Multi QR And Barcode Detection Using Machine Learning Image Data

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Abstract— *Face Recognition (FR) problem is one of the significant fields in computer vision. FR is used to identify the faces that appear over distributed cameras over the network. The efficiency of face recognition systems decreases because of limited references especially (SSPP) and faces taken in the Operational Domain (OD) different from faces in the Enrollment Domain (ED) in illumination, pose, low-resolution, and blurriness. This paper proposed a method that deals with all problems related to face recognition. Besides, the design domain dictionary is used to feed different deep learning models. Face illumination transfer techniques are utilized to overcome the illumination problem. Dataset is used to train Super-Resolution Generative Adversarial Network (SRGAN) to overcome the low-resolution problem. Deblur Generative Adversarial Network (DeblurGAN) is trained the dataset to overcome the problem of blurriness. By using Generative Adversarial Network Deep Learning for Image Super Resolution.*

I. INTRODUCTION

Face Recognition (FR) problem is one of the significant fields in computer vision. FR is used to identify the faces that appear over distributed cameras over the network. The problem of face recognition can be divided into two categories, the first is recognition with more than one sample per person, which can be called traditional face recognition problem. The second is the recognition of faces using only a Single Sample Per Person (SSPP). The efficiency of face recognition systems decreases because of limited references especially (SSPP) and faces taken in the Operational Domain (OD) different from faces in the Enrolment Domain (ED) in illumination, pose, low-resolution, and blurriness. This paper proposed a method that deals with all problems related to face recognition. Besides, the design domain dictionary is used to feed different deep learning models. Face illumination transfer techniques are utilized to overcome the illumination problem. Dataset is used to train Super-Resolution Generative Adversarial Network (SRGAN) to overcome the low-resolution problem. Deblur Generative Adversarial Network (DeblurGAN) is trained the dataset to overcome the problem of blurriness.

1.1 Face Recognition

Face Recognition (FR) is one of the significant Fields in computer vision. FR systems are used to identify faces from videos recorded over several surveillance cameras distributed. It is used in various applications including law enforcement, video monitoring, etc. The main issue in Face Recognition is the limited number of references. Many techniques deal with face recognition the first one is a traditional technique that can identify faces by extracting features or landmarks from the image. An algorithm, for example, will investigate the relative scale, shape, and location of the eyes, nose, cheekbones, and use the features to scan for other photos with similar features such as Support Vector Machine (SVM) and Principal Component Analysis (PCA). The second technique is dimensional recognition technique, which utilizes 3D sensors to capture a lot of information about face shape and use this information to recognize distinctive characteristics on the face, like a nose shape. This information enhances face recognition efficiency. The third technique is skin texture analysis. It is another new pattern that utilizes visual details for the skin. The performance of the face recognition technique increased when adding skin texture analysis. The fourth technique is thermal cameras. It is a different shape of input data being taken for face recognition. The cameras will only recognize head shape by this process. In addition, it avoids the accessories of a person like makeup, hats, or glasses. The most important problem when we use thermal images for face recognition is that the datasets for face recognition are finite. The problem of face recognition can be divided into two categories, the first is recognition with more than one sample per person, which can be called traditional face recognition problem. The second is the recognition of faces using only a Single Sample Per Person (SSPP). However modern face recognition techniques, like deep learning algorithms, achieved high accuracy, these techniques did not achieve good accuracy in the problems that have limited data.

1.2 Image Super Resolution

The term super resolution refers to the process of obtaining higher-resolution images from several lower-resolution ones (resolution enhancement). The quality improvement is caused by fractional-pixel displacements between images. Super resolution allows to overcome the limitations of the imaging system (resolving limit of the sensors) without the need for additional hardware. The goal of super resolution, is to increase the resolution of an image. Resolution is a measure of frequency content in an image, high-resolution (HR) images are bandlimited to a larger frequency range than low-resolution (LR) images. However, the hardware for HR images is expensive and can be hard to obtain. The resolution of digital photographs is limited by the optics of the imaging device. Image super Resolution is used to improve the resolution in the image to obtain the better performance.

