Locating a Missing Person Using an Optimized Face Recognition Algorithm

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Abstract: Investigation of missing person requires data from combination of multiple modalities and heterogeneous data sources. Drawback of the existing fusion model is for each modality of data separate information models are used. It also lacks in application domain to use pre-existing object properties. A new framework with name Trace-Them is developed for multimodal information retrieval. Feature extraction from different modalities and making use of DCNN for mapping them into a video footage is included in the proposed model.

1 INTRODUCTION

It is still difficult to automatically track and locate a person using facial detection and identification in an unrestricted huge crowd gathering. Face-detection cameras, camera mobility, and crowd (Visconti et al 2015).

A person missing is defined as a kid or adult who has vanished, either purposely or by mistake. Only 43% of missing cases fall into one of several categories, making it difficult to identify them due to active factors like low resolution and variable crowd distance from installed cases. Of these cases, 99% involve juvenile abductions, 2500 involve family issues, and 500 involve strangers (both adults and teenagers) kidnapping the victim (Kasar 2016, Zhang 206, Sukhija 2016).

About 52% of missing persons cases are women, and 48% are men. An official source stated, "There are no finances set aside in India to find missing persons. Although a missing person faces many challenges, very few are murdered, raped, or otherwise mistreated. Uncertainty about the missing person's whereabouts causes tension and worry for those who are concerned about them, including parents, friends, relatives, and guardians.

2 LITERATURE REVIEW

The face recognition techniques presented by several researchers This article explains image processing and pattern identification using artificial neural networks (ANNs). In addition to this article also explains the usage of for recognizing face and how it is better than other methods. There are numerous ANN suggested methods available that give an overview of recognition of face using ANN. As a result, this study includes a thorough analysis of detection of face studies and systems that use various ANN approaches and algorithms. The results of different ANN algorithms are taken into consideration for review. This study aims to identify faces from either a single snapshot or a group of faces monitored in a movie. The availability of very large size training datasets and end-to-end learning for the job utilising a convolutional neural network (CNN) have both contributed to recent advancements in this field. First, it is showed the process of placing a very large dataset (2.6M images) using automation. Second, discussion about the difficulties in training deep network and recognition of face is explored (Mehdipur et al 2016, Hsu et al 2017, Al-Dabagh et al 2018).

In this study, a method for detecting skin areas over the whole image is presented. According to the skin patches spatial arrangement, face candidates are then generated. For each potential face, the algorithm creates border, mouth, and eye maps. Results from experiments show that a number of face differences in terms of colour, location, scale, rotation, stance, and expression may be successfully detected across various photo sets.

One of the computer vision literature's most researched subjects, face detection, has been the focus

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of this essay. We review the most recent developments in face detection during the last ten Years (Phillips et al 2018). The first review is on the ground-breaking Viola-Jones face detector. Then, we compare the different methods based on how they extract features and the learning algorithms they use. We anticipate that by examining the several existing methods, newer, more effective algorithms will be created to address this basic computer vision issue.

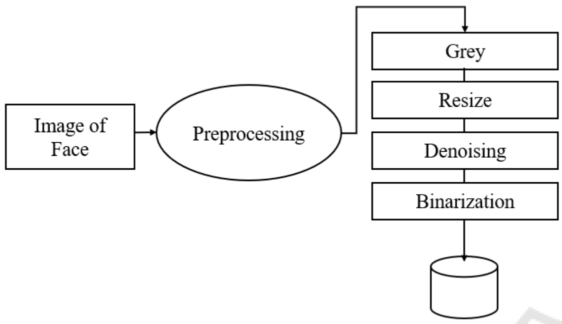

Figure 1: Architectural Diagram.

Due to good computing power and accessible to large data sets, the results of convolution neural networks (CNNs) on a variety of face analysis tasks have considerably improved. In this research, we provide an unconstrained face recognition and verification deep learning pipeline that performs at the cutting edge on a number of benchmark datasets. We outline the major modules used in automatic facial recognition in detail below: Face recognition and landmark location (Trigueros et al 2018).

