Facial Recognition Algorithms

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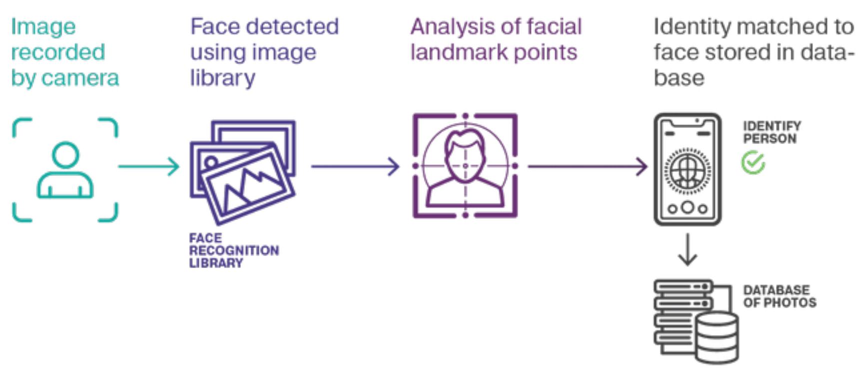
1 Introduction

Facial recognition was first developed in 1964 and 1965 by Woody Bledsoe, Helen Chan Wolf, and Charles Bisson [1]. Although it was much less automated back then, facial recognition has rapidly evolved into a complex, powerful machine learning technique commonly used in a wide range of applications and technologies today. Facial recognition systems learn and extract the physical characteristics of a face and match their features with tested images. The facial recognition process generally can be broken down into primary phases, although approaches to these phases can vary significantly: (1) face detection, (2) preprocessing, (3) feature extraction and (4) feature matching [2].

Facial recognition algorithms are a rapidly growing technology being used across various industries. These algorithms are being applied to personal lives through everyday technologies, with Apple's Face ID perhaps being the most common and well known. Facial recognition algorithms are a complex tool, and given their ability to solve various problems and their increasing prevalence in our lives, it is essential to learn from them and understand how they work, particularly due to the associated ethical concerns and potential biases.

Figure 1: Overview of the Facial Recognition Process [3]



2 Problem Description

This paper aims to deconstruct three well-known facial recognition algorithms, eigenfaces, local binary patterns histograms (LBPH) and convolutional neural networks (ConvNet/CNN), as well as to compare and contrast their processes and performances. It concludes with a discussion of ethical concerns and potential biases of facial recognition algorithms, two of the areas of extreme interest to the authors.

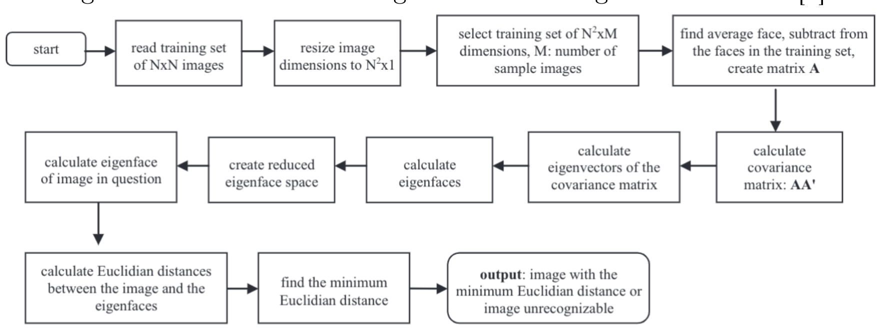
3 Algorithms

3.1 Eigenfaces

Introduction

Eigenfaces for face recognition was developed by Turk and Pentland at the MIT media lab in 1991. As represented by Fig. 2, the Eigenfaces method takes many steps to process the image, extract the features of the image, simplify these features, then match the two given faces in question. What makes the Eigenfaces approach unique is that it uses principal component analysis (PCA) to represent the faces. PCA was first used by Sirovich and Kirby to represent face images efficiently [4]. PCA is a method commonly used in pattern recognition and Turk and Pentland applied PCA in the face recognition to extract the characteristic features of the face and represent them as a linear combination of “eigenfaces”.

