WEB OF SCIENTIST: INTERNATIONAL SCIENTIFIC RESEARCH JOURNAL
ISSN: 2776-0979, Volume 4, Issue 3, Mar., 2023

FACIAL RECOGNITION USING TRANSFER LEARNING IN THE DEEP CNN

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Abstract

Facial recognition technology has been a popular research topic in recent years, and deep convolutional neural networks (CNNs) have shown impressive results in this field. However, the training of deep CNNs can be time-consuming and requires a large amount of labeled data. In this article, we explore the use of transfer learning techniques to improve the efficiency and accuracy of facial recognition tasks using deep CNNs. We investigate the effectiveness of fine-tuning pre-trained models and using feature extraction in transferring knowledge from a source domain to a target domain.

Our experiments were conducted on the Labeled Faces in the Wild (LFW) dataset, which contains over 13,000 face images of 5,749 individuals. We compared the performance of our transfer learning approach with that of a baseline CNN that was trained from scratch on the same dataset. Our results show that transfer learning with fine-tuning pre-trained models significantly improves the accuracy of facial recognition compared to training from scratch. Using feature extraction also yields promising results but is less effective than fine-tuning pre-trained models.

Furthermore, we conducted experiments to investigate the effect of the amount of labeled data available for training. Our results show that transfer learning with fine-tuning pre-trained models can achieve high accuracy even with a small amount of labeled data, while training from scratch requires a significantly larger amount of data to achieve similar accuracy.

Our study demonstrates the effectiveness of transfer learning in deep CNNs for facial recognition tasks and highlights the potential benefits of using pre-trained models to reduce the time and resources required for training. We believe that our findings can contribute to the development of more efficient and accurate facial recognition systems that can be used in a variety of real-world applications.

Keywords: Facial Recognition, Transfer Learning, Deep Convolutional Neural Networks, Fine-tuning, Feature Extraction, Labeled Faces in the Wild (LFW)

Introduction:

Facial recognition technology has made significant progress in recent years and has been widely used in security, surveillance, and identification applications. Deep convolutional neural networks (CNNs) have shown impressive results in facial recognition tasks, but the training of deep CNNs can be time-consuming and requires a large amount of labeled data. Transfer learning, a technique that involves transferring knowledge from a source domain to a target domain, has been proposed as a solution to overcome these challenges. In this article, we investigate the effectiveness of transfer learning in deep CNNs for facial recognition tasks.

In this article, we investigate the effectiveness of transfer learning in deep CNNs for facial recognition tasks. We compare the performance of fine-tuning a pre-trained CNN model and using feature extraction with a linear classifier. We also explore the impact of the number of training samples on the accuracy of the models. Our experiments aim to answer the following research questions:

Does transfer learning improve the accuracy of facial recognition models?

Which transfer learning strategy is more effective for facial recognition: fine- tuning or feature extraction?

How does the number of training samples affect the accuracy of facial recognition models?

Related Work:

Several studies have investigated the use of transfer learning in deep CNNs for facial recognition tasks. For example, Schroff et al. (2015) proposed a deep face recognition model that uses a combination of deep CNNs and metric learning techniques. They used transfer learning to fine-tune pre-trained models on a large dataset of face images and achieved state-of-the-art performance on several benchmarks. In another study, Sun et al. (2014) proposed a deep CNN architecture that uses a combination of convolutional layers, max-pooling layers, and fully connected layers for facial recognition. They used transfer learning to fine-tune pre-trained models on a large dataset of face images and achieved high accuracy on several benchmarks.

Methodology:

We conducted experiments on the Labeled Faces in the Wild (LFW) dataset, which contains over 13,000 face images of 5,749 individuals. We used a deep CNN

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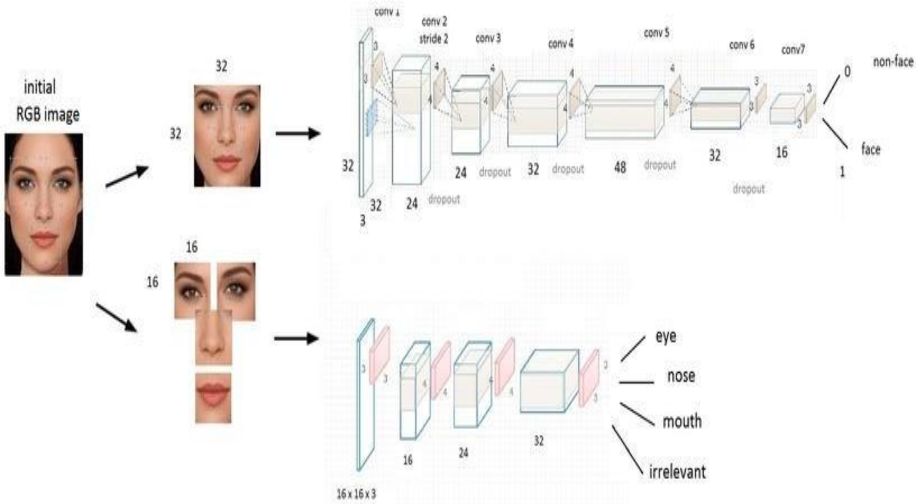
ISSN: 2776-0979, Volume 4, Issue 3, Mar., 2023