Face detection is a well-examined issue in this paper. The prior work has examined a number of difficulties faced by face detectors, including extreme posture, lighting, low resolution, and small scales. But previously suggested models are routinely trained and tested on high-quality photos for practical applications like surveillance systems. This research compares the design procedures of the algorithms after reviewing the performance of the most advanced face detectors using a benchmark dataset called FDDB (Ranjan et al. 2019).

In this article, one of the most difficult aspects of picture analysis is face recognition. From early 1980s, recognition of face has been a point of ongoing research, offering answers to a number of real-world issues. Facial recognition has been the likely biometric technique for identifying people. On the other hand, the method of recognition of faces by human brain is very difficult. For face recognition method based on Genetic Algorithm (GA) for is suggested. Using Kernel Discriminant Analysis (KDA) and Support Vector Machine (SVM) with K-nearest Neighbour (KNN) approaches, a face recognition system is given in this study. For extracting features from input photos, the kernel discriminates analysis is used. Additionally, the face image is classified using SVM and KNN based on the extracted features.

In this study, Person re-identification has advanced significantly over time. However, it is challenging to put into practise because of the issue with super-resolution and the lack of labelled examples. In this article, semi-supervised multi-label-based super-resolution re-identification of person approach is provided. First, a method named Mixed-Space Super-Resolution (MSSR) is built using Generative Adversarial Networks (GAN), with the goal of transforming low-resolution photographs of people into high-resolution photos.

In this article, recovering the provided objects that are concealed within the gallery set is crucial for decision-making and public safety. In order to identify the same person, heterogeneous pedestrian retrieval (also known as person re-identification) attempts to get pictures of the person from many modalities. To solve this issue, we provide a brand-new pedestrian re-identification dataset (CINPID) that includes both character-illustration-style images and regular photos that were taken on campus.

We limit the focus of this work to obstructed face recognition. We first examine what the occlusion problem is and the many problems that might result from it. We have proposed occlusion based face detection, as a part of this review. Face recognition techniques are grouped them into three categories: 1) An approach of resilient feature extraction2) approach for recognition of face 3) approach based on Recovery face recognition. In addition goals, benefits, drawbacks, and effectiveness of representative alternatives are evaluated. Finally, occluded face recognition method and challenges are discussed (Fan et al 2021,M a 2021, Luo 2021, Abbaszadi 2022).

Deep Convolution Neural Network is used for study in this article. By averaging the rating-based identity judgements of many forensic face examiners, we combined their findings. For fused judgements, accuracy was substantially higher than for separate judgements. Fusion helped to stabilise performance by improving the results of those who performed poorly and reducing variability. The best algorithm combined with a single forensic face examiner was more accurate than using two examiners together.

Though the current ReID has produced significant results for single domains, research has recently shifted its attention to cross-domain problems due to domain bias in various datasets. To reduce the impact of cross-domain, distinct datasets are picture style transferred using Generative Adversarial Networks (GAN). The current GAN-based models, however, neglect entire expressions and exclude pedestrian features, leading to low feature extraction accuracy.

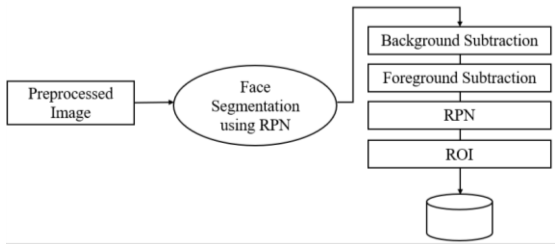

Figure 2: Block Diagram.

In this research, by taking deep features from different stages in CNNs, a Deep Classification Consistency (DCC) layer that implements steadiness of classification is presented. The training procedure of network is standardised by DCC. It significantly alters the distribution of learnt traits, enhancing their ability to discriminate and generalise. Extensive tests on the Market-1501, DukeMTMC-reID, and CUHK03 datasets demonstrate that the proposed method beats state-of-the-art approaches, particularly those sophisticated approaches that are only focused on metric learning.

