonrası yüz tanıma sistemlerinin zamansal doğrulama performansını araştırmaktır.

Gereç ve Yöntemler: Çalışma popülasyonu, Ocak 2022 ile Aralık 2023 arasında kurumumuzda septorinoplasti geçiren erkek ve kadın hastaları içermektedir. Ameliyat öncesi ve sonrası fotoğraflar, aynı kamera kullanılarak, aynı mesafe ve ışık koşullarında 1, 2 ve 4. haftalarda çekilmiştir. Ameliyat öncesi ve sonrası fotoğraflar, septorinoplastinin genel etkisini teknik-agnostik bir yaklaşımla değerlendirmek üzere sekiz farklı yüz tanıma sistemi kullanılarak analiz edilmiştir. Zaman içindeki değişim (ameliyat öncesi, ameliyat sonrası 1, 2, 4. haftalar) yüz tanıma sistemlerindeki ortalama mesafe değerlerine göre karşılaştırılmıştır.

Bulgular: Değerlendirme, ortalama yaşları 26,9±7,34 yıl (aralığı, 18-56 yıl) olan 75 kadın ve 44 erkek olmak üzere toplam 119 hastadan yapılmıştır. Yüz tanıma sistemlerinin doğruluk oranları değerlendirildiğinde, en yüksek performans oranı VGG-Face sistemi için Öklid metriği ile elde edildi (%94,85). Yüz çıkarma yöntemleri arasında, Retinaface (%99,40) ve Mtcnn (%99,19) yöntemleri, VGG-Face yüz tanıma sisteminde Öklid metriği en yüksek doğruluk oranlarına sahipti. Ameliyat öncesi-sonrası 2. hafta değerlendirmesinde (0-2) ortalama mesafe değeri (0,378) ile 2.-4. hafta değerlendirmesinde ortalama mesafe değeri (0,279) arasında anlamlı bir korelasyon vardı (r=0,747, p=0,004).

Sonuç: Septorinoplasti sonrası yüz bileşenlerinin ve görünümünün değişmesi, mevcut yüz tanıma teknolojileriyle ameliyat sonrası biyometrik doğrulama için bir zorluk olmaya

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gies. Rhinologists should be aware of the relationship between septorhinoplasty and facial recognition systems.

Keywords facial recognition technology · septorhinoplasty · biometric identification · rhinoplasty · deep learning

devam etmektedir. Rinologlar septorinoplasti ile yüz tanıma sistemleri arasındaki ilişkinin farkında olmalıdır.

Anahtar Kelimeler Yüz tanıma teknolojisi · septorinoplasti · biyometrik tanımlama · rinoplasti · derin öğrenme

INTRODUCTION

Septorhinoplasty may be performed for cosmetic reasons, to correct the appearance of the nose, or to correct breathing problems caused by structural deformities. Approximately 76,000 rhinoplasty procedures were performed in the United States in 2021, representing a 37% increase in the rate of rhinoplasty procedures over the previous year (1). Although septorhinoplasty is a localised procedure, it can change the position of major reference points on the face, which can lead to a decrease in the verification performance of facial recognition systems after surgery (2, 3).

Facial recognition systems are a type of biometric measurement used to identify and verify the identity of individuals based on their facial features. Facial recognition systems identify individuals by converting facial features into a unique mathematical "faceprint," which is then compared against a database for verification (4-6). Initially, facial recognition systems had very low verification rates 21-37% for individuals after septorhinoplasty (7). However, the use of various algorithms (appearance-based, feature-based, and texture-based) and deep learning techniques has led to an increase in the verification rates of facial recognition systems (70%-94%) (8-10). It has also recently been reported that facial recognition systems achieve better verification results than human performance (11). However, despite the increased verification rates, an early temporal evaluation of the verification performance of facial recognition systems after septorhinoplasty has not been identified in the literature.

The aim of this study was to determine the temporal verification performance of facial recognition systems in the early period of change in facial appearance after septorhinoplasty.

