Table 1

S.no	Title	Author	Year	Citation
1	Attentional Part-based Network for Person Re-identification	Yinsong Xu, Zhuqing, Jiang, Aidong Men, Jiangbo Pei	2019	Z. Huang, S. Sun and Y. Liu, "Person Search Based on Attention Mechanism," 2019 19th International Symposium on Communications and Information Technologies (ISCIT), Ho Chi Minh City, Vietnam, 2019, pp. 555-558, doi: 10.1109/ ISCIT.2019.8905176.
2	Deep Partial person Re-Identification via Attention Model	Junyeong Kim and Chang D. Yoo	2017	J. Kim and C. D. Yoo, "Deep partial person re-identification via attention model," 2017 IEEE International Conference on Image Processing (ICIP), Beijing, 2017, pp. 3425-3429, doi: 10.1109/ ICIP.2017.8296918.
3	Person Re-identification with Cascaded Pairwise Convolutions	Yicheng Wang, Zhenzhong Chen, Feng Wu, Gang Wang	2018	Y. Wang, Z. Chen, F. Wu and G. Wang, "Person Re-identification with Cascaded Pairwise Convolutions," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 1470-1478, doi: 10.1109/CVPR.2018.00159.
4	Deep Network with Spatial and Channel Attention for Person Re-identification	Tiansheng Guo, Dongfei Wang, Zhuqing Jiang, Aidong Men,YunZhou	2018	T. Guo, D. Wang, Z. Jiang, A. Men and Y. Zhou, "Deep Network with Spatial and Channel Attention for Person Re-identification," 2018 IEEE Visual Communications and Image Processing (VCIP), Taichung, Taiwan, 2018, pp. 1-4, doi: 10.1109/ VCIP.2018.8698620.
5	Person Re-identification Based on Combined Gaussian Weighted Fisher Vectors	Salma Ksibi, Mahmoud Mejdoub, Chokri Ben Amar	2016	S. Ksibi, M. Mejdoub and C. Ben Amar, "Person re-identification based on combined Gaussian weighted Fisher vectors," 2016 IEEE/ ACS 13th International Conference of Computer Systems and Applications (AICCSA), Agadir, 2016, pp. 1-8, doi: 10.1109/ AICCSA.2016.7945651.
6	An Improved Deep Feature Learning Method for Person Re-identi˘Cation	Jiazhen Xu, Chinyea Wang	2017	J. Xu and C. Wang, "An improved deep feature learning method for person re-identification," 2017 3rd IEEE International Conference on Computer and Communications (ICCC), Chengdu, 2017, pp. 1637-1640, doi: 10.1109/ CompComm.2017.8322817.
7	Person Re-Identification Based on DropEasy Method	Huiyang Wang , Tao Fang , Yingle Fan , and Wei Wu	2019	H. Wang, T. Fang, Y. Fan and W. Wu, "Person Re-Identification Based on DropEasy Method," in IEEE Access, vol. 7, pp. 97021-97031, 2019, doi: 10.1109/ ACCESS.2019.2929523.

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8	Convolutional Neural Network-Based Representation for Person Re-Identification	Alper Ulu, Hazım Kemal Ekenel	2016	A. Ulu and H. K. Ekenel, "Convolutional neural network-based representation for person re-identification," 2016 24th Signal Processing and Communication Application Conference (SIU), Zonguldak, 2016, pp. 945-948, doi: 10.1109/SIU.2016.7495897.
9	Semantic Constraint GAN for Person Re-Identification in Camera Sensor Networks	Shuang Liu , Tongzhen Si , Xiaolong Hao , and Zhong Zhang	2019	S. Liu, T. Si, X. Hao and Z. Zhang, "Semantic Constraint GAN for Person Re-Identification in Camera Sensor Networks," in IEEE Access, vol. 7, pp. 176257-176265, 2019, doi: 10.1109/ACCESS.2019.2958126.
10	Person Re-Identification By Deep Learning Muti-Part Information Complementary	Xiao Hu, Zhuqing Jiang, Xiaoqiang Guo, Yun Zhou	2018	X. Hu, Z. Jiang, X. Guo and Y. Zhou, "Person Re-Identification by Deep Learning Muti-Part Information Complementary," 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, 2018, pp. 848-852, doi: 10.1109/ICIP.2018.8451645.
11	Light-weight Visual Feature based Labeling (LVFL) for Unsupervised Person Re-identification	Sridhar Raj S, Munaga V N K Prasad, Ramadoss Balakrishnan	2019	S. Raj S., M. V. N. K. Prasad and R. Balakrishnan, "Light-Weight Visual Feature Based Labeling (LVFL) for Unsupervised Person Re-identification," 2019 15th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Sorrento, Italy, 2019, pp. 82-89, doi: 10.1109/SITIS.2019.00025.
