Face Plastic Surgery Recognition Model Based on Neural Network and Meta-Learning Model

Rasha R. Atallah

(Department of Computer Science, Faculty of Computer Science and Information Technology
Al-Aqsa University, Gaza, Palestine,
https://orcid.org/0000-0002-1433-8964, rr.atallah@alaqsa.edu.ps)

Ahmad Sami Al-Shamayleh

(Department of Data Science and Artificial Intelligence, Al-Ahliyya Amman University, Al-
Salt, Amman, 19328, Jordan, a.alshamayleh@ammanu.edu.jo)

Mohammed A. Awadallah

(Department of Computer Science, Al-Aqsa University, Gaza, Palestine; Artificial Intelligence
Research Center (AIRC), Ajman University, Ajman, United Arab Emirates,
https://orcid.org/0000-0002-7815-8946, ma.awadallah@alaqsa.edu.ps)

Abstract: Facial recognition is a procedure of verifying a person's identity by using the face, which is considered one of the biometric security methods. However, facial recognition methods face many challenges, such as face aging, wearing a face mask, having a beard, and undergoing plastic surgery, which decreases the accuracy of these methods.

This study evaluates the impact of plastic surgery on face recognition models. The motivation for conducting the research in that aspect is because plastic surgery treatments do not only change the shape and texture of any face but also have increased rapidly in this era. This paper proposes a model based on an artificial neural network with model-agnostic meta-learning (ANN-MAML) for plastic surgery face recognition. This study aims to build a framework for face recognition before and after undergoing plastic surgery based on an artificial neural network. Also, the study seeks to clarify the collaboration between facial plastic surgery and facial recognition software to determine the issues. The researchers evaluated the proposed ANN-MAML's performance using the HDA dataset.

The experimental results show that the proposed ANN-MAML learning model attained an accuracy of 90% in facial recognition using Rhinoplasty (Nose surgery) images, 91% on Blepharoplasty surgery (Eyelid surgery) images, 94% on Brow lift (Forehead surgery) images, as well as 92% on Rhytidectomy (Facelift) images. Finally, the results of the proposed model were compared with the baseline methods by the researchers, which showed the superiority of the ANN-MAML over the baselines.

Keywords: Meta Learning, Face Recognition, Plastic Surgery Neural Network
Categories: H.5, I.2, I.4
DOI: 10.3897/jucs.98674

1   Introduction

Facial plastic surgery is performed to enhance attractiveness, whereas reconstructive surgery is performed to address facial abnormalities [Singh et al., 2010]. The statistics show plastic surgery is prevalent across all ages, ethnicities, and genders. Similar research from several nations has demonstrated the commonplace of cosmetic surgery

[Truche et al., 2021]. These surgical procedures are helpful for people who suffer from facial deformities. However, these surgeries can be used illegally by criminals who plan to disguise their identity, even for fraud or to prevent regulation enforcement [Sarastri et al., 2021].

Furthermore, facial plastic surgery aims to enhance the facial look or repair the original face, either for motivation by the most popular aesthetic or for psychological and working purposes [Singh et al., 2010]. A facial recognition technique is a piece of technology that can compare a human face with a digital photo or video frame on a database of faces. Face verification and face identification are two categories under which face recognition may be categorized. Face verification works by comparing two photographs, not minding whether the photographs are of the same person. It is a 1:1 matching comparison approach. However, to identify an individual in the image among all potential outputs, face identification of the 1:N matching approach is required.

Face recognition performance can be affected by face aging [Atallah, Kamsin, Ismail, Abdelrahman, & Zerdoumi, 2018], beard, glasses, face direction, and plastic surgery. This paper aims to describe the relationship between facial recognition and facial plastic surgery and explore the open issues in this research domain.

Several algorithms and methods have been investigated by researchers for both human face identification [Atallah, Kamsin, Ismail, & Al-Shamayleh, 2022]and cosmetic surgery face recognition, each with its advantages and disadvantages [Anwarul & Dahiya, 2020; Rathgeb et al., 2020]. In general, it is feasible to differentiate local surgery from global surgery, which can change the entire facial look of a person. Local surgery focuses on repairing certain well-localized flaws and anomalies [Rathgeb et al., 2020]. In the first scenario, the likelihood of identifying a person might rely on the potential combination of alterations and their localization and extension. In reality, as the research presented will show, various facial areas can influence recognition to vary degrees. Developing potential countermeasures to global changes is challenging, except for a procedure like skin peeling that alters the face's texture [De Marsico et al., 2015]. The neural network is one of the most popular techniques used for face identification in general and plastic surgery face recognition.

Several kinds of research on identification and modeling-based methods have recently incorporated neural network approaches [Chaudhuri & Ghosh, 2016]. These approaches include security applications, facial recognition, and age estimates [Vakili et al., 2017]. To achieve an acceptable degree of precision, the researchers employ non-linear functions in the neural network. By altering some facial characteristics and measurements, cosmetic surgery sometimes results in a face that looks different from the original face. Facial recognition models are used as biometric tools to identify a person by who he is. This paper used a modified Artificial Neural Networks [Vedel et al.2020] technique to recognize faces after different plastic surgeries [Rathgeb et al., 2019]. Adding a meta-learning technique to ANN improves the training process for ANNs. Meta-learning is used to extract global and local features [Tyulmankov et al., 2021]. This raises the chance of recognizing the human face after and before plastic surgery. The proposed model was evaluated using the HDA dataset, which has 638 subjects.

The main contribution is:

• To propose a plastic surgery face recognition model based on model-agnostic meta-learning with ANN.

• To enhance the accuracy of the plastic surgery face recognition model.

The remainder of this paper is organized as follows: Section 2 provides the literature review. Sectioon3 presents facial plastic surgery. In section 4, the ANN-MAML is introduced. Section 5 presents the experimental results. Finally, section 6 provides the concluding remarks of the study.

