An Efficient Feature Representation Using CHLOMO and CNN for Person Re-Identification

Dr S Princy Suganthi Bai

*Assistant Professor of Computer Science,*

*Sarah Tucker College,*

*Tirunelveli, Tamil Nadu, India*

*vinodhprincy2003@gmail.com*

Dr M Gethsiyal Augasta

*Assistant Professor of Computer Science,*

*Kamaraj College,*

*Thoothukudi, Tamil Nadu, India*

*augastaglady@gmail.com*

Dr J Stella Janci Rani

*Assistant Professor of Computer Science*

*Sarah Tucker College,*

*Tirunelveli, Tamil Nadu, India*

jstellajara17@gmail.com

ABSTRACT

The re-identification of a person is defined as determining whether a person has previously been in front of a network of cameras. Efficient features always make perfect learning towards individual re-identification. In this research, a new deep feature learning model called CHLFDLF has been proposed with the mixture of handcrafted features and profound features, extracted using CHannel Integrated LOMO (CHLOMO) and Convolutional Neural Network (CNN) respectively to attain an improved person re-identification system. The extracted features are integrated efficiently and learned using the Cross-view Quadratic Discriminant Analysis (XQDA) similarity metric approach for efficient person re- identification. The performance of this proposed approach is demonstrated by applying it to the different benchmark datasets for re-identification such as VIPeR, CUHK03, and Market1501

**Keywords**— Handcrafted feature; Convolutional Neural Network; Deep feature; Person Re-identification; Metric Learning.

# INTRODUCTION

An aspect of image retrieval is person re-identification. This technique is very much significant for community security purposes. While observing big distances, this is important to appropriately equivalent the identical individual in various photographic camera perspectives. An undirected trajectory can be created by corresponding to the destination issue in several camera angles [1]. Deep learning development and the increase in the need for intelligent video surveillance have attracted much more focus in the field of computer vision. Re-identification of a person is a difficult assignment due to the existence of various problems, namely various viewpoints, unconstrained poses, varying low-image resolutions, occlusions, complex camera environments, illumination changes, unreliable bounding box generations, heterogeneous modalities, and background mess [2].

Disjointed and non-overlapping cameras shatter the majority of the individual images. These cameras are fixed in place in an unregulated setting, producing extremely poor-quality images. Extracting a person's representations from shoddy photos is a difficult task. Usually, distance metric learning and feature representation are the two fundamental components of person re-identification methods. Representation of feature and feature extraction techniques are considered very important steps in metric learning. The extracted features in this case are often divided into learned and handcrafted features [3]. The illustration of the feature is necessary since it serves as the basis for metric learning. The efficiency of metric learning is fine recognized with the quality of the feature obtained. Here, the feature extraction process begins with a collection of measured information and then creates a series of derivative values that are intended to be informative and non-redundant.

The majority of feature extraction techniques for person re-identification, it has only employed grayscale textures. In CHLOMO [4] method efficient color texture features with combined Deep learned features have been used. The CHLOMO feature is a combined representation of blue, red, and green textures that delivers efficient outcomes for the re-identification of a person.

Another crucial step in the process of person re-identification is learning a reliable distance or similarity function to handle the challenging matching task. A discriminating metric with the detected features should be learned to match the numerous individual photographs. Features should have been energetically shown through changes in lighting and angle. A variety of similarity measures, including Cross-view Quadratic Discriminant Analysis (XQDA) have been used by researchers for person re-identification.

In this research work, the person re-identification method called CHannel Integrated LOMO features (CHLF) and Deep Learned Features (DLF) based person re-identification model with XQDA (CHLFDLF) is proposed for improving the person re- identification.

The paper is organized as follows: The related studies are presented in Section 2 and the proposed method is discussed in Section 3, and Section 4 offers the proposed algorithm for person re-identification, experimental outcomes and analysis are included in Section 5.