In this research paper, for representation of face using deep learning a thorough investigation is done. Various scenarios like changing angles of head pose, occlusion of upper and lower face, enlightenment changes of various intensities, and misalignment due to incorrect localization of face features are taken into considerations. For face representations extractions, two active and commonly used deep learning methods - VGG-Face and Lightened Convolutional Neural Network are applied.

This research paper, a complete assessment of the literature on popular face recognition techniques, covering deep learning techniques as well as classical (geometry-based, holistic, feature-based, and hybrid) techniques. In this article, main aim is to propose a generalised model that can immediately handle brand-new, unexplored areas without model update. In order to do this, we suggest Meta Face Recognition (MFR), a revolutionary meta-learning face recognition technique. With a meta optimisation objective, MFR synthesises the source/target domain shift, which necessitates that the model learn efficient representations on both the synthesised source and target domains.

3 METHODOLOGIES

Missing Person Finder Webapp: A site created to help with missing person searches is called Missing Person Finder Web App. An DL-based facial recognition system is created on this site to locate those who are missing across the nation. CCTV footage is being integrated into this website. It is created with Python and MySQL with the Flask Framework.

- End user
- Admin
- Police
- Detective Agents

3.1 Face Recognition Module

In Person Enrollment

A few frontal face templates are registered at the start of this module. The models for the additional poses—tilting, moving in or out, and moving left or right are shown. Thes are evaluated and registered for guiding purpose.

Face Image Acquisition

To record pertinent footage, cameras should be placed in public areas. Webcam is utilised here as the link between computer and camera.

Frame Extraction

Frames are extracted from the input form video. The video has to be cut up into sequences of pictures for further processing. The implementation of persons determines how quickly a movie must be split into pictures. From this, we may infer that 20–30 frames are typically captured every second and forwarded to the next stages.

Preprocessing

The actions taken to prepare pictures before they are used by models for training and inference are known as face image pre-processing. The procedures are:

• Reading of Image
•Conversionfrom RGB to Grey Scale
•Resizing of Image
•Noise Removing

Gaussian blur is used to smooth image by removing unwanted noise

•Image Binarization

Grayscale image's of 256 shades is reduced to two: black and white, or a binary image using Image binarization. This process is done by taking the image and converting it it into a black-and-white image.

Face Detection

Because of this, the Region Proposal Network (RPN) in this module generates Region of Interest by swiping feature map windows over anchors of varying sizes and aspect ratios. Face identification and segmentation technique based on enhanced RPN. RPN is used to produce RoIs, and RoI Align precisely conserves the precise spatial locations. These have the responsibility of providing the RPN with a predetermined collection of bounding boxes in various sizes and ratios to act as a guide when predicting the initial locations of objects.

Using the region-growing (RG) approach, segment faces in images

This article describes the region growth process and current related studies.

RG is a straightforward picture segmentation technique based on region's seeds. It is also described as a pixel-based technique because it selects initial seed locations for picture segmentation. This segmentation technique considers the pixels that surround the initial "seed points" before deciding whether or not to include them in the region. The "intensity" constraint is the only one employed in a typical region-growing algorithm to assess nearby pixels.

Prediction of object limits is done by a fully convolution network known as RPN. Each feature (point) on the CNN feature map, on which it operates, is referred to as an Anchor Point. We overlay the image with nine anchor boxes (combinations of various sizes and ratios) for each anchor point. These anchor boxes are trotted at the location in the picture that corresponds to the feature map's anchor point.

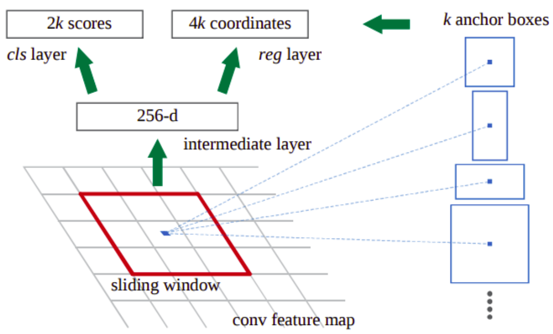

Figure 3: Architecture of RPN.

