Physical Attribute Prediction Using Deep Residual Neural Networks

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Abstract—Images taken from the Internet have been used alongside Deep Learning for many different tasks such as: smile detection, ethnicity, hair style, hair colour, gender and age prediction. After witnessing these usages, we were wondering what other attributes can be predicted from facial images available on the Internet. In this paper we tackle the prediction of physical attributes from face images using Convolutional Neural Networks trained on our dataset named FIRW. We crawled around 61,000 images from the web, then use face detection to crop faces from these real world images. We choose ResNet-50 as our base network architecture. This network was pretrained for the task of face recognition by using the VGG-Face dataset, and we finetune it by using our own dataset to predict physical attributes. Separate networks are trained for the prediction of body type, ethnicity, gender, height and weight; our models achieve the following accuracies for these tasks, respectively: 84.58%, 87.34%, 97.97%, 70.51%, 63.99%. To validate our choice of ResNet-50 as the base architecture, we also tackle the famous CelebA dataset. Our models achieve an average accuracy of 91.19% on CelebA, which is comparable to state-of-the-art approaches.

Index Terms—Machine Learning, Deep Learning, Deep Residual Neural Networks, Computer Vision, Physical Attribute Prediction

I. INTRODUCTION

People’s physical appearance plays a big role in our day-to-day interactions: it affects our first impression of others, it has an effect on whom we are attracted to, whom we find trustworthy, etc. Physical attribute prediction also has many different uses in social media, dating, recommender systems, and surveillance. Recognizing physical attributes in people is a rather easy task for humans, because by seeing different people and observing the changes in their appearance over time, our brains have been gradually trained to perform this task. Giving computers the ability to perform this task requires that exact same training. Our aim in this paper is to train models to perform this prediction using face images and Neural Networks.

Machine learning is a broad area of study, and it offers many approaches for solving a problem. The advantage of deep learning over traditional machine learning algorithms is that there is no need for hand crafted features, the Deep Neural Network itself will perform feature extraction and feature engineering.

Neural Networks have helped us perform some machine learning tasks much better than we ever could, but that is not all. Convolutional Neural Networks (CNNs), a specialized version of Deep Neural Networks, have revolutionized both machine learning and computer vision. They have shown great promise in tasks such as object recognition, object detection and object classification. It was with the appearance of AlexNet [2] and its success in the ImageNet competition [3] that gave rise to the popularity of Deep Neural Networks. AlexNet won the ImageNet challenge in 2012. After that Deep Neural Networks started to get wider, deeper and more complex. To investigate the effect of network depth on accuracy, VGG was released by Karen Simonyan et al. [4]. Rasmus Rothe et al. [5] finetuned VGG for apparent age estimation and won ChaLearn LAP competition in 2015. After the success of VGG, deeper network architectures such as Inception [6] and ResNet [28] were developed.

In this paper, we tackle the task of physical attribute prediction from face images. We created our own dataset containing 61,864 images, details for which is given in table VII. We also train 40 models to predict the attributes in the famous CelebA dataset.

Physical attribute prediction from face images is a difficult task because of the non-standard ways these photographs were taken in, difference in light conditions, angle of the pictures, distance to the camera and background noise. Our models were trained to predict body type, ethnicity, gender, height and weight on our own dataset and to predict the attributes provided in CelebA.

Our contributions in this paper are:

1) Exploring the capabilities of Deep Neural networks in performing complex tasks such as height and weight classification. Training and testing is performed on real world data without performing face alignment, which further complicates the problem.

2) Using our real world data to perform multilabel ethnicity classification, which is a more challenging task compared to the binary classification performed in related works.

3) Training a separate Residual Neural Network for each attribute in CelebA, which will be available for public
The rest of the paper is organized as follows: Section II reviews some of the related work done in recent years. Section III introduces our dataset (FIRW) and CelebA. In Section IV we present details of FIRW, the CelebA data set, network architectures and training details. Section V shows the results of our experiments. Finally, Section VI concludes the paper.

II. RELATED WORKS

Convolutional Neural Networks (CNNs) have been used for many different tasks such as regression, classification, object detection and recognition. The introduction of ImageNet and ILSVRC provided a great opportunity for researchers to compete with each other and come up with novel network architectures. Over recent years we have seen network architectures such as AlexNet, VGG, GoogleNet [7] and ResNet enter this competition and introduce new ideas with their innovations and achieve great results in the competition. In some cases these base networks were used for feature extraction, and classifiers such as SVM were used along these features to perform classification. In some other cases, finetuned versions of these networks were used for either feature extraction or to directly perform classification in an end-to-end manner. Below we will review some of the recent related works.