# LITERATURE REVIEW

There are numerous extant works have focused on increasing strong and refined features in person re-identification. These works also explain features with highly changeable visual appearances produced under considerably various conditions. Wu et al., [1] have applied recent indices for the purpose of person re-identification. Hence, a fair evaluation system is conducted with metric learning methods. The relationships between loss function with deep feature space and metric learning are also considered. There is an analysis of a variety of metric learning features, from handcrafted features to deep features. Moreover, the experimental results show that the elucidation's space is distinct from the space in which the features were initially selected. Ye et al.,[2] have conducted a widespread overview with in detail scrutiny for closed world person re-identification from three various viewpoints, namely deep feature representation learning, deep metric learning, and ranking optimization. Some under-investigated open issues are also analyzed

Liao et al., [5] have designed Local Maximal Occurrence [LOMO] to denote every pedestrian image as a high-dimensional feature. Then, the metric learning technique which is known as Cross-view Quadratic Discriminant Analysis (XQDA) is also used. LOMO feature extracts the horizontal occurrence of local features and maximizes the occurrence to make a sTable analysis against viewpoint changes. Retinex transform and a scale-invariant texture operator are also used to overcome illumination problems.

CHLOMO [4] technique is a new Channel Integrated Local Maximal Occurrence (CHLOMO) for attaining sturdiness on variations in lighting and noise in the images by introducing a novel method named Scale-Invariant Channel Integrated Statistical Pattern (SICISP) with the bettered Scale Invariant Local Ternary pattern (SILTP). Normally SILTP is built using a gray channel only. SICISP, a well-known tool for its invariant texture description of lighting, is incorporated into this model from two distinct kinds of patterns for each color conduit. The Channel Integrated Local Maximum Occurrence features are created using the process of min-max fusion by combining HSV color representation with the statistical texture feature representation. This CHLOMO method remains a feature-based person re-identification model with XQDA.

Tao et al., [3] have applied the XQDA metric learning technique. Here, Deep Multi-View Feature Learning (DMVFL) is proposed to provide the collaboration between handcrafted and deep learning features in an easy way. They have used two challenging person re-identification data sets, namely VIPeR and GRID to show that the XQDA is a sturdy algorithm. According to the results obtained, DMVFL shows improvement in current state-of-the-art methods.

The information on both local texture and global color representations has been combined with a raw source image by Jayapriya et al., [6]. By estimating the highest possible chrominance value in the form of HSV, Scale Invariant Local Ternary Pattern (SILTP) for each pixel of the texture, and the source image is used to create the Prioritized Chromatic Texture (PCTimg) technique. In this method, the combined data is used to extract the features using a convolutional neural network (CNN). The Prioritized Chromatic Texture Image (PCTimg) and the initial source image are combined before being delivered to CNN. To re-identify a person, the XQDA similarity metric algorithm is used. The Multiscale Retinex algorithm is also used for pre-processing the images. Shaojun et al.,[7] have combined local features and global features of images through deep learning networks. This method is called the Multi-level Feature Fusion model, which generates more pedestrian descriptors. Specific features are extracted from different network depths using the Part-based Multi-level Net. Additionally, low-to-high-level local characteristics of pedestrian photos are fused using this method. The highest level is extracted using Global- Local Branches, which extract both local and global features.

Moreover, various person re-identification methods DMVFL [3], SLFDLF [13], and PCTimg [6] have been proposed in recent days with the combination of machine learning and deep learning. These methods have utilized both handcrafted and deep-learned features and used XQDA for metric learning. SLFDLF [13] method is the combination of the Splitted LOMO feature and deep learned feature. The local feature has a more discriminative nature to describe the human structural information, hence it is first horizontally divided into size-based grids, and the LOMO features are individually retrieved from each grid. The extracted LOMO features are combined with deep features to represent that image and XQDA metric learning model is used to learn the combination of Splitted LOMO features and deep learned features (SLFDLF).

As LOMO can handle only gray texture images, this research has focused on creating an efficient feature representation model for handling both HSV color and color texture person re-identification images with an effective technique termed CHLFDLF. The proposed CHLFDLF is the combination of the CHannel Integrated LOMO feature (CHLF) and the deeply learned feature (DLF). In other words, CHLFDLF is an integrated channel having deep features and hand-crafted features with red, green, and blue texture features. The XQDA metric learning is applied on the CHLF and the DLF to obtain the distances on various experimental datasets as it is a reliable metric learning algorithm to learn the distance with the ability to achieve outstanding performance on person re-identification challenges.