Training of RPN.

To be aware that there are nine anchor boxes for each place on the feature map, making a very large total number that does not include all of the essential anchor boxes. If one anchor box contains an item or a portion of an object, we may refer to it as the foreground, and if it doesn't, we can refer to it as the background.

Therefore, based on each anchor box's Intersection over Union (IoU) with the provided ground truth, assign a label to each one for training purposes. We essentially give each anchor box one of the three labels (1, -1, 0).

Label = 1 for Foreground: Label 1 have the following conditions,

If < 0.3.

Label = 0: If it doesn't fit into one of the aforementioned categories, this kind of anchor doesn't help with training and is disregarded.

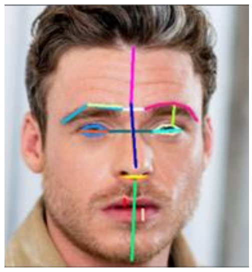

Figure 4: Feature Extraction.

With respect to ground truth, highest IoU is assigned to anchor

If the value is greater than 0.7 for ground truth IoU (IoU > 0.7).

Label = -1 for Background: If IoU, a -1 is given to the anchor.

After labelling the boxes, it generates a mini-batch of 256 anchor boxes that are selected at random from the same picture.

In the mini-batch Ratio should be 1:1 for positive to negative anchor boxes. If the value is less than 128 for positive anchor boxes, to reduce the shortfall negative anchor boxes are added.

RPN can be trained from beginning to end using back propagation and stochastic gradient descent (SGD).

Steps of processing are:

• Initial seed point is choosen

• Neighbouring pixels are to be added —intensity threshold

• Neighbouring pixel's threshold to be checked

• If the thresholds satisfy—select for growing the region.

Feature Extraction

Following face detection, the most crucial features for categorization are found using the facial image as input in the feature extraction module. The facial characteristics of each position, such as the lips, nose,

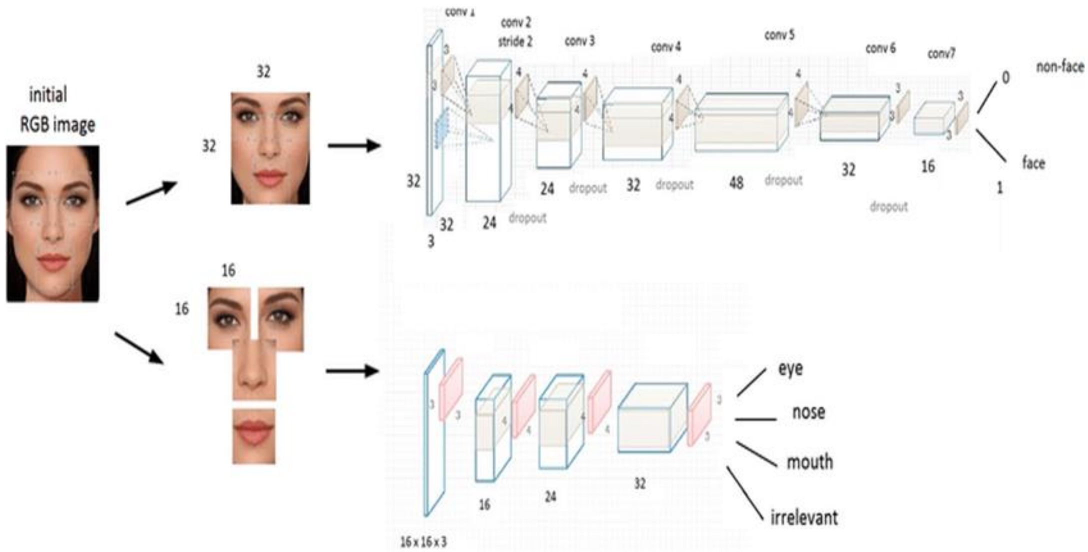

Figure 5: GLCM Architecture.

and eyes, are automatically recovered, and their relation to frontal face templates is utilised to determine the variation's consequences.

Face Features

•Forehead Height is measured as the distance between the tops of the brows and the tops of the forehead.