2   Facial Plastic Surgery

Otolaryngology is the primary discipline that drives facial plastic surgery, which also covers surgery, dermatology, plastic surgery, oral surgery, and maxillofacial [Haiavy, 2018].

Together, the cosmetic and reconstructive elements are included. The range of procedures employed in performing facial plastic surgery by surgeons includes skin cancer removal, rhinoplasty, brow lifts, facelifts, reconstruction of the head and neck, and the repair of facial distortion[Chuang, Barnes, & Wong, 2016].

Facial cosmetic surgery aims to improve the patient's facial look. Regular surgical measures contain rhinoplasty, eyelid surgery, rhytidectomy (facelift), brow lift, chin augmentation, otoplasty, liposuction, and fat transfer. Surgical procedures are frequently used to cure the signs of aging, including loose skin, decreased tissue volume around the face and neck, crow's feet at the corners of the eyes, fine lines on the forehead, loss of jawline shape, and double chin [Diepenbrock et al., 2021].

The degree of change in facial characteristics is examined for each of the most common cosmetic surgeries to better understand the effect of facial plastic surgery on facial recognition [Cai et al., 2019]. Patients may need to be more concerned about the basics of facial recognition technology and the possible impacts of plastic surgery on the effectiveness of this technology. A plastic medical doctor should be arranged to address these inquiries [Jeon et al., 2019].

Plastic surgery is divided into two major groups: local and global plastic surgery. Local plastic surgery alters just one aspect of a person's face, whereas global plastic surgery entirely alters a person's whole facial structure [Chandaliya & Nain, 2022].

Along with position, lighting, emotion, age, and makeup-based concealment, plastic surgery presents a significant barrier for today's face identification technology. It is widely acknowledged as a separate categorical restriction of various facial recognition techniques. In addition, after cosmetic surgery, facial landmarks undergo non-linear changes that may cause it harder to recognize people using biometric facial systems [Dragon et al., 2020].

3   Review of Related Literature

This section provides a literature review of the proposed model by applying ANN to facial recognition for plastic surgery.

3.1   Artificial Neural Networks

Artificial neural networks were used in 2015 to create a model for identifying facial expressions. The system was evaluated using the Cohn-Kanade dataset, which attained

an accuracy of 65% when sixty photos were used to evaluate the model [Huang, Chen, & Hu, 2018] . In 2017, a system was developed to recognize facial expressions using Gabor filters and to categorize a person's facial expressions using an artificial neural network. The accuracy of the model examined using the JAFFE dataset was 85.7%. There are 10 Japanese female models represented in this collection; hence, there is no photograph from other nations or a variety of facial traits. Every nation has distinctive facial characteristics.

In order to detect a human face, a model built on an artificial neural network was developed in 2019. The framework was created to increase facial recognition's precision. The system's performance achieved 82% accuracy. The authors gathered 100 photos from different nations. A framework for categorizing facial expressions based on neural networks was developed in 2020 [Atallah et al., 2022]. The framework's evaluation attained 99% accuracy with the JAFFE dataset. However, only 213 pictures of 10 Japanese women were employed in the modeling. Ten Japanese female models' photos are included in this collection, which further demonstrates the utilization of different facial traits.

3.2   Plastic surgery face recognition

Various techniques are used for facial recognition on plastic surgery datasets, as shown in Table 1. A neural network was able to identify the status of rhinoplasty with an accuracy of 85% of the model, tested with 18,000 images before and after surgery. The proposed model based on patch-based, usually employed for plastic surgery facial recognition, attained an average performance of 76% accuracy. As shown in Table 1, different techniques are used for facial plastic surgery recognition. A PCA model was used to detect types of plastic sugary Rhinoplasty, Blepharoplasty, a Brow lift (Forehead surgery), and Rhytidectomy (Facelift). The models evaluated using HDAAA attained 21.4% accuracy on rhinoplasty, 25.0% on Blepharoplasty (Eyelid Surgery), 20.5% on a brow lift (Forehead surgery), and 0.6 % on rhytidectomy (Facelift) [Singh, Vatsa, & Noore, 2009].

The same HDAA was used to evaluate five models based on different techniques PCA, FDA, G.F., LFA, LBP, and GNN. These five models were evaluated using the HDAA database, showing that GNN improves the model's performance in the five plastic surgery [Singh et al., 2009]. Another model used for the people who underwent the Rhinoplasty surgery is based on DCNN "RhinoNet". The model gives 85 % accuracy [Borsting, DeSimone, Ascha, & Ascha, 2020]. Also, another model built based on Evolutionary granularity attained 78.9% [Bhatt, Bharadwaj, Singh, Vatsa, & Noore, 2011] and 77.9% accuracy, respectively, and the model is based on a combination of recognition by parts and spa [Aggarwal, Biswas, Flynn, & Bowyer, 2012]. It is obvious from the previous work that plastic surgery facial recognition has many open challenges, and some of the challenges were addressed using different techniques.

Paper	Techniques	Database	Performance
(Singh et al., 2009)	PCA	HDA	21.4%
			25.0%
			20.5%

			0.6 %
[Singh et al., 2009]	Fisher Discriminant Analysis (FDA)	HDA	22.1%
			25.0%
			20.8%
			1.0 %
[Singh et al., 2009]	Geometric Features (G.F.)	HDA	31.4%
			34.7%
			31.6%
			1.4 %
[Singh et al., 2009]	Local Feature Analysis (LFA)	HDA	23.3%
			27.6%
			22.8%
			1.4%
[Singh et al., 2009]	Local Binary Pattern (LBP)	HDA	32.0%
			27.6%
			31.5%
			1.8 %
[Singh et al., 2009]	Neural Network Architecture based 2D Log Polar Gabor Transform (GNN)	HDA	37.3%
			40.7%
			37.0%
			2.0 %
[Singh et al., 2010]	GNN	Collected DB	57.2%
			61.4%
			54.3%
			42.1%
[Borsting et al., 2020]	DCNN ''RhinoNet''	Collected D.B.	85%
[Bhatt et al., 2011]	Evolutionary granular	plastic surgery face database	78.9%
[Aggarwal et al., 2012]	Combination of recognition by parts and spa	plastic surgery face database	77.9%

Table 1: Plastic surgery face recognition techniques

4   The Architecture for ANN-MAML

The proposed plastic surgery facial recognition framework is based on ANN and modified model-agnostic meta-learning. Artificial Neural Network is used for face recognition. In this paper, a modified MAML is added to the ANN of two hidden layers to improve the face recognition issue at the training phase. Figure 1 shows the four stages of the proposed framework.

