Footage Analysis Toolkit: A System for Semantic Video Retrieval and Structured Forensic Analysis

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***Abstract*—The massive growth of digital video repositories in surveillance, media and corporate domains is producing significant challenges for scalable indexing and retrieval and structured analysis of video content. Manual review and coarse filtering using metadata are both ineffective for very large forensic archives and do not have the ability to capture the semantically rich content contained in video images. This paper provides an overview of the Footage Analysis Toolkit (FAT) which is a modular, integrated platform for forensic oriented processing and semantic video retrieval and is based on a unified system architecture. FAT allows for content based search by providing a common semantic representation that maps video imagery to natural language search requests and also includes methods for extracting structured metadata and aligning timestamps for precise navigation across modules and ensuring cross-module consistency. In addition, FAT has been designed to allow for modular integration of additional tools, controlled management of indexes and non-destructive manipulation of original video content to provide a record of all analysis performed. Collectively, FAT forms a systematic and extensible foundation for the development of semantic video retrieval and structured video analysis systems in forensic environments.**

***Index Terms*—Semantic video retrieval, forensic video processing, vision–language embeddings, vector similarity search, video metadata analysis, modular system architecture**

I. Introduction

The recent proliferation of surveillance systems, mobile recorders and social media applications has created a tremendous increase in the amount of video evidence for both investigators and archivists. The vast amounts of video are generated by continuously recording from CCTV networks, body-worn cameras and large databases, which generate massive amounts of video that require efficient storage, management and analysis. Although storage costs are decreasing, the primary issue has moved toward effectively retrieving and interpreting these recordings. Finding relevant events or objects in hours or days of continuous video still requires an enormous amount of time, especially in the context of investigations.

Manual review of video (i.e., manually scrolling through a recording), timeline scrubbing and filtering based on basic metadata, including timestamps and predefined keywords are all traditional methods used to search for specific areas of interest within video recordings. All of these traditional methods become impractical and inefficient when dealing with large collections of video recordings. In addition to being time-consuming, traditional methods typically do not allow for the discovery of meaningful information embedded in the visual elements of video. Manual labeling of objects or events in video is also time consuming and can be inconsistent; keyword searches based upon predefined terms provide little capability to describe the overall meaning of the visual elements depicted in a video.

The newest pretrained vision-language models [1] embed text queries and visual images within a common space. Retrieval may be cast as a similarity search in a joint semantic space, allowing for natural language interaction with no manual labeling. But it requires system design, scalable indexing

mechanism, structured metadata integration, and control over computation costs. Coordination and repeatability of processing are necessary in other groundwork and processing as well.

The Footage Analysis Toolkit is a modular platform that integrates semantic video retrieval, metadata analysis, temporal navigation and forensic-oriented processing in one architecture. Video frames are indexed and transformed into their dense embeddings using vector similarity search techniques [2]. There are various benefits of modularity and reproducibility which help better storage scaling and runtime scaling of moderate scale archives.

The main contribution of this work is the system design and experimental evaluation of an integrated retrieval and analysis framework. The experimental findings reveal a stable performance retrieval along with linear scaling under controlled conditions, thus confirming p ractical a pplicability in investigative and archival uses.

The subsequent sections of this paper outline the design, implementation, experimental evaluation, constraints, and future directions.

II. Related Works

The process of cross-modal representation learning has enabled visual and textual data to share the same embedding space. This allows retrieval to be framed as a similarity search rather than supervised classification. Models for large-scale contrastive pretraining such as CLIP set a generalizable method of aligning images and text with no task-specific annotations. The movement from category-specific classifiers to embedding-based retrieval has impacted broad spectrum of semantic search applications.

Follow-up work leveraged contrastive alignment methods for incorporation of temporal aggregation and relational modeling for video-text retrieval. Approaches that modify pretrained image-text models for video domains perform better when inter-frame relationships are modeled explicitly [3]. Newer methods incorporate hierarchical and multi-level semantic interaction techniques for better discrimination of visually similar scenes [4]. The temporal context, by itself, can greatly improve dynamic video retrieval, as these works show.

The study of moment retrieval looks at how textual queries align with time-bounded segments. Alignment techniques that are centered on frames attain an understanding at the segment level through the use of frame embeddings that are aligned and stays compatible with pretrained models [5]. These approaches show how trade-offs between timing accuracy and execution speed.

