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

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***Abstract*—The person re-identification (ReID) task involves the recognition of individuals in various regions covered by distinct security cameras and is a very important computer vision problem. The study compares a number of machine learning methods that include the Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) and color histograms for feature extraction. This study compares the performance of the methods under test on both the easy Kaggle Person ReID dataset and the difficult Market-1501 dataset. Color-based feature analysis on Kaggle results in highest cross-validation accuracy at 0.9703 while HOG yields 0.974 Rank-1 accuracy when combined with cosine similarity in controlled settings. These approaches face a major setback on Market-1501 because real-world conditions such as occlusions as well as pose variations make their test accuracies stay at less than 0.1. Conventional approaches perform well in ideal scenarios but are not adequate for real-world scenarios due to their performance limitations. According to the research, these basic numerical techniques need further improvement to meet actual conditions of real-world ReID and recommends using combination methods or improved methods to improve both reliability and universality.**

***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) forms an essential computer vision task which focuses on identifying and linking people captured in separate surveillance camera viewpoints. A query image from one person goes through a process of comparison against multiple image galleries from different cameras that operate in different conditions. The increasing significance of ReID arises because its practical uses include enhancing security within surveillance systems together with improving operational efficiency in retail environments. The growth of camera networks throughout smart cities together with public areas requires advanced efficient ReID solutions to maintain security standards.

Person ReID functions as a security and surveillance system backbone by helping machines identify moving people between cameras with separate viewing areas. Its various uses produce significant effects in security applications. Law enforcement agencies use ReID technology to track suspects from one surveillance location to another which supports criminal investigations. The system serves retail analytics purposes by monitoring customer behaviors to enhance both store arrangements and marketing approaches. Manufacturers face difficulties in ReID deployment because it presents multiple barriers to achieving accurate identification.

- **Variations in pose**: Individuals may appear in different orientations or postures across camera views.
- **Lighting changes**: Inconsistent illumination can significantly alter a person's appearance.
- **Occlusions**: Objects or other individuals may obscure parts of the target person.
- **Background clutter**: Complex or crowded backgrounds can interfere with distinguishing features.

These obstacles highlight the complexity of ReID and the need for resilient approaches to overcome them.

Our motivation originates from the current research field of ReID where deep learning methods have dominated the domain during recent times. The use of Convolutional Neural Networks (CNNs) resulted in outstanding accuracy which brought new achievements to the field. The computational requirements for deep learning models create a heavy price since they need considerable processing power for both training and running the models. The models lack practical deployment capabilities on devices like edge cameras or real-time surveillance systems because they need higher resources than available. Traditional machine learning algorithms provide efficient and lightweight solutions through HOG and SIFT and color histograms which also enable interpretability in their execution. Practical ReID applications benefit from these simpler methods which require limited computational power even though they have demonstrated promising potential for future use.

The main goals for this study consist of two parts:

- The project will build a person ReID system using conventional machine learning methods followed by feature extraction and dimensionality reduction and classification steps.
- This analysis applies the developed pipeline to assess its functionality when used on the Kaggle Person ReID dataset while also testing it against the Market-1501 dataset which contains real-world dataset complexities.

The study evaluates the effectiveness of conventional approaches under various circumstances through ordered goals.

The research makes several advancements in the domain of Person ReID development:

- A research was conducted to evaluate traditional feature extraction techniques HOG, SIFT, color histograms along with their hybrid combinations for ReID applications.
- Traditional techniques receive practical assessments that identify their success boundaries in controlled scenarios while showing their weaknesses in complex real-world circumstances.

Such research reveals precise insights about lightweight approaches by demonstrating their successful and unsuccessful application areas.

This report follows the following organization for presenting our investigation: Section II provides an examination of person ReID research existing previously. Our research employs the Kaggle Person ReID dataset along with Market-1501 dataset and presents information about these datasets in Section III. Our methodology is described in Section IV which explains the subsequent stages starting from feature extraction and proceeding to dimensionality reduction and classification. Our experimental findings along with thorough analysis appear in Section V before the report concludes with Section VI. Our project concludes in Section **??** through a summary of research outcomes and suggested future investigative paths.

II. Related Work

Person re-identification (ReID) has become a primary research area in computer vision because researchers have developed it using both conventional machine learning and deep learning techniques. The section examines major advancements in traditional machine learning and deep learning for Person re-identification while evaluating their positive attributes and drawbacks and establishes our research spot based on this body of work.

