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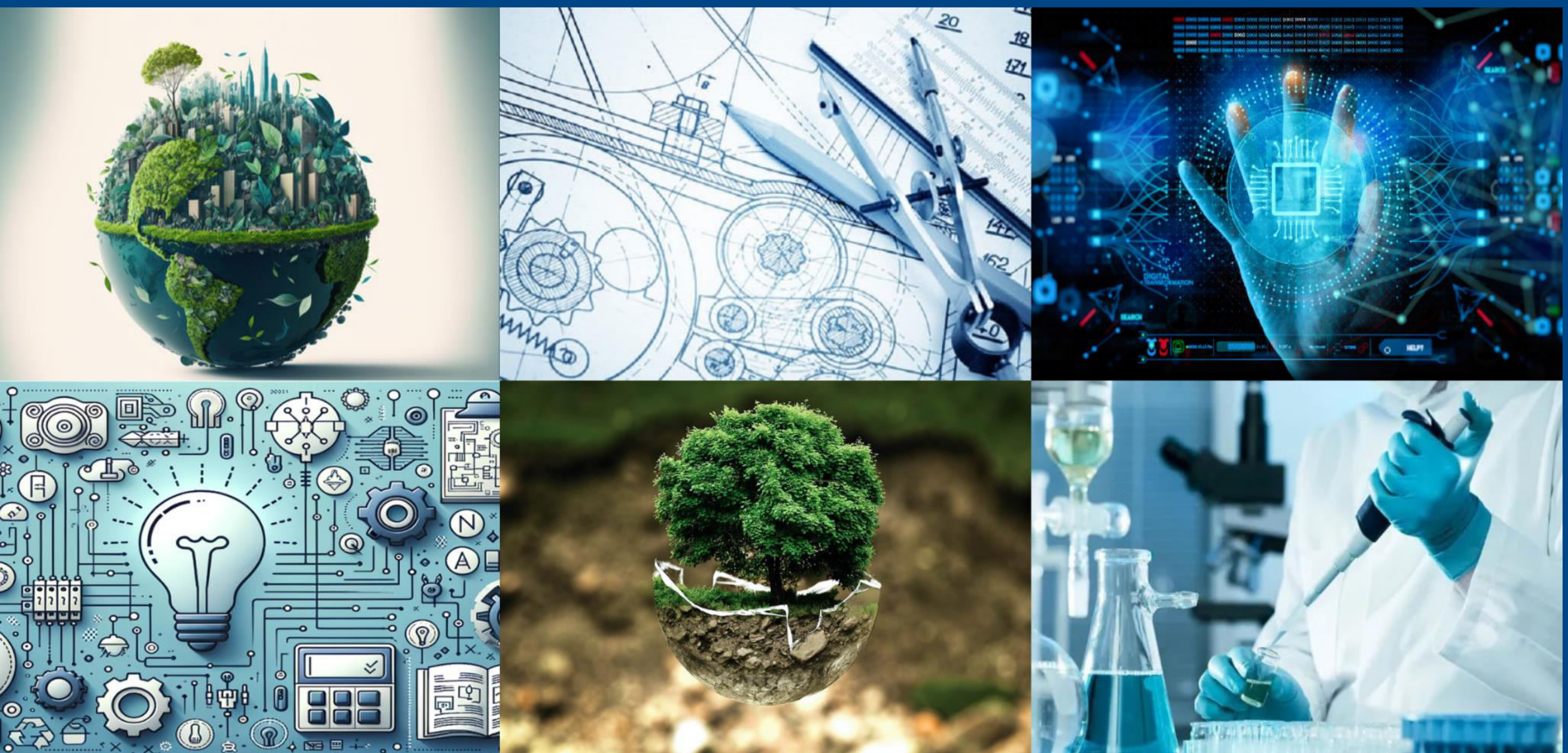