Figure 2: Flowchart of the algorithm of the Eigenfaces Method [4]



Preprocessing

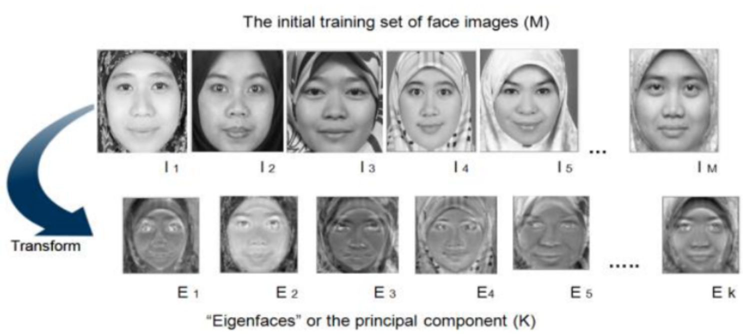
First of all, the intensity of the images are used to represent the images, which means that the images used in the Eigenfaces method will be in greyscale. Every face image has to be normalized to the same size, specifically the same number of pixels. Say every image needs to have the dimension of N x N. Each face image is then converted to a vector with the length of the number of pixels (N^2), so a matrix of size N^2 x 1 is created. Given many images in the training set, say M number of images, the resulting matrix will have a dimension of N^2 x M that contains all pixels of all face images.

Feature Extraction and Simplification

The average face is calculated by averaging across each row of the N^2 x M matrix. The difference of each face from this average face is calculated as a vector, and this set of vectors, say matrix A, is subject to principal component analysis. Principal component analysis reduces the dimensions of a given dataset by replacing the correlated vectors of large dimensions with the uncorrelated vectors of smaller dimensions [4]. In order to do so, the covariance matrix of the matrix A must be calculated first. The eigenvectors of this covariance matrix are the principal components of the images and are called "eigenfaces", which is where the name of this algorithm comes from. Then, each face image can be transformed into its eigenface components by calculating the weight of each eigenface used to represent the face image. More specifically, each eigenface with some weight (coefficient) is put onto the average face and combined to make up the face image. This set of weights can now represent each face image as a vector.

However, not all eigenfaces have to be used to represent the faces. For example, Turk and Pentland found that in a training set with 115 images of caucasian males, about 40 eigenfaces were sufficient for a very good description of the set of face images [5]. Therefore, a number of eigenfaces with the highest associated eigenvalues are selected to represent the faces. In general, some number k less than M is selected as the number of eigenfaces (Fig. 3). In short, the Eigenfaces method has reduced the image from N^2 pixels to a vector with length k.

Figure 3: The Transformation Process [6]



Matching

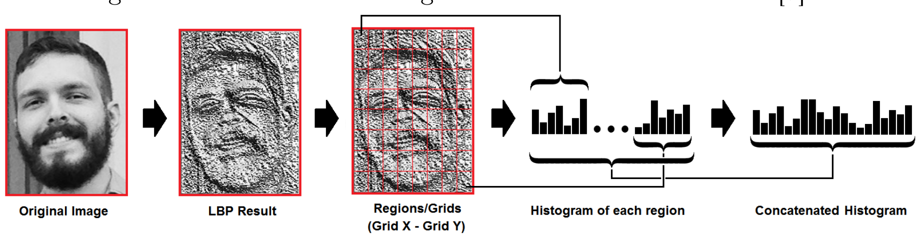
The last step of any face recognition is matching. Given the face image in question, the Eigenfaces method first calculates the set of weights of the eigenfaces. Then, the goal is to find an image in the dataset that has the most similar set of weights. This is done by calculating the Euclidean distance between the vector of eigenface weights in question and the vectors of weights of the original dataset. The face image in the dataset that minimizes the Euclidean distance between its calculated vector of weights and the newly calculated vector of weights is returned as the matched face. However, there is a maximum threshold for the Euclidean distance. If all of the calculated Euclidean distances are larger than the threshold, the face image in question is considered new and unidentifiable. Therefore, it needs to be newly incorporated into the training set before any face recognition can happen.

Conclusion
To summarize, the Eigenfaces method uses PCA to reduce the complex facial image and uses the set of weights of the eigenfaces to represent and match a face to faces in the existing dataset.

