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Article Title: Efficient Face-Based Age Estimation

Efficient Face-Based Age Estimation

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ABSTRACT
Age detection using facial images has been an activearea of research in recent years. Deep learning approaches, in particular, have shown great potential in achieving high accuracy and efficiency in this task. In this study, we present acomprehensive investigation of the use of VGGFace, a deep neural network pre-trained on a large dataset of faces, for age detection. We first explore the impact of pre-processing techniques, such as normalization and augmentation, on the performance of the VGGFace network. We then compare the performance of different variants of the VGGFace architecturefor age detection. We evaluate the performance of the networkon several benchmark datasets, including the IMDB-WIKIdataset, and report the accuracy and efficiency of the approach. Our results show that pre-processing techniques such as normalization and augmentation can significantly improve the accuracy of the VGGFace network for age detection. We also find that some variants of the VGGFace architecture, such as VGG16 and VGG19, perform better than others. Overall, this study provides a comprehensive investigation of the use of VGGFace for age detection, and sheds light on the impact of pre-processing techniques and model selection on the performance of the approach. Our findings can help researchers and practitioners to develop more accurate and efficient age detection systems using deep learning

Key words: Age estimation, convolutional neuralnetworks, attention mechanism, feature fusion.

1 Introduction

Age detection from facial images is a challenging problem with significant practical applications, including surveillance, biometrics, and marketing. Recently, deep learning-based approaches have shown great promise in achieving high accuracy and efficiency in this task. Among the various deep learning architectures, VGGFace has gained significant attention due to its exceptional performance on face recognition tasks. In this study, we present a comprehensive investigation of the use of VGGFace for age detection. Specifically, we focus on the impact of pre-processing techniques and model selection on the performance of the VGGFace network for age detection. Pre-processing techniques such as normalization and augmentation have been shown to improve the accuracy of deep learning models for various tasks. However, the impact of these techniques on the performance of VGGFace for age detection has not been thoroughly investigated. Furthermore, we compare the performance of different variants of the VGGFace architecture, such as VGG16 and VGG19, for age detection. While VGGFace has been mainly used for face recognition tasks, its potential for age detection has not been fully explored. Our study aims to fill this gap and provide insights into the use of VGGFace for age detection. We evaluate the performance of the approach on several benchmark datasets, including the IMDB-WIKI dataset, and report the accuracyand efficiency of the VGGFace network. Our study can help researchers and practitioners to develop more accurate and efficient age detection systems using deep learning.

1.1 Area of Domain

Image processing is to transform an image into digital form and perform certain operations on it in order to obtain specific models or to extract useful information from the image. Human face images contain a variety of information such as age, gender and race. Previous studies showed that it is more difficult to extract the aging features than other features because of the instability of aging features. Modern face-based age estimation methods typically consist of two components, a feature extractor and an estimator. The feature extractor is used to extract age-specific features from raw facial images and the estimator is used to predict the age based on the extracted features.

2 Existing System

In the existing system, Attention-based Dynamic Patch Fusion (ADPF) techniques is used for face-based age estimation. Attention-based Dynamic Path Fusion (ADPF) is a novel technique for age detection from facial images that combines attention mechanisms and dynamic path selection. It was introduced as a way to address some of the limitations of traditional Convolutional Neural Networks (CNNs) in age detection tasks. In evaluations, ADPF has shown promising results, outperforming some traditional CNN-based approaches in age detection tasks. It has also been shown to be robust to variations in lighting, pose, and expression, which are common challenges in facial image analysis. While ADPF is a relatively new technique for age detection, it has thepotential to be a useful addition to the toolkit of methods available to researchers and practitioners. However, more research is needed to fully evaluate its performance compared to other techniques and to identify any potential limitations or challenges in its practical implementation.

