AUTOMATIC AGE AND GENDER DETECTION

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ABSTRACT

Automatic age and gender classification has become relevant to an increasing amount of applications, particularly since the rise of social platforms and social media. Nevertheless, performance of existing methods on real-world images is still significantly lacking, especially when compared to the tremendous leaps in performance recently reported for the related task of face recognition. In this paper we show that by learning representations through the use of deep-convolutional neural networks (CNN) models (agenet. caff mode, gender net. Caffe model) a significant increase in performance can be obtained on these tasks. To this end, we propose a simple convolutional net architecture that can be used even when the amount of learning data is limited.
Keyword:- Deep-Convolutional Neural Networks, Caffe model

1 INTRODUCTION

A Human face provides a lot of information about the age, gender, mood etc. It is affected by many dynamic factors that get changed over period of time such as aging, hair style, expressions, etc. Gender and Age are considered an important biometric attribute for human identification. Bio-metric recognition is the method gathering information about person's physiological and behavioural characteristics for human identification and verification (security models). Biometrics consists of soft biometric (age, gender, ethnicity, height and facial measurements) and hard biometric (Physical, behavioural and biological). Soft-biometric attributes like skin, hair colour, distance between eye and nose, face shape, and etc. can be accessed to accelerate data traversing, or to classify unlabelled subject for various gender and age classes. Furthermore, with the wide spread use of computers, bio-metric identification comes into demand in areas such as home automation and healthcare. Recently, it has come about automatically detecting physical presence and confirming one's identity through pattern recognition, computer vision and image analysis.

One of the Biometric attributes considered is aging. Aging is caused because of many reasons like DNA change, metabolism changes, UV rays from Sun, variation in facial tissues, Restructuring of facial bones etc. Face recognition system are adversely affected by the aging of the face. This idea plays huge role for new research area to be probed in the field computer vision. The age estimation is just carried out extensively to find out some patterns and variations as well as to get the best possible way to find out the various characteristic's that should be thought of. Another attribute is gender. Automatic gender classification is an important for many applications like surveillance, targeted advertisement's etc. This is done to differentiate between male and female based on the features of humans. This literature elaborates descriptive minutiae and comparisons that are performed by author on various aspects like age, gender, and race. Also, different methods for extracting features, classification, evaluation for significant knowledge of research. This helps the enthusiastic researchers to enrol with deep learning aspects in classifying age and gender through human facial images

2. LITERATURE SURVEY AND RELATED WORK

Gender Classification:

Early works on gender classification applied unsupervised methods [9,10], using Adaptive Multi-Gradient (AMG) [9], and Multi-Gradient Directional (MGD) [10] features. Since 2012, traditional machine learning methods in general and Support Vector Ma-chines (SVMs) in particular [11–23], have become most popular. Except for SVMs, such models as Decision Trees and their ensembles (Random Forests or AdaBoost) [11,13,21,24], shallow Artificial Neural Networks [11,12,22,25], Regressions [20], Naïve Bayes [21], K-nearest neighbors [11,26], Fuzzy Rule-Based Classification [16], and Discriminant Analysis [21] were applied. We also observed that attention had been paid lately to ensemble approaches [20], where several different classifiers are combined to create a master model. The majority of the aforementioned models were applied upon textural [9,11–13,15–18,25] and a combination of textural and shape features [14,22,23,27–31]. The best accuracy rates—between 77% and82%—were achieved by the SVM classifiers with textural features [12,16,17,27]. Deep models based on Convolutional Neural Networks started to appear in gender classification works around 2018. Deep neural networks were applied as feature extrac-tors [21], and also end-to-end pipelines, including both feature selection and classification layers [8,32,33]. The main advantage of deep networks is their ability to learn features automatically without manual engineering. In addition, CNNs have been shown to be on par or even outperforming other classifiers on gender classification task [8,33,34]. Due to their benefits in terms of performance and usability, deep networks have recently emerged as a leader in various computer vision applications, including handwriting analysis

