Multi-Attributed Face Synthesis for One-Shot Deep Face Recognition

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Abstract. Nothing is more unique and crucial to an individual's identity than their face. With the rapid improvement in computational power and memory space and recent specializations in deep learning models, images are becoming more essential than ever for pattern recognition. Several deep face recognition models have recently been proposed to train deep networks on enormously big public datasets like MSCeleb-1M [8] and VG-GFace2 [5], successfully achieving sophisticated performance on mainstream applications. It is particularly challenging to gather an adequate dataset that allows strict command over the desired properties, such as hair color, skin tone, makeup, age alteration, etc. As a solution, we devised a one-shot face recognition system that utilizes synthetic data to recognize a face even if the facial attributes are altered. This work proposes and investigates the feasibility of creating a multi-attributed artificial face dataset from a one-shot image to train the deep face recognition model. This research seeks to demonstrate how the image synthesis capability of the deep learning methods can construct a face dataset with multiple critical attributes for a recognition process to enable and enhance efficient face recognition. In this study, the ideal deep learning features will be combined with a conventional one-shot learning framework. We did experiments for our proposed model on the LFW and multi-attributed synthetic data; these experiments highlighted some insights that can be helpful in the future for one-shot face recognition.

Keywords: Deep Learning · Computer Vision · One-Shot Face recognition · Siamese Networks · Image Classification

1 Introduction

The practical significance and great theoretical interest from cognitive scientists have been precisely the reason why facial recognition systems have been the target of such great curiosity and attention for the past few decades, making it impossible to disregard their importance as a non-contact verification method. It has expanded its usage in a variety of digital media, including video indexing,

video analytics, and security departments. Face identification and face verification are often two sub-tasks that make up face recognition. Three phases are involved in each task: face detection, feature extraction, and classification.

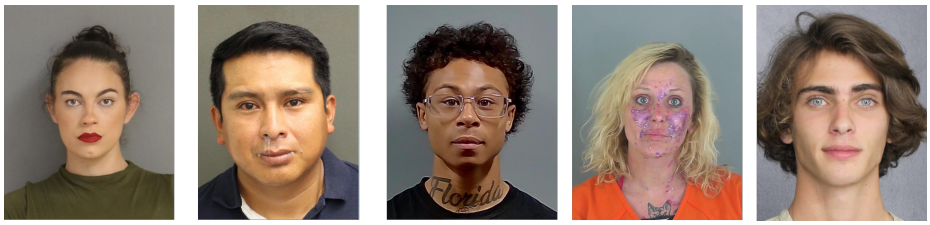

Fig. 1. Examples of Face images in the Smoking Gun's mug shot collection [24]

It is pretty daunting to build a face recognizer, especially with a small dataset. Even though there has been a significant advancement in face detection, problems still prevent the technology from being as accurate as a human. Early research created shallow models with basic facial features, while contemporary face recognition methods are considerably improved and powered by deep CNNs.

A deep convolutional network promises to attain greater accuracy using a straightforward classification approach, but it requires a lot of memory to train. One of the significant challenges is the very volatile and unbalanced amount of training data, where certain classes in the dataset may have a lot of photos. In contrast, others may have relatively few, affecting the quality of the results severely. The latest expansion of methods based on deep learning, including generative adversarial networks (GANs) [10,15], can solve the problem of varying dataset sizes by producing realistic facial images while accepting appropriate control parameters. Additionally, there are other issues, such as various humans having remarkably similar appearances and the fact that the faces of the same person may look very different due to lighting, position, and age variations. Although other deep network approaches can also handle variations in pose, lighting, and facial expressions, their requirement of a significant quantity of annotated data to train the system will always be a considerable drawback. Since GANs continue to be successful in producing artificial data for computer vision tasks [26], a new field of biometric research is beginning to explore how synthetic face images might be produced and utilized to train FR models. Face attribute adjustment is possible with the encoder-decoder architecture by decoding the encoder's latent space representation based on the given attributes. Compared to other synthetic data generation challenges, this research challenges assigning an identity to the synthetically generated faces to render them usable while ensuring variations within identity.

