

Human Activity Classification Using MHI and MEI with SVM, KNN, and MLP Classifiers

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Abstract—This paper presents a human activity recognition system that leverages Motion History Images (MHI) and Motion Energy Images (MEI) in combination with classical machine learning classifiers, including Support Vector Machines (SVM), k -Nearest Neighbors (KNN), and Multi-Layer Perceptrons (MLP). Using Hu moment descriptors extracted from the motion templates, we evaluate how each classifier performs when provided with low-dimensional, global shape features. We also examine the impact of parameter tuning—particularly motion thresholds and temporal decay—on the quality of the templates and the resulting changes in classification accuracy.

Our experiments show that although all three classifiers can make use of Hu moment representations, their performance varies depending on their sensitivity to feature distribution and noise. These findings highlight both the strengths and limitations of compact temporal templates and motivate the exploration of richer feature representations, such as HOG or learned descriptors, as promising directions for future work.

I. INTRODUCTION

Human activity recognition (HAR) plays an important role in applications such as surveillance and security, human–computer interaction, consumer devices, sports analytics, automotive systems, and healthcare monitoring. A core challenge in HAR is to represent the dynamics of human motion in a form that is both compact and discriminative, while remaining robust to variations in subjects, appearance, and viewpoint. Although deep learning methods have become dominant in recent years, classical motion-template approaches continue to offer interpretable and computationally efficient alternatives for video-based action analysis.

Motion History Images (MHI) and Motion Energy Images (MEI), introduced in the seminal work of Bobick and Davis [1], convert a sequence of frames into static temporal templates that summarize where motion has occurred and how it evolves over time. These templates have been widely used in early HAR pipelines due to their simplicity and their ability to encode coarse action structure in a compact form.

Once constructed, MHIs and MEIs allow the extraction of global shape-based features. Hu moments provide a lightweight, invariant descriptor that has been used in template-matching and gesture-recognition tasks within classical computer-vision systems [3]. More expressive local descriptors, such as Histograms of Oriented Gradients (HOG) [4], capture fine-grained spatial information and were foundational to many pre-deep-learning action-recognition methods. Although HOG is not the focus of this work, it

serves as a useful point of comparison for understanding the limitations of Hu moments and for motivating future improvements.

This paper evaluates an MHI/MEI-based action-recognition system using three classical classifiers: Support Vector Machines (SVM) [12], k -Nearest Neighbors (KNN), and a lightweight Multi-Layer Perceptron (MLP). Each classifier is trained on Hu-moment descriptors extracted from motion templates, enabling a controlled comparison of classifier behavior under a low-dimensional, globally defined representation.

The system pipeline includes preprocessing, motion-template construction, feature extraction, classifier training, and evaluation. The experimental results highlight both the strengths and limitations of Hu-moment-based representations, echoing earlier findings that silhouette-driven templates capture coarse motion patterns but struggle with subtle differences among similar actions [1]. These observations, together with trends in modern spatiotemporal feature learning [10], point toward promising future directions such as HOG-based motion descriptors, trajectory-aligned features, or learned CNN representations, as well as temporal modeling using probabilistic or recurrent architectures.

II. RELATED WORK

A. Motion Energy Images (MEI)

Motion Energy Images (MEI) [1], capture the spatial extent of motion over the most recent τ frames. MEI is defined as a binary motion template:

$$E_\tau(x, y, t) = \begin{cases} 1, & \text{if motion occurs in } [t - \tau, t], \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

In this formulation, motion is detected through thresholded frame differencing, following the classical temporal-template approach [1]:

$$D(x, y, t) = \begin{cases} 1, & |I(x, y, t) - I(x, y, t - 1)| > \theta, \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

MEI Templates Across Six Actions: Figure 1 shows MEI templates for six representative actions (walking, jogging, running, boxing, hand waving, and hand clapping). These binary silhouettes highlight the overall spatial footprint of motion

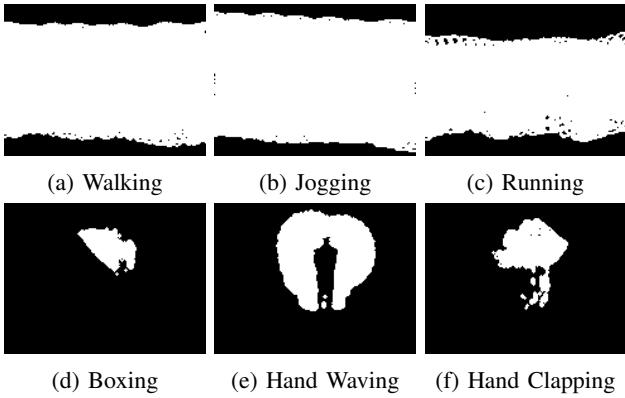


Fig. 1: MEI templates for six actions

accumulated over time, revealing differences in limb usage, displacement, and body posture across actions. For walking, jogging, and running, the MEIs appear as large white blobs because the actor moves left-to-right and back across the frame. Since MEI represents the union of all motion regions over time, any pixel touched during these actions becomes active, resulting in a broad motion band.