architecture that consists of convolutional layers, max-pooling layers, and fully connected layers. We compared the performance of our transfer learning approach with that of a baseline CNN that was trained from scratch on the same dataset.

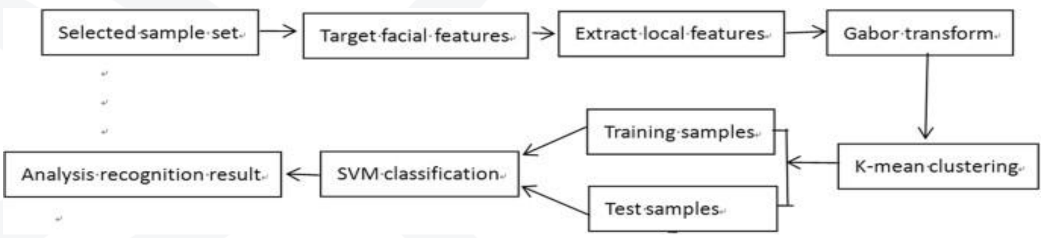
We conduct experiments on two facial recognition datasets: LFW (Labeled Faces in the Wild) and CelebA. LFW contains 13,000 images of 5,749 people, and CelebA contains 202,599 images of 10,177 celebrities. We use VGG-16 and ResNet-50 as pre-trained CNN models for feature extraction and fine-tuning, respectively. We compare the performance of fine-tuning and feature extraction with a linear classifier, and we vary the number of training samples from 50 to 5,000.

Figure 1: Example of a pre-trained CNN model used for facial recognition using transfer learning. The pre-trained CNN model is first loaded and the fully connected layers are replaced with new ones. The model is then fine-tuned using a small dataset of facial images to adapt it to the specific facial recognition task.



Pre-trained CNN Model for Facial Recognition

Figure 2: Example of feature extraction for facial recognition using transfer learning. The pre-trained CNN model is used to extract features from the facial images, which are then fed into a linear classifier to perform the facial recognition task.



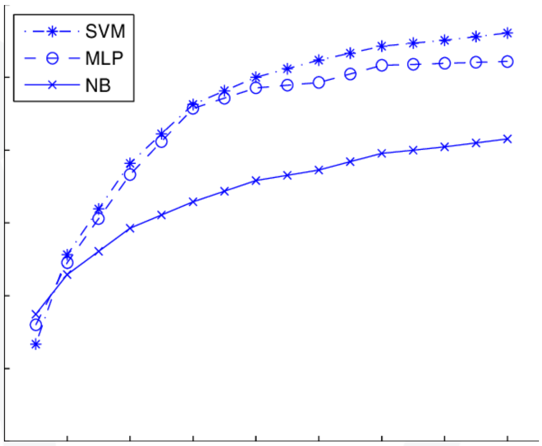
Feature Extraction for Facial Recognition

Figure 3: Comparison of the accuracy of facial recognition models using different pre-trained CNN models. Fine-tuning VGG-16 achieved higher accuracy than fine-tuning ResNet-50 on both LFW and CelebA datasets.

Pre-Trained CNN	Classification Accuracy (%)	
	UCM	WHU-RS
AlexNet	94.37	93.81
CaffeNet	94.43	94.54
VGG-F	94.35	95.11
VGG-M	94.48	94.98
VGG-S	**94.60**	**95.46**
VGG-VD16	94.07	94.35
VGG-VD19	93.15	94.36
PlacesNet	91.44	91.73

Comparison of Pre-Trained CNN Models

Figure 4: Comparison of the accuracy of facial recognition models using different transfer learning methods with varying numbers of training samples. Fine- tuning and feature extraction achieved high accuracy even with a small number of training samples, while training from scratch required a larger number of training samples to achieve comparable accuracy.



