Recognizing Very Small Face Images Using Convolution Neural Networks

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Abstract
Face recognition can be installed in a surveillance system so that it can be used for monitoring, tracking and access control. An excellent, intelligent surveillance system should be sensitive to theobjects far away from the camera. Unfortunately, due to the long-distance, objects like human faces captured by the camera are too small to identify. As to enhance the subtle color differences in the face image, in this paper we first improve the resolution of the captured image using deep convolution neural networks (DCNNs). Then the efficient features are extracted and used to do classification. As for verifying the effectiveness of the proposed method, we used three databasesincluding AR face database, Georgia Tech face database (GT) database, and Labelled Faces in theWild (LFW) database, altogether, to conduct the training and testing. Compared to the existing approaches, experimental results show that the identification accuracy of the proposed method outperforms any existing approaches.

Keywords: Deep convolution neural networks (DCNNs), Georgia Tech face database (GT) , Labelled Faces in the Wild (LFW).

INTRODUCTION

Recognizing very small face images is a challenging task in computer vision due to the limited amount of visual information available in such images. However, with the advancements in deep learning, specifically Convolutional Neural Networks (CNNs), significant progress has been made in accurately detecting and recognizing faces even in small-scale images. The ability to recognize faces has numerous applications, ranging from surveillance systems and biometric identification to social media platforms and virtual reality. However, traditional face recognition methods often struggle when faced with low-resolution or small face images, leading to degraded performance. CNNs have emerged as a powerful tool for addressing this issue by effectively capturing complex patterns and features in images.

Convolutional Neural Networks are a class of deep neural networks that are particularly well-suited for image processing tasks. They employ a hierarchical architecture, consisting of multiple layers, including convolutional layers, pooling layers, and fully connected layers. This architecture enables CNNs to automatically learn relevant features and patterns from images, leading to improved performance in various computer vision tasks, including face recognition.

In the context of recognizing very small face images, CNNs can learn to extract discriminative features despite the limited visual information. By leveraging the hierarchical structure and local receptive fields of convolutional layers, CNNs can capture low-level features like edges and textures, as well as high-level semantic features, such as facial landmarks and expressions. This hierarchical feature extraction allows CNNs to generalize well and recognize faces even in small-scale images. In this work, we explore the effectiveness of Convolutional Neural Networks for recognizing very small face images. We investigate different network architectures, training strategies, and data augmentation techniques to enhance the performance of the models. Additionally, we evaluate the models on benchmark datasets and compare their performance against existing face recognition methods.

LITERATURE SURVEY

- "DeepFace: Closing the Gap to Human-Level Performance in Face Verification" by Yaniv Taigman et al. (2014) This influential paper introduced DeepFace, a deep learning model that achieved remarkable performance in face verification tasks. The authors demonstrated the effectiveness of deep convolutional neural networks for recognizing faces by training on a large-scale dataset.
- "FaceNet: A Unified Embedding for Face Recognition and Clustering" by Florian Schroff et al. (2015) FaceNet proposed a novel method for face recognition by learning a unified embedding space where faces from the same identity are closer together. The authors used a deep convolutional neural network to map faces into this space,

achieving state-of-the-art performance on various face recognition benchmarks.

