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Performance Assessment of Fine-Tuned VGG16 Model on the MDRF Retouched Face Dataset

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Abstract

Background: Objective: Despite being widely employed on digital platforms, facial retouching frequently causes issues since it compromises the truthfulness and trustworthiness of visual data and the present work is focused on it. Method: The classification of retouched face photos using a transfer learning approach is thoroughly examined in this research by fine tuning the VGG16 model pre-trained on “ImageNet” weight. The specific Caucasian ethnicity is used, which includes both actual and retouched face samples, and different intensities of retouching are applied to each sample separately. Finding: The experimental results show that the proposed transfer learning approach and fine-tuning of the existing model can achieve better classification efficiency with training on a smaller dataset. A 60 % - 40 % train-test split ratio outperforms other split ratios mentioned in the paper with 98.12% precision, recall, and F1 score in the classification of retouched face samples. The fine-tuned VGG16 model with Adam optimizer gives an overall accuracy of 97.50 % as compared to existing works. Novelty: For model training, the Adam optimizer is used, which adaptively modifies the network weights and dramatically lowers training and validation loss, improving classification performance overall.

Keywords: Transfer Learning; VGG16; Fine-tuning; MDRF; Adam

1 Introduction

Digital photos have become essential in today’s world. Unfortunately, a profusion of phony photographs has resulted from the extensive availability of sophisticated image editing software on the Internet. Even while some of these pictures might appear to be innocuous, they have been used for evil intent, including fabricating fake court documents, falsifying evidence in court cases, and misrepresenting historical events.

Furthermore, unattainable beauty standards have been promoted by the abundance of edited photos on social media sites, which frequently use filters to produce perfect appearances [1].

In the last decade, many surveys have been carried out on image forgery detection. It is clear from the reviewed literature that facial beautification and image forgery detection have become important areas of study in digital image forensics and biometrics. Research on facial beautification shows that digital retouching, plastic surgery, and cosmetics drastically change facial features, which lowers the precision of face recognition software [2]. There are still difficulties in accurately identifying these changes despite the exploration of several mitigation strategies, including patch-based feature extraction, multi-algorithm fusion, and deep learning models. An overview of digital image tampering detection and the existing blind methods for image forgery detection is carried out in [3] claiming need of universal dataset and techniques to identify both local and global manipulation. It is observed that due to the ease of picture manipulation, the scarcity of publicly available datasets, and algorithms that frequently only pay attention to particular changes, forgery detection in facial photographs is still difficult. For dependable real-world applications, a strong solution needs universal datasets and techniques that can identify both local and global manipulation [4].

The extensive use of passive techniques for identifying manipulations like copy-move, splicing, resampling, and retouching, on the other hand, is highlighted in survey works on digital image forgery [5]. Since most images don't have active protection (like watermarking), passive methods are more useful. Methods include higher-level semantic inconsistencies like lighting or geometry error as well as low-level statistical analysis of pixels and JPEG artifacts.

In 2017, the MDRF dataset is introduced containing real and retouched face images of Caucasian, Chinese, and Indian ethnicities, where retouching detection was performed using semi-supervised autoencoders trained on four facial patches [6]. Photo-Response Non-Uniformity (PRNU) analysis is used for identifying image retouching [7]. The paper examines how image compression affects the ability to identify facial retouching and suggests new methods that make use of deep face representations and texture descriptors. According to the study, texture-based approaches are significantly impacted by deep face representations' resilience to image compression.

A framework for evaluating detection methods were presented under real world conditions, consisting of cross-model, cross-data, and post- processing evaluation, and evaluated state-of-the-art detection methods [8]. Moreover, Human performance on detecting CNN-generated images, along with factors that influence this performance has been evaluated by conducting an on- line survey. The results suggested that CNN-based detection methods are not yet robust enough to be used in real-world scenarios. Machine learning and deep learning algorithms, especially CNN-based techniques, perform better than conventional handcrafted feature-based methods, according to recent comparative studies on facial image forgery and retouching [9]. Although blind detection without access to the original image is still difficult, these techniques can detect minute changes in facial features like skin texture, eye shape, and contour modifications. An improvised patch-based deep convolutional neural network (IPDCN2) was introduced in 2023 [10] and successfully distinguishes between original and altered facial photos using three steps: pre-processing with high-level features and facial landmarks. CNN-based residual learning is used for extraction, and fully connected layers are used for classification.