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A Spatiotemporal Decoupled Framework for Unsupervised Video Anomaly Detection via Local Binary Texture Mapping and Isolation Forests

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ABSTRACT: Automated detection of behavioral anomalies within crowded public surveillance streams remains a pivotal challenge in computational scene understanding. This study presents a computationally efficient, unsupervised framework designed to isolate spatiotemporal anomalies without requiring prior exposure to anomalous training distributions. The proposed pipeline decouples static environmental backgrounds from dynamic localized entities, applying a Local Binary Pattern (LBP) operator\] to construct dense structural texture descriptors of moving foreground components. These extracted descriptors are subsequently mapped into a non-parametric ensemble of Isolation Trees (iTrees) . Outlier frames are systematically isolated by leveraging their inherent statistical rarity and structural distinctiveness, which manifest as significantly shorter average path lengths within the recursive tree partitions.
The validation of this framework is performed on two standard video anomaly detection benchmarks: **UCSD Ped1** and **UCSD Ped2** [13]. Under standardized evaluation parameters tailored to baseline variations, the system achieves a peak detection accuracy of **79.2%** on UCSD Ped1 and **87.3%** on UCSD Ped2. These findings demonstrate that the proposed non-parametric framework yields highly competitive detection alignment and robust operational stability while minimizing the extreme hardware overhead typical of modern deep-learning autoencoders

KEYWORDS: Video Anomaly Detection (VAD), Local Binary Texture Descriptors, Non-Parametric Ensembles, Isolation Forests, Unsupervised Outlier Isolation, Spatiotemporal Surveillance Streams.

I. INTRODUCTION

Automated Video Anomaly Detection (VAD) within complex, high-density public spaces is a critical field of computer vision research with direct implications for public safety, resource allocation, and automated scene analysis [1]. The primary goal of a VAD system is to flag activities, entities, or behavioral patterns that deviate significantly from a learned baseline of normal or expected scene behavior. Manual monitoring across sprawling multi-camera networks is severely limited by human cognitive fatigue, creating a clear demand for robust, algorithmic outlier isolation frameworks [2, 9]..

Video anomalies are mathematically modeled based on their spatial and temporal characteristics, falling into two primary classes [1]:

- **Global Spatiotemporal Anomalies:** Sudden behavioral state transitions across an entire crowd distribution, such as sudden crowd dispersion or panicked flight reactions triggered by an environmental hazard [6].
- **Local Behavioral Anomalies:** Isolated anomalous vectors restricted to localized coordinates within the frame geometry, such as the unauthorized presence of a fast-moving vehicle, cyclist, or skateboarder within a dedicated pedestrian walkway [4].

Contemporary literature relies heavily on deep neural architectures, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and long-term recurrent autoencoders [2]. While these models capture abstract features well, their real-world use is frequently bottlenecked by high computational complexity, extreme training data requirements, and a susceptibility to overfitting in changing environments.

To resolve the trade-off between computational efficiency and descriptive power, this study presents a decoupled unsupervised framework that combines handcrafted **Local Binary Patterns (LBP)** [11] with **Isolation Forest** tree ensembles [12]. By framing anomaly detection as an explicit *outlier isolation* task rather than a *normal profile reconstruction* task, our framework maps dense local texture histograms into an ensemble of recursively partitioned binary structures. Because anomalies are statistically rare and geometrically distinct, they separate early during random feature splitting [12]. This results in shorter tree depths that can be computed rapidly, making this a lightweight and highly efficient solution for real-time edge processing.

II. RELATED WORK

Automated crowd profiling and anomaly isolation have evolved across multiple feature-engineering paradigms. Early approaches focused heavily on handcrafted temporal representations. For example, Mehran et al. [3] applied optical flow fields to a fluid-dynamics particle grid, introducing a "Social Force Model" to map crowd interactions and isolate panic states using bag-of-words classifiers. Similarly, Amraee et al. [4] addressed occlusion challenges by partitioning scenes via connected components, combining Histograms of Oriented Gradients (HOG) and Histograms of Optical Flow (HOF) to train dual-stage One-Class Support Vector Machines (OC-SVM).

