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FACE RECOGNITION IN LOW RESOLUTION USING CONVOLUTIONAL NEURAL NETWORKS

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***Abstract*— Fine-Grained Image Processing (FGIP) is a computer vision task which focuses on identifying or distinguishing objects or species from subordinate categories such as models of cars, fish species categories. The high similarity among the sub-categories of an object or species gives a small inter- class variations. However, species belonging to the same category may look differently i.e, gives a large intra-class variations when the scale, pose or orientation differs. So, FGIP is considered as a challenging task in the computer vision domain. Recognizing or identifying a face from a video frame that holds facial images in different head orientation, lighting conditions and facial expressions can be considered as a FGIP task. In this project, Convolutional Neural Networks and its variations have been employed to study the efficiency of the system in identifying and recognizing human face from video frames collected from a CCTV system.**

Index Terms **CNN, Fine-Grained Image Processing, Super-resolution, low-resolution**

I. Introduction

The main concept of this project is to improve or enhance the quality and understanding. of very low resolution facial images by increasing its resolution by enhancing. the pixels of the image with low. resolution. In this project, we use the concept of fine-grained. image processing, Facial recognition, super resolution and convolutional neural network. method to improve the quality of the low resolution. image. The Fine-grained image processing mainly. focuses on classifying between hard-to-distinguish objects such as wild. animals, birds or a person in crowd and identifying. the required face. The task of facial recognition. process is to match a human face from the database which contains a digital. image or a viedo frame. The process of the super resolution. results in obtaining a high resolution. image from a low resolution image which is given to be processed. Convolutional neural networks (CNN). which can be defined as of deep learning neural networks. And simply it can be defined. as a machine learning algorithm. that takes an input image and assign importance to various objects in the image. and can differentiate. one object from the other. This project can be mainly used for security purpose. By using this. the image of a person can be identified easily even though. the person is in a large crowd. It will useful in police department. for identifying culprits or wanted persons. as the face recorded with the face stored. in the data base. It can also be used in domestic usage for enhancing. the old images, which are important. For the fine-grained. images, researchers have acknowledged that the combined features. of a global object and a local part yield a better classification. performance. This leads the researchers to treat the overall appearance. of the objects and their parts separately. in training CNNs. Unfortunately, fitted from existing fine-grained. image recognition algorithms. The problem is how to effectively .classify the sub-level objects with non-separable object-parts. The food classification. belongs to this problems.

II. LITERATURE SURVEY

F Yeomans et al. [1] included the prior extracted face features as measures of fit of the SR result, and performs SR from both reconstruction and recognition perspectives. Yang et al. [2] proposed a joint dictionary training method for general SR that employs both LR and HR image patches. Zou et al. [3] designed a linear regression model with two elements (new data and discriminative constraints) to learn the mapping. Jiang et al. [4] proposed a coarse-to-fine face

SR approach via a multi-layer locality-constrained iterative neighbor embedding. Kolouri et al. [5] introduced a single frame SR technique that uses a transport-based formulation of this problem. Wang et al. [6] deployed deep learning pre-training with a carefully selected loss function to achieve SR for matching between LR and HR face images, and achieves state-of-the-art performance on a new surveillance dataset. Another approach to solving the LR face recognition problem is to seek a unified feature space that preserves proximity between faces of different resolutions. Li et al. [7] proposed a coupled mapping method that projects face images with different resolutions into a unified feature space. Biswas et al. [8] simultaneously embedded the LR and HR faces in a common space such that the distances between them in the transformed space approximates the distance between between two HR face images of the same subject. Ren et al. [9] used a coupled mapping strategy with both HR and LR counterparts for learning the projection directions as well as exploiting discriminant information.

