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Makeup-Invariant Faces Recognition Using a Pre-Trained Neural Network, Grasshopper Optimization Algorithm, and Random Forest

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Abstract

Makeup-Invariant Face Recognition is a critical area of research that aims to identify and classify manipulated or forged face images in the field of face recognition systems. Advances in deep learning techniques, such as pre-trained neural networks, have shown promising results in this domain. In this paper, a novel approach for detecting manipulated faces is proposed, combining the strengths of the Grasshopper Optimization (GOA) Algorithm, and Random Forest classifier. The proposed method utilizes the powerful feature extraction capabilities of pre-trained deep neural networks to capture intricate details and patterns in face images. Subsequently, the GOA algorithm is employed to select optimal features. Additionally, the Random Forest classifier is utilized for effective classification of face images and identifying different individuals based on the selected features. By integrating these three algorithms, the proposed approach demonstrates significant improvements in detecting manipulated faces, achieving higher detection rates and lower false positive rates compared to existing state of the art methods. Simulation results on data from 330 different individuals with manipulated face images show an average accuracy of 97.23%, which represents an enhancement over the compared methods.

Keywords: Face Recognition, Grasshopper Optimization Algorithm (GOA), Random Forest.

1. Introduction

Facial recognition technology has been more popular in recent years due to its extensive use in smartphones, social media platforms, and security systems. However, there are still issues with this technology's ability to correctly identify people who use cosmetics to alter their face look.

Face identification in situations with bright and dark cosmetics is a difficult biometric application. Due to factors including picture tagging, criminal identification, authentication, identification, and human-computer interaction, face recognition in uncontrolled environments is in higher demand [1]. Pose, emotion, lighting, age variance, makeup, cosmetic surgery, occlusion, and other factors are examples of uncontrolled surroundings. The majority of effort in the last ten years has gone into handling Pose, Illumination, Expression(PIE) variation in face recognition. While face identification under cosmetics has been pioneered by a small number of researchers, face recognition under position, lighting effects, and expression variance is a tough task that many academics are tackling. The majority of offenders conceal their identities from the public by covering their faces with makeup or getting cosmetic surgery. It is necessary to create a makeup invariant facial recognition (MIFR) system in order to detect criminals or ladies who use makeup.

Makeup that is bright or dark alters the look of the face. Variations in expression, skin texture, and contrast level applied to the mouth and eye regions all alter the form of the face. Recent research has shown that facial recognition with makeup reduces performance [2-4]. The look of the face is significantly altered by face makeup. Face cosmetics elements that are used to modify one's look include eyebrow liner, eye primer, eye shadow, mascara, fake eyelashes, foundation, face cream, concealer, powder, highlighter, lipstick, lip primer, lip pencil, and lip gloss, among others.

As a result, the problem of makeup-invariant face recognition calls for further study and advancement to guarantee that the system can correctly identify people, even in the presence of subtle changes.

This research proposes a unique method for Make-up In-variant Face Recognition by integrating the advantages of Random Forest classifier, Grasshopper Optimization (GOA) Algorithm, and pre-trained deep neural networks.

This paper's remaining parts are organized as follows: Researchers' contributions to the field of face recognition under makeup are covered in Section 2; the suggested method is examined in Section 3; the outcome is discussed in Section 4; and the study is concluded in Section 5.

2. Related Works

This section describes the advancements made in the area of face recognition in light and dark makeup, which alters the look of faces and makes them difficult to identify as people or as criminals because of significant changes in texture, color, and form.

Guo et al. (2014) was retrieved Four characteristics, including skin color tone, smoothness, texture, and smoothness variationsand PCA and LDA were used for dimensionality reduction and feature extraction. used cosine similarity to identify faces in over 1002 face photos, including 501 pairs of female faces with different lighting, expressions, and poses. displays an accuracy of 80% but is unable to identify faces with significant position and expression changes, poor picture quality, or both[5]. Wang et al.(2016) used random space to get multiple correlation space in order to achieve face recognition using face verification [6]. Chen et al. (2016)In order to accomplish ensemble learning utilized patch-based descriptors—local gradient Gabor pattern (LGGP) and densely sampled LBP (DS-LBP)—as well as enhanced random subspace LDA. The calculated classifier scores were then fused using a sum rule. A typical YMU dataset including 151 participants with two makeup and two non-makeup face photos was employed. The accuracy of the descriptors is 89.40%. Because of the hairstyle and posture, our method was unable to identify the face[7]. Poon et al. in 2017, introduced a gradient face method and PCA was used to reduce dimensionality. The Euclidean distance has been used as a similarity metric. This method yielded an accuracy of 84.5% using the YMU dataset, however it was unable to manage posture variation[8].