The main framework steps are described below:

Step 1: Named image pre-processing stage. The pre-processing stage has two stages:
- Reshaped the image.
- Histogram equalization

Step 2: Select the features to use Wavelet Transforms.
Face recognition relies heavily on feature extraction. At this step, the wavelet transformation algorithm is explained and employed to extract the features from facial photos.

The functions φ(t) and ϕ(t) are used to satisfy the dilation equations, with φmn (t) and with ϕ mn (t) representing the corresponding dilations and translations.

$$\phi\, mn\,(t) = 2\,\text{-}m/2 \quad \phi\,(\,2\,\text{-}m/2\ y\text{-}\,n\,), n \in Z \tag{1}$$
$$\varphi\, mn\,(t) = 2\,\text{-}m/2 \quad \varphi\,(\,2\,\text{-}m/2\ y\text{-}\,n\,), n \in Z \tag{2}$$

The next phases of feature extraction from the face image were explained as follows:
Firstly, normalize the photos W (x1, x2) before subtracting the average value from the normalization. This results in the images' primary pixels being sharply focused. The photos are dissected by multi-sized wavelets. This is accomplished by separating the distinct, high-frequency components of the signal.

$$W = W0 + W1 +\ldots\ldots+ WM \tag{3}$$

After that, the wavelet decomposition factors are restructured to extract the signals at various frequencies. The decomposed reconstructed signals from low-frequency coefficient and high-frequency coefficient were expressed using W0, W1,....., W.M. W can also function as a signal. The signals are expressed from low and high coefficients using W0, W1,....., and W.M.Facial extraction face component characteristics such as eyes distance, nose, the shape of the eyes, nose distance, eyebrow, and mouth from a human face picture. Eye localization and detection are crucial among all face features since they are used to identify the positions of all other facial features.

Step 3: The third step is the training stage using MAML.
The MAML algorithm utilized during the training stage is termed the Meta-learning algorithm. MAML chooses the network's optimal starting weights to enable quick learning of new tasks even when training only a small number of labeled samples. Any model trained using this approach quickly becomes comfortable with any new function by utilizing several datasets. Existing functions are taken into account in meta-learning as training examples.

Each dataset was randomly divided into two groups: the training and test sets, where 80% of the samples were used for training purposes, and the remaining samples were used for testing.

Consider that in a model f; the input x corresponds to outputs a. Assume a meta-model f defines the parameters by meta-parameters θ. Meta-learning trained the model using different dataset sizes.

T is a task that can be accessed as T = { L (X1, a1,..., X.H., aH), q(X1), q(Xt+1| Xt, at), H }. L is the loss function, q(X1) is the primary iteration, q(Xt+1| Xt, at) is the transition distribution, and H is the period size.

The model produces various samples of length H by selecting the output at each time t. The loss L (X1, a1,..., X.H., aH) $\rightarrow \mathbb{R}$ offers specific feedback that can give the wrong classification.

The proposed model used the parameterized functions $f\theta$ and θ. After the model moves to another task Ti, the parameter θ develops to θ' I. θ' I uses the gradient descent.

$$\theta'i = \theta - \alpha. \tag{4}$$

α is a hyperparameter trained by increasing the performance of $f\theta'$, θ through task samples from p(T), as shown in Algorithm 1.

The meta-aim is:

$$\theta'I = \theta - \alpha \nabla \theta \ L \ T \ i(f\theta) \tag{5}$$

$$Min \ \theta \ \sum Ti{\sim}p(T) \ L \ T \ i(f\theta) = \ \sum Ti{\sim}p(T) \ L \ T \ i(f\theta - \alpha\nabla \theta \ L \ T \ i(f\theta)) \tag{6}$$

The meta-optimization accomplished the parameters θ by calculating the modified parameters θ'. The model objectives are to increase the model parameters. The gradient phases on a new task will produce maximally effective behavior.

Algorithm 1: Model-agnostic meta-learning
Require: p(T): distribution over tasks
Require: α, ß: step size hyperparameters
1: Randomly initialize θ
2: While not done, do
3: Sample batch of tasks Ti $\_$ p(T)
4: For all Ti do
5: Evaluate $\nabla\theta \ L$ Ti ($f\theta$) with respect to K examples
6: Compute adapted parameters with gradient descent : $\theta'i = \theta - \alpha \nabla\theta \ L$ Ti ($f\theta$)
7: End for
8: Update $\theta \leftarrow \theta - ß \nabla\theta \Sigma$ Ti $\_$ p(T) L Ti ($f\theta'$)
9: End while

Algorithm 2: Adaptation MAML
1: function ADAPT (f, Θ, Da; ϕ)
2: $\Theta 0 \leftarrow \Theta$
3: for j ϵ { 1 … adaptation steps } do
4: Lj $\leftarrow$ L (Ya, f (Xa; Θ j-1))
5: Θj $\leftarrow$ Θ j-1 - $\phi \nabla \Theta$ j-1 L j
6: Return Θ adaptation steps

Step 4: The recognition phase based on an artificial neural network is the fourth step. ANN is made up of multiple layers. ANN typically has four layers, which are input photos, two hidden layered (charged with extracting patterns), and output (displays final results) (Atallah et al.f). Each layer has several neurons, each receiving a sum of weighted inputs before sending a signal across a transfer function to form a single output. The learning processes determine the neural network's performance at the transfer functions.