The fundamental pillar of this research is developing a hybrid approach for one-shot face recognition that, while sustaining the true identity, allows for an accurate modification of 14 various multi-attributes of any specified face. One

can utilize our strategy to increase the variety of single faces in a dataset and strengthen face recognition algorithms. This one-shot-based deep face recognition (OS-DFR) method is distinct from typical face synthesizing methods and seeks to learn the synthetic features without giving the original characteristics. Motivated by the ATTGAN [10]'s success in generating realistic facial attributes, OS-DFR integrates the two tasks, one-shot synthetic face generation and face recognition. According to the statistical link between synthetic characteristics and face identification, this method successfully achieves the aim of deep face recognition. It is crucial when only one sample is available for a particular person. Face images generated from the "MugShots" for evaluating the performance of a recognition job and benchmarking are soon to be proposed as our dataset that includes unconstrained face images. The key contributions to this work are:

- We provided a technique for multi-attributed face synthesis for one-shot face recognition, employing synthetic data to replace augmentation approaches for development of realistic and feature enriched images of a person. To the best of our knowledge, this is the first instance of one-shot facial recognition using multi-attributed synthetic data.
- We empirically verified the effectiveness of the approach for multi-attributed synthetic data for face recognition in the real world.

The remainder of the paper is organized as follows: In Section 2, prior studies on the creation of synthetic data, one-shot face recognition, and the use of synthetic data for deep neural network training are reviewed. A thorough explanation of the suggested technique, including an explanation of the network and the created synthetic dataset, is given in Section 3. The outcomes of our methodology are presented in Section 4, along with experimental settings and details. The ideas and algorithms created in this study are summarized in Section 5, which is then followed by a brief discussion of prospective future work.

2 Related Work

The majority of this section covers the current status of one-shot learning in the literature. The most recent low-shot learning work [23], [29] also garners a lot of interest in the broader image recognition scenario. The authors divided the ImageNet data2 into the base and low-shot (referred to as new in [23]) classes, and the goal is to recognize images from both the base and low-shot classes. Their benchmark job is quite similar to one-shot face recognition but in the broader image recognition domain. Since the domain is really distinct from ours, their approach is pretty different from ours.

Overall, one-shot learning remains an unresolved issue. A natural source of information is obtained from new data in numerous ways through "data manufacturing" [2]. There have been several works that tackle this issue in recent years. With little data, transfer learning is a viable method that encourages the usage of deep CNNs in several disciplines. [13, 17] shows that by leveraging

information from similar tasks with more enormous datasets, CNN-based transfer learning can produce superior classification results in our work with limited datasets (target domain). In their research [7, 9], the authors proposed CNN-based novel frameworks. The primary focus of their framework was to address an issue in one-shot learning by constructing generative models to build samples to solve the underrepresented classes' problems.

Bromley et al. [4] suggested the idea of Siamese Networks for the signature verification problem, and [16] demonstrated the application of deep convolutional Siamese networks for one-shot tasks with exceptional accuracy. The approach of deep attribute encoding of faces for one-shot face recognition was proposed in another work [14]. They honed a deep CNN for face recognition using particular features of human faces, such as the face's shape, hair, and gender. One-shot face recognition using mix method of Siamese neural network and deep feature encoding was proposed in [6]. [19] demonstrated the application of deep convolutional Siamese networks for one-shot tasks with substantial accuracy. By relying on a similarity function [8] [9] based on pairs of images, this network seeks to build a deep relevant feature representation. In fact, the neural network learns to distinguish between two inputs associated with distinct classes rather than explicitly learning to categorize its input. Moreover, this network focuses on learning embeddings for the similar classes samples and we can learn semantic similarities. In order to construct a trustworthy face recognition system, the method we propose in this study integrates the concept of Deep Convolutional Siamese Networks and synthetic data generation.

