Learning Practice for Binary Age Group Stratification by Iris-Pupil Thickness

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Abstract— Anticipation of age has a significant role in different fields. It has prime importance in determining age in social networking, forensics and in archaeology. Machine learning has a pivotal role in determination of age and reached to an advanced level in the previous years. Rapid progression of these studies demands its preciseness and highly structured estimation. Categorizers for binary methods are often fairer and more accurate for this sensitive information for age and gender. In this paper, machine learning method is used to categorize age by using iris radius, pupil radius and iris pupil ratio. Dataset was created by implementing CASIA dataset. CASIA Iris Twins and CASIA Iris Intervals were utilized and radius was calculated by determining diameter. It has provided more accurate information and estimation of age and would prove helpful in future.

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1 Introduction

THOMAS Kuhn argued that science progresses by running into problems and them make a major shift in its paradigms or models. People have seen such a shift as available data becomes richer and possible explanations multiply. Age estimation is the determination of age of person based on various features and can be accomplished through different traits. It's a crucial parameter in archaeological and forensic context. Assessing age in archaeology offers important information on demographics of population. In addition, in living age estimation is important in migration crisis that takes place in different parts of the world.

Artificial intelligence, machine learning and computer vision have been carried out in recent years at very advanced level. Undoubtedly, it's a huge contribution in rapid progress of these studies. Some people hide their personal data like age, gender etc. and their social nature changes with age. It also depends on behavior of different people. Sometimes behavior of same age groups is similar and is known as homogeneous behavior. Sometimes visual information also provides age estimation accurately. Binary classifiers are often used because they possess fairness in the sense of not overly discriminating with respect to a feature deemed sensitive e.g age, race etc. Novel methods were introduced for age estimation in which facial detection and speech signals detection were also included.

Age classification is helpful in issuing different permissions at different levels. Now-a-days, a captivating topic in iris biometric is being used to resolve age from image of iris. Studies showed that with time, an increase in false non-matching rate due to enrolled iris. It's more difficult to estimate age on eye snapshot because the tempo at which structure/characteristics of human eye are changed is not very well known. In establishing this biometric research, the community has compromised with earlier findings that iris remains stable throughout life. In this paper data driven approach was utilized by using machine learning to elucidate the categorization in age estimation and obtained and implemented CASIA dataset.

2 Literature Review

A new divided and conquer based method was proposed called fusion of multiple binary age-grouping estimation system for estimation of facial age of human. Multiple binary grouping systems were employed. Each face image was classified into one of the two groups. Two models were trained to estimate ages for faces classified into their groups. Two models were trained to estimate ages. Also, the investigation was done on affect of age grouping on performance accuracy [1].

Primary features of the face are determined first in an implementation and secondary primary features were analyzed. Then the ratios of babies from adults were being computed. In secondary analysis a wrinkle geography map is used to guide the detection and measurement of wrinkles [2].

The database for FG-NET aging was released in 2004 to support activities for research which is related to facial aging. Conclusions were related to the type of research carried out in relation to impact of dataset in shaping up the research topic of facial aging, were presented [3].

A new age estimation method was introduced based on the fusion of local features extracted using histogram-based local texture descriptors. Different performances of well-known powerful texture descriptors with improved modification Local Binary Patterns and Local Phase Quantization, which were not analyzed in depth for age estimation, also investigated. Age estimation accuracy of proposed method was better when compared to FG-NET [4].

Age recognition from face image totally relies on reasonable aging description. Aging description needs to be defined with detailed local information. However, it relies highly on the appropriate definition of different aging affiliated textures. Wrinkles are discernible textures in this regard owing to their significant visual appearance in aging human. Local Edge Prototypic Patterns preserve different variations of wrinkle patterns appropriately in representing the aging description [5].
Estimating human age has become an active research. Kernel partial least square methods were introduced. This method has several advantages over other approaches. This can reduce feature dimensionality and learn aging function simultaneously. It

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can find small number of latent variables and its better than SVM method [6].

Automatic gender and age classification have become relevant to an increasing amount of applications. It was shown that by learning representations by use of deep -convolutional neural networks performance got increased. A simple convolutional net architecture was proposed that could be used even when amount of learning data is limited [7].

A paper proposed an approach to age anticipation from iris images utilizing a combination of a small number of simplest geometric features and more intelligent classifier structure which can get precision to 75% [8].

Anticipation of gender by iris images was also done by utilizing different types of features and by using an intelligent classifier. The gender anticipation accuracy obtained was 90% [9].