Figure 1: Architecture for facial aging recognition framework MAML Artificial Neural Network

The model parameters that could be explicitly specified for an ANN:

1. Number of Layers: two hidden layers and one output layer.
2. Number of Neurons: For each layer, we need to specify the number of neurons. The first hidden layer has 64 neurons, the second hidden layer has 32 neurons, and the output layer has one neuron.
3. Activation Function: the ReLU activation function for the hidden layers and the sigmoid activation function for the output layer.
4. Learning Rate: Set the learning rate to 0.001.
5. Regularization: Use L2 regularization to prevent overfitting.
6. Batch Size: Set the batch size to 32.
7. Optimizer: to minimize the loss function during training.

Fault tolerance for the model by multiple versions of the ANN to be run simultaneously, and if one version encounters an error or fails to produce a result, the other versions can continue processing the input data. Also, redundant dataset images by using copies of data, such as data mirroring, so that if one copy becomes unavailable or corrupted, another copy can be used.

5 Experimental Results

This section's goal is to validate the proposed model, which was created using MATLAB programming language. Based on the HAD plastic surgery database, this study assesses the model's accuracy for facial recognition in plastic surgery. The framework used in this study to identify the face after plastic surgery is novel. The accomplishments of the proposed framework are shown in this section on assessment. The evaluation step demonstrates how well the proposed framework performs. The models run ten times. The dataset HAD plastic surgery database has a unique feature. The descriptions of the datasets used in this evaluation stage are as follows:

5.1 HDA Plastic Surgery Dataset

Database preparation with people's pictures before and after face plastic surgery is one of the biggest obstacles in this research. Database collection raises some questions since people are reluctant to provide their photographs. In addition to privacy concerns, many people who have received disease-correcting face surgery prefer to remain unnoticed [Bauermeister, Zuriarrain, & Newman, 2016].

Multiple web sources were used to compile the HDA plastic surgery database. For each of the five most common forms of plastic surgery introduced in Section 1, at least 100 picture pairings were gathered in every case. Figure 2 depicts examples of the

various forms of plastic surgery in this database. The HDA plastic surgery database has 638 overall subjects, including 540 female participants (85%) and 98 male counterparts (15%).

Figure 2: Face images before and after face lifting

Procedure	No. of Individuals
Eyebrow	128
Eyelid	131
Facelift	98
Nose	100
Facial bones	84

Table 2: List of Procedures Saved in the Plastic Surgery Face Database

Eyebrow correction: A surgical treatment called "eyebrow correction" moves the eyebrows, generally to give the patient a more feminine or youthful look. Eyelid correction: Eyelid correction is a plastic surgery procedure used to treat eyelid flaws, abnormalities, and disfigurements.

Facelift: A facelift is a form of cosmetic surgery that often entails the removal of extra facial skin, with or without tightening of underlying tissues, as well as re-draping of the skin on the patient's face and neck. It helps to restore a more youthful facial look. Nose correction is a plastic surgery process used for repairing and restructuring the nose. It may be in the form of reconstructive surgery, which returns the shape and functions of the nose, or aesthetic surgery, which modifies the nose's look.

Facial bone correction: This is a form of plastic surgery that fixes facial bones such as the jaw or cheekbones.

According to the statistics, facelifts and eyelid corrections account for two-thirds of all facial plastic procedures, with nose corrections accounting for approximately one-quarter. And last, only about 5% of all facial plastic surgery procedures involve correcting the brows or the facial bones.

5.2 Evaluation Metrics

This section outlines the assessment measures utilized in this study to assess the suggested model's performance. Performance metrics are helpful tools for determining a model's efficiency. A confusion matrix can be used to compute a type's classification performance.

Table 5 shows the general form of the confusion matrix for the binary class classification tasks. True Positive (T.P.) and True Negative (T.N.) denote the number of correctly identified spam and actual samples in this table. The number of actual instances categorized as spam is known as False Positive (F.P.), whereas the number of spam instances classified as legitimate is known as False Negative (F.N.).

		Class= correct	Class= Wrong
Actual Class	Class= correct	TP	FN
	Class= Wrong	F.P.	T.N.

Table 3: Confusion matrix

The parameters T.P., TN, F.P., and F.N. in this table can be used to calculate standard metrics like True Positive Rate (TPR), True Negative Rate (TNR), False Positive Rate (FPR), and False Negative Rate (FNR), as demonstrated in Eqns. 1, 2, 3, and 4. TPR, also known as detection rate, sensitivity, or recall, measures a classification model's accuracy on labeled samples. The F-measure or F1-score is a composite statistic frequently used to assess the effectiveness of classification systems. As demonstrated in Eq. 6, this measure is computed as the harmonic mean of accuracy and recall. AUC-ROC has also been used as a metric that displays TPR and FPR on a single graph to produce another robust evaluation measure.

In practice, each classifier's categorized hand signs may or may not correspond to the actual sign status. As a result, four scenarios are defined:

True Positive: correctly classified signs.

False Positive (F.P.): incorrectly classified signs.

True Negative(T.N.): correctly misclassified signs.

False Negative (F.N.): incorrectly misclassified signs.

