AVSUM: Adaptive Video Summarization Using Multi-Modal Temporal Attention and Scene-Aware Keyframe Extraction

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Abstract

Automated video summarization remains a central and unresolved challenge in multimedia understanding: the exponential growth of video content across streaming platforms, surveillance systems, and educational repositories demands efficient mechanisms that can distill hours of footage into concise, semantically coherent representations without human intervention. This paper presents the Adaptive Video Summarization framework (AVSUM), a unified multi-modal architecture that automates keyframe selection and temporal segment extraction for arbitrary-length video inputs. AVSUM integrates three tightly coupled modules: (i) a Multi-Modal Feature Extraction Engine that processes both visual frames and audio-derived transcripts, producing a joint spatio-temporal embedding termed the Video Semantic Signature (VSS); (ii) a Temporal Attention Selector, a trained sequence model that maps VSS embeddings to importance scores and produces ranked keyframe sequences supported by SHAP-based saliency explanations; and (iii) a Scene Coherence Advisor that diagnoses temporal redundancy and prescribes adaptive compression strategies. Unlike existing summarization pipelines that operate as opaque extraction loops, AVSUM delivers interpretable, evidence-backed segment rankings through a self-improving Knowledge Base seeded from benchmark video corpora. Evaluated across 60 benchmark video datasets spanning lecture recordings, news broadcasts, surveillance footage, and cinematic content, AVSUM achieves an F1-Score@Summary of 0.74, a 42-percentage-point improvement over random keyframe selection and a 19-percentage-point improvement over the uniform-sampling heuristic (both significant at $p < 0.001$, Wilcoxon signed-rank test). The system is deployed as a full-stack interactive web application built with Python, PyTorch, OpenCV, FastAPI, and React. AVSUM makes six original contributions to the video summarization literature, including the Video Semantic Signature embedding scheme, multi-modal redundancy analysis, and a closed-loop self-improvement mechanism—capabilities absent from existing open-source tooling.

Index Terms—video summarization, keyframe extraction, temporal attention, multi-modal learning, scene segmentation, explainable AI, SHAP, OpenCV, PyTorch, Video Semantic Signature

I. INTRODUCTION

Video content constitutes the fastest-growing segment of digital information: by 2025, video accounts for over 82% of global internet traffic [1]. Streaming platforms, online education providers, security and surveillance systems, and social media repositories collectively produce hundreds of millions of hours of footage per day. Despite this proliferation, the tools for automatically consuming and navigating video content have not kept pace with its production.

A viewer seeking to review a two-hour lecture recording, extract highlights from a sporting event, or audit a 24-hour surveillance feed cannot feasibly consume the full content. Manual summarization—scrubbing timelines, annotating segments, or producing edited clips—is prohibitively expensive at scale. The Video Summarization Problem (VSP) captures this challenge in its general form: given a video sequence V of arbitrary duration, produce a compact summary $S \subseteq V$ that maximally preserves informational content and semantic coverage while minimising redundancy and temporal extent.

The intractability of a universal solution is affirmed by the No Free Lunch observation that applies equally to summarization as to classification: no single selection criterion performs optimally across all video modalities, genres, and use cases. A shot-boundary heuristic well-suited for cinematic content fails catastrophically on lecture recordings where the visual stream is nearly static; a transcript-driven approach effective for news broadcasts provides no signal for silent surveillance footage.

Existing automated video summarization systems fall into two broad families. Unsupervised methods [5], [6] apply clustering or graph-theoretic techniques to frame-level features, selecting representative frames without reference to ground-truth summaries. Supervised methods [7], [8] train sequence models on annotated importance scores. Both families share a critical limitation: they treat video as a single-modality signal (typically visual frames alone), ignore semantic content carried by audio and transcript streams, and provide no interpretable explanation of why particular segments are selected.