Shekhar et al. [1] proposed robust dictionary learning for LR face recognition that shares common sparse codes. The technique of Qiu et al. learned a domain adaptive dictionary to handle the matching of two faces captured in source and target domains. Li et al proposed several shallow network structures to learn a latent space between LR and HR images, and evaluated the proposed methods on a new surveillance dataset. There are also some other methods such as and , which explore more robust features directly to improve recognition rate in blurry and degraded face images. In addition, methods like those proposed in work to restore the upsampled LR images using deblurring techniques. In the last three years, novel face recognition methods based on deep learning for low-quality face images have been developed. The most relevant approaches are as follows. In , partially coupled networks are proposed for unsupervised super-resolution pre-training. The classifier is obtained by finetuning on a different dataset for specific domain simultaneous super-resolution and recognition. In [5], [6], an attention model that shifts the network's attention during training by blurring the images with various percentage of blurriness is presented for gender recognition. In [7], three obfuscation techniques are proposed to restore face images that have been degraded by mosaicking (pixelation) and blurring processes. In [4], a multi-task deep model is proposed to simultaneously learn face super-resolution and facial landmark localization. The face super-resolution subnet is trained using a generative adversarial network (GAN), (see a comparison of different versions of GANs in the context of face superresolution in [8]) In [2], inspired by the traditional wavelet that can depict the contextual and textural information of an image at different levels, a deep architecture is proposed. In [7] a network that contains a coarse super-resolution network to recover a coarse HR image is presented. It is the first deep face super-resolution network utilizing facial geometry prior to end-to-end training and testing. In a network for deblurring facial images using a Resnet-based non-maxpooling architecture is proposed. In a face hallucination method based on an upsampling network and a discriminative network is proposed. The approach includes feature maps with additional facial attribute information. In global semantic priors of the faces are exploited in order to restore blurred face images. In a new branch network that can be appended to a trunk network to match a different resolution of probe images to the gallery images was designed. In all these methods, we see that automatic face recognition is far from perfect when tackling more challenging images of faces taken in unconstrained environments, e.g. surveillance, forensics, etc. Most of the approaches mentioned above are evaluated on low-quality versions of constrained face datasets like Multi-PIE, FERET or FRGC. The images are created by directly downsampling or blurring original images. However, the LR face recognition problem becomes a challenge when faces captured in an unconstrained environment. In such cases, the LR face recognition problem needs to be explored more We can divide most of the existing methods into two categories: methods employing deep learning, and those without. For the non-deep learning methods, research have proposed and used different handcrafted features such as symmetry-driven accumulation of local features (SDALF) [2], color histograms [8], [9], color names, local binary patterns , aggregation of patch summary features metric learning approaches and various combinations of these. Several deep learning approaches use "Siamese" deep convolutional neural networks for feature extraction and metric learning at the same time providing novel end-toend solutions. Ahmed et al. [1] proposed a new deep learning framework based on the idea from Yi et al. [8], where two novel layers are employed for computing cross-input neighborhood differences by integrating local relationships based on mid-level features.

They additionally showed that the features acquired from the head and neck could be an important clue for person re-identification. Wu et al. [9] improved performance based on Ahmed's idea by using a deeper architecture and a new optimization method. Other deep network structures such as [6] and [5] have been designed which also effectively solved the ReID problem on older ReID datasets. Qui et al. [4] attempted to perform facial ReID by using domain adaptation methods to reconcile different facial poses; however, their experiments were performed on the Multi-PIE [5] dataset, in which face images have controlled poses and illuminations.

Although an increasing number of surveillance cameras have been deployed in public areas, the quality of the video frames is usually low and people captured in the frame are in an uncontrolled pose and illumination condition. Thus, general person re-identification can be a challenging task. As [5] shows, body and gait might play a role in recognizing the target in LR video frames, however, obscuring the target produced a dramatic drop in human-level recognition performance. Also, the face-mask-out experiment in [6] also demonstrates that the face could be an indispensable part of identity recognition. These works help to motivate the LRFR problem as a component of the re-identification problem.

III.METHODOLOGY

Convolutional neural networks (CNN) is a deep learning algorithm and also it is a machine learning algorithm that can take an input image, and various species, aspects/objects in the image, and it can be able to differentiate one from the other. And CNN works by existing from features from the images. CNN is basically consists of three types of layers Convolutional layer, pooling layer and finally connected layer.

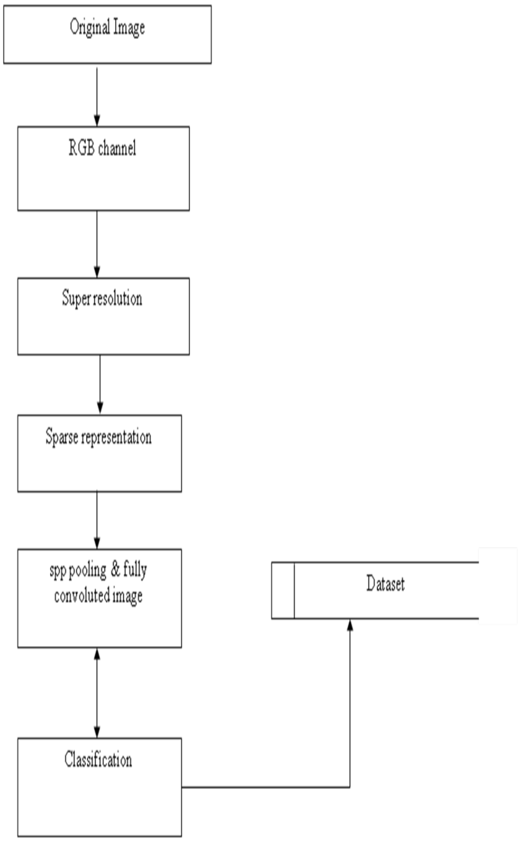

Figure 1: CNN

IV. EXPERIMENTAL RESULTS AND DISCUSSION

1.Datasets: There are some smart police investigation datasets and conjointly some giant scale free face datasets that contain natural LR faces appropriate for coaching and testing LRFR systems. Most of the LR face pictures used for analysis are generated by down sampling a typical face recognition dataset that's collected in a very controlled atmosphere. we tend to choose the AR dataset to analysis the LRFR task below uncontrolled situations and different free LR face datasets for additional exploration. it's wont to illustrate the various information distribution between LR face pictures unnaturally generated from top quality controlled face pictures.