Super-resolution algorithms face a number of challenges in parallel with their main super-resolution task. In addition to being able to compute values for all the super resolution image pixels intensities given the low-resolution image pixel intensities, a super-resolution system must also be able to handle:

- **Image registration –** small image displacements are crucial for beating the sampling limit of the original camera, but the exact mappings between these images are unknown. To achieve an accurate super-resolution result, they need to be found as accurately as possible.
- **Lighting variation –** when the images are aligned geometrically, there may still be significant photometric variation, because of different lighting levels or camera exposure settings when the images were captured.

II. LITERATURE SURVEY

Domain-Specific Face Synthesis for Video Face Recognition from A Single Sample Per Person.

F. Mokhayeri, E. Granger (2019).

In this article, the paper analyses an algorithm for domain-specific face synthesis (DSFS) that exploits the representative intra-class variation information available from the OD. During camera calibration, a compact set of faces from unknown persons appearing in the OD is selected through affinity propagation clustering in the captured condition space (defined by pose and illumination estimation). The domain-specific variations of these face images are then projected onto the reference still of each individual by integrating an image-based face relighting technique inside the 3-D reconstruction framework. Experimental results obtained with videos from the Chokepoint and COX-S2V data sets reveal that augmenting the reference gallery set of still-to-video FR systems using the proposed DSFS approach can provide a significantly higher level of accuracy compared with the state-of-the-art approaches, with only a moderate increase in its computational complexity.

Deblurgan-Blind Motion Deblurring Using Conditional Adversarial Networks.

O. Kupyn, V. Budzan (2018).

In this article, we present DeblurGAN, an end-to-end learned method for motion deblurring. The learning is based on a conditional GAN and the content loss. DeblurGAN achieves state-of-the art performance both in the structural similarity measure and visual appearance. The quality of the deblurring model is also evaluated in a novel way on a real-world problem are object detection on de-blurred images. The method is 5 times faster than the closest competitor DeepDeblur. We also introduce a novel method for generating synthetic motion blurred images from sharp ones, allowing realistic dataset augmentation. Experimental results obtain in the better performance, when compared to the other system.

Deep Convolutional Neural Network Used In Single Sample Per Person Face Recognition.

J. Zeng, X. Zhao, J. Gan, C. Mai (2018)

In this article, the paper proposes a scheme combined traditional and deep learning (TDL) method to process the task. First, it proposes an expanding sample method based on traditional approach. Compared with other expanding sample methods, the method can be used easily and conveniently. Second, it uses transfer learning and introduces a well-trained deep convolutional neural network (DCNN) model and then selects some expanding samples to fine-tune the DCNN model. Third, the fine-tuned model is used to implement experiment. Experimental results on AR face database, Extend Yale B face database, FERET face database, and LFW database demonstrate that TDL achieves the state-of-the-art performance in SSPP FR.

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network.

C. Ledig, L. Theis, F. Huszar (2017).

In this article**,** we present SRGAN, a generative adversarial network (GAN) for image super-resolution (SR). A first framework capable of inferring photo-realistic natural images for 4x upscaling factors. To achieve this, we propose a perceptual loss function which consists of an adversarial loss and a content loss. The adversarial loss pushes our solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images. In addition, we use a content loss motivated by perceptual similarity instead of similarity in pixel space. Our deep residual network is able to recover photo-realistic textures from heavily down sampled images on public benchmarks. An extensive mean-opinion-score (MOS) test shows hugely significant gains in perceptual quality using SRGAN. The MOS scores obtained with SRGAN are closer to those of the original high-resolution images than to those obtained with any state-of-the-art method.

Dynamic Ensembles of Exemplar-Svms for Still-To-Video Face Recognition.