This paper presents AVSUM, the Adaptive Video Summarization framework—a unified, domain-agnostic architecture that addresses these limitations through principled multi-modal feature integration, attention-based importance scoring, and SHAP-grounded explainability. AVSUM is the first video summarization system to jointly process visual, audio, and transcript modalities within a unified importance-scoring pipeline, while providing per-segment natural language explanations of selection decisions.

II. RELATED WORK

A. Video Summarization: Problem Formulation

De Avila et al. [2] provided a canonical formulation of video summarization as an optimisation problem over frame-level importance functions, establishing the dual objectives of representativeness and diversity that remain central to modern approaches. Zhang et al. [3] demonstrated that recurrent architectures trained on TVSum [4] and SumMe [9] annotations could achieve state-of-the-art importance prediction, validating the supervised approach. Apostolidis et al. [10] conducted a comprehensive survey of deep learning methods, documenting the dominance of attention mechanisms after 2019.

B. Multi-Modal Approaches

Early video summarization systems operated exclusively on visual streams. Yeung et al. [11] were among the first to incorporate audio energy as an auxiliary signal for event detection. Li et al. [12] demonstrated that transcript alignment via forced alignment tools substantially improves summarization quality on spoken-content videos such as lectures and interviews. More recently, transformer-based models such as CLIP [13] and BLIP-2 [14] have enabled rich cross-modal embeddings that jointly encode visual and textual information, opening new possibilities for semantic summarization. AVSUM builds on this foundation by constructing a Video Semantic Signature that integrates visual frame embeddings, audio spectral features, and transcript sentence embeddings into a unified per-segment representation.

C. Explainability in Video Understanding

Lundberg and Lee's SHAP framework [15] has been applied to image and video classification tasks to identify spatially salient regions. However, its application to the output of video summarization systems—explaining why particular temporal segments are selected rather than why a classification label is assigned—remains unexplored. AVSUM introduces SHAP attribution at the temporal segment level, mapping attention weights and feature contributions to natural language explanations of segment importance.

D. Benchmark Datasets and Evaluation

Song et al. [4] introduced TVSum, a benchmark of 50 YouTube videos with per-frame importance annotations obtained via crowdsourcing. Gygli et al. [9] introduced SumMe with 25 personal videos and eye-tracking–derived importance scores. Both benchmarks have driven progress but are limited in genre diversity. The OpenVideo Project [16] and Kinetics-400 [17] provide larger-scale resources that enable evaluation across a broader range of content types. AVSUM is evaluated on a composite benchmark spanning all four of these sources, supplemented by domain-specific corpora for surveillance and lecture content.

III. AVSUM SYSTEM ARCHITECTURE

AVSUM is organised as three tightly integrated modules operating within a unified data flow. The system accepts any video file in standard encoding formats (MP4, AVI, MKV, MOV) alongside an optional transcript file and produces: (a) a ranked list of selected keyframes and temporal segments with importance scores and SHAP explanations, and (b) a structured Scene Coherence Report with redundancy analysis and compression recommendations.

A. High-Level Data Flow

- The user uploads a video file and specifies summarization parameters (target summary ratio, modality preferences, domain) via the web interface.
- The Multi-Modal Feature Extraction Engine processes the video and outputs per-segment Video Semantic Signature (VSS) embeddings alongside a human-readable video characterization report.
- The VSS embeddings are passed to the Temporal Attention Selector, which applies the trained importance model and returns a ranked list of all temporal segments with confidence scores and SHAP-derived explanations.
- In parallel, the raw segment sequence is analysed by the Scene Coherence Advisor, which returns a structured redundancy report with severity-ranked issues and transformation code snippets.
- The user can submit manual annotation corrections via the feedback interface, appending new observations to the Video Knowledge Base and triggering periodic model retraining—closing the self-improvement loop.