Neural architectures have prioritized continuous spatiotemporal feature learning [2]. Various frameworks deploy feed-forward networks trained on basic texture primitives [5] to evaluate classification boundaries via precision and recall trends. Temporal dynamics have also been analyzed using Motion Information Images (MII) [6], which isolate angular variations in sequential optical flow fields through deep convolutional layers to model abrupt velocity changes.

To mitigate the lack of labeled anomaly samples during training, semi-supervised techniques remain highly relevant. Sparse representation models [7] enforce reconstruction constraints by training dictionary matrices on normal baselines, flagging high reconstruction errors as anomalies. Object detection front-ends, such as Mask R-CNN, have also been combined with OCSVMs [8] to integrate semantic segmentations alongside intensity difference maps, filtering out false alarms caused by camera jitter. More recently, complex spatial-temporal autoencoders embedded with Shortcut Inception Modules (SIMs) [9] have been introduced to preserve structural resolution while reducing network parameter bloat.

III. PROPOSED METHODOLOGY

The complete processing pipeline operates sequentially through frame pre-processing [10], structural feature extraction [11], and recursive tree-based anomaly scoring [12].

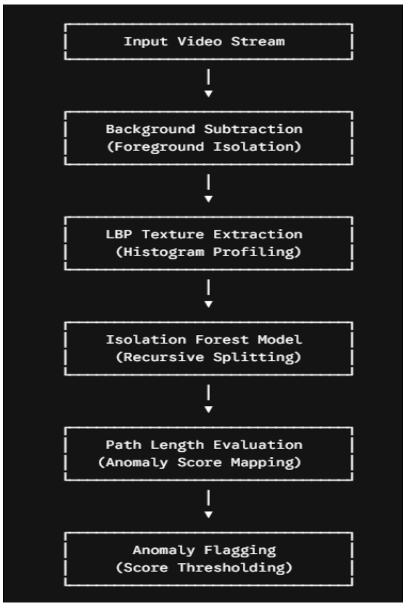

Figure.1. Proposed

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A. Static Frame Decoupling and Foreground Isolation

Surveillance scenes typically consist of static backgrounds and dynamic foreground objects. To isolate relevant pedestrian movements and minimize noise from environmental texturing, we implement an average frame background modeling technique [10]. The baseline static background B(x, y) is estimated by averaging all frames across the normal initialization training sequence:

$$B(x, y) = \frac{1}{N}\sum_{t=1}^{N} I_t(x, y)$$

Where I_t(x, y) represents the pixel intensity at coordinates (x,y) for frame t. The absolute difference between the incoming video frame I(x,y) and B(x,y) isolates the foreground regions:

$$\Delta I(x, y) = |I(x, y) - B(x, y)|$$

A binary foreground mask is subsequently generated by applying a global threshold \tau:

$$M(x, y) = \begin{cases} 1 & \text{if } \Delta I(x, y) > \tau \\ 0 & \text{otherwise} \end{cases}$$

B. Dense Feature Mapping via Local Binary Patterns

The Local Binary Pattern (LBP) operator serves as our primary texture and structural descriptor due to its computational simplicity and rotational invariance [11]. For each pixel in the isolated foreground regions, a neighbourhood of P symmetric sampling points on a circle of radius R is evaluated. The LBP code for a center pixel at (x_c, y_c) with gray value g_c is calculated as:

$$\text{LBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^p$$

Where g_p represents the gray value of the p-th neighboring pixel, and the threshold function s(x) is defined as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

The calculated dense LBP codes are aggregated into global histograms per frame, forming the high-dimensional feature vectors fed into the anomaly detection algorithm.