S. Bashbaghi, E. Granger (2017)

In this article, the paper demonstrated an efficient multi-classifier system (MCS) is proposed for accurate still-to-video FR based on multiple face representations and domain adaptation (DA). Specific ensemble of exemplar-SVM (e-SVM) classifiers is thereby designed to improve robustness to intra-class variations. Ensemble is used to model the single reference still, where multiple face descriptors and random feature subspaces allow to generate

a diverse pool of patch-wise classifiers. This paper also investigates the impact of using different training schemes for DA, as well as, the validation set of non-target faces extracted from stills and video trajectories of unknown individuals in the operational domain. The performance of the proposed system was validated using videos from the COX-S2V and Chokepoint datasets. Results indicate that the proposed system can surpass state-of-the-art accuracy, yet with a significantly lower computational complexity.

Dynamic Dictionary Optimization for Sparse-Representation-Based Face Classification Using Local Difference Images.

C. Shao, X. Song (2017)

In this article, we present a new sparse-representation-based face-classification algorithm that exploits dynamic dictionary optimization on an extended dictionary using synthesized faces. First augment the dictionary with a set of virtual faces generated by calculating the image difference of a pair of faces. This results in an extended dictionary with hybrid training samples, which enhances the capacity of the dictionary to represent new samples. Second, to reduce the redundancy of the extended dictionary and improve the classification accuracy, we use a dictionary-optimization method. We truncate the extended dictionary with a more compact structure by discarding the original samples with small contributions to represent a test sample. Finally, we perform sparse-representation-based face classification using the optimized dictionary. Experimental results obtained using the AR and FERRET face datasets demonstrate the superiority of the proposed method in terms of accuracy, especially for small-sample-size problems.

Face Recognition Using Deep Multi-Pose Representations.

W. Abdalmageed, Y. Wu, S. Rawls (2016).

In this paper**,** we introduce our method and system for face recognition using multiple pose-aware deep learning models. In our representation, a face image is processed by several pose-specific deep convolutional neural network (CNN) models to generate multiple pose-specific features. 3D rendering is used to generate multiple face poses from the input image. Sensitivity of the recognition system to pose variations is reduced since we use an ensemble of pose-specific CNN features. The paper also presents extensive experimental results on the effect of landmark detection, CNN layer selection and pose model selection on the performance of the recognition pipeline. Our novel representation achieves better results in the state-of-the-art methods.

Facenet-A Unified Embedding for Face Recognition and Clustering.

F. Schroff, D. Kalenichenko (2015)

In this paper, we present a system, called FaceNet, that directly learns a mapping from face images to a compact Euclidean space where distances directly correspond to a measure of face similarity. Once this space has been produced, tasks such as face recognition, verification and clustering can be easily implemented using standard techniques with FaceNet embeddings as feature vectors. Our method uses a deep convolutional network trained to directly optimize the embedding itself, rather than an intermediate bottleneck layer as in previous approaches. To train, we use triplets of roughly aligned matching / non-matching face patches generated using a novel online triplet mining method. We achieve state-of-the-art face recognition performance using only 128 bytes per face and then widely used Labeled Faces in the Wild (LFW) dataset, our system achieves a new record accuracy of 99.63%.

Deep Face Recognition.

Parikh, A.Vedaldi (2015)

In this article, the Paper demonstrated the face recognition from either a single photograph or from a set of faces tracked in a video. It can be analysed the two factors (i) end to end learning for the task using a convolutional neural network (CNN), and (ii) the availability of very large-scale training datasets. We make two contributions: first, we show how a very large-scale dataset (2.6M images, over 2.6K people) can be assembled by a combination of automation and human in the loop, and discuss the trade-off between data purity and time. Second, we traverse through the complexities of deep network training and face recognition to present methods and procedures to achieve comparable state of the art results on the standard LFW and YTF face benchmarks.

A Benchmark and Comparative Study of Video-Based Face Recognition on COX Face Database.