The use of synthetic data in face recognition has gained popularity in recent times. The behavior of face image quality generated by [15] has been examined in [31]. Furthermore, Shen et al. [22] concluded that synthetic face images could deceive humans. The excellent quality images that GANs and their various variations [15, 19, 25, 27] can create have attracted more and more attention. To address the insufficient dataset, images generated by MorphGan [20] can severely assist with their data augmentation. There is a spike and improvement in performance by up to 9% by merely augmenting the faces with new expressions and poses – consequently addressing the issue of limited datasets. It is, however, limited to the head and expression of the face image. Three methods based on meta-learning, disentangling, and filtering were described by Zhai et al. [30] to lessen the modal difference between synthetic and real data. Then, they trained face recognition model using a hybrid of a synthetic and real dataset. Recent work proposed in the field of face recognition using synthetic data [3] has come to light, where the authors examine the viability of training face recognition algorithms using a synthetically created face dataset and raise a variety of privacy, legal, and ethical issues in relation to the gathering, use, and sharing of real biometric data.

Face recognition is abstracted into two phases. Extraction of facial features is the first phase, and estimation of the person's identification from the extracted face features is the second. Face recognition has recently paced due to the rapid development of deep convolutional neural networks and put great emphasis on

learning a clear facial feature space where faces of the same person are close to each other and faces of different people are far apart. This representative technique aimed to learn the discriminative face representations directly from the original picture space. In limited circumstances, face recognition performance has significantly increased. In order to obtain the SOTA accuracy of 97.35% , DeepFace { [23] introduced classification loss and three-dimensional normalized alignment processing in 2014 on the LFW dataset [12]. FaceNet [21] achieved 99.63% on LFW using the triplet loss function in 2015. However, there are significant problems for the use of the face recognition system in genuine unconstrained scenarios [18]. One of the most significant issues is that the quality of the input facial image might impact the system's accuracy. Even ArcFace, which is extremely strong, can only attain an accuracy of 63.22% on the RealWorld Masked Face Recognition Dataset (RMFRD) [28]. This result is based on [11], which was obtained when ArcFace was not retrained on this dataset. As a result, how to improve facial recognition in unconstrained real-world settings is now the most pressing topic.

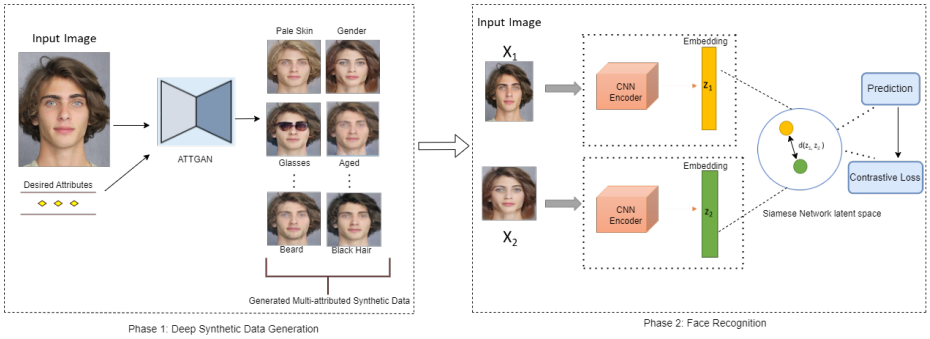

Fig. 2. Overview of the proposed approach. On the left, ATTGAN [10] is used to create synthetic face dataset from the one-shot image with multi attributes. The identity label is assigned to each generated synthetic images. The learning strategy is shown on the right, where the face recognition will be trained on the synthetic dataset using Contrastive loss. The trained model will be used for better face recognition.

3 ONE-SHOT SYNTHETIC FACE RECOGNITION

Deep learning algorithms requiring hundreds or thousands of images to bear effective results have always been one of their vast drawbacks. This section describes the method for creating and using synthetic face images to train a Face recognition model that accounts for the various subject variables, such as hair color, age, mustache etc. Two distinct phases will comprise the One-Shot based synthetic face recognition. Overall architecture can be shown in Figure. 2. In

this section, we outline these processes as well as our suggested technique for one-shot face recognition using synthetic data.