# III THE RESEARCH METHOD (CHLFDLF)

This section provides an explanation of the CHLFDLF technique, which was developed by combining deep-learned features with enhanced handcrafted features. The suggested CHLFDLF method involves three stages. Using CHLOMO, effective handcrafted features are first retrieved from images of pedestrians. In the subsequent stage, the deep-learned features are extracted from the images using the convolutional neural network (CNN). Finally, utilizing XQDA, the deep-learned features and handcrafted features are effectively integrated to learn the distance:

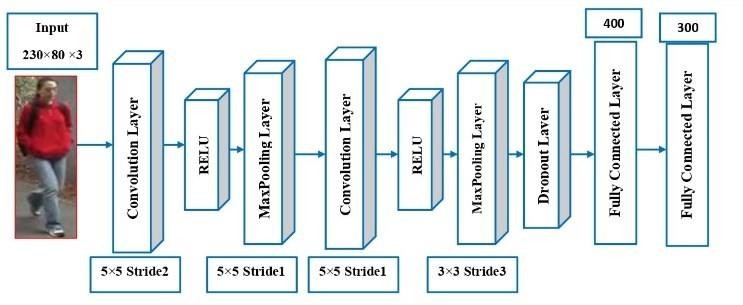
## **Stage I: CHLOMO Feature (CHLF)**

Local Maximal Occurrence (LOMO) is a well-organized feature representation. The handcrafted features of LOMO are used in person re-identification. Normally, features of LOMO are combined with SILTP features, Retinex transforms, and the HSV color histogram to account for variations in light. Moreover, the LOMO [5] descriptor examines and leverages the flat incidence of constrained characteristics to produce a consistent representation that is robust to changing perspectives. SILTP was proposed for gray channels only. This LOMO feature is robust to changes in illumination and viewpoint. The Splitted Lomo Feature (SLF) [13] method is in the form of a grid-based. Using this technique, handcrafted features are not extracted for the entire image, but from the split images. i.e., all the images are splitted into grid form.

The CHLOMO [4] is an efficient feature representation model with the introduction of SICISP. SICISP is the new operator that is introduced in place of the SILTP. For color texture images, the existing SILTP has been expanded as the Scale-Invariant Channel Integrated Statistical Pattern (SICISP) operator. A SICISP, an HSV color histogram, and Retinex transforms are used in the CHLOMO approach to cope with differences in lighting. In this method, CHLOMO features are extracted for the whole image.

## **Stage II: Deep learned Feature (DLF)**

The architecture of the proposed technique with CNN for VIPeR, Market1501, and CUHK03 has been depicted. Figure ure 1 shows the proposed framework of DLF. This model consists of 12 layers. A Dropout layer, Softmax layer, two max- pooling layers, two fully connected layers, two rectified linear unit (ReLU) activation, two convolutional layers, classification layers, and image input layers are included. The pooling layer entails a dropout for alleviating the qualified model. The first convolutional layer utilized a stride parameter size is two and 5×5 kernel size, and the fourth convolutional layer used a stride parameter is one and 5×5 kernel size. For the pooling process, the max-pooling layer is used. The first pooling layer's pool size is 5x5, whereas the second pooling layer's pool size is 3x3. Finally, the second fully connected layer is used to extract the deep features. This method has been used to employ a dropout to steady the learned model and a data augmentation training technique to extend the dataset because most extant re-identification of person databases are small-scale such as the VIPeR dataset. Triplet loss can be used with Convolutional Neural Networks and seen as an entire system. In order to optimize the distances, triplet loss training aims to create an effective feature depiction.



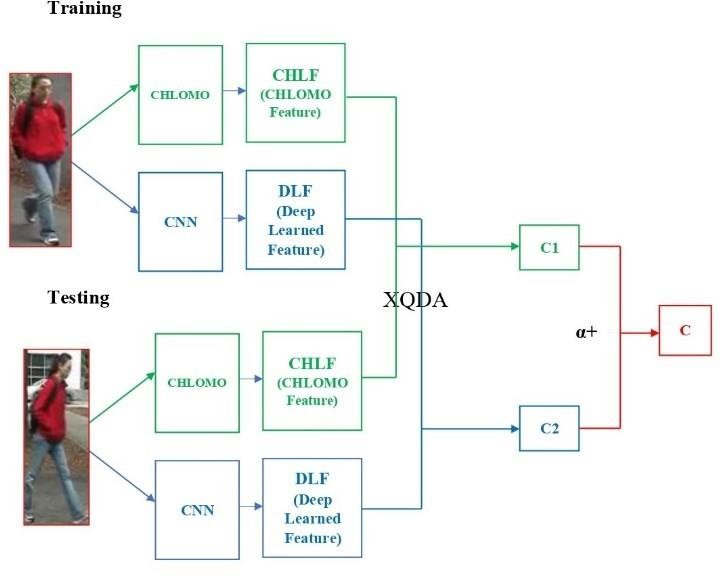
**Figure 1: DLF Network Architecture Model**