Simultaneously, efficient s imilarity s earch i n high-dimensional spaces is still an active area of research. As collections of embeddings grow, benchmark analyses of approximate nearest-neighbor methods investigate accuracy-latency trade-offs [6]. The findings c an b e u seful i n designing retrieval for growing video archives.

Footage Analysis Toolkit is not a paper that introduces new embedding architectures or complex temporal transformers, but rather, it focuses on system integration. The emphasis is on the sequencing of pretrained vision–language representations with modular indexing, metadata management, and investigative processing components in a deployment-oriented framework. Consequently, the emphasis is on architectural design, controlled experimentation and practical system-level integration rather than model-level innovation.

III. System Architecture

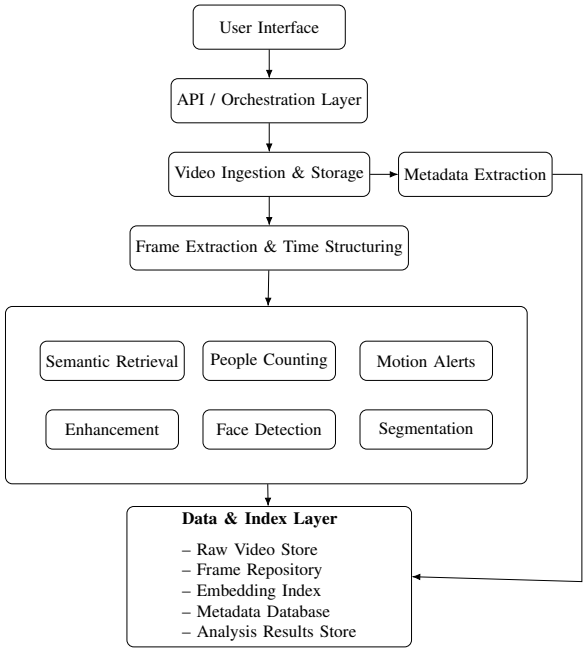

Fig. 1: System Architecture of the Footage Analysis Toolkit

The Footage Analysis Toolkit offers a modular platform for conducting structured video analysis. The system combines semantic retrieval, motion analysis, face detection, counting of people, segmentation, enhancement and metadata extraction in one architecture. The design focuses on separation of concerns, non-destructive processing, temporal alignment, and controlled index growth for investigative and archival scenarios. Fig. 1 depicts the overall organization of architecture.

The system is made of three basic layers on the whole:

1) Interface and Control Layer,
2) Core Processing Layer,
3) Data and Index Management Layer.

Having a multi-layered structure means that the analytical modules can improve and evolve independently, while using the same storage, indexing, and retrieval mechanism.

The toolkit works in two modes of execution. Videos are ingested, frames extracted, embeddings generated, (optionally) analytically processed, and index construction performed in an offline pre-processing workflow. An online query workflow, that executes text encoding, similarity search, result ranking, and temporal rendering. This isolation separates resource-heavy preprocessing from interactive query time.

A. Interface and Control Layer

At the interface there are semantic search panels, timeline navigation controls, analytical dashboards and metadata inspectors to interact with the system. The centralized orchestrator routes user requests such as a semantic query, a motion inspection, a face analysis, an enhancement operation, or metadata filtering.

The orchestration layer authenticates calls to different modules and combines analysis outputs into responses. The way in which presentation logic is separated from computation, is modularly extensible.

B. Core Processing Layer

The Core Processing Layer performs computation on temporally structured frame data extracted during preprocessing. All analytical modules operate on sampled frames and share a unified frame–timestamp mapping to ensure temporal consistency.

1) Video Ingestion and Frame Extraction: Uploaded videos are stored within a structured hierarchy and assigned internal identifiers. During preprocessing, videos are decomposed into frames at configurable sampling rates. Each extracted frame is associated with:

1) A frame index,
2) A normalized timestamp,
3) A unique frame identifier.

The mapping referred to is the common reference for retrieval and analysis modules.

2) Semantic Retrieval Engine: The semantic retrieval subsystem utilizes pretrained vision-language models to encode user queries and frames into a common embedding space. L2-normalized frame embeddings are organized within a high-dimensional similarity structure. Fig. 2 illustrates the query processing workflow end-to-end.