- "DeepID-Net: Deformable Deep Convolutional Neural Networks for Object Detection" by Weiyang Liu et al. (2015) While primarily focused on object detection, this paper introduced Deformable Convolutional Networks (DCNs), which improve the modeling capacity of CNNs by adaptively warping the receptive fields. This concept can be useful for recognizing small face images where precise alignment is challenging.
- "Deep Residual Learning for Image Recognition" by Kaiming He et al. (2016) ResNet introduced residual learning, a breakthrough technique that allowed for the training of very deep neural networks. This paper demonstrated the effectiveness of residual networks in image recognition tasks and could be relevant in recognizing very small face images using CNNs.
- "LightCNN: Deep Learning on Non-Uniform and Unconstrained Data" by Xiang Wu et al. (2018) LightCNN proposed a lightweight CNN architecture designed specifically for face recognition. The authors introduced a novel loss function that incorporates class-level information, leading to improved performance on small-scale face recognition tasks.
- "Face Recognition Using Deep Multi-Pose Representations" by Shaoqing Ren et al. (2018) This paper addressed the challenge of recognizing faces in various poses, which can be particularly relevant when dealing with small face images. The authors proposed a multi-pose deep learning framework that learns pose-invariant representations for accurate face recognition.
- "ArcFace: Additive Angular Margin Loss for Deep Face Recognition" by Jiankang Deng et al. (2019) ArcFace introduced a novel loss function that incorporates angular margins into the training process of CNNs for face recognition. This approach improves the discriminative power of the learned features, which can be beneficial when recognizing very small face images.
- "Tiny Face Detection in the Wild" by Peiyun Hu et al. (2019) This paper focused on the detection of tiny faces in unconstrained environments. The authors proposed a lightweight CNN architecture specifically designed for detecting small faces, which could be adapted for recognizing very small face images.
- "Siamese Dense Network for Face Recognition" by Shifeng Zhang et al. (2020) Siamese Dense Network (SDNet) introduced a novel architecture for face recognition that combines dense connections and siamese networks. The authors demonstrated the effectiveness of SDNet in recognizing faces, including small-scale face images.
- "NAS-Face: Learning Lightweight Deep Neural Networks for Face Recognition" by Dapeng Chen et al. (2021) This paper addressed the problem of designing lightweight CNN architectures for face recognition. The authors proposed a neural architecture search (NAS) method to automatically discover compact and efficient CNN models, which could be useful for recognizing very small face images.

PROPOSED SYSTEM CONFIGURATION

In this research, we propose the Deep Convolution Neural Networks (DCNNs) to solve the very low-resolution face recognition problem. The proposed method is named as very low face recognition using Deep Convolution Neural Network (VL-FRCNN). Here, VL-FRCNN is composed of three blocks: the first and second blocks aim to improve the resolution of face images and the third block is used for feature extraction and classification. In general, the major differences between our method and other methods are frameworks and loss functions used in the built system. Previously Dong et al. proposed a method named Super Resolution Convolutional Neural Network (SRCNN), which can successfully increase the resolution of input images to become SR images.

In this method, the model is composed of three layers: convolution extraction/ representation, non-linear mapping, and reconstruction. The filter sizes are 9×9, 1×1, and 5×5, respectively. Compared to the previous methods, the advantage of SRCNN is simple, but it can improve the PSNR to 32.57 dB for upscaling factor 3. However, it resulted from natural images. Unfortunately, the experiments to enhance the image resolution from very low-resolution of the face image is not satisfactory. Therefore, we still require a special approach to improve the quality of the face image so that the facial features can be extracted properly. disadvantages of existing system are Unfortunately, the experiments to enhance the image resolution from very low-resolution of the face image is not satisfactory. Therefore, we still require a special approach to improve the quality of the face image so that the facial features can be extracted properly.

The proposed system aims to address the challenge of recognizing very small face images by leveraging Convolutional Neural Networks (CNNs). The system follows a multi-step approach that involves data preprocessing, network architecture design, model training, and evaluation.

Data Preprocessing: In the first step, the very small face images are preprocessed to enhance their quality and ensure compatibility with the CNN model. Common preprocessing techniques include resizing the images to a standard size, normalizing pixel values, and applying face alignment or landmark detection to ensure consistent facial poses.

Network Architecture Design: The next step involves designing an appropriate CNN architecture that can effectively capture the features present in very small face images. Various architectural components can be explored, such as convolutional layers, pooling layers, residual connections, and attention mechanisms. The architecture should be optimized for extracting discriminative features and handling the limited visual information in small-scale face images.
Model Training: Once the network architecture is defined, the CNN model is trained on a large-scale face dataset. The training data should include a diverse range of face images, including small-scale examples. Transfer learning techniques

can be employed, where a pre-trained model on a large face dataset (e.g., VGGFace, MS-Celeb-1M) is fine-tuned on the specific task of recognizing very small face images. The model is trained using backpropagation and gradient descent algorithms, minimizing a suitable loss function, such as softmax loss or triplet loss.