## **Stage III: Fusion Strategy**

XQDA’s approach to metric learning is effective and efficient. This approach is utilized to train a low-dimensional subspace with a distance. As a result, only learning the similitude measure will suffice. Figure ure 2 depicts the technique's fusion strategy. For the training and testing data sets of the suggested method, XQDA is employed to determine the distance C1 amongst handcrafted CHLOMO features and the distance C2 amongst deep-learned features. These two lengths are added to determine the ultimate distance using equation (1).

𝐶 = 𝐶1 + 𝛼 ∗ 𝐶2 (1)

where α is the trade-off parameter. The matching rank for person re-identification is calculated using the final distance.



**Figure 2: Fusion Process of CHLOMO and Deep Features**

## **IV THE PROPOSED ALGORITHM (CHLFDLF)**

This section describes the step-by-step procedure of proposed CHLFDLF for person re-identification based on CHLOMO features and deep learned features.

Input

PRimg – Person Re-identification Datasets with different angle posed person images.

Procedure

1. For all images in PRimg
2. Extract handcrafted features CHLF from HSV color and color textures using CHLOMO
3. Extract deep features DLF automatically using CNN
4. Split the extracted CHLF as training CFtrn and testing CFtst
5. Split the extracted DLF as training DFtrn and testing DFtst
6. Learn CFtrn using the XQDA similarity metric learning approach and compute the distance C1 on CFtst.
7. Learn DFtrn using the XQDA similarity metric learning approach and compute the distance C2 on DFtst.
8. Compute overall distance C using equation (1)
9. Re-identify the person by computing the images with a minimum distance

Output:

The re-identified person image

In this algorithm, Step 1(a) is utilized to obtain CHLOMO features for every image in the data set. The CNN is trained in step 2 in order to extract deep features. The similarity of the XQDA between the training and test images is computed in steps 4 and 5. Step 7 determines the matching accuracy depending on the calculated distance C. The output represents the re-identified person.

# V EXPERIMENTAL RESULTS

Every experiment was performed on a personal computer with Windows 10, an Intel®CoreTMi5-7200U Central Processing Unit running at 2.50GHz and 2.71GHz, and 8GB RAM. The suggested technique was created using MATLAB R2017b, which includes a Deep Learning tool as well as a toolkit for image processing. CUHK03 [10], Market 1501 [9], and VIPeR [8] were used as actual datasets to test this technique. Table 1 provides a full overview of the experimental datasets. Only 632 images are included in the VIPeR dataset. The dataset has grown by a factor of 64 as a result of the data augmentation process. Every experimental dataset was scaled to 230x80 pixels for efficiency because each one's size differs. Each class's training and testing images are chosen at random.

**Table 1: Datasets used for Evaluating CHLFDLF**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | Classes | Images | Training Images | Testing Images | Image size |
| VIPeR | 632 | 1264 | 316 | 316 | 128×48 |
| Market1501 | 300 | 5933 | 4747 | 1186 | 128×64 |
| CUHK03 | 742 | 7239 | 5756 | 1473 | vary |

# Datasets

Each experimental dataset is thoroughly discussed in this section. On university campuses, a variety of cameras were used to capture the images in all three datasets. Using automated detection on a big scale (for Market-1501 and CUHK03) produces significant image misalignment, Nevertheless, likened to lesser person re-identification databases, this makes these datasets more realistic.

# VIPeR dataset

The utmost popular dataset for person re-identification is the VIPeR dataset [8], which contains 1264 photos of 632 distinct persons. Each person is made up of two images captured from two distinct random perspectives. It is difficult to re-identify an individual using the VIPeR dataset, since there are substantial differences in the backdrop, viewpoint, and illumination, making it impossible to match the same person with only two different viewpoints. Here, Images acquired in one sight with Camera B are used as testing, while pictures captured in another sight with Camera A are used as training to evaluate the proposed approach. In order to facilitate training and testing, the 632-person VIPeR dataset is divided in half.