3.2 Local Binary Patterns Histograms (LBPH)

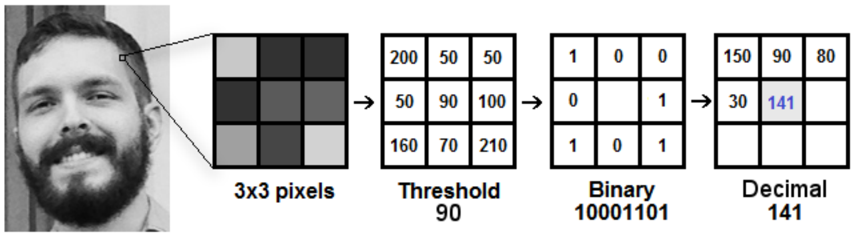
Introduction
Local Binary Patterns Histograms (LBPH) algorithms are one of the simplest face recognition algorithms. They are a combination of Local Binary Patterns (LBP) and Histograms of Oriented Gradients (HOG) descriptors and can recognize both the side and front of a human face [7]. The LBPH algorithm makes use of 4 parameters: radius, neighbors, grid X, grid Y. As shown in Fig. 4, the LBPH, like many early facial recognition algorithms, starts with an input image and first simplifies it. The most unique feature of the LBPH algorithm is that it makes use of histograms to match pixels of similar facial features. Due to the standardized structure of the algorithm, the LBPH can also measure it's correctness of matching a face [8].

Figure 4: Flowchart of the algorithm of the LBPH Method [9]



Preprocessing
The first step of the LPBH algorithm is applying the LPB operation in order to simplify the input image into a grayscale version intermediate image, highlighting distinct facial characteristics, using a circular local binary pattern. In order to do this, the algorithm makes use of the radius parameter, representing the radius around the central pixel (typically set to one), and the neighbors parameter, representing the number of sample points to build the circular local binary pattern (typically set to 8) [10]. As shown in Fig 5, the LPB operation takes in a facial image in grayscale and separates part of it into a 3x3 image of pixels. Next, it takes the central value of the matrix to be used as the threshold, and defines its neighbors to binary values, 0 for values below the threshold and 1 for values above. Finally, it converts the binary value to a decimal value, which denotes a pixel from the original image. The resulting image is known as the LPB result of the image [11].

Figure 5: Flowchart of the LPB Operation [9]



Feature Extraction and Simplification

Using the LPB result along with the grid X, the number of cells in the horizontal direction (typically set to 8), and the grid Y, the number of cells in the vertical direction (typically set to 8), the algorithm divides the image into multiple grids. A histogram is extracted from each region representing intensity patterns within the cells. A taller bar in the histogram would denote a more intense pixel within the cell. In the case of an 8x8 cell image, there would be 64 cells and thus 64 histograms. Finally, the histograms are concatenated into one comprehensive histogram to represent the characteristics of the original image [11].

Matching

The actual face recognition happens in the matching phase of LPBH. In this step, the algorithm takes the concatenated histogram of the input image and compares it to histograms of images in the training dataset (which were created the same way the histogram of the input image was created). To reiterate, each image in the training dataset, as well as the input image, has its own histogram. The algorithm returns the image from the training dataset with the closest histogram. There are many approaches used to compare histograms such as euclidean distance, chi square, and absolute value [12]. The LBPH algorithm also returns a confidence value to show the correctness of the match between the input image and the closest match in the training dataset. A smaller confidence value denotes a more accurate match [9].

Conclusion

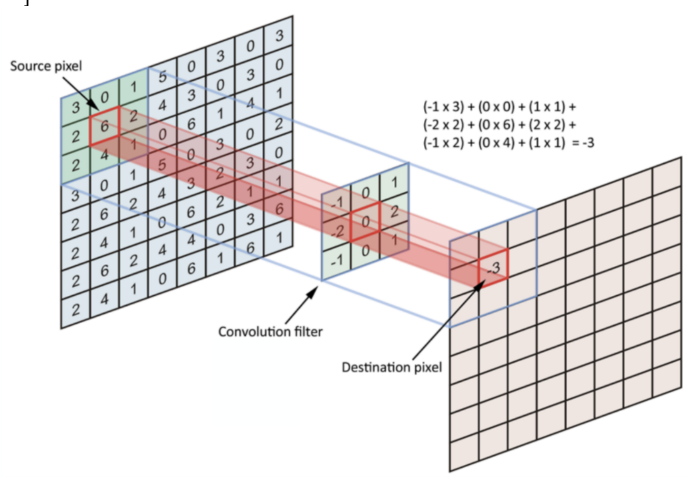
To conclude, the LBPH is one of the simplest face recognition algorithms, and it produces great results within a controlled environment. Additionally, it is robust against monotonic gray scale transformations. LPBH is commonly applied within texture analysis, biometrics, and computer vision [9].