12	Cross Domain Person Re-Identification With Large Scale Attribute Annotated Datasets	Bolei Xu, Jingxin Liu, Xianxu Hou, Ke Sun, And Guoping Qiu	2019	B. Xu, J. Liu, X. Hou, K. Sun and G. Qiu, "Cross Domain Person Re-Identification With Large Scale Attribute Annotated Datasets," in IEEE Access, vol. 7, pp. 21623-21634, 2019, doi: 10.1109/ACCESS.2019.2896663.
13	Local To Global With Multi-Scale Attention Network For Person Re-Identification	Lingchuan Sun, Jianlei Li,Yingxin Zhu, Zhuqing Jiang	2019	L. Sun, J. Liu, Y. Zhu and Z. Jiang, "Local to Global with Multi-Scale Attention Network for Person Re-Identification," 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 2254-2258, doi: 10.1109/ICIP.2019.8803292.
14	Cross-View Identical Part Area Alignment For Person Re-Identification	Dongshu Xu, Jun Chen , Chao Liang, Zheng Wang, Ruimin Hu	2019	D. Xu, J. Chen, C. Liang, Z. Wang and R. Hu, "Cross-view Identical Part Area Alignment for Person Re-identification," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, United Kingdom, 2019, pp. 2462-2466, doi: 10.1109/ICASSP.2019.8683137.

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15	DeepList: Learning Deep Features With Adaptive Listwise Constraint for Person Reidentification	Jin Wang, Zheng Wang, Changxin Gao, Nong Sang, and Rui Huang	2016	J. Wang, Z. Wang, C. Gao, N. Sang and R. Huang, "DeepList: Learning Deep Features With Adaptive Listwise Constraint for Person Reidentification," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 27, no. 3, pp. 513-524, March 2017, doi: 10.1109/ TCSVT.2016.2586851.
16	Resetting-Label Network Based on Fast Group Loss for Person Re-Identification	Yewen Huang, Suian Zhang, Haifeng Hu, Dihu Chen, Tao Su	2019	Y. Huang, S. Zhang, H. Hu, D. Chen and T. Su, "Resetting-Label Network Based on Fast Group Loss for Person Re-Identification," in IEEE Access, vol. 7, pp. 119486-119496, 2019, doi: 10.1109/ ACCESS.2019.2932073.
17	Multi-Level Supervised Network For Person Re-Identification	Junpeng Zhang, Fei Jiang	2019	J. Zhang and F. Jiang, "Multi-level Supervised Network for Person Re-identification," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, United Kingdom, 2019, pp. 2072-2076, doi: 10.1109/ ICASSP.2019.8683858.
18	Discrimination-Aware Integration for Person Re-Identification in Camera Networks	Tongzhen Si, Zhong Zhang, And Shuang Liu	2019	T. Si, Z. Zhang and S. Liu, "Discrimination-Aware Integration for Person Re-Identification in Camera Networks," in IEEE Access, vol. 7, pp. 33107-33114, 2019, doi: 10.1109/ ACCESS.2019.2903099.
19	End-to-End Deep Kronecker-Product Matching for Person Re-identification	Yantao Shen, Tong Xiao, Hongsheng Li, Shuai Yi, Xiaogang Wang,	2018	Y. Shen, T. Xiao, H. Li, S. Yi and X. Wang, "End-to-End Deep Kronecker-Product Matching for Person Re-identification," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, 2018, pp. 6886-6895, doi: 10.1109/CVPR.2018.00720.
20	Deep Hybrid Similarity Learning for Person Re-Identification	Jianqing Zhu, Huanqiang Zeng, Shengcai Liao, Zhen Lei, Canhui Cai, and Lixin Zheng	2018	J. Zhu, H. Zeng, S. Liao, Z. Lei, C. Cai and L. Zheng, "Deep Hybrid Similarity Learning for Person Re-Identification," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 28, no. 11, pp. 3183-3193, Nov. 2018, doi: 10.1109/ TCSVT.2017.2734740.
21	Adversarial Erasing Attention for Person Re-Identification in Camera Networks Under Complex Environments	Shuang Liu, Xiaolong Hao, Ronghua Zhang, Zhong Zhang, And Tariq S. Durrani	2020	S. Liu, X. Hao, R. Zhang, Z. Zhang and T. S. Durrani, "Adversarial Erasing Attention for Person Re-Identification in Camera Networks Under Complex Environments," in IEEE Access, vol. 8, pp. 56469-56479, 2020, doi: 10.1109/ ACCESS.2020.2982032.

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22	SIF: Self-Inspirited Feature Learning for Person Re-Identification	Long Wei , Zhenyong Wei, Zhongming Jin, Zhengxu Yu , Jianqiang Huang, Deng Cai, Xiaofei He and Xian-Sheng Hua	2020	L. Wei et al., "SIF: Self-Inspirited Feature Learning for Person Re-Identification," in IEEE Transactions on Image Processing, vol. 29, pp. 4942-4951, 2020, doi: 10.1109/TIP.2020.2975712.