Laboratory-developed features compose the core of ReID systems because traditional machine learning approaches built this foundation. The computer vision community frequently adopts publicized image representation techniques including Histogram of Oriented Gradients (HOG) [1], Scale-Invariant Feature Transform (SIFT) [2] as well as color histograms [3]. The edge detection capabilities of HOG make it suitable for silhouette detection yet SIFT offers rotation-invariant keypoints suitable for identifying robust features. Color histograms serve as an efficient method for encoding color distributions because they support crucial identification of individuals by their clothing appearance.

Because these methods provide quick processing while remaining understandable they work well in applications that need to be light in operation. Their operational effectiveness diminishes whenever challenging conditions such as pose variation and lighting variations as well as disruptions in camera vision arise. Research investigators have studied combined approaches to overcome the system weaknesses. The researchers at Wang et al. [4] merged HOG and SIFT features to create a system with improved stability than individual methods. The accuracy achieved by advanced models exceeds traditional methods when these techniques operate in complex real-world conditions.

The development of deep learning methods has paved the way to transform ReID research since it enables computers to automatically extract discriminatory attributes from initial datasets. Convolutions Neural Networks (CNNs) within Deep-ReID [5] produce current best results on Market-1501 benchmarks by delivering rank-1 accuracies higher than 90% [**?**]. The models use extensive labeled datasets for learning abstract representations that improve their resistance to changes in lighting and body pose.

The achievement of deep learning models mandates exceptionally high computing resources together with substantial resource requirements. The hardware requirements for running these models are too demanding to make them suitable for operation in resource-limited real-time surveillance systems and edge devices. Alternatives must be developed to achieve effective operation on systems that have limited computational resources because these tradeoffs between accuracy requirements and computational efficiency exist.

Although deep learning controls the majority of current ReID research traditional machine learning techniques maintain their advantages by being efficient and easy to interpret. This research initiative investigates how traditional HOG, SIFT, color histogram and hybrid features match up against modern person ReID requirements. This study evaluates the traditional methods on both Kaggle Person ReID controlled dataset and the more difficult Market-1501 dataset to understand their performance across various operational environments. We have added valuable knowledge regarding lightweight ReID solutions to current research while showing how traditional methods maintain usefulness in specific situations.

Building on this foundation, we now turn to the datasets and methodology employed in our study.

III. Datasets

The text presents details about our two datasets for Person ReID experiments including the Kaggle Person ReID and Market-1501 databases. We selected these datasets because they have different properties which helped us test standard machine learning approaches across managed testing scenarios and actual-world implementation environments.

A. Kaggle Person ReID Dataset

Within the Kaggle Person ReID dataset [**?**] researchers collected 1,500 different identities through 684,287 images which averaged 456 pictures for each identity. The dataset manifests controlled imaging conditions because all images have consistent lighting and pose variations and standardized backgrounds. The dataset provides uniform conditions which work well for evaluating our ReID pipeline performance at its initial stage.

A normalization step took place before splitting the data where every image received a transformation to 128×256 pixel resolution for standardization in feature extraction operations. Stratified sampling distributed the data into 80% training parts and 20% validation parts to preserve proportional representation of identities. The division method balances identity groups in the training data and validation data ensuring objective performance evaluation.

B. Market-1501 Dataset

The research community uses Market-1501 dataset [?] as a benchmark for ReID studies because it contains 1,501 identities with 32,668 images. The Market-1501 benchmark represents a more complex environment for ReID systems because it adds realistic elements such as object coverings together with camera angle modifications and background interference.

Specially constructed data distribution split configurations led to assigning 80% of images from each identity group to training data while designating the remaining 20% to testing data. The split format includes all 1,501 identities present in both training and testing sections thus allowing model assessment of its ability to recognize similar identity features throughout its various appearances separately from different person discrimination. The model architecture functions appropriately in real-life ReID applications in which the system must identify identical subjects across different environmental settings.

The prepared datasets lead to our methodology for constructing and assessing the ReID pipeline.

IV. Methodology

The following section details our person re-identification (ReID) system through traditional machine learning techniques that enables cross-view identification. Our system contains five essential steps which unite into an integrated workflow beginning with feature extraction and proceeding to dimensionality reduction before classification followed by evaluation. This section details the system components which receive uniform implementations in the examined datasets including Kaggle Person ReID and Market-1501 unless stated otherwise.