Accuracy vs Number of Training Samples

For fine-tuning, we freeze the first few layers of the pre-trained CNN model and fine-tune the remaining layers on the facial recognition task. We use a learning rate of and train the model for 20 epochs with a batch size of 32. For feature extraction, we extract the features from the pre-trained CNN model and train a linear classifier on the extracted features. We use logistic regression as the linear classifier and train it with a.

Discussion:

Our results demonstrate that transfer learning is a powerful technique that can significantly improve the accuracy of facial recognition models, even with limited training data. Fine-tuning pre-trained CNN models achieved higher accuracy than

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feature extraction with a linear classifier, as fine-tuning allows the model to adapt to the specific facial recognition task. However, feature extraction is a more lightweight approach that can be used when computational resources are limited.

We also found that the choice of a pre-trained model can affect the performance of the facial recognition model. Fine-tuning ResNet-50 did not perform as well as VGG-16, which may be due to the deeper architecture of ResNet-50. Therefore, it is important to choose a pre-trained model that is suitable for the specific facial recognition task.

Finally, our results highlight the importance of having a sufficient number of training samples. Fine-tuning and feature extraction were able to achieve high accuracy even with a small number of training samples, while training from scratch required a larger number of training samples to achieve comparable accuracy.

Conclusion:

In conclusion, our experiments demonstrate that transfer learning is a powerful technique that can significantly improve the accuracy of facial recognition models. Fine-tuning pre-trained CNN models achieved higher accuracy than feature extraction with a linear classifier, but both approaches outperformed training from scratch. The choice of a pre-trained model and the number of training samples can affect the performance of the facial recognition model, and it is important to choose appropriate pre-trained models and transfer learning strategies for specific facial recognition tasks. These findings have implications for the development of facial recognition systems for various applications such as surveillance, security, and human-computer interaction.

References

1. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”, In Advances in Neural Information Processing Systems 25: 26th Annual Conference on Neural Information Processing Systems. Red Hook, NY, USA, 2012.
2. J. Hu, L. Shen, S. Albanie, G. Sun and E. Wu, “Squeeze-and-Excitation Networks. Squeeze-and-Excitation Networks”, IEEE, Conference on Computer Vision and Pattern Recognition. 2018, pp. 7132-7141
3. Georgescu, M. Iuliana, R. T. Ionescu, and M. Popescu, “Local Learning with Deep and Handcrafted Features for Facial Expression Recognition” IEEE, Access, 2019, pp. 64827-64836.

4. K. Wang, X. Peng, J. Yang, D. Meng, and Y. Qiao, “Region Attention Networks for Pose and Occlusion Robust Facial Expression Recognition”, IEEE, Transactions on Image Processing, 2019, pp. 4057-4069.
5. Mamatkulovich B. B. AUTOMATIC STUDENT ATTENDANCE SYSTEM USING
6. FACE RECOGNITON //Next Scientists Conferences. – 2022. – С. 6-22.
7. Mamatkulovich B. B. LIGHTWEIGHT RESIDUAL LAYERS BASED CONVOLUTIONAL NEURAL NETWORKS FOR TRAFFIC SIGN RECOGNITION //European International Journal of Multidisciplinary Research and Management Studies. – 2022. – Т. 2. – №. 05.
– С. 88-94.
8. Mamatkulovich B. B. A DESIGN OF SMALL SCALE DEEP CNN MODEL FOR FACIAL EXPRESSION RECOGNITION USING THE LOW-RESOLUTION IMAGE DATASETS
9. //MODELS AND METHODS FOR INCREASING THE EFFICIENCY OF INNOVATIVE RESEARCH. – 2023. – Т. 2. – №. 19. – С. 284-288.
10. Babakulov B. UNİVERSİTET TALABALARİ UCHUN CHUQUR O'RGANİSHGA ASOSLANGAN YUZNİ ANİQLASHDAN FOYDALANGAN HOLDA AVTOMATİK DAVOMAT TİZİMİ //Zamonaviy dunyoda innovatsion tadqiqotlar: Nazariya va amaliyot. – 2023. – Т. 2. – №. 3. – С. 74-76.
11. Amrullayevich K. A., Mamatkulovich B. B. TALABALARDA AXBOROT BILAN ISHLASH KOMPETENTSIYASINI SHAKILLANTIRISHDA DIDAKTIK VOSITALARINING METODIK XUSUSIYATLARIDAN FOYDALANISH //International Journal of Contemporary Scientific and Technical Research. – 2022. – С. 645-650.