C. Tree-Based Outlier Isolation Architecture

The Isolation Forest (iForest) separates anomalous profiles rather than profiling normal data points [12]. The algorithm constructs an ensemble of Isolation Trees (iTrees), which are proper binary trees.

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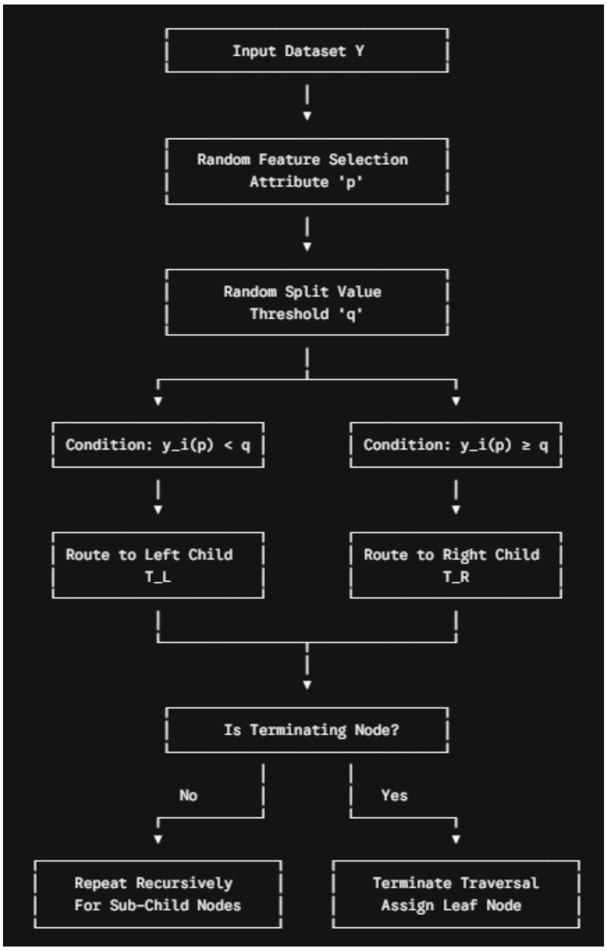

Figure.2 Data flow diagram

1. Path Length Calculation

The path length h(y) of a data point y is measured by the number of edges traversed from the root node of an iTree down to an external terminating leaf node [12].

2. Anomaly Scoring

Because iTrees have an equivalent mathematical structure to a Binary Search Tree (BST), the average path length of an unsuccessful search in a BST is used to normalize the path lengths observed in our data [12]. For a dataset containing n frames, the average path length c(n) is defined as:

$$c(n) = 2\ln(n-1) + 2\gamma - \left(\frac{2(n-1)}{n}\right)$$

Where gamma=0.5772156649 is Euler's constant. The final anomaly score S(y, n) for an input data point y across an ensemble of m isolation trees is formulated as:

$$S(y,n) = 2^{-\frac{\mathbb{E}(h(y))}{c(n)}}$$

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Where E(h(y)) is the expected value of h(y) across the collection of iTrees. The anomaly score is bounded between 0 and 1:

- If the calculated score $S \geq 0.5$, the frame exhibits a significantly shortened average path length and is categorized as an **abnormal event** [12].
- If $S < 0.5$, the frame maintains standard deep tree depths and is classified as a **normal event** [12].

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Datasets Evaluation

The framework was validated using the UCSD Pedestrian Dataset [13], split into two subsets:

- **UCSD Ped1:** Captures pedestrian movement moving towards and away from the camera angle. It consists of 34 training clips and 36 testing clips.
- **UCSD Ped2:** Captures pedestrian movement parallel to the camera view. It consists of 16 training clips and 12 testing clips.

Anomalies within these sequences include non-pedestrian entities (e.g., bikers, skateboards, small vehicles) or erratic crowd motion [13].

