Third International Conference on "Materials, Computing and Communication Technologies"
in association with International Journal of Scientific Research in Science, Engineering and Technology
Print ISSN: 2395-1990 | Online ISSN : 2394-4099 (www.ijsrset.com)

# Deep Learning-Based Person Re-Identification – A Comparative Study

**S. Gomathi Meena[1], V. Kavitha[1], S.Sumithra[2], P.Bharathi[2]**

[1]Assistant Professor, Department of Computer Science, Vidhya Sagar Women's College, Chennai, Tamil Nadu, India

[2]Student, Department of Computer Science, Vidhya Sagar Women's College, Chennai, Tamil Nadu, India

## ABSTRACT

In a Pattern recognition problem the vision of computing technology is a challenging task for person re-identification in a real time scenario. Main target with the matching of person image in an existing with basic color and gray scale pattern coordinates points with implementing of three set of magnetic color.In homogenous matching the features of person re-identification model to image –image or video-video matching in tracking the location of a lost human and criminal tracking. Facing difficulties in solving the problem of illumination person, occlusion and changing of attitude with complex background it becomes a hot spot field in person re-identification research. This paper gives a small survey report on the traditional methods in the supervised frame work methods and unsupervised frame work on the basis of deep learning by fixing their Re-Id achievement. Finally, we summarise and propose the future directions and research on deep learning with public dataset is used for evaluating these improved system to be discussed in current issues.

**Keywords:**-Colour, Re-identification, Shape Feature, Texture, Colour, Re-identification, Shape Feature, Texture

## I. INTRODUCTION

Person re-identification is an important process to be attracted recent in monitoring the behaviour activities of a person or an object by deploying camera network in public places to preventing crimes and terrorist activities for security purposes for surveillance system. Basically the two methods of person re-identification based on feature learning and distance learning. [1]. To analysis the properties of few existing system is to recognize an image of person based on the fixing to cameras.To recognize a person re-identification is very accurate which is based on fixing the camera in a distributed network to recognize the output. Really a challenging task in Person Re-ID is based on the different point view of observation points[2][3], very accurate resolution of an image[4][5],changes in the illumination[6], poses occlusions[7][8]. When compared to early researchers focuseswith hand-crafted body structured metric learning[9–19]. Two type of Person Re-Id techniques is one considered as image based and other one considered as video and they facing problem for matching is illustrated in ***Figure1***. Matching is done between the two set of images fall under the category[20–29] with the hope of homogenous matching.

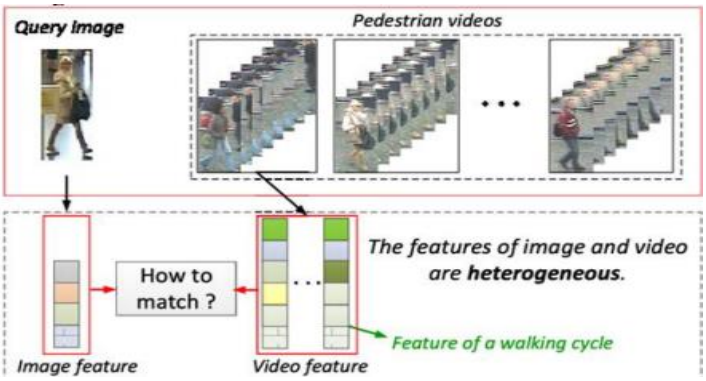


**Fig 1 Facing problem in image and video**

Challenges arise during the process of intra class variation of different set person appearance in person re-identification at different areas and inter class variation of the same person looks different areas. Accurate matching between the view pair of complex challenges in the minimum size of the person will move on the floor for learning with individual gallery of efficient of pose consistent. The main problem affects the accuracy in a time schedule for identifying person in a long term. Basically in many part of divisions areas a person may fails to identify clearly and properly with the effect of low quality of camera object in the presence of overlapping of other people wearing clothes. The problem is to be rectify with the help of segmentation algorithm is nothing but the process of classifying a single person from the remaining available person. Color changes at a significant accuracy that affects the color properties and appearance of images is given in ***Figure 2***

