The British University in Egypt

AGE Classification

Age, Gender and Ethnicity

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Abstract

This research project delves into the domain of age detection and its intricate connection with other soft biometrics, namely gender and ethnicity. The primary objective revolves around the optimization of a model specifically designed for age classification from faces on a challenging and high-variance dataset called UTKFace while using realistic age bins, as well as investigate the interplay between age, gender, and ethnicity in the process. The outcomes of the research efforts are exceptionally promising. The optimized **classification model achieves state-of-the-art results in age classification with an F1 score of 73.27%,** while scoring 93.41% gender, and 80.25% for ethnicity that are still competitive with state-of-the-art models. Further optimization is suggested for ethnicity, particularly regarding data balancing and classifying the 'other' ethnicity label. Most notably, the age classification results surpassed those of existing models in the same age categories.

Methodology

- UTKFace [1] is the dataset used for this project. It is a large-scale face dataset with a wide age range (0 to 116 years old). The dataset contains over 20,000 200x200px face images with age, gender, and ethnicity labels.
- The optimal model AGECNN is shown in Figure 1. The model start with a batch normalization layer to ensure the input is normalized. Then, it goes through 4 CNN[1] blocks with the following architecture: A convolution layer -> ReLU activation function -> batch normalization layer -> max pooling layer. After that, the output of the last CNN block is flattened and passed through a fully connected layer -> ReLU and a dropout probability of 60%. Finally, the output goes through one final fully connected layer are through a softmax function to get the final predictions.
- The same model is used for age, gender, and ethnicity detection with all the same hyperparameters. The only differences are the number of hidden layers, kernel filters, and the size of the last fully connected layer based on the number of classes.