3.1 Deep Synthetic Data Generation

The primary objective of our generative model is to provide valuable auxiliary data for the one-shot classes in order to facilitate one-shot deep face recognition. We can span the feature space for these classes by doing this. We initially generated multi-attributed synthetic face data from one mugshot face image. This step utilizes an Attribute GAN (AttGAN) [10] due its high reliability in altering attributes to the generated image. The attribute classification constraint, the reconstruction loss, and the adversarial loss are combined to generate a unified AttGAN. With the knowledge of the omitted characteristics preserved, this enables alteration of the desired attributes. Overall, the encoder and decoder network's objectives are as follows:

$$\min_{G_{enc},G_{dec}} L_{enc,dec} = \lambda_1 L_{rec} + \lambda_{2cls_g} + L_{adv_g} \tag{1}$$

These hyper parameters λ_1, λ_2 and λ_3 are used to balance the losses.

The code for AttGAN implemented in machine learning framework Tensorflow [1] is publicly accessible at `https://github.com/LynnHo/AttGAN-Tensorflow`. For additional information about implementation, please visit the website. We create our synthetic face dataset by creating 14 images for each individual from a mugshot one-shot face image, as depicted in Figure. 3. We have generated 14 images with multiple attributes from just one shot of the person. Another important characteristic of AttGAN is its direct applicability for attribute intensity control. Although AttGAN is taught using binary attribute values (0/1), its basic principle may still be used when testing with continuous attribute values. So, additionally, we produced nine photos for each feature with varying intensities, and we obtained more than 50+ synthetic face images with actual attributes for a single person from a single shot image. With a continuous input value between [0, 1], as seen in Fig. 4, the progressive shift of the generated images is natural and smooth.

3.2 Face Recognition

The convolutional Siamese network utilized in this research is constructed to learn properties of the input images independent of previous domain knowledge using very few samples from a given distribution. One-shot learning can be accomplished using a Siamese network design [6]. The twin networks' shared weights, which need fewer training parameters and reduce the possibility of overfitting, were another factor in the decision to utilize this model. For the investigation, a small labeled support set of classes used for train, test and validation.

In addition to this, several approaches may be investigated while taking into account the loss functions. One that is highly popular uses the softmax loss, whose goal is to increase the probability associated with the correct class. This

straightforward strategy, however, has poor feature derivation performance for the face recognition task. To acquire highly discriminative deep features for face recognition, Euclidean-distance-based loss is preferred because of the maximization of inter-class variance and minimization of intra-class variance. It is the main reason we choose Contrastive loss function shown in eq. 2

$$L = (1-y)\,\frac{1}{2}\,(D_w)^2 + (Y)\,\frac{1}{2}\,\{\max(0, n - D_w)\}^2 \tag{2}$$

where $m > 0$ represents margin, D_w is the distance function between two samples, and Y stands for the output label. The Siamese network produces a distance value. We measured the distance between two image's feature embeddings using the Euclidean distance.

The core idea in this phase is to learn discriminative facial characteristics with a wide gap across classes throughout the training phase. A neural network (with a certain structure) is trained for this phase under a specified loss function, which controls how the network's parameters vary. After getting optimal feature representation from input images, it can be used to perform face verification. The significant conclusions will be how helpful the first step in producing synthetic face characteristics will be for computer vision in the future. The testing data is supplied to the Siamese Network during the testing phase in order to extract facial features, which are then utilized to compute the euclidean distance to conduct face verification and identification. A benefit of this strategy is that by creating synthetic data, the Siamese Network can distinguish between several people who have multiple attributes and can become more resilient to high-level feature fluctuation. The time- and space-complexity of the network can be a drawback.

4 Evaluation Experiments

We carried out assessment studies utilizing two publicly available datasets to assess the efficacy of the proposed OS-DFR approach.