# Market1501 dataset

The Market 1501 [11] group comprises 32668 pictures of 1501 persons. This dataset contains photos that present a variety of difficulties for person re-identification, including body misalignment, different viewing angles, pose distortion, missing sections, and occlusion. To evaluate the effectiveness of the suggested method, 5933 pictures of 300 persons from the market 1501 dataset were used. 80 percent of each person is chosen arbitrarily for training, while the remaining 20% is chosen arbitrarily for testing.

# CUHK03 dataset

The 14,097 images in the CUHK03 dataset [10] depict 1,467 different personas. In this dataset, the pedestrians captured in several camera views faced challenges from illumination, positions, points of view, camera background boundaries, picture sizes, and congested backdrops. 7240 photos of 742 persons were taken from the CUHK03 dataset to test the suggested approach. 80 percent of each class/person is chosen at casual for training purposes, while the remaining 20% is chosen at casual for testing purposes.

# VI RESULT ANALYSIS

In this research, initially, CHLOMO features are obtained as CHLF from every image. Then, each image is erudite using CNN for extracting Deep Features. For VIPeR, Market1501, and CUHK03, the layer of the first fully connected dimension is 400 and the layer of the second fully connected dimension is 632. By reckoning the right match from the topmost m matches, the proposed CHLFDLF's results are evaluated. In relation to the probe set, it assigns a rank to each and every sample in the gallery set. CMC curves are created by repeating this technique ten times. The quantitative evaluation of performance is carried out using the Cumulative Matching Characteristic (CMC) technique [11]. Table 2, Table 3, and Table 4 display the precise top 1, 5, 10, 15, and 20 ranking outcomes of CHLF, DLF, and the proposed CHLFDLF on all experimental datasets. Moreover, the VIPeR, Market1501, and CUHK03 dataset’s person re-identification matching ranks using CHLFDLF are plotted in the CMC curve and are shown in Figure 3.

**Table 2: Outcomes of the Chlomo Feature (CHLF)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Dataset** | **R1** | **R5** | **R10** | **R15** | **R20** |
| CUHK03 | 92.66 | 97.83 | 98.78 | 99.05 | 99.32 |
| Market 1501 | 85.69 | 95.62 | 97.81 | 98.99 | 99.32 |
| VIPeR | 42.41 | 72.47 | 83.54 | 91.46 | 94.94 |

**Table 3: Outcomes of the Deep Learned Feature (DLF)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Dataset** | **R1** | **R5** | **R10** | **R15** | **R20** |
| VIPeR | 45.22 | 57.41 | 63.26 | 68.99 | 90.73 |
| Market 1501 | 93.56 | 95.83 | 96.47 | 98.69 | 98.91 |
| CUHK03 | 72.06 | 73.78 | 76.31 | 78.74 | 80.72 |

**Table 4: Outcomes of the Proposed Method (CHLFDLF**)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Dataset** | **R1** | **R5** | **R10** | **R15** | **R20** |
| VIPeR | **48.34** | 75.03 | 88.48 | 93.04 | 97.78 |
| Market 1501 | **94.29** | 97.84 | 98.46 | 98.98 | 99.45 |
| CUHK03 | **96.39** | 97.61 | 98.07 | 98.87 | 99.1 |

While comparing the results of CHLF, DLF, and CHLFDLF, the proposed CHLFDLF method provides outstanding results for person re-identification on the experimental datasets.

A graph of a number of datasets

Description automatically generated

**Figure 3: CMC Curve of CHLFDLF on VIPeR, Market1501 & CUHK03 Datasets**

## **Evaluation of Performance**

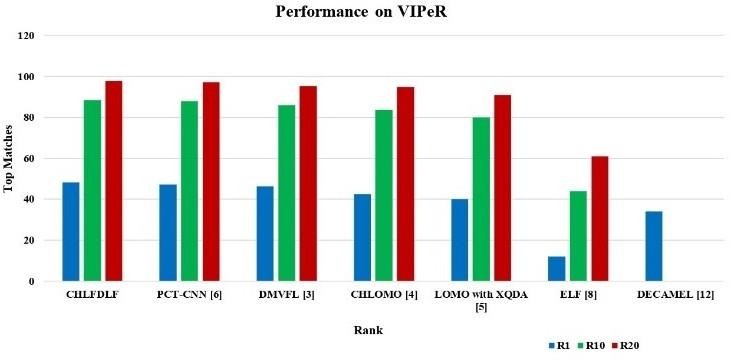
This section compares the effectiveness of the CHLFDLF approach for person re-identification on the Market1501, CUHK03, and VIPeR datasets with that of several feature representation and metric learning approaches.