B. Motion History Images (MHI)

Motion History Images (MHI) encode the recency of motion by assigning larger intensity values to pixels where motion has occurred more recently:

$$M_\tau(x, y, t) = \begin{cases} \tau, & \text{if } B_\tau(x, y) = 1, \\ \max\{0, M_\tau(x, y, t-1) - 1, 0\}, & \text{if } B_\tau(x, y) = 0. \end{cases} \quad (3)$$

Binary Motion Mask and Background Subtraction: Both MEI and MHI use a binary motion mask derived from frame differencing:

$$B_\tau(x, y, t) = \begin{cases} 1, & |I_\tau(x, y) - I_{\tau-1}(x, y)| \geq \theta, \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

This mask identifies regions of movement by comparing consecutive frames. Light smoothing can be applied before differencing to suppress noise. Where MEI simply accumulates these binary masks, MHI applies temporal decay, producing a gradient that reflects *how motion evolves over time*.

C. Preliminaries: Image Moments and Normalized Central Moments

The Hu moment invariants used in this work are derived from standard image moment definitions [7]. These expressions describe how spatial information in an image is aggregated and normalized to achieve invariance to translation, rotation, and scale.

Raw Image Moments.: Given an image intensity function $I(x, y)$, the (p, q) -th raw moment is defined as:

$$M_{pq} = \sum_x \sum_y x^p y^q I(x, y). \quad (5)$$

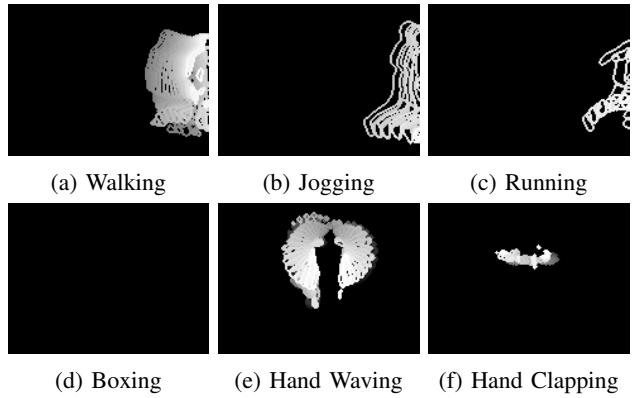


Fig. 2: MHI templates for six actions.

Centroid of the Image.: The centroid (\bar{x}, \bar{y}) is computed from the first-order raw moments:

$$\bar{x} = \frac{M_{10}}{M_{00}}, \quad \bar{y} = \frac{M_{01}}{M_{00}}. \quad (6)$$

Central Moments.: Translation-invariant central moments are computed by shifting coordinates relative to the centroid:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q I(x, y). \quad (7)$$

Normalized Central Moments.: Scale-invariant normalized central moments are obtained as:

$$\nu_{pq} = \frac{\mu_{pq}}{\mu_{00}^{1+\frac{p+q}{2}}}. \quad (8)$$

These normalized moments form the basis for the Hu invariant descriptors used in the next subsection, allowing activity templates such as MHI and MEI to be represented using compact shape measures that are invariant to geometric transformations.

MHI Templates Across Six Actions: Figure 2 displays MHI templates for the same six actions. Unlike MEI—which only shows where movement occurred—MHI distinguishes between recent and older motion. Brighter areas correspond to more recent movement, making MHI a richer temporal descriptor.

Evidence: Binary Motion Detection Across Time

To demonstrate the foundation upon which MEI and MHI are constructed, Figure 3 presents binary motion masks extracted at three different time instants[1]. Each image is produced by thresholding pixel differences between consecutive frames, highlighting only the regions where motion occurred at that moment.

These examples show how different actions produce distinct temporal patterns: locomotion actions such as walking and jogging generate smoother, periodic silhouettes, whereas high-frequency actions like boxing or hand clapping produce denser, rapidly changing motion regions.

