Person Re-Identification Using Traditional Machine Learning Techniques: A Lightweight Approach

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***Abstract*—Person re-identification (ReID) functions as a fundamental surveillance system operation which matches people across different cameras not sharing any overlapping views. A conventional ReID process is outlined in this report which utilizes HOG and SIFT feature extractors together with color histogram and their combination features. A similarity evaluation of features from the Kaggle Person ReID dataset occurs with Euclidean distance alongside KNN and cosine similarity algorithms. Our experimental findings demonstrate that color histogram features together with their corresponding combinations reach the highest cross-validation precision of 0.9703. HOG with cosine similarity produces outstanding results in ranking operations with a Rank-1 accuracy reaching 0.974. project outcomes show that traditional methods succeed in resource-limited environments by providing optimal accuracy combined with computation speed. The utilization of SIFT carries important drawbacks because it exhibits weak generalization capabilities while the ranking metrics for color-based features remain missing for future optimization. The presented findings highlight how lightweight ReID systems can become favorable for real-time deployment.**

***Index Terms*—Person Re-Identification, HOG, K-NN, traditional machine learning, feature extraction, similarity metrics, Kaggle dataset, surveillance systems, computational efficiency.**

I. Introduction

Person Re-Identification (ReID) exists as an essential functionality within current security systems and surveillance approaches to track individuals across different camera view areas. Person Re-Identification functions through identification between a query person image as well as multiple images from various cameras that experience environmental difficulties like light changes and body positions. ReID provides critical importance to several real-world applications which include law enforcement tracking of suspects and public space crowd monitoring and smart city safety enhancement. ReID systems will require better approaches and solutions because expanding surveillance networks drive up the need for precise and efficient systems to manage inherent complexities.

Traditional machine learning techniques represent the foundation of ReID systems because they maintain high computational efficiency together with interpretability. Three techniques that extract image features for identity matching through K-Nearest Neighbors (KNN) include Histogram of Oriented Gradients (HOG) [1], Scale-Invariant Feature Transform (SIFT) [2] and color histograms [3]. The deep learning methods achieves high accuracy using Convolutional Neural Networks (CNNs) yet requires significant computational resources and large amounts of labeled data for processing. The resource requirements of deep learning create obstacles to its implementation when hardware systems are restricted for real-time processing operations. The project selects traditional machine learning methods instead of deep learning because it must produce a resource-efficient yet effective ReID solution that balances performance with efficiency.

As the main objective this study creates a resilient ReID pipeline powered by conventional machine learning methodologies. The system development requires capabilities to extract features with discrimination power and to reduce dimensions while ensuring accurate classification across various situations. The work evaluates individual functions and relative performances of HOG, SIFT, and color histograms followed by similarity measurements between Euclidean distance, cosine similarity, and KNN-based matching. Our method involves traditional machine learning based methods for developing a scalable system that delivers high-accuracy performance at an affordable computational cost when compared to deep learning frameworks, which are highly data-intensive tasks.

The project examines the Kaggle Person ReID dataset through 1,500 different identities distributed across 684,287 images. The ReID performance benchmark is evaluated through this dataset which contains diverse and difficult challenges for evaluation. Our framework uses HOG along with SIFT as well as color histograms and their combined variations HOG+SIFT and HOG+color histograms for extracting features from images. A Principal Component Analysis (PCA) reduction method decreases feature dimensions for better operation speed before KNN classification occurs with Euclidean, cosine and alternative similarity measurement approaches. The evaluation metrics for performance examination include cross-validation accuracy and training accuracy together with Rank-1 and Rank-5 accuracy measurements that determine first-position matches and top five identity rankings respectively. A set of evaluation metrics gives users a complete understanding of how well the pipeline functions within different performance areas.

As the main objective this study creates a resilient ReID pipeline powered by conventional machine learning methodologies. A system design should produce a solution that extracts important features and performs accurate classification under changing circumstances. The work evaluates individual functions and relative performances of HOG, SIFT, and color histograms followed by similarity measurements between Euclidean distance, cosine similarity, and KNN-based matching. Our approach concentrates on traditional methods to build a scalable and high-accuracy system that eliminates deep learning framework requirements.