• Height of Middle Face: Distance between the nose point and the top of the brows.

• Height of Lower Face: the distance between the chin's base and the tip of the nose.

•Jaw Shape: A number used to distinguish between different jaw forms.

• Area of the Left Eye

•Area of the Right Eye

• Distance between Eye to Eye which are closest edges

•Distance between eyebrow and eye horizontal distance between eyebrows

• Shape Detector 1 for Eyebrow: To differentiate between eyebrow shapes the angle between left edge eyebrows, centre of the eyebrow, right edge of eyebrow is determined

• Shape Detector 2 for Eyebrow: For differentiating between Curved eyebrow shape and angled eyebrow shape a number is used

• Slope of the Eyebrow

•Slope Detector 1 for Eye: A method for calculating the eye slope. Slope of the line between centre point of the eye's and eye's edge point is determined. This method is used to determine Upward, Downward and Straight eye slopes.

•Slope Detector 2 for Eye: For calculating slope of the eye another method is used. Y-axis difference between center point and edge point of eye's is taken. This is a number that can group 3 types of eye slope which are Upward, Downward and Straight.

• Nose Length

• Width of the Nose Lower Part

•Angle of the curve lower edge of the nose which is taken as the Arch of the Nose (longer nose = larger curve = smaller angle)

• Upper Lip Height

• Lower Lip Height

	image_id	lefteye_x	lefteye_y	righteye_x	righteye_y
0	000001.jpg	69	109	106	113
1	000002.jpg	69	110	107	112
2	000003.jpg	76	112	104	106
3	000004.jpg	72	113	108	108
4	000005.jpg	66	114	112	112

	image_id	nose_x	nose_y	leftmouth_x	leftmouth_y
0	000001.jpg	77	142	73	152
1	000002.jpg	81	135	70	151
2	000003.jpg	108	128	74	156
3	000004.jpg	101	138	71	155
4	000005.jpg	86	119	71	147

	image_id	rightmouth_x	rightmouth_y
0	000001.jpg	108	154
1	000002.jpg	108	153
2	000003.jpg	98	158
3	000004.jpg	101	151
4	000005.jpg	104	150

Figure 6: Facial Attributes.

Feature	Measure
forehead height	82.0
middle face height	68.0
lower face height	86.0
left eye area	216.0
right eye area	194.0
eye to eye dist	47.0
eye to eyebrow dist	17.5
upper lip height	6.0
lower lip height	11.0
eyebrows distance	29.0
nose length	46.0
nose width	41.0
nose arc	147.0
eyebrow shape detector 1	141.0
eyebrow shape detector 2	1.0
eye slope detector1	-0.265
eye slope detector2	1.847
eyebrow slope	-0.145

Figure 7: Facial Feature Measurement.

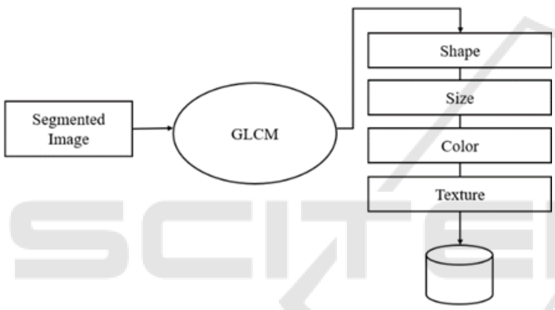

Figure 8: GLCM Flow.

Grey Level Co-Occurring Matrix

The second-order statistical texture analysis approach is called GLCM. Each image is divided into 16 grey levels (0–15), after which 4 GLCMs (M) are produced for each angle of 0, 45, 90, and 135 degrees with d = 1. Five characteristics (Eq. 13.30–13.34) are retrieved from each GLCM. Therefore, each image has 20 features.

Three categories may be made out of the features we retrieved. Characteristics such as maximum intensity, minimum intensity, mean, median, 10th percentile, 90th percentile, standard deviation, variance of intensity value, energy, entropy describes the tumour region's Grey level intensity.

