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Masked face recognition using single shot learning

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Abstract: In this study, we used deep learning techniques to recognize the face using only a single image instance for training. Model can also recognize faces under masks and other occlusions. We used a Siamese neural network to implement one shot learning to overcome the problem of data availability.

Keywords: One Shot Learning, Siamese Neural Network, Generative Adversarial Networks, Face Recognition.

INTRODUCTION

A facial recognition system is a technology capable of matching a human face from a digital image or a video frame against a database of faces, typically employed to authenticate users through ID verification services, works by pinpointing and measuring facial features from a given image. Facial recognition systems are employed throughout the world today by governments and private companies. Their effectiveness varies, and some systems have previously been scrapped because of their ineffectiveness. The use of facial recognition systems has also raised controversy, with claims that the systems violate citizens' privacy, commonly make incorrect identifications, encourage gender norms and racial profiling, and do not protect important biometric data.

Face recognition requires a tremendous amount of data to achieve decent performance. To overcome this problem we implemented our system to learn to recognize faces using only a single image instance, our system is so robust that it can recognize any person wearing a mask.

LITERATURE REVIEW

S No.	Name	Year	Author	Method	Review
1	FaceNet: A unified embedding for face recognition and clustering	2015	F. Schroff, D. Kalenichenko and J. Philbin	Deep Learning	Mapping from face images to a compact Euclidean space where distances directly correspond to a measure of face similarity.
2	Generative Adversarial Networks	2014	Ian J. Goodfellow, Jean Pouget-Abadie, eds.	Adversarial Learning	Generative model which learn via adversarial learning
3	DeepFace: Closing the Gap to Human-Level Performance in Face Verification	2014	Y. Taigman, M. Yang, M. Ranzato and L. Wolf	Deep Learning	A face recognition method that used 3D approach to increase accuracy and robustness
4	Deep Residual Learning for Image Recognition	2015	Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun	Deep Learning	Residual learning framework to ease the training of networks that are substantially deeper than those used previously
5	ElasticFace: Elastic Margin Loss for Deep Face Recognition	2021	Fadi Boutros, Naser Damer, Florian Kirchbuchner, Arjan Kuijper	Deep Learning	elastic penalty margin loss (ElasticFace) that allows flexibility in the push for class separability

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6	Deep Polynomial Neural Networks	2020	Grigorios Chrysos, Stylianos Moschoglou, Giorgos Bouritsas, eds	Deep Learning	proposed Π -Nets, a new class of function approximators based on polynomial expansions.

PROPOSED METHODOLOGY

In this covid era, we present a method to recognize the faces under masks. We only use a single image instance of a person to train the model as we can't possibly have multiple masked images of a given person. We implemented a siamese neural network to achieve the same. The model takes a training input image and puts a mask on a person's face using a Generative Adversarial Network(GAN), this image and unmasked image is then stored in a database where the siamese network searches when a testing instance is presented. An instance is matched in both masked database and unmasked database, the person with lowest distance from test instance is given as the result output.

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