Age classification

In contrast to the gender classification task, not many works reported on automatic age classification, while in most of them, age was only one of many demographic features identified from handwriting documents. Bouadjenek et al. [15] applied an SVM classifier on two gradient features for a gender, handedness, and age range prediction. Three SVM predictors, each applied on a specific data feature, were subsequently combined in [16,35] to identify a writer’s gender, age range, and handedness. Em ran et al. [36] investigated different classifiers—K-Nearest Neighbors, Random Forests, and SVM—using various visual appearance features for the prediction of a writer’s age, gender, and handedness. Only a few works developed models solely for age prediction. Upadhyay and Singh [37] studied the estimation of age through handwriting characteristics in females and found that such characteristics as slant, alignment, spacing, hesitation marks, tremor, and speed are really valuable and helpful for age determination. Zouaoui et.al [38] investigated the co-training approach for age range prediction from handwriting analysis. The authors proposed several descriptors for feature generation and applied an SVM predictor for classification. Basavaraja et al. [39] proposed a new unsupervised method for age estimation using handwriting analysis with Hu invariant moments, disconnectedness features, and k-means clustering. In [40], the efficacy of using the dynamic features generated by users of smartphones and tablets to automatically identify their age group was examined. The study with the KNN classifier provides evidence that it is possible to detect user age groups based on the words they write with their fingers on touchscreens. Research in [41] applied SVM and Random Forests to automatically classify people as adults or children based on their handwritten data, collected using a pen tablet. The best accuracy (up to 81%) was achieved by the SVM classifier with textural features [16], leaving much room for performance improvement in age prediction from hand writing. As can be seen, all works utilized feature engineering in conjunction with conventional classifiers. Deep learning algorithms for age classification have not been used in any research

3 EXISTING SYSTEM

Gaussian Mixture Models (GMM) was used to represent the distribution of facial patches. In GMM were used again for representing the distribution of local facial measurements, but robust descriptors were used instead of pixel patches. Finally, instead of GMM, Hidden-Markov Model, super-vectors were used for representing face patch distributions.

SVM classifiers were used by, applied directly to image intensities. Rather than using SVM, used AdaBoost for the same purpose, here again, applied to image intensities. Finally, viewpoint-invariant age and gender classification

4 PROPOSED WORK AND ALGORITHM

One of the first applications of convolutional neural networks (CNN) is perhaps the LeNet-5 network described by for optical character recognition. Compared to modern deep CNN, their network was relatively modest due to the limited computational resources of the time and the algorithmic challenges of training bigger networks. Though much potential laid in deeper CNN architectures (networks with more neuron layers), only recently have they become prevalent, following the dramatic increase in both the computational power (due to Graphical Processing Units), the amount of training data readily available on the Internet, and the development of more effective methods for training such complex models. One recent and notable examples is the use of deep CNN for image classification on the challenging Image net benchmark.

Advantages

For age classification, we measure and compare both the accuracy when the algorithm gives the exact age-group classification and when the algorithm is off by one adjacent age-group (i.e., the subject belongs to the group immediately older or immediately younger than the predicted group). This follows others who have done so in the past, and reflects the uncertainty inherent to the task – facial features often change very little between oldest faces in one age class and the youngest faces of the subsequent class.