Several convolutional neural network-based classifiers are proposed to identify the fruits by visualizing via the camera for establishing a quick billing procedure in order to speed up the billing [11]. Transfer learning reduces learning costs and helps prevent reinventing the wheel [12]. The pre-trained models VGG16, VGG19, ResNet50, Inceptionv3, and EfficientNet are among the most widely used [13] [14]. A transfer learning approach is used to differentiate between authentic and altered facial photos produced by photo editing software [15]. The ND-IIITD retouched face dataset is used to refine pre-trained models like VGG16 and ResNet50, and accuracy metrics like precision, recall, and F1-score are used to assess each model's performance [16].

The major problem with image forgery is that, when done correctly, it might be visually undetectable. The research works listed here show the detection and classification can be done using machine learning and deep learning easily. but it requires huge or large datasets [17] containing image samples to train the model. In order to make sure that the model does not overfit or underfit for any particular train–test division, the split ratio is a crucial consideration [18].

This research proposed a transfer learning approach to detect and classify the real and retouched face images. The VGG 16 model, which is pre-trained on ImageNet weights, is trained on the MDRF retouched faces dataset. To minimize the training and validation loss, Adam optimizer is used during training of the VGG16 model. The model accuracy is checked over different train-test split ratios, i.e., 50%-50%, 60%-40%, 70%-30%, and 80%-20%.

2 Proposed Methodology

This research leverages a Transfer Learning knowledge to classify real vs retouched face images of MDRF retouched face dataset by using VGG16 model which is pre-trained with ImageNet weights. algorithm of the proposed method is depicted in Figure 1. MDRF retouched face images [6] dataset is split into train and test (validation) sets of 80 % - 20 %, 70 % - 30 %, 60 % - 40 %, and 50 % - 50 %, where 80% represents the images of train set and 20% represents the equally divide images into validation sets. Data transformation is applied with data augmentation. To minimize the loss and update the weights efficiently, Adam optimizers are used during initial training and fine-tuning. All the suggested model is used to evaluate the test photos, and the categorization outcomes are contrasted and examined over all splits. The most fine-tuned TL VGG16 model based on this evaluation is determined and suggested.

```
Input: Image dataset MDRF = {I_real, I_retouched}
Output: Classification label for each test image (Real / Retouched)

Begin
  # Step 1: Dataset Preparation
  Split MDRF into MDRF _train, MDRF _val, MDRF _test
  For each image I in MDRF do
    Resize I to 224 × 224 × 3
    Normalize pixel values
    Apply data augmentation (rotation, flipping, zoom, etc.)
  End For

  # Step 2: Transfer Learning with VGG16
  Load pre-trained VGG16 model with ImageNet weights
  Replace fully connected layers with custom layers:
    Flatten → Dense → Dropout → Dense (Sigmoid)
  Compile model with optimizer = Adam,
            loss = Binary Cross-Entropy,
            metric = Accuracy
  Train model on MDRF _train with validation using MDRF_val
  Fine-tune selected convolutional layers of VGG16

  # Step 3: Evaluation and Testing
  Load fine-tuned VGG16 model
  For each image I in MDRF _test do
    Compute prediction score P(I)
    If P(I) ≥ Threshold then
      Label ← Retouched
    Else
      Label ← Real
    End If
  End For
  Report performance metrics (Accuracy, Precision, Recall, F1-score)
End
```

Fig 1. Algorithm for classification of real and retouched face images

2.1 VGG16 Architecture

Researchers from the University of Oxford's Visual Geometry Group (VGG) introduced the VGG16 model, a deep CNN [19]. On numerous benchmark datasets, it has demonstrated state-of-the-art performance and is a popular model for image classification tasks. Thirteen convolutional layers and three FC (fully connected) layers make up the sequential architecture of the VGG16 model. While the FC layers handle the classification task, the convolutional layers are utilized to extract the input image's attributes. The design maintains minimal parameters while learning increasingly sophisticated properties from the input. For retouching categorization, a new FC layer is added once the original VGG16's FC layers are eliminated. All convolution layers are frozen during the model's initial training, and the weight parameter of the recently introduced FC layer is modified. A small number of the updated model's convolution layers are unfrozen during fine-tuning. As a result, the FC layer and unfreeze convolution layers' weights are modified. Table 1 shows the parameters count trained before and after fine-tuning.