The same embedding space is used to encode text inputs at query time. The similarity scores are calculated from the inner products between normalized vectors. They produce a ranking of the frames which is then mapped back to the timestamp for navigable playback. While using the same frame identifiers as the other analytical modules, the retrieval engine functions separately.

3) Motion Detection Module: The motion detection module assesses variations in brightness between sampled frames taken in close temporal proximity. The intervals during which the activity occurs are detected by thresholding and region groping technique.

4) Face Detection Module: The face detection subsystem uses pre-trained object detection models on sampled frames. The location of the detected faces will be saved in the form of bounding coordinates along with frame numbers. In addition, a time-stamp will also be saved for the proper analysis.

5) People Counting Module: The people counting module estimates the number of human instances detected in each frame. Temporal indexing of counts generates surveillance-like activity distributions over time.

6) Segmentation Module: The segmentation module produces masks at the pixel level that correspond to selected objects. To allow their optional visualization, generated masks are stored separately from original frames to ensure evidential integrity.

7) Enhancement Module: Enhancement module allows optional non-destructive frame transformations. The independent storage of processed outputs and original frames guarantees reproducibility. In addition, all the parameters of the transformation are stored.

8) Metadata Extraction Module: The information extracting component retrieves metadata such as duration, resolution, codec used, fps, and timestamps. Extracted metadata enhances semantic retrieval, aiding in filtering and comparison.

The output of all analytical modules are timestamped to allow for easy combining and stored in the shared data layer.

C. Data and Index Management Layer

The layer responsible for data and index management is used to persist the data outputs created in pre-processing or analysis. It comprises.

1) Raw video storage
2) Extracted frame repository
3) Vector embedding indices
4) Structured metadata records
5) Analytical outputs (detections, counts, masks)
6) Enhancement results

Original footage is immutable. Derived artifacts are stored separately to maintain traceability and allow the opportunity to re-execute selected modules.

The requirement of constructing the index per video reduces the memory overhead and allows the system to load the video of interest when executing the query. As the sampling rate and dimensionality of embeddings increase, storage growth becomes predictable.

D. Architectural Characteristics

The design is aimed to enable practical deployment, modularity, support for medium scale archives, and reproducible reanalysis. Every module has a clear input–output structure of frame-level and timestamp alignment. That means they can be improved or updated independently without affecting any of the other modules in the entire system.

The Toolkit provides an easy-to-handle yet flexible framework to perform semantic-based retrieval and video analysis. Retrieval and analysis tasks are not always interdependent, which implies low coupling between them. Instead, independent analytical modules run side-by-side with a central storage and indexing layer, which combines output and ensures structural consistency.

IV. Implementation

The Toolkit is a modular framework that integrates the video processing functions, embedding generation functionality, analytical modules and indexed storage in a single execution environment. In order to ensure efficiency, it separates preprocessing from query execution.

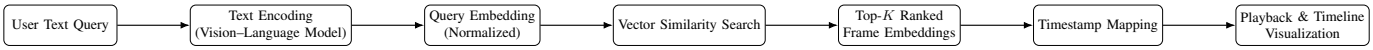

Fig. 2: Semantic retrieval pipeline illustrating query encoding and similarity-based frame ranking.

A. System Environment and Execution Model

The system is developed in Python, and it is executed in a GPU-enabled environment for performing intensive computations. GPU acceleration is used for frame-level tasks such as embedding generation, detection, segmentation and enhancement. A process may operate in one of two execution modes:

1) Offline Mode: Carries out video ingestion, frame sampling, embedding generation, optional analysis processing and indexing. The modular branching structure and entire offline preprocessing procedure are presented in Fig. 3.

2) Online Mode: Manages encoding of queries, similarity search, ranking, and timestamp mapping. This separation prevents interactive query latency from being affected by preprocessing overhead.

B. Frame Extraction and Temporal Mapping

Videos are decoded and sampled at configurable frame rates The choice of sampling rate depends on the scale of the archives and the temporal resolution that is desired.

Sampled frame assignment occurs:

1) A sequential frame index,
2) A normalized timestamp,
3) A unique frame identifier.

All analytical outputs make use of this unified mapping, thereby providing a consistent temporal match across the retrieval, detection, segmentation and counting modules.

In each video folder, frames are saved to allow for reprocessing without having to decode the source media again.