B. System Stack

The backend is implemented in Python 3.10 using PyTorch [18] for deep learning primitives, OpenCV [19] for frame extraction and visual preprocessing, Whisper [20] for automatic speech recognition, Sentence-Transformers [21] for transcript embedding, SHAP [15] for explainability, SQLAlchemy for Knowledge Base persistence, and FastAPI with Uvicorn for the REST API layer. The frontend is a React single-page application with Recharts for interactive visualisation and a timeline scrubber component for summary review. The Video Knowledge Base is a SQLite database persisted across sessions.

IV. MULTI-MODAL FEATURE EXTRACTION ENGINE: VIDEO SEMANTIC SIGNATURE

The Multi-Modal Feature Extraction Engine accepts a raw video file with an optional transcript and outputs a fixed-length 128-dimensional numerical vector per temporal segment—the Video Semantic Signature (VSS)—regardless of the original video's resolution, frame rate, or duration. This fixed-size property is essential: the temporal attention model requires a fixed-size representation for each segment.

A. VSS Feature Groups

The VSS vector is partitioned into five complementary feature groups, each capturing a distinct dimension of segment content.

1) Group A: Visual Frame Features (32 Dimensions):

These dimensions capture the visual content and dynamics of each segment:

- frame_entropy, frame_variance, edge_density: perceptual complexity indicators.
- optical_flow_magnitude: motion intensity averaged across segment frames.
- clip_embedding_mean (16-d): CLIP visual encoder output averaged over sampled frames.
- scene_change_rate: frequency of detected scene boundaries within the segment.
- face_presence_ratio: fraction of frames containing detected human faces.
- colour_histogram_spread: diversity of dominant colour palette.

2) Group B: Audio-Spectral Features (24 Dimensions):

For each segment, spectral features are extracted from the audio waveform using librosa [22] and aggregated to produce segment-level statistics:

- mfcc_mean (13-d), mfcc_var (13-d): Mel-frequency cepstral coefficients capturing timbral texture.
- spectral_centroid, spectral_bandwidth: frequency distribution summary.
- rms_energy, zero_crossing_rate: energy and noise indicators.
- speech_activity_ratio: fraction of segment classified as speech by a VAD model.

3) Group C: Transcript-Semantic Features (32 Dimensions):

When a transcript is available (either user-provided or generated by Whisper), sentence embeddings are computed and aligned to segments:

- sentence_embedding_mean (24-d): Sentence-BERT embedding averaged over transcript sentences aligned to the segment.
- lexical_density: ratio of unique content words to total words.
- sentiment_score: compound sentiment polarity from a fine-tuned sentiment model.
- keyword_density: frequency of domain-specific high-importance terms.
- sentence_count, avg_sentence_length: structural complexity indicators.

4) Group D: Temporal Context Features (20 Dimensions):

These features capture the temporal position and inter-segment relationships:

- relative_position: normalised position of the segment within the video (0 = start, 1 = end).
- segment_duration_ratio: relative duration compared to median segment duration.
- cosine_sim_prev, cosine_sim_next: VSS similarity to adjacent segments, measuring redundancy.
- novelty_score: inverse cosine similarity to the running segment mean—high values indicate fresh content.
- cumulative_coverage: fraction of the semantic space already covered by previously selected segments.

5) Group E: Domain Complexity Features (20 Dimensions):

These features capture domain-specific and structural complexity:

- video_pca_d90, video_pca_d50: intrinsic visual dimensionality required to explain 90% and 50% of frame variance.
- transcript_topic_count: number of distinct LDA topics detected across all segments.
- visual_topic_entropy: diversity of visual content categories predicted by a ResNet-50 classifier.
- event_density: rate of detected discrete events (shot changes, loud audio events, face appearances) per minute.

B. Implementation Notes

All VSS values undergo two post-processing steps before storage: (i) NaN and Inf values are replaced with 0.0, and (ii) all values are L2-normalised per segment to ensure modality balance. The complete extraction pipeline for a typical video (30–90 minutes, 1080p) completes in under 8 minutes on commodity GPU hardware (NVIDIA RTX 3060), including the Whisper transcription step.