Table 1. Trainable and frozen parameters before and after fine-tuning of VGG16 model with "ImageNet" weight

	Before fine-tuning	After fine-tuning
Trainable parameters	513	7,079,937
Non-trainable parameters	14,714,688	7,635,264

2.2 Adam (Adaptive Moment Estimation) Optimizer

The Adam optimizer modifies learning rates during training by combining the benefits of Momentum and RMSprop methods[20]. Because it uses memory efficiently and automatically adjusts the learning rate for each parameter, it performs well with complex models and big datasets.

$$F_t = \beta_1 * F_{t-1} + (1-\beta_1) * g \tag{1}$$

$$S_t = \beta_2 * S_{t-1} + (1-\beta_2) * g^2 \tag{2}$$

$$\widehat{F_t} = \frac{F_t}{1-\beta_1^t} \tag{3}$$

$$\widehat{S_t} = \frac{S_t}{1-\beta_2^t} \tag{4}$$

Updated Rule,

$$\theta_{t+1} = \theta_t - \alpha * \widehat{F_t} \div \sqrt{\widehat{S_t}} + \epsilon \tag{5}$$

Where,

F_t and S_t : the 1st and 2nd moment estimates of the gradients, respectively.

β_1 and β_2 : hyper parameters which control the exponential decay rate of the moment estimates.

α : L earning rate, and ϵ : Small value added for numerical stability.

2.3 MDRF (Multi Demographic Retouched Faces) dataset

The MDRF dataset contains the original and retouched images of Caucasian, Indian and Chinese human faces[6]. This research uses images of both original and retouched faces belonging to the Caucasian demography. This dataset contains facial images of 100 male and 100 female objects. There are 1200 images, which include 400 authentic images and 800 digitally enhanced images using the Portrait Pro and BeautyPlus photo editing tools. The original and retouched image samples are shown in Figure 2 with generated heatmap. Notably, in MDRF, retouching was performed individually on each image rather than applying a uniform retouching percentage to all samples, unlike Dataset used in our previous research[15], and employs two widely used photo editing tools for image manipulation.

3 Result And Discussion

3.1 Experimental Arrangement

The right split ratio should allow the model to generalize well and provide a meaningful evaluation of its performance on unseen data[21]. Hence, this research effort aimed to determine the optimal split ratio for the proposed fine-tuned model, one that

Fig 2. Sample images of MDRF Retouched faces dataset. 1st column real images, 2nd & 3rd columns fake images doctored by Portrait Pro Max tool, 4th and 5th columns fake images doctored by Beautyplus photo editing tool [6]

would enable the model to generalize effectively and deliver a substantial evaluation of its performance on unseen data. Table 2 displays facial images of MDRF Dataset categorized by various split ratios. Each split consists of an equal number of original and retouched image samples. The testing set specifically comprises samples from non-overlapping subjects, encompassing both male and female individuals.

Table 2. Train-Test Splitting for MDRF Dataset for Retouching classification

Training-Testing Split Ratio	80-20	70-30	60-40	50-50
Train Dataset	960	840	720	600
Validation Dataset	120	180	240	300
Test Dataset	120	180	240	300

3.2 Performance Matrix for Evaluation

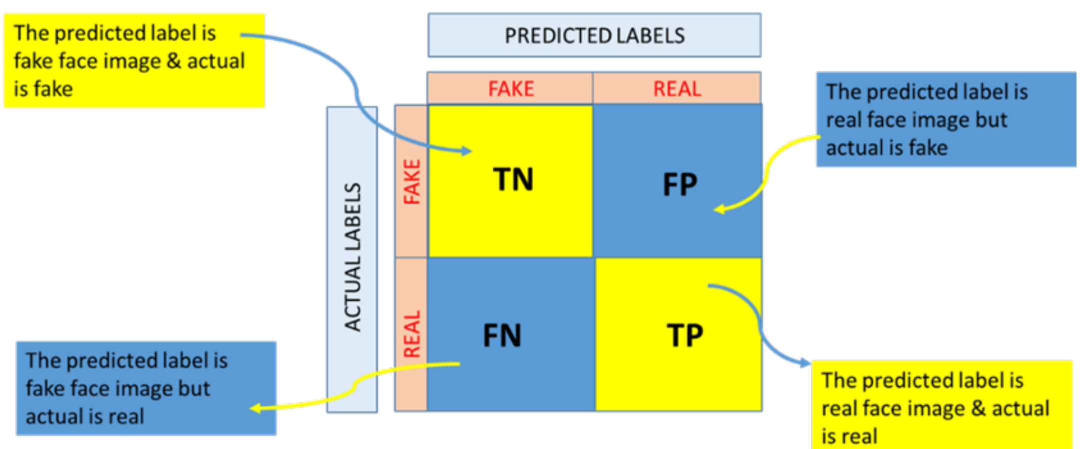

Fig 3. Understanding of Confusion Matrix

Four parameters called precision, sensitivity, F1-score, and accuracy are used to assess the model's performance for the classification of both real and retouched face samples [22], [23]. The AUC (Area under curve) compares the capacity of the model to provide the highest TPR (true positive rate). The percentage of correctly calculated results is called Precision. The ratio of TP (True Positives) to the sum of TP and FN (False Negatives) is expressed as Recall. Harmonic mean of precision and recall is described as F1 score. Figure 3 shows the matrix representation of actual and predicted binary labels.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \tag{8}$$