Zheng et al. in (2017) was introduced the multi-level feature learning strategy for face recognition. Here, feature augmentation was used, and classification was handled using an SVM classifier. Two datasets were employed in this method: BEAUTY and FAM. FAM consists of 1038 photos with 519 subjects, each with varying lighting, poses, and picture resolutions. 1001 subjects with frontal poses, no makeup, and high resolution make up BEAUTY. With FAM and BEAUTY datasets, our technique scored 76.68% and 81.11%, respectively. Lighting effects and position variation were not well handled by this method[9]. Sun et al.(2017) used a triplet network as a result, which forms a positive and negative pair from three face inputs. Training and testing have been conducted using a pre-trained Alexnet model. Two datasets, dataset 1 and dataset 2, were employed in this method. 1002 face photos with 501 female pairings with PIE variation make up Dataset 1. 406 facial photos of 203 girls make up Dataset 2. On dataset1, this approach produced results of 82.4%, and on dataset2, 68.0%. The drawback of this method is the small set of face photos that are used for fine tuning[10].

Sajid et al.(2018) used an augmentation technique in 2018 to create six pictures of makeup faces from the original photographs. VGG-19 was then used for testing and training. 16 convolutional, 5 pooling, and 3 fully linked layers make up VGG-19. Using the YMU and VMU datasets, this deep learning method produced accuracy levels of 90.04% and 92.99%, respectively. This approach's tiny dataset size is a drawback[11].

Wang et al. in 2020. improved outcomes across four datasets. Face morphological multi-branch network for make-up invariant face identification was recently reported by [12]

Melzi P et al.(2023) presents GANDiffFace, a new framework for developing synthetic datasets for face recognition that combines the power of generative adversarial networks (GANs) with diffusion models in order to overcome the limitations of existing synthetic datasets. GANs may be used to generate extremely realistic identities that follow desired population distributions, according to the developers of GANDiffFace. Then, diffusion models are altered so that they can combine several pictures of the same figure taken in various locations, attires, poses, and facial expressions. They produce a number of synthetic datasets by modifying the GANDiffFace settings and compare resulting paired and nonhomogeneous score distributions to those provided by well-known real-world face recognition datasets, like VGG2 and IJB-C. Their findings demonstrate the viability of the proposed GANDiffFace, particularly when diffusion models are used to scale up the (relatively) small intra-class variability provided by GANs to the level of real-world datasets. [13].

Faizal MM et al.(2023) focuses mostly on the facial recognition detection using several DL techniques from such photographs of distorted faces. Several DL techniques are effectively compared, with ViT transform outperforming Resnet, RNN, and CNN in terms of accuracy. This paper presents an overview of different deep learning strategies for detecting those face identification images in order to handle the challenges and issues in face datasets from Kaggle's face recognition dataset by training and testing the picture dataset. It evaluates the face-detected images with an improved image and determines whether the image performance has a higher contrast[14].

Peng Y (2023) is examined in a study in relation to libertarianism, right-wing authoritarianism, and social dominance orientation. First, use of facial recognition software was positively connected with right-wing authoritarianism and negatively correlated with libertarianism, although social dominance orientation had little of an impact, according to two studies of crowdsourcing workers (N = 891 and N = 587). Second, information about demographic biases in facial recognition software was provided to trial participants (N = 496). Face recognition resistance increased as a result of this message, and the three ideological dimensions had little effect on it. In conclusion, people's support for particular ideologies can predict whether face recognition technology will be used, but messages about algorithm biases in face recognition can still affect people's attitudes regardless of their prior ideology[15].

Patil GG et al.(2021), is presented a partial facial recognition (PFR) method. It has the advantages of optimization logic and perfect feature matching. For better recognition, fully complex networks (FCN) and sparse representation classification (SRC) are combined. This work is novel because it aims to minimize the reconstruction error by carefully choosing the dynamic feature matching (DFM) scatter coefficient. The structural similarity index measure, which can be used to compare the probing feature map to the sub-gallery feature map, is also provided in this work. This work employs an optimization technique called Sealion Updated Gray Wolf Optimization (SUGWO) [16].

Saeed U et al.(2012). Are examined the study of The usefulness of lighting normalization approaches in reducing the differences brought on by cosmetics in a face recognition system. To account for the impacts of cosmetics, they used photometric light normalization techniques that were especially tailored for face identification. They then used texture-based techniques to extract facial traits, and Support Vector Machines were used to recognize faces. It is abundantly obvious from experimental results from both limited and unconstrained databases that illumination normalization techniques boost face recognition performance[17].

3. Proposed Method

In this section, the explanation, along with the detailed presentation of the proposed method for detecting manipulated faces. The proposed method includes the utilization of a deep neural network called Residual Neural Networks(ResNet) for feature extraction, the Grasshopper Optimization Algorithm (GOA) for feature selection, and the Random Forest algorithm as the classifier for identifying the identities of different individuals with manipulated facial images. The diagram of the proposed method is illustrated in Figure (1). Further details are provided in the following sections.

