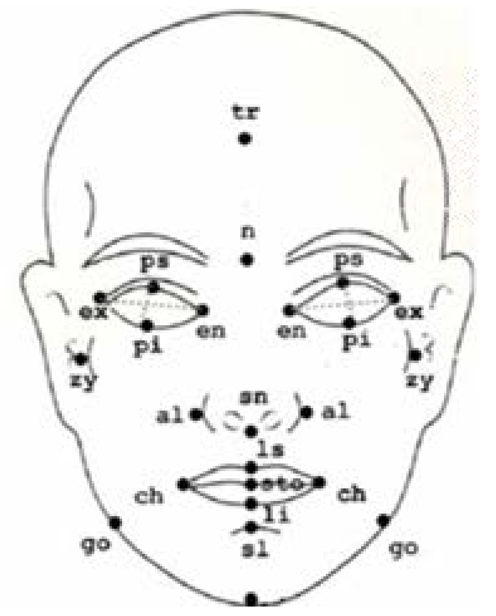

Age Estimation from Frontal Images of Faces

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ABSTRACT

Humans have the ability to automatically look at the face of the person and estimate the age. For a computer to be able to do this automatically, we require algorithms that extract appropriate features from the faces and use them to learn how they map to ages. This poster summarizes the result of using anthropometric models with varying parameters.

INTRODUCTION

Humans can estimate information such as age, gender, expression etc. by simply looking at faces. Automated age estimation has several challenges such as variance among different ethnicities, facial deformities etc. Aging progress is uncontrollable depending on various factors such as lifestyle, climatic conditions, health etc. Hence, we can't have an accurate estimation process for every possible case. We try to predict age groups of people by exploiting various biologically defined ratios in facial features and relations between them.

METHODS

In this experiment, we are using the Datatang Aging database to train and test our set of classifier. The database consists of approximately front facing images of around 82 individuals. There are approximately 12 images at different ages for each individual. We use the dlib library to recognize the faces and extract facial features such as a set of points that represent the boundaries of eyes, nose, eyebrows, lips, jaws. We calculate anthropometric ratios of the facial features and use that for classification.

In this poster, we have attempted to compare the performances of various classifiers, such as: Bayesian Classifier, Nearest Neighbors, Neural Networks, and one wherein two Neural network outputs are combined. A set of 7 ratios as shown in Fig. 2 and a set of 14 angles that form the jaw boundary as in Fig. 3(individually and combined) are used as feature vectors into the above classifiers. In addition to the above, we run the classification process over different age groups and compare the accuracy. The set of classifiers and feature sets and other parameters are pictorially represented in the process flow diagram in Chart. 1.

Detect Faces
Use Dlib library to detect faces

Extract Facial Features
Use Dlib library to detect an array of points that represent facial features

Compute Feature Vectors
Calculate the 7 facial ratios | Calculate the angles of jaw boundary

Classify
Bayesian Classifier | Neural Networks | K Nearest Neighbor

Chart 1. Overall process

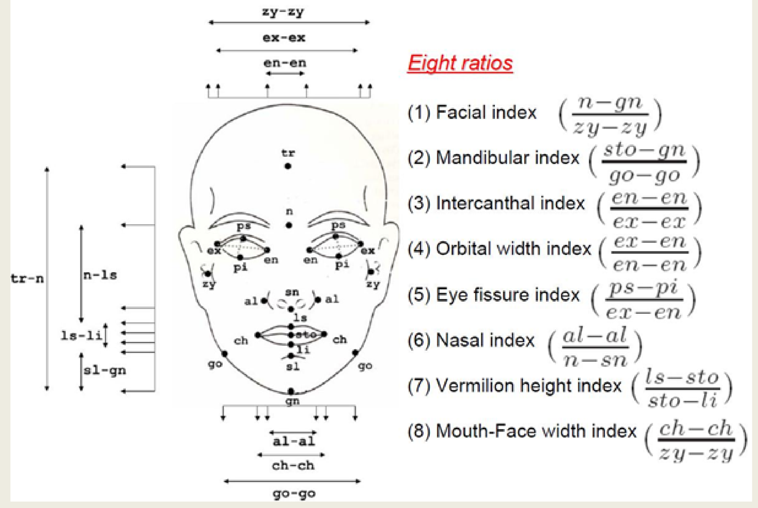

Figure 1. Facial Ratios[1]