Specificity (True Negative Rate): Specificity measures the number of valid negative predictions that are divided by the total number of negatives. It is also known as a true negative rate (TNR). The highest level of specificity is 1.0, while the lowest level is 0.0. Equation 7 evaluates the accuracy with which erroneous instances are classified:

$$\text{Specificity} = TN / (TN + FP) \qquad (7)$$

The sensitivity (recall or actual positive rate) is the number of correct positive predictions divided by the total number of positives. It is also known as the recall rate (REC) or the true positive rate (TPR). The highest level of sensitivity is 1.0, while the lowest level is 0. In Equation 8, the classification accuracy of actual instances is measured:

$$\text{Sensitivity} = TP / (TP + FN) \qquad (8)$$

False Positive Rate (FPR): This is computed by dividing the total number of negatives by the number of erroneous positive predictions. The best rate of false positives is 0.0, while the worst rate is 1.0. It is also possible to compute it by subtracting the value of specificity from 1; that is, 1- specificity:

$$FPR = FP / (FP + TN) = 1\text{- Specificity} \qquad (9)$$

Precision: is computed by dividing the number of positive predictions by the number of correct positive forecasts. It is also known as positive predictive value (PPV). The best precision is 1.0, while the least precision is 0.0. It describes random errors and measures the statistical variability.

$$Precision = TP / (TP + FP) \qquad (10)$$

F1- Score (F- measure): It measures the balance between sensitivity and precision, in which its best value is 1.

$$F1\text{- Score} = 2* ((precision * sensitivity)/(precision + sensitivity)) \quad (11)$$

False Negative Rate (FNR): It is the percentage of positives that offered negative results

$$FNR = FN/ (TP + FN) = 1 – Sensitivity \qquad (12)$$

The commonly used performance evaluation metrics for waste prediction are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The equations of these metrics are shown below:

Root Mean Square Error (RMSE) = $\sqrt{\dfrac{\sum_{i=1}^{N}\left(y_i - x_i\right)^2}{N}}$ $\qquad (13)$

Mean Absolute Percentage Error (MAPE) = $\dfrac{1}{N}\sum_{i=1}^{N}\left|\dfrac{y_i - x_i}{y_i}\right|$ $\qquad (14)$

Where y_i is the actual value for the period i

x_i is the forecasted value for the period i

N is the number of observations

5.3 Experimental Evaluation

As shown above that the dataset has five types of plastic surgery facial bone, eyebrow, eyelid, facelift, and nose. The performance of the proposed model employing the five distinct datasets for plastic surgery is demonstrated in this section.

5.3.1 Facial Bones Plastic Surgery Dataset

From applying the facial bones dataset to the proposed model, the Confusion Matrices for facial bones were calculated, as shown in Table 4.
Accuracy = (TP+TN) / (TP+TN+FP+FN) = (159)/ (80+79+4+5) = 0.94.
Precision = TP / (TP + FP) = 80/(80+5) = 0.9411.
Specificity = 79/ (79 + 5) =0.9404.
False Positive Rate = FP / (FP + TN) == 5/(5+79)= 0.061.
Sensitivity = TP / (TP + FN) = 80/(80+4)=0.952.
False Negative Rate = FN/ (TP + FN) = 4/ (80 + 4) = 0.04766

Actual P.C.	Same person	Not the same person
Same person	80	4
Not the same person	5	79

Table 4: Calculate the Confusion Matrices for facial bones

From the data shown in table3, the accuracy becomes 94% at facial bones plastic surgery, and precision is 94.11%

Nose plastic surgery Dataset

From applying the Nose dataset to the proposed model, the Confusion Matrices for facial bones were calculated, as shown in Table 5
Accuracy = (TP+TN) / (TP+TN+FP+FN) = (27+27)/ (60) = .90.
Precision = TP / (TP + FP) = 27/(30) = 0.9.
Specificity = TN / (TN + FP) = 27/ (30) =0.9.
False Positive Rate = FP / (FP + TN) == 3/(30)= 0.1.
Sensitivity = TP / (TP + FN) = 27/(30)=0.9.
False Negative Rate = FN/ (TP + FN) = 3/ (30) = 0.1.

Actual P.C.	Same person	Not the same person
Same person	27	3
Not the same person	3	27

Table 5: Calculate the Confusion Matrices for facial bones

Facelift plastic surgery Dataset

From applying the facelift dataset to the proposed model, the Confusion Matrices for facial bones were calculated, as shown in Table 6.
Accuracy = (TP+TN) / (TP+TN+FP+FN) = (50+48)/ (50+48+3+5) = 0.924.
Precision = TP / (TP + FP) = 50/(50+5) = 0.9090.
Specificity = TN / (TN + FP) = 48/ (48+5) =0.9056.
False Positive Rate = FP / (FP + TN) == 5/(5+48)= 0.094.
Sensitivity = TP / (TP + FN) = 50/(50+3)=0.943.
False Negative Rate = FN/ (TP + FN) = 3/ (50+3) = 0.0566.

Actual P.C.	Same person	Not the same person
Same person	50	3
Not the same person	5	48

Table 6: Calculate the Confusion Matrices for facial bones

Eyelid plastic surgery Dataset

From applying the eyelid dataset to the proposed model, the Confusion Matrices for facial bones were calculated, as shown in Table 7.
Accuracy= (TP+TN)/(TP+TN+FP+FN)=(120+119)/ (120+119+11+12) = 0.91.
Precision = TP / (TP + FP) = 120/(120+12) = 0.9090.
Specificity = TN / (TN + FP) = 119/ (119+12) =0.9083.
False Positive Rate = 12 / (12+119) == 5/(5+79)= 0.091.
Sensitivity = TP / (TP + FN) = 120/(120+11)=0.916.
False Negative Rate = FN/ (TP + FN) = 11/ (120+11) = 0.083.

Actual P.C.	Same person	Not the same person
Same person	120	11
Not the same person	12	119

Table 7: Calculate the Confusion Matrices for facial bones

Eyebrow plastic surgery Dataset

From applying the Eyebrow dataset to the proposed model, the Confusion Matrices for facial bones were calculated, as shown in Table 8.
Accuracy is calculated as follows: (TP+TN) / (TP+TN+FP+FN) = (120+122)/ (122+120+6+8) = 0.94
Precision = TP / (TP + FP) = 120/(120+6) = 0.952
Specificity = TN/(TN+FP)= 122/ (122 + 6) =0.953.
False Positive Rate = FP / (FP + TN) == 6/(122+6)= 0.0468.
Sensitivity = TP / (TP + FN) = 120/(120+8)=0.937.
False Negative Rate = FN/ (TP + FN) = 8/ (120+8) = 0.0625.

