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ANALYSIS OF GENDER CLASSIFICATION TECHNIQUE USING ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT

As a result, ANN is an attempt to mimic the human brain by learning it to perform tasks it has never done before. All of the neurons in the human brain are interconnected, forming a huge, well-connected network that allows us to perform difficult tasks like voice and image recognition relatively easily. If you repeat the same task on a regular computer, you will get an incorrect result. Thus, ANN uses a technique comparable to human brain cells to build a link between input and targets. Gender classification from face images is a complex operation due to the presence of a complicated background, object occlusion, and fluctuating lighting conditions. Face images can be utilised for tracking, recognition, and expression analysis, among other things. This study looks at two deep learning-based approaches to gender classification using face images.

INTRODUCTION

One of the most significant challenges in computer vision is determining a person's gender. Recognizing a person's gender is simple for humans but challenging for computers. Gender recognition has several potential uses, including in law enforcement, forensics, and other fields. Several methods have been developed over the past few years to determine a person's gender from a photograph of their face, and a small number of similar research have made use of the features of iris images to make such determinations.

Artificial intelligence has made gender detection as crucial for robots and automated machines as it is for humans. Certain aspects of a scene, such as edges, lines, motion, etc., are processed by our visual cortex with greater sensitivity and responsiveness. Our brain organizes the details of a situation into patterns, which it then uses to recall relevant details when we need to classify objects. Attempts at gender recognition for facial photos began with SEXNET, and the problem of categorizing people into predetermined categories has remained appealing ever since. However, it is not recommended to use face photographs because to the low quality that results from cropping, which diminishes information, and the possibility that the image will be obscured by a mask, spectacles, or facial hair. Gait analysis was also advocated by researchers, although this did not immediately remedy the problems. Facial image processing is a method whereby the face of an separate is constructed onto the skull for the determination of identification.

FACE DETECTION METHOD

Face detection techniques are divided into three categories: those that use intensity images, those that use video sequences, and those that use other sensory data to detect faces, such as 3D data or infrared imagery. The various techniques of face detection includes Feature based method

Template matching



Figure 1: Face detection methods

Feature Based Method

The invariant features of the face image are extracted using the Feature based method. Features such as facial expression and pose are not fixed as a result of this method. The distance between the eyes, the brows, the size of the lips, the nose, and other factors are all taken into account in this technique. Several methods for extracting face features from a photograph have been proposed. On the basis of the extracted features, a number of statistical models for face detection have been developed.



Figure 2: Geometrical features (white) of the face image

Feature-based methods have the advantage of being relatively resistant to changes in input image position. In principle, size, orientation, and/or lighting are not constraints for feature-based schemes. Two more advantages of these schemes are the compactness of the face image representation and the speed with which they can be matched. You'll have to make arbitrary decisions about which features are important if you want to implement any of these approaches. This is the primary drawback of these methods.

Template Matching

Both feature-based and template-based methods exist for doing template matching. When trying to determine where in a picture a given template should be placed, the feature-based technique relies heavily on features inside both the search and template images, such as borders and corners, to determine the best candidate. Using the full template and a sum comparing measure, you can determine the optimal place inside a search image with a template-based or global approach (using SAD, SSD, cross-correlation, etc.).

Age classification

There has been a lot of focus on categorizing people based on their age and gender recently because it is the most efficient and effective approach to gather implicit and crucial social information. To begin, the concept of age classification from human face photos was provided, along with the idea that facial features may be divided into several age groups by using ratio calculations and wrinkle detection. The same strategy was then used to simulate craniofacial growth taking into account both psychophysical evidence and anthropometric evidence, both of which required precise localization of facial characteristics. a technique for dealing with subspace termed "A Ging pattern" A locally adjusted robust regress was developed to predict human ages, and a subspace was introduced in to automatically estimate age while an age manifold learning method was presented in to automatically extract aspects of facial aging. While these approaches have demonstrated usefulness, they suffer from the limitation that input images must be near-frontal and well-aligned. It's not hard to see that the datasets they use in their studies are limited, which means that they're not appropriate for many real-world uses, such as unrestricted image jobs. The past year has seen a proliferation of proposals for age and gender classification systems.

LITERATURE REVIEW

Levi, G., & Hassner, T. (2015) A variety of solutions have been proposed in recent years to the problem of automatically extracting age-related information from facial photos. Both and, more recently, provide a comprehensive overview of these techniques. Although we're primarily interested in using this article to classify people into different age groups, the methods described here can also be used for more exact age estimate (i.e., age regression).

Buolamwini, J., & Gebru, T. (2018) Using the new Pilot Parliaments Benchmark, which is evenly distributed across both sexes and ethnicities, we evaluated the efficacy of three commercial gender classification systems. We applied the Fitzpatrick skin classification system's annotations to the dataset and evaluated the accuracy of our gender classifiers on four distinct groups of people: women and men of all skin tones, women and men of all hair colors, and women and men of all eye colors. In general, and especially for men, we observed that lighter people and males fared the best in all categories. For women of color, the classifiers' performance was the poorest.