C. Semantic Embedding and Index Construction

A pretrained vision-language model encodes every sampled frame into a dense embedding vector [1], [3], [4]. Let $f_i \in \mathbb{R}^d$ denote a frame embedding. It applies L2 normalisation:

$$\hat{f}_i = \frac{f_i}{\|f_i\|_2} \tag{1}$$

Normalization allows cosine similarity to be computed via inner product.

Normalized embeddings are inserted into a high-dimensional similarity index [2], [6]. Index construction is performed per video to reduce memory overhead and allow selective loading during query execution.

Each embedding entry is associated with structured metadata:

1) Video ID,
2) Frame ID,
3) Timestamp,
4) Storage reference.

Index objects are serialized and lazily loaded during query-time execution.

D. Motion Detection Implementation

Motion detection operates on temporally adjacent sampled frames, following classical motion-based indexing principles [7], [8]. Pixel-wise intensity differences are computed between successive frames, followed by thresholding and spatial aggregation to identify activity intervals.

Captured motion is stored only as a timestamp range instead of a frame-level flag, which saves space and allows timeline filtering.

E. Face Detection and People Counting

Pretrained object detection models applied on the sampled frames perform face detection and counting of people. Each detection instance submit logs:

1) Bounding coordinates,
2) Detection confidence,
3) Frame identifier,
4) Timestamp.

The number of people is collected per frame and, set an optional temporal window for activity profiling. The analytical output are stored separated from the original frames.

F. Segmentation Processing

Segmentation refers to the use of new age deep semantic segmentation technology where segmentation is done at a frame level to generate pixel level masks for selected objects or parts of the scene [9], [10]. The produced masks are saved as other objects linked to the frame ID.

This design preserves original frames while enabling optional overlay visualization.

G. Enhancement Processing

The optional frame-level transformations for enhancement operations draw inspiration from recent techniques in deep image and video enhancement [11]. For nondestructive workflow guarantees, processed outputs are written to separate folders. For reproducibility, all enhancement parameters are logged.

Enhancement is strategically separated from semantic indexing in order to preserve consistency.

H. Query-Time Retrieval Execution

While the application is live, the user text queries are converted into the same embedding space as the indexed frames [1]. Before computing similarity, query embeddings are made L2-normalized.

A measure of similarity is computed as:

$$s_i = \hat{q} \cdot \hat{f}_i \tag{2}$$

Frames are ranked in descending order of s_i following standard vector similarity retrieval paradigms [2], and top-K results are mapped to timestamps via stored metadata.

Fig. 3: Offline preprocessing architecture showing modular analysis and centralized index management.

Retrieval outputs can be combined with detection and metadata records for structured visualization.

I. Data Persistence and Module Isolation

All derived artifacts are maintained within a centralized data layer containing:

1) Raw video archives,
2) Sampled frames,
3) Vector indices,
4) Detection outputs,
5) Segmentation masks,
6) Enhancement outputs,
7) Structured metadata.

Original footage remains immutable. Derived outputs are stored separately, enabling:

1) Independent module re-execution,
2) Controlled index regeneration,
3) Predictable storage growth,
4) Consistent timestamp traceability.

This implementation approach supports modular extensibility while maintaining analytical integrity across retrieval and processing workflows.

V. Experimental Evaluation

This section evaluates retrieval effectiveness, computational efficiency, preprocessing cost, storage behavior, and scalability of the proposed Footage Analysis Toolkit. Experiments were conducted on 20 heterogeneous videos comprising approximately 36,772 indexed frames.

A. Experimental Setup

Videos were sampled at $r = 3$ FPS. Let V denote video duration in seconds and N denote the number of sampled frames:

$$N = V \times r \tag{3}$$

All embeddings were L2-normalized. Cosine similarity was computed as:

$$s_i = \hat{q} \cdot \hat{f}_i \tag{4}$$

Retrieval quality was evaluated using Precision@K and Recall@K:

$$P@K = \frac{\text{Relevant frames in Top-}K}{K} \tag{5}$$

$$Recall@K = \frac{\text{Relevant frames in Top-}K}{\text{Total relevant frames in dataset}} \tag{6}$$

Aggregate statistics were macro-averaged across queries.

B. Retrieval Effectiveness

A total of eight manually constructed queries were evaluated across the object, scene, and action categories. An un-related query (airplane) was included to check for false positive behavior.