A. Feature Extraction

Feature extraction processes raw input images to convert them into useful representations that preserve discriminative aspects of people. We utilize a blend of classical feature extractors that are designed to extract particular visual properties:

- **Histogram of Oriented Gradients (HOG)**: Built with OpenCV, HOG retains edge and gradient information by computing histograms of oriented gradients in localized image regions. Images are processed beforehand by resizing to 128×256 pixels and converting them to grayscale. This feature descriptor is particularly good at detecting structural patterns, such as the silhouette of a person, and hence is a reliable option for ReID tasks.
- **Scale-Invariant Feature Transform (SIFT)**: Also applied through OpenCV, SIFT recognizes keypoints in an image that are insensitive to scale, rotation, and illumination variance. These keypoints are matched between images to give a consistent feature set, improving robustness to viewpoint variance, a frequent issue in ReID.
- **Color Histograms**: Calculated using scikit-learn [?], color histograms represent the distribution of pixel intensities in the red, green, and blue (RGB) channels. This straightforward yet powerful approach captures color-based features, like clothing, that are frequently essential for separating people.
- **Hybrid Features**: To take advantage of the complementary strengths of the above approaches, we form hybrid features by combining their outputs. For example, the combination of HOG and SIFT (hog+sift) combines gradient and keypoint information, while hog+color_hist combines structural and color information for a richer representation.

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, concatenate
    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

These extractors were chosen due to their proven utility in computer vision and computational cost-effectiveness, which is commensurate with the objective of a practical ReID system. Feature extraction is managed by tools such as OpenCV, with subsequent processing capabilities provided by scikit-learn.

B. Dimensionality Reduction

The extracted feature vectors tend to have high dimensions, which may contribute to computational complexity and the likelihood of overfitting in classification. To alleviate this, we use Principal Component Analysis (PCA), a linear method that simplifies the feature space without compromising important information.

- **PCA Implementation**: By employing scikit-learn, we project the feature vectors down to 100, 200, or 400 principal components. We empirically select the number

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.

of components based on a performance-computational trade-off.

- **Rationale**: PCA compresses the data into a lower-dimensional subspace by keeping components that explain most of the variance. This is computationally cheaper for classification and avoids overfitting, hence suitable for low-resource or real-time ReID scenarios.

By maintaining important discriminative information, PCA allows later parts of the pipeline to work effectively on a dense yet informative set of features.

C. Classification

We apply the K-Nearest Neighbors (KNN) algorithm for querying images against a gallery of identities to classify, which is a simple yet effective method for similarity-based matching.

- **KNN Details**: Tensored with scikit-learn, KNN computes feature vector similarity based on both Euclidean distance and cosine similarity. Both measures are selected for their appropriateness for use in high-dimensional space and their interpretability in matching tasks.
- **Parameter Testing**: We experiment with various values for K (e.g., 3, 5, 9) to determine the best number of neighbors. For robustness, we apply five-fold cross-validation to the training set, giving a good estimate of generalization performance and preventing overfitting.

This strategy seeks to balance efficiency with simplicity and thus makes KNN a sensible option for our ReID pipeline.

D. Evaluation Metrics

To analyze the performance of our ReID system, we employ a detailed set of evaluation metrics that estimate both classification and ranking ability:

- **Cross-Validation Accuracy**: Average accuracy on five folds measuring the model's generalization power to unseen instances.
- **Training Accuracy**: Accuracy on the entire training set, indicating how well the model is fitting the training data.
- **Test Accuracy**: Accuracy on an independent test set, giving a final performance measure on new data.
- **Precision, Recall, and F1-Score**: These measures assess classification performance by quantifying false positives (precision), false negatives (recall), and their harmonic mean (F1-score), providing a balanced measure of errors.
- **Rank-1 Accuracy**: An important ReID metric, indicating the proportion of query images in which the correct identity is ranked number one in the gallery set, essential for ranking-based identification tasks.

In combination, these measurements give a complete evaluation of the pipeline's performance in various areas of functioning.

V. RESULTS

This section introduces the experimental results of our person re-identification (ReID) pipeline, tested on the Kaggle Person ReID and Market-1501 datasets. We first outline the experimental setup, followed by in-depth results for each dataset. The relative performance between these datasets indicates the strengths and limitations of classical machine learning approaches in controlled versus practical settings.

