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Transfer Learning Based Fine-Tuned Novel Approach for Detecting Facial Retouching

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Abstract
Facial retouching, also referred to as digital retouching, is the process of modifying or enhancing facial characteristics in digital images or photographs. While it can be a valuable technique for fixing flaws or achieving a desired visual appeal, it also gives rise to ethical considerations. This study involves categorizing genuine and retouched facial images from the standard ND-IIITD retouched faces dataset using a transfer learning methodology. The impact of different primary optimization algorithms—specifically Adam, RMSprop, and Adadelta—utilized in conjunction with a fine-tuned ResNet50 model is examined to assess potential enhancements in classification effectiveness. Our proposed transfer learning ResNet50 model demonstrates superior performance compared to other existing approaches, particularly when the RMSprop and Adam optimizers are employed in the fine-tuning process. By training the transfer learning ResNet50 model on the ND-IIITD retouched faces dataset with the "ImageNet" weight, we achieve a validation accuracy of 98.76%, a training accuracy of 98.32%, and an overall accuracy of 98.52% for classifying real and retouched faces in just 20 epochs. Comparative analysis indicates that the choice of optimizer during the fine-tuning of the transfer learning ResNet50 model can further enhance the classification accuracy.

Keywords
Fine-tune, Image Retouching, ResNet50, Optimizers

I. INTRODUCTION

The process of changing a person's face in a photo or video using digital editing tools is known as facial retouching. This might involve a variety of changes, including as erasing wrinkles or blemishes, modifying skin tone, altering the size or form of facial features, or boosting specific facial features to give the face a more polished or glamorous appearance. In this digital era, the face images are widely used for different purposes like to provide as an evidence for passport or PAN Card, as an electronics traveling document, too many legal task etc. if retouched or altered, this may affect the facial recognition system as mentioned above. As the people are too much attached with the social media, they are uploading the beautified photos over the social media like Instagram, Facebook, telegram or many matrimonial sites, to make the profile more appealing. Fashion industries and advertising agencies use to use the over-retouched photos of celebrities for the profit making. It may perpetuate misleading representations or propagate unattainable beauty ideals, which can have a detrimental effect on society's perception of beauty, self-worth, and body image.

Transfer Learning can be used in variety of fields like medical, weather reporting, forecasting, road map detection, image retouching to classify the deceases, or cancer or tumors, sky conditions, map detection and to detect forgery on images, etc. As compared to ML & DL approach, TL(transfer learning) approach is faster and trained more accurately than other traditional methods like manual grading and other machine vision techniques or other classifiers [1]. There are several challenges ,when using DL(Deep Learning) model to detect retouching on facial images. 1. Need of large facial dataset containing real and retouched face images 2. Properly labeled dataset 3. Large amount of images for training the model for accurately detecting retouched images, which is difficult to obtain such a large and standard facial dataset. 4. The DL models are prone to overfitting too which leads to give biased output. Using, TL, all these challenges are overcome and optimal detection accuracy can be achieved. TL offers following advantages in ML and DL tasks [2],

- Reduced Training Time
- Lower Data Requirement
- Improved Generalization
- Avoiding the ”Cold Start” Problem
- Effective in Domain Adaptation
- Useful for Small-Scale Deployment

The contribution of our work is as follows:

- The ResNet50 CNN model is suggested in this work to distinguish between real and retouched images of ND-IIITD retouched faces dataset. The ResNet50 is pre-trained on a large dataset ImageNet which offers more than 10000 classes. Hence, the model is able to easily learn and generate the features vector for classification task.
- ResNet50 model is modified by removing default FC layers and adding one fully connected layer on top to apply fine tuning. the new RenNet50 is trained on the standard dataset ND-IIITD using epochs of the order of tens. This consequently, reduces the computation time and increases the classification accuracy.
- In Transfer learning, the Fine-tuned CNN model with choice of proper optimizer affect the classification accuracy more. Hence, three different first order optimizers are used on fine-tuned ResNet50 and consequently the classification parameters like precision, recall, F1-score, accuracy and ROC are compared.

The content of this research is organized as follows: The literature review and research gap is discussed in Section2. Proposed transfer learning models and methodology are introduced in Section 3. Afterwards, implementation setup in this work is briefly described in Section 4. Classification results are summarized in Section 5 and conclusion and future work is discussed.

II. MOTIVATION

The motivation behind research in facial retouching stems from the desire to enhance and improve the appearance of human faces in digital media. In an era where social media and digital imaging are pervasive, there is a growing demand for tools and techniques that can help individuals present themselves in the best light. Facial retouching research aims to develop algorithms and methods that can automatically and realistically enhance facial features, correct imperfections, and provide users with control over their digital appearance. Additionally, research in this field seeks to address ethical concerns surrounding the potential misuse of retouching techniques, promoting responsible use and fostering a healthy body image.

A. LITERATURE REVIEW

Advertisers and editors of magazines had come under heavy fire for using excessive amounts of digital photo editing on billboard commercials, and cover pages of magazines, showcasing models and celebrities with unnaturally tall, slender, and free of wrinkles and blemishes. The prevalence of those overly idealized and exaggerated images has been connected to eating disorders and poor body images in men, women and children. In response, many nations have thought about passing legislation requiring manipulated photo labeling. The Photoshop laws are defined by several countries to reduce the adverse effect of photo retouching, [3–5]. This leads to the increasing demand of the application of deep learning models for forgery classification.

