**Age estimation based on facial images using Deep Learning techniques**

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**1. Introduction**

Age estimation plays a significant role in different scenarios, from law enforcements identifying individuals to social interactions. Because the aging process does not only dependents on intrinsic factors (e.g. genetic factors) but also on extrinsic factors (e.g. environment, lifestyle), estimating someone’s age based only on their face is a challenging problem[[1]](#footnote-1).

Therefore, the literature offers a wide variety of approaches to this problem. Lots of researcher tried approaching this problem by using traditional ML techniques such as K-Nearest Neighbors[[2]](#footnote-2) and Support Vector Machines[[3]](#footnote-3). Since deep learning showed great potential on images, some have proposed working with deep learning techniques. Sithungu and Van der Haar for example focussed on a lightweight model and proposed a modified LeNet-5 architecture[[4]](#footnote-4). While Ozbula, Aytar and Ekenel researched the potential of using transfer learning with pre-trained model such as AlexNet aand VGG. [[5]](#footnote-5) Lastly, Fariza, Mu’arifin and Arifin also proposed using convolutional layers by following the ResNe(x)t-50 architecture[[6]](#footnote-6).

In this paper, we will focus on the following research question: ‘*To what extent can we apply deep learning techniques on age estimation using facial images?’*

Table 1: Dataset

|  |  |  |  |
| --- | --- | --- | --- |
| **Age class** | **Age range** | **Total samples (balanced)** | **Total samples (imbalanced)** |
| 0 | 1-10 | 3,492 | 1,183 |
| 1 | 11-20 | 1,682 | 1,183 |
| 2 | 21-30 | 7,806 | 1,183 |
| 3 | 31-40 | 4,345 | 1,183 |
| 4 | 41-50 | 2,103 | 1,183 |
| 5 | 51-60 | 2,226 | 1,183 |
| 6 | 61-70 | 1,183 | 1,183 |

**2. Experimental procedure**

**2.1 Dataset**

In this experiment we used the Aligned&Cropped Face from UTKFace dataset (24,106 images). We binned the data into 7 classes, applied under sampling because the data was highly imbalanced and removed images with ages over 70. This resulted in the following Table 1. We split the data into three sets, 75% training, 20% validation and 5% test.

**2.2 Experimental setup**

In this experiment we used Python code and the Keras library to implement deep learning techniques, Table 2 displays which models are used in this experiment:

Table 2: Models used in the experiment

|  |  |
| --- | --- |
| **Model architecture** | **Compiler** |
| LeNet-5 architecture | Optimizer = rmsprop, metrics = accuracy, loss = categorial\_crossentropy |
| LeNet-5 architecture (with batch normalization) | Optimizer = rmsprop, metrics = accuracy, loss = categorial\_crossentropy |
| Modified LeNet-5 architecture proposed from paper Sithungu and Van der Haar (2019) | Optimizer = rmsprop, metrics = accuracy, loss = categorial\_crossentropy |
| VGG16 (weights = ‘imagenet’, include\_top = False, layers set to non-trainable) and adding trainable three dense layers (512, 512, 7). | Optimizer = rmsprop, metrics = accuracy, loss = categorial\_crossentropy |
| ResNet-50 (weights = ‘imagenet’, include\_top = False, layers set to non-trainable) and adding GlobalAveragePooling2D and output dense layer with 7 nodes. | Optimizer = adam, metrics = accuracy, loss = categorial\_crossentropy |
| ResNet-50 (weights = ‘None’, include\_top = False, layers set to trainable) and adding GlobalAveragePooling2D and output dense layer with 7 nodes. | Optimizer = adam, metrics = accuracy, loss = categorial\_crossentropy |

**2.3 Evaluating the performance**

We decided to evaluate the performance based on the validation accuracy, where we can take into account two baselines. The first one is an accuracy of 14% (1,183 /8,281 total balanced samples) and second one is 45.3%, the highest validation accuracy Sithungu and Van der Haar achieved by using the modified Le-Net-5 architecture.

**3. Results**

**4. Discussion and conclusion**

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6. Fariza, A., Mu’arifin, & Arifin, A. Z. (2019). Age Estimation System Using Deep Residual Network Classification Method. *2019 International Electronics Symposium (IES)*. <https://doi.org/10.1109/elecsym.2019.8901521> [↑](#footnote-ref-6)