A. Experimental Setup

All the experiments were carried out on a machine with an Apple M3 processor (8 cores) and 16GB of RAM. The software platform had Python 3.8, OpenCV 4.5 for feature extraction, scikit-learn 0.24 for dimensionality reduction and classification, and NumPy 1.20 for numerical computation.

The evaluation protocols and dataset splits were the same as specified in Section III. For the Kaggle Person ReID dataset, we adopted an 80% training and 20% validation split. We divided the Market-1501 dataset into 80% training and 20% testing by identity, to ensure coverage of all 1,501 individuals in both sets. We applied five-fold cross-validation to the training set to optimize hyperparameters, i.e., the number of neighbors (K) in the KNN classifier, with final performance measured on the validation or test set.

B. Kaggle Person ReID Results

The Kaggle Person ReID dataset, which has controlled conditions and consistent images, showed robust performance using our conventional machine learning pipeline. As Table I displays, color-based features, like color histograms and their hybrids, yield cross-validation accuracies of around 0.97. This indicates that color information is highly effective in identifying people under controlled conditions. In particular, the HOG feature extractor combined with cosine similarity was outstanding in ranking tasks and achieved a Rank-1 accuracy of 0.974, which is one of the leading configurations.

These findings confirm the pipeline's strength in scenarios where conventional features can successfully achieve discriminative patterns.

C. Market-1501 Results

In comparison, the real-world complexities like occlusions and viewpoint changes in the Market-1501 dataset presented tough challenges to our conventional approaches. Table II gives the performance metrics in terms of test accuracies varying from 0.0476 to 0.0953, along with low precision, recall, F1-scores, and low Rank-1 accuracies. These performance metrics reveal that conventional feature extractors are not capable of generalizing well in challenging, real-world ReID situations.

The substantial performance difference between the two data sets highlights the restrictions of classical machine learning methods in real-world environments. The divergent results encourage a closer inspection of the reasons why our pipeline succeeded or failed, as discussed in the next section.

VI. Discussion

This section explores the performance of our baseline machine learning pipeline on two different datasets: the Kaggle Person ReID dataset and the Market-1501 dataset. Through an examination of the outcomes, we find the merits and drawbacks of classical approaches in both simulated and real-world ReID settings. The discussion is organized into three segments: a review of the Kaggle dataset, a review of the Market-1501 dataset, and comparative observations based on both.

A. Kaggle Dataset Analysis

Kaggle Person ReID dataset with controlled conditions and generous data per identity was a great testing domain for our legacy machine learning pipeline. Cross-validation accuracy was achieved as high as 0.97, specifically with the usage of color-based features like color histograms and hybrids. These worked remarkably well considering uniform image conditions that enabled the utilization of color histograms to abstract clothing patterns for several images of one person. This continuity made them a strong discriminative tool within this environment.

Further, the Histogram of Oriented Gradients (HOG) feature descriptor, when paired with cosine similarity, performed exceptionally well in ranking tasks with a Rank-1 accuracy of 0.974. HOG's strength is that it can capture the edge and gradient structures, which are important in finding a person's silhouette even in the presence of slight pose changes. The richness of images per identity in the dataset—averaging 456—also contributed to the model's strength by allowing it to learn stable and consistent representations for every individual. These findings show that classical features, when used on datasets with stable imagery and adequate training data, can provide competitive performance in ReID tasks.

B. Market-1501 Dataset Analysis

In contrast, the Market-1501 dataset with its real-world complexities exposed severe limitations in our conventional approaches. Test accuracies varied between 0.0476 and 0.0953, along with equally low precision, recall, F1-scores, and Rank-1 accuracies. These dismal metrics indicate the pipeline's inability to generalize when faced with issues like occlusions, pose variations, and background noise.