A common feature of communicating in online networks happens through short messages. These features make non-standard language texts a little bit complex. An exploratory study was done in which text categorization was applied. For prediction of age and gender on a corpus of chats and it was determined that what features suits best [10].

Recognition of gender is fundamental operation in face analysis. Gender recognition was done on real life faces using recently built database. Higher precision was obtained by this method [11].

In a research it was proposed to learn a set of high-level feature representations through deep learning for face verification. It was proposed that DeepID can be effectively learned through multi-class face identification tasks. Proposed features were taken from various face regions to form complementary and over-complete representations. Any state-of-the-art classifiers can be learned from these levels [12].

A detailed outline was made on MRPH a longitudinal face database developed for researchers investigating different facets of adult age. It contributed to several active research areas. This got highlighted in the evaluation of standard face recognition algorithm which illustrated the impact that age progression has on recognition rates [13].

Face recognition has benefitted greatly from many databases. Most of them were created under controlled conditions. The database exhibits natural variability in pose, lighting, facial expression, background and photographic quality. Specific experimental paradigms were provided for which database was suitable [14].

Resting state functional MRI investigations have demonstrated that much of the large-scale functional network architecture supporting motor, sensory and cognitive functions in older pediatric and adult population in present term and prematurely born infants. Applications of new analytical approaches helped translating the improved understanding of early functional connectivity. Support vector regression enabled quantitative estimation of birth gestational age [15].

A recent study showed that the three traits can be estimated simultaneously based on multi-label regression problem. An investigation was done on canonical correlation analysis-based methods including linear CCA, regularized CCA and kernel CCA and PLS models were compared in solving joint estimation problem and found a consistent ranking of five methods in age, gender estimation [16].

Recent studies human faces in Human Computer interaction field revealed significant potentials for designing automatic age estimation systems via face image analysis. This success brought many innovative HCL tools used for applications of human centered multimedia communication. Through manifold method of analysis on face images, the dimensionality redundancy of the original image space can be significantly reduced with subspace learning [17].

A paper discussed about different configurations for estimating soft biometric traits. A recent framework was introduced which includes an initial facial detection, the subsequent facial traits description, the data reduction step and final classification step. The algorithmic configurations were featured by different descriptors and different strategies to build the training dataset [18].

A method was proposed for using dynamic methods for age estimation. The temporal dynamics can be used in age estimation and static image-based features. This showed significant improvement in accuracy in comparing sole use of appearance-based features [19].

There were findings of adult-age related craniofacial morphological changes. The aims were based on two things which were on factors influencing craniofacial aging and general features about aging of head and face. Then this application proved helpful in forensic science research [20].

3 Methodology

In this research work, from CASIA Iris version 4.0 a total 1214 images was selected to predict the age group of people. In the proposed system, we divided the two subsets in a binary group as youth and adult.

The total system is divided into three parts. The input images were taken for segmentation. The images were segmented to iris circle and pupil circle. The main feature iris-pupil ratio was calculated by using the pupil inner and outer boundary. The segmentation part was implemented by the popular method of Daugman's Integro-Differential Operator. For some images the iris was not visible due to the imbalanced angle or presence of eyelids.

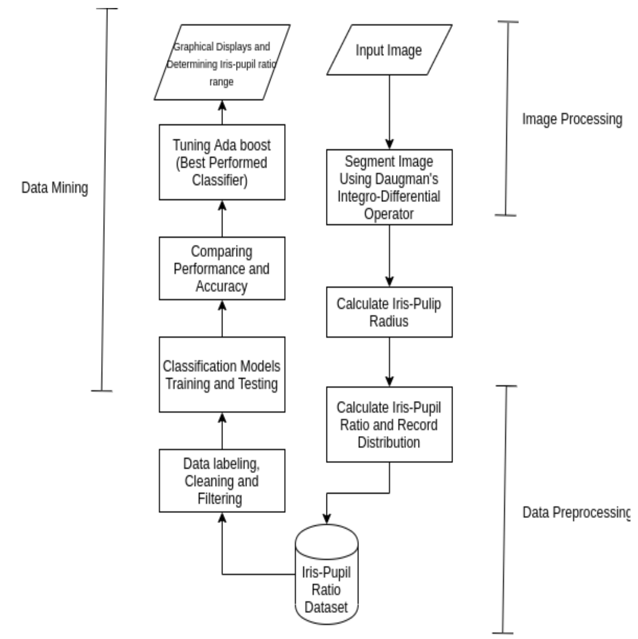

Fig. 1. Diagram of Proposed method

MATLAB functions used to compute the ratio then create the CSV format for both subsets of data numerical data of visualization. The ratio was labeling to ‘0’ and ‘1’ of output data set of iris-pupil ratio uses to train for further classification of age grouping as next part.

