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AUTOMATIC AGE AND GENDER IDENTIFICATION USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

With the emergence of social platforms and social media, automatic age and gender classification has gained relevance for a growing number of applications. However, current approaches still perform remarkably poorly on real-world photographs, particularly in comparison to the remarkable improvements in performance recently documented for the related job of facial identification. In this paper, we demonstrate that a notable improvement in performance on these tasks may be achieved by learning representations using deep-convolutional neural networks (CNN) models (agenet. caff mode, gender net. Caffe model). Towards this goal, we suggest a straightforward convolutional net architecture that can be applied even in situations with a restricted supply of training data.

Keywords: Caffe model, deep convolutional neural networks

1 INTRODUCTION

A person's face can reveal a lot about their age, gender, temperament, and other characteristics. Numerous dynamic aspects that alter over time, like age, hairstyles, expressions, etc., have an impact on it. Age and gender are regarded as crucial biometric characteristics for identifying people. The process of collecting data on an individual's physiology and behavior for the purpose of human identification and verification (security models) is known as bio-metric recognition. Age, gender, ethnicity, height, and face measurements are examples of soft biometrics. Hard biometrics include physical, behavioral, and biological characteristics. Soft-biometric characteristics, such as skin tone, hair type, distance between nose and eye, facial form, and so on, can be used to categorize unlabeled subjects according to age and gender groups and to speed up data traversal. Additionally, as computer use grows, bio-metric identification becomes more and more necessary in sectors like healthcare and home automation. The ability to automatically recognize physical presence and verify an individual's identification through pattern recognition, computer vision, and image analysis has emerged recently.

Aging is one of the biometric variables taken into account. Numerous factors contribute to aging, including changes in DNA, metabolism, UV radiation from the sun, variations in the tissues of the face, rearranging of the facial bones, and more. The aging of the face has an unfavorable effect on facial recognition systems. This concept is crucial for exploring new ground in the field of computer vision research. The purpose of the thorough age estimation is to identify patterns and variations and determine the most effective method for identifying the many characteristics that need to be taken into consideration. Gender is an additional characteristic. For numerous applications, such as targeted advertising and monitoring, automatic gender classification is crucial. This is done in order to distinguish between male and female human traits. The author's comparisons and descriptive details on a range of factors, including age, gender, and race, are elaborated in this literature. Additionally, several techniques for feature extraction, categorization, and assessment for noteworthy study knowledge. This facilitates the eager researchers' enrollment in deep learning components for identifying age and gender from photos of people's faces.

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.

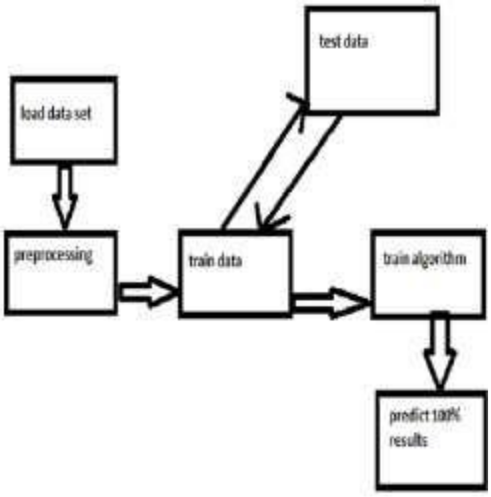

Fig 1:System architecture

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.

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- 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

Fig 1:-FEMALE (25-32)

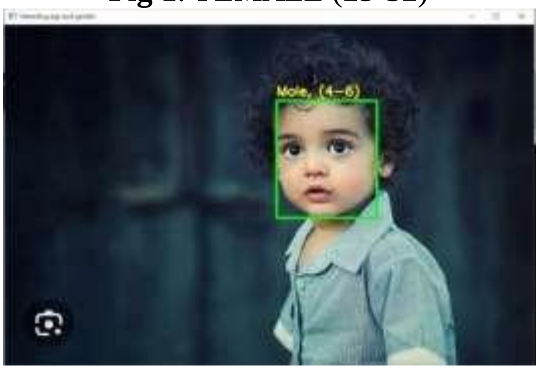

Fig 2:-MALE(4-6)

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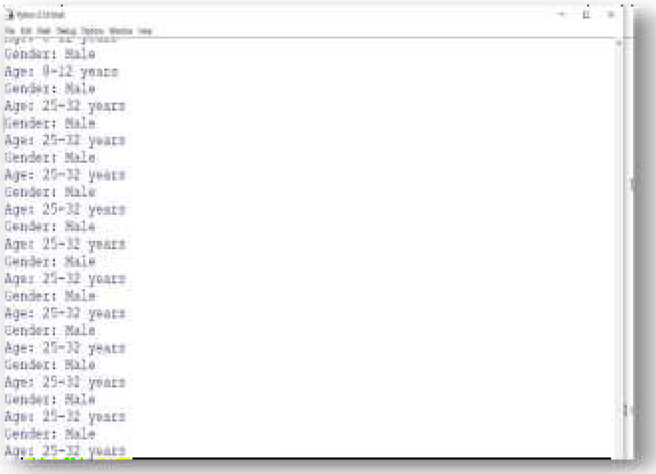

Fig 3:-BACK OUTPUT SCREEN

6. CONCLUSION AND FUTURE SCOPE

The two primary categories of research on age and gender estimation are: (1) developing features that accurately reflect the age and gender; and (2) using deep neural networks (DLNNs), which automatically learn features from large amounts of training data. In this study, we have suggested a way to leverage both approaches by pushing CNN to employ relevant custom features. Our scheme's benefit, in our opinion, is that it allows the network to concentrate on functional aspects, as evidenced by the trials, which enhances performance.

