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Face Recognition Using Python and Deep Learning

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Abstract- In their daily lives, people who work in the chemical sector come into contact with hazardous or caustic compounds. They also come across a variety of substances and particles that, when inhaled, cause a variety of negative effects. Some of the gases used in these industries are so toxic that they can make a worker dizzy and cause a temporary loss of concentration. When working with chemicals, it is therefore suggested that you use a breathing mask. These masks shield you from hazardous particles and gases in the air. They remove contaminants from the air that might cause injuries, infections, or death. As a result, respirators are required to protect you from gas and other toxic chemicals. In this research, we offer a method for detecting face mask.Abounding box drawn across the person's face indicates whether or not the person is wearing a face mask. If a person's face is recorded in the database, the name of the person who is not wearing a face mask is spotted, and an email is sent to the authority informing them that the worker is not wearing a mask so that precautions can be taken.sksonhumans using TensorFlow andOpenCV.

Keywords- Tensorflow, OpenCV, Face Mask, Image Processing, Computer Vision.

I. INTRODUCTION

A surgical mask is a disposable, loose-fitting device that forms a physical barrier between the wearer's lips and nose and potentially harmful pollutants in the immediate surroundings. Surgical masks are governed by the 21 CFR 878.4040 standards. Surgical masks, which may be branded as surgical, isolation, dental, or medical procedure masks, are not to be shared. They may or may not come with a face shield. Although not all face masks are licensed as surgical masks, they are sometimes addressed to as face masks, as outlined above. Surgical masks are available in a variety of thicknesses and abilities to protect you from liquid contact.These aspects may also influence how readily you can breathe through the surgical mask and how well it protects you.

A surgical mask, when worn fittingly, can help block large particle droplets, splashes, sprays, or spatter that may carry germs (viruses and bacteria) from reaching your mouth and nose. Surgical masks may also help to keep your saliva and respiratory secretions from being exposed toothers.While a surgical mask may be effective in inhibiting splashes and large-particle droplets, a face mask is not designed to filter or block very small particles in the air that are spread by coughs, sneezes, or some medical operations. Because of the poor fit between the mask's surface and your face, surgical masks may not provide total protection from germs and otherimpurities.

Surgical masks aren't meant to be worn more than once. If your surgical mask becomes broken or soiled, or if breathing through it becomes difficult, you should remove it, dispose of it carefully, and replace it. Place your surgical mask in a plastic bag and toss it in the garbage to safely dispose of it. After using the mask, wash yourhands. There are no reliable face mask detection applications that can detect whether or not a person is wearing a face mask and alert authorities to a security breach. To maintain safety, more efficient systems for identifying face masks on individuals are needed for transportation, largely urbanized places, residential districts, large-scale manufacturing, and other companies. To detect facemasks on humans, this project employs machine learning classification with OpenCV andTensorflow.

II. DEEP LEARNING

Deep learning is a machine learning technique that teaches computers to learn by doing what people do naturally, study by instances. Deep learning is a critical component of self-driving automobiles, allowing them to detect a stop sign or discriminate between a pedestrian and a lamppost. A computer model learns to conduct classification tasks directly from images, text, or sound in deep learning. Deep learning models can attain state-of-the-art accuracy, even surpassing human performance in some cases. Models are trained utilising a huge quantity of labelled data and multilayer neural networktopologies.

1. Opencv:

Open CV is a cross-platform library that may be used to create real-time computer vision apps. It focuses primarily on image processing, video recording, and analysis, with capabilities such as face detection and object detection.

2. DLIB:
Dlib is a C++ framework that allows you to create real-world machine learning and data analysis applications. Despite the fact that the library was initially designed in C++, it has excellent Python bindings. Face detection and facial landmark detection are two areas where we've utiliseddlibextensively.

3. Tensor Flow:
It is a free machine learning framework for creating and training neural networks. It contains a set of tools, libraries, and community resources that aid in the development and deployment of machine learning-powered applications. Google created and maintains this, which was released in 2015.

4. Mask R-CNN:
Mask R-CNN, also known as Mask RCNN, is a Convolutional Neural Network (CNN) that is the state-of-the-art in image and instance segmentation. Faster R-CNN, a Region-Based Convolutional Neural Network, was used to create Mask R-CNN.

5. Res Net:
An artificial neural network called a residual neural network (Res Net) is a type of artificial neural network (ANN). Skip connections, or shortcuts, are used by residual neural networks to jump past some layers. The majority of ResNet models use double- or triple-layer skips with nonlinearities (ReLU) and batch normalisation in between.

III. RELATED WORK

Proposes a novel image representation method dubbed the Stretched Natural Vector (SNV) method, which is based on a two-dimensional grayscale picture matrix directly. In terms of SNV construction, the first group of components is the grayscale amounts, which determine the number of all level grayscales, respectively. The average locations across rows and columns in the picture matrix of all level grayscales are the second group of components in SNV. Meanwhile, the normalised higher order central moments, which might indicate the distribution of grayscales with regard to their associated average locations, are the third group of components in SNV.

