Efficient Transfer Learning Combined Skip-Connected Structure for Masked Face Poses Classification

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ABSTRACT: Targeting the new requirements of the classification of masked face poses during the epidemic, this article proposes an efficient transfer learning approach combined with a connected jump structure to improve the accuracy of the classification of masked face poses during the epidemic. lack of masked face pose data. We have worked on the following two aspects: 1) Based on the transition of the characteristics of convolutional neural networks, we propose an efficient transfer learning approach and opt for a more suitable source domain to solve the problem than the specificity. features in the pre - deep trained networks will degrade performance when transferring to the target domain. First, a semi-synthetic masked pose dataset is made to exchange ImageNet because the source domain, which may reduce the transfer interval and improve the relevance of transfer learning. learn more effectively; 2) To further improve the overall accuracy by improving the accuracy of masked face pose classes with subtle differences

.INDEX TERMS: Masked face pose classification, transfer learning, skip-connected structure, detailed feature and semantic feature, deep learning.

I. INTRODUCTION

Since the global epidemic of the novel coronavirus (COVID-19), humanity has been struck by a major disaster and all fields are making their efforts to fight the epidemic. Artificial intelligence (artificial intelligence) technologies supported by deep learning make many contributions such as mask detection, COVID-19 diagnosis, epidemic prediction and drug research, etc. AI provides support with its strong data processing capabilities and is expected to help with epidemic analysis and control, medical assistance and vaccine research, etc. The associate editor coordinating the revision of this manuscript and approving its publication was Joewono Widjaja. In recent years, facial pose estimation has become one of the important subjects of face information research with the continuous development of computer vision and intelligent analysis technology. Face pose estimation can be a key technology in the field of human behavior analysis, human-machine interaction and motivation detection, etc. And that's a good range of application perspectives. Due to the COVID-19 epidemic, wearing a mask in public places has become a standard phenomenon and this trend is on the rise. Therefore, the study of masked face pose estimation has become a surrogate challenge and has significant practical importance. the essential approaches to estimating the pose of the face have been exhaustively summarized in the many new methods recently proposed. Wang et al. proposed a totally unique neural tree specification integrating a continuity connection in the laying intervals Li et al.

II. METHODOLOGY

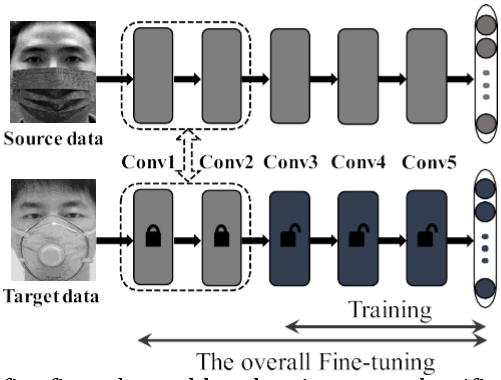
CONVOLUTIONAL NEURAL NETWORKS CNN, a well-known deep learning framework, is widely used in the field of computer vision. CNN research dates back to the 1990s, but it gained a lot of attention when Krizhevsky et al. . It consists of convolutional levels, pooling levels, fully connected levels and an activation function. Figure 1. shows the structure of CNNs. Features are taken from a series of convolutional layers and alternately stacked grouped layers, which contain low-level features, such as color spots and texture features, and shallow to deep high-level semantic features . And the fully connected layers is a classifier that integrates the characteristics extracted from the last convolutional layer

TRANSFER LEARNING

Transfer learning is an outstanding method in the fewshot learning field, which uses the knowledge learned from the source domain to solve new problems in the target domain .Here we give some definitions, the domain is represented as D = {χ , P(X)}, where χrepresents the feature space, P(X) represents the marginal distribution of X = {x1, x2, · · · xn} ∈ χ, xi ∈ R d , i = 1, 2, . . . n. Given a specific domain, a task is represented as 0 = {Y , f (·)}

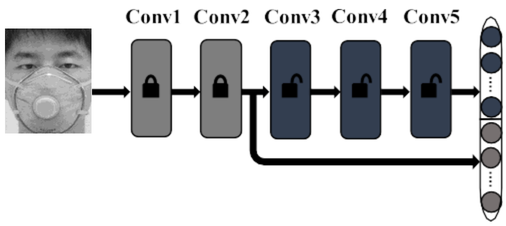
PROPOSED TRANSFER LEARNING STRATEGY

The traditional method of learning transfer is to freeze the pre-trained convolutional base as a feature extractor and remove the



classifier first, then add and train a new classifier on the target domain, Figure 2.shows the traditional transfer learning process. This transfer learning method is clear and easy to implement, but it ignores the transition mechanism of CNN functionality. As the networks deepen, the extracted features gradually shift from detailed features, such as splashes of color and texture features, to abstract and semantic features. The characteristics of surface networks are general but the semantic characteristics of deep networks are specific during transfer. Semantic features make particular contributions to specified tasks in the specific data domain, which means that they are better suited to solving specific tasks than general features. Semantic characteristics specific to the source domain will inevitably damage the transfer effect if the entire convolutional base is transferred to the destination domain without any enhancement.