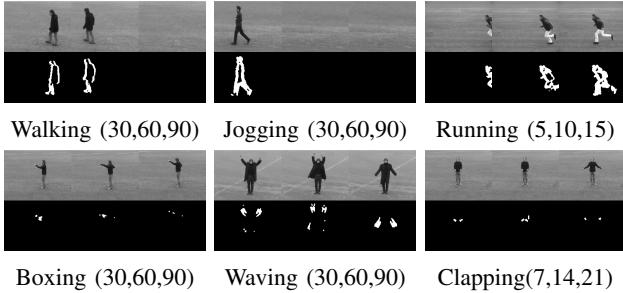


Fig. 3: Binary motion evidence at different frames is indicated in braces for each action sequence.

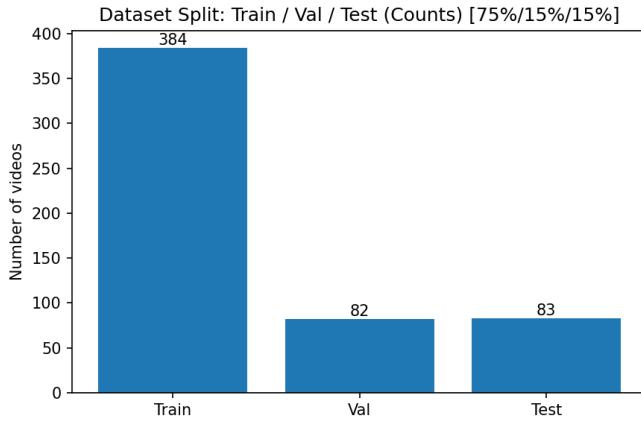


Fig. 4: Dataset split visualization showing the number of videos allocated to the 75/15/15 train-validation-test partitions.

III. CLASSIFICATION

This work evaluates three supervised classifiers—SVM, KNN, and MLP—using Hu moment descriptors extracted from MHI and MEI templates in the human action dataset. The dataset was divided into a **75% training, 15% validation, and 15% test split**. This ensures that all models are evaluated consistently while preventing overlap between subjects across splits. Because all models operate on the same compact, low-dimensional feature representation, the comparison highlights differences in how each classifier handles these constraints rather than differences arising from the features themselves.

A. Dataset Split Overview

To provide a clear view of how the video samples were distributed across the three subsets, Figure 4 presents a simple histogram-style visualization showing the number of videos assigned to training, validation, and testing.

This visualization emphasizes that the majority of samples contribute to model training, while dedicated validation and test subsets enable unbiased hyperparameter tuning and final performance assessment.

B. k-Nearest Neighbors (KNN)

KNN assigns labels based on the nearest samples in the Hu-moment feature space. Since it makes no assumptions about how classes should be separated, its performance is strongly influenced by the structure and noise inherent in the descriptors. Earlier studies have noted that KNN is particularly prone to overfitting in low-dimensional spaces where class clusters lie close together [2]. This behavior is reflected in our dataset as well: actions involving whole-body motion, such as walking, jogging, and running, produce Hu features that overlap significantly. As a result, KNN performs extremely well on the training data but struggles to generalize to new sequences, where differences in subjects, motion style, lighting, or camera instability cause small variations that shift samples across class boundaries.

C. Support Vector Machine (SVM)

SVM seeks a decision boundary that maximizes the margin between action classes in the Hu-moment feature space. Because the descriptors are compact and the classes partially overlap, margin-based separation is generally more robust than distance-based approaches. This aligns with earlier work demonstrating the effectiveness of SVMs in such settings [12]. In our dataset, actions like walking, jogging, and running share similar global motion patterns, which makes them difficult to separate cleanly. Even so, the SVM maintains relatively stable generalization performance, handling variations in subject appearance, execution speed, and recording conditions better than KNN.

D. Multi-Layer Perceptron (MLP)

The MLP introduces a simple neural network capable of modeling nonlinear relationships in the feature space. Although neural networks typically excel with rich, high-dimensional inputs [13], the MLP here receives only a 14-dimensional Hu descriptor per frame. Because Hu moments capture only coarse global structure, the network's expressive capacity is not fully utilized. As a result, the MLP behaves similarly to the SVM: it improves slightly on some classes but is ultimately limited by the information available in the Hu features. This reinforces the idea that the main challenge lies in the representation rather than in the choice of classifier.

