Machine Learning-Based Approach for Person Re-Identification

Rushi Moliya*, *AU2240020*, Shlok Shelat*, *AU2240025*, Dhananjay Kanjariya*, *AU2240023*,
Shrey Salvi*, *AU2240033*, Purvansh Desai*, *AU2240036*,
*School of Engineering and Applied Science, Ahmedabad University, Ahmedabad 380009, India
Emails: {rushi.m, shlok.s1, dhananjay.k, shrey.s2, purvansh.d}@ahduni.edu.in

***Abstract*—Person re-identification (ReID) is a critical task in surveillance systems, aiming to match individuals across non-overlapping camera views. This study explores a traditional machine learning pipeline using Histogram of Oriented Gradients (HOG) for feature extraction, with and without color information, followed by K-Nearest Neighbors (K-NN) for classification. We investigate the impact of color features, varying K values in K-NN (3, 5, 10, 15), and dimensionality reduction using Incremental PCA with 100, 200, and 400 features. Evaluated on a Kaggle person ReID dataset, our method achieves a peak accuracy of 94.28% with 200 features and K=3 using color HOG features. Future work will explore additional feature extractors, similarity metrics, and datasets like CUHK and Market-1501 to enhance performance.**

***Index Terms*—Person Re-Identification, HOG, K-NN, Dimensionality Reduction, Feature Extraction**

I. Introduction

Information retrieval systems for person re-identification (ReID) plays a critical role within the computer vision domain because it supports surveillance as well as security operations and public safety monitoring. ReID achieves the purpose of identifying individuals across independent camera system views thus addressing a growing need caused by expanding urban camera infrastructure. Through this technology authorities can monitor extensive areas for surveillance and achieve suspect identification and perform public space crowd analysis. The positive performance of deep learning approaches in ReID has led to their recent dominance yet their implementation requires sizeable datasets together with heavy computing power. The restricted practicality and resource requirements and the inability to interpret their operational logic become major hurdles for their use in real-time applications and resource-limited contexts where security-relevant decision understanding remains crucial.

Traditional machine learning serves as a robust practical approach to solve the issues that arise during person ReID processes. Traditional ML differs from deep learning because it applies simple classification algorithms while depending on features created manually. The system's functionality works well in real-time applications and limited computational resources environments. Traditional ML approaches provide understandable explanations about decision processes while practitioners can explore their decision mechanisms which is crucial for security and law enforcement applications that need transparency. Among existing algorithms traditional ML provides both efficient performance and practical methods that create a minimal yet powerful solution for ReID data operations with limited resources.

The project develops a person ReID traditional ML pipeline that utilizes HOG features with color data extraction before classifying through K-NN. The shape and texture identification capabilities of HOG together with color features that incorporate clothing characteristics enhance system discrimination effectiveness. The efficiency optimization of this system utilizes Principal Component Analysis (PCA) to shrink the feature space dimensionality which decreases running time demands. Using K=3 along with Euclidean distance measure the K-NN classifier performs individual identification through feature similarity matching. This approach reaches 94.28% cross-validation accuracy when tested on a Kaggle ReID dataset by using 200 features while maintaining both efficiency and interpretability as alternatives to deep learning systems. Traditional ML shows through this method that it can achieve powerful results in real-world ReID applications.

II. Methodology

Our pipeline involves feature extraction, dimensionality reduction, and classification, applied to multiple person ReID datasets.

A. Datasets

This study leverages four datasets for person re-identification (ReID) tasks: the Kaggle Person Re-Identification Dataset (currently used), Market-1501, CUHK03, and RAPv2. Each dataset offers unique characteristics and variations, making them suitable for training and evaluating robust ReID models. Below is a summary of their key statistics:

TABLE I
Dataset Statistics

Dataset	#Classes (IDs)	Total Images	Images per Class (Avg.)
Kaggle (Current)	1,500	684,287	456
Market-1501	1,501	32,668	22
CUHK03	1,467	13,164	9
RAPv2	4,118	84,928	21

1) Dataset Descriptions:

- **Kaggle Person Re-Identification Dataset (Currently Used)**: Sourced from Kaggle [2], this dataset contains 1,500 unique identities with 684,287 images, averaging 456 images per identity. The images are organized into subfolders by person ID. We split the data into 80% training and 20% validation sets (1,500 images for validation), using stratified sampling to ensure balanced representation of identities.
- **Market-1501**: A benchmark dataset with 1,501 identities and 32,668 images, averaging 22 images per identity. It reflects real-world ReID challenges, making it ideal for evaluating practical applications.
- **CUHK03**: Includes 1,467 identities and 13,164 images, averaging 9 images per identity. It is challenging due to sparse representation and tough conditions.
- **RAPv2**: The largest in terms of identities, with 4,118 classes and 84,928 images, averaging 21 images per class. It includes rich attribute annotations (e.g., gender, age, clothing).

