



شبكة المعلومات الجامعية
التوثيق الإلكتروني والميكروفيلم

بسم الله الرحمن الرحيم



MONA MAGHRABY



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شبكة المعلومات الجامعية التوثيق الإلكتروني والميكروفيلم



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جامعة عين شمس التوثيق الإلكتروني والميكروفيلم

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MONA MAGHRABY



GANKIN: GENERATING KIN FACES USING DISENTANGLED GAN

By

Fady Saad Said Ghatas

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
Computer Engineering

FACULTY OF ENGINEERING , CAIRO UNIVERSITY
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Title of Thesis:

GANKIN: Generating Kin faces using disentangled GAN

Key Words:

GAN; Kin Generation; GAN Modularity; CNN;

Summary:

Kin image generation from parents' images is a high-level prediction and generation problem. This study presents a new method to predict and generate a kin face using parents' faces, i.e. Tri-subject prediction or two-to-one prediction. We use a pipeline of unconditional GANs to overcome mode-collapse in conditional GANs. The model achieves promising results compared to the state-of-the-art, our model achieves a retrieval score of 0.19 versus 0.107 by the state-of-the-art. Our model is validated against SelfKin kinship verification model and achieved an accuracy of (63 % \pm 7 %).

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute. I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

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List of Symbols and Abbreviations

AI	Artificial Intelligence
CIFAR	Canadian Institute For Advanced Research
CNN	Convolutional neural network
DeepID	Deep Identity Network
FIW	Families in the Wild
GAN	Generative Adversarial Network
HOG	Histogram of Oriented Gradients
IMDB	Internet Movie Database
KNN	K-Nearest Neighbor
LBP	Local Binary Patterns
NN	Neural Network
MNIST	Mixed National Institute of Standards and Technology
PGGAN	Progressive Growth of Generative Adversarial Network
RFIW	Recognizing Families in the Wild
SBM	Symmetric Bilinear Model
SIFT	Scale-Invariant Feature Transform
SVM	Support Vector Machine
VGGNet	Visual Geometry Group Network
WGAN	Wasserstein Generative Adversarial Network