3.3 Result analysis based on Training Accuracy and Loss

During initial training considering epochs 1 through 10, training and validation losses continuously dropped across all split ratios, indicating that the model had acquired the fundamental feature representations. During this stage, successful generalization is shown by the decrement in both training and validation loss. When fine tuning is applied on the VGG16 model, training loss decreases more sharply in epochs 11 to 20, with values as low as 0.0700 (80%–20% split ratio) and 0.0913 (70%–30% split ratio). Particularly for the 60%–40% and 70%–30% splits, which obtained the lowest values of 0.1013 and 0.1019, respectively, validation loss also improved as show in Table 3. These findings imply that fine-tuning improved performance stability by increasing the model's capacity to capture additional discriminative characteristics. After epoch 15, however, validation loss in the 80%–20% split ratio started to deviate from training loss, suggesting a minor overfitting tendency when there is less data available for validation. The VGG16 model is first frozen and trained over ten epochs using train and validation datasets. Following this learning, a few vgg16 model layers are unfrozen, allowing them to be trained again using the same dataset. Model VGG16 Both initial and fine tweaking are done using the Adam optimizer.

Table 3. Comparison of loss at every epoch for MDRF Train and validation dataset for the proposed model w.r.t Adam optimizer. Epoch 11-20 represents data of fine-tuning

		VGG16_Adam	
Split ratio	Epoch nos.	Train loss	Validation loss
50%-50%	1	1.0213	0.6348
	5	0.5960	0.4827
	10	0.4522	0.4473
	15	0.2838	0.2838
	20	0.1445	0.4397
60%-40%	1	0.9565	0.8369
	5	0.5252	0.4722
	10	0.4245	0.3963
	15	0.2266	0.1939
	20	0.1153	0.1013
70%-30%	1	1.1348	0.8315
	5	0.5401	0.4981
	10	0.4244	0.4284
	15	0.2266	0.1974
	20	0.0913	0.1019
80%-20%	1	1.2225	0.7371
	5	0.5744	0.4544
	10	0.4170	0.3999
	15	0.2237	0.2413
	20	0.0700	0.2503

3.4 Result analysis based on performance metrics

Figure 4 to 7 shows the images of the performance matrix achieved during experiments. The experimental results show that the suggested model consistently performs well in categorizing photographs with and without makeup at various train-test split ratios (50%-50%, 60%-40%, 70%-30%, and 80%-20%). The AUC scores all above 0.99 demonstrate the model's extremely dependable discriminative capacity. Table 4 shows the comparison of AUC obtained across the different splits. The research finds that the best AUC score attained is 0.9990 at the 80%-20% split as depicted in Figure 8. The model's durability was confirmed by its good accuracy and balanced precision-recall values, even at lower split ratios.

	precision	recall	f1-score	support
Makeup	0.8333	1.0000	0.9091	200
NoMakeup	1.0000	0.6000	0.7500	100
accuracy			0.8667	300

Fig 4. Performance Matrix for 50%-50% split ratio

	precision	recall	f1-score	support
Makeup	0.9812	0.9812	0.9812	160
NoMakeup	0.9625	0.9625	0.9625	80
accuracy			0.9750	240

Fig 5. Performance Matrix for 60%-40% split ratio

	precision	recall	f1-score	support
Makeup	0.9597	0.9917	0.9754	120
NoMakeup	0.9821	0.9167	0.9483	60
accuracy			0.9667	180

Fig 6. Performance Matrix for 70%-30% split ratio

	precision	recall	f1-score	support
Makeup	0.8696	1.0000	0.9302	80
NoMakeup	1.0000	0.7000	0.8235	40
accuracy			0.9000	120

Fig 7. Performance Matrix for 80%-20% split ratio

Table 4. AUC Comparison for all split ratio for Fine-tuned VGG16 model

Fine-tuned VGG16 Model	AUC
50%-50%	0.9915
60%-40%	0.9976
70%-30%	0.9947
80%-20%	0.9991