3.3 Convolutional Neural Networks (ConvNet/CNN)

Introduction

In addition to Eigenfaces and LBPH algorithms, more recently, convolutional neural networks (CNNs) have emerged as the main method used for facial recognition, and they are only increasing in popularity and ability. A CNN, also known as a ConvNet, is a class of deep neural networks that essentially condenses a given image into a more easily processed form, assigns importance to various objects in the image, and are able to distinguish these objects from one another. They are preferred over alternate approaches to facial recognition due to their level of accuracy and speed. CNNs facilitate machines in understanding more visual signals than could previous facial recognition techniques, and because other techniques require engineering filters by hand, whereas CNNs are able to learn to optimize its filters, CNNs require much less preprocessing than other classification algorithms and are independent in this aspect from human intervention.

Figure 6: The convolution operation, with the end product being the convolved feature [13]



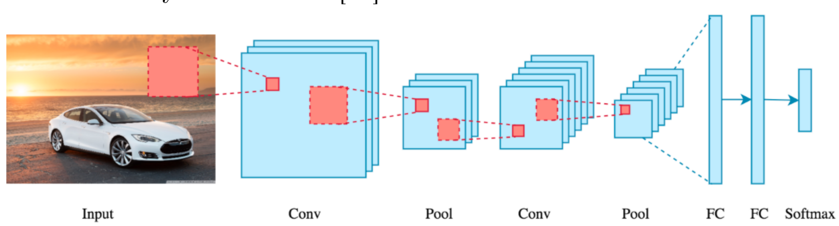
The connectivity patterns of neurons in CNN architectures resembles that of the neurons in the human brain and was inspired by the structure of the visual cortex. This adapted connectivity pattern is a way in which CNNs differ from traditional neural networks. Individual neurons, each having learnable weights and biases, are connected to and react only to stimuli within a local region of a previous neuron's activations, the receptive field, whereas neural networks are fully connected [14]. Referred to as local connectivity, this feature reduces the amount of parameters in CNNs, thereby improving the efficiency of the overall system, as well as reducing overfitting. The reduction in the number of parameters and the reusability of the neurons' weights also enables more accurate results [15]. CNNs impose a local connectivity pattern between neurons in consecutive layers.

One of the most important operations performed by a CNN, after which it is named, is convolution. Depicted in Figure 6, convolution is a mathematical operation performed on two functions, intertwining two sources of information: here, the image or feature map and a filter, a set of cube-shaped weights, with the same depth as the input image, which are applied throughout the image.

Layers

Through deep learning, a CNN independently learns the features depicted in the input images layer by layer, with each individual one transforming its input of a multidimensional array of activations to another, using a differentiable function. Layers in CNN architectures fall into three basic categories: convolutional, pooling, and fully-connected.

Figure 7: An overview of the layers in a CNN, used here for image classification. Local connectivity is illustrated [16]



Convolutional

The convolutional layers in a CNN apply filters to the original image input–or to feature maps, in a deep CNN, with multiple convolutional layers–to extract its features and activations. Each of its filters abstract the image or map into a convolved feature. A filter, or kernel, could be related to any feature, such as eyes, with an eye filter indicating how strongly an eye appears in the image, as well as how frequently and where they occur. Not only does this decrease the amount of weights the CNN must learn, in comparison to other neural networks, but it also means the network is robust to changes in the location of features. When the CNN is built, random values are generated for the filters, which update themselves as the network is trained, so a CNN is highly unlikely to have redundant filters, unless an extremely large number of filters are used [17].

The filters in a convolutional layer have a small receptive field but extend to the full depth of the input volume, and they carry out the convolution operation: each filter is convolved section by section across the width and height of the input volume and computes a dot product from its weights and the subset of the input to which it is connected [17]. Because of local connectivity, the filters can be reused for different pixels. During this process, the network autonomously learns filters. The computations performed by the filter, once the filter has covered the entire input, produces the convolved feature, a two-dimensional feature map, and an activation function is then applied to all the values of this map, with the function identifying the locations at which a given feature map's feature is present. The dimensions of this convolved feature can be the same as those of the input if same padding is applied, smaller if valid padding is applied, or larger if full padding is applied [18]. Padding refers to the amount of pixels added on the edges of an image to increase the image's area. For instance, with valid padding, no pixels are added, and with same padding, the amount of pixels that are added is the amount required to ensure that the output and input have the same size.