Retouching is a doctoring technique to be done over any digital images. This attack can be active or passive. The branches of forgery attacks are again different based on the altering done on images. The performance of the forgery detection is based on the dataset used and the software applications used for implementation [6, 7].

Reference [8] developed a perceptual matric learned on support vector regression (SVR) to estimate the map the between user rating and summative statics of the retouched images (geometric and photometric alteration).The real and retouched images of total 468 images are collected from different on-line sources.

The ND-IIITD dataset were developed consists of 2600 unretouched and 2275 retouched images. the database contains male and female face images. Research work carried out in Reference [9] used unsupervised and supervised deep learning algorithm for detecting the retouched and real images of the ND-IIITD database. The same approach is carried out for Celebrities database consists of 165 objects (330 real plus retouched) from on-line sources. The overall accuracy achieved was 90.9% and 96.8% for ND-IITD and Celebrities dataset respectively using unsupervised DBM. The overall accuracy achieved was 93.9% and 98.7% for ND-IITD and Celebrities dataset respectively using supervised DBM.

In 2017, the algorithm was proposed which uses semi supervised auto encoders to report the retouching accuracy on the Multi-Demographic Retouched Faces (MDRF) dataset [10].

MDRF dataset is introduced by the author with subjects from three different ethnicities and forgery from two tools is applied.
Moreover, besides using photo editing tools, the Generative Adversial Network(GAN) generated retouched images are widely used to train the deep learning models. Reference [11] proposed a CNN approach to detect and classify retouched images of ND-IIITD retouched faces dataset and CelebA dataset. The real images of CelebA dataset is used to generate the retouched images using StarGAN. 99.70% and 99.42% accuracy is achieved which is 6% higher compared to [9] using Thresholding and SVM classifier.
Studies demonstrate that when a makeup is applied, face recognition systems doesn't work well. The publically available makeup dataset are YMU(YouTube Makeup Dataset) [12], MID(Makeup in the wild dataset) [13] and FCD(facial Cosmetic Dataset) [14]. The research described in [15] was able to extract a features vector that accurately depicted the input face's shape and texture. Following feature extraction, two different classifiers—namely, SVM and Alligator—are used for comparison. 99.30% overall accuracy is achieved for inter database classification.
Plastic surgery is another type of forgery class which offers adverse effect on face recognition task. Reference [16] offer an experimental study to quantitatively assess face recognition algorithms' performance on a database of people who have undergone both local and global plastic surgery. The research demonstrates that the algorithms PCA, FDA, GF, LFA, LBP, and GNN are unable to successfully offset the variances brought on by the plastic surgery treatments where overall accuracy achieved is 34% maximum.
As variety of photo editing tools are available freely and easily, photo retouching can be done even any layman with ease. The evaluation of 32 beauty apps were conducted in [17]. A database of 800 enhanced face photos is created using five apps namely Airbrush, Instabeauty, Fotorush, Polarr and Youcam perfect based on this evaluation. A commercial face recognition system is used to compare biometric performance before and after retouching. The analysis of photo response non-uniformity (PRNU), which forms the basis of a retouching detection system, is provided and the approach achieved the avg detection error rate 13.7%.

B. CHALLENGES

facial forgery attack in the span of plastic surgery, makeup detection or digital photo alteration affect the accuracy of face recognition system. Based on the literature review carried out here, still very few work is conducted on classification of facial forgery. Numerous challenges are notified based on the presented literature review (section 2.1) and listed out in terms of research gap as follows which motivates to do work in the field of facial retouching detection and classification.
1) From three specified facial retouching attacks (plastic surgery, make up and digital photo retouching), use of photo retouching is widely applied and used for the social media or to present as an identity proof to show cased oneself very attractive. Now a day, most of the photo editing tool are in built in almost all smart phones or freely available and less time consuming. Hence, as compared to rest two forgery attacks, digital photo retouching is widely used. So, a novel approach is required which can detect and classified the retouching on facial images.
2) The literature reveals that the approach used for detecting the retouching, used deep learning approach, which required very large amount dataset containing the real and retouched(fake) images to train the model. Moreover, very large amount of training and validation dataset is needed to achieve optimal classification accuracy.
3) Again, the epoch required during training phase are again in terms of hundreds. This ultimately increase the computational time.
4) As the facial dataset needed to generate the feature vectors and the epoch to train the model requires to be too high, the powerful CPU system is required.
The above challenges are tried to overcome in the proposed work using transfer learning approach and with the help of different first order optimizers. Three different experiments are carried out on ND-IIITD dataset and compare it with the existing methods to show the expediency of the work.