23	Pose-Invariant Embedding for Deep Person Re-Identification	Liang Zheng , Yujia Huang, Huchuan Lu , and Yi Yang	2019	L. Zheng, Y. Huang, H. Lu and Y. Yang, "Pose-Invariant Embedding for Deep Person Re-Identification," in IEEE Transactions on Image Processing, vol. 28, no. 9, pp. 4500-4509, Sept. 2019, doi: 10.1109/TIP.2019.2910414.
24	Learning Deep Context-aware Features over Body and Latent Parts for Person Re-identification	Dangwei Li, Xiaotang Chen,Zhang Zhang, Kaiqi Huang	2017	D. Li, X. Chen, Z. Zhang and K. Huang, "Learning Deep Context-Aware Features over Body and Latent Parts for Person Re-identification," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, 2017, pp. 7398-7407, doi: 10.1109/CVPR.2017.782.
25	Weakly Supervised Person Re-ID: Differentiable Graphical Learning and a New Benchmark	Guangrun Wang, Guangcong Wang, Xujie Zhang, Jianhuang Lai, Zhengtao Yu and Liang Lin	2020	G. Wang, G. Wang, X. Zhang, J. Lai, Z. Yu and L. Lin, "Weakly Supervised Person Re-ID: Differentiable Graphical Learning and a New Benchmark," in IEEE Transactions on Neural Networks and Learning Systems, doi: 10.1109/TNNLS.2020.2999517.
26	Person Reidentification by Joint Local Distance Metric and Feature Transformation	Zimo Liu, Huchuan Lu, Xiang Ruan, and Ming-Hsuan Yang	2019	Z. Liu, H. Lu, X. Ruan and M. Yang, "Person Reidentification by Joint Local Distance Metric and Feature Transformation," in IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 10, pp. 2999-3009, Oct. 2019, doi: 10.1109/TNNLS.2018.2890289.
27	Deep Feature Embedding Learning For Person Re-Identification Using Lifted Structured Loss	Zhangping He, Zhendong Zhang and Cheolkon Jung	2018	Z. He, Z. Zhang and C. Jung, "Deep Feature Embedding Learning for Person Re-Identification Using Lifted Structured Loss," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, 2018, pp. 1957-1961, doi: 10.1109/ICASSP.2018.8462118.
28	Person Re-Identification with Effectively Designed Parts	Yali Zhao, Yali Li, and Shengjin Wang	2020	Y. Zhao, Y. Li and S. Wang, "Person re-identification with effectively designed parts," in Tsinghua Science and Technology, vol. 25, no. 3, pp. 415-424, June 2020, doi: 10.26599/TST.2019.9010031.
29	Deep Multi-Metric Learning For Person Re-Identification	Yongxin Ge, Xinqian Gu, Min Chen , Hongxing Wang, Dan Yang	2018	Y. Ge, X. Gu, M. Chen, H. Wang and D. Yang, "Deep Multi-Metric Learning for Person Re-Identification," 2018 IEEE International Conference on Multimedia and Expo (ICME), San Diego, CA, 2018, pp. 1-6, doi: 10.1109/ICME.2018.8486502.

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30	Multi-Branch Context-Aware Network For Person Re-Identification	Yingxin Zhu, Xiaoqiang Guo, Jianlei Liu, Zhuqing Jiang	2019	Y. Zhu, X. Guo, J. Liu and Z. Jiang, "Multi-Branch Context-Aware Network for Person Re-Identification," 2019 IEEE International Conference on Multimedia and Expo (ICME), Shanghai, China, 2019, pp. 712-717, doi: 10.1109/ICME.2019.00128.
31	Pseudo Label based on Multiple Clustering for Unsupervised Cross-Domain Person Re-Identification	Shuni Chen, Zheyi Fan, Jianyuan Yin	2015	S. Chen, Z. Fan and J. Yin, "Pseudo Label based on Multiple Clustering for Unsupervised Cross-Domain Person Re-Identification," in IEEE Signal Processing Letters, doi: 10.1109/LSP.2020.3016528.
32	Enhance Part-Based Model For Person Re-Identification With Fused Multi-Scale Features	Xi-Peng Lin, Yu-Bin Yang , Zhong-Han Niu	2020	X. Lin, Y. Yang and Z. Niu, "Enhance Part-Based Model for Person Re-Identification with Fused Multi-Scale Features," ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 2020, pp. 4092-4096, doi: 10.1109/ICASSP40776.2020.9054659.