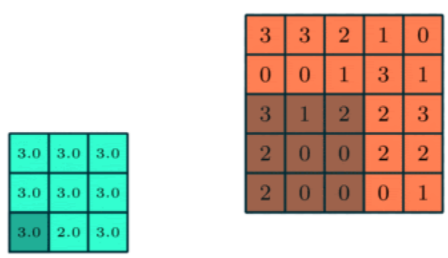
The final output of a convolutional layer is three-dimensional: one two-dimensional convolved feature, a feature map, for each filter. Since there can be multiple convolutional layers in a single CNN architecture, while the initial convolutional layer captures low-level features like edges and color, the following layers can capture high-level features as well [14].

Pooling

Pooling layers are responsible for progressively reducing the width and height dimensions of the feature maps in a process called downsampling, or subsampling. This reduces the amount of parameters and computational power necessary to process the data in the network, thus speeding up the recognition process without affecting the dimension depth, and can also control overfitting. It also contributes to extracting dominant features [14].

Max pooling and average pooling are the two most common strategies used in the pooling layer. Max pooling involves returning the maximum value from the image correlated to a filter's receptive field, and average pooling, the average of all the values from this same portion of the image [19]. Max pooling has the additional benefit of suppressing noise by discarding noisy activations and thus has a better performance.

Figure 8: 3x3 pooling over a 5x5 feature map [20]



Fully-Connected

Lastly are fully connected layers, which are fully connected, as the name suggests, to all the neurons in the previous layer and which aggregates information provided by the final feature maps. A fully connected layer calculates class scores for each feature and thereby flattens the two-dimensional feature maps into a one-dimensional feature vector of scores [14]. A CNN thus transforms an image layer by layer from its original pixel values to class scores. It is through these scores that a CNN makes its predictions, by comparing this vector to those previously generated.

Conclusion

First developed in the 1980s, CNNs have since undergone significant enhancement and been adopted as the dominant, most widely used approach to facial recognition. Their accuracy and speed have established them as a popular choice for applications such as facial recognition, image classification, recommendation systems, and more. Famously, in 2014, Facebook proposed DeepFace, among the earliest facial recognition algorithms based on a CNN, and it was able to reach 97.35 percent accuracy: reducing error by 27 percent from what was previously the best alternative and approaching human-level accuracy [21]. Since, the use of CNNs in facial recognition have subsequently escalated, Meta plans to shut down its facial recognition system, and a variety of CNN architectures have been made available, which allow for the building of additional and even more powerful CNN-based algorithms. Based on the numerous advantages of using CNNs, they will likely be an important part of machine learning for the foreseeable future.

4 Similarities and Differences

Figure 9: Overall recognition accuracy of different facial recognition methods. Test A used 40 training images and 400 test images; Test B, 120 and 400, respectively; Test C, 200 and 400, respectively; and Test D, 320 and 400, respectively [14]

	Number of training and test images			
	A	B	C	D
PCA (%)	75.2	77.5	82.1	85.6
LBPH (%)	78.1	81.3	86.7	88.9
KNN (%)	71.4	73.8	79.2	81.4
Proposed CNN (%)	93.9	95.7	97.5	98.3

To evaluate their proposed CNN, Kamencay et al. tested its performance, along with those of PCA (Eigenfaces), LBPH, and K-Nearest Neighbor methods, and their overall accuracy is compared in Figure 9 [14]. It should be noted that these results are not necessarily representative of the algorithms as a whole.

Their proposed CNN, for example, includes a Rectified Non-Linear unit layer, which is not found in all CNN architectures.

Based on these results, CNNs outperform PCA and LBPH significantly, and LBPH consistently outperforms PCA as well. The discrepancy between the accuracy of a CNN and the two other methods could be partially attributed to PCA and LBPH analyzing their images after applying a grayscale feature and consequently losing color information that contributes to identifying and differentiating features. The ability of CNN's filters to learn autonomously and continually also contributes to this, as well as to CNN's faster speed.