Actual P.C.	Same person	Not the same person
Same person	120	8
Not the same person	6	122

Table 8: Calculate the Confusion Matrices for facial bones

Comparing the result of the proposed model with previous work

This section provides the performance evaluation of the proposed model with five types of plastic surgery datasets and compares the performance with the previous works using different techniques such as PCA, FDA, G.F., LFA, LBP, and GNN. The evaluation results indicated that the proposed model gives the best results. As shown in Table 9, the performance of the proposed model for Rhinoplasty (Nose surgery) outperformed the previous techniques, such as PCA, FDA, G.F., LFA, and GNN. The proposed model gives 90% accuracy, and comparison with the previous techniques shows that the PCA attains 21.4%, FDA attains 22.1%, G.F. attains 31.4%, LFA attains 23.3%, L.B. attains 37.3%, and GNN attains 37.3%.

Paper	Techniques	Database	Plastic Surgery	Performance
[Singh et al., 2009]	Principal Component Analysis (PCA)	HDA	Rhinoplasty (Nose surgery)	21.4%
[Singh et al., 2009]	Fisher Discriminant Analysis (FDA)	HDA	Rhinoplasty (Nose surgery)	22.1%
[Singh et al., 2009]	Geometric Features (G.F.)	HDA	Rhinoplasty (Nose surgery)	31.4%
[Singh et al., 2009]	Local Feature Analysis (LFA)	HDA	Rhinoplasty (Nose surgery)	23.3%
[Singh et al., 2009]	Local Binary Pattern (LBP)	HDA	Rhinoplasty (Nose surgery)	32.0%
[Singh et al., 2009]	Neural Network Architecture based 2D Log Polar	HDA	Rhinoplasty	37.3%

	Gabor Transform			
[Rathgeb et al., 2020]	ArcFace	HDA	Rhinoplasty	56%
	The proposed model	HDA	Rhinoplasty (Nose surgery)	90%

Table 9: Compared the performance of the proposed model for Rhinoplasty (Nose surgery) with the previous work
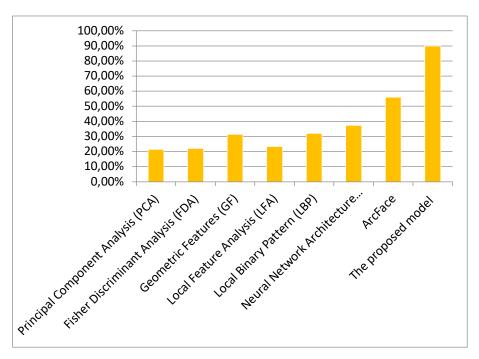

Figure 3: Pictorial performance representation of the proposed model for Rhinoplasty (Nose surgery) with the previous work

As shown in Table 10, the performance of the proposed model for Blepharoplasty surgery is the best among previous techniques such as GNN, FDA, FDA, G.F., LFA, and PCA. The proposed model gives 91% accuracy. After comparing the performance with previous techniques, the result shows that PCA produced 25%, FDA produced 25%, G.F. produced 34.7%, LFA produced 27.6%, LBP produced 27.6%, and GNN produced 40.7%. That is clearly shown in Figure 4.

Paper	Techniques	Database	Plastic Surgery	Performance
[Singh et al., 2009]	Principal Component Analysis (PCA)	HDA	Blepharoplasty (Eyelid surgery)	25.0%
[Singh et al., 2009]	Fisher Discriminant Analysis (FDA)	HDA	Blepharoplasty (Eyelid surgery)	25.0%
[Singh et al., 2009]	Geometric Features (G.F.)	HDA	Blepharoplasty (Eyelid surgery)	34.7%
[Singh et al., 2009]	Local Feature Analysis (LFA)	HDA	Blepharoplasty (Eyelid surgery)	27.6%
[Singh et al., 2009]	Local Binary Pattern (LBP)	HDA	Blepharoplasty (Eyelid surgery)	27.6%
[Singh et al., 2009]	Neural Network Architecture based 2D Log Polar Gabor Transform (GNN)	HAD	Blepharoplasty (Eyelid surgery)	40.7%
[Rathgeb, Dogan, Stockhardt, De Marsico, & Busch, 2020]	ArcFace	HDA	Blepharoplasty (Eyelid surgery)	60%

The proposed model	HDA	Blepharoplasty (Eyelid surgery)	91%

Table 10: Performance Comparison of the proposed model for Blepharoplasty (Eyelid Surgery) with previous work
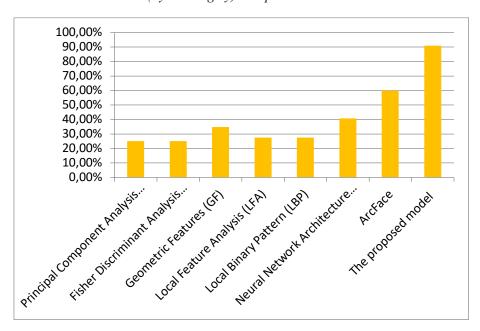

Figure 4: Chart for the performance of the proposed model for Blepharoplasty with previous work

As shown in Table 11, the performance of proposed model for a Brow lift (Forehead surgery) performed better than the existing techniques such as PCA, FDA, G.F., LFA, and GNN by attaining 94% accuracy. Comparing the performance with the existing techniques, PCA attained 20.5%, FDA attained 20.8%, G.F. attained 31.6%, LFA attained 22.8%, LBP attained 31.5%, and GNN attained 37% accuracy, respectively, as clearly shown in figure 5.