MATERIAL AND METHODS

Patient selection and treatment

This prospective single-centre, repeated-measures cohort study, approved by the Ethics Committee of Kütahya Health Sciences University (Date: 22.12.2021, No: 17-09), initially enrolled 143 patients who underwent septorhinoplasty between January 2022 and December 2023. Of these patients, 119 (83.2% –119/143) who were photographed preoperatively and postoperatively at weeks 1, 2, and 4 were included in the study. This study was planned as a technique-agnostic, pragmatic assessment of early postoperative effects (weeks 1, 2, 4) on automated face verification. The analytic plan prespecified within-person, repeated comparisons across multiple algorithms and time points; procedure-level attribution (e.g., osteotomy, dorsal modification, alar-base narrowing) was out of scope for the present study and is reserved for a pre-stratified prospective cohort.

The study inclusion criteria were age >18 years, postoperative follow-up of 1 month, and primary rhinoplasty. The exclusion criteria were as follows: lack of photographic documentation during postoperative follow-up, previous septorhinoplasty, a history of facial trauma or facial paralysis, and facial plastic surgery (blepharoplasty, facelift, brow lift). All patients underwent septorhinoplasty under general anaesthesia after the purpose and possible complications of the surgery were fully explained and written informed consent was obtained.

Surgical technique of septorhinoplasty

The senior author (BŞ) performed the surgery under general anaesthesia. Septorhinoplasty was performed using an open or closed technique through transcolumellar and endonasal incisions depending on the patient's anatomical problems. The surgical procedure included septoplasty, dorsal modification, cartilage resection, grafting, and osteotomy. Standard postoperative care included cold compresses to the periorbital areas, head elevation, and supine positioning for the first week to minimise oedema. The external nasal splint was removed at the end of postoperative week 1 and taping was reapplied after removal of the Doyle sutures. The tapes were removed at the end of postoperative week 2. The tape was removed during photography.

Photographs

All photographs were taken in the Frankfurt plane with the face in a neutral pose, in a standardised frontal orientation with a phone camera (iPhone X, Apple Inc., Cupertino, CA, USA) aligned with the patient's eye (12). There was a 90º angle between the phone lens and the Frankfurt plane. The photographs were taken in portrait mode using the iPhone X smartphone camera (Apple Inc., Cupertino, CA, USA) with a camera-to-patient distance of 60 cm under the same lighting conditions as in our clinic (13, 14). When taking the photographs, the patient was without makeup or jewellery and was not wearing eyeglasses. All the photographs of the patients were taken against a plain background. All the photographic data collected were anonymised to comply with the United States Health Insurance Portability and Accountability Act of 1996 (15). In addition, parts of the faces presented in the article were masked to protect the identity of the patients.

For the comparison of the temporal verification performance between the septorhinoplasty and face recognition systems, the photographs used were as follows: (0-1) preoperative photograph and photograph taken in the first week after surgery, (0-2) preoperative photograph and photograph taken in the second week after surgery, (0-4) preoperative photograph and photograph taken in the fourth week after surgery, (1-2) photograph taken in the first week after surgery and photograph taken in the second week after surgery, (1-4) photograph taken in the first week after surgery and photograph taken in the fourth week after surgery, (2-4) photograph taken in the second week after surgery and photograph taken in the fourth week after surgery.

Face recognition systems

After face extraction in OpenCV, SSD, Dlib, MTCNN and RetinaFace backend programmes, the images were submitted to the eight different face recognition systems of VGG-Face, FaceNet, FaceNet-512, OpenFace, Dlib, DeepID, DeepFace and ArcFace (16-30). The methodology of the study is summarised in Figure 1 (31).

All images underwent a standard face-recognition pipeline comprising detection, alignment, embedding, and verification. First, a face detector (OpenCV, SSD, Dlib, MTCNN, or RetinaFace) localised the facial bounding box and returned landmarks (typically the centres of both eyes, nose tip, and mouth corners). Second, the faces were aligned to a canonical pose using a similarity transform that

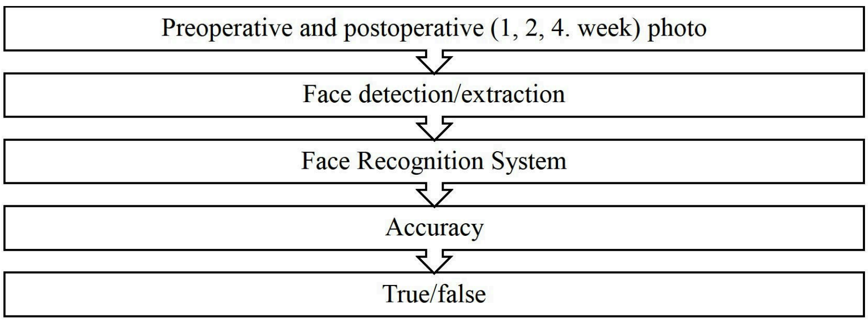

Figure 1. Study methodology (31)