Another aspect of CNN that allows for its increased speed is the fact that PCA and LBPH make use of the entirety of a given input image throughout their respective algorithms, whereas CNNs perform downsampling, resulting in simultaneous information loss that reduces the computational power necessary to process the image data.

Eigenfaces vs LBPH

Eigenfaces and LBPH are different in their feature extraction methods but similar in the matching methods. While both use the intensity of the image as the input, Eigenfaces uses the variance between face images as its feature. On the other hand, LBPH uses the circular local binary patterns of the image as its feature. Despite this difference in feature extraction, they are similar in that once they have their features extracted (as either a vector of weights or histograms), they both match by looking at how similar their existing vector or histogram are to the newly calculated one.

LBPH + CNN

Although the LBPH and CNN approaches to facial recognition differ independently, CNNs with local binary convolution (LBC) layers, based on local binary patterns, forming local binary CNNs (LBCNN), have been proposed as an alternative to the standard CNNs that use convolutional layers. In one study, the LBC layer allows for a reduction in parameters by a factor of 9 to 169, and the convolutional weights further allows for a reduction in computational complexity and memory requirements during both training and inference [22]. The LBC layers thus seem to approximate effectively a standard convolutional layer, while also improving performance.

5 Ethical Concerns

Privacy Concerns

Since the conception of facial recognition, ethical concerns have arisen regarding the extent to which facial recognition systems have compromised privacy. Face recognition can be used not just for identification purposes, but also to find other personal data, including social media profiles, general online presence, travel patterns, and even current whereabouts. Given the lack of transparency provided by many of the companies and organizations that use this technology, concerns have understandably been expressed as to who would be able to access such data and what other data can and has been linked to an individual's face. Avoiding the identifying and tracking allowed by facial recognition is also a challenge due to the generally exposed nature of the face; there is little that protects an individual from having their facial data and associated personal information collected by any given person, company, or organization without their consent.

For an example of facial data collected without consent, most facial recognition algorithms are trained on large datasets of images with uninformed, non-consenting subjects, which is particularly concerning when images of the most vulnerable groups of people are used in these datasets. In a specific example, the National Institute of Standards and Technology is the very group assigned to develop best practices and standards for the use of technology in the United States. They maintain the Facial Recognition Verification Testing program, which allows for the evaluation of a facial recognition software's accuracy by providing multiple datasets. Cash prizes are awarded in some cases for the best programs, but even without, testing well on these datasets provides a mark of approval and is often mentioned in the marketing of new products that use facial recognition. But in a turn for the sinister, it has been uncovered and confirmed that this testing program includes in their datasets images of children who were exploited for child pornography, applicants for U.S. visas, and people who were once arrested and have since passed away. Individuals who were arrested and not even necessarily convicted are the subject for most of the images that constitute this program's datasets [23].

Although a lack of consent in such cases is a serious violation of one's privacy, the granting of consent does not necessarily eliminate issues of privacy or ethics in general; often, people are asked to consent without being informed as to what exactly they are consenting to or how their data will be used, and even when people have the ability to refuse to consent, governments and companies can simply turn to vulnerable populations who cannot withhold consent, as mentioned.

In addition to privacy concerns at an individual level, there is always the risk of breach of a dataset so large. If the dataset is accidentally breached, personal information from all those involved will be available for public viewership, including personal information of individuals who never gave consent to use in the first place.

Controversial Uses

In addition to the privacy concerns associated with these algorithms, the specific uses of facial recognition algorithms have also been the subject of significant contention. Facial recognition algorithms have applications in law enforcement and the workforce. Especially in terms of law enforcement and surveillance, there is a grey line of when it is okay to use facial recognition and when it is not. For example, some may argue that it seems ethical to use facial recognition for a serious, urgent crime, such as finding a murderer or a terrorist who is under search warrant. However, is it ethical to use facial recognition for a suspected petty theft? In these cases, the threat of invasion of privacy and of identifying the wrong individual, especially when considering bias, as discussed later, is arguably greater than successfully identifying and charging the suspect [23].