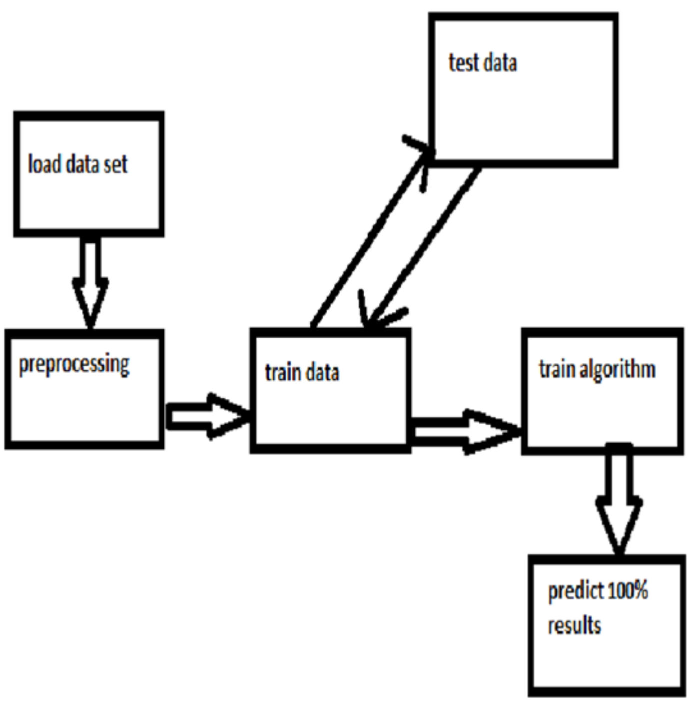

Fig 1: System architecture

5 METHODOLOGIES

MODULES

- image data
- pre- processing
- segmentation image
- feature extraction
- data training and testing
- deep learning algorithm
- detection

Dataset collection

- Collecting data heavy use of collections of images called datasets. A dataset in computer vision is a curated set of digital photographs that developers use to test, train and evaluate the performance of their algorithms.
- Data can be gathered by different means like scraping from the web, gathering from third-party sources or you could even buy datasets from re-sellers etc.
- Auto ecncoders work best for image data.
- Support file type filters.
- Support Bing.com filterui filters.
- Download using multithreading and custom thread pool size.
- Support purely obtaining the image URLs.

Data Cleaning

- Data cleaning is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within a dataset.
- When combining multiple data sources, there are many opportunities for data to be duplicated or mislabeled.
- data cleaning or data scrubbing, is the process of fixing incorrect, incomplete, duplicate or otherwise erroneous data in a data set.
- It involves identifying data errors and then changing, updating or removing data to correct them.

Feature Extraction:

- Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups.
- So when you want to process it will be easier. The most important characteristic of these large data sets is that they have a large number of variables.
- These variables require a lot of computing resources to process. So Feature extraction helps to get the best feature from those big data sets by selecting and combining variables into features, thus, effectively reducing the amount of data.
- These features are easy to process, but still able to describe the actual data set with accuracy and originality.
- Image Processing –Image processing is one of the best and most interesting domain. In this domain basically you will start playing with your images in order to understand them.

Model training

- Plan and simplify. In the beginning we must think about how does the computer sees the images.
- Collect. For all the tasks try to get the most variable and diverse training dataset.
  Sort and upload. You have your images ready and its time to sort them.
- Train and precise.
- Load and normalize the CIFAR10 training and test datasets using torch vision.
- Define a Convolutional Neural Network.
- Define a loss function.
- Train the network on the training data.
- Test the network on the test data.

Testing model:

- In this module we test the trained deep learning model using the test dataset
- A type of test that makes detailed pictures of areas inside the body. Imaging tests use different forms of energy, such as x-rays (high-energy radiation), ultrasound (high-energy sound waves), radio waves, and radioactive substances. They may be used to help diagnose disease, plan treatment, or find out how well treatment is working.
- Examples of imaging tests are computed tomography (CT), mammography, ultrasonography, magnetic resonance imaging (MRI), and nuclear medicine tests. Also called imaging procedure

Performance Evaluation

- In this module, we evaluate the performance of trained deep learning model using performance evaluation criteria such as F1 score, accuracy and classification error.
- To evaluate object detection models like R-CNN and YOLO, the mean average precision (map) is used. The map compares the ground-truth bounding box to the detected box and returns a score. The higher the score, the more accurate the model is in its detections.
- Model evaluation is the process of using different evaluation metrics to understand a machine learning model's performance, as well as its strengths and weaknesses.
- Model evaluation is important to assess the efficacy of a model during initial research phases, and it also plays a role in model monitoring.

Detection

- Object detection is a process of finding all the possible instances of real-world objects, such as human faces, flowers, cars, etc. in images or videos, in real-time with utmost accuracy.
- The object detection technique uses derived features and learning algorithms to recognize all the occurrences of an object category.
- First, we take an image as input.
- Then we divide the image into various regions.
- We will then consider each region as a separate image.
- Pass all these regions (images) to the CNN and classify them into various classes.