33	Deep Feature Embedding Learning For Person Re-Identification Using Lifted Structured Loss	Zhangping He , Zhendong Zhang and Cheolkon Jung	2018	Z. He, Z. Zhang and C. Jung, "Deep Feature Embedding Learning for Person Re-Identification Using Lifted Structured Loss," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, 2018, pp. 1957-1961, doi: 10.1109/ICASSP.2018.8462118.
34	Person Re-Identification Using Visual Attention	Alireza Rahimpour, Liu Liu, Ali Taalimi, Yang Song, Hairong Qi	2017	A. Rahimpour, L. Liu, A. Taalimi, Y. Song and H. Qi, "Person re-identification using visual attention," 2017 IEEE International Conference on Image Processing (ICIP), Beijing, 2017, pp. 4242-4246, doi: 10.1109/ICIP.2017.8297082.
35	Person Re-Identification via Group Symmetry Theory	JIAHUAN ZHANG , XUELONG HU, MINJIE WANG, HUIXIANG QIAO, XIAN LI, AND TIANBAO SUN	2019	J. Zhang, X. Hu, M. Wang, H. Qiao, X. Li and T. Sun, "Person Re-Identification via Group Symmetry Theory," in IEEE Access, vol. 7, pp. 133686-133693, 2019, doi: 10.1109/ACCESS.2019.2913559.
36	Person Re-Identification With Triplet Focal Loss	Shizhou Zhang , Qi Zhang , Xing Wei2 , Yanning Zhang, And Yong Xia	2018	S. Zhang, Q. Zhang, X. Wei, Y. Zhang and Y. Xia, "Person Re-Identification With Triplet Focal Loss," in IEEE Access, vol. 6, pp. 78092-78099, 2018, doi: 10.1109/ACCESS.2018.2884743.
37	Feature Affinity-Based Pseudo Labeling for Semi-Supervised Person Re-Identification	Guodong Ding, Shanshan Zhang, Salman Khan, Zhenmin Tang, Jian Zhang, Fatih Porikli	2019	G. Ding, S. Zhang, S. Khan, Z. Tang, J. Zhang and F. Porikli, "Feature Affinity-Based Pseudo Labeling for Semi-Supervised Person Re-Identification," in IEEE Transactions on Multimedia, vol. 21, no. 11, pp. 2891-2902, Nov. 2019, doi: 10.1109/TMM.2019.2916456.

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38	Person Re-Identification by Semantic Region Representation and Topology Constraint	Jianjun Lei, Lijie Niu, Huazhu Fu, IEEE, Bo Peng, Qingming Huang, and Chunping Hou	2019	J. Lei, L. Niu, H. Fu, B. Peng, Q. Huang and C. Hou, "Person Re-Identification by Semantic Region Representation and Topology Constraint," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 29, no. 8, pp. 2453-2466, Aug. 2019, doi: 10.1109/TCSVT.2018.2866260.
39	Pedestrian-Aligned Multiscale Features Network for Person Re-identification	Yongxia Wu, Wensheng Sun	2019	Y. wu and W. Sun, "Pedestrian-Aligned Multiscale Features Network for Person Re-identification," 2019 Chinese Automation Congress (CAC), Hangzhou, China, 2019, pp. 362-366, doi: 10.1109/CAC48633.2019.8996826.
40	AsNet: Asymmetrical Network for Learning Rich Features in Person Re-Identification	Suofei Zhang , Lei Zhang, Wenlong Wang, and Xiaofu Wu	2020	S. Zhang, L. Zhang, W. Wang and X. Wu, "AsNet: Asymmetrical Network for Learning Rich Features in Person Re-Identification," in IEEE Signal Processing Letters, vol. 27, pp. 850-854, 2020, doi: 10.1109/LSP.2020.2994815.
41	Multi-Pseudo Regularized Label for Generated Data in Person Re-Identification	Yan Huang , Jingsong Xu, Qiang Wu, Zhedong Zheng , Zhaoxiang Zhang, and Jian Zhang	2019	Y. Huang, J. Xu, Q. Wu, Z. Zheng, Z. Zhang and J. Zhang, "Multi-Pseudo Regularized Label for Generated Data in Person Re-Identification," in IEEE Transactions on Image Processing, vol. 28, no. 3, pp. 1391-1403, March 2019, doi: 10.1109/TIP.2018.2874715.
42	An Enhanced Deep Convolutional Neural Network For Person Re-Identification	Tiansheng Guo, Dongfei Wang, Zhuqing Jiang, Aidong Men,Yun Zhou	2018	T. Guo, D. Wang, Z. Jiang, A. Men and Y. Zhou, "An Enhanced Deep Convolutional Neural Network for Person Re-Identification," 2018 IEEE International Conference on Multimedia & Expo Workshops (ICMEW), San Diego, CA, 2018, pp. 1-6, doi: 10.1109/ICMEW.2018.8551570.