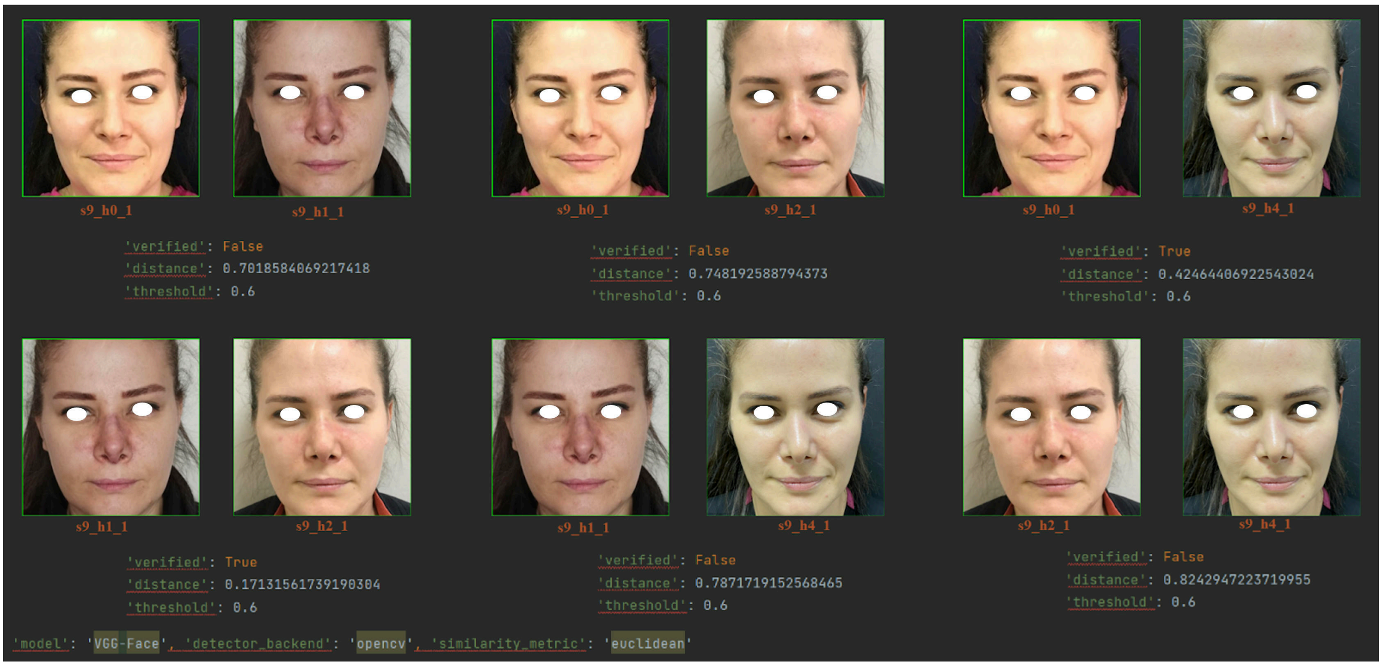

Figure 2. Temporal identity verification during septorhinoplasty using OpenCV-based face extraction, VGG-Face recognition, and Euclidean distance similarity

normalised the inter-ocular axis and head tilt; the aligned region (forehead-to-chin, ear-to-ear) was then cropped/resized to the default input resolution required by each recognition network (e.g., VGG-Face ≈224×224; FaceNet ≈160×160; ArcFace ≈112×112). Third, each network produced a fixed-length embedding vector that integrated information from the entire aligned face crop (i.e., no single landmark or patch was weighted by us), after routine intensity normalisation. Finally, face verification was performed by calculating the cosine, Euclidean, and Euclidean L2 distances between the desired image and the database images (32, 33). In the cosine metric, the distance between two vectors is calculated using the trigonometric cosine function, which measures the angular similarity between them (34). The Euclidean metric computes the straight-line distance between two points in a coordinate system by applying the Euclidean theorem, which involves taking the square root of the sum of the squared differences between corresponding coordinates (35, 36). The Euclidean L2 metric, while also based on Euclidean principles, calculates the distance using values that are normalised within a vector space, thereby providing a scale-invariant measure of similarity (37). For each neural network model, the thresholds that determine whether it is the same image or not are determined by calculating the distances of the same images obtained as a result of training and are different for each model (37). This procedure ensures that the reported effects capture global changes in facial embeddings after septorhinoplasty rather than measurements at a single point or contour.

