Proposal: Age Detection Using Convolutional Neural Networks

1. INTRODUCTION

Age detection is an important aspect in various domains, including security, marketing, and medical research. It can be used to verify the age of individuals accessing restricted websites or resources in security, analyze consumer behavior based on age groups in marketing, and study the aging process and its impact on human health in medical research.The motivation for the need of deep learning is the ability of deep neural networks to learn from raw data and automatically extract complex features which is not possible with traditional machine learning techniques.

By leveraging automation, this process can be highly efficient, and the scalability of deep learning models allows them to be applied to large datasets and perform accurate age detection for a wide range of applications. It can be used for age detection by training a deep neural network on a large dataset of labeled images to classify facial images. By using deep learning models, such as Convolutional Neural Networks (CNNs). The deep learning model can automatically learn to identify facial features and patterns associated with different age groups, allowing it to predict the age of an individual based on their facial image. Challenges in age detection include variations in lighting conditions, pose, facial expressions, and limited size of the training datasets. Our goal is to explore and evaluate different CNN architectures on 3 different datasets and learn the impact of Transfer Learning. Expectations from this project is to analyze and gain experience in evaluating by comparing 3 CNN architectures on 3 different datasets for specific task using similar hyperparameter tuning.

2. DATASET

All the datasets have images of individuals age varying from 1-100 and are in JPG format. The project will make use of three datasets: **APPA-REAL**[1], **UTKFace**[3][4], and **Adience**[2].
APPA-REAL and UTKFace datasets were divided into 5 and 4 classes by using 'qcut' method in pandas. The selected Adience dataset is a preprocessed dataset. All datasets are divided into train, test, valid in the ratio 80:10:10 using 'splitfolders' module in python with a random seed. We will further check if there are images not related to face or not have clear image of face.

Dataset Specifications	1	2	3
No of classes	5	4	8
Total Number of Images	7,591	23,706	11,030
Image Resolution	-	200x200	816x816
Image Format	JPG	JPG	JPG

Table 1. Specifications of all three datasets (numbered in table as follows 1.APPA-REAL 2.UTKFace 3.Adience)

3. METHODOLOGY

Image preprocessing will be done by using techniques such as Resizing, Normalization, Data Augumentation (Flipping, rotating, cropping) and transformation techniques(image to tensor) and then fed to the CNN Model using a deep learning Library such as PyTorch. We will be training 9 different models with different Learning rates on these networks (RESNET-18, VGG-16 and MobileNet-v2) and 2 Transfer learning Models. ResNet-18: ResNet introduced residual learning, utilizing skip connections to improve the flow of information during training, enabling training of deep neural networks with improved performance and avoiding vanishing gradients. Mobile-Net-V2: This lightweight CNN model for age detection is optimized for mobile devices with fewer parameters, making it a suitable choice for resource-limited environments. Vgg-16: The VGG model is well-known for its ability to extract high-level features from images, making it a suitable option for age detection tasks. To further improve the performance, techniques such as Hyperparameter Tuning will be applied on learning rate, Loss function and batch size. Model evaluation will be performed using metrics such as accuracy, Confusion Matrix and ROC Curve by treating each class as binary classification problem against all the other classes. The results of all the models will be compared and analyzed to learn/understand the tradeoff between different learning rates and impact of transfer learning. For our novelty, we will be using the methods of OpenCV in order to integrate our models with live cameras. The proposed project has several potential benefits for researchers in the field of age classification. Additionally, the insights gained from this project may have implications for related fields, such as facial recognition and emotion recognition. Overall, the project has the potential to contribute to the ongoing efforts to develop more accurate and reliable methods for age classification, which has numerous real-world applications.

4. REFERENCES

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