III. PROPOSED APPROACH

In this paper, we suggested a TL (Transfer Learning) method to classify real vs retouched images from ND-IIITD retouched face database by utilizing various optimizers including pre-trained ResNet50 TL models "ImageNet" weight. The flow diagram of the suggested approach is shown in Fig. 1.
ND-IIITD retouched faces dataset is used and we split the

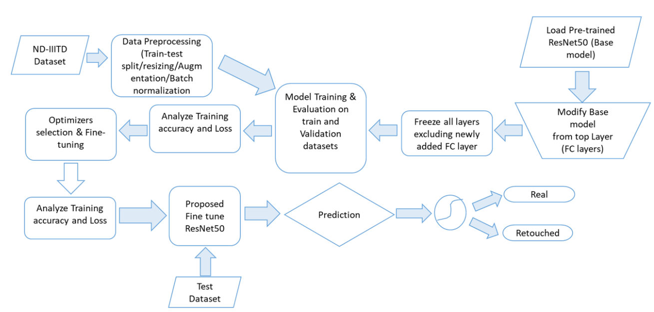

Fig. 1. Flow diagram of the proposed Transfer Learning approach

dataset 50%-50% into train and test (validation) sets as per the protocol followed by [9, 11]. Pre-trained ResNet50 model with "ImageNet" weights are used which are trained on 20K different types images. ResNet50 [18] model has loaded with these pre-trained weights with fine-tuning the model for better performance. Moreover, the choice of optimizer affects the accuracy of the model. Hence, during inference mode, Adam optimizer is used and Adam, RMSprop, and Adadelta optimizers are used with fine-tuned ResNet50 model. Then training and evaluation are applied on these ResNet50 fine-tuned TL models.
Finally, the non-overlapped images (i.e. none of the samples neither real or retouched are in the train dataset) are input into the proposed model and, it provides the predicted output as either real or retouched(fake) using binary classification. Adam optimizer is used during initial training of ReNet50 model. For training of Fine-tuned ResNet50 TL model, three different optimizers namely Adam, RMSprop and Adadelta are used. Hence, total 3 experiments are conducted on TL ResNet50 model where the effect on classification accuracy of the model is observed. Three different optimizers (Adam/RMSprop/Adadelta) are used during Fine-tuning of the proposed model and best ResNet50 TL model is chosen.

A. *RESNET50 ARCHITECTURE*

ResNet-50 is a widely used pre-trained convolutional neural network (CNN) model for image classification tasks. It consists of 50 layers and employs residual connections to alleviate the vanishing gradient problem during training.2shows the ResNet50 model's architecture along with the ResNet50 TL's fine-tuning setup. The input to ResNet50 is an image of size 224x224x3 (RGB). The initial layer is a convolutional layer with 64 filters, a kernel size of 7x7, and a stride of 2. This layer reduces the spatial dimensions of the input by a factor of 2. Following the initial convolutional layer, a max pooling layer with a pool size of 3x3 and a stride of 2 is applied. This layer further reduces the spatial dimensions by a factor of 2. ResNet50 consists of four stages, each containing several residual blocks. Each residual block has three convolutional layers. The stride values differ depending on the stage as follows:

- Stage 1: The first residual block in each stage has a stride of 1, while the rest of the blocks have a stride of 2. This allows for down sampling of feature maps in subsequent stages.
- Stage 2, 3, 4: All residual blocks within these stages have a stride of 2, reducing the spatial dimensions by a factor of 2 at each stage.

After the residual blocks, a global average pooling layer is applied. It performs average pooling over the entire spatial dimensions of the feature maps, resulting in a fixed-size feature vector for each channel. The ResNet50 model is modified by replacing FC layer 1000 out-features by new FC layer with 2048 in-features and 2 out-features (i.e. real and retouched) followed by drop out of 0.2, as shown in Fig. 2.

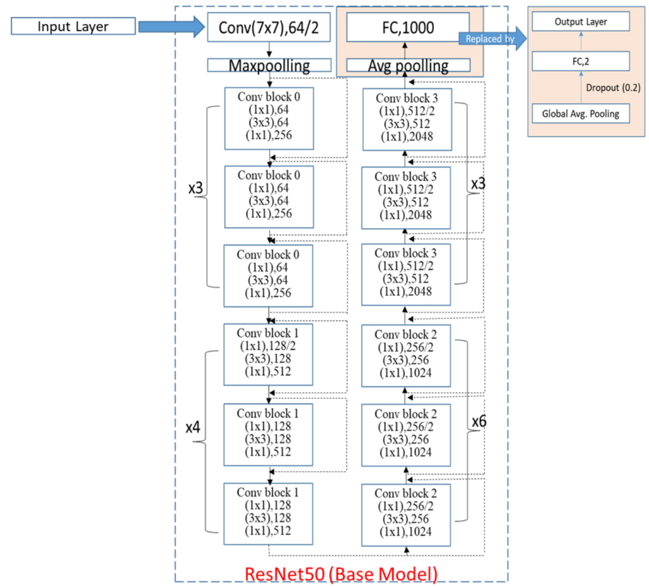

Fig. 2. A sequential model is formed with Modified ResNet50 Architecture (shown in pink rectangles)

B. *DATASET DESCRIPTION*

By providing a signed Biometric Database release agreement, the Notre Dame University will provide the ND-IIITD Retouched faces dataset [9]. 4875 face images of dataset are divided in 2600 real images and 2275, as stated in Table I, are edited. Advanced software named Portrait Pro Studio Max is used for the retouching. As shown in Fig. 3, first image is the real subject and rest are seven separate probe sets, each featuring distinctive portraits and retouching instances. As the probe sets are increasing the level of retouching is also increasing. Hence, probe set 1 underwent minimum alteration and probe set 7 undergone to maximum alteration.