43	A Hybrid of Hard and Soft Attention for Person Re-Identification	Xuesong Li, Yating Liu, Kunfeng Wang, Yong Yan, Fei-Yue Wang	2019	X. Li, Y. Liu, K. Wang, Y. Yan and F. Wang, "A Hybrid of Hard and Soft Attention for Person Re-Identification," 2019 Chinese Automation Congress (CAC), Hangzhou, China, 2019, pp. 2433-2438, doi: 10.1109/CAC48633.2019.8997406.
44	Robust Discriminative Subspace Learning for Person Reidentification	A. Venkata, Vanshika Gupta , and Rahul Ahuja	2019	A. V. Subramanyam, V. Gupta and R. Ahuja, "Robust Discriminative Subspace Learning for Person Reidentification," in IEEE Signal Processing Letters, vol. 26, no. 1, pp. 154-158, Jan. 2019, doi: 10.1109/LSP.2018.2882301.
45	Learning View-Specific Deep Networks for Person Re-Identification	Zhanxiang Feng, Jianhuang Lai , and Xiaohua Xie	2018	Z. Feng, J. Lai and X. Xie, "Learning View-Specific Deep Networks for Person Re-Identification," in IEEE Transactions on Image Processing, vol. 27, no. 7, pp. 3472-3483, July 2018, doi: 10.1109/TIP.2018.2818438.

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46	Foreground-aware Pyramid Reconstruction for Alignment-free Occluded Person Re-identification	Lingxiao He, Yinggang Wang, Wu Liu, He Zhao, Zhenan Sun, Jiashi Feng	2019	H. Lingxiao, Y. Wang, W. Liu, H. Zhao, Z. Sun and J. Feng, "Foreground-Aware Pyramid Reconstruction for Alignment-Free Occluded Person Re-Identification," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South), 2019, pp. 8449-8458, doi: 10.1109/ICCV.2019.00854.
47	Efficient PSD Constrained Asymmetric Metric Learning for Person Re-identification	Shengcai Liao and Stan Z. Li	2015	S. Liao and S. Z. Li, "Efficient PSD Constrained Asymmetric Metric Learning for Person Re-Identification," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015, pp. 3685-3693, doi: 10.1109/ICCV.2015.420.
48	View Confusion Feature Learning for Person Re-identification	Fangyi Liu Lei Zhang	2019	F. Liu and L. Zhang, "View Confusion Feature Learning for Person Re-Identification," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South), 2019, pp. 6638-6647, doi: 10.1109/ICCV.2019.00674.
49	Sharp Attention Network via Adaptive Sampling for Person Re-Identification	Chen Shen , Guo-Jun Qi , Rongxin Jiang, Zhongming Jin, Hongwei Yong, Yaowu Chen, and Xian-Sheng Hua	2019	C. Shen et al., "Sharp Attention Network via Adaptive Sampling for Person Re-Identification," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 29, no. 10, pp. 3016-3027, Oct. 2019, doi: 10.1109/TCSVT.2018.2872503.
50	Cross-Camera Person Re-Identification With Body-Guided Attention Network	Yixiang Xie, Yan Wang, Chuanrui Hu, Caifeng Shan, Teng Li, Yongjian Hu	2020	Y. Xie, Y. Wang, C. Hu, C. Shan, T. Li and Y. Hu, "Cross-Camera Person Re-Identification With Body-Guided Attention Network," in IEEE Sensors Journal, vol. 20, no. 1, pp. 359-368, 1 Jan.1, 2020, doi: 10.1109/JSEN.2019.2942106.