4.1 Datasets

First dataset mugshots (citation: [24] for the initial experiments Due to the scant amount of annotation available for these images, we used some of the dataset's image samples to train the ATTGAN. Since a mugshot is a photographic portrait of a person from the shoulders up and we have just one image of each person, there is a good chance that ATTGAN hasn't been trained on it yet, which is why we chose these mugshot face images. In all of our experiments, 14 attributes that have a significant visual impact are used. These are "Bags Under Eyes," "Bald," "Bangs," "Black Hair," "Blond Hair," "Brown Hair," "Bushy Eyebrows," "Eyeglasses," "Gender," "Mouth Open," "Mustache," "No Beard," "Pale Skin," and "Age," which cover the majority of the attributes used in the previous works depicted in Figure. 3.

Moreover, we have also used the attribute intensity control characteristic of ATTGAN and generated multiple synthetic images for single attributes shown in Figure. 4.

Fig. 3. Editing results of the Facial attributes on the custom one-shot dataset: the first is the original image, and the rest 14 images result from multi-attributed synthetic face images generated by ATTGAN [10]

Fig. 4. Illustration of pale skin with several degrees of intensity.

4.2 Network Settings

The network was implemented using PyTorch. On a batch size of 16, we trained networks for 30 epochs. Rmsprop was used as the optimizer, with a learning rate of 0.001. The NVIDIA Titan Xp with 12GB of RAM was used to train and test the system. Two convolutional layers with kernel sizes of 11x11 and 7x7 make up the Siamese network. 2D max pooling immediately follows each layer.

4.3 Results

The network showed poor performance in our initial tests while trying to deal with 5, 10 and 15-way one-shot recognition. After epochs and network layer settings we achieve the the highest accuracy of 78% as shown in fig 7. We tried our experiments with the following settings: Table 1 shows the appropriate resultant

performances. It is clear from that table that the verification work becomes more challenging the more dissimilar the training and testing sets are.

Table 1. Performance based on the characteristics of the training and the testing set

Experiment Data Set	Train accuracy		Val accuracy		Test accuracy	
	LFW	Combined	Synthetic	LFW	Synthetic	Combined
5-Way Shot	98%	93%	65%	73%	65.66%	78%
10-Way Shot	99%	94%	67%	77%	68%	72.50%
15-Way Shot	96.50%	91%	68%	75%	62.29%	66%

There are some serious takeaways from the results. It can be seen that the performance of the model is strongly dependent on how different the images are in both the training and validation sets. If we take an example of just identifying the person from the face that is already present in the database, then the trained model on multi-attributed synthetic data would be enough to support that case.

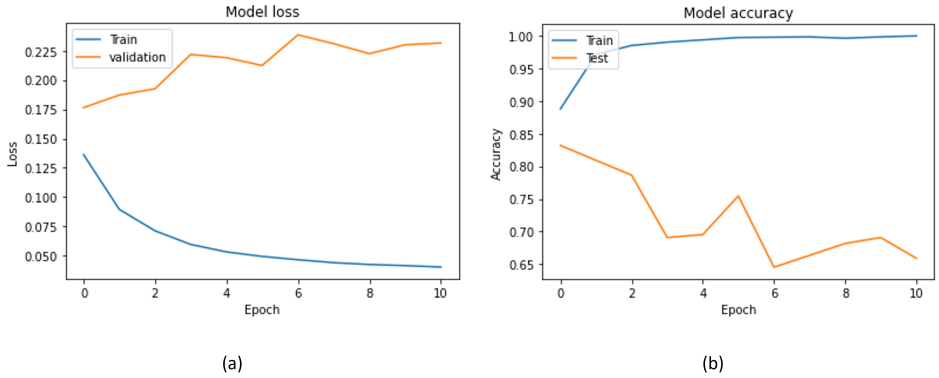

Fig. 5. 10-Way One shot on LFW & Synthetic Test Data (a) Model Loss (b) Model Accuracy

It is demonstrated in fig 6 as an ablations study the accuracy of 10-way shot when the model was solely testes on synthetic dataset.