Characteristics of shape features such as sphericity, elongation, Volume, surface area, and surface area to volume ratio as well as maximum 3D diameter, maximum 2D diameter for axial, coronal, and sagittal planes, major axis length, minor axis length, and least axis length describes how the tumour area is shaped.

Texture features is the third category, which includes five neighbouring grey tone difference matrix (NGTDM) features, sixteen grey level run length matrix (GLRLM) features, twenty-two grey level co-occurrence matrix (GLCM) features, and fourteen grey level features of dependence matrix (GLDM). The tumour area texture is characterised by these characteristics.

During the enrollment process, DCNN algorithms were proposed for detection and rejection of improper face images. Guarantee of appropriate enrolment will be the result.

The activations of the convolved feature maps are then computed using a non-linear rectified linear unit (ReLU). Local response normalisation, or LRN, is used to normalise the new feature map that the ReLU produced. Spatial pooling (maximum or average pooling) is used to further compute the result of the normalisation. Then, some unused weights are initialised to zero using the dropout regularisation scheme, which is typically done in the levels that connect completely before the categorization layer. Finally, the completely linked layer recognises image labels using the SoftMax activation algorithm. The face detection module receives the picture of the face after it has been captured by the camera. This module finds areas of a picture where people are most likely to be present. Following face detection using the Region Proposal Network (RPN), the feature extraction module uses the face image as input to identify the most important characteristics that will be categorised. The module generates a very concise feature vector that precisely represents the facial image. Comparison of face image's retrieved characteristics is done with those kept in the face database using DCNN and a pattern classifier. Facial picture is categorised as known or unknown after comparison. The specific person's covid vaccination information is provided if the picture face is known.

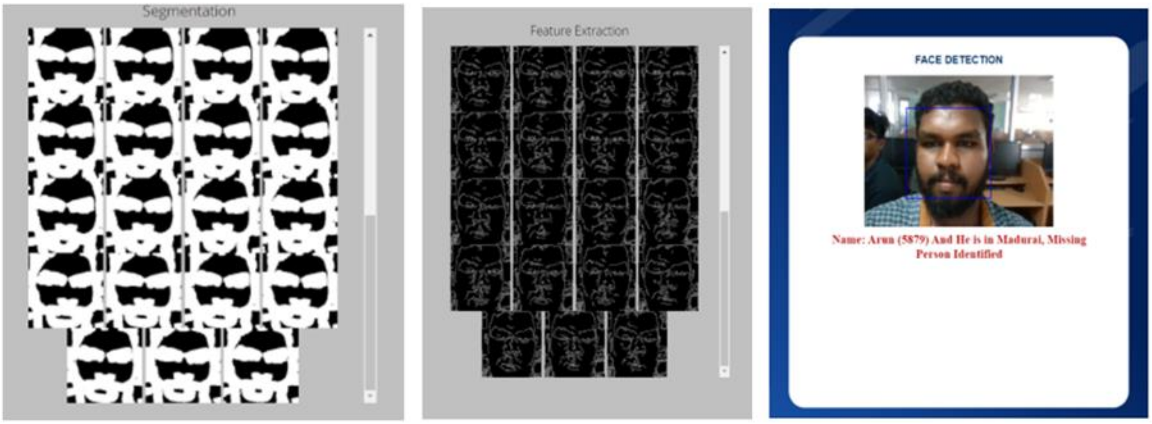

Figure 9: Demonstration of the Proposed Facial Recognition System.

Prediction

In this module, the matching procedure is carried out using test live camera-captured classified files and trained classified results. Hamming distance is used for calculating the difference and the results are given along with the prediction accuracy.

Missing Person Finder

By comparing and evaluating the patterns, forms, and proportions of a missing person's face characteristics and contours from the trained categorised file, this module can identify or confirm them. Encoding automatically a face picture (probe image) by an algorithm is done and associated with the profiles previously kept in the database of criminals when it is submitted into the system.

Notification

The police who gave the photographs are then informed, for anyone who may be alarmed by the match. Better results are provided to allow for prompt follow-up action.