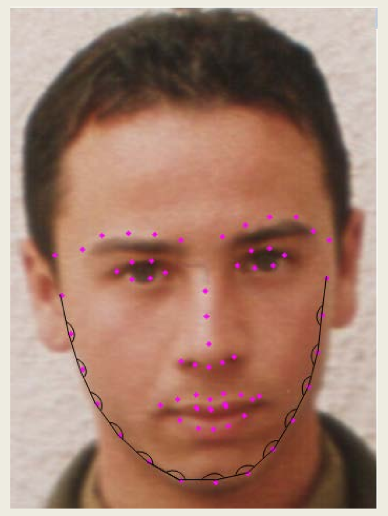

Figure 2. Jaw boundary[2]

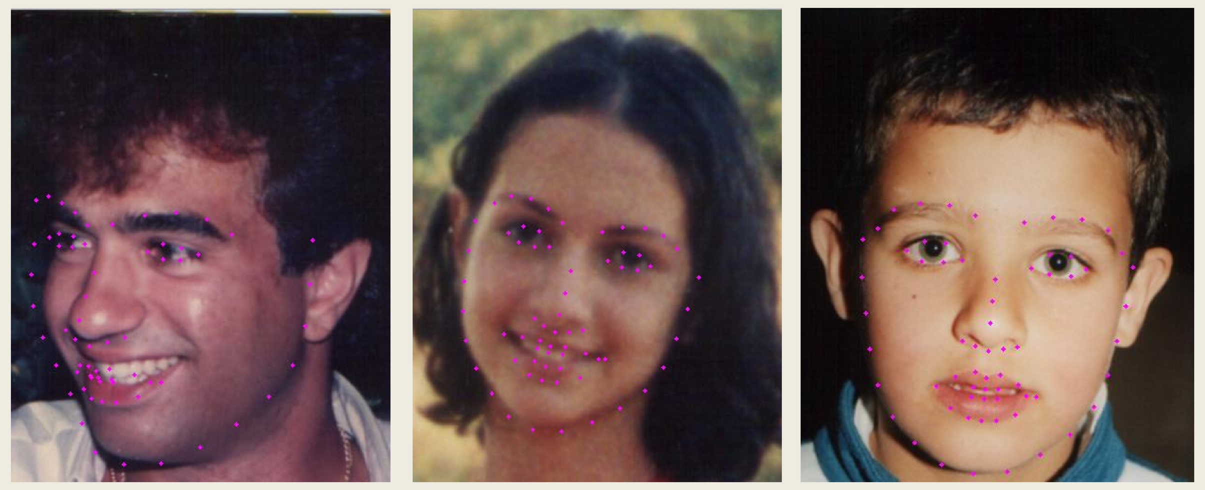

Figure 3. Facial Ratios[2]

RESULTS

We studied the effect of tuning various parameters of classifiers on the overall accuracy and have summarized the results below. We tweaked parameters like number of nodes in the hidden layer of Neural network and number of nearest neighbors in KNN. We further experimented with the 3 set of features and various age groups. Summary of the results appears below.