## **Comparative Analysis of CHLFDLF on VIPeR dataset**

Comparing the CHLFDLF results on the VIPeR dataset against those of other approaches like CHLOMO [4], LOMO+XQDA [5], PCT-CNN [6], DMVFL [3], ELF [8], and DEep Clustering-based Asymmetric Metric Learning DECAMEL [12]. Table 5 displays the comparative findings from the VIPeR dataset. Table 5 shows that the proposed technique outperforms PCT-CNN and DMVFL by 1.19% and 1.95%, respectively, and reaches the most recent technology with 48.34% at Rank 1 (R1). While considering PCT-CNN by 1.19%, 0.51%, and 0.63% and it outperforms all R1, R10, and R20 the proposed CHLFDLF outperforms the other feature extraction and metric learning algorithms in comparison. The proposed method outperforms all previous methods individually, obtaining 48.34% Rank1 (R1) accuracy. The effectiveness of the proposed method is compared with the existing approaches in Figure 4.

**Table 5: The proposed CHLFDLF method compared with existing methods on the VIPeR dataset**

|  |  |  |  |
| --- | --- | --- | --- |
| **Method** | **R 1** | **R 10** | **R 20** |
| **CHLFDLF** | **48.34** | **88.48** | **97.78** |
| PCT-CNN [6] | 47.15 | 87.97 | 97.15 |
| DMVFL [3] | 46.39 | 86.1 | 95.32 |
| CHLOMO [4] | 42.41 | 83.54 | 94.94 |
| LOMO with XQDA [5] | 40.0 | 80 | 91 |
| DECAMEL [12] | 34.15 | - | - |
| ELF [8] | 12.0 | 44.0 | 61.0 |



**Figure 4 : Performance Comparison of CHLFDLF on VIPeR**

## **Comparative Analysis of CHLFDLF on the Market1501 dataset**

Comparing the CHLFDLF results on the VIPeR dataset against those of other approaches like CHLOMO [4], LF [13], LFDLF [13], DLPR [15], BoW [9], and k-reciprocal Encoding [14]. Table 6 provides a comparison of the proposed approach with previous works. The results of the comparison show that the proposed CHLFDLF approach outperforms other CNN- based methods, including DECAMEL [12], DSML [16], UTAL [17], and PersonNet [18]. With an R1 accuracy of 94.29%, the suggested approach exceeds every other method individually.

**Table 6 : The Proposed CHLFDLF Method Compared with Existing Methods on the Market1501 Dataset**

|  |  |
| --- | --- |
| **Method** | **R1** |
| **CHLFDLF** | **94.29** |
| CHLOMO [4] | 85.69 |
| LFDLF [13] | 84.15 |
| LF [13] | 81.92 |
| DLPR [15] | 81 |
| DSML [16] | 84.4 |
| k-reciprocal Encoding [14] | 77.11 |
| DECAMEL [12] | 60.24 |
| UTAL [17] | 56.3 |
| PersonNet [18] | 37.21 |
| BoW [9] | 34.4 |

Table 6 shows that the suggested approach reaches the new state-of-the-art, 94.29% at (Rank1) R1. In comparison to previously studied approaches, the outcome shows that the proposed CHLFDLF features provide better consequences. In Figure . 5, the performance of the suggested approach is contrasted with that of the existing approaches.



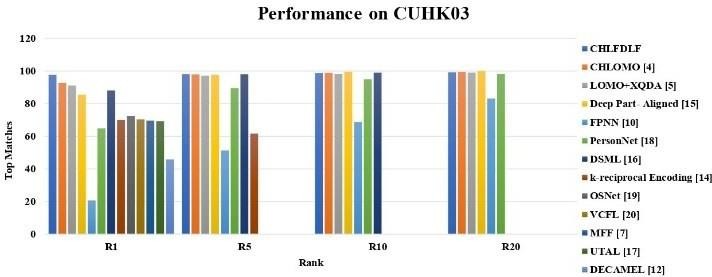
**Figure 5 : Performance comparison of CHLFDLF on Market1501**