2) Types of Variations in Images: The datasets exhibit intra-class, inter-class, and environmental/contextual variations:

- **Intra-Class Variations**: Kaggle offers the most (456 images/ID) with variations in pose, lighting, backgrounds, camera angles, and clothing. Market-1501 and RAPv2 (22 and 21 images/ID) include camera angles, lighting, and background changes. CUHK03 (9 images/ID) has occlusions, lighting, and perspective variations.
- **Inter-Class Variations**: All datasets feature diverse identities (1,467–4,118), with differences in physical appearance, clothing, and traits.
- **Environmental/Contextual Variations**: Lighting and background changes are common across all datasets. CUHK03 includes occlusions. Market-1501 and CUHK03 have varied camera angles and image quality. RAPv2 adds attribute-based variations (e.g., gender, age, clothing).

B. Feature Extraction

We used HOG for feature extraction:

- **Grayscale HOG**: Images resized to 128×256, converted to grayscale, and HOG features extracted (8×8 pixels per cell, 2×2 cells per block).
- **Color HOG**: RGB channels split, HOG applied per channel, and features concatenated with grayscale HOG to capture color information.

Other methods (SIFT, color histograms) were implemented but not fully evaluated due to time constraints.

C. Dimensionality Reduction and Classification

PCA performed via incremental procedure cut down features to either 100, 200, or 400 dimensions to handle computational complexity. We used K-NN classification on the reduced features via Euclidean distance with K values set to 3, 5, 10 and 15 under five-fold cross-validation. Our analysis of ranking methods included evaluation of Euclidean and cosine similarity but we are currently waiting for results.

Algorithm 1 Feature Extraction and Evaluation

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
```

III. Results

The analysis will use an extensive comparison table (similar to Table III) to evaluate how different feature extractors (HOG, SIFT, color histograms, and combinations) together with similarity metrics (Euclidean, cosine, K-NN) and K values influence cross-validation accuracy and training accuracy and establish Rank-1 and Rank-5 accuracy metrics.

TABLE II
ACCURACY RESULTS WITH COLOR HOG FEATURES

Features (PCA)	K (K-NN)	Accuracy (%)
100	3	81.56
	5	79.44
	10	77.25
	15	75.08
200	**3**	**94.28**
400	3	87.00
	5	85.60
	10	82.55
	15	80.27
1000	3	87.82
	5	86.24

CMC curves and Rank-1/Rank-5 accuracy evaluations are in progress, as we explore additional feature extractors and similarity metrics.

IV. Discussions

The inclusion of color information in HOG features produces better ReID performance due to its important role as a key matching criteria [7]. A feature dimension of 200 strikes the best balance between accuracy and operational efficiency but excessive dimensions above 400 cause overfitting in the model. The selection of K=3 leads to optimal results since values above K diminishes the effect of authentic neighboring relationships. Our approach remains lightweight compared to deep learning methods [1], [3]–[5] because of its limited resistance to pose and lighting changes in the images. Generalization becomes restricted due to the restricted diversity of examples in the Kaggle dataset. Additional research will solve present limitations through the use of new extraction features alongside new datasets.

V. Conclusion

TThe research shows that color-enhanced HOG features together with K-NN and PCA-based dimensional reduction yield a maximum 94.28% accuracy when used on a Kaggle person ReID dataset. This method delivers good computation speed yet its performance is restricted by both the constrained dataset size and the established traditional techniques' stability. The research team plans to integrate bigger datasets together with cutting-edge approaches in order to boost performance levels.

VI. Future Work

Future efforts will focus on:

- **Datasets**: Extending evaluation to CUHK, Market-1501, and RAPv2 for greater diversity.
- **Feature Extraction**: Exploring additional methods like SIFT, color histograms, and hybrid approaches [7].
- **Dimensionality Reduction**: Testing alternatives like t-SNE to better preserve feature structure.
- **Evaluation**: The analysis will use an extensive comparison table (similar to Table III) to evaluate how different feature extractors (HOG, SIFT, color histograms, and combinations) together with similarity metrics (Euclidean, cosine, K-NN) and K values influence cross-validation accuracy and training accuracy and establish Rank-1 and Rank-5 accuracy metrics.

TABLE III
Planned Future Comparison Table Format

Feature Extractor	Similarity Metric	K	Cross-Val Accuracy	Rank-1 Accuracy	Rank-5 Accuracy
HOG+SIFT	euclidean	-	-	-	-
HOG+color hist	euclidean	-	-	-	-
SIFT+color hist	cosine	-	-	-	-
HOG+SIFT+color hist	cosine	-	-	-	-

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