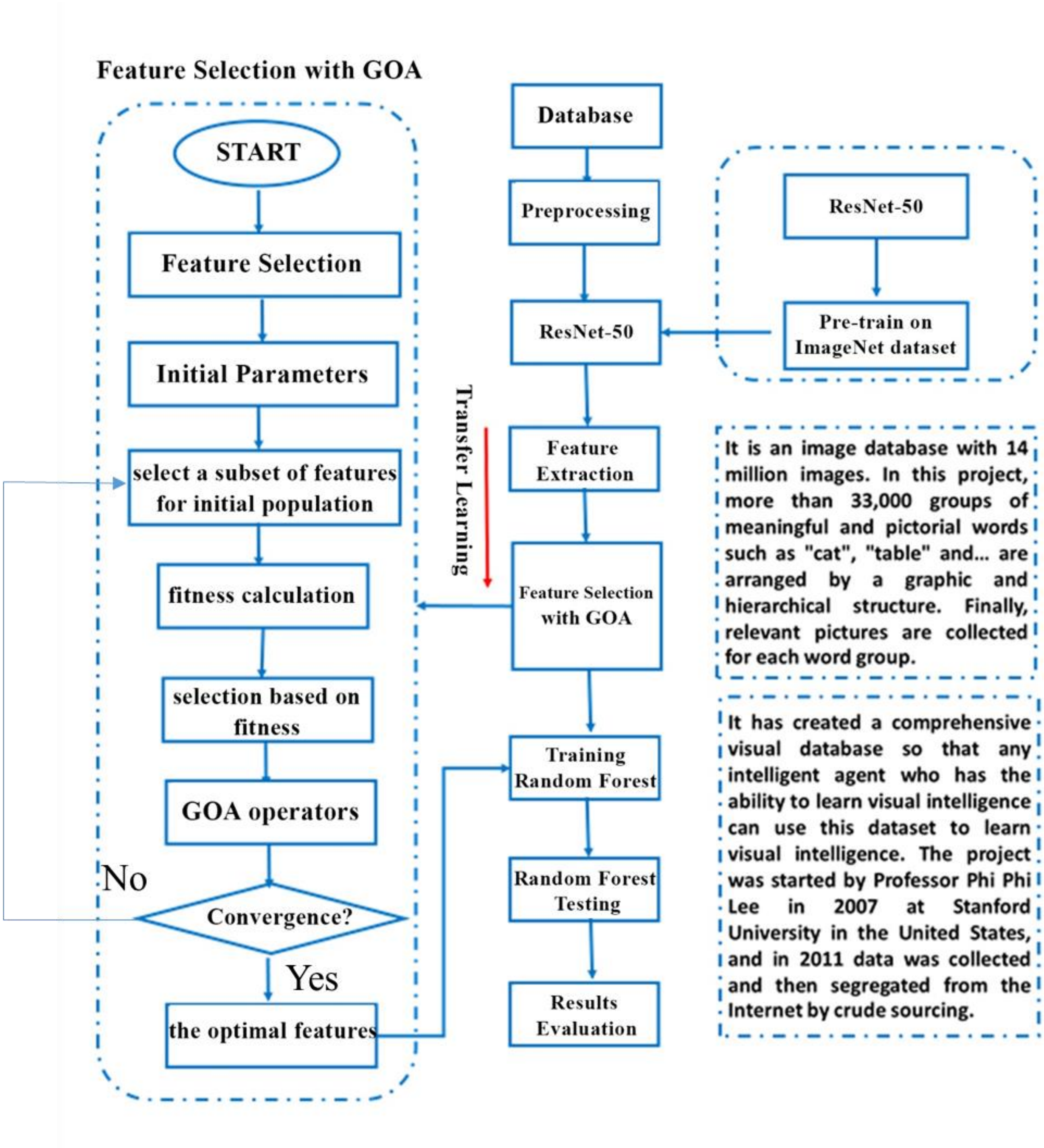

Figure 1: The Proposed Method Diagram

3.1. Feature Extraction with ResNet

Deep Convolutional Neural Networks (CNN) are among the best methods for feature extraction from images. Using convolutional filters, CNNs first extract a comprehensive set of features from images and then classify the images in fully connected layers. Pre-trained networks such as ResNet are based on convolutional layers.

In this study, only identity-related facial features are extracted using the ResNet deep neural network. The best identity-related features from facial images can only be retrieved by fine-tuning the parameters of the ResNet network since this network is a pre-trained and refined through millions of learning operations.