There were a number of reasons behind this performance decline:

- **Inability of Conventional Features to Capture Fine Details**: Features such as HOG, SIFT, and color histograms are tailored to capture coarse patterns—e.g., edges, keypoints, and color distributions—but tend to miss the fine-grained details required to differentiate individuals in crowded or occluded scenes. For example, HOG's gradient focus might ignore fine texture distinctions, and color histograms ignore spatial relationships altogether.
- **Custom Split and Intra-Class Variation**: Our custom 80/20 split across identity was meant to test the model's capacity to accommodate appearance differences within the same individual (e.g., bagged or bag-less). Yet, this process might have resulted in overfitting over the training images, as the model learned to identify particular instances instead of generalizing over the identity's varied appearances.
- **Limitations of KNN and PCA**: The KNN classifier, especially with Euclidean distance, is afflicted by the curse of dimensionality, whereby distances become non-discriminative in high-dimensional space. Although PCA reduces dimensionality, it makes a linear separability assumption, which does not apply to the high, non-linear variations in Market-1501. This discrepancy most probably hurt the classifier's prediction accuracy.

TABLE II
PERFORMANCE METRICS FOR VARIOUS FEATURE EXTRACTORS (COMBINED INTO ONE TABLE)

Feature Extractor	**Similarity**	**k**	**CV Acc.**	**Train Acc.**	**Test Acc.**	**Prec.**	**Recall**	**F1**	**Rank-1**
Combined Feature Extractors									
hog+sift	Euclidean	3	0.1041	0.4282	0.0556	0.0038	0.0042	0.0037	0.0363
	Euclidean	5	0.1167	0.3250	0.0700	0.0051	0.0044	0.0041	0.0363
	Euclidean	9	0.1297	0.2615	0.0848	0.0052	0.0042	0.0038	0.0363
	Cosine	3	0.1223	0.4027	0.0606	0.0042	0.0060	0.0041	0.0354
	Cosine	5	0.1337	0.3047	0.0731	0.0044	0.0049	0.0035	0.0354
	Cosine	9	0.1436	0.2479	0.0825	0.0036	0.0050	0.0032	0.0354
hog+color_hist	Euclidean	3	0.2530	0.5654	0.0479	0.0139	0.0157	0.0130	0.0386
	Euclidean	5	0.2448	0.4953	0.0580	0.0151	0.0154	0.0128	0.0386
	Euclidean	9	0.2400	0.4455	0.0668	0.0162	0.0144	0.0124	0.0386
	Cosine	3	0.2757	0.5749	0.0561	0.0181	0.0169	0.0153	0.0439
	Cosine	5	0.2679	0.5029	0.0650	0.0192	0.0158	0.0147	0.0439
	Cosine	9	0.2602	0.4468	0.0683	0.0142	0.0145	0.0122	0.0439
sift+color_hist	Euclidean	3	0.2529	0.5654	0.0476	0.0137	0.0156	0.0129	0.0386
	Euclidean	5	0.2448	0.4953	0.0577	0.0150	0.0152	0.0127	0.0386
	Euclidean	9	0.2402	0.4458	0.0667	0.0163	0.0146	0.0126	0.0386
	Cosine	3	0.2756	0.5748	0.0564	0.0182	0.0169	0.0153	0.0439
	Cosine	5	0.2679	0.5026	0.0654	0.0195	0.0160	0.0150	0.0439
	Cosine	9	0.2600	0.4466	0.0685	0.0145	0.0148	0.0124	0.0439
hog+sift+color_hist	Euclidean	3	0.2529	0.5654	0.0476	0.0137	0.0156	0.0129	0.0386
	Euclidean	5	0.2448	0.4953	0.0577	0.0150	0.0152	0.0127	0.0386
	Euclidean	9	0.2402	0.4458	0.0667	0.0163	0.0146	0.0126	0.0386
	Cosine	3	0.2756	0.5748	0.0564	0.0182	0.0169	0.0153	0.0439
	Cosine	5	0.2679	0.5026	0.0654	0.0195	0.0160	0.0150	0.0439
	Cosine	9	0.2600	0.4466	0.0685	0.0145	0.0148	0.0124	0.0439
Individual Feature Extractors									
SIFT	Euclidean	3	0.1054	0.4013	0.0704	0.0049	0.0055	0.0047	0.0406
	Euclidean	5	0.1201	0.2943	0.0827	0.0059	0.0048	0.0046	0.0406
	Euclidean	9	0.1316	0.2324	0.0953	0.0067	0.0042	0.0045	0.0406
	Cosine	3	0.1154	0.3881	0.0644	0.0045	0.0047	0.0038	0.0390
	Cosine	5	0.1296	0.2860	0.0780	0.0051	0.0059	0.0045	0.0390
	Cosine	9	0.1432	0.2328	0.0864	0.0030	0.0039	0.0024	0.0390
Color Histogram	Euclidean	3	0.2530	0.5654	0.0479	0.0139	0.0157	0.0130	0.0386
	Euclidean	5	0.2448	0.4953	0.0580	0.0151	0.0154	0.0128	0.0386
	Euclidean	9	0.2400	0.4455	0.0668	0.0162	0.0144	0.0124	0.0386
	Cosine	3	0.2757	0.5749	0.0561	0.0181	0.0169	0.0153	0.0439
	Cosine	5	0.2679	0.5029	0.0650	0.0192	0.0158	0.0147	0.0439
	Cosine	9	0.2602	0.4468	0.0683	0.0142	0.0145	0.0122	0.0439
HOG	Euclidean	3	0.1955	0.5514	0.0528	0.0081	0.0049	0.0055	0.0321
	Euclidean	5	0.1900	0.4734	0.0655	0.0075	0.0036	0.0044	0.0321
	Euclidean	9	0.1884	0.4128	0.0801	0.0078	0.0039	0.0045	0.0321
	Cosine	3	0.2331	0.5752	0.0544	0.0128	0.0073	0.0083	0.0327
	Cosine	5	0.2270	0.5078	0.0683	0.0122	0.0062	0.0075	0.0327
	Cosine	9	0.2267	0.4553	0.0831	0.0110	0.0064	0.0074	0.0327