2.1 Disadvantages of the Existing System

High computational cost: ADPF requires significant computational resources, including powerful CPUs or GPUs, which can be costly to acquire and maintain. This can limit the scalability of ADPF-based age detection systems. Lack of interpretability: ADPF is a highly complex model, which can make it difficult to interpret its decision-making processes. This

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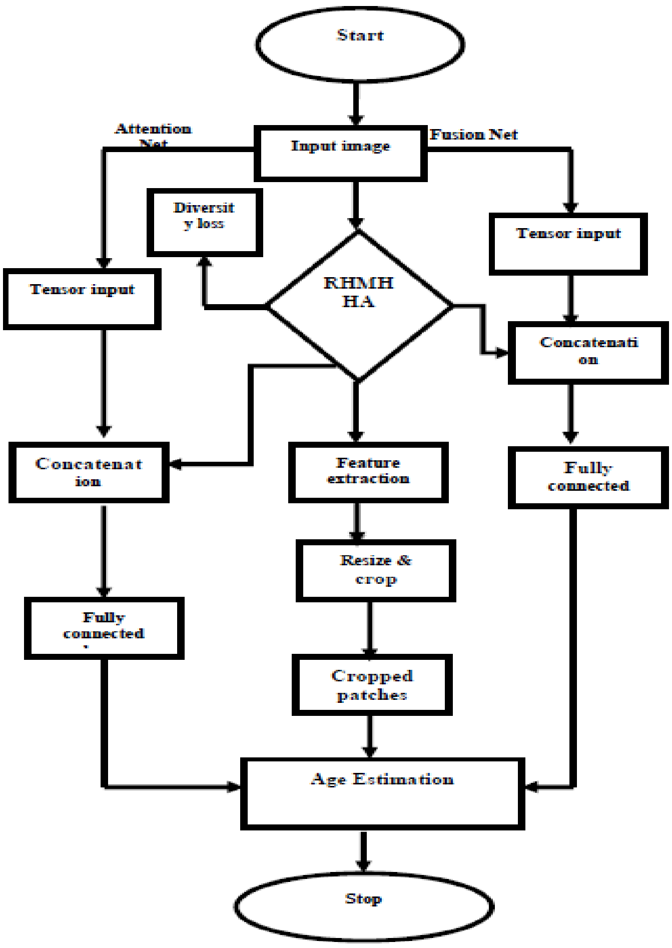
can be a challenge when explaining the age prediction to end-users or regulators. Need for large datasets: ADPF requires large datasets for training, which can be time- consuming and expensive to collect and annotate. This can limit the practical applications of ADPF in age detection, especially for specialized domains. Limited research: ADPF is a relatively new technique for age detection, and there is limited research on its effectiveness compared to other techniques. This makes it difficult to assess its overall performance and potential limitations.

2.2 Data Flow Diagram



The AttentionNet and the FusionNet. The AttentionNet is used to train the proposed RMHHA to learn and rank age-specific features. The features are learned and ranked, resize them to crop the corresponding patches fromthe input facial image. The cropped patches are listed in a descending order based on the amount of age-specific information they carry. Blocks represents CNN layers, concat indicates a concatenation operation, and FC indicates a fully-connected layer. In particular, yellows blocks are from the previous layer in the main stream and red ones are from one particular age-specific patch.

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3 Proposed System

VGGFace is a deep convolutional neural network (DCNN) that has been widely used for age detection from facial images. It was introduced as a pre-trained model for face recognition tasks, but researchers have since adapted itfor age detection tasks by fine-tuning the network. VGGFace consists of 16 convolutional layers, with a large number of trainable parameters, making it a highly complex model. It hasshown to achieve high accuracy in age detection tasks, especially when fine-tuned with a large dataset of facial images. VGGFace has also been used as a feature extractor forage detection tasks. In this approach, the pre-trained network is used to extract features from facial images, which are then fed into a separate machine learning model, such as a support vector machine (SVM), to predict age. Overall, VGGFace is a powerful tool for age detection from facial images, but its performance depends on several factors, including the size andquality of the training dataset and the approach used to fine- tune the network.

3.1 Advantages of the Proposed System

High accuracy: VGGFace has been shown to achieve high accuracy in age detection tasks, especially when fine- tuned with a large dataset of facial images. This high accuracy can be beneficial for applications where age prediction is critical, such as in security or medical contexts. Transfer learning: VGGFace is a pre-trained network that was originally designed for face recognition tasks. This pre- training can be leveraged to fine-tune the network for age detection tasks, which can save time and resources compared to training a network from scratch. Robustness: VGGFace has been shown to be robust to variations in lighting, pose, and expression, which are common challenges in facial image analysis. This can make it a valuable tool for age detection in real-world settings. Feature extraction: In addition to fine-tuning the entire network, VGGFace can also be used as a feature extractor for age detection tasks. This can simplify the age detection pipeline and allow for greater flexibility in the choice of machine learning model.