Shan, C. (2012) One of the earliest and most important jobs in face analysis is gender identification. Existing research largely relies on staged photoshoots of subjects' faces. Gender classification on real-world faces, however, is far more difficult due to considerable appearance differences in unconstrained circumstances, and is thus necessary for practical applications. Using the newly created Labeled Faces in the Wild collection, we explore gender detection on natural images of faces in this work (LFW). Adaboost is used to pick the most distinguishing Local Binary Patterns (LBP) features that are then utilized to describe the faces.

Lapuschkin, S., Binder, A. et al,(2017) Recently developed models of deep neural networks have proven adept at analyzing photographs of human faces, specifically in determining the

ages, sexes, and emotional states of the people depicted In this paper, we used Layer-wise Relevance Propagation to uncover the black-box classifier and discover the specific face features that are employed in age and gender prediction. With the difficult Adience dataset in mind, we analyzed various picture preprocessing, model initialization, and architecture options and talked about their effects on performance.

Duth, S., & Mirashi, M. P.(2018) Ridge and valley in a fingerprint make for a unique design. Some sort of fingerprint Among the many significant traits, biometrics shines as a reliable means of determining sex. The strategy accepts the challenge of determining a person's gender from a fingerprint. The project presented a feature extraction-based method for gender classification. Gender discrimination and feature removal can be achieved with the help of Gabor filters, Minutiae extraction, and region-of-interest (ROI) analysis. An artificial neural network is trained using the extracted features.

Sreya, K. C., & SB, R. J. (2020) Predicting a person's gender based on their iris pattern is a common application of biometric identification methods. In biometrics, chronological age is a crucial consideration. Researchers today often use a subject's biometric traits to learn more about them, including things like their hair color, age, gender, weight, ethnicity, and more. Comparing iris recognition's results to those of other biometric checks, it emerges as the clear winner. Given that the irises of two eyes belonging to the same person are not interchangeable, this method of authentication has greater credibility when compared to other forms of biometric recognition. Improvements in the iris recognition system's ability to accurately estimate a person's gender based just on a photograph of their eyes are credited with improving this method.

Duan, M., Li, K. et al,(2018) When speaking to persons of different ages, there is a specific vocabulary and set of grammar rules that must be followed in every language. Whether or whether we are able to distinguish individual features like gender and age from face appearances at one glance impacts the decision linked with its use. Rapid adoption of AI-based systems across industries has prompted the assumption that these tools can make decisions on par with humans.

Haider, K. Z., Malik, K. R. et al,(2019) Image processing computerization is often used to do things like recognize faces, figure out how old someone is, link people of the same race, and sort people by gender. We can easily tell if someone is male or female based on their hair, nose, eyes, mouth, and skin. Can we teach a computer to do the same? This study is mostly about the problem itself. It is common practice to do five steps in real time while processing facial images: detection, noise removal, alignment, feature representation, and classification. Gender detection via smartphone has necessitated a second look at the face alignment and feature vector extraction phases.

Park, S., & Woo, J. (2019) By monitoring online conversations about a brand, product, or service, businesses can gain insight into how those conversations are being received socially through a process called sentiment analysis, which is essentially textual context mining that identifies and extracts subjective information in source material. As machine learning has developed, text mining methods have also advanced. Innovative use of cutting-edge AI

methods can facilitate exhaustive investigation. Because more people are communicating with one another through mediums like e-mail, websites, forums, and chat rooms, sentiment analysis of web material is becoming increasingly relevant. You may learn what people think and feel about various policies, products, companies, etc. by collecting and evaluating these articles and the sentiments expressed by the authors.

Garain, A., Ray, B. et al,(2021) Many academics have tried to solve the age and gender identification problem, but they have paid far less attention to it than they have to other facial recognition-related issues. Not much progress has been made in this area relative to other facial recognition issues.

Wang, Z., Meng, Z. et al,(2022) In this research, we used deep learning to categorize the sex of 178 persons over the age of 65 based on their appearance in sit-to-stand (StS) Doppler radar scans. Tests conducted with 11 sets of processed photos and five different CNN models demonstrated that gender can be accurately classified from StS Doppler radar images with an accuracy of up to 90%. Additional StS data will be collected and converted into Doppler radar images or data augmentation will be used to expand the current dataset in future work. With the goal of improving the CNN classification rate, we want to either train with more recent CNN models or make changes to the current CNNs.

Proposed methodology

When a computer program mimics the way a human brain does its work, it is said to be using artificial neural networks (ANN). That the system makes an effort to mimic the way a human would carry out a specific task. In general, a computer will perform any task in the manner in which it has been taught in the form of code, but it will lack the ability to complete tasks in which it has never been taught. If we think about the brain, however, we realize that it has the ability to learn on its own, allowing it to carry out a variety of tasks for which it has neither been trained nor instructed. Neurons are equipped with this feature to prevent the unnecessary discarding of collected data. Because in the brain, unlike in traditional computers, information is not transmitted from vegetative cell to vegetative cell but is instead encoded within the neuron network, the human brain is many thousands of times faster than the ancient standard conventional pc. And this is why connectionism is another word for a neural network.