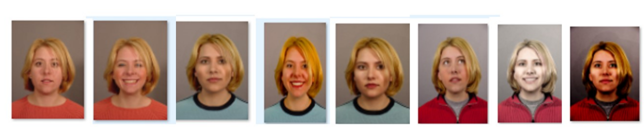

Fig. 3. A Sample of real and retouched faces taken from ND-IIITD [9]. First image is real and the rest are retouched with alteration level increases as goes to the right

TABLE I.
ND-IIITD DATASE

Real	Retouched	Total
2600 Male(215) Female(109)	2275	4875

TABLE II.
TRAIN-TEST SPLIT OF ND-IIITD DATASET

	Real	Retouched	Total
Train	1133	1134	2267
Validation	567	566	1133
Test	572	574	1146

For deep learning models, data preprocessing, augmentation, and transformation are crucial components. As the dataset used here is not large enough, data augmentation techniques are used in our research. As a data transformation, the images are downsized to 224 224 pixels for the TL ResNet50 model. Here, only horizontal flipping and rotation of 20 degree is applied on the train and testing dataset. As per the protocol followed by [9, 11], the dataset is divided into 50-50% train-test split. 50% images of subjects (Male:109 and Female:53) are used for train dataset. remaining non-overlapped i.e. subjects (Male:106 & Female:56) are used for testing dataset. The train-test split ratio with no. of samples is mentioned in Table II.

C. OPTIMIZER

An optimizer is a method or algorithm that alters neural network properties like, weights or biases [19]. As a result, it aids in decreasing total loss and raising precision. A deep learning model typically has millions of parameters, making selecting the proper weights for the model challenging. The state-of-the-art optimizers used for classifications problems are Gradient Descent, Stochastic Gradient Descent, Stochastic Gradient descent with momentum, Mini-Batch Gradient Descent, Adagrad, RMSProp, AdaDelta, and Adam. In this research, the Adam, RMSprop, and Adadelta are selected during fine tuning for their advantages over others. the parameters.

1) Adam Optimizer

Adam employs estimates of the first and second moments of the gradient to change the learning rate for each weight of the neural network, which is how it gets its name, adaptive moment evaluation. The formula for weight update is as follows:

$$W_{t+1} = W_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{1}$$

Where, w_{t+1} is the model weight estimate at time step t+1 w_t is the weight estimated at time step t. $\hat{m}_t$ and $\hat{v}_t$ are the bias corrected first moment and second moment estimate at time step t respectively. η= learning rate parameter ε=small positive number to avoid the denominator equal to 0

2) RMSprop Optimizer

As a stochastic method for mini-batch learning, RMSprop was developed. RMSprop addresses the aforementioned problem by normalizing the gradient using a moving average of squared gradients. Simply said, RMSprop treats the learning rate as an adjustable learning rate rather than a hyper parameter. This implies that the rate of learning fluctuates throughout time. The formula for weight update is as follows:

$$W_{t+1} = W_t - \eta \frac{g_t}{\sqrt{\hat{v}_t} + \varepsilon} \tag{2}$$

Where, $w_{t+1}$is the model weight estimate at time step t+1 w_t t is the weight estimated at time step t $\sqrt{\hat{v}_t}$ is the square root of moving average of squared gradient at time step t g_t is the gradient at step t η= learning rate parameter ε =small positive number to avoid the denominator equal to 0

3) adelta Optimizer

Adadelta is an optimization algorithm that is commonly used for training deep neural networks. It is a variant of the Adagrad algorithm that aims to reduce its aggressive and monotonically decreasing learning rate. The weight is updated by limiting a gradient window to some fixed size. The default learning rate need not be set for this optimizer.

$$W_{t+1} = \frac{w_t}{\sqrt{\hat{s}_t} + \varepsilon} \tag{3}$$

Where, $w_t$is the model weight estimate at time step t+1 w_{t-1} is the weight estimated at time step t $\hat{s}_t$ is the weighted avg. of accumulated gradient for specified window at time step t

IV. IMPLEMENTATION SETUP FOR TRAINING & EVALUATION

As a part of transfer learning, the model is trained initially by keeping all convolution layers freeze. During this initial training, Adam optimizer is used. During second training, i.e. fine-tuning of the ResNet50 TL model, few convolution

TABLE III. SOFTWARE REQUIREMENT FOR IMPLEMENTATION

Platform	Google Colab
Hardware	GPU runtime
Library	Tensorflow- open source software libray
Storage	Google drive

