Adult2Child Age Regression Using CycleGANs

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ABSTRACT

This work displays the capabilities of the Cycle-Consistent Generative Adversarial Network (CycleGAN) in adult to child age regression. Adult to child age regression is motivated by stopping the spread of child trafficking. The CycleGAN demonstrates proficiency in learning high level features and performs better in age classification.

CCS CONCEPTS

• **Computing methodologies → Neural networks**; *Image processing*;

KEYWORDS

Age Regression, Cycle-Consistency, CycleGAN

1 INTRODUCTION

There is a large body of work on changing the apparent age of people in photographs, motivated by applications such as entertainment and missing persons searches[Y. Fu and Huang 2010]. The PyramidGAN is the most recent in the state-of-the-art because it is capable of changing hairline and hairstyle[H Yang and Jain 2018]. However, the PyramidGAN only works for age progression. For age regression, we introduce using the CycleGAN architecture.

The CycleGAN was introduced in 2018[J. Zhu and Efros 2018]. The CycleGAN uses cycle-consistent loss. Cycle-consistent loss attempts to create a one-to-one function between a source feature space and a target feature space. In this instance, cycle-consistency works by taking the adult input image, converting the adult face to child-like, and then reverting the child-like face back to an adult face. The difference between the twice converted image and the input image is measured by taking a pixel-wise L1 norm. Through back-propagation, the network then makes changes to minimize the distance between the two images.

2 METHOD

The training dataset was created by programatically taking images of children between the ages of 4 to 10 from other research datasets, removing images with low quality or occluded faces. The backgrounds of the images were then removed and the faces cropped. The training set consisted of 499, 233, 271, and 566 images from the IMDB Face, CAFE, UTK Face, and Adience Bechmark Datasets respectively. The training set also consisted of 874 and 1328 images age 60 and above from the UTK Face and IMDB Face dataset.

The testing dataset was created by taking 1574 images of people over the age of 60 from the Cross-Age Celebrity Dataset. Those images were normalized using the same process used on the training dataset. The CycleGAN trained for 102 epochs using a learning rate of 0.0002. The trained model was then applied to the testing dataset, and the CycleGAN's results were compared to Snapchat's Baby Filter as shown in Figure 1.

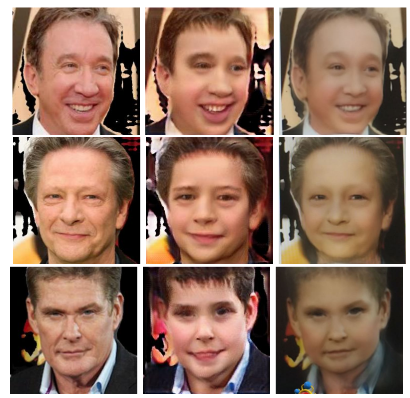

Figure 1: Results on adult2child regression

57 outputs for CycleGAN and Snapchat were inputted to Amazon Web Service's Face Analysis Tool. The tool attempts to estimate the true age of the person in the image by outputting an age range: (min age, max age). Table 1 below summarizes these results.

Method	Min μ	Min σ	Max μ	Max σ
CycleGAN	9.12	3.49	15.32	5.73
Snapchat	9.01	4.78	15.42	7.54

Table 1: Average (μ) and standard deviation (σ) on testing set

3 DISCUSSION

Qualitatively, as Figure 1 shows, the CycleGAN restores the hairline as well as keeps a more realistic skin color. In addition, the CycleGAN rounds the face to make it more childlike. Quantitatively, the mean maximum and minimum age ranges for CycleGAN and Snapchat were close, varying in only a tenth of a year. The mean age for both methods was also within the target age of 4 to 10. However, the standard deviations show that the CycleGAN regressed the inputted images more consistently. CycleGAN produced a standard deviation that was 1.29 less than Snapchat's minimum standard deviation and a maximum standard deviation that was 1.81 lower than Snapchat's. The introduction of cycle-consistency opens new applications for GANs, such as law enforcement honeypots that can catch child traffickers.

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