**Fig2 Image is the same with different dresses & Poses**

Three modules for the query image at very first detection, next step need to track and last is to retrieval the image working together based on supervised learning process is shown in ***Figure 3***

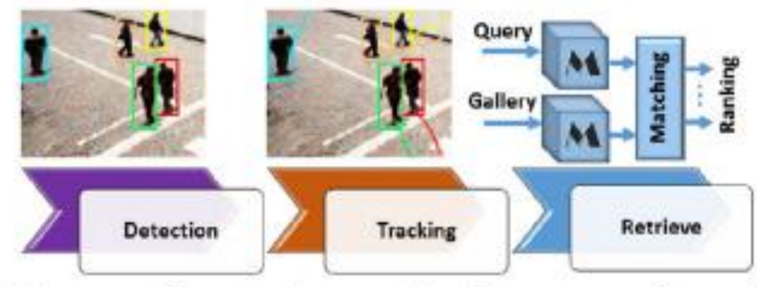


**Fig 3 End- end operations for Person Re-ID**

## II. PERSON RE-ID METHODS

Recentupdated techniques of person re-id divided into feature based, content based and metric based with multi using camera for tracking approaches and classify the image still information among the large volume of data[30][31]. Appearance of person in image or video is to be captured by bounding the boxes for identity and classify into same identity with annotations of model learning and training data are correct in query image. Feature representation focus for development for future, deep metric learning aims is to design the training objectives using different loss function and sampling optimization strategies.

### 2.1 Person Re-Id based on image

Image based Person Re-ID focus on the feature representation of the image by matching with distinct feature[32]. Appearance based representation of an image is known as Symmetry Driven Accumulation of Local Features(SDALF). By follows this method first the horizontal axes of body symmetry divide the whole body into head, torso and legs and next with the same of vertical axis of symmetry is estimated into the effect of pose variations. Follow this features of matching the similarity measures between the image of candidate in a single or multiple shot frame to give the result of highest performance is observed. Different postures and viewpoints of each person is being monitored. To matching the image follow the specific learning metric method to achieve the improvement of two dimensional in Microsoft Kinect dataset compared to SDALF[33]. Propose in the non-overlapping cameras with clothing attributes, they facing difficulties in identifying the faces in images. By calculating the metric based on optimal distance follows the method on distance learning for large data using the equivalence constraints complexity use fo distance learning method similar to the ratio test using statistical inference perspective. This method refer in Keep It Simple and Straight(KISS) metric given to small size training set result in poor performance to the co-variance matrix[34].

### 2.2 Person Re-Id based on Video

In considering the method of video based Person Re-Id it must depend on single frame to refer the feature of an image and remove the unwanted information from the sequences of an image available in video based[35]. A new model is more reliable to select the video fragments are the most importance method is used to remove the noisy sequence of an image and this method also used in space time and appearances features computing to gain powerful in recognition an image. Spatial alignment is most commonly used with the appearance of different body parts and specify the issues in poses, illumination variations and occlusions with alignment of appearance of a body part issues by walking in a certain action primitives[36]. At last a fixed length vector is obtained.

## III. PERSON RE-ID ON DEEP LEARNING

When considering the learning deep model the methods of Person Re-Id is divided into some parts of the model, they are hand fused crafted deep model of person image, learning representation model, local feature learning, video based deepest, GAN deep based model, unsupervised deepest model and metric learning model.

### 3.1 Fused hand-crafted features deep model

Taking advantages couldn't solve by CNN based method with insufficient dataset samples using the deep learning methods. Some works based on hand-crafted features in depth complementary features is achieved better performance when compared to early techniques of deeply based Person Re-ID[37–39]. Deeping learning alone will achieve with the best recognition rate of accuracy in the powerful performance increasing. Several methods of deep learning methods will gradually replace the hand-crafted feature methods and give the way for the researchers to analysis data based on performing such task of Person Re-ID.

### 3.2 Learning representation model

Deep learning success of Person Re-Idfor an individual image identity based on Convolution Neural network(CNN) which automatically learnt the representation of future from training data is to presented for verification and classification problem. Usually a pair of images is to be taken as input for verification and value of similar output is to be determine that it may be related to the same person under weekly supervised learning process and next classification it will be taken the same image from that and next implement to the train network the process of strongly supervised .