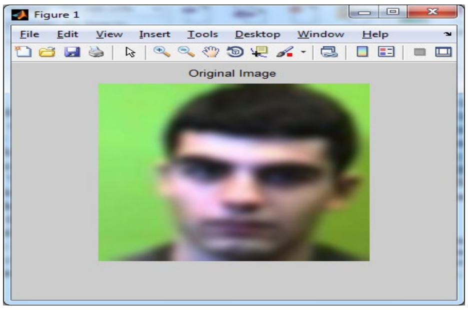

Figure 2: Datasets

2. RGB Channel: After the info set assortment the initial image is born-again into red down sampling channel and inexperienced down sampling channel and blue down sampling channel.

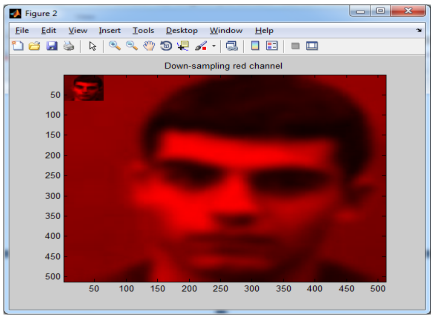

Figure 3: RGB Channel

3. Super Resolution: In order to explore the gap between the forced and free LR face recognition performance, we tend to designed a tiny low super-resolution (SR) experiment with the AR datasets. during this experiment, the concept is to guage the matching performance of 2 face images: a LR image and a unit of time image.

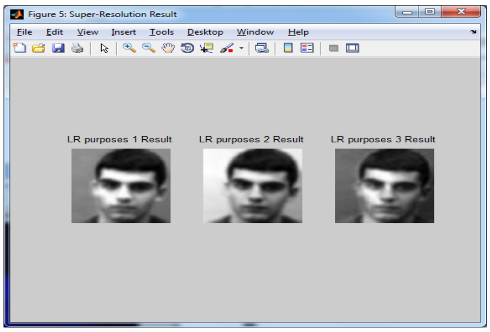

Figure 4: Super Resolution

4.Low resolution face identification: We initial target cross-resolution face identification that applies once the registered face pictures are principally collected in controlled situations with unit of time Associate in Nursing LR faces are captured with police investigation cameras with an uncontrolled cause and lighting conditions. this can be a difficult recognition task that depends powerfully on a decent resolution invariant illustration.

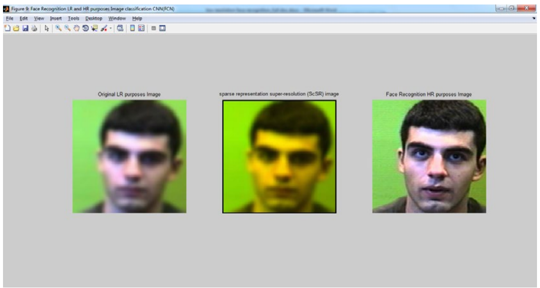

Figure 5: Low resolution face identification

5. Classification: The in depth experiments on hand-picked datasets and find out that dimensional mismatching is that the most difficult purpose, particularly in low-to-high resolution face identification task.

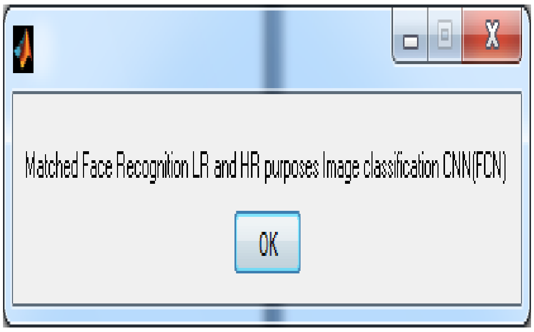

Figure 6: Classification

V. CONCLUSION

We provide several novel contributions. First, we illustrate the performance gap between LR unconstrained face and LR constrained face recognition when using a state of-the-art super-resolution algorithm. Secondly, two important application scenarios based on LR face recognition are defined: unconstrained LR face identification in the wild or in crowd and LR face re-identification. For general LR face identification, we exploit a novel approach to handle the multi- dimensional mismatching due to the quality difference of the face images in probe and gallery. We also design different deep networks solving the person re-identification problem to demonstrate better performance compared to our previous work. We demonstrate the result from the extensive experiments on selected datasets and discover that dimensional mismatching is the most challenging point, especially in low-to-high resolution face identification task.

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