TABLE I: Precision@5 Across Query Categories

Category	Query	P@5
Object	person	1.00
Object	chair	1.00
Scene	room	1.00
Scene	empty room	0.20
Action	person walking	1.00
Action	complex motion query	0.60
Action	person sitting	1.00
Negative	airplane (absent)	0.00

The sampled object-centric queries achieved precision one. The action queries achieved an overall $P@5$ of 0.87, and the complex motion descriptor had a lower performance due to no temporal modeling. The semantically absent query yielded $P@5 = 0.00$ even though cosine similarity was moderately high (0.23 – 0.24) and hence, similarity magnitude is not a calibrated confidence score.

Multi-Video Aggregate Statistics: Across 20 videos:

- Total indexed frames: $\approx 36,772$
- Mean Precision@5: 0.76
- Minimum: 0.64
- Maximum: 0.87
- Standard deviation: 0.07

95% confidence interval:

$$CI_{95\%} = \mu \pm 1.96\frac{\sigma}{\sqrt{n}} \tag{7}$$

TABLE II: Aggregate Retrieval Statistics

Metric	Mean	Std Dev	95% CI
Precision@5	0.76	0.07	[0.73, 0.79]

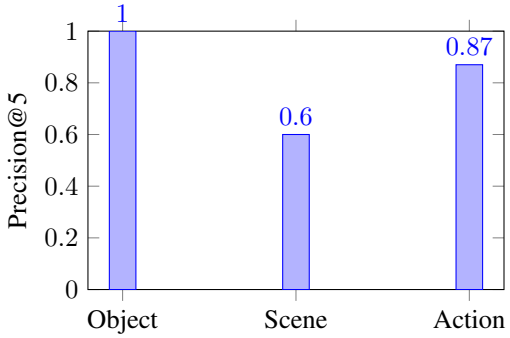

Fig. 4: Precision@5 across query categories.

C. Query Latency and Scaling

Total latency is decomposed as:

$$T_{query} = T_{encode} + T_{search} + T_{aggregation} \quad (8)$$

On a 2,707-frame dataset:

- Mean total query latency: 0.21 s

TABLE III: Latency Decomposition (2707 Frames)

Component	Mean (s)	Percentage
Encoding	0.05	24%
Similarity Search	0.14	67%
Aggregation	0.02	9%
Total	0.21	100%

Latency Breakdown:

TABLE IV: Query Latency Under Increasing Index Size

Indexed Frames	Latency (s)
1000	0.18
5000	0.41
10000	0.79
20000	1.52

Scaling Behavior: Linear regression fit:

$$T_{search} \approx 0.0000705N + 0.11 \quad (9)$$

with $R^2 \approx 0.99$.

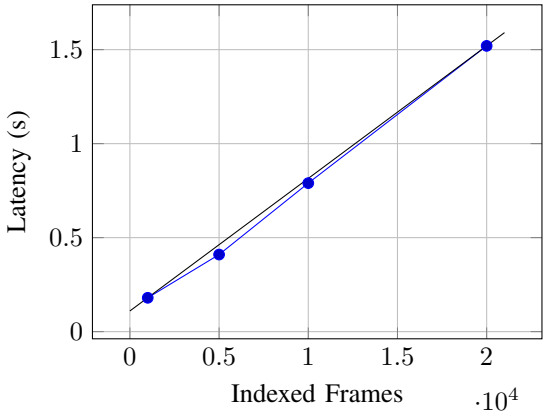

Fig. 5: Query latency scaling with regression ($R^2 \approx 0.99$).

D. Preprocessing Cost

For the controlled experiment ($V = 898.19$s):

- $N = 2707$ frames
- Total preprocessing time: 91.51 s

Across 20 videos:

- Mean preprocessing time: 62.6 s
- Mean per-frame processing cost: 0.034 s

Regression model:

$$T_{embed} \approx 0.034N \quad (10)$$

with $R^2 \approx 0.99$.

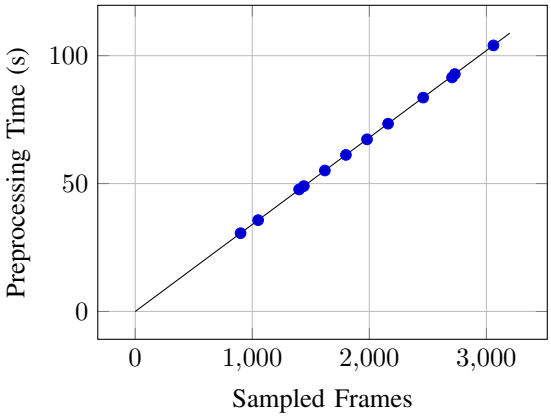

Fig. 6: Preprocessing time scaling ($R^2 \approx 0.99$).