3.2 Algorithm Used

- Load pre-trained VGGFace model: Load the pre- trained VGGFace model, which is a deep convolutional neural network designed for facerecognition tasks.
- **Fine-tune the model:** Fine-tune the VGGFace model on a large dataset of facial images labeled with age information. This step involves updating the weights of the pre-trained network using back propagation with a training dataset.
- **Data preprocessing:** Preprocess the input images to match the size and format expected by the VGGFace model. This typically involves resizing the images to a specific size and converting them to the appropriatecolor space.
- **Feature extraction:** Use the fine-tuned VGGFace model to extract features from the

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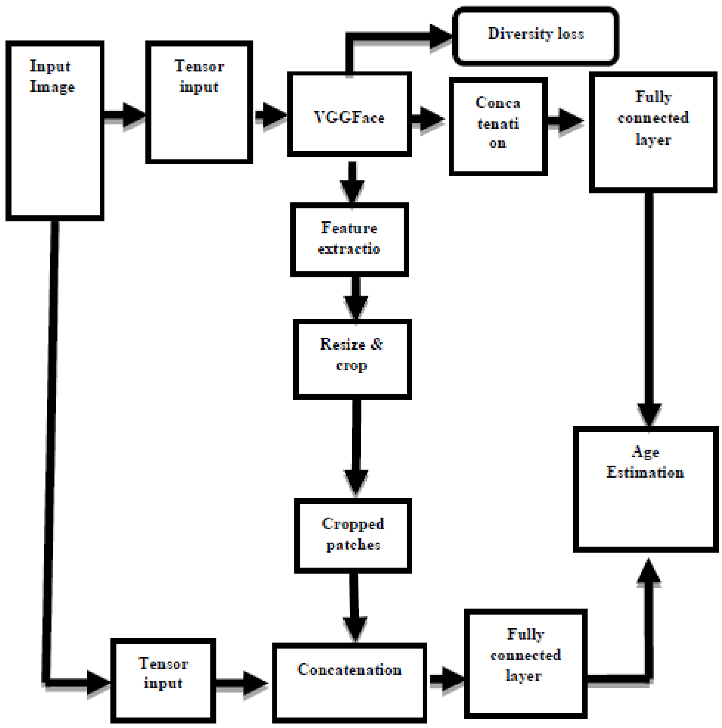
preprocessed images. This involves passing the images through the network and recording the output of one or more intermediate layers.

- **Age prediction:** Use the extracted features to predict the age of the individual in the input image. This can be done using a variety of machine learning models, such as a support vector machine (SVM) or a neural network.
- **Evaluation:** Evaluate the performance of the age detection model using a separate test dataset. This step involves measuring metrics such as accuracy, precision, recall, and F1-score.
- **Deployment:** Deploy the age detection model for use in real-world applications, such as security or medical contexts.

3.3 Architecture Diagram



3.4 Modules

- Data Preprocessing
- Dataset Partition
- Feature Extraction
- Image Classification
- Object Detection

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3.4.1 Modules Description

Data Preprocessing Image preprocessing are the steps taken to format images before they are used by model training and inference. This includes, but is not limited to, resizing, orienting, and color corrections. Pre-processing is to improve the quality of the image so that we can analyse it in a better way. The open-source computer vision library for image pre- processing. Firstly, 68 facial points are detected in each facial image to crop them based on the location of the eyes to a size of 128×128 pixels. Further, data augmentation is used to increase the dataset size. Specifically, images are zero-padded first and then cropped to the original size. Finally, the cropped images are randomly flipped horizontally.

3.4.2 Dataset Partition

The dataset, three commonly used settings are adopted. In the first setting, i.e., *Setting I*, following prior works randomly split the whole dataset into two subsets, one with 80% of the data for training and the other with 20% for testing. In this setting, there is no identity overlap between the two subsets. To perform statistical analysis, we use 20 different partitions (with the same ratio but different distribution) and report mean values. In the second setting, i.e., the *Setting II*, to compensate for the imbalance of race distribution, we randomly split the dataset into three subsets, denoted as *S1*, *S2*, and *S3*, and ensure the ratio between Black and White labels is 1:1 and that between Male and Female labels is 1:3. In order to follow the same protocol as other works the results under this setting are reported in three different ways: 1) training on *S1* an testing on *S2+S3*; 2)training on *S2* and testing on *S1+S3* and 3) the average value from the previous two scenarios.