A. In [5] R. Rothe et al. trained a network for apparent age estimation. They gathered their training data by scraping images from IMDB and Wikipedia websites. VGG-16 network architecture was used to perform age estimation. They showed that treating the age estimation as a classification problem yields better results than treating it as a regression task. They achieved an ϵ-error of 0.264975. Dex was the winner of the ChaLearn LAP 2015 apparent age estimation challenge.

B. L. Wen et al. [8] used ASM to detect a number of fiducial points in each face image. Facial features such as CJWR (The ratio of cheekbone width to jaw width), WHR (the ratio of the cheekbone width to upper facial height) and ES (Average size of eyes) were automatically extracted. These features along with different regression models (SVR, LSE and GP) were used to predict BMI. The data was split into two sets, set 1 was used for training and set 2 for testing, and vice versa. The results were presented as mean absolute error for different age groups and also the average for each regression model. Table I shows the average results (measured by mean absolute error):

| Training Set / Test Set | Set 1 / Set 2 | Set 2 / Set 1 |
|-------------------------|--------------|--------------|
| Avg.                    | SVR | LSE | GP | SVR | LSE | GP |
| Avg.                    | 3.14 | 3.21 | 3.25 | 3.14 | 3.22 | 3.20 |

TABLE I: Results on BMI from [8].

C. In [9], Deep Neural Networks were used to infer BMI. VGG-16 and VGG-Face were used to extract features and then a regression model was trained on those features. Table II shows the Pearson r correlations on the test set for the BMI prediction task, broken down by gender. Features extracted by VGG-Face performed better than VGG-Net features.

| Model                        | Male | Female | Overall |
|------------------------------|------|--------|---------|
| Face-to-BMI - VGG-Net        | 0.58 | 0.36   | 0.47    |
| Face-to-BMI - VGG-Face       | 0.71 | 0.57   | 0.65    |

TABLE II: Results on BMI from [9].

D. Y. Lewenberg et al. [10] used FAD (Face Attributes Dataset) to predict 10 most sought-after traits. Table III shows the results of LACNN:

| Train | LACNN |
|-------|-------|
| Gender (Male) | 98.33% |
| Ethnicity (White) | 83.35% |
| Hair Colour (Dark) | 91.96% |
| Makeup | 92.87% |
| Age (Young) | 88.83% |
| Emotions (Joy) | 88.33% |
| Attractive | 78.85% |
| Humorous | 69.06% |
| Chubby | 61.38% |

TABLE III: Physical attribute prediction results from [10].

E. Ziwei Liu et al. [11] used Deep Neural Networks for predicting face attributes such as heavy makeup, hair colour, presence of eye glasses and facial hair. Their model is comprised of a pipeline of two networks: first Lnet locates the face region in an image and then Anet is used for feature extraction and prediction. It was shown that the performance increases by using different pre-training strategies for LNet and ANet. They also introduced the CelebA dataset. The results for LNets+ANet with an average accuracy of 87% are shown in Table XII.

With the availability of the CelebA dataset and the large number of samples, other researchers began their work on this data set. Below is a brief review of some of the work done on the CelebA dataset.

F. Y. Zhong et al. [12] demonstrate that using features from the middle layers of a CNN performs better than high level features of the last layers. Features from various layers (Conv2, Conv3, Conv4, Conv5, Conv6, FC1 and FC2 layers) of a modified version of FaceNet NN were used to perform classification by training Linear SVM classifiers. The overall
The reported accuracy is 89.8%. Table XII shows the results for each attribute.

G.

E. M. Hand et al. [13] took advantage of the relations between attributes. Low layers of a Deep CNN (MCNN) were shared among all attributes, while higher layers were shared between related attributes. Forty attributes were grouped together into smaller groups based on their locations in the face or on the head. Eight attribute groups were created based on the location of attributes. A fully connected layer named AUX is put on top of MCNN to allow the whole network to better learn the relations between outputs of MCNN and improve the accuracy for each attribute. After adding AUX on top of the network, the weights of the trained MCNN network are frozen, and only the AUX layer is trainable. The results for MCNN-AUX are shown in XII.