Next, the architecture and functionality of the ResNet network will be explained. Convolutional neural networks consists of 50 layers or more are known as ResNet-50. Residual Networks, commonly known as ResNet, are a well-established and prevalent type of neural network in the field of computer vision.

ResNet's ability to learn with up to 150 layers has led to significant advancements in various computer vision domains. "Vanishing Gradient" is one of the main challenges in convolutional neural networks. This occurs because, during backpropagation, the gradient value significantly decreases, leading to scattered weight updates. ResNet addresses this problem by using the "Hop Connection". The output of a convolutional block is enhanced by incorporating the original input through a skip connection.The architecture of the ResNet network is depicted in Figure (2).

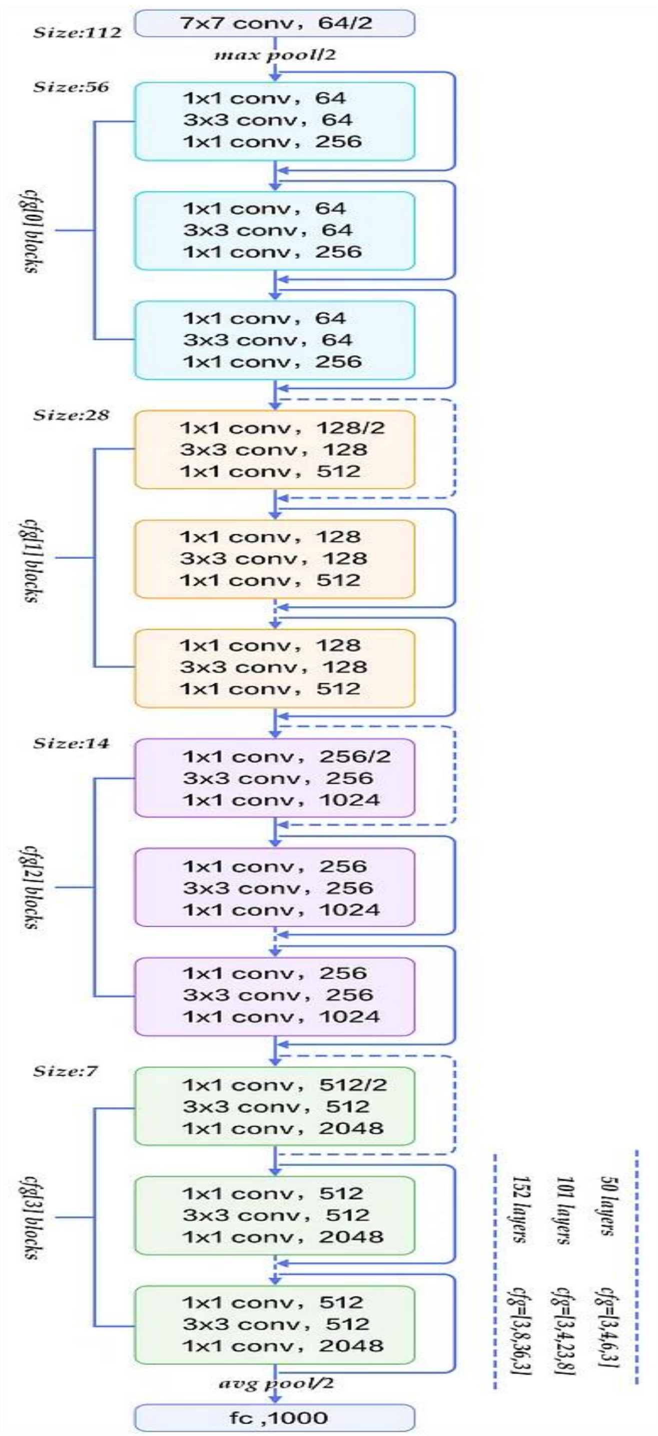

Figure 2: ResNet Architecture[17]

3.2. Optimal Feature Selection using Grasshopper Optimization Algorithm

In supervised machine learning, a set of features and their corresponding labels (target class) are provided to the selected network, and during training, the network seeks a robust mathematical relationship between the features and their labels. As the number of features increases, finding a strong relationship quickly becomes more challenging. However, some features may not only fail to improve pattern recognition but also make the task more challenging.

The best subset of features is selected at this stage. One of the best methods for selecting the optimal subset of features is to utilize metaheuristic algorithms. By employing parallel search, these algorithms can quickly select the features for classification. In this research, the Grasshopper Optimization Algorithm (GOA) is utilized for feature selection. The feature selection process involves considering a subset of features as the initial population. Then, using this subset, the accuracy of the classifier model (in this case, Random Forest) is evaluated. This accuracy is treated as a metric by the GOA optimization approach. Consequently, the subset that yields the best accuracy is selected as the optimal subset. In general, the accuracy of the Random Forest-neural network acts as the evaluation function for the Grasshopper Optimization Algorithm, and it is aimed to be maximized.