V. VIDEO KNOWLEDGE BASE CONSTRUCTION

The Video Knowledge Base (Video-KB) stores historical (VSS sequence, ground-truth summary) pairs on which the temporal attention model is trained. AVSUM employs a hybrid construction strategy that balances annotation quality, temporal diversity, and domain coverage.

A. Benchmark Sources

Primary Source—TVSum and SumMe Annotations. TVSum [4] provides per-frame importance scores from 20 crowdsourced annotators across 50 YouTube videos spanning ten categories. SumMe [9] provides eye-tracking and user study–derived importance scores for 25 personal videos. For each video, AVSUM computes mean annotator importance per 2-second segment and assigns binary ground-truth labels (top-15% of segments by importance score are labelled as summary-worthy), producing 3,750 labelled segment instances.

Secondary Source—Kinetics-400 Subsampled Validation. A local annotation pass is run on 30 Kinetics-400 [17] clips using a 25% duration subsample to validate that benchmark annotations transfer to longer-form content. This produces a Spearman rank correlation between benchmark and local importance rankings and contributes locally-annotated rows to the Video-KB with a source='local_validated' provenance tag.

B. Annotation Portfolio

TABLE I
VIDEO KNOWLEDGE BASE SOURCES

Source	Videos	Segments	Domain
TVSum [4]	50	7,200	YouTube (mixed)
SumMe [9]	25	2,100	Personal video
Kinetics-400 [17]	30	1,440	Action recognition
OpenVideo [16]	40	3,600	Lecture / Documentary
User Feedback	Variable	Variable	Self-improvement

C. Ground Truth Label Assignment

For each benchmark video, the top-15% of segments ranked by mean annotator importance score are assigned as ground-truth summary segments. In case of ties, a temporal-diversity tie-breaking criterion is applied: segments that maximally increase temporal coverage of the selected set are preferred, prioritising representativeness over redundancy.

VI. TEMPORAL ATTENTION SELECTOR

The Temporal Attention Selector is a trained sequence model that maps a sequence of VSS embeddings to per-segment importance scores and produces a ranked selection of summary-worthy segments. It constitutes the core intelligence of AVSUM.

A. Model Architecture

The selector is implemented as a bidirectional GRU [23] with a multi-head self-attention layer [24] applied over the hidden state sequence. Given a video represented as a sequence of N segment VSS vectors $v1, v2, ..., vN \in R128$, the model produces importance scores $s1, s2, ..., sN \in [0,1]$. The training procedure follows Algorithm 1.

Algorithm 1 Temporal Attention Selector Training Procedure

```
Require: Video-KB rows {(V_i, y_i)}^N, V_i∈R^{T×128}, y_i∈{0,1}^T
Load all rows from video_knowledge_base
Normalise VSS vectors per video: v¯ ← L2Normalise(V_i)
Evaluate M1: BiGRU + MultiHeadAttention via 5-fold CV
Evaluate M2: Transformer Encoder via 5-fold CV
Evaluate M3: LSTM + Attention via 5-fold CV
M* ← argmax_{M∈{M1,M2,M3}} F1@Summary(M)
Retrain M* on full dataset with focal loss
φ ← GradientSHAP(M*)
Serialise M*, φ, normaliser
```

B. Inference and Ranking

At inference time, given a new VSS sequence Vnew, the selector produces importance scores S = {s1,...,sN}. Segments are sorted by descending score; the top-k segments are selected to form the summary, where k is determined by the target compression ratio r specified by the user (default: r = 0.15, i.e., 15% of video duration). A minimum-diversity constraint ensures that no two adjacent segments both appear in the summary unless their cosine similarity falls below a configurable threshold (default: 0.85).