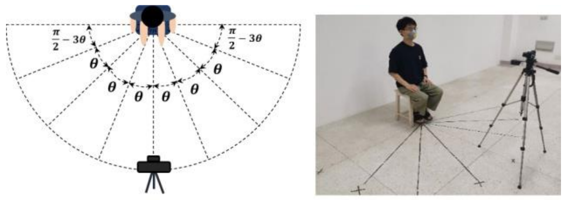
III. PROPOSED SKIP-CONNECTED STRUCTURE An effective transfer learning strategy is an important way to improve accuracy, but we find that further improvement in overall accuracy is subject to the accuracy of masked face pose classes with subtle differences. There are subtle differences between classes, resulting in difficult distinction and low precision.



Therefore, improving the accuracy of pose classes with subtle differences is another key to improving overall accuracy. For classification of fine-grained images, local detail information has an excellent ability to distinguish such subtle differences between classes. Detailed information is therefore more important than semantic information in distinguishing minor differences, and classification can be done efficiently using local information. Taking full advantage of local CNN news is an important way to improve accuracy. As networks deepen, features extracted from CNNs gradually shift from spatial details, such as splashes of color and texture features, to high-level semantic features. Figure 4 shows part of the feature display results, which are taken from VGG16. You can intuitively see from the results in which the features.

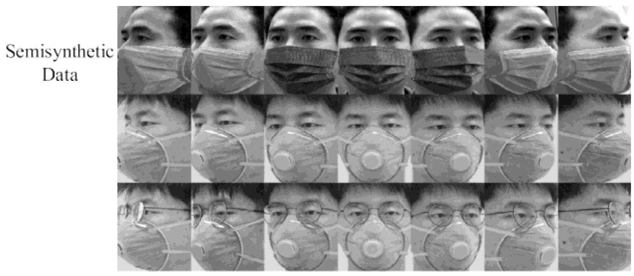
DATASET GENERATION

To simulate the masked face pose images more realistically, we create the semi-synthetic data of

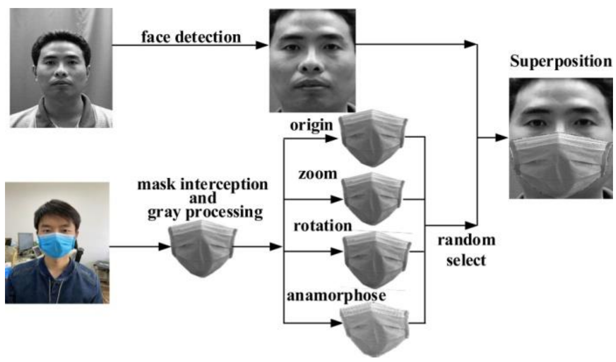


(a) (b)

superimpose the images of the general pose of the face and the images of the mask. The general face pose dataset is from the CAS-PEAL-R1 dataset created by the Institute of Information Technology, Chinese Academy of Sciences. And the subset of this data set in the yaw direction is used in this document



.. shows the production process. There is a large amount of background and non-facial parts in general face pose images.



IV. EXPERIMENTS AND ANALYSIS

A. DATA PREPARATION AND EXPERIMENT SETTINGS

The semisynthetic dataset includes the masked face pose images of 1050 people in 6 different poses, a total of 7250 images. 5880 images are used as the training samples, and the remaining 2700 images are used as the testing same. The real dataset includes the masked face pose images of 67 people in the same pose, a total of 698 images. And 758 images are used as the training samples, and the remaining 940 images are used as the testing samples. The image size is uniformly resized to 128 × 128px to meet the input

B. RESULTS AND ANALYSIS

The overall precision (OA), which is the percentage of all samples correctly classified and can represent the overall performance of a model, is used to assess the performance of different methods, OA is defined as: OA = KN × 100% (2) where N is the number of test samples, K is the number of correctly classified samples

TRANSFER LEARNINGAND ANALYSIS

The OA of the -FT method based on AlexNet (AlexNet-FT) can reach 86.42% and that of VGG16 (VGG16-FT) can reach 95.71%. But we are curious about the precision of each pose class, so we give each class precision (CA) to assess the precision of each masked face pose class according to different methods. In our further research, we find that the CA of classes with subtle differences is lower. Fig. 11. shows that if based on AlexNet or VGG16, the CA in attitudes ± 45 ∘

V. CONCLUSION

The objective of this article is to propose an efficient transfer learning strategy combined with a skipped structure to meet the new requirements for the classification of masked face pose in the absence of data. In our work, we first analyze how the characteristics of shallow and deep networks affect the classification accuracy of masked face poses in the transfer learning process. We then make improvements in the original domain and transfer learning approach to solve the specificity problem. In the comparative experiment, it was shown that the semi-synthetic dataset as the source domain can improve the relevance of the learning transfer. In addition, the proposed transfer learning approach can optimize specific characteristics by upgrading them on the target domain. Finally, we propose a hop-connected structure to send detailed characteristics in shallow networks to the MLP, which further improves the overall accuracy by effectively improving the accuracy of classes with subtle differences. The experimental results illustrate the importance of the fusion of features and the efficiency of the tied-jump structure.

VI .REFERENCES

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