Grasshoppers belong to the insect family and are recognized as pests due to the damage they cause to products and agriculture. Equation (1) is presented to model the behavior of grasshoppers.

$$X_i = S_i + G_i + A_i \qquad (1)$$

Here, x represents the grasshopper's position (feature selection variable), S_i denotes the social interaction among grasshoppers (the objective function), G indicates the gravitational force of the grasshopper (movement toward the best position), and A represents the wind direction (a random variable for movement). The last three terms indicate the grasshopper's position. To introduce random behavior, Equation (2) can be employed, where r can randomly change between 0 and 1.

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \qquad (2)$$

The value of S_i (the objective function) equals the rate of mutual interaction, calculated according to Equation (3).

$$S_i = \sum_{j=1}^{N} S(d_{ij})\widehat{d_{ij}} \tag{3}$$

$j \neq i$

In Equation (7-3), d_{ij} represents the distance between grasshopper i and j. It is defined as $d_{ij} = |x_j - x_i \,|\, Xj$ (another selected feature). The function s is a mapping for the distance between features and is obtained based on Equation (4).

$$s(r) = fe^{\frac{-r}{l}} - e^{-r} \tag{4}$$

In this equation, f indicates the intensity of gravity (the best objective function), l denotes the gravitational scale length, and its general formula is according to Equation (5).

$$X_i = \sum_{j=1}^{N} S(|x_j - x_i \,|)\frac{x_j - x_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \tag{5}$$

Here, N represents the number of grasshoppers (other features). Since grasshoppers move on the ground, their position should not exceed a specific threshold. This leads us to use the modified cohesion (Equation 6).

$$X_i^d = c(\sum_{j=1\ j\neq i}^{N} c\frac{ub_d - lb_d}{2})s(|x_j - x_i \,|)\frac{x_j - x_i}{d_{ij}}) + \hat{T}_d \tag{6}$$

In this equation, C is an important parameter in GOA and a reduction factor that influences regions of repulsion, attraction, and gravity. The parameter update is obtained from Equation (7).

$$C = cmax = l\frac{cmax - cmin}{L} \tag{7}$$

In Equation (7), $cmax$ and $cmin$ represent the maximum and minimum values, respectively, and l denotes the current iteration number, while L is the maximum number of algorithm iterations.

3.3. Classification with Random Forest

The Random Forest algorithm is employed in the final stage of classification. Random Forest is a popular and powerful machine learning technique used for classification and regression tasks. It is an ensemble learning method that combines multiple decision trees to make predictions. The idea behind the Random Forest algorithm is to create a "forest" of decision trees and aggregate their predictions to obtain a final prediction. The steps involved in the Random Forest algorithm are as follows:

Step 1 Data Collection: The first step involves collecting a training dataset containing input features and their corresponding output values for the classification problem.

Step 2 Random Sampling: In this step, a random subset of the training data is selected with replacement. This means that some samples may be repeated in the subset, while others may not be included.

Step 3 Feature Selection: For each decision tree, a random subset of features is chosen. This helps to introduce diversity among the decision trees in the forest.

Step 4 Decision Tree Construction: Using the selected subset of features, a decision tree is constructed using a splitting criterion like Gini impurity or information gain. The tree continues to grow until a stop condition is met, such as reaching the maximum depth or having a minimum number of samples in a node.

Step 5 Repeating Steps 2 to 4: Steps 2 to 4 are repeated multiple times to create a collection of decision trees. The number of trees in the forest is a hyperparameter that can be adjusted based on the specific problem and dataset.

Step 6 Ensemble Prediction: During prediction, each decision tree in the forest independently predicts the output value based on the input features. For classification problems, the final prediction is determined by the majority vote of all the decision trees. The most common predicted class among all the trees is chosen. For regression problems, the final prediction is usually the mean or median of all the predicted values.

Step 7 Evaluation: Once the Random Forest is trained, it can be evaluated using a test dataset. The performance of the Random Forest can be measured using evaluation metrics such as accuracy, recall, or mean squared error, depending on the problem.

Random Forest has several advantages. It can handle large datasets with high-dimensional feature spaces and is robust against data noise. However, it may be computationally expensive compared to some other algorithms, especially when dealing with a large number of trees.

4. Results and Discussion

simulation results of proposed method are presented in this section. All simulations in this paper were conducted using MATLAB 2022 software. Additionally, a comparison of the results obtained from the proposed method with other existing research works is provided. In the following sub-sections, first, an explanation of the database used in the simulations is presented. Then, evaluation metrics for the simulation results are defined, followed by the simulation settings and outcomes.