C. SHAP-Based Explanations

For each selected segment, SHAP values φj are computed for each VSS dimension j using GradientSHAP, attributing the importance score to specific multi-modal properties of the segment. The top-5 SHAP contributors are extracted and supplemented with a rule-based reasoning template that translates high-magnitude SHAP features into natural language. Examples include:

- High optical_flow_magnitude and scene_change_rate → "This segment contains high motion and visual dynamism, indicative of a key event."
- High sentence_embedding novelty and keyword_density → "This segment introduces semantically distinct content not covered in prior segments."
- High speech_activity_ratio and lexical_density → "Dense spoken information in this segment suggests high informational value for lecture content."
- Low cosine_sim_prev combined with high face_presence_ratio → "A new speaker or subject enters the scene, marking a topic or scene transition."

A library of 24 such pattern rules is maintained, with the top-2 applicable rules combined to produce the explanation string returned to the user.

D. Self-Improvement Feedback Loop

When a user submits manual correction annotations via the feedback endpoint (POST /feedback), the system appends a new row to video_training_rows with source='user_feedback'. When accumulated feedback exceeds a configurable threshold (default: 20 videos), an asynchronous retraining job is triggered and the serialised model is updated on disk. This closed-loop mechanism enables AVSUM to grow progressively more accurate without manual intervention.

VII. SCENE COHERENCE ADVISOR

The Scene Coherence Advisor analyses the raw temporal segment sequence for structural weaknesses and produces a severity-ranked, actionable transformation report. This component is unique to AVSUM and has no equivalent in existing video summarization frameworks.

A. Diagnostic Checks

The advisor implements ten diagnostic checks, each returning an issue record with severity (Low / Medium / High), a natural language description, a targeted recommendation, and an executable Python code snippet:

- Temporal Redundancy. cosine_sim > 0.90 between adjacent segments: High (merge or drop); > 0.80: Medium (flag for review).
- Scene Boundary Misalignment. Shot changes detected within segments rather than at boundaries: Medium (re-segment using PySceneDetect).
- Audio-Visual Desynchrony. Speech activity in transcript not aligned to corresponding visual frames: High (force alignment with Gentle or Whisper timestamps).
- Static Segment Detection. optical_flow_magnitude < 0.05 and face_presence_ratio < 0.1: High (mark as low-importance candidate).
- Transcript Gap Analysis. Segments with zero speech activity but high visual novelty: Medium (flag for manual review; may represent important visual-only events).
- Over-Compression Warning. target_ratio < 0.05: Medium (risk of losing critical content; recommend minimum 8% compression ratio).
- Dominant Topic Imbalance. topic_distribution_entropy < 0.3: High (summary over-represents one topic; activate diversity constraint).
- Resolution Inconsistency. Frame resolution changes mid-video: Low (normalise to consistent resolution before extraction).
- Missing Modality Alert. No audio stream or transcript available: Medium (visual-only mode activated; transcript features zeroed in VSS).
- Target Leakage in Annotation. Annotator-assigned importance score > 0.95 for >50% of segments: High (annotation quality warning; crowdsourced labels may be unreliable).

B. Overall Coherence Score

A scalar video coherence score is computed analogously to the dataset health score introduced in AMLA [25]:

$$C\_score = max(0,\ 1.0 - \Sigma_{i \in issues}\ w\_i) \quad (1)$$

where wi ∈ {0.05, 0.10, 0.20} for Low, Medium, and High severity issues respectively. The score is displayed as a colour-coded gauge (green: > 0.7; yellow: 0.4–0.7; red: < 0.4) in the web interface.

VIII. EXPERIMENTAL EVALUATION

A. Experimental Setup

Benchmark Suite. 60 videos were drawn from TVSum, SumMe, OpenVideo, and Kinetics-400, spanning diverse characteristics: video duration (3–90 minutes), frame rate (24–60 fps), genre (lecture, news, sports, surveillance, cinematic), audio availability (silent, mono, stereo), and transcript availability (none, ASR-generated, manually annotated). The selection criterion required at least five independent annotators for each video, ensuring statistical reliability of the ground-truth importance labels.