4 CONCLUSIONS

This technology can help law enforcement locate missing people during amber alerts, elderly people, mentally disabled people who have strayed, or persons of interest in an inquiry. Authorities hunt locate the individual in issue by getting in touch with acquaintances, watching video feeds, or researching any pertinent prior histories. Authorities rely on public assistance from sources like tweets or tip lines in the absence of any leads. Promising future is there for Facial recognition expertise. Facial recognition technology will generate significant income in the years is what anticipated by the forecasters. Security and Surveillance will be the two most significantly impacted areas. Other places that are now embracing are Private businesses, public spaces, and educational institutions.

Shops and financial institutions are anticipated to embrace in the forthcoming years for preventing fraud in online payments and debit/credit card transactions. There is a chance to close the gaps by this technique in the most commonly used yet ineffective password scheme. It is predicted that Robots using face recognition technology may ultimately will make a presence. Robots will be used to finish the jobs that are impractical or thought-provoking for people to do.

REFERENCES

Visconti di Oleggio Castello, M., & Gobbini, M. I. (2015). Familiar face detection in 180ms. PloS One, 10(8), e0136548.

Kasar, M. M., Bhattacharyya, D., & Kim, T. H. (2016). Face recognition using neural network: A review. International Journal of Security and Its Applications, 10(3), 81-100.

Zhang, C., & Zhang, Z. (2016). A survey of recent advances in face detection.

Sukhija, P., Behal, S., & Singh, P. (2016). Face recognition system using genetic algorithm. Procedia Computer Science, 85, 410-417.

Mehdipour Ghazi, M., & Ekenel, H. K. (2016). A comprehensive analysis of deep learning based representation for face recognition. Proceedings of the IEEE conference on computer vision and pattern recognition workshops.

Hsu, R. L., Abdel-Mottaleb, M., & Jain, A. K. (2017). Face detection in color images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(5), 696-706.

Al-Dabagh, M. Z. N., Alhabib, M. H. M., & Al-Mukhtar, F. H. (2018). Face recognition system based on kernel

discriminant analysis, k-nearest neighbor and support vector machine. International Journal of Research and Engineering, 5(3), 335-338.
Phillips, P. J., et al. (2018). Face recognition accuracy of forensic examiners, super recognizers, and face recognition algorithms. Proceedings of the National Academy of Sciences, 115(24), 6171-6176.
Trigueros, D. S., Meng, L., & Hartnett, M. (2018). Face recognition: From traditional to deep learning methods. arXiv preprint arXiv:1811.00116.
Ranjan, R., et al. (2019). A fast and accurate system for face detection, identification, and verification. IEEE Transactions on Biometrics, Behavior, and Identity Science, 1(2), 82-96.
Cheng, H., et al. (2019). Person re-identification over encrypted outsourced surveillance videos. IEEE Transactions on Dependable and Secure Computing, 18(3), 1456-1473.
Zeng, D., Veldhuis, R., & Spreeuwers, L. (2020). A survey of face recognition techniques under occlusion. arXiv preprint arXiv:2006.11366.
Bian, Y., et al. (2020). Deep Classification Consistency for Person Re-Identification. IEEE, 191683-191693.
Guo, J., et al. (2020). Learning meta face recognition in unseen domains. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.
Xia, L., Zhu, J., & Yu, Z. (2021). Real-world person re-identification via super-resolution and semi-supervised methods. IEEE Access, 9, 35834-35845.
Fan, X., Zhang, J., & Lin, Y. (2021). Person re-identification based on mutual learning with embedded noise block. IEEE Access, 9, 129229-129239.
Ma, F., et al. (2021). Person Re-Identification with Character-Illustration-Style Image and Normal Photo. IEEE Access, 9, 30486-30495.
Luo, X., et al. (2021). Cross-Domain Person Re-Identification Based on Feature Fusion. IEEE Access, 9, 98327-98336.
Abbaszadi, R., & Ikizler-Cinbis, N. (2022). Merging Super Resolution and Attribute Learning for Low-Resolution Person Attribute Recognition. IEEE Access, 10, 30436-30444.