4.1. Database

In this work, the VMU database [18] is utilized. It consists of a total of 330 images belonging to 25 different individuals. Among these individuals, 5 subjects have 14 images each with various makeup styles, while the rest have 13 images each with different makeup styles. The makeup styles are categorized as follows: (A) Only lipstick used. (B) Only eye makeup applied. (C) Complete makeup, including lipstick, foundation, blush, and eye makeup.

4.2. Evaluation Metrics

For evaluating the proposed approach, the following metrics are utilized in this study.

$$Precison = \frac{TP}{TP + FP} \times 100 \quad (8)$$

$$Recall = \frac{TP}{TP + FP} \times 100 \quad (9)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$F1 = \frac{2 * Precision * TPR}{Precision + TPR} \quad (11)$$

In the above equations, TP indicates true positive rate and TN indicates true negative rate of detection. FP represents false positive rate and FN represents false negative rate of detection in the process.

4.3. Simulation Settings

As mentioned earlier, the database used in this study contains 330 images, of which 70% (231 images) were considered for training the proposed model, and the remaining 30% (99 images) were reserved for testing the model's performance. These images were fed into the ResNet network to extract 1000 different features from each image. Among these extracted features, the GOA algorithm selected 400 features. The initial parameters for the GOA algorithm are provided in Table (1). Furthermore, in the simulations, the Random Forest algorithm was employed, comprising a total of 5 decision trees.

Table 1: The Initial Parameters of GOA Algorithm

Parameter	**Value**
Population size	10
Maximum iterations	40
The allowed interval for variables	[1-1000]
The objective function	$Accuracy(acc) = \frac{TP + TN}{TP + TN + FP + FN}$

4.4. Simulation Results

In this section, the simulation results of the proposed method are presented. As described in the database section, images of 25 different individuals with various make-up styles were captured, and the goal of this study is to detect the identity of each person from manipulated face images. In this process, 70% of the images of the 25 individuals are fed into the proposed method, and their corresponding labels representing the identity of each individual are used to train the model. After completing the training process, the remaining images are provided to the model, and the proposed method predicts the labels or identities of each image. The results presented in this section are for the test dataset. Figure (3) displays the numerical values of evaluation metrics, Accuracy, Precision, Recall, and F-score, which are 98%, 98.4%, 98%, and 97.77%, respectively.

In general, There are a 25-class classification problem, where each class corresponds to the identity of different individuals. For instance, out of the 99 test images, 4 images may belong to the first class, and among these 4 images, our proposed model correctly identifies 3 images belonging to the first individual. Finally, the accuracy of the proposed model in detecting the 99 test images is obtained and evaluated.