#### 3.2.1 Mode of Verification

From the network of Siamese network basic structure the mode of verification takes an input be paired images and output will be also the similar pair only[40].

Model of verification the image is shown in ***Figure4*** for the purpose of using the Filter Pairing Neural Network(FPNN).

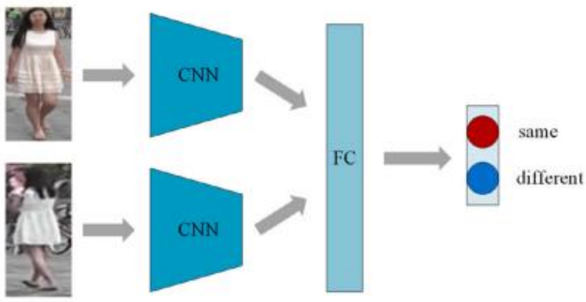


**Fig4 Mode of Verification**

To extract the different features view of camera filters for the different images with the method of block matching layer Atlast the layer soft max is to implement that the two input images will belong to the same person[41]. This technology will consequently divides the image into three overlapping parts into jointly trained with shared parameters. At the end i.e last stage all are connected to the similarity score of the two images as output with the frame of deep learning framework[42] to learn Single Image Representation(SIR) and Cross Image Representation(CIR) in high accuracy rate and efficient.

### 3.2.2 Mode of Classification

Classification mode tasks in the deep learning is same as that cognitive process. First to obtain the knowledge with new samples of training to obtain "knowledge"[43]be correctly classified in training subsequent and believed that multi-classification mode and is shown in ***Figure 5*** .

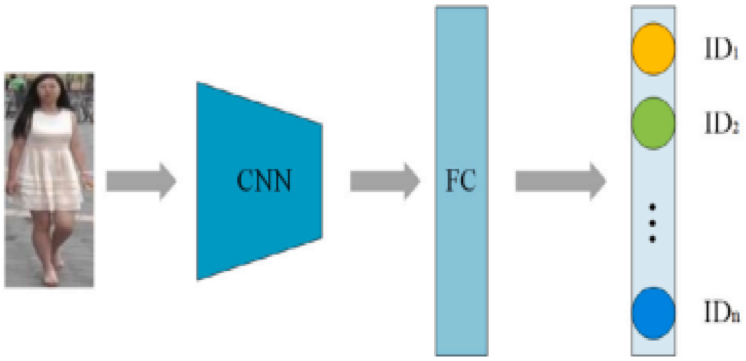


Fig 5 Mode of Classification

### 3.3 Metric learning model

It is very hard to evaluate the various factors in similarity of two person images in influence of resolution of an image with changes of pose and illumination, Deep learning is an effective tool to learn the non-linear metric function. Most common learning in loss function are loss of continuous, triplet & quadric loos[44–46], Centre loss. Basically the network uses the paired images as an input optimized by loss of continuous[47] and triplet loss is aimportant type of loss in identification of an images to overcome the pose changes of global and local feature of an images. Many set of variants of triple loss in metric learning is an application of triple loss in metric learning[48–50]. To calculate the loss function of triplet is composed of positive and negative sample is employed to calculate the better loss function with poor generalization performance on the test set of data in the intraclass gap on a triplet loss. This method implement the four set of input images with margin based online hard negative mining and adaptively selects difficult. Main purpose of learning metric is to reduce the distance and similarity between similar classes for the various classes set of images in training phase. Both the training and testing phase of metric are same when combined together for the representation learning end-end framework capable with the feature of discriminative learning features is shown in ***Figure 6***.