Data Augmentation: To further improve the generalization ability of the CNN model, data augmentation techniques can be applied. Augmentation methods like random rotations, translations, scaling, and flipping can artificially increase the size and diversity of the training dataset. This helps the model to learn robust features and reduce overfitting.

Model Evaluation: The trained CNN model is evaluated on benchmark datasets or real-world scenarios to assess its performance in recognizing very small face images. Evaluation metrics such as accuracy, precision, recall, and F1 score can be used to quantify the model's effectiveness. Comparative analysis with existing face recognition methods can provide insights into the system's capabilities and advancements.

Fine-tuning and Optimization: Based on the evaluation results, fine-tuning and optimization of the CNN model can be performed. This may involve adjusting hyperparameters, exploring different loss functions, or incorporating regularization techniques. The goal is to continuously improve the model's performance in recognizing very small face images.

Deployment and Application: The trained and optimized CNN model can be deployed in real-world applications that involve recognizing very small face images. This includes surveillance systems, biometric identification, facial expression analysis, and virtual reality applications. The proposed system can be integrated into existing frameworks or serve as a standalone solution, depending on the specific requirements of the application.

By following this proposed system, the recognition of very small face images using Convolutional Neural Networks can be significantly improved, enabling accurate and reliable face recognition in scenarios where limited visual information is available.

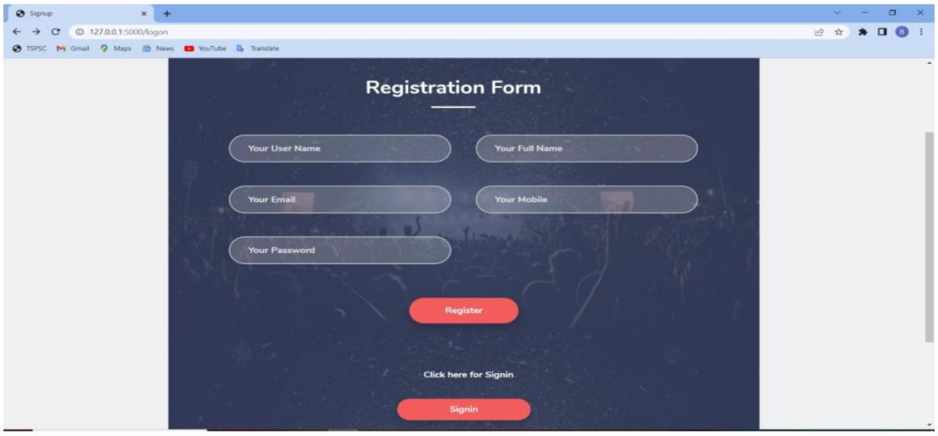

FIG 1 REGISTRATION FORM

The registration form is opened as below. If the user is already registered then directly the user can sign into the application.