In a chilling example of the dangers of incorporating facial recognition into government and/or law enforcement use, the Chinese government's expanding system of surveillance cameras has been reported to scan exclusively for Uyghurs, a largely Muslim minority in the country, and record their movements for review. This in itself is deeply worrying, but taking into context the human rights abuses that the Chinese government has committed against this minority group, including incarcerating at least a million Uyghurs in internment camps, with multiple reports of mass deaths within, paints a horrifying picture of the atrocities that facial recognition software can enable [24].

In terms of the workforce, companies have increasingly begun to use facial recognition algorithms when hiring. Many recorded video interviews, on platforms such as HireVue, use facial recognition algorithms to make preliminary decisions regarding applicants. This method of screening has ignited controversy, because in many cases, facial analysis is unrelated to job performance, and the accuracy of the analysis is dubious. Research scientist Meredith Whittaker has found that the study of the shape and size of one's facial expressions is not an indicator of character or intelligence [25]. Although these systems claim to measure personality and worker engagement, there is not much robust scientific evidence behind these claims. It is also unknown what such companies and platforms do with the data they collect and how long it is kept or what such software actually looks for, with discrimination being in the realm of possibility. The issue of consent also applies here, with the facial analysis capabilities often not clearly expressed and the question of whether these often desperate job applicants are truly given a chance to deny their consent.

6 Bias

As seen in the original Eigenfaces [5], only images of Caucasian males were used to not only create and but also verify the effectiveness of these algorithms in the early days. This is alarming given that face recognition algorithms fail to recognize and identify a person if they do not already exist in the dataset. Therefore, if input is biased, the algorithm will also be biased. The lack of representative input data likely causes these biases in face recognition algorithms. But with that being said, greater diversity in datasets and reducing bias does not resolve ethical issues alone. In some cases, not being able to be detected may actually be beneficial. When considering facial recognition technology in crime prevention, Zoé Samudzi writes, "it is not social progress to make black people equally visible to software that will inevitably be further weaponized against us" [26]. The NIST datasets are diverse, but the ethics associated are questionable at best. And keeping in mind past applications of facial recognition, such as the Chinese government's surveillance of Uyghurs, addressing an algorithm's bias does not address the bias of its users, and it is crucial to focus on regulation in conjunction, if not first and foremost.

Algorithmic Demographic Bias

Facial recognition algorithms are notorious for showing demographic bias, meaning that there is a significant difference in the accuracy of the algorithm when interacting with different demographic groups. Specifically, facial recognition algorithms have been shown to be biased against people of color and women, and especially women of color. Joy Buolamwini, a researcher at MIT, found that facial recognition in commercial artificial-intelligence systems showed an error rate of 0.8 percent for light skinned men and 34.7 percent for dark-skinned women [27]. The NIST also conducted a study testing algorithmic demographic bias from 189 software algorithms from 99 developers. They found that the algorithms produced higher false positives for Asian and African American relative to Caucasians, with Asian and African Americans being up to 100 times more likely to be misidentified than white men [28]. In addition, they saw a higher false positive rate for African American women, consistent with other previous studies. However, the algorithms developed in Asian countries did not show dramatic differences in the false positives between Asian and Caucaisian faces. Regarding this unique exception, the researchers at NIST suggest that there is a possible relationship between an algorithm's performance and the data used to train it [29]. Therefore, it is especially important to be mindful during the data training process in the development of facial recognition algorithms.

The presence of such bias is particularly problematic when considering the various controversial applications of facial recognition software. For example, as of December 2020, there have been three known instances of people wrongfully arrested due to inaccurate identification by facial recognition technology. All three have been black men [30]. With facial recognition algorithms tested by biased humans, they inevitably involve some degree of bias, and given that studies have demonstrated facial recognition algorithms to disproportionately produce false positives for racial and gender minorities, careful consideration needs to be applied to how these algorithms are used to avoid perpetuating bias.

7 Summary

Due to its wide range of applications, facial recognition technology has grown increasingly widespread, and since its initial conception in 1960, numerous new methods have been adopted and adjusted to enhance its accuracy and efficiency. In this paper, we explore several such methods–Eigenfaces, LBPH, and CNNs–, as well as the ethical ramifications of incorporating this technology into our everyday lives. Facial recognition is a powerful, convenient, and growing technology that has made great impacts in our lives, but just as it has a powerful potential for benefiting users, it also has a powerful ability to harm. While it is easy to get lost in the success and power of these algorithms, it is important to consider the many ethical concerns and biases that come with them.

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