IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Relative Attributes SVM+ Learning for facial age Estimation

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ABSTRACT:

Human experts can estimate a person's age based on their experience and knowledge. There are many methods of age estimation like cameriere method of age estimation, Demirjian's method of age estimation, age estimation using teeth, age estimation from skeletel remains. The age estimation mechanism we are trying to develop uses facial features which are responsible for aging like, smoothness, wrinkles, face shape, under eye bags to estimate a his/her age. These are all called privileged information available to develop a machine learning model for estimating age. The age estimation model is used in forensic to identify the age of unknown bodies at the time of death which is useful to help the criminal investigators in further investigation. Machine learning technology is used to classify the model and train the facial images and provide the estimated output. The relative attributes for support vector machine (SVM+) algorithm is used to improve the performance of age estimation. The overall system reaches mean absolute error 4.06 on our Dataset.

Keywords: Machine Learning, Forensic, Support Vector Machine, Facial Images.

1.INTRODUCTION

A Person's age is an influential factor in his/her behavior and lifestyle and therefore age information is widely used in biometrics, security control, government exam age eligibilities, computer vision applications and human computer interactions. Age information is used in finding the demographic evolutions. There is a large variability that people can look very identical at the same age and the same person can look unrelated on application of makeup, mood, health, face injuries, and many other lifestyle changes. It is very difficult for both humans and machine to estimate a person's age only based on his/her facial features alone. If a machine learning model is trained using a large amount of images including men, women, children, senior citizens. This improves the overall accuracy of the model by providing the accurate output. The given input image is first preprocessed and converted to grey scale to improve the light intensity of the input image and the image is cropped to identify the important features or attributes on the face. Then, classification model is selected, the images present in the dataset are cleaned, splitted into training and testing dataset, visualized and the images are fed to model to train. Then the model is tested using the unit test method to find the accuracy and performance of the model. The SVM+ model is used to improve the accuracy of age estimation model.

1.1. OBJECTIVE

Our objective is to estimate the age of a person using his/her facial features with the Relative Attributes SVM+ Algorithm. In mechanical age estimation, right information was not available to test the images. In this paper, we theories that unsymmetrical data can be traversed and utilized to improve the generalizability of the training model.

1.2. EXISTING SYSTEM

Age estimation is a subject of discussion for nearly a ten years. There have been many approaches on estimating age. With time, the approaches have Been more structured and productive. Originally, the accuracy was below 60% but now the methods assure accuracy above 75%, but trails and approaches are being made every day to improve the accuracy to a maximum level by addition of varying Attributes and implementation using leading technologies. Few of these technologies used are: age-specific local regression algorithm named KINN-SVR is Proposed to capture the complex human old age process. The FG-Net Aging database Is used for simulating outcome and it is found that the system checks for the lowest Mean Absolute Error (MAE) versus existing methods. A hierarchical method for age estimation is presented in this paper. Analysis of the influence of old age on the individual Face elements by using a component-based representation is also done. After examining, the conclusion was drawn that the performance of the proposed system is better the other way similar to the age estimations applied by humans on the FG-Net dataset and a subset of the PCSO dataset.

A vital characteristic in establishing the identity of the person is the age. Age estimation from face images continues to be an extremely challenging task compared to other perception problems. Age is a crucial factor in discovering the identity of a person. Age is estimated from the human face images available in the database by existing age estimation systems like dental tooth enamel and skeletal morphological age estimations . But, they cannot estimate the age of an unknown individual. A new age estimation system is employed to overcome this issue.

1.3. PROPOSED SYSTEM

An important attribute in signifying the person is age. This paper proposes the use of SVM+ algorithms in estimating the age of an individual through the estimation of facial features on both front and side-view face inclination. Linear regression algorithm, Forest regression and Boosted regression algorithms and neural networks were also used for feature extraction. During experiments, training sets composed on 2000 front view images and 2000 side view images were used to train the network. Testing was performed to 1400 front view facial images and 1500 side view facial images. Result of the experiment shows age recognition of 75 .85% for front view images and 78.3% for side view images. The proposed system also uses the machine learning methods to estimate the age of a person on unknown individuals at the time of expiration which helps the forensics and the investigators in further process of identifying the individuals. The relative attributes used are the facial features responsible for age estimation like face shape, eyes, chin, cheeks, under eyes, nose. These features will be selected using the AAM (Active Appearance Model)which selects only the important attributes or features on the person's face.