Z. Huang, S. Shan, R. Wang (2015).

In this article, the paper implemented an contributes a benchmarking and comparative study based on a newly collected still/video face database, named COX [1] Face DB. Specifically, we make three contributions. First, we collect and release a largescale still/video face database to simulate video surveillance with three different video-based face recognition scenarios (V2S, S2V, and V2V). Second, for benchmarking the three scenarios designed on our database, we review and experimentally compare a number of existing set-based methods. Third, we further propose a novel Point-to-Set Correlation Learning (PSCL) method, and experimentally show that it can be used as a promising baseline method for V2S/S2V face recognition on COX Face DB. Extensive experimental results clearly demonstrate that video-based face recognition needs more efforts, and our COX Face DB is a good benchmark database for evaluation.

Problem Definition

Face Recognition (FR) problem is one of the significant fields in computer vision. FR is used to identify the faces that appear over distributed cameras over the network. The problem of face recognition can be divided into two categories, the first is recognition with more than one sample per person, which can be called traditional face recognition problem. The second is the recognition of faces using only a Single Sample Per Person (SSPP). The efficiency of face recognition systems decreases because of limited references especially (SSPP) and faces taken in the Operational Domain (OD) different from faces in the Enrollment Domain (ED) in illumination, pose, low-resolution, and blurriness. In our Exiting Method, The Existing method of face recognition is processed using many type of pre-trained Convolution Neural network. The CNN method recognizes face and classifies the particular face. This is also one of the best methods to for such applications. But here the Super Resolution GAN is advance technique of deep learning method. This is used to deblur the image to overcome the blurriness images.

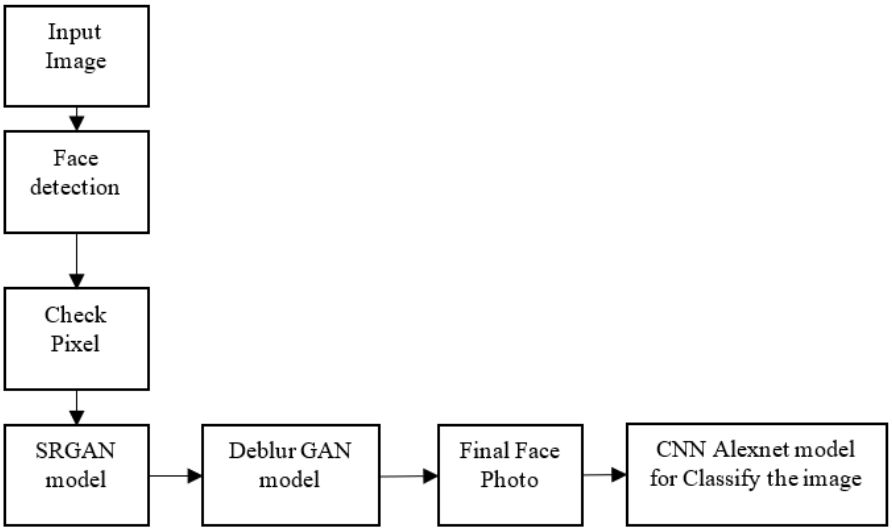
Drawbacks

- Resize of image or not enough to apply.
- Less loss of GAN function.
- Inefficiency.
- Less Performance.

III. METHODOLOGY

Face Recognition (FR) is one of the significant fields in computer vision. FR systems are used to identify faces from videos recorded over several surveillance cameras distributed. It is used in various applications including law enforcement, video monitoring, etc. Face Recognition (FR) problem is one of the significant fields in computer vision. FR is used to identify the faces that appear over distributed cameras over the network. The efficiency of face recognition systems decreases because of limited references especially (SSPP) and faces taken in the Operational Domain (OD) different from faces in the Enrollment Domain (ED) in illumination, pose, low-resolution, and blurriness. This paper proposed a method that deals with all problems related to face recognition. Besides, the design domain dictionary is used to feed different deep learning models. Face illumination transfer techniques are utilized to overcome the illumination problem. Dataset is used to train Super-Resolution

Generative Adversarial Network (SRGAN) to overcome the low-resolution problem. Deblur Generative Adversarial Network (DeblurGAN) is trained the dataset to overcome the problem of blurriness. We train different deep learning approaches to identify the person's face using a design dictionary that produced in the design phase. SRGAN is trained on the dataset to overcome the problem of low-resolution faces. DeblurGAN is trained on the dataset to overcome the problem of blurred faces. SRGAN and DeblurGAN work as a pre-processing step on the image that comes from the input images or camera. Check if the face photo less than size 96 x 96 (low- Resolution image). Then, the SRGAN model takes the face photo and generates a high-Resolution face photo. Check if the face photo is a blurred image, then the DeblurGAN model takes the face photo and generates a sharp face photo. Deep learning takes the final face photo to identity the person's face. The advantages of the system are Accurate, high Performance, when compared to other system.