H.

X. Hou et al. [14] try to improve the quality of images generated by Variational Autoencoders. They used perceptual loss instead of pixel-by-pixel loss for this improvement. To show their model's capability in capturing semantic and conceptual information in face images, they used latent vectors from their network to perform attribute prediction on CelebA dataset. Ground truth landmark points were used to crop faces from the dataset, instead of face detectors. Latent vectors are extracted by feeding these cropped faces into the encoder network. These latent vectors are then used to train Linear SVMs to perform attribute classification. The result of their VAE-345 model with an average accuracy of 88.73% can be seen in Table XII.

I.

R. Ranjan et al. [15] used a single network to perform face detection, face alignment, pose estimation, gender recognition, smile detection, age estimation, and face recognition. A network trained for face recognition was used to initialize their CNN. To perform attribute prediction, this network branches out from different layers based on each attribute's dependency on local or global information of the face. Several different datasets were used for training: Casia [31] (for identification and gender), MORPH [32] (for age and gender), IMDB-WIKI [5] (for age and gender), Audience [33] (for age), CelebA [11] (for gender and smile), ALFW [34] (for detection, pose, and fiducials). Their work achieves 99% accuracy in gender classification and 93% in smile classification on CelebA, 93.12% and 90.83% on Faces of the World for gender and smile respectively.

J.

Y. Zhong et al. [16] used representations extracted from levels of CNNs, which were trained for face recognition, to perform attribute prediction. Binary linear SVMs were trained for each representation to perform classification. The average accuracies were 86.6% and 84.8% for CelebA and LF Kaw respectively. The results for CelebA are shown in the Table XII.

K.

R. Torfason et al. [17] use a subset of attributes to predict other attributes to show the correlation between attributes. 1, 10, 20, 30 and 39 attributes were used to predict the missing attribute(s). An average accuracy of 87.44% was achieved when using 39 attributes to predict the missing attribute. Table IV shows the results.

| Number of training attributes | 39   | 30   | 20   | 10   | 1    | Flat Prediction |
|------------------------------|-----|-----|-----|-----|-----|----------------|
| SVM                          | 87.44 | 86.76 | 85.98 | 84.23 | 80.76 | 80.04          |
| LASSO                        | 87.18 | 87.11 | 85.92 | 84.20 | 80.76 | 80.04          |

TABLE IV: Results from [17]. Different number of attributes are used in predicting the missing attribute.

They also used different combinations of handcrafted features such as LBP, SIFT, Color Histograms and Deep Features to predict attributes. Features from the fc6 layer of a finetuned network along with handcrafted features were used for prediction. The results for the fc6 ft+hc-attr combination, which achieved an average accuracy of 91%, are reported in Table XII.

L.

D. Gao et al. [19] trained a network named ATNet_GT to perform classifications. Motivated by the work done in [11] they also grouped the attributes together. Due to the small size of their network, the 40 attributes of the CelebA dataset were grouped into 3 different groups, instead of 6. Each group was trained by branching from a different depth of the network. The final results for ATNet_GT with an average accuracy of 90.18% are shown in Table XII.

M.

E. M. Hand et al. [20] propose a method called Selective Learning in order to overcome label imbalances in CelebA. Selective Learning works on batch level during training. The goal is to have a balanced number of positive and negative samples in each batch, according to the target distribution, by reducing the number of oversampled data and assigning more weight to undersampled data. The average accuracy for their method is 90.97%.
Y. Lu et al. [18] use a multi-task learning framework for attribute prediction. Instead of creating the multi-task learning network manually, they use an automatic approach. In this method, a thin version of VGG-16 network architecture, gets dynamically wider in a greedy manner during training. The authors experimented with several methods, the average accuracies of which are shown in the table below.

| Method                  | Accuracy |
|-------------------------|----------|
| VGG-16 Baseline         | 91.44    |
| Low-rank Baseline       | 90.88    |
| Baseline-thin-32        | 89.96    |
| Branch-32-1.0           | 90.74    |
| Branch-32-2.0           | 90.90    |
| Branch-64-1.0           | 91.26    |
| Joint Branch-32-2.0     | 90.4     |
| Joint Branch-64-2.0     | 91.02    |

TABLE V: Results from [18].