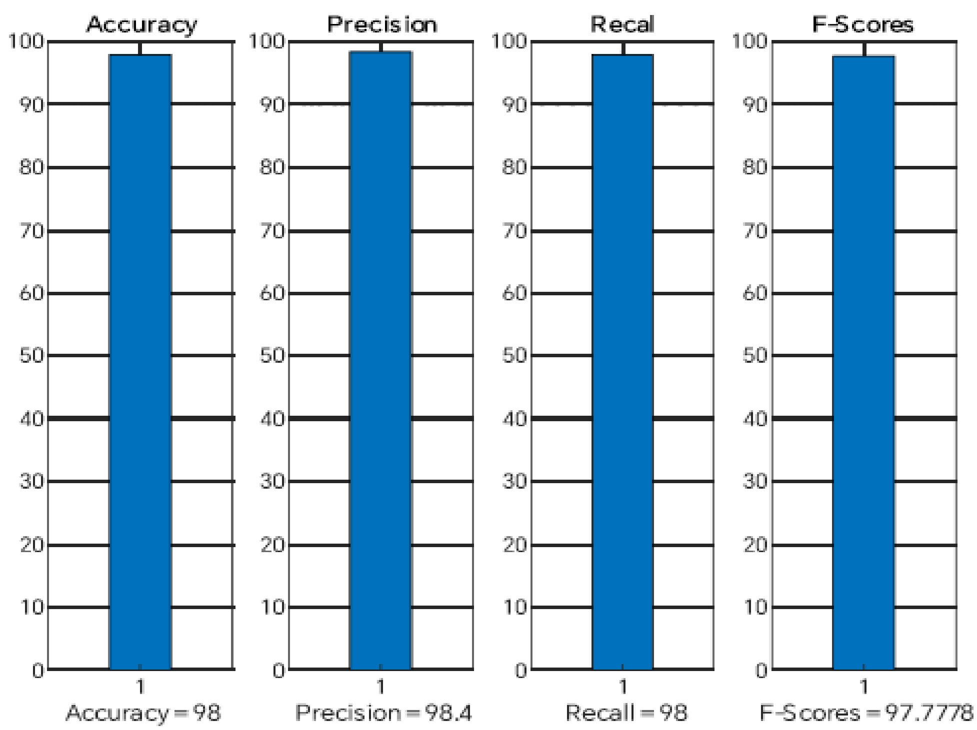

Figure 3: The Numerical Values of Evaluation Metrics for Test Dataset

In Figures (4) and (5), the regression plot and ROC curves are respectively depicted. The linear regression curve in machine learning illustrates the linear relationship between a dependent variable, such as Y, and one or more independent variables, such as X. Therefore, it is referred to as linear regression. In other words, linear regression reveals how the value of the dependent variable changes with respect to the value of the independent variable. The linear regression model represents a straight line with a slope and depicts the relationship between the variables. In the regression curve, the blue line or the Fit line represents the regression line, and the data points are shown as hollow circles. If the data points align with the regression line, it means the prediction error is zero. However, as the data points deviate from the regression line, the prediction error increases.

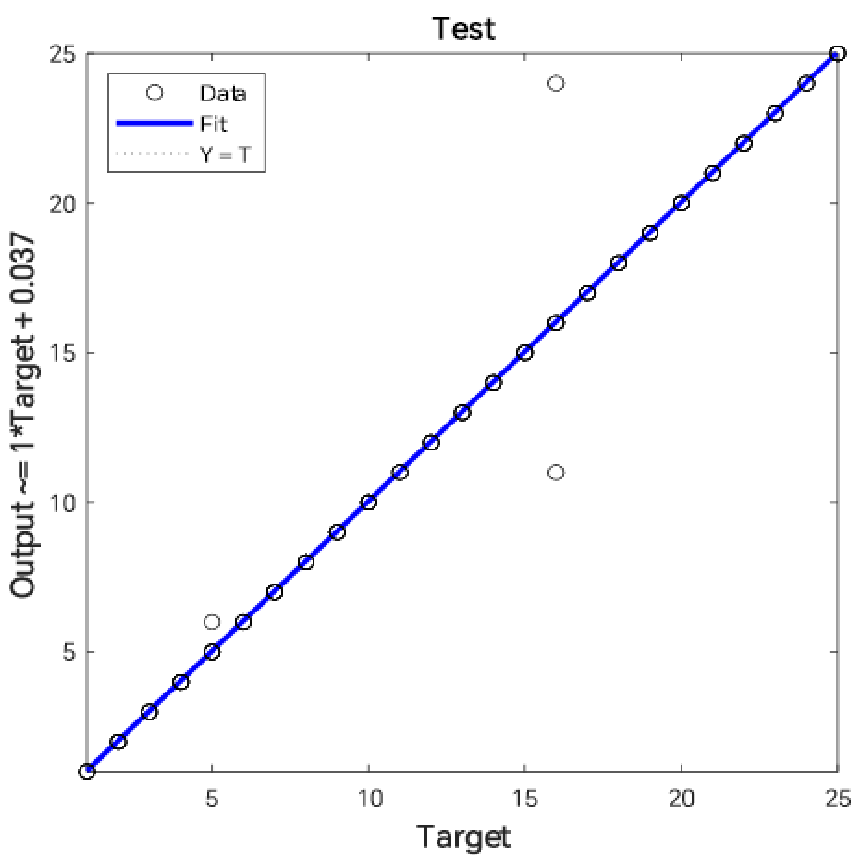

Figure 4: The Regression Plot for Test Dataset

The ROC curve is created by plotting the True Positive Rate (TPR), also known as sensitivity, against the False Positive Rate (FPR). It is important to note that the threshold for these values is variable, leading to a continuous curve. The ROC curve illustrates the accuracy of each class separately. As the Figure (5) presents, there are 25 continuous lines, each representing a class. For instance, the class 19 exhibits the lowest identification accuracy, as its corresponding line deviates the most from the value of 1 on the vertical axis, i.e., TPR.