layers of the model is kept unfreeze. Hence, the weights of those layers are updated. In this work, three optimizers are used during fine-tuning of the model. Total three experiments are performed on ResNet50 TL model. The validation dataset is used for model evaluation, while the training dataset is utilized for model training. We determine the cross-entropy loss on the train and validation sets for each epoch. During initial training of the proposed model, learning rate(LR) of 0.001 and epoch 10 are considered. As it gives better performance result to use lower LR during fine-tune [20]. Hence, the LR and epoch is set to 0.0001 and 10 respectively. Software requirement for performing the training and evaluation task is mentioned in Table III. the hyperparameters are set as per in Table IV.
Fig.4 & Fig.5 shows how the model performance over training and validation accuracy. It is observed that training and validation accuracies are nearly same 85-86% till epoch 10 for all three proposed models. when Adam and RMSprop optimizers are used during fine tuning shot, the accuracies are increases up to 98% at epoch 20. The training and validation losses at epoch 10 is observed reduced by 30% and 20% respectively which is nearly same for all three proposed models. The model performance is nearly similar for all three models, as Adam optimizer is used till epoch 10. The cross entropy losses are again reduced very fast by applying fine-tuning to the proposed models and using Adam and RMSprop optimizers. But Despite the fine-tuning, training and validation loss are not reducing when Adadelta optimizer is used. The accuracy and loss comparison for all three proposed models over epoch 1 to 20 is shown in Table V. However, the model with Adadelta do not shows improvement in training and validation accuracy across a greater number of epochs. Another thing we observed was that the rate of loss reduction was relatively high during initial training (fewer epochs) and losses are further reduced during fine-tuning. This is due to the transfer learning method and use of different first order optimizers.

A comparative summary of train losses and train accuracies of all the models is shown in Fig. 6. Till epoch 10, the proposed model is trained on train and validation dataset where weights of only newly added FC layers are updates and fine-tuning start at epoch 10. By comparing the train

TABLE IV. HYPERPARAMETER SET FOR PROPOSED RESNET50 TL MODEL

Training Mode	Parameters	Parameters Value
Initial training	Optimizer	Adam
	Batch Size	32
	Epoch	10
	Learning Rate (LR)	0.001
	Criteria	Cross Entropy Loss
	Trainable parameter	2049
Fine-tune	Optimizer	Adam RMSprop Adadelta
	Batch Size	32
	Epoch	10
	Learning Rate (LR)	0.0001
	Criteria	Cross Entropy Loss
	Trainable parameter	19,454,977

losses, the proposed TL models for Adam and RMSprop optimizers shows that the losses are reducing and reached to around 0.06% over 20 epochs of training. Validation losses are remarkably reducing around 0.03% when RMSprop optimizer is used in the fine-tuning shot. The train and validation losses are around 23% and 37% when the Adam and Adadelta optimizers are used during fine-tuning shot over 20 epochs of training, as per Fig.6 & Fig.7. In terms of training and validation accuracy, the fine-tuned ResNet50 with RMSprop optimizer comes first with 98.32% and 98.76% respectively as shown in Table 5 with bold letters.

V. RESULT ANALYSIS

For the classification of retouched images, as a standard method of evaluation, confusion matrix is used here. The CM represents the output in form of matrix which mainly includes four set of parameters namely True positive (TP), False positive(FP), True negative(TN) and False negative(FN) [21]. Based on this four terms, further more parameters of classification task are calculated. Those are as follows:
P(Precision), is number of correctly identified real images from all images identified as real.

$$P = TP/[TP+FP] \tag{4}$$

R(Recall), is number of correctly identified real images from all actual real images.

$$R = TP/[TP+FN] \tag{5}$$

F1(F1-score), is average value of precision and recall.

$$F1 = 2(P*R)/(P+R) \tag{6}$$

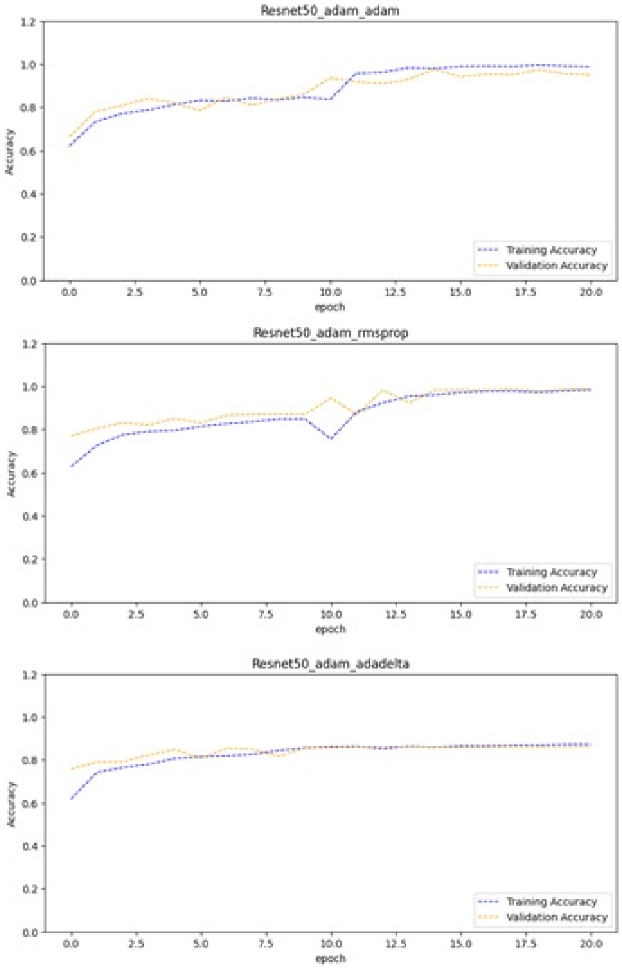

Fig. 4. Training and Validation Accuracy of proposed TL models. *ResNet50_adam_rmsprop* describes that the Adam optimizer is used during the initial training of ResNet50 TL model and RMSprop is used during fine tuning of the model