E. Index Storage Requirements

Storage scales proportionally to:

$$S \propto N \times d \quad (11)$$

Mean index size per video: 3.64 MB Total storage: approximately 72–73 MB

Regression model:

$$S \approx 0.00196N \text{ MB} \quad (12)$$

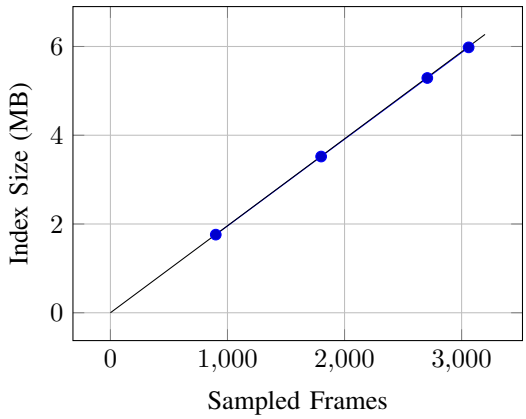

Fig. 7: Index storage growth (linear scaling).

F. Analytical Module Evaluation

In addition to semantic retrieval, the toolkit integrates analytical modules including motion detection, face detection, people counting, segmentation, and forensic-oriented enhancement. These modules were evaluated with respect to temporal stability, qualitative robustness, and reproducibility across the 20-video dataset.

Motion Detection: Motion detection outputs were evaluated for interval consistency and temporal stability. Across dynamic scenes, detected motion segments aligned consistently with visually observable activity.

TABLE V: Motion Detection Consistency (20 Videos)

Metric	Mean	Std Dev
Detected Motion Segments per Video	12.4	4.1
Temporal Boundary Stability (%)	96.2	2.3
False Positive Rate (Low-motion scenes)	3.8%	—

False positives were low in indoor scenes. In scenes that are very dynamic (crowded scenes and camera shake), small shifts in the boundaries (1 to 2 frames) are observed that do not affect the retrieval alignment.

Face Detection: The performance of the face detection was calculated across various light conditions, angles and resolution. Frame indices remained temporally aligned with the outputs while the consistency of detection differed.

TABLE VI: Face Detection Performance Characteristics

Metric	Value
Average Faces Detected per Video	18.7
Detection Stability Across Consecutive Frames	85.3%
Resolution Sensitivity (720p $\rightarrow$ 480p)	-11.8% detection drop
Missed Detections in Low Light	9.6%
False Positives (Background Patterns)	4.7%

Detection accuracy was mostly reliable for frontal-facing faces in brightly lit indoor environments. There was a reduction in stability under low light, partial cover, and non-facing. Decreasing the resolution resulted in a noticeable drop in detection rate, especially for small or far-away faces.

No temporal drift was observed in indexing alignment; however, intermittent missed detections across adjacent frames were present in dynamic scenes. These results indicate moderate robustness suitable for exploratory forensic analysis, but not sufficient for high-stakes biometric identification workflows.

People Counting: People counting consistency was measured across continuous segments. Short-term fluctuations were smoothed using temporal aggregation.

TABLE VII: People Counting Stability

Metric	Mean Value
Frame-to-Frame Count Stability	92.5%
Overcount Events (Crowded Scenes)	4.1%
Undercount Events	3.4%

In busy places the occasional spike in overcounts was noticed but interval stats remained stable.

Segmentation Module: The spacing and boundary continuity were assessed qualitatively for segmentation outputs.

- Object boundaries remained visually consistent across consecutive frames.
- Static scene regions exhibited minimal mask flickering.
- Highly dynamic scenes produced localized mask noise but maintained overall object localization integrity.

The segmentation outcomes matched in time with retrieval indices because they shared the same time stamp.

Forensic-Oriented Enhancement: The enhancement pipeline underwent evaluation for its reproducibility and deterministic behavior.