Overall, the comparison indicates that when using compact global descriptors such as Hu moments, classifier performance is largely constrained by feature limitations rather than model complexity.

IV. ANALYSIS

To compare the behavior of the three classifiers, we consolidate the main performance metrics in Table I. This provides a unified view of training, validation, test, and video-level accuracy across SVM, KNN, and MLP when all three models are trained using Hu moments extracted from MHI and MEI. The table is reported in the Results section; here we focus on interpreting the trends it reveals.

A. Key Observations

Limited discriminative power of Hu features.: Hu moments provide compact global shape descriptors, but they offer limited ability to separate visually similar activities, a limitation noted in prior template-based action recognition research [1]. Because all classifiers rely on the same low-dimensional representation, their performance is inherently constrained by the descriptive power of Hu moments.

B. Effect of Subject and Scene Variability

The dataset includes substantial intra-class variability: different subjects perform the same action with variations in body shape, clothing, motion style, and execution speed. Similar challenges in human action recognition datasets have been documented in earlier evaluations [6]. Because Hu moment features extracted from MHI/MEI templates encode only coarse global motion shape, they are not expressive enough to disentangle these variations. Consequently, actions such as walking, jogging, and running—already visually similar—become even harder to discriminate when performed by different individuals under different conditions.

KNN exhibits pronounced overfitting.: KNN achieves nearly perfect training accuracy but shows a substantial drop in validation and test performance. This behavior is consistent with classical observations that KNN is highly sensitive to small variations when classes are not well separated in feature space [2]. In our case, overlapping Hu moment descriptors cause unstable nearest-neighbor relationships, limiting generalization.

SVM shows more stable generalization.: SVM avoids the extreme overfitting observed in KNN and produces more balanced performance across training and test sets. Prior work has shown that SVMs generalize effectively in low-dimensional settings with overlapping features by maximizing the decision margin [12]. Nevertheless, their accuracy remains constrained by the limited separability inherent in Hu-based representations.

MLP performs comparably but is feature-limited.: Although MLPs can model nonlinear relationships, their performance does not substantially exceed that of SVM when trained on simple descriptors. Similar effects have been reported in earlier neural-network-based action analysis, where limited features restrict the benefits of nonlinear models. Because the MLP receives only 14 global shape features, its expressive capacity is underutilized.

Upper-bound limitations.: Across all three classifiers, accuracy remains below higher performance thresholds due to factors commonly cited in template-based action-recognition systems: (i) compression of temporal information in silhouette templates, (ii) similarity among certain actions (walking, jogging, running), and (iii) subject-level variability [1], [6]. These factors contribute to classification ambiguity that is not fully resolved by Hu-based descriptors.

Taken together, the analysis highlights that while classifier choice influences generalization behavior, the primary perfor-

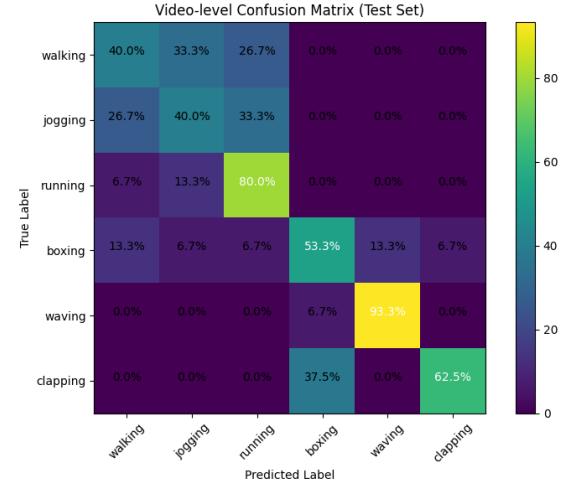


Fig. 5: SVM classifier using Hu moment features.

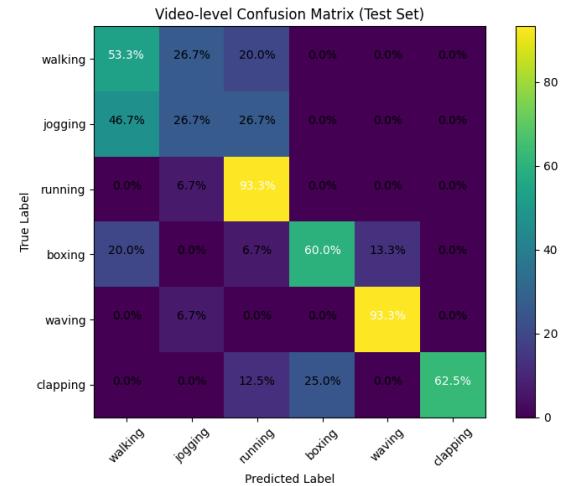


Fig. 6: KNN classifier using Hu moment features.

mance limitations stem from the restricted descriptive capacity of Hu moments.