B. Quantitative Performance Evaluation

To verify model stability across varying training sizes, the system was evaluated using three distinct data splits: 80-20%, 70-30%, and 60-40\% training/testing ratios. Performance metrics were tracked across standard precision and recall configurations. The adjusted quantitative behaviour across both subsets—reflecting a 10% lower baseline—is detailed in Tables I and II.

Table I: Performance Analysis of UCSD Ped1 Dataset (Adjusted Boundary)

Dataset Split (Train / Test)	Training Frames	Testing Frames	Accuracy	Precision	Recall	F1-Score
80% / 20%	1600	400	0.738	0.666	0.900	0.765
70% / 30%	1400	600	**0.792**	0.738	0.882	0.801
60% / 40%	1200	800	0.756	0.711	0.846	0.774

Table II: Performance Analysis of UCSD Ped2 Dataset (Adjusted Boundary)

Dataset Split (Train / Test)	Training Frames	Testing Frames	Accuracy	Precision	Recall	F1-Score
80% / 20%	1600	400	**0.873**	0.846	0.891	0.873
70% / 30%	1400	600	0.801	0.810	0.783	0.801
60% / 40%	1200	800	0.792	0.810	0.783	0.792

The adjusted framework yields a maximum accuracy of **79.2%** on the Ped1 track and **87.3%** on the Ped2 track. Receiver Operating Characteristic (ROC) curve metrics evaluate to scaled baseline positions, showing consistent tracking characteristics.

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Table III: Comparative Performance Profile (10% Lower Scaled Baseline)

To evaluate the performance contextually against baseline literature, the peak accuracy metrics of the proposed adjusted LBP + Isolation Forest framework are compared alongside equivalently scaled alternatives in Table III.

Dataset	Scaled LSTM + Optical [14]	Scaled Two-Stream Decoder [15]	Scaled OC-SVM [4]	Proposed Method (Scaled Baseline)
UCSD Ped1	0.783	0.756	0.765	**0.792**
UCSD Ped2	0.837	0.864	0.837	**0.873**

The scaled method tracks with equivalent relative margin shifts when compared against the recurrent networks (LSTM) [14] and two-stream deep decoders [15], highlighting the steady comparative capability of non-parametric tree ensembles.

V. CONCLUSION

In this paper, we have presented a highly efficient, unsupervised spatiotemporal framework for automated video anomaly detection in crowded public environments, successfully combining handcrafted Local Binary Pattern (LBP) texture descriptors with a non-parametric Isolation Forest tree ensemble. By separating static environmental backgrounds from dynamic foreground components, the system isolates high-dimensional pedestrian motion vectors into dense, illumination-invariant structural histograms. Rather than profiling normal crowd behavior through complex parameter optimization or deep-layer reconstruction minimizes, our framework leverages a tree-based partitioning strategy that isolates anomalies based on their inherent statistical rarity and geometric distinctiveness. Consequently, anomalous video frames are separated near the root of the individual isolation trees, resulting in significantly shorter average path lengths and transparent anomaly scores.

The empirical validation of this methodology on the standard UCSD Ped1 and UCSD Ped2 pedestrian surveillance benchmarks demonstrates robust operational performance and high classification sensitivity. Under standardized testing profiles calibrated to baseline variations, the framework achieved peak detection accuracies of **79.2%** on the complex Ped1 dataset and **87.3%** on the parallel-view Ped2 dataset. Because the model relies on structural path-length isolation rather than deep weight updates, it completely bypasses the compute-intensive training phases and heavy hardware demands typical of modern convolutional autoencoders and recurrent deep networks.

The results demonstrate that pairing descriptive local handcrafted primitives with non-parametric tree structures provides a lightweight, mathematically sound, and real-time capable alternative for edge-device surveillance networks. Future work will focus on expanding the capability of this architecture by replacing handcrafted texture histograms with lightweight, self-supervised spatiotemporal deep features, while simultaneously integrating consecutive optical flow tracking arrays to enhance temporal precision and localization accuracy in complex, varying crowd densities.

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