For each model and metric, we adopted the recommended default verification thresholds (τ) from the original library without re-calibration on our cohort. In our study, we did not re-train or re-calibrate any network on the cohort; for each model and metric, we adopted the recommended default threshold (τ) from the original implementation/library. Verification then followed a fixed decision rule: for Euclidean/Euclidean-L2, a match was declared if $d(u, v) \le \tau$; for cosine similarity, a match was declared if $\cos(u, v) \ge \tau$ (Figure 2). For L2-normalized embeddings, cosine and Euclidean are related by $\|u-v\|^2 = 2(1-\cos\theta)$, which explains the differing numeric cut-off points across metrics. To limit dependence on any single threshold choice, our primary analyses evaluated continuous embedding distances over time, whereas threshold-based verification rates were reported as secondary descriptive outcomes; here, Accuracy (Acc) denotes the proportion of correctly classified comparisons and reflects the overall system performance (38).

In addition, a correlation analysis was performed to investigate the relationship between the average similarity distance values and the temporal phase of the postoperative period (preoperative, postoperative week 1, postoperative week 2, and postoperative week 4). This approach enabled us to assess whether the progression of healing after septorhinoplasty influenced facial recognition performance over time, as reflected by measurable changes in the mean facial embedding distances.

Our primary endpoint quantified genuine-pair (same-identity) verification over time using continuous embedding distances; threshold-based verification was reported as a secondary descriptive outcome. We did not construct impostor (different-identity) pairs or estimate the False Accept Rate (FAR), Receiver Operating Characteristic (ROC), and Equal Error Rate (EER), which are deferred to a prospectively designed, population-level evaluation.

Statistical analysis

The Kolmogorov-Smirnov test was used for data distribution. When the distribution was found to be normal, parametric tests were used. The comparison of preoperative and postoperative photographs in the face recognition systems was evaluated using Pearson correlation analysis (r) over the mean distance. Correlation analyses assessed temporal concordance by correlating per-subject mean embedding distances between distinct time-pairings (e.g. d (0–1w) is d (0–2w), d (0–1w) is d (0–4w), d (0-2w) is d (0–4w). The level of statistical significance was defined as $p<0.05$. All analyses were performed using IBM SPSS Statistics ver.20 Software (IBM, Armonk, NY, USA).

RESULTS

Evaluation was made of a total of 119 patients, comprising 44 males with a mean age of 28±8.58 years (range, 19-56 years) and 75 females with a mean age of 26.3±6.48 years (range, 18-52 years). The mean age of the whole patient group was 26.9±7.34 years (range, 18-56 years). The female to male ratio was 1.7:1. The mean postoperative follow-up period was 7.94 weeks (median, 7 weeks; range, 4-34 weeks). The dataset contained a total of 476 frontal photographs of patients before septorhinoplasty (0), at the end of the first week after surgery (1), the second week after surgery (2), and the fourth week after surgery (4).

When OpenCV, SSD, Dlib, Mtcnn, and RetinaFace were used for face detection and extraction with the photo dataset, the best results were obtained with RetinaFace (99.40%) and Mtcnn (99.19%) in the VGG-Face face recognition system.

The verification rates obtained in the face recognition systems according to different metrics (cosine, Euclidean, and EuclideanL2) are shown in Table 1. The highest performance was obtained using the Euclidean metric in the VGG-Face face recognition system (94.85%). In the eight different face recognition systems, the Euclidean metric was determined to have the highest average verification rate (68.98%). The face recognition systems with the highest average verification rates were Dlib (84.03%) and Facenet512 (83.76%), and the facial recognition systems with the lowest verification rates were OpenFace (41.49%) and DeepID (27.26%) (Table 1). We report aggregated time-course effects across routine clinical heterogeneity in septorhinoplasty and do not ascribe non-recognition to any specific surgical manoeuvre in this dataset.