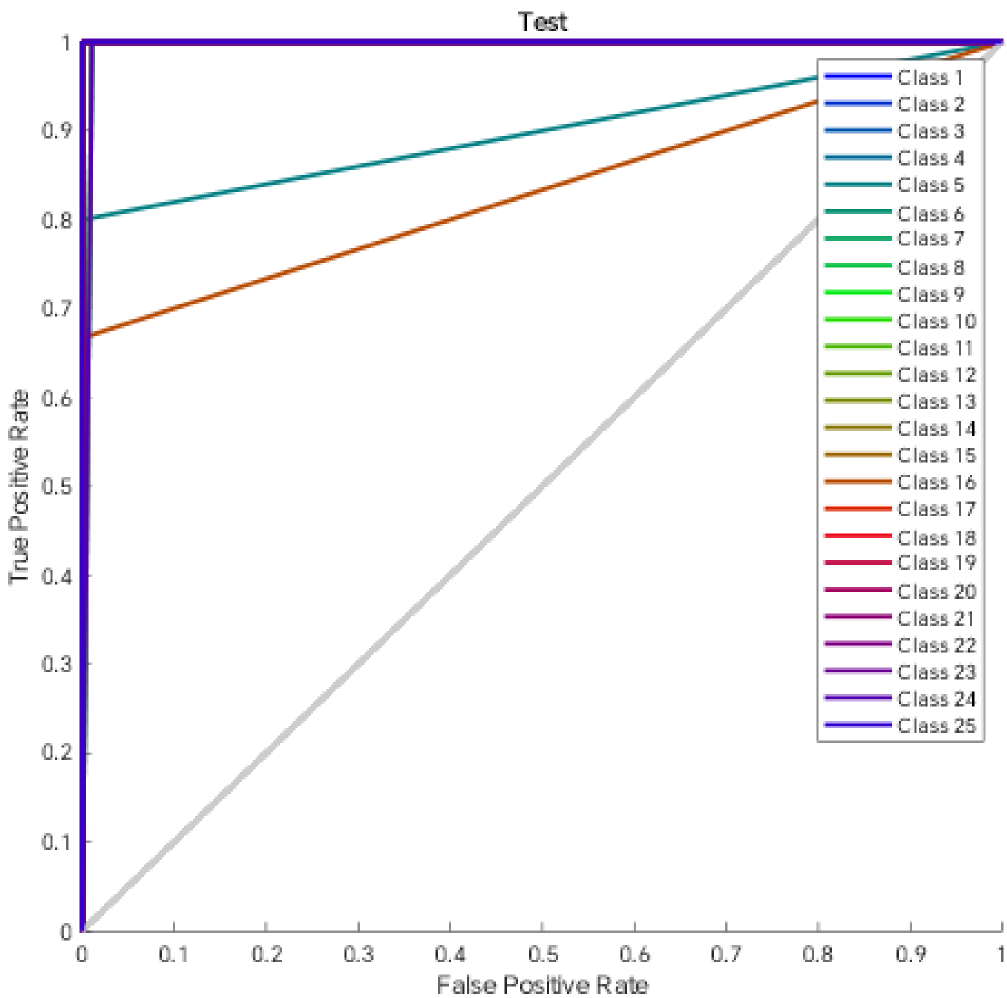

Figure 5: The ROC Curve for Test Dataset

Finally, a comparison between the performance of the proposed method and the other methods has been conducted to evaluate the accuracy of Make-up In-variant Face Recognition. The aim of this comparison is to provide a more precise evaluation of the proposed method. It is worth mentioning that the accuracy results presented in Table (2) for the proposed approach are the average of 50 simulation runs. The reason for averaging the results is that the accuracy values vary stochastically in each simulation run. As evident, the accuracy of the proposed method is higher than the accuracy of the methods employed in the reference article.

Table 2: Results Comparison

Method	Accuracy (%)
GFB+FEGEM [19]	96
LGBP [3]	82.20
FGGNet Transfer learning without augmentation [11]	88.48
SVM+Wavelet [17]	93.82
SVM+WeberFaces [17]	95.32
The proposed method (ResNet-GOA-RF)	**97.23**

The superiority of the proposed method over other examined approaches is attributed to its multi-step nature, where each step is performed by a highly powerful algorithm. For instance, the best tool for feature extraction from images is deep learning, especially pre-trained deep neural networks. Additionally, the feature selection step has a significant impact on the final performance of the classification model. By employing a combination of effective algorithms at each stage, the proposed method achieves enhanced performance in detecting manipulated faces. The integration of these robust techniques enhances the overall accuracy and robustness of the proposed approach compared to other methods, ultimately leading to superior results.

5. Conclusion

Advances in deep learning techniques, such as pre-trained neural networks, have shown promising results in Makeup-Invariant Face Recognition. However, there is still a need for stronger and more accurate methods to address challenges arising from more complex tampering techniques. In this study, a novel approach for detecting manipulated faces is proposed, combining the strengths of pre-trained neural networks, the Grasshopper Optimization (GOA) Algorithm, and Random Forest classifier. The proposed method utilizes the powerful feature extraction capabilities of pre-trained neural networks to capture intricate details and patterns in face images. Subsequently, the GOA algorithm is employed to select optimal features. Additionally, the Random Forest classifier is utilized for effective classification of face images and identifying different individuals based on the selected features. This algorithm utilizes ensemble learning techniques, improving the overall accuracy and robustness of the system by aggregating multiple decision trees. By integrating these three algorithms, the proposed approach demonstrates significant improvements in detecting manipulated faces, achieving higher detection rates and lower false positive rates compared to existing state of the art methods.

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