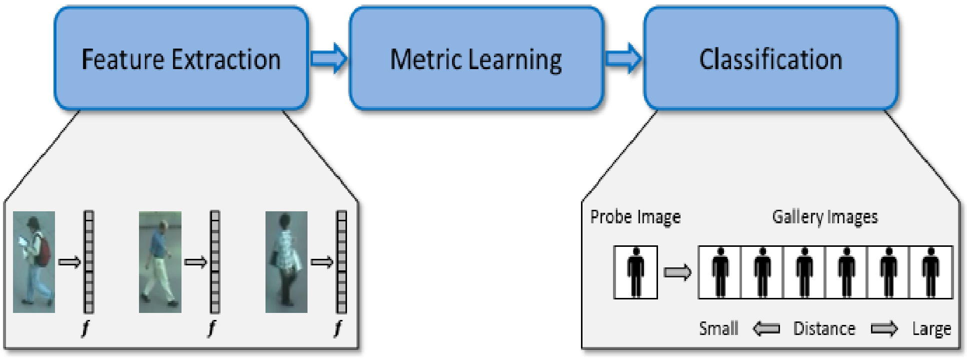


Fig 6 Sample of metric learning model

### 3.4 Part based deep learning for Person Re-Id

Input of deep hashing is employed as the input image of deep hashing in the Part-based Deep Hashing(PDH). Triplet sample contains two set of pedestrian images one set of images with the same identity of same person image and next with the different identity of one part of the image. With the hamming distance of same image with different part of an image using of triplet loss function to show that part based deep hashing deep algorithm. Local feature generation region of the image into three categories, first to locate the region of part from prior knowledge with estimation of pose, key point estimation [51–53] with deep block points.

#### 3.4.1 Estimation of Pose

Fourteen key points to estimate the feature weighting subnet with the Pose Driven deep Convolution to six body region parts of the human image in ***Figure 7*** be single with different local and global features to locate the part area in the severe misalignment problem matching and reduce the power of semantic information of the personal retrieval algorithm with the different parts to fuse local and global feature for solving the severe misalignment problem and to reduce the error in weightage of estimation of pose[52]

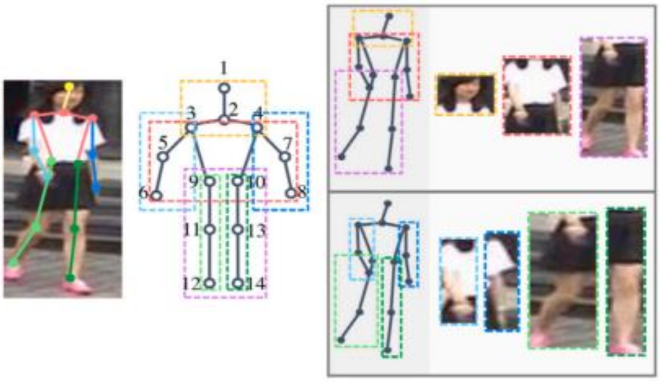


**Fig 7 Key point estimation of an image**

#### 3.4.2 Mechanism of attention

Some sequences of recognition data with excellent performance is more challenging sequence of data implicit sentiment analysis [54,55] to locate the end to end. How human will process the some information be visual and incorporates level of timing to locate discriminative part of Re-Id region with local areas.

### 3.5 Video-based model

Video based Person Re-ID is a challenging task to solve the problem in the amount of data. In recent years, with the increase in the amount of data, research onvideo-based person Re-ID has been increasing. The image-based personReID method can only obtain limited information from a single image,and it is challenging to solve the problems of occlusion, pose change,and camera perspective in a single image. In contrast, video-basedpeople's ReID contains more information than a single image. Becauseimage sequences usually contain rich temporal information, they aremore suitable for Re-ID of persons in complex environments. Moreover,the video sequence-based method is more in line with the requirementsof the person Re-ID task of the actual monitoring system. It can avoidsome pre-processing processes of the monitoring video.

## IV. CONCLUSION AND FUTURE WORK

In the field of computer vision Person Re-identification is a effective and most interested the researcher hotspot topic till now proposed and side by side it is very difficult for maintaining the security of social and stability. Anyhow updated technology was developed so far, but still it reaches the success with the excellent performance on existing datasets and also facing a hug set of problems for image based or video based in many aspects areas like pose person transformation and view of camera changes under the different focus of research on person Re-ID tasks. Most the updated research use the feature learning to solve the local feature complexity address of camera scene perceptive to learn further study. A large amount of training data for model the deep learning concept will realize the training and large scale in environmental dataset. Future research needs to effectively combine these three technology to complete and achieve good in image and video based surveillance system.

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