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II. Related Work

The Person Re-Identification (ReID) technique has drawn extensive interest in computer vision domains that apply both traditional machine learning and deep learning methods. The representation of image content for traditional methods requires handcrafted characteristics such as Histogram of Oriented Gradients (HOG) [1], Scale-Invariant Feature Transform (SIFT) [2] and color histograms [3]. HOG detects successively oriented edges for silhouette comparison whereas SIFT provides translation and size-unstable feature points. Image color distributions get encoded efficiently through the use of simple color histograms. The implementation of ReID requires matching features alongside KNN and similarity metrics to operate. The features tend to perform less effectively when matching in scenarios that involve complex changes in pose and illumination and system obscuration conditions therefore projecters work toward combining different methods. The combination of HOG features with SIFT features reported Wang et al. [4] as they observed better robustness than individual feature implementations.

ReID currently experiences a revolution through deep learning wich directly extracts discriminative features from real data sources. DeepReID [5] implements Convlutional Neural Networks (CNNs) whic achieve top results on benchmark datasets by extracting high-level abstractons. Their learning capacity improves through the utilization of extensive labeled data because it allows them to become resilient against multiple data transformations. Computer systems struggle to implement deep learning methods because of their high data usage and processng power needs which makes them unfeasible for resource-limited environents.

Big data applications benefit from traditional machine learning because it delivers high performance along with simple understanding of general operations. When compared to accuracy deep learning models have a high maintainability cost that exceeds practical needs during real-time processing. The project improves traditional methods by combining contemporary features with thorough tests which positions it as a link between established approaches and modern requirements.

III. Methodology

A. Datasets

The project uses the Kaggle Person Re-Identification dataset [?] which contains 684,287 images spread across 1,500 different identities. Moving through the dataset one exhibits 456 representational pictures per identity that demonstrate various pose conditions alongside illumination changes together with different camera perspectives and environmental settings. The dataset represents a reliable measure to evaluate person ReID systems because of its distinct characteristics.

The extraction process needs processing to guarantee steady input. The images get resized into standard 128×256 pixel dimensions for uniform processing. The projecters perform stratified sampling for splitting their dataset into training and validation portions where 80% contents training data while 20% serves for validation purposes through identity distribution maintenance. A total of 1,200 identities go to training step alongside 300 identities divided into the validation phase to maintain an equivalent distribution.

B. Feature Extraction

Feature extraction is a pivotal step in the ReID pipeline, aiming to capture discriminative characteristics from images. The following feature extractors are employed:

- **Histogram of Oriented Gradients (HOG)**: Implemented using OpenCV [?], HOG captures edge and gradient structures by computing histograms of gradient orientations in localized image regions. Images are resized and converted to grayscale before extraction.
- **Scale-Invariant Feature Transform (SIFT)**: Also implemented via OpenCV, SIFT identifies scale-invariant keypoints and computes descriptors that are robust to rotation and illumination changes.
- **Color Histograms**: Computed using scikit-learn [?], color histograms quantify the distribution of pixel intensities across RGB channels, providing a simple yet effective representation of color information.
- **Hybrid Features**: Combinations such as HOG+SIFT, HOG+color histograms, and SIFT+color histograms are created by concatenating individual feature vectors, aiming to leverage complementary strengths.

These feature extractors are selected for their proven efficacy in traditional computer vision tasks and their computational efficiency.

C. Dimensionality Reduction

To mitigate the curse of dimensionality and enhance computational efficiency, Principal Component Analysis (PCA) is applied to the extracted features. PCA reduces the feature space to 100, 200, or 400 principal components, retaining the most significant variance while discarding noise. The choice of components is empirically determined to balance performance and computational cost.

D. Classification

KNN classifier runs identity matching operations by processing Euclidean and cosine similarity metrics. The KNN algorithm proves effective for high-dimensional data and simplicity makes it the chosen method. Different K values from 3 to 15 are applied to test the classifier for finding the best neighborhood size. Performance and overfitting prevention through five-fold cross-validation occurs on the training set for generalization assessment.

E. Evaluation Metrics

The performance of the ReID pipeline is evaluated using the following metrics:

- **Cross-Validation Accuracy**: The average accuracy across five folds, providing an estimate of the model's generalization capability.
- **Training Accuracy**: The accuracy on the entire training set, indicating how well the model fits the training data.
- **Rank-1 Accuracy**: The percentage of query images for which the correct identity is ranked first in the gallery set.
- **Rank-5 Accuracy**: The percentage of query images for which the correct identity appears within the top five ranks.

These metrics offer a comprehensive view of the system's performance, from overall accuracy to ranking precision.

F. Pipeline

The end-to-end ReID pipeline is summarized in Algorithm 1, which outlines the sequential steps from data loading to evaluation.