2.LITERATURE SURVEY

In this paper, we institute a age estimation method that will Relative attribute and SVM (Support Vector Machine) to improve the accuracy of age estimation over the existing techniques of bone age estimation and tooth age estimation. Age group is a range of ages. Persons whose real age is within the defined scales are said to be in the same age group. Notable research has been done to automatically extract visual remnants from faces and group persons in respective age groups.

Kwon and Lobo estimated age group based on anthropometry and density of wrinkles. They separated adults from babies using distance ratios between frontal face landmarks on a small dataset of 47 images. They also extracted wrinkle features from specific regions using snakes. Young adults were differentiated from senior adults using these wrinkle indices. Baby group classification accuracy was lower than 68%, but overall performance of their experiments was not reported. Furthermore, ratios used were mainly from baby faces.

Horng, Et. Al. used geometric features and Sobel filter for texture analysis to classify face images into four groups. They used Sobel edge magnitude to extract and analyze wrinkles and skin variance. They achieved an accuracy of 81.6% on subjectively labeled age-groups.

Tiwari et al. [182] developed a morphological-based face recognition technique using Euclidean distance measurements between fiducial facial landmarks. Using morphological features with back propagation neural network, they reported superior recognition rate than performance of principal component analysis (PCA) with back propagation neural network. This technique recognized faces but it was independent of aging factor due to variations in these distances as one ages. This signifies that distances between facial landmarks differ at different age, especially in young age-groups, and therefore, it could be used in age estimation. Gunay and Nabiyev used spatial LBP histograms to classify faces into six age groups. Using nearest neighbor classifiers, they achieved accuracy of 80% on age groups 10 ± 5, 20 ± 5, 30 ± 5, 40 ± 5, 50 ± 5, and 60 ± 5. Gunay and Nabiyev trained three support vector machine (SVM) models for age-group estimation using AAM, LBP, and Gabor filter features. They fuse decisions from these classifiers to obtain final decision. Although they reported 90% accuracy of subsequent age estimation, overall performance of age-group estimation was not reported.

Hajizadeh and Ebrahimnezhad represented facial features using histogram of oriented gradients (HOG). Using probabilistic neural network (PNN) to classify HOG features extracted from several regions, they achieved 87% accuracy in classifying face images into four groups. Liu et al. build a region of certainty (ROC) to link uncertainty-driven shape features with particular surface features. Two shape features are first designed to determine face certainty and classify it. Thereafter, SVM is trained on gradient orient pyramid (GOP) features for age-group classification. Testing this method on three age groups, 95% accuracy was reported. They further used GOP with analysis of variance (ANOVA) for feature selection to classify faces into age groups using linear SVM to model features from the eyes, nose, and mouth regions. They achieved 91% on four age groups on FG-NET dataset and 82% on MORPH dataset

3.METHODOLOGY

In the beginning Training images were fed to the model before testing of other images was performed. In both scenarios, all images passed through pre-processing, feature extraction, and classification modules.

A. Data Collection

All the images used in the training and testing stage of this paper were captured using a digital camera having a resolution of 2048×1536px. Image acquisition was also done in a managable environment with proper illumination and lighting and with a light colored background.

B. Importing modules

The different modules required to create a age estimation model are imported. The modules and the libraries are pandas, numpy, os, matplotlib, seaborn, warnings, tqdm, tensorflow which is used as backend technology keras model for preprocessing the images, Dense, Conv2D, Dropout, Flatten, Maxpooling2D, and Input.

C. Loading the Dataset

The dataset containing around 23,000 images are processed with three layers of RGB and converted to pixels and binary format which is understandable by machine while training all these images for age estimation. The files containing all the images are loaded in the model with image paths and age labels. Then it is converted to a Data frame with image and age labels and mapping those labels with images.