Future scope:

Future scope: An overall analysis of the age estimation and gender classification contributions made can be utilized to address real-time application issues. Convolutional neural networks are the subject of the majority of the research in this work. Eleven distinct varieties of neural networks have been examined, along with their mean approximate error (MAE) and model accuracy. Furthermore, function extraction and the separation of specific functions are performed with a single element extractor or one-time classifier, and in other works, attribute extraction or distinction is accomplished through the use of fusion. Regarding the future, transfer learning methodologies with increased dependability can be used to obtain outcomes that are good for gender recognition and years' opinion. Combinations of fusions and attribute datasets may be in store for the development of ethnicity estimates, affective behavior analysis, and many other demographic traits, all of which may have their effectiveness as classifiers for neural networks tested.The most popular methods for classifying building maintenance have been identified in his study. Numerous academics have noted that, even while corrective maintenance makes sense when a breakdown has a large impact, doing the necessary repair right away If not, unanticipated errors that occur at inconvenient times and cause user annoyance as well as downtime for independent components or systems may result in higher than anticipated expenses. The authors further claimed that if the expense of correcting a mistake in advance lowers its likelihood, then preventative maintenance is justified (Lind and Muyingo, 2012). The drawbacks of this maintenance strategy are that it may be necessary to perform unnecessary chores or that the manufacturer's recommendations may not fully account for local conditions and the actual procedure. The literature analysis also shows that information from building inspections and records of prior conservation efforts are needed to create a logical maintenance schedule. It is difficult to choose a maintenance policy and calculate the costs for a budget without this knowledge. Historically, the building status was primarily determined visually, making it difficult to identify all issues with the asset. New techniques and tools, such building information modeling and 3D scanning, haven't been extensively used in these fields yet. Furthermore, maintenance failures have occasionally happened as a result of poor communication between various maintenance management levels, as well as a lack of prior maintenance experience on the part of the building manager and internal staff who are in charge of maintenance activities in the (Yin, 2008; Shah Ali, 2009). Zavadskas et al. (2010) highlight the knowledge management system as one idea that can help with the problem. The system's primary concerns are which parts and systems ought to be automatically monitored and how to use the lessons discovered from earlier preservation efforts and comparable structures.

REFERENCES

[1] Philip Smith, Cuixian Chen Transfer Learning with Deep CNNs for Gender Recognition and Age Estimation, IEEE International Conference on Big Data 2018.

[2] Ke Zhang, Liru Guo, Miao Sun, Xing fang Yuan, TonyX. Han, Zhenbing Zhao and Baogang Li Age Group and Gender Estimation in the Wild with Deep RoR Architecture, IEEE Access COMPUTER VISION BASED ON CHINESE CONFERENCE ON COMPUTER VISION Volume 5 (CCCV)2017.

[3] Sepidehsadat Hosseini, Seok Hee Lee, Hyuk Jin Kwon, Hyung Ii Koo and Nam Ik Cho Age and Gender Classification Using Wide Convolutional Neural Network and Gabor Filter, Institute for Information and communications Technology Promotion (IITP) 2018.

[4] Jia-Hong Lee, Yi-Ming Chan, Ting-Yen Chen and Chu-Song Chen Joint Estimation of Age and Gender from Unconstrained Face Images using Lightweight Multi-task CNN for Mobile Applications, IEEE Conference on Multimedia Information Processing and Retrieval 2018.

[5] Gil Levi and Tal Hassner Age and Gender Classification using Convolutional Neural Networks, Intelligence Advanced Research Projects Activity (IARPA) 2015. [6] Nisha Srinivas, Harleen Atwal, Derek C. Rose, Gayathri Mahalingam, Karl Ricanek Jr. and David S. Bolme, Age, Gender, and Fine-Grained Ethnicity Prediction using Convolutional Neural Networks for the East Asian Face Dataset, 12th International Conference on Automatic Face & Gesture Recognition 2017.
[7] M Uri car, R Timofte, R Rothe, J Mata's and L Van Gool Structured output svm prediction of apparent age, gender and smile from deep features, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops 2016.

[8] M. Fatih Aydogdu and M. Fatih Demirci Age Classification Using an Optimized CNN Architecture, Association for Computing Machinery 2017.

[9] ByungIn Yoo, Youngjun Kwak, Young sung Kim, Changkyu Choi and Junmo Kim, Deep Facial Age Estimation Using Conditional Multitask Learning with Weak Label Expansion, SIGNAL PROCESSING LETTERS, VOL. 25, NO. 6 2018.

[10] Abhijit Das, AntitzaDantcheva and Francois Bremond Mitigating Bias in Gender, Age and Ethnicity Classification: A Multi-Task Convolution Neural Network Approach, European Conference of Computer Vision (ECCV) 2019.

[11] Marco Del Coco, Pierluigi Carcagni, Marco Leo, Paolo Spagnolo, Pier Luigi Mazzeo and Cosimo Distante Multi-branch CNN for Multi-Scale Age Estimation, Springer ICIAP 2017, Part II, pp. 234–244, 2017.

[12] F. Dornaika, Arganda-Carreras and C. Belver, Age estimation in facial images through transfer learning, Machine Vision and Applications 2018.