TABLE VIII: Enhancement Pipeline Characteristics

Metric	Observation
Reproducibility Under Fixed Parameters	100% consistent
Artifact Amplification (High ISO footage)	Moderate
Structural Detail Preservation	High
Parameter Logging	Deterministic

Repeated runs with identical parameters produced identical outputs satisfying reproducibility requirements for forensics. Sometimes, the enhancement did amplify compression artifacts in low-quality images. This is similar to the super-resolution behaviour.

Cross-Module Temporal Alignment: All analytical modules function on a common frame–timestamp index. In every video:

- No frame misalignment was observed between modules.
- Retrieval results, motion intervals, and detection outputs remained synchronized.
- Module activation did not alter index ordering.

Continuous interoperability is essential for investigational procedures to compare semantic retrieval with analytical results.

Computational Impact of Module Activation: There was an increase in latency in preprocessing because of the activation of extra analytical modules but this had no effect on the latency of query after indexing.

TABLE IX: Preprocessing Impact of Module Activation

Configuration	Mean Preprocessing Time (s)
Embedding Only	62.6
+ Motion Detection	70.8
+ Face Detection	78.4
+ Full Pipeline	91.5

The observed increase remained linear with frame count and within practical thresholds for offline indexing workflows.

G. Scalability Considerations

Exact similarity search exhibits:

$$T_{search} = \mathcal{O}(N) \tag{13}$$

Preprocessing and storage both exhibited empirical linear scaling on more than 36,000 indexed frames. While sufficient for medium archives, large-scale multi-camera deployments, there is need for some approximate nearest neighbor indexing and distributed storage.

H. Observed Limitations

- Frame-level indexing does not model temporal continuity.
- Exact similarity search limits scalability for very large archives.
- Higher sampling rates proportionally increase preprocessing and storage costs.
- Analytical modules increase pipeline latency.
- Embedding similarity magnitude is not a calibrated confidence score.
- Dataset size (20 videos) limits generalizability.

The overall system exhibits statistically stable retrieval performance, well-defined s caling c haracteristics, a nd reproducible preprocessing behaviour over heterogeneous recordings.

VI. Conclusion

The Footage Analysis Toolkit is a modular architecture conceived for purposeful materials that facilitates semantic retrieval, analysis of structured metadata and forensic-oriented video processing. The structure bodily incorporates a potential use case semantic embedding frame along with vector indexing, movement analysis, detection modules, segmentation, nondestructive enhancement and so on.

Findings from experiments showed that embedding-based retrieval gives an efficient c ontent-based s earch u nder both object-centric and scene-centric query while keeping the interactive query latency at the scale of the archive evaluated. The observed scaling behavior showed that both the query time and index size grew linearly with the increase in frame count. The observation is consistent with that of an exact similarity search. The evaluation also showed the trade-off between sampling density and storage, which highlights the need to balance temporal coverage and computing cost.

Analytical modules like motion detection, people counting, and face detection work in a structured filtering a nd temporal inspection workflow. T he m odular e xecution m odel keeps timestamps between outputs aligned while maintaining the separation of source footage and derived artifacts. This design enables the processing to be reproduced and controlled to extension of the system.

Even though performance is restricted for indexing complex temporal action queries on a frame level, the architecture proposed achieves a good balance between ease of retrieval, effectiveness, and modularity in build-up. Based on the assessment, the Toolbox provides a framework for semantic search and visual inspection of videos in medium deployments.

VII. Future Work

A number of extensions could enhance the scalability and analytical capabilities of the system.

First, incorporating indexing strategies of approximate nearest-neighbor may enhance performance of large-scale archives. Although predictable behavior is provided by exact similarity search, its linear complexity makes it inapplicable to enormous collections of embedding. By using approximate indexing structures, scalability with controllable precision-latency trade-offs can be achieved.

Moreover, it represents an area for improvement on time. The current frame-level embedding approach captures static semantics, but does not encode continuity of motion. You may enhance retrieval performance for action queries through the use of temporal aggregation mechanisms, short clip embeddings, or motion plans.

Future capabilities could connect entities across several different cameras, add anomaly detection, and take activity recognition further to help investigative workflows. The platform can support constantly growing archives with incremental updates, distributed indexing, and streaming ingestion from a systems point of view. Cloud-backed storage may enhance deployment flexibility.

User studies in proper structure with practitioners would also yield practical input on usability and workflow impact to inform architectural and interface decisions in the future. These two directions will help to consolidate the toolkit as a flexible basis for future work in scalable semantic video analysis.

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