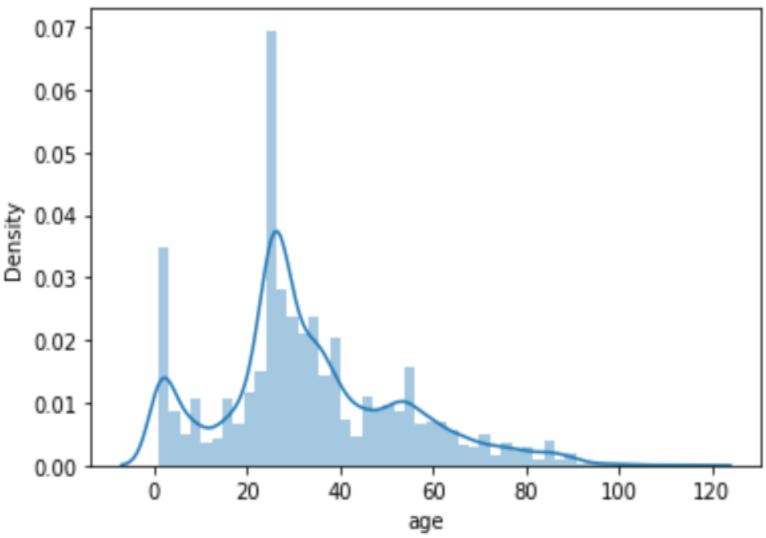
	image	age
0	UTKFace/100_0_0_20170112213500903.jpg.chip.jpg	100
1	UTKFace/100_0_0_20170112215240346.jpg.chip.jpg	100
2	UTKFace/100_1_0_20170110183726390.jpg.chip.jpg	100
3	UTKFace/100_1_0_20170112213001988.jpg.chip.jpg	100
4	UTKFace/100_1_0_20170112213303693.jpg.chip.jpg	100

D. Exploratory data analysis

This is the visualization of all the images in the dataset. Distplot and countplot techniques are used to represent the dataset on graph. The graph shows the amount of images which represents different age groups from 0-120 among 23,000 images in the dataset. Then a grid of images can also be shown from the dataset into the model.

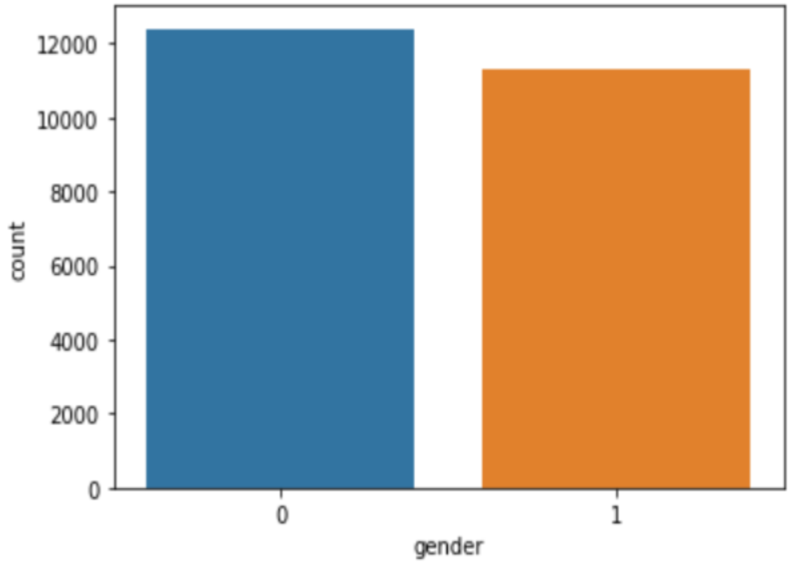
```
sns.distplot(df['age'])
```

```
<AxesSubplot:xlabel='age', ylabel='Density'>
```



```python
sns.countplot(df['gender'])
```

```
<AxesSubplot:xlabel='gender', ylabel='count'>
```