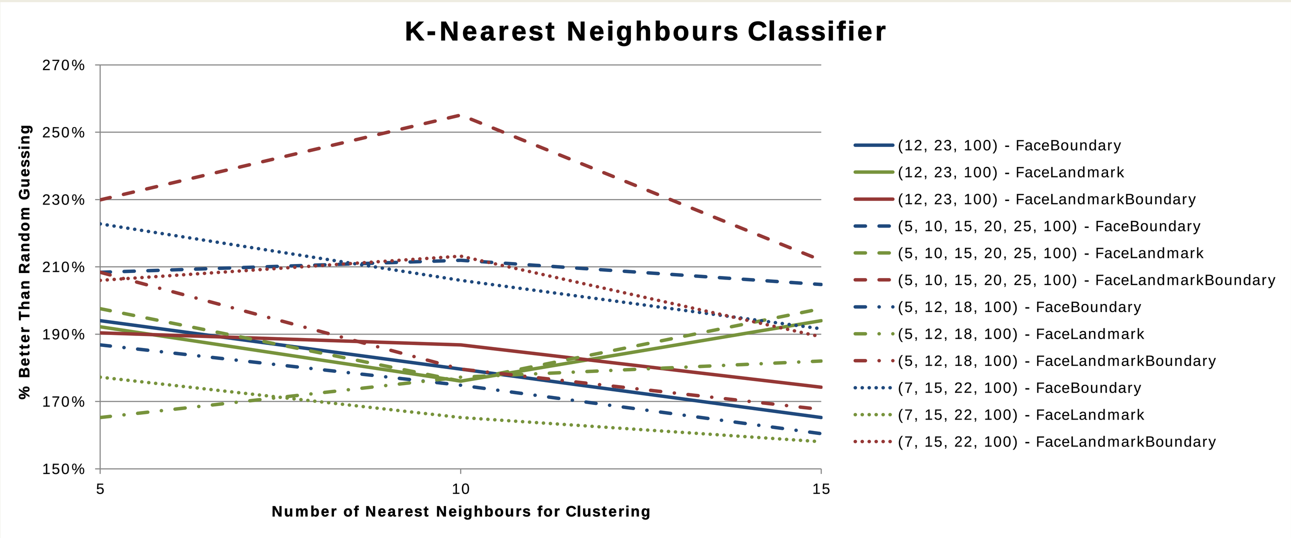

Chart 2. KNN Classifier performance

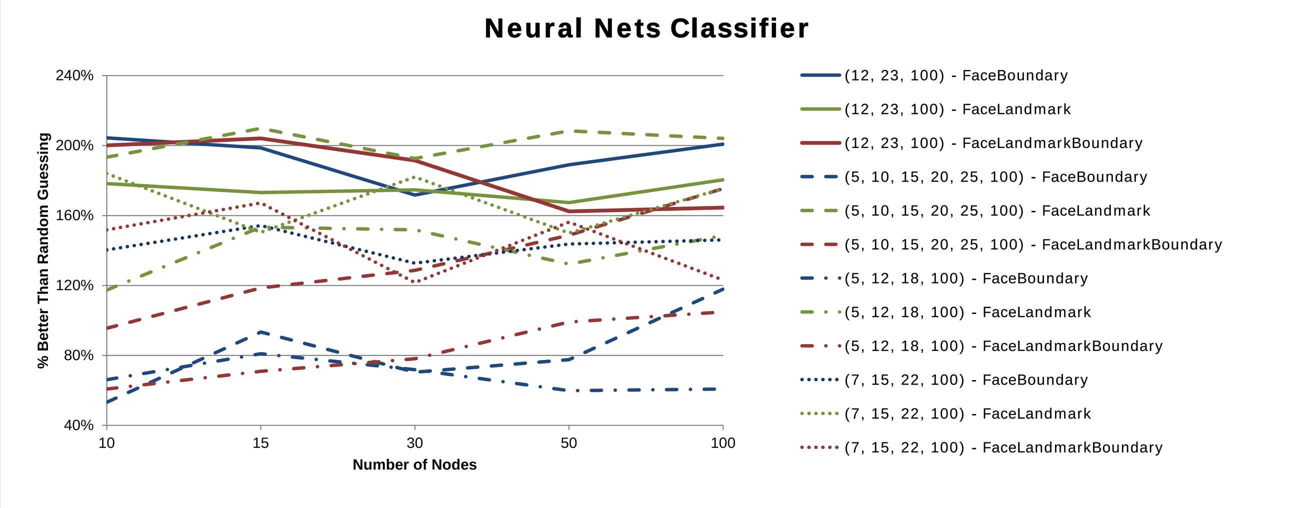

Chart 3. Neural Network Classifier Performance

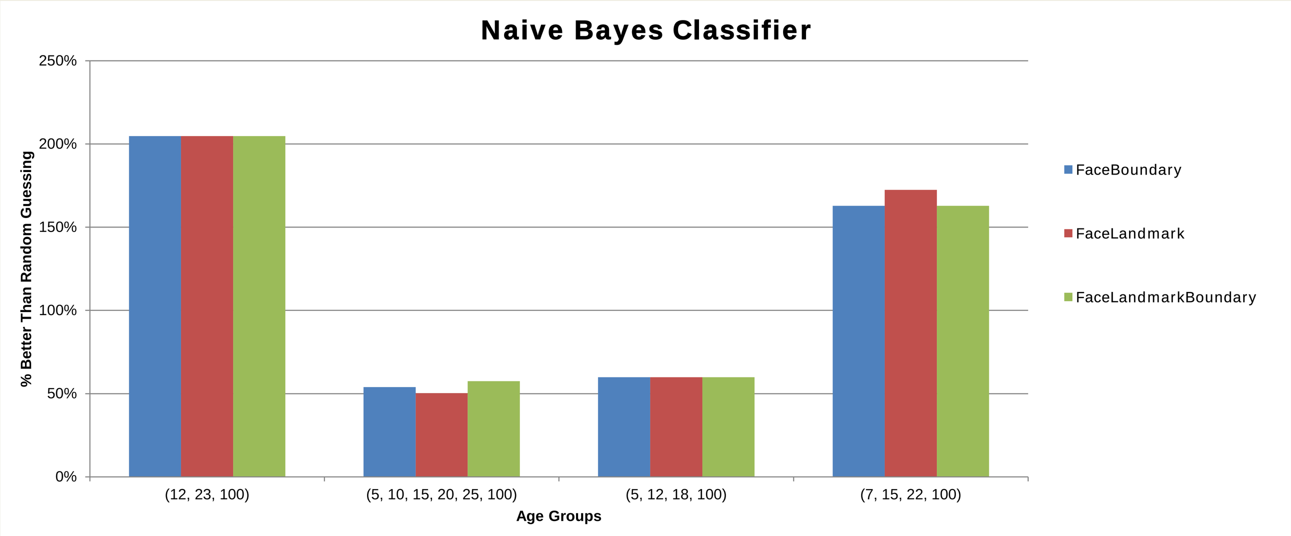

Chart 4. Naïve Bayes Classifier Performance

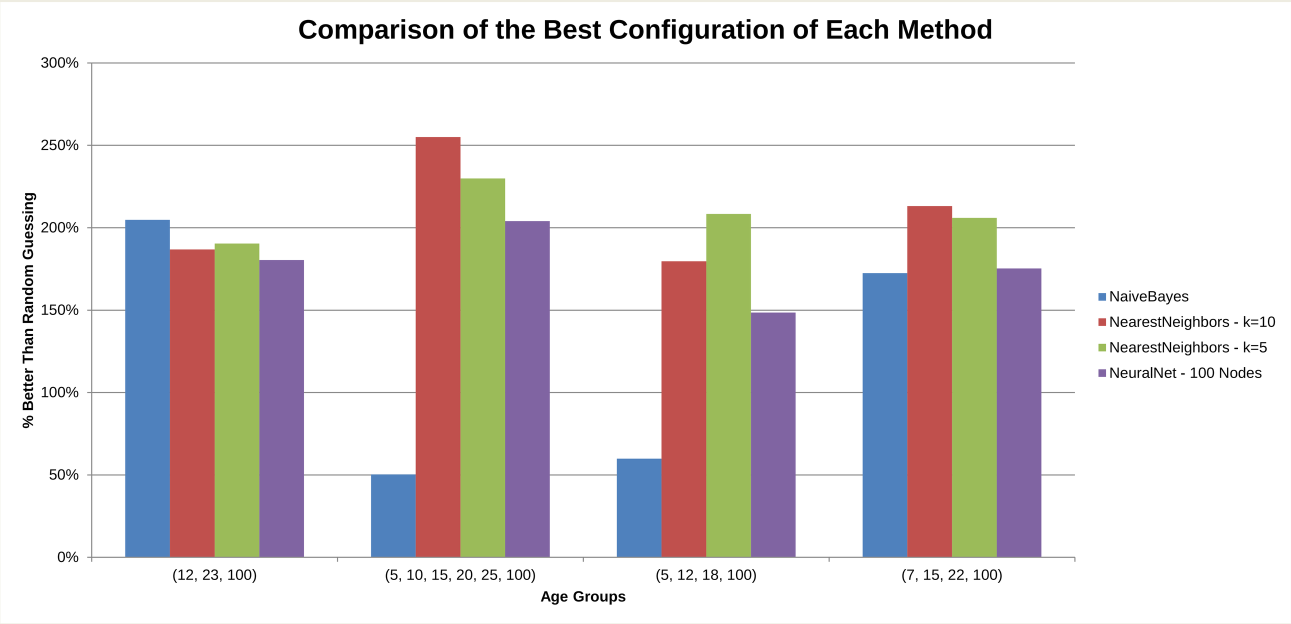

Chart 5. Best Configuration Performance

OBSERVATIONS

From the experiments that we performed, we observe:

- Although the classifiers give a relatively good accuracy for more granular age groups, we found that the output is often unstable for higher ages because the face structure stops changing significantly after a certain age. In other words, the classifiers are able to distinguish better between kids and adults. However, it does not perform well when tasked with predicting more accurate ages.
- The curvature of the jaw can also be used to predict the age group of the person. However, it gives a lower accuracy as compared to using facial ratios. We have also implemented the three classifiers using a combination of facial ratios and jaw boundary angles and this gave better results for KNN.
- The classification is highly dependent on the pose of the face. The accuracy of proper prediction is higher when the face is not looking away from the camera. In Fig. 3, the first image does not work well while the other two image get predicted accuractely.
- Among the 3 classifiers, KNN gives us the best results for the different age groups and feature set as compared to Neural Nets and Bayes' classifier.

CONCLUSIONS

- The models that we have built can efficiently distinguish between kids and adults, for relatively smaller number of age groups.
- The detection of facial features and classification of age is highly sensitive to the pose of the person and somewhat sensitive to the facial expression.
- The accuracy of classification reduces as we increase the number of age buckets.

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