For classification data mining is a faster approach to training and testing. For classification algorithms, the inputs were given in a numeric format of data, not in image format. So, it took a shorter time to train the data.

3.1 Segmentation

Daugman's Integro-Differential Operator specially uses to detect the inner and outer boundary of iris as a circular age detector. This operator performs based on illumination difference is maximum between inside and outside of pixels in iris edge circle.

$$max(r,x_0,y_0)\left|G_\sigma(r)*\frac{\partial}{\partial r}\oint_{r,x_0,y_0}\frac{I(x,y)}{2\pi r}\,ds\right| \qquad (1)$$

In the equation expressed above, I(x,y) contains an iris image, r is the increasing radius, center coordinates 〖(x〗 _0,y_0), * denotes convolution, G_σ is the Gaussian smoothing function, and (r,x_0,y_0) defines the path of contour integration [8]. The line integral part firstly, calculates the area of iris without the inner circle (pupil).

Here in the case of CASIA version 4.0 dataset images, the range of pupil radius is from 16 to 30 mm and the iris outer boundary is approximately a minimum 20% to maximum 50% radius size than inner boundary [21].

4 Experiment

4.1 Implementation

Data set was labelled at first place. For categorization, using PyCaret. For this investigation 1214 distinct data of more than 400 subjects were used. In case of this research images of both left and right eye images were taken into consideration. Different representations like ‘0’ for child and ‘1’ for adult were used.

For reading data from CSV file Panda was used. 90% of data was used for modelling purpose and for anticipation rest were used by utilizing sample function. Before training various categorizers following pre-sets were used.

1	Target Type	Binary	26	Remove Outliers	False
2	Label Encoded	None	27	Outliers Threshold	None
3	Original Data	(1093, 4)	28	Remove Multicollinearity	False
4	Missing Values	False	29	Multicollinearity Threshold	None
5	Numeric Features	2	30	Clustering	False
6	Categorical Features	1	31	Clustering Iteration	None
7	Ordinal Features	False	32	Polynomial Features	False
8	High Cardinality Features	False	33	Polynomial Degree	None
9	High Cardinality Method	None	34	Trignometry Features	False
10	Sampled Data	(1093, 4)	35	Polynomial Threshold	None
11	Transformed Train Set	(765, 16)	36	Group Features	False
12	Transformed Test Set	(328, 16)	37	Feature Selection	False
13	Numeric Imputer	mean	38	Features Selection Threshold	None
14	Categorical Imputer	constant	39	Feature Interaction	False
15	Normalize	False	40	Feature Ratio	False
16	Normalize Method	None	41	Interaction Threshold	None
17	Transformation	False			
18	Transformation Method	None			
19	PCA	False			
20	PCA Method	None			
21	PCA Components	None			
22	Ignore Low Variance	False			
23	Combine Rare Levels	False			
24	Rare Level Threshold	None			
25	Numeric Binning	False			

Fig. 2. Pre-set elements for model tuning

4.2 Result

Training and testing dataset were proportioned as 9:1. The experimental results show that among all these data mining techniques, Ada Boost Classifier gives the most balanced F1 score. Fourteen varied classifiers were utilized for training and gave following results:

From table 1 it can be concluded that Ada Boost classifier is giving the highest accuracy and then tuned the classifier with respect to dataset. An output of approximately 70% was obtained from tuned version of Adaboost which was the most accurate and highest value.

TABLE 1
RESULTS ACCURACY USING VARIOUS CLASSIFIERS

Model	Accuracy	AUC	Recall	Prec.	F1
Ada Boost Classifier	0.7083	0.7935	0.8210	0.6337	0.7116
Extreme Gradient Boosting	0.7070	0.7906	0.8122	0.6334	0.7091
Gradient Boosting Classifier	0.6966	0.7841	0.7708	0.6305	0.6905
CatBoost Classifier	0.6966	0.7790	0.7260	0.6402	0.6769
Light Gradient Boosting Machine	0.6939	0.7783	0.6991	0.6444	0.6682
Random Forest Classifier	0.6756	0.7625	0.6602	0.6269	0.6402
K Neighbors Classifier	0.6731	0.7540	0.6515	0.6305	0.6357
Decision Tree Classifier	0.6705	0.7507	0.5892	0.6417	0.6096
Extra Trees Classifier	0.6692	0.7465	0.5951	0.6355	0.6104
Linear Discriminant Analysis	0.6640	0.7230	0.7197	0.6003	0.6530
Naïve Bayes	0.6550	0.7432	0.8184	0.5760	0.6755
Quadratic Discriminant Analysis	0.6535	0.7125	0.7291	0.5891	0.6436
Ridge Classifier	0.6483	0.0000	0.5950	0.6005	0.5958
Logistic Regression	0.6247	0.6882	0.5201	0.5806	0.5464
SVM-Linear Kernel	0.5635	0.0000	0.5403	0.3673	0.4013