As can be seen in Figure 3, dendrites, a cell body or soma, and a nerve fiber make up the bulk of a biological model of a vegetative cell. The neuronal nucleus is located in the cell body, also called the soma.





The dendrites are the outgrowths of a neuron that are attached to the cell body and wrap inward around it to pick up impulses from other neurons. The nerve cell acts as a transmitter through the nerve fiber. It does this via communicating with nearby neurons. The junction or conjunction terminal is the connection between the dendrites of one neuron and the axons of its neighboring neuron, providing a pathway for information to go between the two cells. The junction is the source of chemical signals. The vegetative cell will "fire," or transmit a chemical signal to its neighboring neurons, once the total signal it receives is greater than the junction threshold. It is believed that the power of the conjunction association, the primary basis of memory in the human brain, has been depleted due to the alterations. By altering the weights between neurons, ANN mimics the way in which our bodies' many sensory organs transmit messages to the brain's vegetative cells, where the neuron interprets the information and provides the desired output in order to carry out a certain task. It's important to note, though, that one vegetative cell's output can be used to fuel another. A neural network is a collection of these neurons. Figure 3 depicts the process by which the biological model of a vegetative cell is translated into a mathematical model.





"x" are different inputs which are weighted by a weight corresponding to a path that the signal travels. The neuron is then expected to create a change in the form of an activation function Θ and the complete signal then goes through a transformation S which produces the output of the neural network .Consider a signal s_1 traveling through a path p_1 from dendrites with weight w_1to the neuron. Then the value of signal reaching the neuron will be

$$Y = \sum_{i=1}^{n} X_i \cdot W_i + \theta_i$$

s_1. w_1.If there are "n" such signals traveling through n different paths with weights ranging from w_1 to w_n and the neuron has an internal firing threshold value of θ_n , then the total activation function of the neuron is given by equation below.

Where,

 X_i = the signals arriving through various paths W_i = weight corresponding to the various paths θ = bias

All the details of the mathematical model of the neuron or the neural network can be shown in a picture, or the picture can be turned into a mathematical model. A mathematical model of the neural network architecture is possible. The more sophisticated the neural network's design, the more challenging problems it can tackle. To better comprehend the aforementioned reasoning, please refer to figure 5-

and



Figure 5 The mathematical formulation of the neural model.

The heart of the aforementioned model is the system's attempt to simulate brain activity in the following ways: -

It works in a complex parallel computation manner.

High speed of performance due to the parallel architecture.

It learning and adapt according to the modified link weights.

Since its inception, work on ANN has been motivated by the realization that the human brain processes information in a fundamentally different manner than a typical modern computer.

ANN has a remarkable ability to establish a connection between completely non-linear data, which may be utilized to identify patterns and so uncover the impossible-for-human-minds-to-recognize pattern followed by our targets.

Artificial neural networks (ANNs) have the impressive capacity to self-train using only the data used in their initial training. It's capable of self-organization during the learning phase and functioning in real time.

ANN takes in data and uses it to learn and get information that can be used to make predictions, sort patterns, etc. All processing of information takes place inside a neuron. In the figure above, the connections between neurons are shown. This is an example of how a learning algorithm can be used to train using data from the past. Weights are the building blocks of the connections between neuronal circuits. The input values will be transformed using these weights in order to generate reliable forecasts. The weights are determined by the input and target data, as well as the selected activation function (usually nonlinear). Some difficult tasks in forecasting or sorting can be simplified by considering the value of weight. Accuracy training involves constant adjustments to the weights.

Results And Discussion FEMALE DATA SETS



MALE DATA SETS





Figure 6 ANN Layer.



Figure 7 MSE curves.



Figure 8 Validation parameters.



Figure 9 Error graph.



Figure 10 True and False rate.

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Detected Class=1	The mean square error is 0.04. The PSNR = 62.00	FEMALE
OK	ОК	ОК
if det class=1	L	1

Figure 11 Output Window.



Figure 12 Feature Extraction-1.

Figure 13 Feature Extraction-2.



Figure 14 Feature Extraction-3.

Figure 15 Feature Extraction-4.

CONCLUSION:

We proposed an ANN design that works well for gender classification. Layers of convolution and subsampling combine to form the architecture. In the processing layers, cross-correlation is employed instead of convolution. Benchmarking results reveal that the proposed ANN outperforms the competition, with classification rates of 98.75% on the SUMS face database and 99.38% on the AT&T face database. Furthermore, the pace of our proposed design has been substantially enhanced. On a PC platform, it can process and categorize a 3232 pixel image in less than 0.3 ms. So far, this is one of the first experiments to investigate how weight flipping affects an ANN's performance in terms of how effectively it can classify and how quickly it can do tasks. The findings can be extended to face detection and alignment tasks using comparable ANN structures to create a full gender recognition system. The technology can be used to create custom hardware for real-time processing in resource-constrained applications. So far, it has been attempted to discuss all of the new and improved methodologies that have been utilized to estimate demographic data.

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