Because the coefficients are functions of some of the SNV components, the essential idea is that for each k, a photo provides a set of row positions i1,..., ink, which are roots of a symmetric polynomial whose coefficients must match those from another photo with the same SNV. The problem is that more is necessary than simply demonstrating that the SNV specifies the set of row and column locations for both photographs. It must be demonstrated that both photographs with the same SNV have the same exact placements (i.e., the (i,j) row–column pairs). In this case, SNV may identify picture matrices in a one-to-onemanner.

Heterogeneous Face Recognition (HFR) is discussed in [2], and it entails matching faces from several picture modalities. The fundamental challenge in matching faces from different environments is that photos of the same individual can look different due to image domain differences, such as between visual spectrum images (VIS) and near-infrared images (NIR), or between VIS images and drawings. This shift caused large differences within classes, and a direct comparison of images across different domains may reduce recognition accuracy. This work makes three distinct contributions. First, they looked at how well several cutting-edge Deep Convolutional Neural Networks (DCNN) architectures trained on VIS images performed in theHF R task.

This type of analysis sets a benchmark against which future comparisons can be made. As a second contribution, we present Domain Specific Units, a lightweight framework for learning domain specific feature detectors for HF R. When compared to DCNNs trained using VIS images and state-of-the- art, the deployment of such a framework in various HFR contexts significantly improved recognitionrates.

Inspired by a simple deep learning model principal component analysis network, the authors introduced a new deep learning network termed circular symmetrical Gabor filter (2D) 2PCA neural networks [CSGF (2D) 2PCANet] in [3]. (PCANet). Previous face recognition methods had three key flaws: data redundancy, computation time, and a lack of rotation invariance. To address these challenges, they established the CSGF. The feature extraction stage employs two-directional 2- D PCA [(2D) 2PCA]. The output stage employs binary hashing, block wise histograms, and linear SVM. During the training phase, the proposed CSGF (2D) 2PCANet learns high-level features and gives more recognition information, perhaps leading to a higher recognition rate when testing the sample. n the XM2VTS, ORL, AR, Extend Yale B, and LFW databases, we tested the proposed technique. The CSGF (2D) 2PCANet is more resilient to variations in occlusion, lighting, posture, noise, and expression, according to test results, making it a viable technique for face recognition.

The CSGF (2D) 2PCANet model, proposed in this study, is a straightforward and efficient solution to the problems of data redundancy, long calculation times, and rotation variance. Image feature extraction is a crucial stage in face recognition that is critical to improving the overall performance of the algorithm. However, by enhancing image feature extraction, it will be possible to improve CSGF (2D) 2PCANet's face recognition accuracy.

They proposed a joint face alignment and 3D face reconstruction method in [4], which solves both challenges for 2D face images of arbitrary poses and expressions at the same time. This technique sequentially and alternately applies two cascaded regressors, one for updating 2D landmarks and the other for updating 3D shape, based on a summing model of 3D faces and cascaded regression in 2D and 3D shape spaces. A 3D-to-2D mapping matrix connects the 3D shape and landmarks, which is changed in each iteration to fine-tune the location and visibility of 2D landmarks.

Unlike existing methods, the suggested method can fully automate the generation of both PEN and expressive 3D faces, as well as the localization of both visible and unseen 2D landmarks. They devised a method to improve face recognition accuracy across poses and expressions based on the PEN 3D faces.

While several 3D face reconstruction algorithms exist, most of them rely on landmarks on the face image as input, making it challenging to handle huge pose faces with hidden landmarks due toself occlusion. They use a 3D-to-2D mapping matrix to project the updated 3D shape to the 2D image in order to refine landmarks. They do not, however, take into account the visibility of landmarks from various perspectives. Those approaches are typically difficult to use and do not detect self-occluded landmarks.

They offered a project in paper [5] that used the notion of 2D- DWT for picture reduction as a preprocessing step before feature extraction. In fact, because the DWT is carried out at various scales and orientations, it is sensitive to harsh lighting and facial details. The LL sub-band of the processed image is used as an input image for feature extraction using ICA, PCA, LDA, and SVM algorithms, based on the DWT benefits. Where the input image has the highest detailed representation, feature extraction using PCA, ICA, and LDA algorithms is more efficient. The wavelet transform is virtually as common as signal and image analysis. Its capacity to gather image-specific time frequency information drives its usage for feature extraction.

The 2D-DWT separates an image's information into deconstructing images to approximate the Low-Low (LL) subband and three detail subbands Low-High (LH), High-Low (HL), and High-High (HH) (HH). For data representation in a high-dimensional space, Principal Component Analysis is performed.

The statistical and computational technique of component analysis (ICA) is used to identify distinct sources from mixed sources. It has been effectively employed in image processing for feature extraction. Support Vector Machines (SVMs) are supervised learning algorithms that use decision planes to determine decision boundaries. To separate data of distinct classes, SVM is presented as a hyper plane that maximises the margin of separation and minimises classification error. The main idea behind nonlinear classifiers is to translate the input data to a high-dimensional space and then separate it using a linear classifier. To begin, the 2D-DWT is used to extract the crucial information from the source photos. The essential characteristics are then retrieved from each image's LL sub-bands using the PCA, LDA, and ICA algorithms.