6 RESULTS AND DISCUSSION SCREENSHOTS

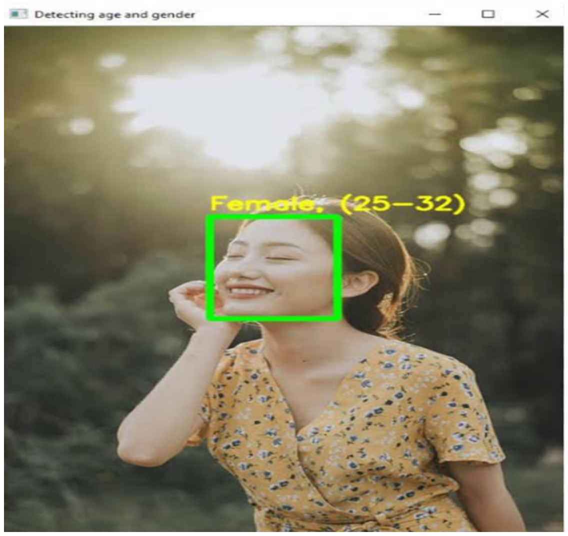

Fig 1:- FEMALE (25-32)

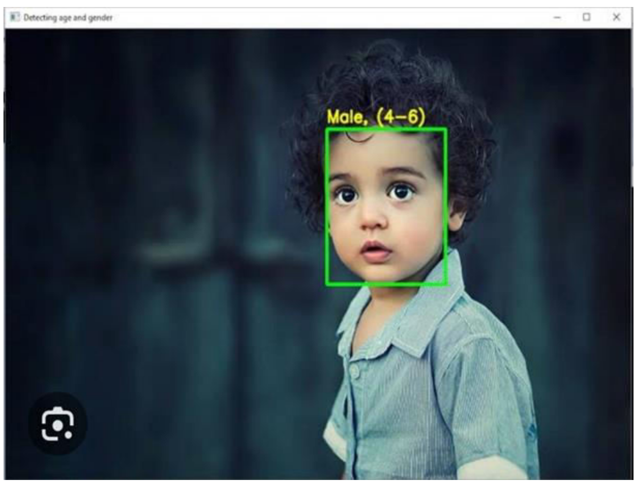

Fig 2:- MALE(4-6)

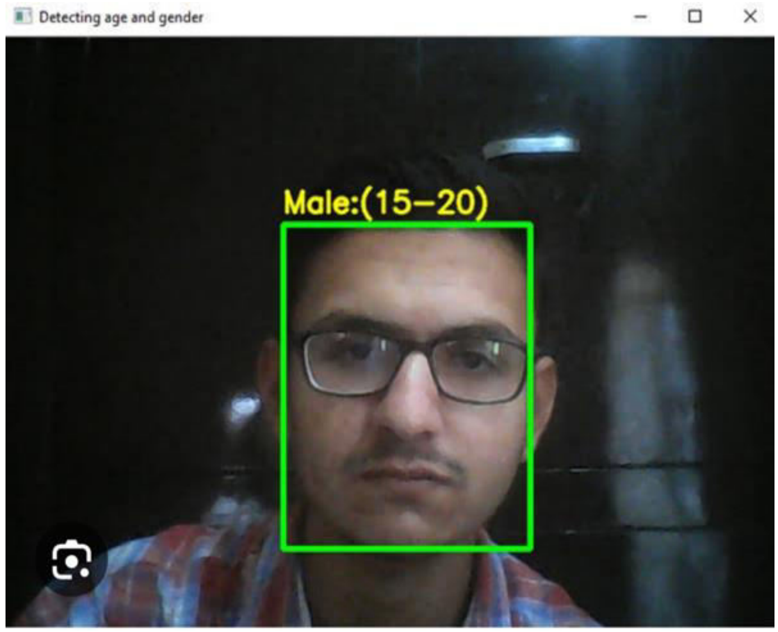

Fig 3:- MALE(15-20)