O. H. Han et al. [21] use Deep Multi-Task Learning for attribute estimation. The proposed method learns shared features at lower levels of the network, and category-specific features at upper levels of the network. They also introduced the LFW+ dataset in their work. They achieve an average accuracy of 93%. Detailed results are shown in table XII.

Table VI shows some of the recent papers on the CelebA dataset. Detailed results of these papers (except for [18] and [20], since results for individual attributes were not present in corresponding papers) are presented in Table XII.

### III. Datasets

There are several datasets of face images which can be used for supervised learning, such as IMDB-Wiki [5] for gender and age prediction, Apparent Age [22] for apparent age recognition, CelebA and LFWA [11] for attribute prediction. CelebA and LFWA datasets cover a broad range of attributes. After studying the work done on these datasets, we were wondering what other physical attributes can CNNs predict? Are CNNs capable of predicting more complex physical attributes such as weight and height just by looking at face images?

Since to the best of our knowledge there were no publicly available data sets to provide height and weight attributes, we scraped the Internet and gathered our own data. Our data set, FIRW (Faces In the Real World), is not limited to height and weight, we also gathered information about body type, ethnicity and gender. Subsection III-A introduces our dataset and subsection III-B is a quick overview of CelebA.

#### A. FIRW (Faces In the Real World)

Our web crawler is written in Python. We used Beautiful Soup [23] for HTML parsing and Selenium Web Driver [24] to load web pages and handle web browsing. The result is a dataset containing 61, 864 images. Since some people preferred not to share some information, an image may have all the attributes or a subset of them associated with it. For example, an image may have height and ethnicity attributes but no weight attribute. For each attribute of interest, we created a separate list to train a separate model for that attribute, so that we could benefit from all the available data. Height and weight values in the dataset are specified in range.

Table VII gives a summary of the classes in FIRW and Table VIII shows number of samples for each attribute:

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**TABLE VII: Summary of the classes in FIRW.**

| Attribute     | Classes                  |
|---------------|--------------------------|
| Body type     | Average | Curvy | Large |
| Gender        | Male | Female |
| Ethnicity     | Black | Asian | White | Hispanic/Latino | Middle Eastern | Native American |
| Height        | < 5'7 | 5'7 - 6'1 | ≥ 6'1 |
| Weight        | < 141 lbs. | 141 lbs. - 201 lbs. | ≥ 201 lbs. |

**TABLE VIII: Number of samples for each attribute.**

| Attribute     | Number of Samples |
|---------------|-------------------|
| Body Type     | 61, 258            |
| Ethnicity     | 50, 188            |
| Gender        | 61, 864            |
| Height        | 61, 663            |
| Weight        | 53, 912            |

Table IX and X show the available data based on gender and ethnicity respectively:

**Fig. 1** shows some samples from FIRW.
### TABLE IX: Number of samples based on gender.

| Attributes | Female | Male |
|------------|--------|------|
| Body Type  | 44,349 | 16,909 |
| Ethnicity  | 36,550 | 13,638 |
| Gender     | 44,790 | 17,085 |
| Height     | 44,701 | 16,962 |
| Weight     | 37,450 | 16,482 |

### TABLE X: Number of samples based in ethnicity.

| Attributes | Black | Asian | White | Indian | Hispanic/Latino | Middle Eastern | Native American |
|------------|-------|-------|-------|--------|----------------|----------------|-----------------|
| Body Type  | 2,445 | 1,801 | 41,364 | 728    | 2,720          | 383            | 460             |
| Ethnicity  | 2,459 | 1,823 | 41,636 | 729    | 2,749          | 385            | 407             |
| Gender     | 2,459 | 1,823 | 41,636 | 729    | 2,749          | 335            | 407             |
| Height     | 2,355 | 1,819 | 41,594 | 724    | 2,745          | 383            | 407             |
| Weight     | 2,169 | 1,712 | 36,111 | 683    | 2,511          | 356            | 355             |

### B. CelebA

Z. Liu et al. [11] introduced CelebA dataset. CelebA consists of 202, 599 images. Each image is annotated with 40 attributes. Table XII shows the attributes in CelebA and Fig. 2 shows samples from CelebA dataset.