Paper	Techniques	Database	Plastic Surgery	Performance
[Singh et al., 2009]	Principal Component Analysis (PCA)	HDA	Brow lift (Forehead surgery)	20.5%
[Singh et al., 2009]	Fisher Discriminant Analysis (FDA)	HDA	Brow lift (Forehead surgery)	20.8%
[Singh et al., 2009]	Geometric Features (G.F.)	HDA	Brow lift (Forehead surgery)	31.6%
[Singh et al., 2009]	Local Feature Analysis (LFA)	HDA	Brow lift (Forehead surgery)	22.8%
[Singh et al., 2009]	Local Binary Pattern (LBP)	HDA	Brow lift (Forehead surgery)	31.5%
[Singh et al., 2009]	Neural Network Architecture based 2D Log Polar Gabor Transform (GNN)	HDA	Brow lift (Forehead surgery)	37.0%

	The proposed model	HDA	Brow lift (Forehead surgery)	94%

Table 11: Performance comparison of the proposed model on Blepharoplasty (Eyelid Surgery) with the previous work
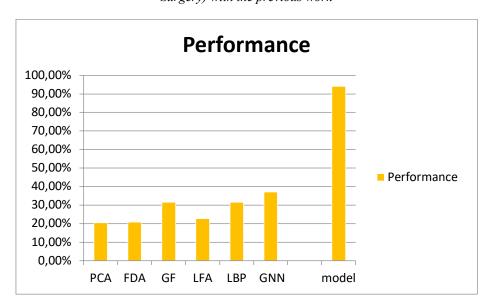

Figure 5: The performance of the proposed model compared with   previous models for Brow lifts (Forehead surgery)

As shown in Table 12, the performance of the proposed model for a Brow lift (Forehead surgery) outperformed the previous techniques, such as PCA, FDA, G.F., LFA, and GNN, by attaining 92% accuracy. The performance comparison of the proposed model with the previous techniques shows that PCA attained 6%, FDA attained 1%, G.F. attained 1.4%, LFA attained 1.4%, LBP attained 1.8%, and GNN attained 2% accuracy, respectively, as clearly shown in figure 6.

Paper	Techniques	Database	Plastic Surgery	Performance
[Singh et al., 2009]	Principal Component Analysis (PCA)	HDA	Rhytidectomy (Facelift)	0.6 %

[Singh et al., 2009]	Fisher Discriminant Analysis (FDA)	HDA	Rhytidectomy (Facelift)	1 %
[Singh et al., 2009]	Geometric Features (G.F.)	HDA	Rhytidectomy (Facelift)	1.4 %
[Singh et al., 2009]	Local Feature Analysis (LFA)	HDA	Rhytidectomy (Facelift)	1.4%
[Singh et al., 2009]	Local Binary Pattern (LBP)	HDA	Rhytidectomy (Facelift)	1.8 %
[Singh et al., 2009]	Neural Network Architecture based 2D Log Polar Gabor Transform (GNN)	HDA	Rhytidectomy (Facelift)	2.0 %

[Rathgeb et al., 2020]	ArcFace	HDA	Rhytidectomy (Facelift)	60%
	The proposed model	HDA	Rhytidectomy (Facelift)	92%

Table 12: The performance of the proposed model for Rhytidectomy (Facelift) with previous work
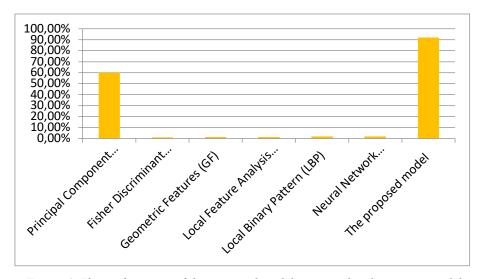

Figure 6: The performance of the proposed model compared with previous models for Rhytidectomy (Facelift)

As shown in Table 13, the performance of the proposed model on Facial Bone outperformed the previous techniques by attaining 94% accuracy. After comparing the performance with the previous technique, the results show that ArcFace produced 2% accuracy, as clearly shown in Figure 7.

Paper	Techniques	Database	Plastic Surgery	Performance
[Rathgeb et al., 2020]	ArcFace	HDA	Facial Bone	93%
	The proposed model	HDA	Facial Bone	94%

Table 13: The performance comparison of the proposed model on Facial Bone with previous work
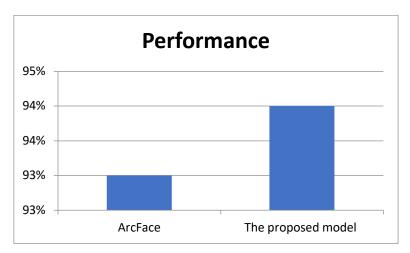

Figure 7: The performance of the proposed model compared with   previous models for Facial Bone

6   Conclusion

The ANN-MAML model for face aging recognition is built on Artificial Neural Network collaboration with MAML.MAML was added to improve the training stage, which considers a new technique for training ANN. This ANN-MAML architecture is helpful in identifying the same individual photos taken before and after cosmetic surgery, which considers one of the face detection issues. The dataset's images were all frontal face views; this considers a limitation of the model. MATLAB was used to implement the model, which was assessed using HDA. Finally, a comparison between the model and earlier efforts has been conducted.

Additionally, the accuracy of the model was assessed using the HDA dataset. The Rhinoplasty (Nose surgery) attained 90%, Blepharoplasty surgery (Eyelid surgery) 91%, a Brow lift (Forehead surgery) 94%, and Rhytidectomy (Facelift) 92% accuracy, respectively. In the Future, the authors will improve the accuracy and suggest the best plastic surgery for the individual.