IV. Results

A. Experimental Setup

The computing environment used an Apple M3 chip (8 cores) while having 16GB of RAM for all experimental procedures. The system ran with three core libraries of Python 3.8 alongside OpenCV 4.5 and scikit-learn 0.24 and NumPy 1.20. The dataset from Kaggle Person ReID provided 80 percent training data and 20 percent validation data before setting aside a test set to use for evaluation. This report dedicates its analysis mainly to validation results.

KNN-based approaches selected the best value of neighbors (K) through five-fold cross-validation procedures executed on training data. Performance metrics were generated with the validated configurations on the validation dataset.

Algorithm 1 Person Re-Identification Pipeline

```
Require: Training images, validation images, feature method,
    K values
Ensure: Accuracy, CMC scores
Load and split dataset into train and validation sets
for each image in train set do
    Resize image to 128×256
    if feature method = "hog" then
        Extract grayscale HOG features
    else if feature method = "hog_color" then
        Split RGB channels, extract HOG per channel, con-
        catenate
    end if
    Append features to train_features
end for
Fit Incremental PCA (n_components = {100, 200, 400})
Transform train_features and val_features
for each K in {3, 5, 10, 15} do
    Train K-NN with Euclidean distance
    Compute cross-validation accuracy
end for
Compute CMC using Euclidean and cosine similarity
return Best K, accuracy, CMC scores
```

B. Accuracy Results

Table I summarizes the performance of various feature extractors and similarity metrics on the Kaggle Person ReID dataset. It includes the best K value, cross-validation accuracy, training accuracy, and, where applicable, Rank-1 and Rank-5 accuracies.

C. Key Observations

- **Color-Based Features Excel**: Feature extractors incorporating color information (e.g., `color_hist`, `hog_color_hist`, `sift_color_hist`, `hog_sift_color_hist`) consistently achieve the highest cross-validation accuracies, ranging from 0.9692 to 0.9703.
- **HOG Performance**: The HOG feature extractor with cosine similarity achieves a notable Rank-1 accuracy of 0.974 and Rank-5 accuracy of 0.986, highlighting its strength in ranking tasks.
- **SIFT Struggles**: SIFT-based methods perform poorly, with cross-validation accuracies between 0.3503 and 0.3704, likely due to its reliance on local keypoints that fail to capture sufficient discriminative information.

V. Discussion

The experimental results provide significant insights into the effectiveness of various feature extractors and similarity metrics for person ReID on the Kaggle dataset.

A. Performance of Feature Extractors

Among all tested feature extractors the ones that rely on color information produce the most consistent results through

TABLE I
PERFORMANCE METRICS FOR FEATURE EXTRACTORS AND SIMILARITY METRICS ON THE KAGGLE PERSON REID DATASET

Feature Extractor	Similarity Metric	Best K	Cross-Val Accuracy	Training Accuracy	Rank-1 Accuracy	Rank-5 Accuracy
hog	euclidean	3	0.9428	0.9859	0.9693	0.9833
hog	cosine	3	0.9468	0.9872	0.974	0.986
hog	knn	3	0.9428	0.9859	0.0007	0.0007
sift	euclidean	5	0.3675	0.6136	0.4353	0.5827
sift	cosine	3	0.3503	0.6379	0.4407	0.576
sift	knn	7	0.3704	0.5912	0.0007	0.0007
color_hist	euclidean	3	0.9702	0.9919	N/A	N/A
color_hist	cosine	3	0.9692	0.9923	N/A	N/A
color_hist	knn	3	0.9702	0.9919	N/A	N/A
hog_sift	euclidean	5	0.7185	0.8891	N/A	N/A
hog_sift	cosine	3	0.664	0.8714	N/A	N/A
hog_sift	knn	5	0.7185	0.8891	N/A	N/A
hog_color_hist	euclidean	3	0.9702	0.9919	N/A	N/A
hog_color_hist	cosine	3	0.9692	0.9923	N/A	N/A
hog_color_hist	knn	3	0.9702	0.9919	N/A	N/A
sift_color_hist	euclidean	3	0.9703	0.9919	N/A	N/A
sift_color_hist	cosine	3	0.9692	0.9923	N/A	N/A
sift_color_hist	knn	3	0.9703	0.9919	N/A	N/A
hog_sift_color_hist	euclidean	3	0.9703	0.9919	N/A	N/A
hog_sift_color_hist	cosine	3	0.9692	0.9923	N/A	N/A
hog_sift_color_hist	knn	3	0.9703	0.9919	N/A	N/A

Note: "N/A" indicates that Rank-1 and Rank-5 Accuracy metrics are still being evaluated, as code for it is still running.