Selector Evaluation. The temporal attention selector was evaluated using leave-one-video-out cross-validation (LOVO-CV): for each of the 60 videos, the model was trained on the remaining 59 and evaluated on the held-out video. F1-Score@Summary (harmonic mean of precision and recall against ground-truth summary segments at 15% compression) and Kendall's τ correlation between predicted and annotated importance rankings were computed.

Baselines.

- Random: Uniformly random segment selection at 15% compression ratio (expected F1 ≈ 0.15).
- Uniform Sampling: Select every Nth segment to achieve target compression ratio.
- Visual-Only: AVSUM with transcript and audio features zeroed (Group C and B features = 0).
- Transcript-Only: AVSUM with visual features zeroed (Group A and D features = 0).

Statistical Testing. Wilcoxon signed-rank tests were applied pairwise between AVSUM and each baseline, treating per-video F1 scores as paired observations.

B. Results

1) F1-Score and Kendall's τ: Table II reports the main evaluation results. AVSUM achieves an F1-Score@Summary of 0.74, substantially outperforming all baselines. All improvements are statistically significant at $p < 0.001$.

TABLE II
VIDEO SUMMARIZATION PERFORMANCE (LOVO-CV, N = 60 VIDEOS)

Method	F1@Sum.	Kendall τ	ΔF1	p-val.
Random Selection	0.152	0.09	—	—
Uniform Sampling	0.321	0.23	—	—
Visual-Only	0.548	0.41	—	—
Transcript-Only	0.512	0.38	—	—
AVSUM (Ours)	0.740	0.61	+0.192	<0.001

2) Ablation Study: VSS Feature Group Contribution: To assess the relative contribution of each VSS feature group, ablation experiments were conducted by training the selector with each group removed in turn. Table III reports results.

TABLE III
ABLATION STUDY: VSS FEATURE GROUP CONTRIBUTION (LOVO-CV)

Configuration	F1@Sum.	Δ from Full
Full VSS (all 5 groups)	0.740	—
w/o Temporal Context (Group D)	0.631	−0.109
w/o Transcript-Semantic (Group C)	0.668	−0.072
w/o Audio-Spectral (Group B)	0.689	−0.051
w/o Domain Complexity (Group E)	0.712	−0.028
w/o Visual Frame (Group A)	0.609	−0.131

Visual frame features (Group A) are the single most informative group (−0.131 when removed), with temporal context features (Group D) a close second (−0.109). The significant contribution of Group D validates the redundancy-aware novelty scoring approach, while the contribution of Group C (−0.072) confirms the value of transcript integration even when ASR quality is imperfect.

3) Genre-Stratified Performance: Table IV reports F1-Score@Summary stratified by video genre. AVSUM performs best on lecture content (F1 = 0.81), where the transcript modality provides strong semantic signal, and on news broadcasts (F1 = 0.78), where structured visual-verbal correspondence is high. Performance is lowest on surveillance footage (F1 = 0.61), where ground-truth annotations are sparse and the absence of spoken content limits transcript features.

TABLE IV
GENRE-STRATIFIED PERFORMANCE (LOVO-CV)

Genre	N Videos	F1@Sum.	Kendall τ	Dominant SHAP
Lecture / Education	18	0.810	0.68	keyword_density
News Broadcast	14	0.780	0.65	face_presence
Cinematic / Narrative	12	0.723	0.59	scene_change_rate

Sports / Action	10	0.706	0.57	optical_flow_mag
Surveillance	6	0.612	0.44	novelty_score

4) SHAP Feature Importance at the Meta-Level: Across all 60 videos, aggregated SHAP importance values identified the top-5 most globally predictive VSS features: (1) novelty_score, (2) optical_flow_magnitude, (3) keyword_density, (4) cosine_sim_prev, and (5) speech_activity_ratio. These findings confirm that temporal novelty and motion energy are the dominant importance signals, while transcript semantics provide complementary discriminative power.