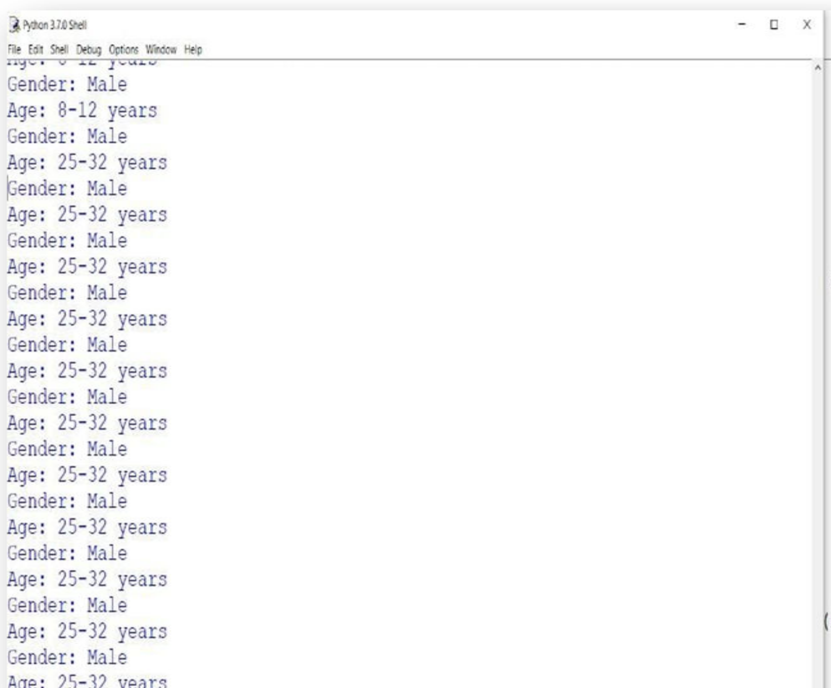

Fig 4:- BACK OUTPUT SCREEN

6.CONCLUSION AND FUTURE SCOPE

Researches on age and gender estimation have been divided into two main groups: one is to devise appropriate features that reflect the age and gender correctly, while the other is to use deep CNN which automatically learn the features from the massive training data. In this paper, we have proposed a method to get the benefits of both methods by enforcing the CNN to use appropriate hand-crafted features. We believe that the advantage of our scheme is to let the network to focus on useful features, which improves the performance as demonstrated in the experiments.

Future scope:

Overall study of contribution made on gender classification and age estimation can be used in to solve the real-time application problems. In this paper most of the research work done is in Convolutional Neural Networks. Eleven unlike types of neural networks have been discussed with their MAE and accuracy obtained by models. Additionally, function extraction in addition to distinction of a few functions is actually carried out using just an individual element extractor or maybe a one-time classifier along with in various additional works, fusion is actually followed to do distinction process or maybe attribute extraction. On the future direction, results that are Good for gender recognition as well as years' opinion can continue to be received utilizing transfer learning strategies with expansion in reliability. Combos of fusions as well as datasets of attributes might be what is on the horizon for the development ethnicity estimation, Affective behaviour analysis and numerous additional demographic features could be verified for the performance of them by the classifier of Neural Networks.His paper has identified the most widely used approaches for maintenance classification of building maintenance. Many researchers pointed out that although corrective maintenance is rational when the impact of failure is rather than small, carrying out the corrective maintenance required performing immediately

Otherwise, higher costs than expected may be consequences when these faults happen in unexpected ways and at the wrong time, causing inconvenience to users and downtime independent components or systems. The authors also stated that preventive maintenance is justifiable if the consequence of fault is high about the cost of doing omething that in advance reduces the risk for the fault (Lind and Muyingo,2012). However, limitation of this maintenance approach is redundant tasks may be carried out or manufacturer's recommendation has limited local conditions and the actual process.

The literature review also indicates that to develop a rational maintenance plan requires both building inspection data and recording data on previous conservation works. Without this information, it is hard to decide on a maintenance policy estimate the expenditure for a budget. Traditionally, to the asset, the building condition usually by visual only hardly to discover all problems. However, new methods and technologies such as a 3D scanner and Building Information Modelling have not been applied widely yet in the areas. Additionally, failures of maintenance sometimes have occurred since lack of communication between different management evels of maintenance and lack of previous maintenance knowledge of building manager and in-house staff whose responsible for maintenance activities in the (Yin, 2008; Shah Ali, 2009). One idea can support the issue is knowledge management system which is discussed in Zavadskas et al., (2010). Key questions of the system are what components/systems should be monitor automatically and how test lesson-learned from previous conservation and similar buildings

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