Acc(Accuracy), is the ratio of correctly identified samples to the total predicted samples.

$$ACC = \frac{Correctly\ Identified\ Samples}{Total\ Predicted\ Samples} \tag{7}$$

ROC (Receiver Operating Characteristic Curve), is a graph that displays how well a classification model performs across all categorization levels. It gives the graph of TPR (True Positive Rate) and FPR (False Positive Rate).

$$TPR = TP/[TP+FN] \tag{8}$$

$$FPR = TP/[TN+FP] \tag{9}$$

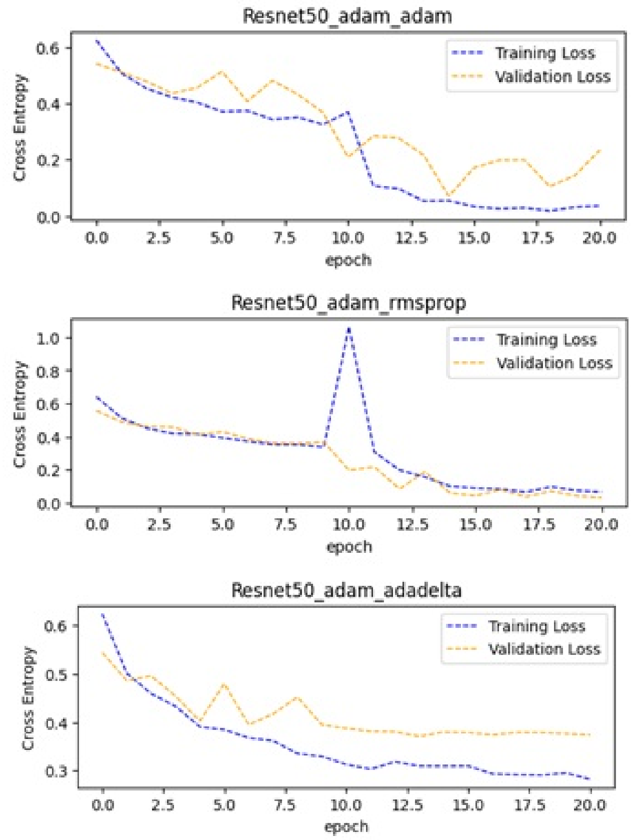

Fig. 5. Training and Validation loss of proposed TL models

The confusion matrix(CM) of all three evaluated models are shown in Fig.8. Based on the CM, the evaluation parameters like precision, recall, F1-score, and accuracy are calculated and tabulated in Table 6. By comparing the parameters of Table VI, the ResNet50_adam_adam model predicted correctly 86.23% fake (retouched) and 99.83% real face images. ResNet50_adam_rmsprop predicted correctly fake face images with 97.39% of samples and real face images with 99.65% of samples. ResNet50_adam_adadelta shows poor classification accuracy with 54.01% fake face images. However, it shows 97.03% accuracy in identifying the real face images of the test dataset. The transfer learning approach, presented here, with properly choosing the optimizer during fine-tuning yields an overall accuracy of around 98.52% (max).

When comparing the performance parameters of all three proposed models, as depicted in Fig.9(a), it becomes evident that specifically, when utilizing the RMSprop optimizer during fine-tuning, the proposed model achieves max. values of 99.64%, 97.39%, and 98.50% for precision, recall, and F1-score for retouched images respectively. As per Fig. 9(b), the fine-tuned ResNet50 model with RMSprop optimizer yields

TABLE V. TRAINING SUMMARY OF PROPOSED TL MODELS

	Accuracy		Cross Entropy Loss	
Epoch No.	Train	Validation	Train	Validation
		ResNet50_Adam_Adam		
1	0.6219	0.6637	0.6259	0.5415
5	0.8129	0.8225	0.4042	0.4556
10	0.8473	0.8614	0.3252	0.3687
15	0.9894	0.9417	0.0334	0.1712
20	0.9876	0.9496	0.0358	0.2347
		ResNet50_Adam_RMSprop		
1	0.6277	0.7705	0.6393	0.5553
5	0.7957	0.8508	0.4144	0.4116
10	0.8486	0.8693	0.3357	0.3664
15	0.9722	0.9841	0.0875	0.0419
20	0.9832	0.9876	0.0642	0.0306
		ResNet50_Adam_Adadelta		
1	0.6184	0.7581	0.6245	0.5441
5	0.8072	0.8481	0.3906	0.4026
10	0.8561	0.8552	0.3294	0.3949
15	0.8663	0.8596	0.3096	0.3786
20	0.8729	0.8623	0.2825	0.3740

max. values 99.74%, 99.65% and 98.53% of Precision, recall and F1_score parameters for real face images.
Fig. 10 represents the ROC curves for all three proposed models. The ROC curve comparison reflects that ResNet50_adam _rmsprop and ResNet50_adam_adam models give better performance across both classification levels i.e. retouched and real face images. ResNet50_adam_adadelta performs well for classifying the real images than the retouched or fake faces. Based on ROC. In recent years, numerous studies have been conducted to identify and categorize facial retouching, which is compared with our proposed model and tabulated in Table VII. Our model shows overall accuracy improvement of 11% for classification and 50% compared to supervised deep learning methods [9] and reference [8] respectively. Our proposed models (ResNet50_adam_adam & ResNet50_adam_rmsprop) show improvement in low TPR compared to [9]. In proposed methodology, the model is learned on whole face image rather than patches, still it gives better accuracy in terms of class classification compared to the other methods shown in Table IV.