### IV. Experiments

To see the performance of Residual Neworks in predicting attributes, we used ResNet-50 to perform our experiments on two datasets:

1) FIRW, introduced in III-A
2) CelebA dataset, introduced in III-B

First, we will briefly review the motivation behind Residual Networks in IV-A and subsection IV-B presents our experiments.

### A. Deep Residual Neural Networks

It was the success of AlexNet in using Deep Neural Networks to perform classification that caught the attention of researchers. Over time, the focus shifted from smaller and shallower architectures such as AlexNet, to deeper networks like VGG. To see the effect of network depth on performance and accuracy, K. Simonyan et al. [27] started stacking convolutional layers on top of each other, while other network parameters were kept fixed. This resulted in various VGG models with different number of layers, from 11 to 19. VGG models also differ from their previous counterparts in the size of receptive fields (convolutional mask) and the stride used in the network (stride is set to 1). While previous networks used larger receptive fields, such as $11 \times 11$ or $7 \times 7$, VGG models use $3 \times 3$ receptive fields throughout the whole network. Stacking several of these receptive fields on top of one another achieves the same result as using larger receptive fields (depending on the number of layers stacked together). These changes result in a stack of convolutional layers with a smaller receptive field, to have fewer parameters than their equivalent convolutional layer with a larger receptive field. The final verdict was that the increase in depth helps in achieving higher accuracy.

Unfortunately because of the vanishing/exploding gradient

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**Fig. 1:** Sample images from the dataset. (High quality images are not provided to protect user privacy).

**Fig. 2:** Samples images from CelebA dataset. (Each row represents true samples for each attribute).
problem, simply stacking layers on top of each other to gain better performance will not be an easy task. Vanishing/exploding gradients can prevent networks from converging. Several solutions such as normalized initialization were proposed to overcome this obstacle. Even by utilizing these solutions, we encounter another problem, which is the degradation problem. The degradation problem states that with the increase in network depth, accuracy might get saturated or even decrease. K. He et al. introduce a Deep Residula Learning framework to solve this issue. In Residual Learning, instead of learning a direct mapping between inputs and outputs, the network learns a residual mapping. This goal can be achieved by using shortcut connections, which are connections that skip some layers. Shortcut connections proposed in perform other prediction and classification tasks and can be used as a base network to finetune these networks using our dataset.

By using them, we will not be starting with random weight initialization and use their weights instead. We use networks and fine tune our networks. Pre-trained networks are networks that have been trained on large datasets for classification and recognition tasks. These pre-trained networks and their weights can be used as a base network to perform other prediction and classification tasks and can be finetuned using the dataset associated with the task in hand. By using them, we will not be starting with random weight initialization and use their weights instead. We use networks and weights provided by the VGG-Face implementation in Keras. This network was trained for face recognition on the VGG-Face dataset.

Subsections present the experiment details on FIRW and CelebA, respectively.

1) FIRW: Predicting features based on profile picture is a daunting task because of the different conditions profile pictures were taken in, bad lighting conditions, occlusions, distance to the camera, surrounding environment and other factors. After data gathering and preparation, we performed face detection on images and cropped the face from the image. We used an off-the-shelf face recognition and manipulation library based on dlib and Deep Learning for face detection. When a face was detected in an image, we added padding to left, right and upper borders and to the bottom part of the detected face whenever possible. If these paddings were not possible, we tried padding with smaller values for each border of the face bounding box. These cropped faces are then saved to be used during training, validation and testing. These cropped face images may have different sizes, so all images are resized before being fed to the network, by specifying a target size of in Keras. We use data augmentation during the training phase. During validation and test phases, images are only resized and rescaled before going through the models for prediction.

We want to train our models on real world data, so we did not perform any face alignment on the images before feeding them to our models. This results in a more challenging classification task compared to the CelebA dataset. We also believe that since images on CelebA are from celebrities, they are taken in better conditions compared to images in FIRW, which further complicates the classification task.

For each label, a separate ResNet-50 network was trained. The top parts of these networks are replaced by a Flatten layer and a Dense Layer with several Softmax nodes, equal to the number of classes in the task at hand, for example 3 nodes for height classification and 7 for ethnicity classification. We finetune these networks using our dataset.

Before starting the training process, of the data for each label was set aside to be used for testing. For validation, of training data was used. For each attribute a separate model was trained.

We chose categorical crossentropy as the loss function and accuracy as the metric to train the networks on our own dataset. Our choice of optimizer is the Adam optimizer with the default configuration.

