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Neural networks course project: Age Estimator

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1. Introduction

In this project, we aim to develop a neural network model that can accurately predict an individual's age based on their appearance. This problem is of particular interest because it has a wide range of practical applications. In the healthcare industry, accurately predicting the age of patients can help with diagnosis and treatment planning. Additionally, being able to accurately predict age can be useful in this digital social media age, such as in the context of identity verification.

2. Literature overview

All related work uses Convolutional Neural Networks. They are proven to be effective and quickly became the go-to method in Computer Vision tasks. One of the key advantages of CNNs is that they are able to automatically learn hierarchical representations of the data, which allows them to achieve state-of-the-art performance on a wide range of image recognition tasks.

3. Our solution

We were using convolutional neural networks (CNNs), which have proven to be effective and are used extensively. By training our CNN on a large dataset of images and their corresponding ages, we learned a model capable of generalization on before unseen images.

While we were experimenting we tried to find the best model architecture to use for our problem.

The **first** models architecture was rather simple. It consisted of two convolutional layers each followed by a max pooling layer and batch normalization. After that there is a linear layer that outputs the models age prediction. Even though this model produces alright results (accuracy of 72%), there is room for improvement.

The **second** model added some complexity. The architecture consisted of three more convolutional layers, five in total. It achieved better results than the first model.

The **third** and final model was even more complex. The first, CNN part, consisted of 5 convolutional layers, followed by a linear neural network. The linear neural network consists of five fully connected linear layers. This is the model that is referenced in later parts of this paper.

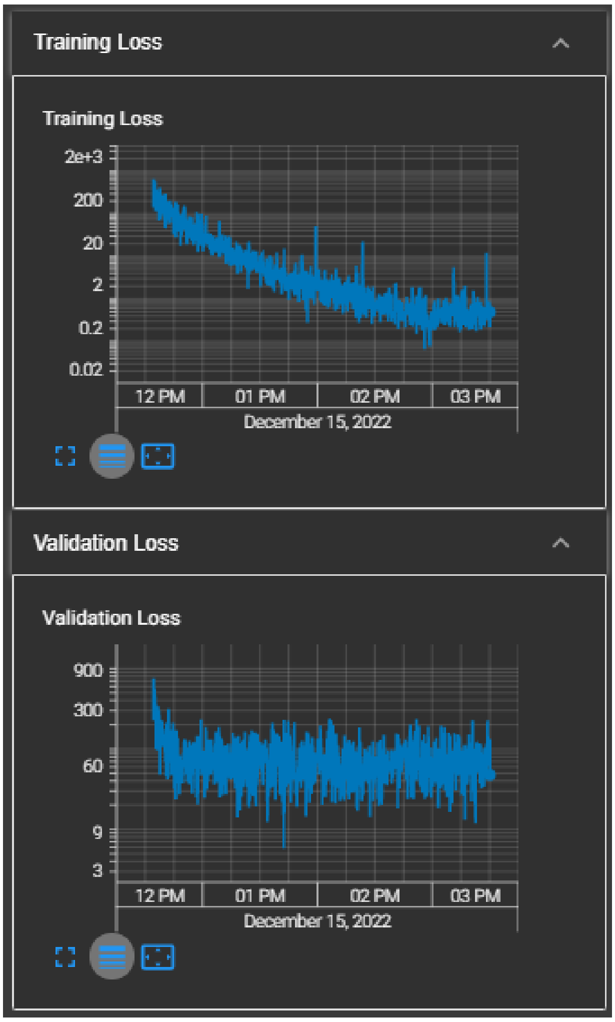
It is obvious that by using more complex models we achieved better generalization and accuracy, but that doesn't always have to be the case. Very large neural network models are prone to overfitting. Nevertheless, by experimenting more and with bigger computational power there is a possibility of finding an even better model architecture.