To understand the performance of any classification algorithms the precision and recall value can be calculated from the confusion matrix. From the precision value, we can determine, out of all the positive classes we have predicted correctly, how many are actually positive as to how useful the search results are.

$$precision = {}^{tp}/_{tp + fp} \qquad (2)$$

Where tp and fp define True Positive and False Positive value

Following is the confusion matrix from where we can see all the data. This model has wrongly classified kids as adult 74 times. This was the consequence because of non-uniform dataset or error of segmentation in image processing step.

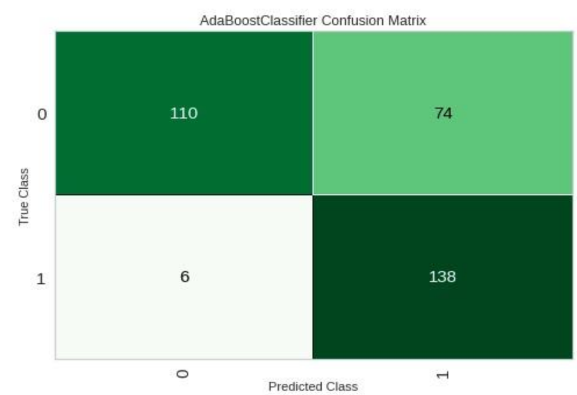

Fig. 3. Confusion Matrix of Ada Boost Classifier

And the recall is the idea of find of all the positive classes, how much we predicted correctly as to how complete the results are. It should be as high as possible. Here, fn is called False Negative result.

$$recall = {}^{tp}/_{tp + fn} \qquad (3)$$

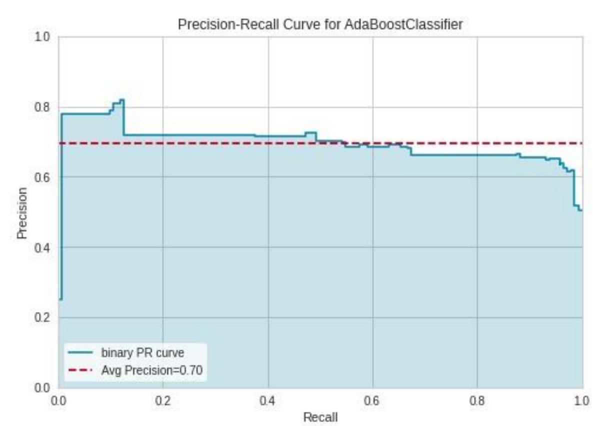

Fig. 4. Precision-recall value in graph of Adaboost classifier Confusion Matrix of Ada Boost Classifier

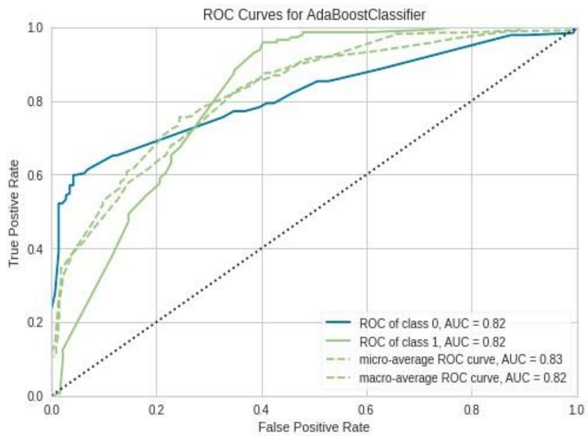

Fig. 5. ROC curves of Ada Boost Classifier

From the above graphs, the results indicate that iris-pupil thickness has a significant effect in aging and the stratification of binary classification using the proposed technique is much faster than most of the traditional statistical method.

5 Conclusion

Various categorizers were used for determining the accuracy but Adaboost classifier has proved to be highly precise. As from pre-defined studies we knew that Iris-pupil contributes in aging but confusion matrix has showed that it has wrongly classified kids as adults many times due to segmentation errors and non uniform dataset. As a future dimension its intended to do more research on other age groups to determine template aging.

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