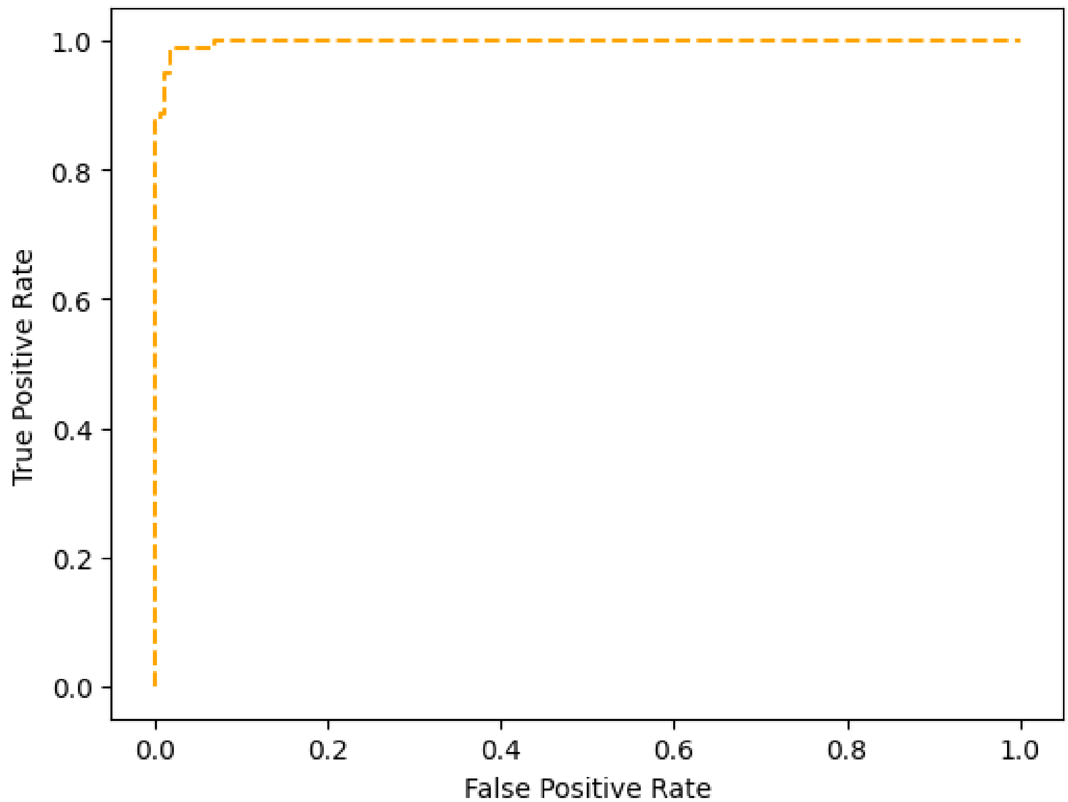

Fig 8. AUC achieved for 60%-40% split ratio for MDRF dataset

3.5 Comparison with existing works

Since AI-generated photos may readily generate a large number of altered face samples with different beautifying effects, current research is focusing more and more on these images. As far as we are aware, the MDRF dataset has not been the subject of any previous studies, because this dataset is rather small and might not be enough for training from scratch. We use a transfer learning strategy to enable efficient classification, save training time, and decrease validation loss. In contrast to previous research[6], our work provides a thorough examination of both loss and training and validation accuracy over different split ratio. The existing works shown in table 5 reported their accuracies using an 80%-20% split ratio, which is expected since models often perform better when trained on a bigger percentage of the dataset. Nonetheless, our study reveals the suggested Fine-tuned VGG16 model with Adam Optimizer can perform better even with relatively smaller training sets 60%-40% split, achieving an overall accuracy of 97.50%.

Table 5. Comparison of proposed TL model with other state-of-the-art for MDRF Dataset

Reference Paper	Method	Overall Accuracy
Bharati et al.[6]	VGG Face+SVM	79.30%
	Supervised DBM	84.20%
Proposed Fine-tuned VGG16 model	Adam Optimizer	97.50%

4 Conclusion

For the classification of altered face photos, this research shows that transfer learning using fine-tuned VGG16 pre-trained with ImageNet weights is quite successful. The model produced 98.12% precision, recall, and F1-score, demonstrating exceptional performance, especially with a 60%–40% train-test split. In addition, the VGG16_Adam model outperformed current methods with an overall accuracy of 97.50%. These results demonstrate how the suggested approach is robust in obtaining accurate classification, even with smaller training datasets, which helps to improve the reliability of facial retouching detection on digital platforms.

The generalizability of the model would be enhanced by extending the study to encompass more datasets and a wider range of races. Furthermore, experimenting with different deep learning architectures like RenNet50, MobileNet or EfficientNet may improve classification performance even more. Robustness may also be strengthened by including real-world unrestricted photos with different backdrops, lighting, and stances.

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