This particular Siamese network was chosen since it is a basic net that was trained using a contrastive loss with feature normalization at the end and no final linear layer following the computation of feature distance.

5 Limitations and Discussion

Face data augmentation is the most complicated of the other data augmentation techniques. Several techniques, including pose transfer, hairdo transfer,

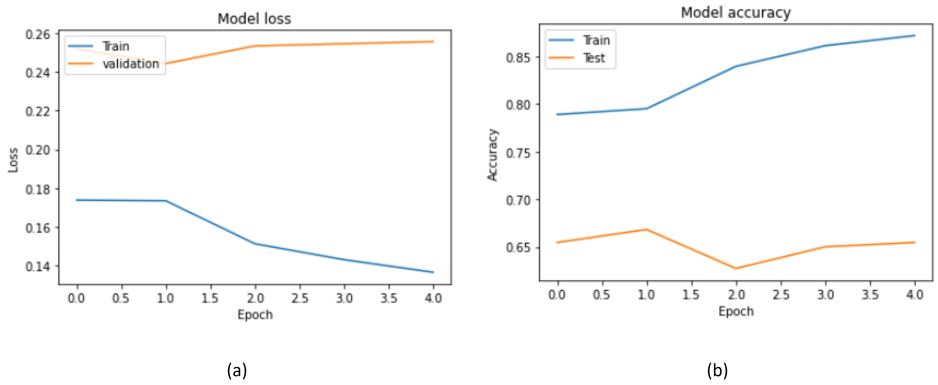

Fig. 6. 10-Way One shot on Synthetic Test Data

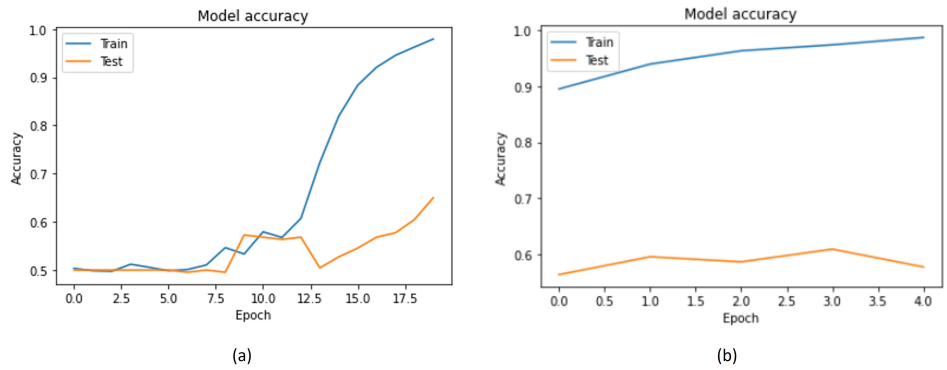

Fig. 7. Accuracy of 5-Way One shot on (a) Model Loss on Combined Data (b) Model Accuracy on Combined Data

expression transfer, cosmetics transfer, and age transfer, have been suggested to change the appearance of an actual face image. In the meantime, the simulated virtual faces can also be improved to match the realism of the genuine ones. We proposed a one-shot synthetic data generation for deep face recognition in this work. The model is based on the image generation capability of GANs, whereby we try to use the data variance of the base set to synthesize more efficient augmented data for one-shot face recognition. The idea was built to aid researchers in making efficient facial recognition technology and minimizing the impact of the obstacle of limited data. Our solution can also identify a person who keeps changing their facial appearance. Our architecture shares the same constraints and is based on synthetic image generation with multiple attributes. Any new findings that enhance the image generation capability with multiple attributes should directly be applicable to our technique. Our approach, irrespective of the current limitations, has shed some light that, with the help of computer graph-

ics, will allow for efficient training and recognition of facial models from just one-shot face images. Future research plan is to use more efficient GAN network for generating high quality multi-attributed synthetic face images and train a deeper face recognition system.

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