E. Feature Extraction

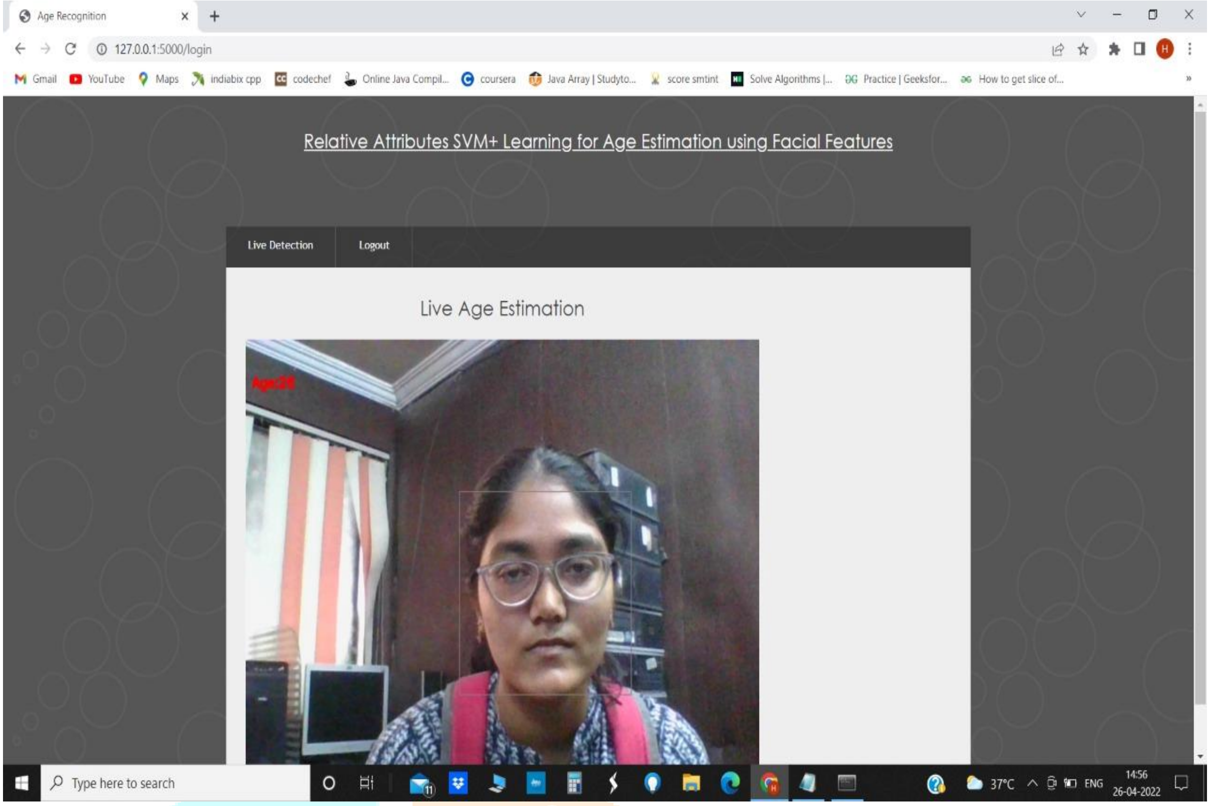
The features of every image in the dataset are extracted randomly into the model using a for loop. This process selects the important features from the facial images like face shape, wrinkles, forehead, cheeks, chin, eyes, nose and under eyes which are responsible for age estimation. It provides new features from the existing features. The feature selection eliminates the unwanted data, missing values, redundant features, irrelevant data to clean up the dataset from unwanted things and provides a processed images to be read for training. Then x and y values are assigned for the dataset.