Each network was trained for 100 epochs with a batch size of 32. Keras callbacks were used to save the model with the best performance on the validation data, and then these saved models were used to perform predictions on the test data.

2) CelebA: As mentioned in there are images in CelebA dataset each annotated with 40 attributes. Train, validation and test sets were created based on the specified values in CelebA webpage. Aligned images available in the webpage are used for training, validation and testing. Data augmentation is used during the training to prevent the networks from overfitting. For validation and test phases, images are resized and rescaled. Input size for all networks is .

For each attribute, a separate model was trained. Once again we used ResNet-50 architecture provided in the Keras VGG-Face library, and finetuned it using CelebA dataset. The top parts of the networks are replaced by a Flatten layer and a Dense layer with a single Sigmoid node. Training configuration is as follows: binary crossentropy as loss function, Adam optimizer with the default configuration as the optimizer and accuracy as the metric. Due to the bigger size of CelebA dataset we trained each model for 50 epochs with a batch size of 32. Keras callbacks were used to save the model with the
best performance on the validation data, and these models were used to perform prediction on the test data.

All the experiments, both on FIRW and CelebA, were performed on a system running Ubuntu 16.04 with an Nvidia GTX 1080Ti GPU.

V. RESULTS

A. FIRW

We have trained separate ResNet-50 models for each attribute in our dataset. Table XI shows the results of these models:

| Attributes   | Accuracy (%) |
|--------------|--------------|
| Body Type    | 84.58        |
| Ethnicity    | 87.34        |
| Gender       | 97.97        |
| Height       | 70.51        |
| Weight       | 63.99        |

**TABLE XI: Results on FIRW.**

Fig. 3 shows the training history of each ResNet-50 model based on loss per epoch.

![Fig. 3: Loss Histories of ResNet-50 models trained on FIRW.](image)

Except for the gender classification problem, which is a binary classification problem, all other tasks are multiclass classifications. Gender classification is popular among researchers and we have reviewed several related works devoted to this task. Even though our dataset is smaller than the datasets used in related works, ResNet-50 still manages to achieve 97.97% accuracy.

We performed a multiclass prediction in body type classification and our trained models achieve an accuracy of 84.58%. Considering that our model is performing multiclass classification and with fewer training samples, our model performs well in this classification task. The availability of more training data can further improve the result.

Height and weight prediction from face images are challenging problems, especially considering that the labels for each image in FIRW were provided by users and that we did not perform any face alignment on images. Regarding these tasks, our ResNet-50 models achieve good results, 70.51% and 63.99% in height and weight prediction, respectively. We believe that with the availability of more training data with more accurate labels for height and weight, it would be possible to achieve better results.

In ethnicity prediction, ResNet-50 achieves an accuracy of 86.12%. Ethnicity prediction is a multiclass problem in our dataset and we achieve a higher accuracy than the binary classification performed in [10].

B. CelebA

For each attribute in CelebA, a separate ResNet-50 model was trained. Table XII shows the results we achieved for each attribute. The average accuracy of our models is 91.19%.

Our models perform classification in an end-to-end manner. Final representations learned by each ResNet-50 model are used by the network to predict the target. Our simple end-to-end networks only use the aligned & cropped images provided on the CelebA web page. Except for data augmentation (used only on training set during training), resizing and rescaling, we did not perform any other preprocessing on images.

Table XII shows our results and that of related works.

VI. CONCLUSION

Our purpose in this work was to investigate what physical attributes Deep Neural Networks can predict, other than those investigated by the research community in datasets such as CelebA and LFWA. Predicting height and weight seem to be more challenging problems. Our results showed that ResNet-50 performs well in classifying these attributes. We achieved higher accuracies for predicting gender, body type and ethnicity compared to the more demanding tasks of height and weight classification. The availability of more training data along with having more accurate labels for height and weight is crucial in further exploring this task.

We also used ResNet-50 in classifying CelebA attributes. Our models achieve good accuracies and are comparable to state-of-the-art approaches.
We plan to train a multi-task learning version of ResNet-50 in future to see how its performance compares with the works we have reviewed here and investigate how big of a role network depth can play in a multi-task framework.

| Table XII: Detailed results of papers in Table VI (except for [18] and [20]) and our results on CelebA dataset. |
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