## **Comparative Analysis of CHLFDLF on the CUHK03 dataset**

On the CUHK03 dataset, the results of CHLFDLF are compared to those of CHLOMO [4], Deep Part-Aligned [15], LOMO+XQDA [5], DSML [16], UTAL [17], DECAMEL VCFL [20], k-reciprocal Encoding [14], OSNet [19], FPNN [10], and PersonNet [18]. The performance of re- identification using various methodologies is evaluated using the Rank1(R1), Rank5 (R5), Rank10 (R10), and Rank20 (R1) accuracies. Table 7 shows that the suggested method beats all other approaches in comparison, with a re-identification accuracy of 97.61 % at rank 1. A comparison of the suggested strategy and the earlier approaches is shown in Table 7. Also, approaches based on CNN, like OSNet [19], DSML [16], UTAL [17], and PersonNet [18], are outperforming the proposed CHLFDLF handcrafted features and deep features method. The concert of the suggested method on the dataset for CUHK03 is compared with that of the existing approaches in Figure . 6. The suggested strategy exceeds all other approaches individually with a rank-1 accuracy of 97.61%.

**Table 7 : The Proposed CHLFDLF Method Compared with Existing Methods on the CUHK03 Dataset**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Method** | **R1** | **R5** | **R10** | **R20** |
| **CHLFDLF** | **97.61** | **98.07** | **98.63** | **99.16** |
| CHLOMO [4] | 92.66 | 97.83 | 98.78 | 99.32 |
| LOMO+XQDA [5] | 91.05 | 97.05 | 98.25 | 99.02 |
| Deep Part- Aligned [15] | 85.4 | 97.6 | 99.4 | 99.9 |
| FPNN [10] | 20.65 | 51.32 | 68.74 | 83.06 |
| PersonNet [18] | 64.8 | 89.4 | 94.92 | 98.2 |
| DSML [16] | 88 | 98 | 99 |  |
| k-reciprocal Encoding [14] | 69.9 | 61.6 |  |  |
| OSNet [19] | 72.3 | - | - | - |
| VCFL [20] | 70.36 | - | - | - |
| MFF [7] | 69.6 | - | - | - |
| UTAL [17] | 69.2 | - | - | - |
| DECAMEL [12] | 45.82 | - | - | - |



**Figure 6: Performance comparison of CHLFDLF on CUHK03**

**VII CONCLUSION**

The combination of CHLOMO and Deep features (CHLFDLF) has been suggested in this research. It merges with efficient handcrafted features and CNN features to augment the representation. Here, the CHLOMO feature is extracted in the form of a color texture known as CHLF. Besides CHLOMO, deep-learned features are extracted as DLF by applying CNN. In order to effectively learn the distance, the deep features and CHLOMO features are integrated. The outcomes of the suggested CHLFDLF are depicted on VIPeR, CUHK03, and Market 1501 datasets. The experimental analysis represents that data sets used with these enhanced features drastically improve person re-identification and also handle small and large sample size problems in a well-organized way. The Rank1 accuracy of the proposed method CHLFDLF is 48.34 %, 94.29 %, and 96.39%, respectively. In the future, the proposed feature representation method can be implemented with more layers of deep learning networks and evaluated by using small-scale and large-scale datasets.

**VIII ACKNOWLEDGMENT**

We sincerely express our gratitude to the editors and reviewers for their insightful comments which helped us to enhance the quality of the manuscript.

*NOMENCLATURE*

|  |  |  |
| --- | --- | --- |
| *LFDLF* | *–* | *LOMO Feature and Deeply Learned Feature* |
| *SLFDLF*  *LF* | *-*  *–* | *Split LOMO Feature and Deeply Learned Feature*  *LOMO Feature* |
| *DLF* | *–* | *Deep Learned Feature* |
| *CHLOMO* | *–* | *CHannel Integrated Local Maximal Occurrence* |
| *CHLF* | *–* | *CHannel Integrated LOMO Feature* |
| *CHLFDLF* | *–* | *Channel integrated LOMO feature and Deep- Learned Feature* |
| *SICISP* | *–* | *Scale-Invariant Channel Integrated Statistical Pattern* |
| *XQDA* | *–* | *Cross-view Quadratic Discriminant Analysis* |

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