5) Scene Coherence Advisor Evaluation: The Scene Coherence Advisor was applied to all 60 benchmark videos. The mean coherence score was 0.58 (SD = 0.16), indicating moderate structural quality issues even after standard preprocessing. Temporal redundancy and missing transcript issues were the most frequently triggered warnings (72% and 48% of videos, respectively). Target leakage warnings were triggered in 8% of videos, all confirmed as genuine annotation artefacts on manual inspection.

IX. DISCUSSION

A. Original Contributions

AVSUM makes six original contributions to the video summarization literature:

1) **Video Semantic Signature (VSS).** A principled, 128-dimensional multi-modal per-segment embedding combining five feature groups across visual, audio, transcript, temporal, and complexity dimensions. No existing open-source tool implements all five groups in a unified inference pipeline.
2) **Novelty-Aware Temporal Scoring.** The novelty_score and cumulative_coverage features explicitly penalise redundant segment selection within the importance model, combining representativeness and diversity objectives in a single learned criterion.
3) **SHAP-Augmented Temporal Selector.** Per-segment SHAP explanations ground summarization decisions in interpretable multi-modal evidence—the first such system in the video summarization literature.
4) **Scene Coherence Advisor.** Proactive, structured video quality assessment and pre-summarization diagnostics, entirely absent from existing automated summarization systems.
5) **Hybrid Video-KB Construction.** Benchmark-seeded, locally-validated Knowledge Base construction with a Spearman alignment score as a quality metric, enabling principled cross-dataset generalisation assessment.
6) **Closed-Loop Self-Improvement.** An operational feedback loop that continuously updates the Video-KB with real-world user annotations without manual curation, analogous to the mechanism introduced in AMLA [25].

B. Comparison to Existing Systems

Table V positions AVSUM against representative video summarization systems across key capability dimensions.

TABLE V
CAPABILITY COMPARISON WITH REPRESENTATIVE SYSTEMS

System	Multi-Modal	Explainable	Scene Advice	Self-Impr.	API/Fast
vsLSTM [3]	No	No	No	No	No
SUM-GAN [7]	No	No	No	No	No
DSNet [8]	No	No	No	No	Partial
VideoSum [12]	Partial	No	No	No	No

AVSUM (Ours)	Yes	Yes	Yes	Yes	Yes

C. Future Work

Planned extensions include: (i) query-driven summarization, where a natural language query conditions the importance model to surface query-relevant segments; (ii) integration of visual question answering (VQA) models to enable semantic segment filtering; (iii) active learning for Video-KB growth, prioritising videos that maximally reduce model uncertainty; (iv) a video similarity retrieval interface enabling case-based reasoning across the knowledge base; and (v) real-time summarization mode for live stream processing using a sliding-window attention variant.

X. CONCLUSION

This paper presented AVSUM, the Adaptive Video Summarization framework—a comprehensive, interpretable, and self-improving architecture for automated multi-modal video summarization. By introducing the Video Semantic Signature embedding scheme, a SHAP-augmented temporal attention selector, and a first-of-its-kind Scene Coherence Advisor, AVSUM advances the state of the art along three axes: modality richness, recommendation interpretability, and actionable video quality guidance. Evaluated on 60 benchmark videos, AVSUM achieves an F1-Score@Summary of 0.74, representing a 19.2-percentage-point improvement over the strongest single-modality baseline at $p < 0.001$. The multi-modal integration is validated by the ablation study: removing any single feature group degrades performance, confirming the complementary nature of visual, audio, transcript, temporal, and complexity signals. Deployed as an interactive full-stack web application, AVSUM democratises expert-level video summarization for practitioners without specialist ML knowledge. The self-improvement mechanism ensures that recommendations grow progressively more accurate as real-world annotation evidence accumulates.

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