3.1 Datasets

All facial recognition and detection systems require the use face datasets for training and testing purposes. In particular, the accuracy of CNNs is highly dependent on large training datasets. Here, a lot of data's can be obtained to detect the face. A input image is taken as face recognition datasets. This face dataset is limited, and thus one area of improvement could include the creation of a largescale annotated dataset containing a broad range of applications.

3.2 Face Detection

Face detection is a fundamental step in face recognition and verification. Face detection methods as applied to facial recognition and verification. The greatest obstacle faced by face detection algorithms was the ability to achieve high accuracy. Consequently, their usability in real life applications was limited. So, the significant progress has since been made by system due to the development of powerful feature extraction techniques including Histograms of oriented Gradients (HoGs), Local Binary Patterns (LBPs) etc. Face detection classify the feature of the image in resolution, illumination, pose, expression, and color. In face detection process, pre-processing techniques is used to convert the image into pixel size for further process the system in efficient way.

3.3 Feature Extraction

Feature extraction usually occurs immediately after face detection and can be considered as one of the most important stages in face recognition systems, as their effectiveness is dependent upon the quality of the extracted features. Face recognition differs to object recognition in that it involves alignment before extraction. This is reflected in the differences between CNNs used for face recognition and those used for object recognition. An increase in data availability has resulted in development of learning-based methods as opposed to engineered features due to their inherent ability to discover and optimize features specific to a task.

3.4 Srgan Model

GANs are deep neural network architectures and consist of two main networks (the Generator network and the Discriminator network). The aim of GANs is to generate new data that matches the training data distribution. It is like a game in which the Generator tries to generate some data from the distribution of probability and the Discriminator serves as a judge. Discriminator determines either the input comes from a true training dataset or fake generated data. The generator attempts to optimize data in order to match true training data. The discriminator guides the generator to generate realistic data. Discriminator and generator both learn concurrently and once the generator has been trained, it has enough knowledge of the distribution of training samples. Now SRGAN is used to produce higher resolution images and we will train it and use it to overcome the problem of low-resolution faces that come from the operational domain. Processing the High-Resolution (HR) face photos for down-sampling Low-Resolution (LR) face photos. Now, we have HR and LR face photos for the training dataset. Passing LR face images through Generator which up-samples and gives Super Resolution face images. Using a discriminator to distinguish the HR face images and back-propagate the GAN loss to train the discriminator and the generator. SRGAN after training can take a low-resolution image and generate a high-resolution image. We use SRGAN after training in the operational domain. Check if the face photo less than size 96-96 (low-Resolution image). Then, the SRGAN takes the face photo and generates a high-Resolution Face photo. But the transfer image from low to high resolution, one of the drawbacks will be obtained. To overcome the drawback, Deblur GAN model is used.

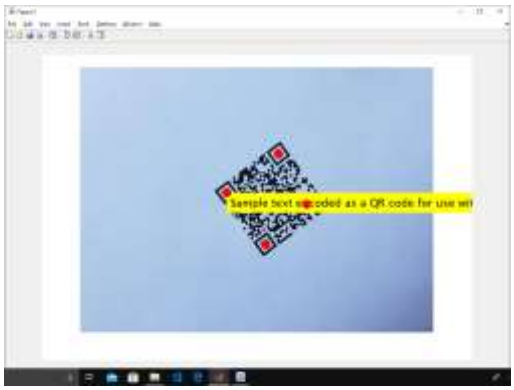
3.5 Deblur Generative Adversarial Network (Deblur-Gan)