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
1	First, we partition feature map into several horizontal stripes. Second, we use attention selection in each stripe to align the pedestrian images. Inside, we introduce a free-parameter attention model with skip-layer connection which maximises the complementary information of different levels without increasing the complexity of network.	CUHK03,Market-1501,DukeMCMT-ReID	Attentional Part-based CNN (AP-CNN) model	Rank-1 and mAP
2	The RoI Pooling layer enables the extraction of feature vector corresponding to predefined part of input im- age. The attention model selects a subset of CNN feature vec- tors.	CUHK03	Convolutional neural network (CNN), RoI Pooling layer and attention model	Cumulative match curve (CMC) metric
3	Specially designed WConv layer, and the cascaded WConv structure learns to extract the comparison features of two images, which are robust to misalignments and color dif- ferences across cameras	CUHK03-Detected, CUHK03-Labeled, CUHK01, Market-1501 and DukeMTMC-reID	CNN - Sample Rate Learning strategy	Rank-1, Rank-10, Rank-20 scores
4	Channel attention selection mechanism to integrate the global image feature maps and regional feature maps more effectively by explicitly modelling interdependencies between channels and recalibrate feature response in each channel	CUHK03, Market-1501	Spatial attention selection mechanism	CMCs, rank-1,rank-5,ran k-10,mAP
5	By designing a super Fisher vector representation, we aim to improve both the rate and the speedup of the person matching process. (2) By weighting the Fisher vector encoding scheme, we aim to remove noisy and busy background clutters surrounding a person throughout the Topological weight	CUHK03, VIPeR	CNN and Fischer Scheme	Cumulated Matching Characteristics Curve, mAP, rank-1
6	Learns similarity by the distance between a training example and its center in favor of that of two examples so that no more sampling needed	CUHK03, Market-1501	Improved CNN	rank-1, mAP
7	Features are classified into discriminative and indiscriminative ones, according to the distance between the feature vectors of positive or negative sample pairs wherein the discriminative features are zeroed out, while the indiscriminative features are reserved, and the network only learns through indiscriminative features .DropEasy2d searches discriminative feature areas in the feature maps by sliding and zeroing windows while reserving the indiscriminate features areas to constrain network learning.	CUHK03, Market-1501, DuckMTMC-reID	Drop-Easy based CNN	rank-1, mAP

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
8	For feature extraction, we used the seventh layer of the CNN model, which was re-trained with the available datasets. Then, we used cosine similarity metric to calculate the similarity between extracted features	CUHK03, Market-1501, VIPeR	General convolutional neural network (CNN) model	rank-1,rank-10,rank-20,rank-30
9	Generate multiple style pedestrian images with high-level semantic information and design two types of semantic constraints, attention constraint and identity constraint. The attention constraint aims to restrict the significant areas in the attention map to be consistent before and after image transformation.	CUHK03, Market-1501, DuckMTMC-reID	Semantic Constraint Generative Adversarial Network (SCGAN)	rank-1, mAP
10	The global and body-part features of a specific person can be complementary to each other to enhance the final feature representation	Market1501, CUHK03, CUHK01	Global-Part Network (GPN) and Feature Weighting Structure (FWS)	rank-1,rank-5, rank-10, mAP, CMC Curve
11	The computation overhead is reduced at three stages namely model initialization, neural network utilization and algorithmic complexity. Method reports a reduced computation complexity than the traditional unsupervised person re-identification methods by determining a tight bound fine-tuning with a very less CMC score trade-off.	DukeMTMC re-id, Market1501 and CUHK03	Light-weight Visual Feature based Labeling (LVFL) method, Clustering	Cluster silhouette coefficient variation, CMC Curve
12	Deep neural network with three branches: 1) the attribute branch predicts the attributes of the input image; 2) the augmentation branch generates complementary features that are fused with the output of the attribute branch to form the augmented attribute features; and 3) the reconstruction branch to refine augmented attribute features on the target dataset.	CUHK03 and Market-1501	Deep convolutional neural network framework called *deep augmented attribute network* (DAAN), Image pre-processing	Avg prediction accuracy and rank-1 CMC Scores
13	Exploit the contextual information and spacial attention information. By pooling operation, an image generates the feature maps of different dimensions. Then, we learn local to global descriptors by partitioning these feature maps with the same scale. The other is multi-scale attention branch, which captures the contextual dependencies from different convolution layers.	Market-1501, DukeMTMC-reID and CUHK03	CNN - multi-scale attention network (LGMANet)	Rank-1 and mAP
14	Viewpoint changes and pose variations often cause body part self-occlusion and misalignment. To deal with the problem, local features from human body parts are extracted. Comparing identical areas provides a new way to pay attention to the details of person images.	Market-1501, DukeMTMC-reID and CUHK03	Rotation Invariant Network to find the identical areas in cross-view images to extract robust local features	Rank-1 and mAP

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