References

[Aggarwal, 12] Gaurav Aggarwal , Soma Biswas , Patrick J. Flynn , Kevin W. Bowyer. (2012). *A sparse representation approach to face matching across plastic surgery.* Paper presented at the 2012 IEEE workshop on the applications of computer vision (WACV), p. 113-119.

[Atallah, 18] Atallah, R. R., Kamsin, A., Ismail, M. A., Abdelrahman, S. A., & Zerdoumi, S. (2018). Face recognition and age estimation implications of changes in facial features: A critical review study. *IEEE Access, 6*, 28290-28304.

[Atallah, 22] Atallah, R. R., Kamsin, A., Ismail, M. A., & Al-Shamayleh, A. S. (2022). Neural network with agnostic meta-learning model for face-aging recognition NN-MAML for face-aging recognition. *Malaysian Journal of Computer Science, 35*(1), 56-69.

[Bauermeister, 16] Bauermeister, A. J., Zuriarrain, A., & Newman, M. I. (2016). Three-dimensional printing in plastic and reconstructive surgery: a systematic review. *Annals of plastic surgery, 77*(5), 569-576.

[Bhatt, 11] Bhatt, H. S., Bharadwaj, S., Singh, R., Vatsa, M., & Noore, A. (2011). *Evolutionary granular approach for recognizing faces altered due to plastic surgery.* Paper presented at the 2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG), p. 720-725.

[Borsting, 20] Borsting, E., DeSimone, R., Ascha, M., & Ascha, M. (2020). Applied deep learning in plastic surgery: classifying rhinoplasty with a mobile app. *Journal of Craniofacial Surgery, 31*(1), 102-106.

[Cai, 19] Cai, L. Z., Kwong, J. W., Azad, A. D., Kahn, D., Lee, G. K., & Nazerali, R. S. (2019). Where do we look? Assessing gaze patterns in cosmetic face-lift surgery with eye tracking technology. *Plastic and reconstructive surgery, 144*(1), 63-70.

[Chandaliya, 22] Chandaliya, P. K., & Nain, N. (2022). PlasticGAN: Holistic generative adversarial network on face plastic and aesthetic surgery. *Multimedia Tools and Applications*, 1-22.

[Chuang, 16] Chuang, J., Barnes, C., & Wong, B. J. (2016). Overview of facial plastic surgery and current developments. *The Surgery Journal, 2*(01), e17-e28.

[Diepenbrock, 21] Ryan M. Diepenbrock, Tirbod Fattahi, Salam Omar Salman, Anthony S. Alessi, John B. Holds, Krishna Priya Kalyam, Michael G. Niemkin, Jaclyn A. Tomsic, Zach Farhood, Manik S. Bedi. (2021). Cosmetic Surgery. In *Oral Board Review for Oral and Maxillofacial Surgery* (pp. 133-178): Springer.

[Dragon, 20] Dragon, C. B., Shroff, B., Carrico, C., Stilianoudakis, S., Strauss, R., & Lindauer, S. J. (2020). The effect of orthognathic surgery on facial recognition algorithm analysis. *American Journal of Orthodontics and Dentofacial Orthopedics, 158*(1), 84-91.

[Haiavy, 18] Haiavy, J. (2018). Cosmetic surgery history of the specialty: the importance of AACS fellowships and the Webster legacy. *The American Journal of Cosmetic Surgery, 35*(2), 64-73.

[Huang, 18] Huang, Y., Chen, W., & Hu, H. (2018). *Age-puzzle facenet for cross-age face recognition.* Paper presented at the Asian Conference on Computer Vision, p. 603-619.

[Jeon, 19] Byoungjun Jeon, Boseong Jeong, Seunghoon Jee, Yan Huang, Youngmin Kim, Gee Ho Park, Jungah Kim, Maierdanjiang Wufuer, Xian Jin, Sang Wha Kim, Tae Hyun Choi. (2019). A facial recognition mobile app for patient safety and biometric identification: Design, development, and validation. *JMIR mHealth and uHealth, 7*(4), e11472.

[Rathgeb, 20] Rathgeb, C., Dogan, D., Stockhardt, F., De Marsico, M., & Busch, C. (2020). Plastic surgery: An obstacle for deep face recognition? Paper presented at the Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, pp. 10492-10502.

[Singh, 10] Singh, R., Vatsa, M., Bhatt, H. S., Bharadwaj, S., Noore, A., & Nooreyezdan, S. S. (2010). Plastic surgery: A new dimension to face recognition. IEEE Transactions on Information Forensics and Security, 5(3), 441-448.

[Singh, 09] Richa Singh, Mayank Vatsa, Afzel Noore (2009). Effect of plastic surgery on face recognition: A preliminary study. Paper presented at the 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, p.72-77.

[Truche, 21] Truche, P., Moeller, E., Wurdeman, T., Zimmerman, K., Cruz, N., Nakarmi, K., Rai, S. M., Eado, Y., Pompermaier, L., & Meara, J. G. (2021). The plastic surgery workforce and its role in low-income countries. Plastic and Reconstructive Surgery Global Open, 9(4)

[Tyulmankov, 21] Tyulmankov, D., Yang, G. R., & Abbott, L. (2021). Meta-learning local synaptic plasticity for continual familiarity detection. bioRxiv, doi: https://doi.org/10.1101/2021.03.21.436287.

[Vakili, 17] Vakili, M., Sabbagh-Yazdi, S. R., Khosrojerdi, S., & Kalhor, K. (2017). Evaluating the effect of particulate matter pollution on estimation of daily global solar radiation using artificial neural network modeling based on meteorological data. Journal of cleaner production, 141, 1275-1285.

[Vedel, 20] Anna Vedel, Kaare B. Wellnitz, Steven Ludeke, Christopher J. Soto, Oliver P. John, and Simon Calmar Andersen. (2020). Development and Validation of the Danish Big Five Inventory-2. European Journal of Psychological Assessment, Volume 37, Issue, ISSN: 1015-5759eISSN: 2151-2426.