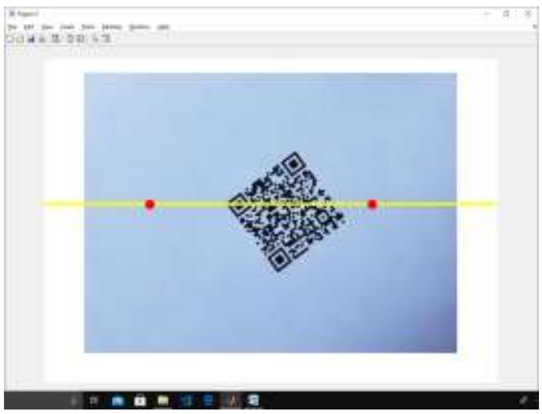
DeblurGAN architecture consists of the network of generators that inputs the blurred image and generates a sharp image and the discriminating network to decide whether an input image is created artificially. We will train DeblurGAN to work on blurred face images. DeblurGAN after training can take a blur face image and generate a sharp face image. We use DeblurGAN after training in the operational domain. If the image that comes from the operational domain is blurred, then DeblurGAN takes the image to generate a sharp image to overcome the problem of the blurred face image.

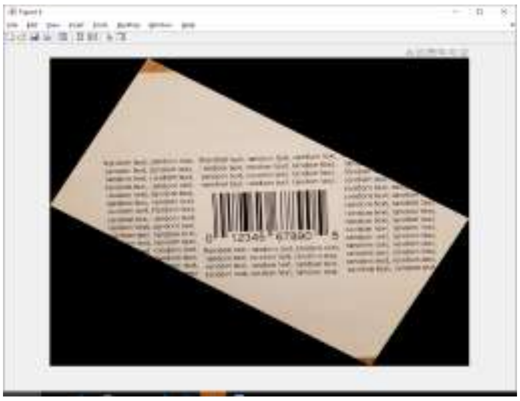
3.6 Classification

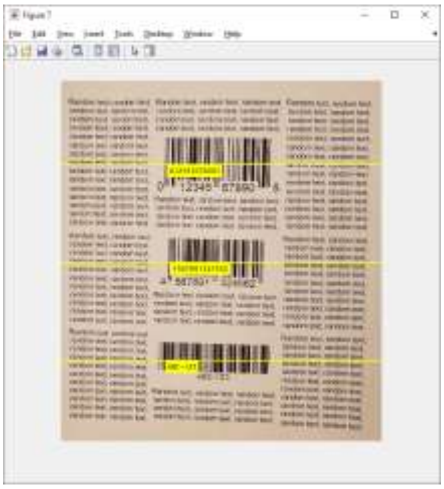
Classification process is used in the output layer of the system. Here, CNN Alex net model is used for classify the image in face recognition system. CNN-Alexnet model is used to solving the problem of multi-classes classification. Alexnet consists of the layers of convolution and the max-layer and finished with two layers completely connected. The loss was measured using a SoftMax classifier, using multinomial logistic loss. Finally, a predicted output is obtained in this layer to classify the output images and display it.