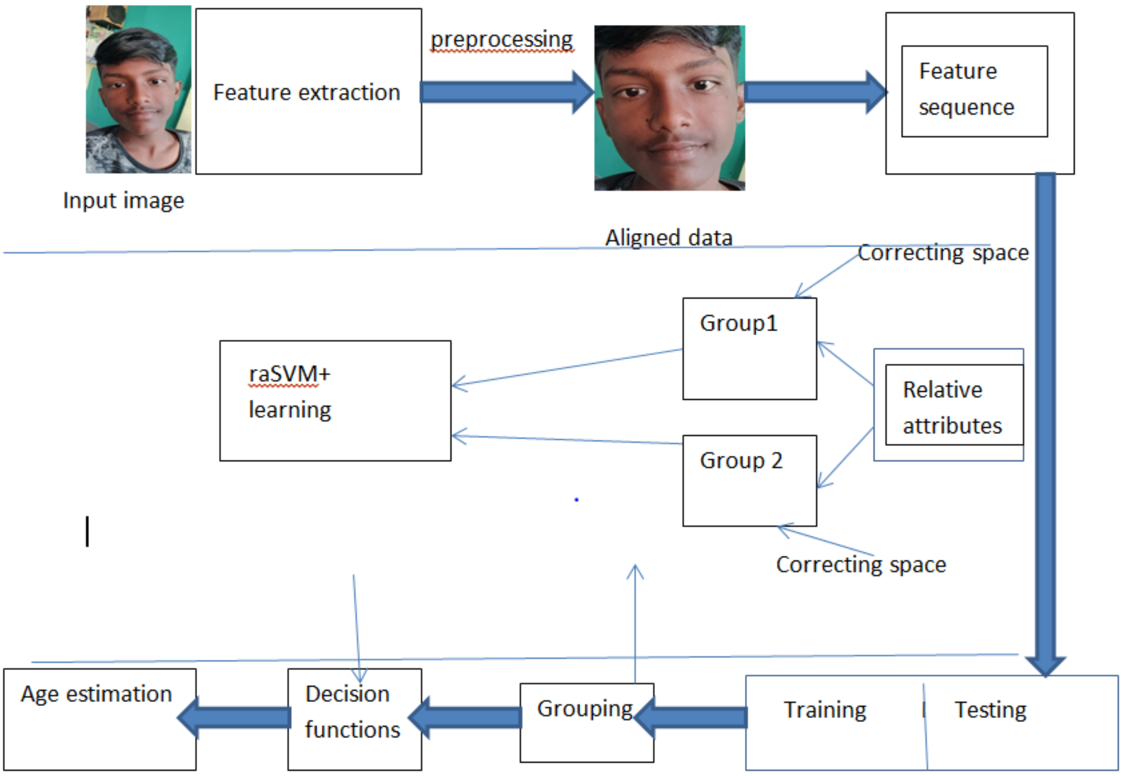
F. Splitting the Dataset

The Dataset is then splitted into training and testing phases. 80% is used for Training purpose and 20% of the images in dataset are used for the purpose of Testing. Variable X is for testing and variable Y is for training and the relative attributes for training are np.array(x), y_age, test_size, random_state. The images are taken randomly from the dataset for training and the time taken for training is about 72 hours. Then normalization of training and testing is done and is reshaped to 2D array.

G. Testing the images

Eventually classifiers and pickle files are imported. Accuracy of the model is estimated along with confusion matrix and classification report. Ftest and test are plotted and the predicted values are mapped with the estimated values. The accuracy of the model is 90%. With this the model can be used for live age estimation by creating a user interface web application.





Framework of Age estimation using facial features

4.CONCLUSION

In this paper, we initiated various elements into the age estimation model and effectively improved the accuracy and robustness of age estimation. We tried to find appropriate facial features to describe the age characteristics for age estimation by analyzing and comparing various feature extraction approaches. We acquired the rank relationships of the human aging process by registering privileged information in the faces and using the relative attributes learning algorithm. In inclusion, we proposed a raSVM+ algorithm to distinguish the relative age groups. This approach utilized relative attributes as privileged data for raSVM+ learning, which improved the accuracy of age estimation by controlling outliers in the training datasets. We also provided a robust and efficient algorithm to solve raSVM+. Experimental analysis established that the proposed method has superior performance compared to existing approaches.We also analysed the reasons that would describe large age estimation errors. Our future work is based on methods to define more facial attributes in terms of different ROI. This will further improve the accuracy and robustness of age estimation.

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