15	Learn deep representations with an adaptive margin listwise loss. First, ranking lists instead of image pairs are used as training samples, in this way, the problem of data imbalance is relaxed. Second, by introducing an adaptive margin parameter in the listwise loss function, it can assign larger margins to harder negative samples, which can be interpreted as an implementation of the automatic hard negative mining strategy	CUHK03, CUHK01, and VIPeR	4 convolutional neural network architecture	CMC Curve
16	RLFGL-ReID that includes resetting-label (RL) and fast group loss (FGL). Two main contributions of our network are as follows. First, a new method, the resetting-label method, which resets the ID labels, is proposed for the Re-ID network. Second, a fast group loss, i.e., an advanced version of variance group loss (VGL), is proposed to simplify the training process.	Market-1501, DukeMTMC-reID and CUHK03	Convolution Neural Network	rank-1,rank-5, rank-10, mAP
17	The backbone CNN ex- tracts multi-level semantic feature maps at each middle layer and the part-wise sub-networks transform the feature maps to part-based pedestrian descriptors through a designed super- vised learning. By fusing these descriptors, MLSN can utilize both low level information and high level information for re- id.	Market-1501, DukeMTMC-reID and CUHK03	Convolution Neural Network - Multi-Level Supervised Network	Rank-1 and mAP
18	Employ different data sources to train learning features from different views in multiple images. To effectively integrate these features, the proposed DAI learns integration weights for each feature dimension according to their importance.	Market-1501, DukeMTMC-reID and CUHK03	Convolution Neural Network with Discrimination-Aware Integration	rank-1,rank-5, rank-10, mAP
19	Match feature maps of different persons in an end-to-end trainable deep neu- ral network. soft warping scheme is de- signed for aligning the feature maps based on matching results, which is shown to be crucial for achieving supe- rior accuracy.	Market-1501, DukeMTMC-reID and CUHK03	Deep Neural Network with proposed Kronecker Product Matching module	rank-1, mAP
20	A light CNN learning feature pair for the input image pair is used. Then, both the elementwise absolute difference and multiplication of the CNN learning feature pair are calculated. Finally, a hybrid similarity function is designed to measure the similarity between the feature pair.	QMUL GRID, VIPeR, and CUHK03	Convolution Neural Network - Deep hybrid similarity learning	CMC, Similarity Fréquence, rank-1,rank-10,rank-20,rank30, FET, SCT
21	Take salient features into account. Normal feature learning from the CNN. Learn features complementary to the basic network, we propose the adversarial erasing operation, that locates non-salient areas with the help of attention map, to generate erased pedestrian images. This is used the complementary network and adopt the dynamic strategy to match the dynamic status of AEA in the learning process.	Market-1501, DukeMTMC-reID and CUHK03	Basic CNN and a Complementary Network. This is called Adversarial Erasing Attention (AEA)	rank-1, mAP

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
22	Self-Inspirited Feature Learning (SIF) method to enhance the performance of given ReID networks from the viewpoint of optimisation. Done by adding an auxiliary branch to the Network.	Market-1501, DukeMTMC-reID and CUHK03	Simple adversarial learning scheme in CNN	rank-1, mAP
23	PoseBox structure is introduced, which is generated through pose estimation followed by affine transformations. Second, a PoseBox fusion (PBF) to reduce the impact of pose estimation errors and information loss during the PoseBox construction	Market-1501, DukeMTMC-reID and CUHK03	CNN with pose-invariant embedding (PIE) as a pedestrian descriptor	rank-1,rank-5, rank-10, rank-20, mAP
24	Learn powerful features over full body and body parts, which can well capture the local context knowledge by stacking multi-scale convolutions in each layer. learn and localize deformable pedestrian parts using Spatial Transformer Networks (STN) with novel spatial constraints	Market-1501 and CUHK03	CNN with Multi-Scale Context-Aware Network (MSCAN)	rank-1,rank-5, rank-10, rank-20, mAP
25	Replacing the accurate annotation with inaccurate annotation, i.e., group the images into bags in terms of time and assign a bag-level label for each bag.	SYSU-30k (Primary), CUHK03 (Compared Against)	Graphical Learning	rank-1,rank-5, rank-10
26	Learn local models from subsets of training samples with regularisation imposed by the global model which is trained among the entire data set to improve discrimination strength and generalisation	Queen Mary University of London ground reidentification, CUHK01, and CUHK03	Convolution Neural Network	rank-1,rank-10,rank-20, CMC Curves
27	Lifted structured loss with neural nets that to learn better feature embedding by minimising intra-class variation and maximising inter-class variation	CUHK03, CUHK01 and VIPeR	Lifted structured loss for deep neural networks	rank-1, rank-5, rank-10
28	Using variously designed pedestrian parts instead of the horizontal partitioning routine typically applied in previous hand-crafted part works.	Market-1501, CUHK03 and VIPeR	Convolution Neural Network	rank-1 rank-5 rank-10, mAP
29	Aims to learn different metrics for the global-body and body-parts features. Also, A new multi-metric loss function under which the distance of each negative pair is greater than that of each positive pair.	CUHK03, CUHK01, VIPeR and iLIDS	Deep multi-metric learning (DMML) network	rank-1,rank-5, rank-10, rank-20, CMC

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