Table 1. Average verification rates of the eight different facial recognition systems according to different metrics

Facial recognition systems	Rhinoplasty database: cosine %	Rhinoplasty database: Euclidean%	Rhinoplasty database: Euclidean L2 %	Method means
VGG-Face	86.22	94.85	84.16	**88.41%**
Dlib	81.05	86.49	84.56	**84.03%**
FaceNet 512	70.46	91.01	89.79	**83.76%**
FaceNet	78.31	75.10	70.86	**74.76%**
DeepFace	65.01	70.95	59.10	**65.02%**
ArcFace	54.92	58.5	55.43	**56.28%**
OpenFace	25.67	49.4	49.40	**41.49%**
DeepID	29.30	25.53	26.94	**27.26%**

VGG-Face: Visual Geometry Group Face, FaceNet: FaceNet, FaceNet-512: FaceNet 512-dimensional embedding, OpenFace: Open-source face recognition, Dlib: C++ library, DeepID: Deep Identity features, DeepFace: Deep-learning face recognition, ArcFace: Additive Angular Margin face recognition, Euclidean L2: Euclidean (ℓ2) norm–based distance

The thresholds and temporal validation rates obtained according to the cosine, Euclidean, and EuclideanL2 metric in the eight different face recognition systems are shown in Table 2, Table 3, and Table 4.

Table 2. Thresholds and weekly verification rates according to the cosine metric for the eight different facial recognition systems

Method	Cosine threshold	(0-1w) %	(0-2w) %	(0-4w) %	(1-2w) %	(1-4w) %	(2-4w) %
VGG-Face	0.400	86.58	88.57	85.00	88.80	85.26	83.08
Dlib	0.070	80.26	82.29	76.43	83.20	81.05	83.08
Facenet512	0.300	55.00	52.00	65.71	84.80	85.26	80.00
Facenet	0.400	72.63	72.00	75.00	84.00	83.16	83.08
DeepFace	0.230	59.47	64.57	59.29	72.80	63.16	70.77
ArcFace	0.680	55.50	54.13	55.26	54.70	54.54	55.38
OpenFace	0.100	22.37	25.71	17.86	33.60	25.26	29.23
DeepID	0.015	23.16	22.86	33.57	40.00	31.58	24.62
Means		**56.87**	**57.77**	**58.52**	**67.74**	**63.66**	**63.65**

Method	Cosine threshold	(0-1w) %	(0-2w) %	(0-4w) %	(1-2w) %	(1-4w) %	(2-4w) %

w: Week, VGG-Face: Visual Geometry Group Face, FaceNet: FaceNet, FaceNet-512: FaceNet 512-dimensional embedding, OpenFace: Open-source face recognition, Dlib: C++ library, DeepID: Deep Identity features, DeepFace: Deep-learning face recognition, ArcFace: Additive Angular Margin face recognition

The temporal validation rate graph of the eight different face recognition systems with RetinaFace extraction in the Euclidean metric is shown in Figure 3. VGG-Face, Dlib, and Facenet512 were found to have high validation performance, Facenet, DeepFace, and ArcFace to have moderate validation performance, and OpenFace and DeepID to have low validation performance. The highest accuracy was determined for the VGG-Face face recognition system (using Euclidean metric and RetinaFace face extraction) when comparing the preoperative photograph of the subject with the photographs of the subject at postoperative weeks 1 (95.26%), 2 (93.14%), and 4 (91.43%), and the accuracy rates were seen to decrease over the postoperative period (Figure 3). The threshold-based 'accuracy' values reported here reflect genuine acceptance under fixed thresholds and should not be interpreted as the overall accuracy inclusive of false positives.

Table 3. Thresholds and weekly verification rates according to the Euclidean metric for the eight different facial recognition systems

Method	Euclidean threshold	(0-1w) %	(0-2w) %	(0-4w) %	(1-2w) %	(1-4w) %	(2-4w) %
VGG-Face	0.600	95.26	93.14	91.43	96.00	97.89	95.38
Dlib	0.600	86.58	88.00	84.29	89.60	87.37	83.08
Facenet512	23.56	92.63	89.71	87.86	92.00	91.58	92.31
Facenet	10.00	65.79	65.14	73.57	84.00	82.11	80.00
DeepFace	64.00	67.89	72.00	65.71	76.80	69.47	73.85
ArcFace	4.150	62.84	62.34	59.14	55.41	55.90	55.38
OpenFace	0.550	43.95	41.14	41.43	58.40	48.42	63.08
DeepID	45.00	17.89	18.86	27.86	39.20	26.32	23.08
Means		**66.61**	**66.29**	**66.41**	**73.93**	**69.88**	**70.77**

w: Week, VGG-Face: Visual Geometry Group Face, FaceNet: FaceNet, FaceNet-512: FaceNet 512-dimensional embedding, OpenFace: Open-source face recognition, Dlib: C++ library, DeepID: Deep Identity features, DeepFace: Deep-learning face recognition, ArcFace: Additive Angular Margin face recognition