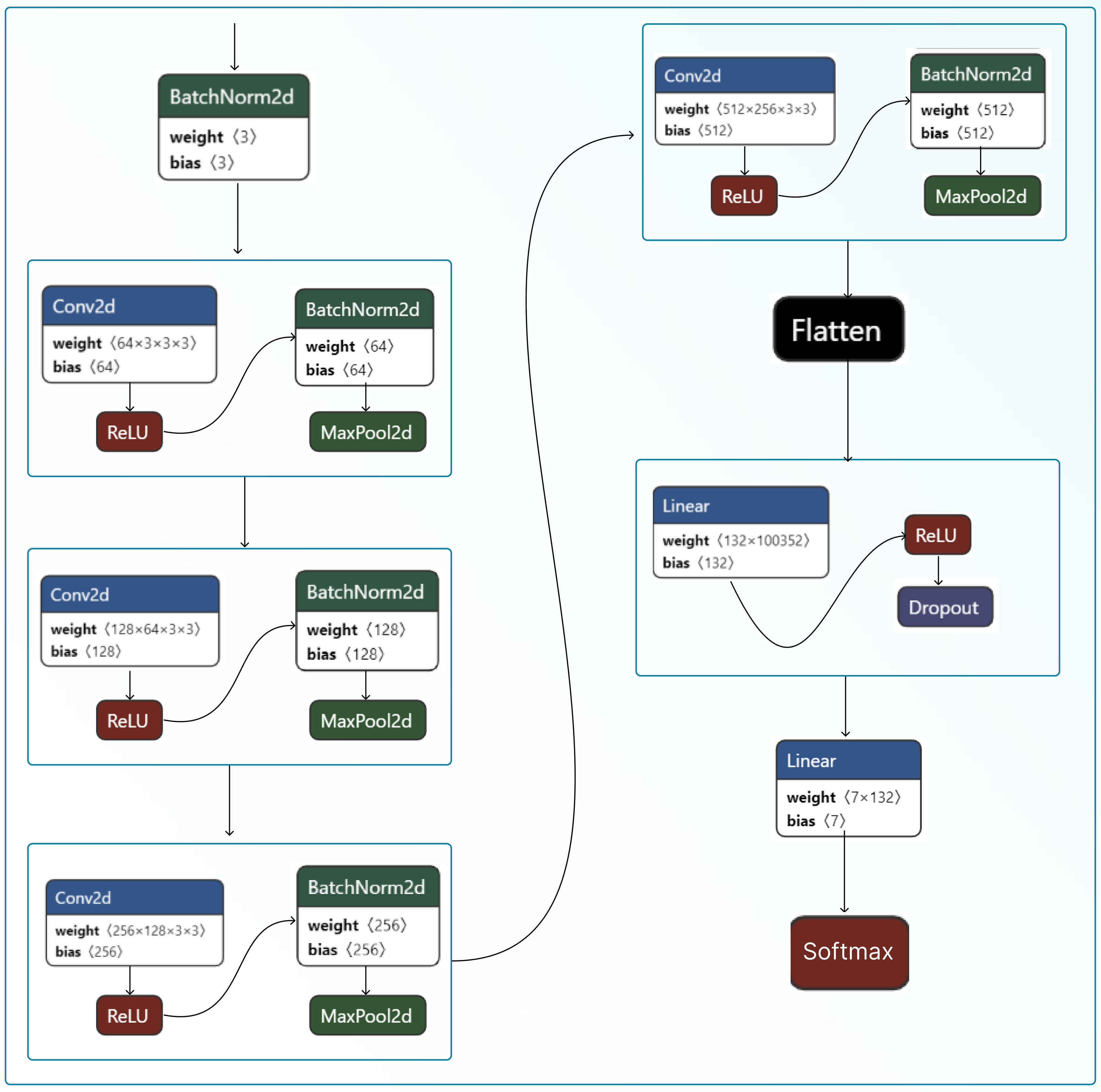

Figure 1. AGECNN model architecture

Results

An example of model output is shown below in Figure 2. The input is a facial image of a 28-year-old, white female. The input goes to three very similar models with slight differences explained in the Methodology. Finally, each model outputs its respective task. It can be observed that the model is able to predict the three classes correctly and with a very high certainty.

Figure 2 Example input, and output predicted correctly for the three tasks

AGECNN achieved F1 scores of 73.27% for age, 93.41% for gender, and 80.25% for ethnicity as shown in Figure 3 after training for an average of 55 epochs, each model taking an hour to train.

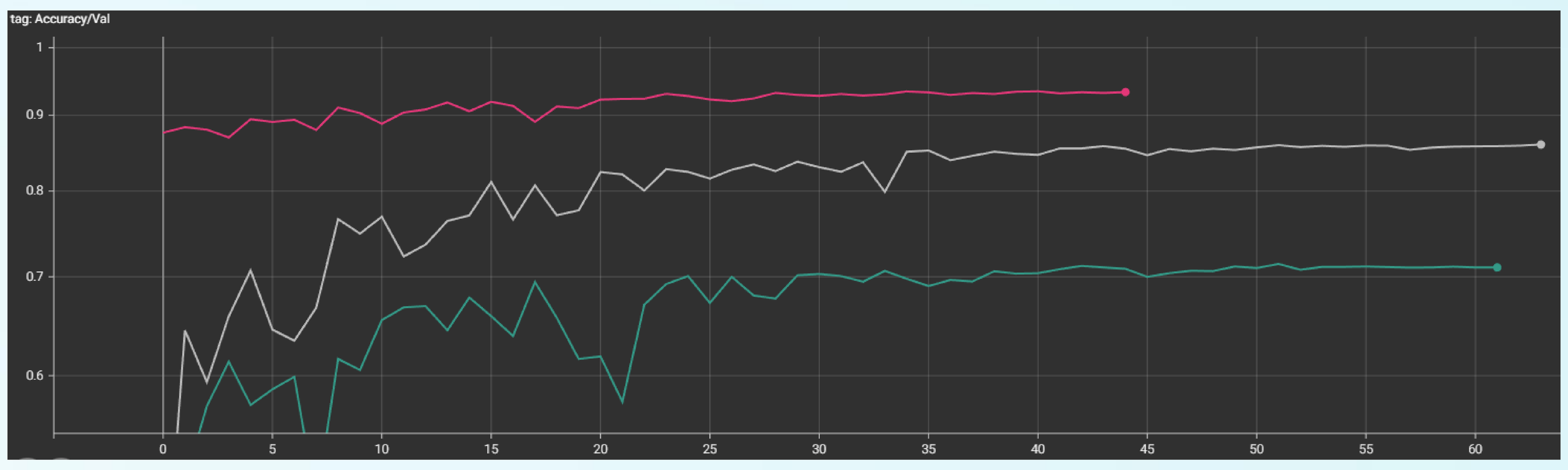

Figure 3 AGECNN testing results in age (green), gender (pink) and ethnicity (white)

Conclusion

- AGECNN model achieved state-of-the-art results in age classification using this set of age bins, while still maintaining competitive results in gender and ethnicity classification
- Selected optimized age category bins based on domain knowledge and data analysis
- Experimented with several model architectures and learning techniques including:
  - Residual attention
  - Transfer learning with FaceNet
  - Multitasking
  - Hierarchical models
- Detected a data leak while optimizing the models and handled it by separating the data from the code logic.

References

[1] Z. Zhifei, S. Yang, and Q. Hairong, "Age progression/regression by conditional adversarial autoencoder," in IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2017

[2] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in 2017 international conference on engineering and technology (ICET), 2017, pp. 1–6.