Finally, the SVM algorithm classifies the resulting eigenvectors. They proposed three face recognition approaches based on these methods: the first is based on 2D-DWT + PCA+ SVM algorithms. The second technique is based on 2D-DWT + ICA+ SVM. The training sample set's feature space is obtained using the PCA technique, and the fusion feature space is obtained using the FLD algorithm. The projected face in the feature space is then trained and recognised. Face recognition technology is a type of biometrics recognition technology that provides direct, friendly, convenient, and rapid qualities.

The following methods are used in this paper: To begin, divide the samples with comparable features (expression, angle, and brightness) into a matrix by dividing them into blocks, resulting in a Gaussian distribution of the samples. Second, equalised samples are represented by histograms, which can improve sample contrast to show facialfeatures.

High-dimensional data was dimensionalized using principal component analysis (PCA), and then Fisher linear analysis was utilisedfor projection in this research [6], allowing the classification direction of each type of image to be accurately determined. Faces were detected using a combination of two algorithms: principle component analysis (PCA) and Fisher linear discriminant analysis (FLDA) (FLD). The ORL face database and self-collected photos were used to verify the possibility of combining the PCA and FLD algorithms. The results show that by combining these two methods, a high identification rate may be achieved in the presence of a complex background, changing light, changing attitude, and occlusion. Of course, some face recognition rates are low; the fundamental reason is that the notion of a face is not well defined. The results show that by combining these two methods, a high identification rate may be achieved in the presence of a complex background, changing light, changing attitude, and conclusion.

They computed the eigenfaces for three separate datasets using a geometrical approximation PCA (gaPCA) algorithm in paper [7]. A similarity score based on the inverse Euclidean distance for the face recognition challenge is used. In the first two cases, a neural network used, and in the third case, a neural network was used. All of the results are compared to those obtained using traditional PCA. These results demonstrate that gaPCA is a feasible alternative to the traditional statistical method

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for computing the principal components. PCA has the disadvantage of a relatively high computing cost and technical challenges in algorithm parallelization, despite being a feasible method with good recognition accuracyoutcomes.

They previously suggested a geometric construction-based approach for PCA approximation (gaPCA) based on the observation that the direction given by the furthest points is very near to the one supplied by the first principal component, depending on the correlation of data.

On three separate face databases, they used gaPCAfor face identification and compared the recognition accuracy to that obtained using regular PCA in a paper [7]. The findings in this paper suggest that gaPCA is a feasible alternative to the traditional statistical methodfor computing principal components. Because the gaPCA technique is simpler to construct than regular PCA, future research will focus on parallelizing it to obtain faster executiontimes.

Publication	Approach	Advantages	Dis advantages
Dong, Wenhui, and Stephen s-t. Yau	Stretched natural vector method	Reduce data dimensions and computational loads without discarding too Much information.	Parallel computation is difficult to achieve in a lot of real applications.
De freitaspereira, Fiago, André anjos, and sébastien marcel	Heterogeneous face recognition	Improves the recognition rates compared with DCNSS trained with vis images and with state-of-the-art	Need of reducing the domain gap through either learning domain-invariant features or common space projection methods
Kong, jun, Min chen, Min jiang, jinhua sun, and jianhou	Csgf 2d^2 PCA Net	Robust to the variation of occlusion, illumination, pose, noise, and expression.	Must improve image feature extraction, algorithm versatility, And classifier.
Liu, feng, Gijunzhao, Xiaomingliu, danzeng	3d face reconstruction	Directly estimate landmark locations by applying cascaded regressors to an input image.	Do not consider the visibility of landmarks under different view angles.
Lahaw, Ziedbannour, Dhekraessaidani, and Hasseneseddik.	PCA, ICA, LDA based on DWT, and SVM algorithms	Use the discrete wavelet transform as image's pre-processing to generate good Accuracies.	Does not work properly for faces of yaw angles beyond 60 degree.
Shen, Shaorun, Chao zhang, Ruixiao, Wanliang he, and Ninghuizhang	PCA and FLD	Can achieve a high recognition rate in the presence of complex background, illumination change.	Has the disadvantage of a relatively high computational cost and technical difficulties in algorithm parallelization
Machidon, Alina l., Octavian m. Machidon, and Petre l. Ogrutan	Geometrical approximated PCA	A viable alternative to the classical statistical approach for computing the principal components.	Have to work on parallelization in order to achieve faster execution times.

IV. CONCLUSION

This system can inspect masks on people's faces without the assistance by humans .This technique can be used in public locations such as train stations and shopping malls. It will be extremely useful in large corporations and organisationswith a large workforce. This system will be very useful since it is simple to get and store the data on the employees working in that company, and it will be very easy to locate people who are not wearing masks, and a message will be sent to that person to take precautions if they are not wearingmasks.

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