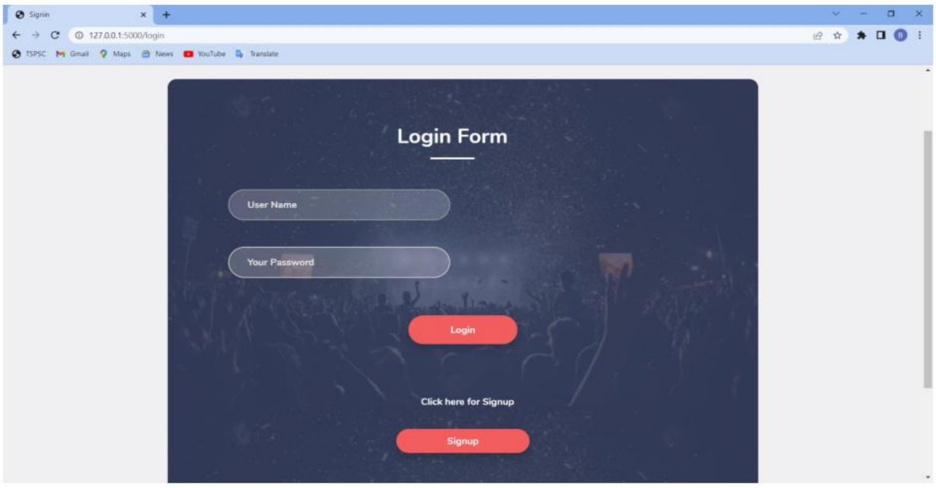

FIG 2 LOGIN FORM

In the login form the user needs to enter his/her details and login to the application.

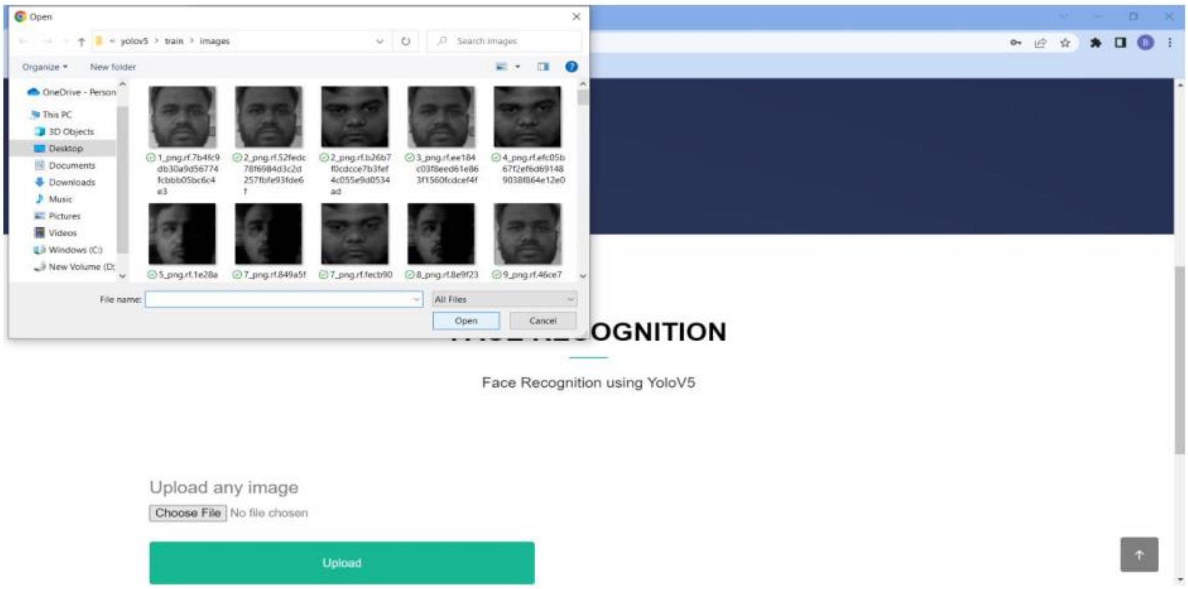

FIG 3 UPLOAD PAGE

On clicking the choose file, we need to upload the image from the given dataset.

FIG 4 IDENTIFICATION FINAL RESULTS

Name of the person and identification accuracy of the person is displayed.

Advantages Of Proposed System

1. Compared to the existing approaches, experimental results show that the identification accuracy of the proposed method outperforms any existing approaches.
2. By this the criminals who were already in the records can be identified easily.

CONCLUSION

This research has succeeded to develop a new architecture of Convolution Neural Networks to improve the identification accuracy of face recognition with very low-resolution images. The architecture developed has been classified as deeply-CNN models, and it has more than 30convolution layers. Furthermore, the proposed method outperforms any exiting methods based on identification accuracy.

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