TABLE VI. EVALUATION PARAMETERS CALCULATED FOR PROPOSED RESNET50 MODELS FOR TEST

Model	P	R	F1	Samples	Acc
Adam_Adam	0.9977	0.8624	0.9252	574(Fake)	0.9302
	0.8785	0.9983	0.9345	572(Real)	
Adam_RMSprop	0.9964	0.9739	0.9850	574(Fake)	0.9852
	0.9744	0.9965	0.9853	572(Real)	
Adam_Adadelta	0.9480	0.5401	0.6881	574(Fake)	0.7548
	0.6777	0.9703	0.7980	572(Real)	

TABLE VII. COMPARISON OF PROPOSED WORK WITH EXISTING WORKS

Sr. No.	Reference	Method	Accuracy(%)
1	[8]	—-	48.80
		Unsupervised DBM	81.90
2	[9]	Supervised DBM	88.89
		TL+ Adam Optimizer	93.02
		TL + r RMSprop Optimize	98.52
3	Proposed Fine-tuned ResNet50 model	TL + Adadelta Optimizer	75.48

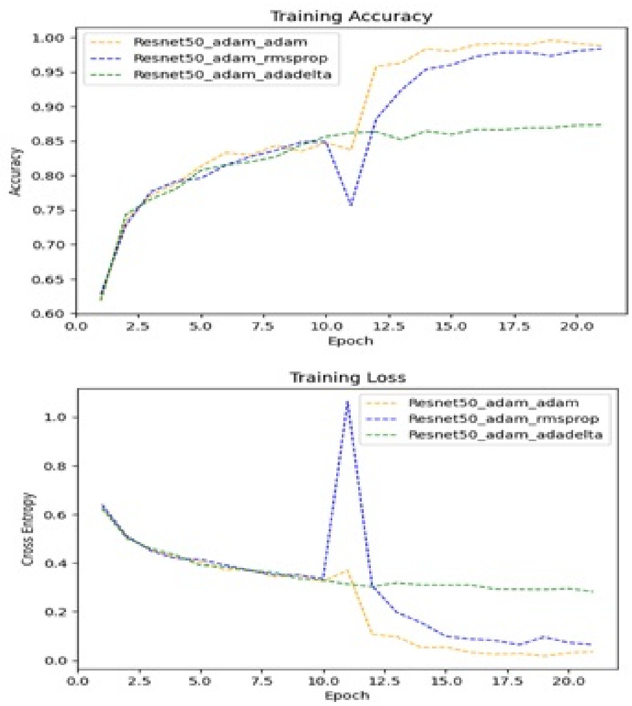

Fig. 6. Comparison of training accuracy and loss for the proposed TL models

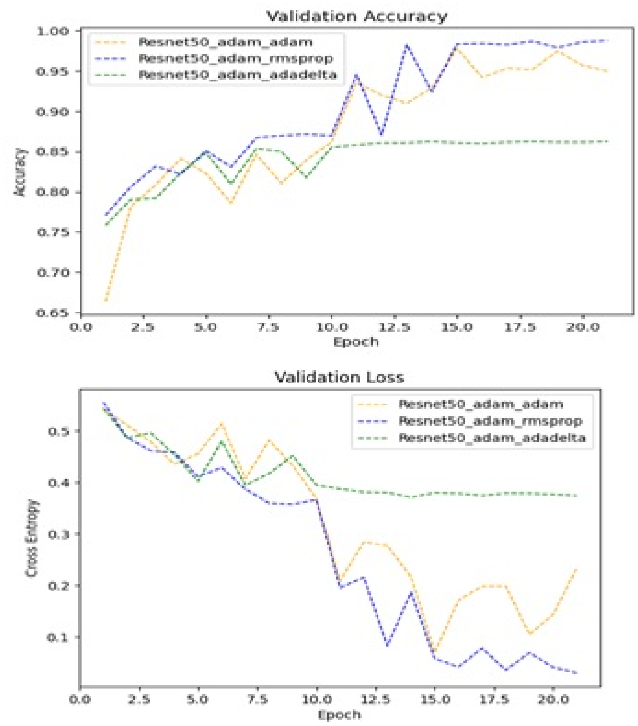

Fig. 7. Comparison of validation accuracy and loss for the proposed TL models

VI. CONCLUSION

In this study, we demonstrate an improved ResNet50 model with ImageNet weight that uses transfer learning to accurately categorize picture retouching on the ND-IIITD retouched faces dataset. To achieve this, we changed the standard ResNet50 model by including an additional FC layer. To improve the classification accuracy and to update the weights of the fine-tuned model, we used three first order optimizers i.e. Adam, RMSprop and Adadelta during fine-tuning training. Among these, ResNet50_Adam_RMSprop outperforms and achieved 98.76% validation accuracy, 98.32% train accuracy, 99.64% precision, 97.39% recall, 98.50% F1-score and 98.50% accuracy for retouched cases in two-class classification. the research shows that transfer learning approach with Adam and RMSprop optimizers (during fine tuning training) gives better performance in classifying the retouched images. Overall, the accuracy during fine-tuning is improved by 13-14% when Adam and RMSprop are used. Whereas, the Adadelta optimizer doesn't show promising result in detecting retouched images. Moreover, the train and validation accuracy are improved by only 1-2% during fine-tuning. We can do additional research to illustrate transfer learning qualitatively across various train-test split ratios to classify the retouching on facial images.