C. Confusion Matrix Visualization

To further illustrate how each classifier distributes predictions across activity classes, Figures 5, 6, and 7 present the confusion matrices for SVM, KNN, and MLP. These matrices visualize class-specific behavior, including which actions are consistently recognized and where misclassifications occur.

V. RESULTS

This section presents the quantitative outcomes obtained from the three classifier configurations evaluated in this work. To avoid redundancy, we summarize all measured performance metrics in a single consolidated table (Table I). These values include training, validation, test, and video-level accuracy for each classifier trained on Hu moment descriptors extracted from MHI and MEI templates.

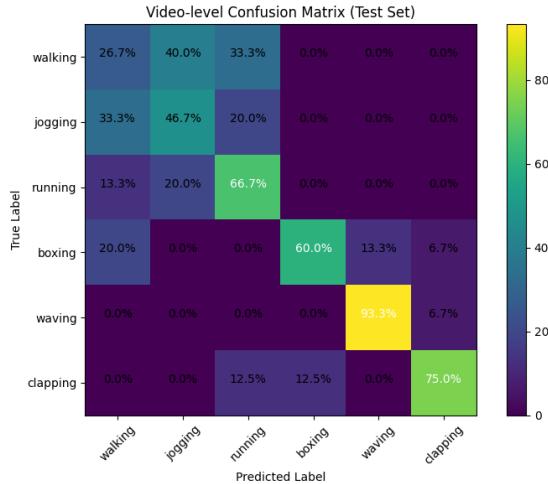


Fig. 7: MLP classifier using Hu moment features.

TABLE I: Performance results for all classifiers using Hu moment features.

| Classifier | Train | Val | Test | Video Acc. |
|------------|-------|-------|-------|------------|
| SVM (Hu) | 0.764 | 0.577 | 0.514 | 0.627 |
| KNN (Hu) | 1.000 | 0.476 | 0.453 | 0.651 |
| MLP (Hu) | 0.748 | 0.553 | 0.512 | 0.627 |

For completeness, confusion matrices for each classifier configuration were generated and are included as figures in the results section. These matrices illustrate the distribution of predicted labels across classes but are not interpreted here, as further discussion is provided in the Analysis section.

In addition to accuracy values, the trained pipelines for each experiment (SVM, KNN, and MLP) were saved for reproducibility. The corresponding feature matrix dimensions reflect the use of Hu moment descriptors, resulting in a 14-dimensional feature vector for every video frame.

VI. IMPROVEMENTS

After evaluating SVM, KNN, and MLP on Hu moment features, SVM consistently offered the most stable performance. It was therefore selected as the primary candidate for improvement. The refinements described below build on a baseline Hu-only model that had already been tuned to a reasonable level before additional enhancements were introduced.

A. Feature Expansion: From 14D Hu Moments to a 20D Motion Descriptor

The original feature representation consisted of 14 values: the seven Hu moments extracted from the MHI and the seven Hu moments extracted from the MEI. While compact and effective for capturing global shape, this 14D descriptor omits several important characteristics of human motion, such as intensity, localization, and temporal variability. To address this limitation, six additional motion descriptors were introduced, expanding the feature vector from 14 to 20 dimensions.

TABLE II: Comparison of SVM performance before and after adding auxiliary motion features.

| Model | Train | Val | Test | Video Acc. |
|---------------------------------|-------|-------|-------|------------|
| Baseline SVM (Hu-only) | 0.764 | 0.577 | 0.514 | 0.627 |
| Improved SVM (Hu + extra feats) | 0.939 | 0.682 | 0.622 | 0.807 |

This expansion strengthens the representation in three key ways:

- **Capturing motion magnitude:** Aggregated motion-pixel counts provide a direct measure of how much motion occurs in a frame, helping distinguish high-intensity actions (running, boxing) from lower-intensity ones (walking).
- **Encoding temporal dynamics:** Features such as the frame-to-frame change in the MHI and the short-term standard deviation of motion quantify how stable, periodic, or bursty an action is—properties not encoded by Hu moments.
- **Preserving spatial structure:** Lower-body motion, central-region motion, and central-to-side ratios describe how motion is distributed across the frame. These cues differentiate actions with similar overall silhouettes but different spatial emphasis (e.g., running vs. boxing).