These challenges highlight the limitations of traditional approaches in meeting real-world ReID applications, where variability and complexity of data require more sophisticated feature representations.

C. Comparative Insights

The divergent performance between the Kaggle and Market-1501 datasets presents key insights into the relevance of conventional machine learning methods in ReID. On the Kaggle dataset, where images are homogeneous and identities are well-covered, techniques like color histograms and HOG attained accuracy and ranking measures on par with more advanced models. However, on Market-1501, these same techniques attained test accuracies of less than 0.1, which underscores their failure to adapt to real-world scenarios such as occlusions and pose variations.

Although the Kaggle results were encouraging, Market-1501 revealed inherent shortcomings, especially when dealing with intra-class variations and challenging backgrounds. This gap implies that conventional solutions are appropriate for controlled settings but need significant boosts—like better feature extractors or sophisticated classification methods—to be suitable for usable, real-world ReID problems.

These insights guide our judgment regarding the current status and the way forward in lightweight ReID solutions.

D. Key Observations

- **Color Dominates on Kaggle**: Feature extractors incorporating color (e.g., `color_hist`, `hog_color_hist`) achieve top accuracies (0.9692–0.9703).
- **HOG Excels in Ranking**: HOG with cosine similarity yields strong ranking metrics (Rank-1: 0.974, Rank-5: 0.986) on Kaggle.
- **Market-1501 Challenges**: Traditional methods fail in real-world conditions, with test accuracies below 0.1.

E. Summary and Future Directions

On the Kaggle dataset, color data fuels top accuracy, and `color_hist` and other extractors dominate performance, with cosine similarity HOG optimizing ranking. These approaches however fail on Market-1501, highlighting their weakness in intricate environments. Subsequent work ought to test for missing ranking scores of color features on Kaggle, correct KNN's ranking shortcomings, streamline hybrids for real-time applications, and investigate deeper features to counter datasets such as Market-1501. All these results influence our conclusions on lightweight ReID solutions.

VII. Conclusion

This research compares classical machine learning methods for person re-identification (ReID) on two datasets, revealing their strengths and limitations. On the Kaggle Person ReID dataset with its controlled environment, our method performs well, with cross-validation accuracies of up to 0.9703 based on color histograms and a Rank-1 accuracy of 0.974 based on HOG and cosine similarity. These findings highlight the capability of classical methods when data is uniform and training is sufficient. But on the real-world complexity of the Market-1501 dataset, with occlusions and changing lighting, performance collapses to test accuracies of less than 0.1. This gap points to the essential trade-off: classical approaches provide computational efficiency but at the expense of robustness for real-world deployment. In the future, augmenting these methods with more sophisticated features or the incorporation of deep learning would help overcome these limitations, though at the cost of heightened resource needs. This analysis gives a clear reference point for conventional ReID approaches, highlighting their pragmatic limitations and paving the way for future research on scalable, effective solutions that optimize performance and complexity in varied settings.

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