Table 4. Thresholds and weekly verification rates according to the Euclidean L2 metric in the eight different face recognition systems

Method	Euclidean L2 threshold	(0-1w) %	(0-2w) %	(0-4w) %	(1-2w) %	(1-4w) %	(2-4w) %
VGG-Face	0.86	83.95	84.57	81.43	88.80	83.16	83.08
Dlib	0.400	84.74	86.29	82.14	84.80	86.32	83.08
Facenet512	1.040	88.68	86.86	87.86	90.40	92.63	92.31
Facenet	0.800	58.68	57.71	72.14	80.80	75.79	80.00
DeepFace	0.64	53.95	59.43	53.57	68.80	55.79	63.08

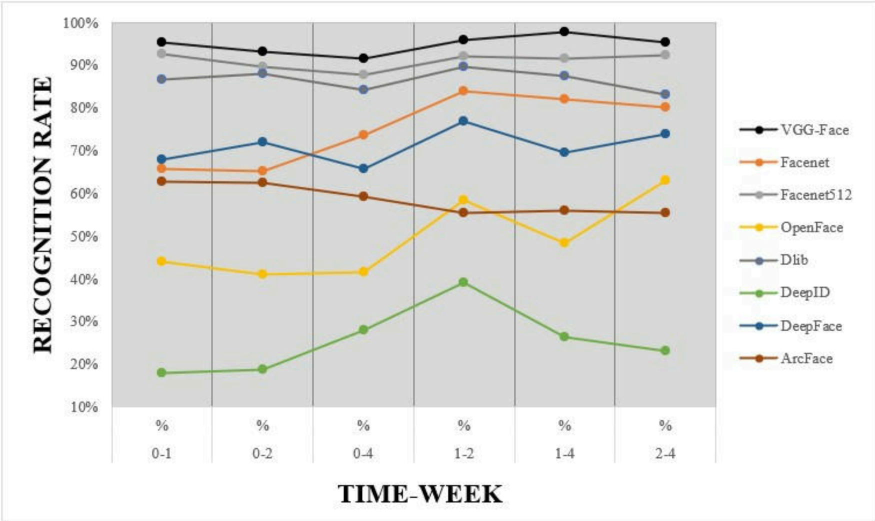

Figure 3. Weekly verification rate graph of the eight different face recognition systems using RetinaFace extraction on the Euclidean metric.
VGG-Face: Visual Geometry Group Face, FaceNet: FaceNet, FaceNet-512: FaceNet 512-dimensional embedding, OpenFace: Open source face recognition, Dlib: C++ library, DeepID: Deep Identity features, DeepFace: Deep-learning face recognition, ArcFace: Additive Angular Margin face recognition

Method	Euclidean L2 threshold	(0-1w) %	(0-2w) %	(0-4w) %	(1-2w) %	(1-4w) %	(2-4w) %
ArcFace	1.13	55.84	54.93	56.53	54.70	55.20	55.38
OpenFace	0.550	43.95	41.14	41.43	58.40	48.42	63.08
DeepID	0.170	20.53	20.00	32.86	35.20	28.42	24.62
Means		**61.2**	**61.3**	**63.49**	**70.24**	**65.72**	**68.08**

w: week, VGG-Face: Visual Geometry Group Face, FaceNet: FaceNet, FaceNet-512: FaceNet 512-dimensional embedding, OpenFace: Open-source face recognition, Dlib: lib C++ library, DeepID: Deep Identity features, DeepFace: Deep-learning face recognition, ArcFace: Additive Angular Margin face recognition, Euclidean L2: Euclidean (ℓ2) norm–based distance

In VGGFace, the best performing face recognition system (retinal face extraction and Euclidean metric), there was a significant correlation (r =0.807, p<0.01) of the mean distance value (0.363) between the preoperative and first week (0-1w) images with the mean distance value (0.378) between the preoperative and second week (0-2w) images (Table 5). There was also a significant correlation (r=0.792, p<0.01) between the mean distance value (0.363) between preoperative and postoperative week one (0-1w) and the mean distance value (0.355) between preoperative and postoperative week four (0-4w) (Table 5). There was a significant correlation (r=0.747, p=0.004) between the mean distance value (0.378) between 0-2 w and the mean distance value (0.279) between 2-4 w (Table 5).