30	Exploits both global and local information to learn latent complementary feature representation.	Market-1501, DukeMTMC-reID and CUHK03	Convolution Neural Network - Multi-Branch Context-Aware Network	rank-1, mAP
31	Combines the information learned from global features and local features by training two stages alternately	Market-1501, DukeMTMC-reID and CUHK03	a Pseudo Label based on Multiple Clustering	rank-1, mAP
32	Address the part-misalignment problem and learn a more discriminative embedding. Upscales the low-layer features by using UpShuffle Modules and smoothly integrates the high-layer features.	Market-1501 and CUHK03	Convolution Neural Network - Part-based model with fused Multi-Scale features	rank-1, mAP
33	Better feature embedding by minimizing intra-class variation and maximizing inter-class variation	CUHK03, CUHK01 and VIPeR	Convolution Neural Network - deep feature embedding with lifted structured loss.	rank-1, rank-5, rank-10
34	Focus selectively on parts of the input image for which the networks' output is most sensitive to.	CUHK03 and CUHK01	Convolution Neural Network - with Attention	rank-1,rank-5, rank-10, rank-20, CMC
35	Use symmetry theory to maximise feature extraction levels from middle layers of CNNs. New branch - At each tail to the backbone and branch, sphere loss and triplet loss are used.	Market-1501, DukeMTMC-reID and CUHK03	Convolution Neural Network - ResNet/ Symmetry theory	rank-1, mAP
36	Triplet focal loss can up-weight the hard triplets' training samples and relatively down-weight the easy triplets adaptively via simply projecting the original distance in the Euclidean space to an exponential kernel space	Market-1501, DukeMTMC-reID and CUHK03	Triplet loss-based CNN	rank-1, mAP
37	Training the network with the joint supervision of cross-entropy loss together with a center regularization term, ensures discriminative feature representation learning and simultaneously predicts pseudo-labels for unlabeled data	Market-1501, DukeMTMC-reID and CUHK03	CNN - feature affinity-based pseudo labeling method with two possible label encodings	rank-1, mAP

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38	Integrates semantic representations for similarity comparison between the corresponding regions via parsing the body into multiple parts, which focuses on the foreground context against the background interference.	VIPeR, SYSU-sReID, QUML GRID, CUHK03, and Market-1501	CNN - with semantic region representation and metric learning with mapping space topology constraint	rank-1,rank-5, rank-10, rank-20
39	Employ pedestrian alignment network to work out image misalignment problems with pedestrian alignment and multi-scale features network through spatial transformer networks.	Market-1501, DukeMTMC-reID and CUHK03	CNN - Pedestrian-Aligned Multiscale Features Network	rank-1, mAP
40	Simple multi-branch structure consisting of a global branch as well as a part branch in an asymmetrical way	Market-1501, DukeMTMC-reID and CUHK03	CNN - with multi-branch structure	rank-1, mAP
41	To train a CNN, virtual label assigned to generated data. These data are used for semi-supervised learning	Market-1501, DukeMTMC-reID, CUHK03, VIPeR, and CUHK01	CNN - with Multi-pseudo regularized Label	rank-1, mAP
42	Take advantage of the complementarity between hand-crafted features and CNN features by making hand-crafted features participate in the construction of our CNN model and the generation of the final features.	Market-1501, CUHK03, CUHK01 and VIPeR	CNN - with feature reconstruction block (FRB)	rank-1,rank-5, rank-10, rank-20, CMC
43	Combines pose information and attention mechanism to deal with the challenges.	Market-1501, DukeMTMC-reID and CUHK03	CNN - Hard/Soft hybrid Attention Network (HSAN)	rank-1,rank-5, rank-10, CMC
44	Learn the subspace by maximizing the ratio of between class covariance and within class covariance using L1 norm instead of the conventional L2 norm	Market-1501, DukeMTMC-reID and CUHK03	CNN - a robust discriminative subspace learning technique	rank-1,rank-5, rank-10, CMC
45	Learns a view-specific network for each camera. We utilise the CV-EC to decrease the margin of the features between diverse views and extend the centre loss metric to a view-specific version to better adapt the re-id problem.	VIPeR, CUHK01, CUHK03, SYSU-mReId, and Market-1501	CNN - with cross view Euclidean Constraint and Centre Loss	rank-1,rank-5, rank-10, rank-20, CMC

S.no	Proposed Methodology	Dataset	Algorithm	Performance Measure
46	Foreground-aware Pyramid Reconstruction (FPR), is developed to accurately compute matching scores between occluded persons, despite their different scales and sizes	Market-1501, DukeMTMC-reID and CUHK03	Full CNN and Pyramid Pooling	rank-1, mAP
47	A logistic metric learning approach with the PSD constraint and an asymmetric sample weighting strategy. Apply the accelerated proximal gradient approach to find a global minimum solution.	VIPeR, QMUL GRID, CUHK Campus, and CUHK03	CNN - with Logistic Metric Learning	Training Time, Rank-1, CMC
48	View-invariant identity-wise features, and it is a kind of combination of view-generic and view-specific methods. Classifiers and feature centers are utilized to achieve view confusion	CUHK01, CUHK03, and MARKET1501	CNN - View Confusion Feature Learning (VCFL)	top-1, mAP
49	Effectively trim irrelevant features by enforcing the resultant feature masks to focus on the most discriminative features	Market-1501, DukeMTMC-reID and CUHK03	CNN - a differentiable Gumbel-Softmax sampler	rank-1,rank-5, rank-10, mAP
50	Attention based on the body masked images which are obtained by a reliable pixel-level segmentation strategy. 3 Attention Branches.	Market-1501, DukeMTMC-reID and CUHK03	CNN - with attention model - Body-guided Attention Network	rank-1, rank-10, mAP