By augmenting the Hu feature space with these lightweight descriptors, the SVM operates in a richer but still low-dimensional space where classes are more separable. This expansion from 14D to 20D significantly enhances the model’s ability to discriminate between actions with subtle motion differences, as validated by improved validation and video-level accuracy.

B. Parameter Calibration

Several parameters controlling MHI/MEI construction were adjusted:

- τ (decay): balanced temporal smoothing vs. motion persistence,
- θ (threshold): reduced noise in motion masks,
- k_size (Gaussian blur): stabilized differencing,
- reset frequency: prevented MHI saturation.

These refinements produced cleaner templates and more reliable features, helping the SVM separate visually similar actions such as walking, jogging, and running.

C. Performance Comparison

Table II summarizes the improvement over the baseline Hu-only SVM. The largest gain appears in video-level accuracy, rising from approximately 0.63 to over 0.80.

D. Confusion Matrix Evidence

Figure 8 shows the confusion matrix of the improved model. Compared to earlier runs, the diagonal is noticeably stronger and confusions between locomotion classes are substantially reduced. This reflects the added discriminative value of the auxiliary motion descriptors.

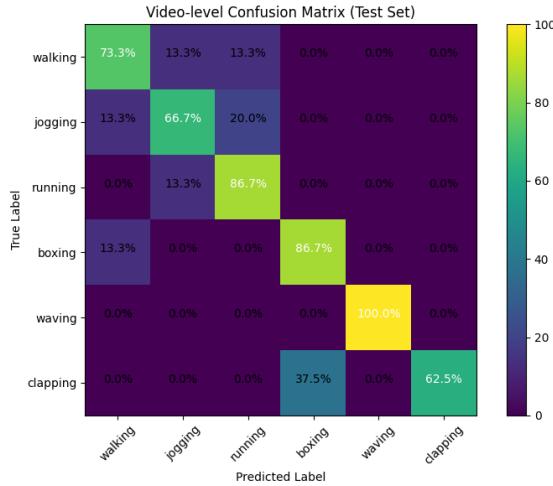


Fig. 8: Confusion matrix of the improved SVM classifier using Hu moments plus auxiliary motion features. Strengthened diagonal entries reflect clearer class separation.

E. Summary

Overall, the improvements result from:

- a richer feature set augmenting Hu moments,
- calibrated motion-template parameters,
- cleaner and more stable MHI/MEI representations.

These changes enabled the SVM to outperform all earlier Hu-based models while preserving interpretability and computational simplicity.

VII. FUTURE WORK

The results obtained using Hu moments across SVM, KNN, and MLP indicate that the primary bottleneck lies in the limited expressive power of the features rather than in the classifiers themselves. To overcome these constraints and achieve higher recognition accuracy, several focused directions offer strong potential for improvement.

A. Richer Spatial Descriptors: HOG Features

Since Hu moments capture only coarse global shape, a natural next step is to explore more expressive handcrafted descriptors. Histogram of Oriented Gradients (HOG) provides detailed local gradient information and has been shown to be highly effective for human-related classification tasks [4]. Incorporating HOG features into the same MHI/MEI pipeline would allow a direct comparison against Hu moments and may significantly strengthen class separability.

B. Deep Feature Extraction Using CNNs

Deep convolutional neural networks can learn high-level spatial representations directly from image data. CNN-based feature extraction has proven highly effective for action recognition when applied to appearance or motion cues, including silhouette-style inputs and video frames [11]. Applying such models to MHI/MEI templates—or directly to grayscale video frames—could yield richer and more robust descriptors than

handcrafted features, allowing the model to learn discriminative motion cues without relying solely on static global shape descriptors.

C. Temporal Modeling Beyond Static Templates

Although MHI and MEI encode motion compactly, they collapse the temporal dimension into a single image. Future work could incorporate models that preserve sequential information, such as LSTMs, GRUs, or temporal CNNs. These approaches have shown strong performance in capturing temporal structure in video-based action recognition [14]. Models of this kind can operate on frame-level or clip-level features and capture motion patterns that unfold over time, improving recognition for actions where temporal ordering is essential.

Overall, these three directions—richer handcrafted descriptors, deep learned features, and explicit temporal modeling—provide promising pathways for advancing the performance of template-based human activity recognition systems.

VIII. REFERENCES

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