Table 5. Correlations between the changes from preoperative to postoperative weeks 1, 2, and 4 (Pearson's rho)

Change between time periods (weeks)	The outcome of the correlation tests
(0-1)-(0-2)	Pearson's rho=0.807, **p<0.01**
(0-1)-(0-4)	Pearson's rho=0.792, **p<0.01**
(0-2)-(2-4)	Pearson's rho=0.747, **(p=0.004)**

DISCUSSION

The data obtained in this study demonstrate a wide range of verification (DeepID, 27.2%; VGGFace, 88.4%) as well as variations in the verification performance of face recognition systems in the early postoperative period after SRP. Patients should also be informed about the possibility of non-verification with facial recognition systems after septorhinoplasty in the first 4 weeks postoperatively (Figure 3). The problem of non-verification can cause difficulties in transactions that require biometric verification of the face (banking, identity verification, unlocking smartphones, international travel, etc.) (4, 39). Physicians interested in health tourism should be aware of these problems and offer patients a certificate of identity to overcome this difficulty (40). Although there is information in the literature about the possibility of non-authentication in facial recognition systems after aesthetic facial surgery, there is no research on the temporal evaluation of early postoperative authentication (41). To the best of our knowledge, this is the first study to demonstrate the early temporal relationship between septorhinoplasty and facial recognition systems.

Face detection and extraction is a pre-processing stage used before face verification of the data in the background. In this stage, the face is identified in the image and the face information is transferred to the recognition system. In the current study, 5 different backend programmes (OpenCV, SSD, Dlib, Mtcnn, and RetinaFace) were used because the lack of backend programmes used for face detection and extraction negatively affects the performance of similarity measurement. The study results showed that the face extraction programme RetinaFace had the highest validation rate (99.4%), which is consistent with the literature (20, 21). In addition, the higher success rates of face extraction programmes using deep learning methods (RetinaFace, Mtcnn) compared to other programmes (Opencv) were similar to the data in the literature (16).

Facial plastic surgery decreases the verification rates in facial recognition systems (42). A landmark study by Singh et al. reported an approximately 24% decrease in the recognition rates in 192 rhinoplasty patients compared with unoperated patients (3). In the present study, a decrease was observed in the early detection rate, but the difference was small (Figure 3). Erdoğmus et al. also reported that the verification rate decreased by approximately 10% for nasal modifications of the original images in the test set (43). In another study that quantitatively measured the effect of changing the width and length of the nose on face recognition systems, it was found that when the nose width was increased by more than 40% of the original width, there was an average decrease in face recognition performance of up to 14% (44). The specific anatomic requirements of patients (bone/cartilage humps, tip deformities, mid-roof collapse, etc.) may lead to differences in surgical technique and affect verification rates. In the current study, the effect of the technique on facial recognition systems could not be determined because the difference in the surgical technique was not specifically isolated. This limitation could be addressed in future research by incorporating subgroup analyses based on specific surgical manoeuvres, such as osteotomies, cartilage grafting, dorsal reshaping, and tip modifications. Such stratification would enable a clearer identification of the procedural elements responsible for impacting facial recognition performance, thereby enhancing interpretability and informing clinical guidelines more precisely. Additionally, larger patient cohorts with narrower exclusion criteria and improved standardisation of surgical procedures would further enhance the reproducibility and generalizability of the findings. This could be overcome with larger patient numbers, which would allow for narrower exclusion criteria and better standardisation of surgical procedures.

Although the present study primarily focused on false-negative outcomes—cases in which the facial recognition system failed to verify the identity of the same individual following septorhinoplasty—an equally important aspect of system performance is the false-positive rate. False positives occur when the system incorrectly matches two different individuals, posing significant implications for the reliability and security of biometric systems. The exclusion of the false positive analysis represents a methodological limitation of this study. Future investigations should incorporate comprehensive performance metrics, including both false positive and false negative rates, to more accurately evaluate the discriminative capacity of face recognition models. In addition, receiver operating characteristic (ROC) analysis and the calculation of the area under the curve (AUC) may offer a more holistic and quantitative assessment of model accuracy and verification robustness in postoperative scenarios.