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CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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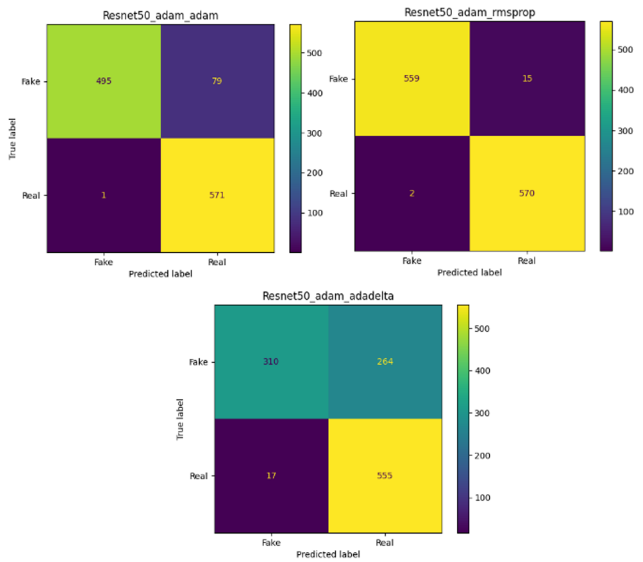
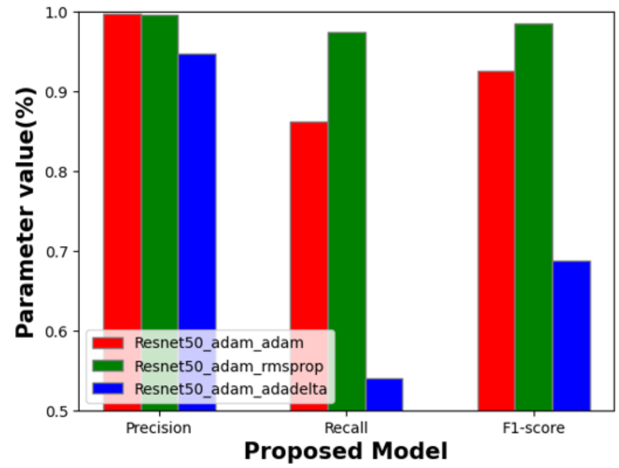
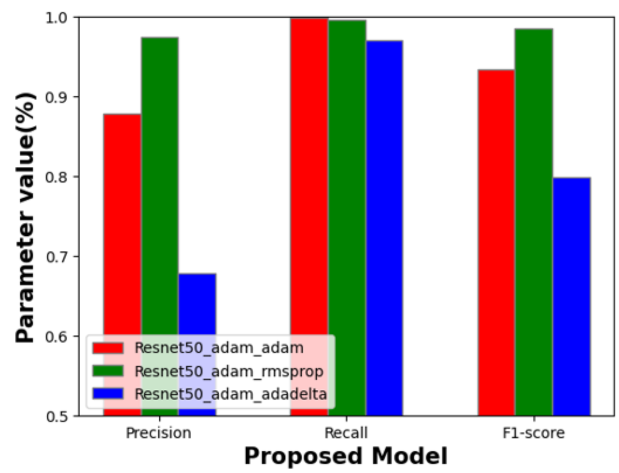


Fig. 8. Confusion Matrix of fine-tuned ResNet50 TL models



(a)



(b)

Fig. 9. Performance parameters comparison of all models for (a)Retouched (b)Real face images

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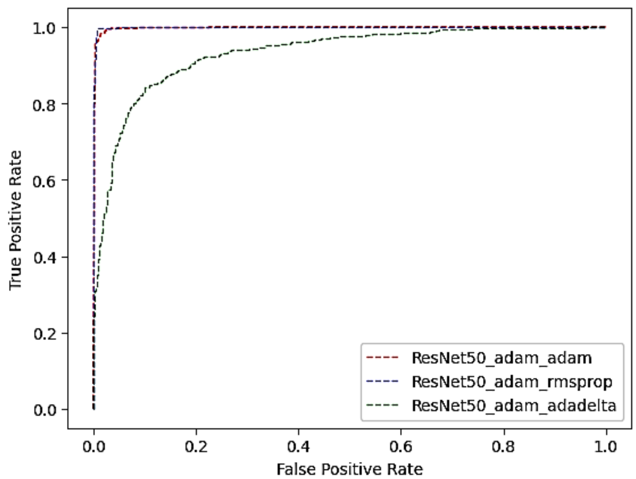

Fig. 10. ROC curve for the proposed ResNet50 TL models

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