4. Results and comparison to existing work

In this chapter we will report several measures of our model's performance following existing papers. We will also compare our results with those presented in the papers. All of the measures are obtained by evaluating our model on a previously unseen test set containing 25% of the UTKFace (Zhang and Qi, 2017) dataset.

First, we show the mean squared error (MSE) of our model during training in Figure 4.1.

Figure 4.1: MSE during training



Following (Shin et al., 2022), we report the mean absolute error (MAE) of our model in Table 4.1. (Shin et al., 2022) outperform our model, however, we find the results to be comparable, which suggests that our model is not far from state-of-the-art on this dataset.

Following (Raman et al., 2022), we group the dataset into four age classes: $0 - 12$ (childhood), $13 - 19$ (teenage), $20 - 59$ (adulthood) and $60+$ (senior). We report the accuracy of our model in predicting the classes on the test set in Table 4.1. Our model outperforms (Raman et al., 2022) using this measure.

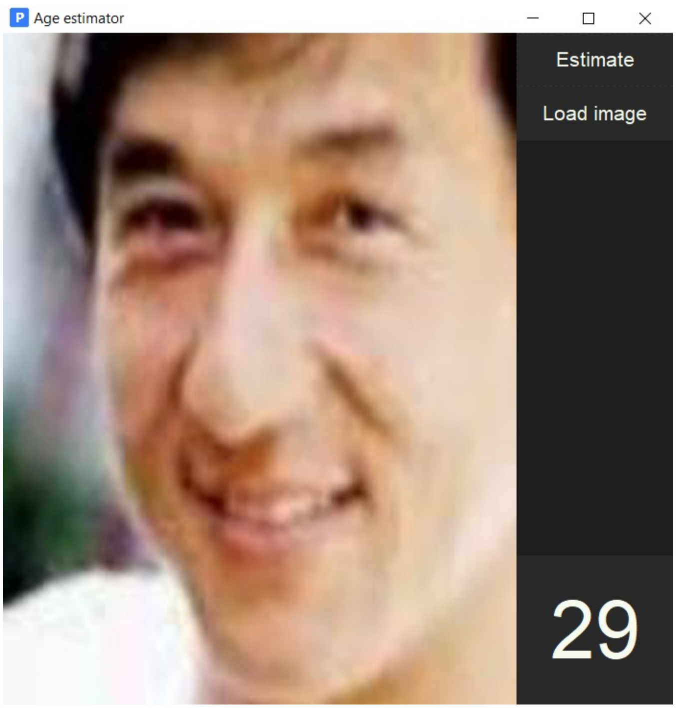
Table 4.1: Results

Measure	Value	Comparison
MAE	5.90	4.37 by (Shin et al., 2022)
Accuracy (four classes)	87.26%	80.76% by (Raman et al., 2022)
AABD	0.57	0.11 by (Abdolrashidi et al., 2020)

Following (Abdolrashidi et al., 2020), in Table 4.1 we also report the average age-bucket absolute difference (AABD), which is the average of the absolute differences between the true age buckets and the predicted age buckets. The age buckets correspond to intervals of ten years. More precisely, an age bucket is equal to $\lceil \frac{age}{10} \rceil$. Once again, we find the results to be comparable.

We built a graphical user interface for a more practical use of our model. The interface is shown in Figure 4.2.

Figure 4.2: Graphical user interface



5. Conclusion

In conclusion, we developed a deep convolutional neural network for age estimation, consisting of 5 convolutional layers with $2D$ max-pooling and batch normalization followed by 5 fully connected layers. We trained and evaluated the model on the UTKFace (Zhang and Qi, 2017) dataset. We also built a graphical user interface for more convenient use of the model.

We evaluated our model using different measures from recent work, achieving near state-of-the-art age estimation results on the UTKFace dataset. In the future, we could try experimenting with different architectures, potentially adding more layers or increasing the size of the layers, as we had limited computational power for this work. Additionally, we could train and/or evaluate our model on different age estimation datasets and see if it is able to perform well in different environments.

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