The age estimation algorithm realizes hierarchical approach (fig. 10). First of all, the input fragments are divided into three age groups: less smaller than 18 years old, from 18—45 years old, and more bigger than 45 years old. Second, Afterwards the results of this in the first stage are more subdivided into seven smallerness groups, with each limited to one single decade. Thus, the problem of multiclass classification is therefore reduced to a set of binary “one-against-all” classifiers (BCs). These classifiers calculate then ranks these images each based one of the associated class, and the final total decisions are obtained then by the analyzing these previously received rank histograms of ranks.

These BCs are constructed using a two-level approach. After bin is applied first with the transition to an adaptive feature space, as equal to this described earlier, the images are classified and supported vector machines classification with RBF kernel.

The input fragments were preprocessed for their luminance characteristics to align and to transform them to a uniform scale. This preprocessing step includes color-space transformation and scaling, both operations similar to those used in the that of a gender recognition algorithm. Features are calculated for each color component and are combined to form a uniform feature vector.

Training and testing require a sufficiently large enough coloring image database. We combined used the state-of-the-art image databases MORPH and FG-NET image databases with our own image database, gathered obtained from many different sources and which comprises of 10,500 face images. The faces in the images were detected automatically by the AdaBoost face detection algorithms.
A total number of seven thousand 7000 images were used to train and test the first stage of the age classification algorithm. Training and testing on the first stage. Three binary classifiers were created, utilizing 144 adaptive features each.

The first-stage classifier showed on the first stage are: 82% accuracy for young faces, 58% accuracy for middle-aged faces, and 92% accuracy for elderly faces. The overall age classification accuracy for the three age categories was 77.3%.

The second-stage binary classifiers of the second stage were constructed in the same way as for equal to the first stage (described above). Fig. 11 shows a visual example of age estimation by the first stage of the proposed algorithm on its first stage is presented in Figs. 11.