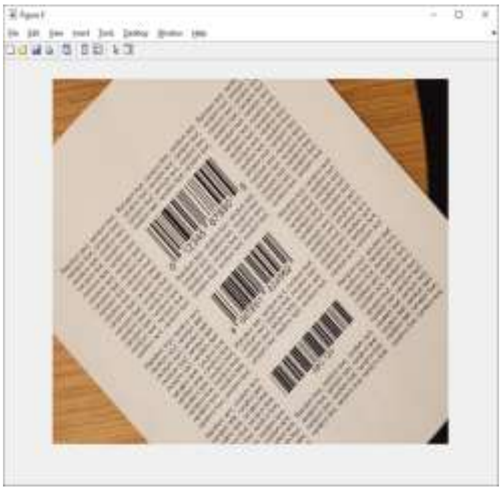
IV. IMPLEMENTATION

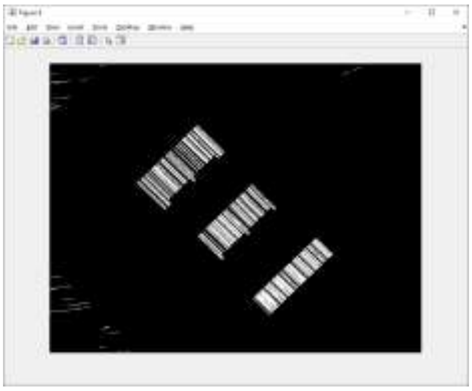


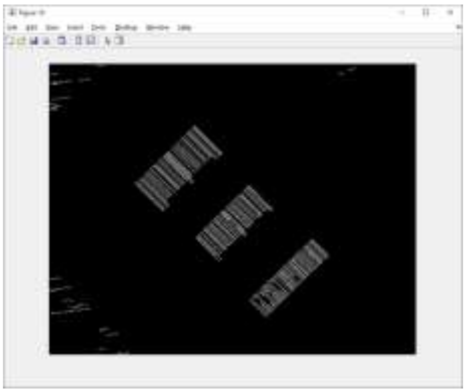


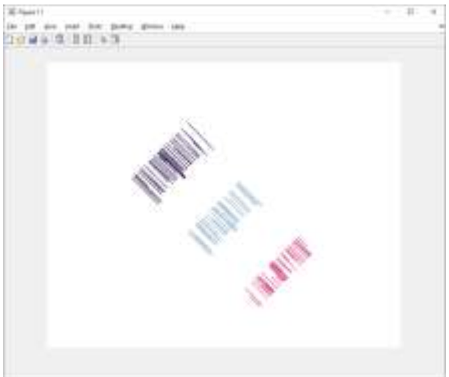


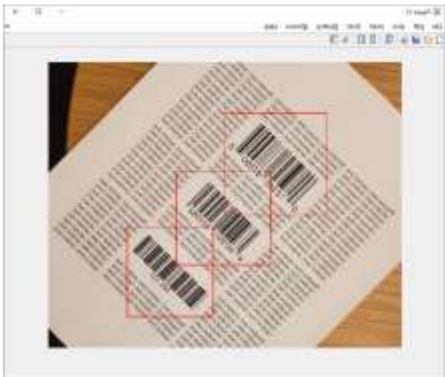












Output:

Detection and message: EAN-13, 1234567890128 ans = ""

ans = "012345678905"

Decoded format and message: UPC-A, 012345678905

Decoded format and message: EAN-13, 4567891324562

Decoded format and message: CODE-39, ABC-123

ans = ""

Decoded format and message: UPC-A, 012345678905

Decoded format and message: EAN-13, 4567891324562

Decoded format and message: CODE-39, ABC-123

V. CONCLUSION

Face recognition is a both challenging and important recognition technique. Among all the biometric techniques, face recognition approach possesses one great advantage, which is its user-friendliness (or non-intrusiveness). We focus on Face Recognition with Single Sample Per Person (SSPP) problems. Faces captured under controlled circumstances in the enrollment domain different from taken under uncontrolled circumstances in the operational domain in illumination, pose, and blurriness. Our proposed method deals with the problem of limited references and overcomes the issue of a pose, illumination, blurriness, and low-resolution image. We overcome the problem of a pose by using 3D Face Reconstruction to reconstruct a 3D face from 2D face image. To overcome the problem of low-Resolution using Super Resolution Generative Adversarial Network (SRGAN) And overcome the problem of blurriness using Deblur Generative Adversarial Network (DeblurGAN). Furthermore, overcoming the problem of illumination by making the illumination of the system constant by extracting the illumination from the enrollment domain and apply this illumination to the operational domain. Therefore, the proposed method achieved high accuracy compared to techniques that use SSPP for face recognition (generic learning and face synthesizing approaches). Also, the proposed method out performs of Traditional and DeepLearning (TDL) method accuracy, which uses SSPP for face recognition.

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