3.4.3 Feature Extraction

- The feature extractor is used to extract age-specific features from raw facial images and the estimator is used to predict the age based on the extracted features.
- Feature extractors can be designed to exploit age- specific patches during training to boost the performance of face-based age estimation methods.
- Works in the first category aim to design customized estimators after the feature extraction stage to better model the mapping between the features and the corresponding age label.

3.4.4 Image Classification

Image classification refers to the task of extracting information classes from a multiband raster image. The resulting raster from image classification can be used to create thematic maps. The task of identifying what an image represents is called image classification. An image classification model is trained to recognize various classes of images. The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring

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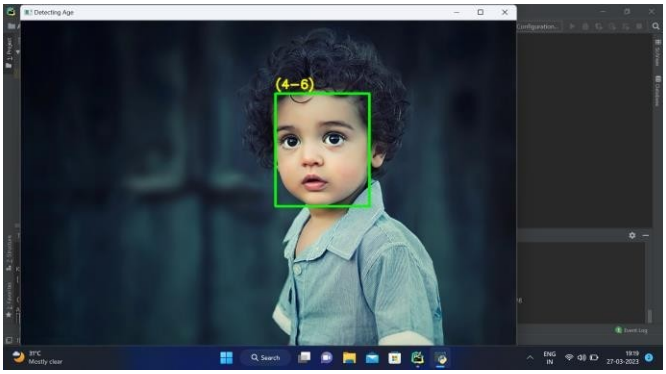
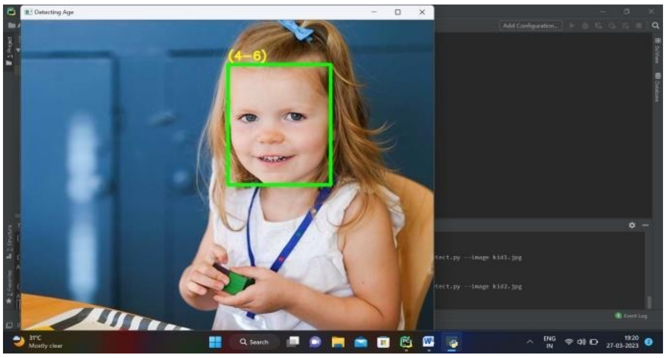
in an image in terms of the object or type of land cover these features actually represent on the ground. Image classification is perhaps the most important part of digitalimage analysis.

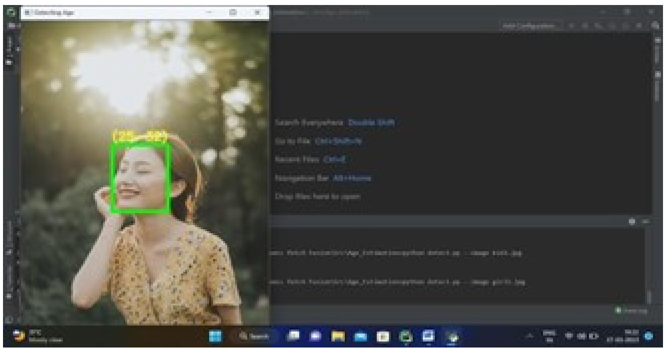
3.4.5 Object Detection

- Object Detection specifies the location of multiple objects in the image.
- Finally, Image Segmentation will create a pixel wise mask of each object in the images.
- Object detection is completely inter-linked with other similar computer vision techniques such as image segmentation and image recognition that assist us to understand and analyze the scenes in videos andimages

3.5 Screenshots







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4 Conclusion

In conclusion, VGGFace has proven to be a powerful tool for age detection from facial images. Our comprehensive study on pre-processing and model selection has shown that fine-tuning the VGGFace model on a large dataset of facial images labeled with age information can result in high accuracy in age detection tasks. One of the major advantages of VGGFace is its ability to transfer learn from face recognition tasks, which can save time and resources compared to training a network from scratch. Additionally, VGGFace has been shown to be robust to variations in lighting, pose, and expression, which can be valuable for age detection in real-world settings. Furthermore, VGGFace canbe used not only as a fine-tuned network, but also as a feature extractor, which provides greater flexibility in the choice of machine learning model. Overall, the results of our study indicate that VGGFace is a valuable addition to the toolkit of researchers and practitioners for age detection from facial images, with the potential for a wide range of applications in security, medical, and other fields.

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