`color_hist`, `hog_color_hist`, `sift_color_hist`, and `hog_sift_color_hist` which yield cross-validation accuracies within a range of 0.9692 to 0.9703. All similarity metrics indicate that color proves to be a fundamental discriminative feature in ReID because it shows resistance to pose, lighting and occlusion disturbances which are typical in ReID datasets. The performance of `color_hist` with Euclidean distance reaches 0.9702 cross-validation accuracy which closely matches the best performance of the complex hybrid `hog_sift_color_hist` (0.9703).

The performance of sift remains low since accuracies reach between 0.3503 (cosine K=3) and 0.3704 (KNN K=7). The SIFT model bases its operation on local keypoints that demonstrate limited generalization in the face of data variability. When combining SIFT features with hog features using the hybrid `hog_sift` method the performance improves over SIFT alone (e.g., 0.7185 with Euclidean, K=5) although it remains inferior to color-based approaches because color information is crucial to achieve satisfactory results.

The standalone hog extractor demonstrates superior performance using cosine similarity and realizes cross-validation accuracy at 0.9468 together with excellent ranking metrics (Rank-1: 0.974, Rank-5: 0.986). Gradient-based features demonstrate outstanding potential in identifying structural patterns which leads to their suitability in ranking systems devoted to precise identity matching.

B. Similarity Metrics and Ranking

projecters must consider carefully when selecting a similarity metric because it provides various subtle effects on performance. When measuring `hog` features cosine similarity demonstrates slightly superior performance than Euclidean distance (0.9468 vs. 0.9428) yet color-based features produce minimal metric difference (0.9702 vs. 0.9692 for `color_hist`). The performance of KNN and Euclidean metrics matches exactly in accuracy levels (0.9428) when examining `hog` data but KNN produces subpar results in ranking accuracy where the Rank-1 and Rank-5 scores remain at 0.0007. The poor ranking results measured by KNN implementation point towards existing flaws that require additional project.

Cosine similarity proves to improve performance rates for all configurations that provide ranking metrics (`hog` and `sift`). The evaluation framework lacks sufficient data to compare color-based features because Rank-1 and Rank-5 accuracies are missing from the results (marked N/A).

C. Impact of K

The selection of K value in KNN-based methods tends to be low at 3 or 5 based on most experimental results. When K reaches seven in the combination of `sift` with KNN the performance fails to grow because distant neighbors introduce unwanted noise. Experimental evidence indicates Person ReID operates best through close and specific comparison operations.

D. Practical Considerations

The `color_hist` solution operates effectively and efficiently (0.9702) which enables real-time applicable deployments. The resource requirements of `sift` and `hog` are high and utilizing their combined versions such as `hog_sift_color_hist` leads to additional computational complexity. These hybrid techniques achieve identical accuracy to `color_hist` but need assessment of performance benefits versus processing expenses for practical implementation.

E. Key Observations

- **Color-Based Features Excel**: Feature extractors incorporating color information (e.g., `color_hist`, `hog_color_hist`, `sift_color_hist`, `hog_sift_color_hist`) consistently achieve the highest cross-validation accuracies, ranging from 0.9692 to 0.9703.
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F. Summary and Future Directions

Person ReID accuracy on the Kaggle dataset relies primarily on color information through continuous success of color-based feature extractors for high performance results. The hog feature method with cosine similarity achieves optimum rankings among all solutions tested. The next phase of project requires evaluation of unlisted ranking metrics for color-based features while examining KNN performance limitations and determining methods to achieve real-time performance of hybrid approaches.

VI. Conclusion

The project proves how conventional machine learning methods perform effectively for person re-identification tasks by demonstrating remarkable results on the Kaggle Person ReID dataset. The combination of color-based features through color histograms and their hybrids provides the most consistent cross-validation accuracy results which go up to 0.9703. The ranking precision of HOG with cosine similarity reaches a benchmark of 0.974 in Rank-1 accuracy. The project confirms that color information enhances total identification performance yet gradient features bring the most precision during comparisons. This streamlined pipeline possesses lightweight attributes which recommend its use in resource-limited devices used for real-time surveillance systems or edge devices. The inadequate results from SIFT analysis combined with insufficient ranking measures for color-based features emphasize the need for additional improvements. The project establishes the correlation of traditional methods with contemporary ReID processes by combining efficiency with accurate results.

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