The effect of oedema and swelling observed in the early postoperative period on the reduction of verification rates in facial recognition systems is not well understood. In a three-dimensional morphometric study evaluating oedema after rhinoplasty, Pavri et al. found a two-thirds reduction in oedema in the first postoperative month (45). In the current study, the highest mean distance value was found in the second postoperative week (Table 5), and the mean distance value decreased in the fourth postoperative week. This may have been due to decreased oedema. However, it was not possible in this study to distinguish between volume changes due to structural changes of the surgical procedure (e.g., cartilage resection, fat grafting, soft tissue remodelling) and volume changes due to oedema. Further studies are needed to clarify this difference, as understanding this difference will allow surgeons to provide more comprehensive counselling to their patients.

Considering these findings, facial recognition systems demonstrated considerable variability in post-septorhinoplasty performance. While certain models preserved relatively high verification accuracy, their outcomes remained lower than those reported non-surgical benchmarks reported for VGG-Face and FaceNet-family models (22–24)—and even lower than results reported on challenging datasets like the Disguised Faces in the Wild (DFW), where VGG-Face achieved over 91.75% (46). This discrepancy highlights the sensitivity of the recognition algorithms to morphological alterations introduced by rhinoplasty, likely due to changes in the nasal architecture that affect facial embeddings and thus impair match reliability. Moreover, the wide range of verification performance observed across systems in this study aligns with previously reported variability (26%–83%) in the literature when analysing altered facial morphology (47, 48). Temporal variation in system accuracy further shows that recognition success is influenced not only by the model architecture but also by the postoperative phase, reflecting dynamic anatomical changes during healing. These findings underscore the importance of model selection, metric awareness, and threshold calibration when applying facial recognition systems in surgically modified populations.

The benefits of using smartphone cameras for photography include easy access, portability, and lower cost (49). Of these features, the use of the wide-angle lens in close-up photography in particular causes the peripheral elements to bend and the central element to swell. This distortion is known as the fish-eye effect. This effect is a widening of the central part of the image and an inappropriate change in anatomic proportions compared to both DSLR and point-and-shoot cameras (14). To overcome this problem, a distance of 60 cm between the camera and the patient is recommended (50). The use of telephoto lenses attached to smartphones is also recommended for photography (49). In the current study, the distance between the camera and the patient was 60 cm to avoid distortion, and telephoto lenses were not used. As smartphone camera technology continues to improve, these limitations may further decline, providing surgeons with a cheaper, more portable option with comparable quality and detail in analysis and planning.

This single-centre study with a modest sample size limited the power for large-scale statistical analyses. Furthermore, the inherent technique-level heterogeneity of septorhinoplasty—and our technique-agnostic design—precluded the attribution of the effects on specific surgical manoeuvres, which may affect the reproducibility and external validity. The use of two-dimensional, monochromatic photographs restricted the capture of three-dimensional facial structure and variation in skin tones, and the mean postoperative follow-up was 7 weeks. In addition, we did not estimate false-positive rates or receiver-operating characteristic/equal-error-rate curves because the study was prespecified for within-person temporal verification; future work will incorporate cross-subject impostor pairing and cohort-specific threshold calibration to characterise false-acceptance alongside false-rejection behaviour. constraints warrant confirmation in larger, multicenter cohorts with longer follow-up, ideally incorporating standardised operative annotations, three-dimensional morphometrics, and more diverse imaging to enable robust assessment of technique-specific effects and long-term outcomes.

CONCLUSION

The change in facial components and appearance caused by septorhinoplasty poses a challenge for postoperative biometric verification using the existing facial recognition technologies. Rhinologists should be aware of the relationship between septorhinoplasty and facial recognition systems and inform patients of potential non-verification. The development of accurate models for assessing changes after septorhinoplasty may improve the verification performance of facial recognition systems.

Ethics Committee Approval	Ethics committee approval was received for this study from the ethics committee of Kütahya Health Sciences University (Date: 22.12.2021, No: 17-09).
Informed Consent	Written informed consent was obtained from all participants who participated in this study.
Peer Review	Externally peer-reviewed.
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