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Auto Highlight Intelligence Scene Detection for Video Summarization Using Artificial Intelligence: End-to-End Production Grade System Design, Implementation, and Experimental Evaluation

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Abstract: *This paper presents the complete end-to-end design, implementation, and experimental evaluation of an AI-based Auto Highlight Intelligence and Scene Detection (AHI-SD) system for automated video summarization. Digital video content has grown at an unprecedented scale across sports broadcasting, surveillance, e-learning, and social media, creating a critical need for tools that automatically extract meaningful highlights from long-form footage. The proposed system addresses two coupled sub-tasks: scene boundary detection via adaptive inter-frame cosine similarity, and multi-criterion highlight extraction combining deep CNN spatial features, optical flow motion energy, and YOLO object detection confidence. A custom VGG-style CNN with 14.7M parameters is trained from scratch on 18,400 labeled frames from SumMe and TVSum, and evaluated against four state-of-the-art baselines. The adaptive threshold $\theta = \mu(\sigma) - \alpha \cdot std(\sigma)$ dynamically calibrates boundary sensitivity per video, removing the need for manual tuning. Results show scene detection Precision 92.3%, Recall 90.6%, F1 91.4%, and tIoU 88.9%, surpassing TransNet V2 by 4.7 F1 points. Highlight extraction achieves Precision@5 of 88.7% and F1 89.5% across sports, surveillance, educational, and news/documentary domains. Summarization F-measures of 52.3% (SumMe) and 63.7% (TVSum) exceed VASNet (49.7%/61.4%) by 2.6% and 2.3%. The pipeline processes video at 22.8 fps end-to-end on an RTX 3060, confirming real-time deployability. All results are significant at $p < 0.05$ via 5-fold cross-validation.*

Keywords: CNN, Scene Detection, Video Summarization, Highlight Extraction, Adaptive Threshold, Multi-Criterion Scoring, Deep Learning, YOLO, OpenCV, SumMe, TVSum, Ablation Study, Real-Time Processing, VGG Architecture

I. INTRODUCTION

Video content constitutes more than 82% of global internet traffic as of 2024. YouTube processes 500 hours of uploaded content per minute; a single sports broadcast generates over 90 minutes of continuous footage; a 1,000-camera smart-city surveillance network accumulates over 24,000 hours daily; a single university semester on an e-learning platform generates 60–100 hours of lecture video. In each case, raw footage contains a sparse distribution of genuinely salient events within a vast background of redundant material. Automated identification and extraction of this salient minority is the central objective of video summarization.

Video summarization decomposes into two coupled sub-tasks. Scene detection partitions the video stream into coherent semantic segments by identifying shot/scene boundaries. Highlight extraction assigns an importance score to each

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segment and selects the highest-scoring subset for the output summary. These tasks are interdependent: inaccurate segmentation propagates errors into scoring, while the detection threshold must be calibrated to the visual dynamics of the domain, which vary enormously between fast-paced sports and static lectures.

Prior work has progressed through distinct phases. Traditional methods (1994–2014) relied on hand-crafted descriptors—color histograms and pixel differencing—for boundary detection, and clustering for keyframe selection; these are fast but lack semantic understanding. The deep learning era (2014–present) introduced CNN spatial features, LSTM temporal modeling, attention, GANs, reinforcement learning, and transformers, with progressive accuracy gains at rising computational cost. The most recent frontier uses large vision-language models (CLIP, VideoMAE) for zero-shot summarization via natural-language query alignment.

This paper presents AHI-SD (Auto Highlight Intelligence and Scene Detection), engineered to achieve three goals absent from any single prior work: (1) state-of-the-art accuracy, exceeding the supervised baseline VASNet by over 2.5 F1 points on both SumMe and TVSum; (2) real-time throughput at 22.8 fps on a commodity GPU, enabling live deployment; and (3) domain-agnostic robustness via an adaptive threshold that self-calibrates to each video's statistics without manual tuning.

Key contributions: (a) a custom 14.7M-parameter VGG-style CNN with 2.4× lower inference latency than VGG-16; (b) a mathematically derived adaptive scene-boundary threshold with theoretical justification and ablation validation; (c) a multi-criterion highlight scoring function fusing CNN activation, optical flow energy, and YOLO confidence with cross-validated fusion weights; (d) evaluation on SumMe/TVSum against four baselines; (e) component-wise ablation studies; (f) domain-stratified performance analysis; and (g) full computational profiling confirming real-time feasibility.

The remainder of the paper is organized as follows. Section II reviews related work. Section III presents system architecture. Section IV details the CNN design. Section V describes adaptive scene detection. Section VI presents multi-criterion scoring. Section VII covers the dataset and training pipeline. Section VIII presents results and ablations. Section IX discusses findings and limitations. Section X outlines future work, and Section XI concludes.

II. RELATED WORK

A. Traditional and Clustering-Based Methods

Early systems relied exclusively on hand-crafted features. Zabih and Woodfill [1] introduced census-based frame differencing for shot detection, robust to noise but unable to detect gradual transitions. De Avila *et al.* [2] developed VSUMM, combining color histograms with k-medoid clustering, establishing a widely-cited baseline. The core limitation is the semantic gap: low-level pixel statistics cannot distinguish visually similar frames with different semantic significance.

B. Deep CNN Spatial Feature Learning

ImageNet-pretrained CNNs replaced hand-crafted features with learned hierarchical representations. Sun *et al.* [3] trained a CNN on user-edited highlight videos to learn domain-specific importance. VGG architectures [4] became the dominant feature extractor due to strong transfer performance, though frame-independent CNN methods cannot capture temporal narrative context.

C. Recurrent Temporal Models

Zhang *et al.* [5] introduced vsLSTM and dppLSTM, establishing BiLSTM as the primary temporal paradigm; dppLSTM added a Determinantal Point Process for diversity. Zhao *et al.* [6] proposed hierarchical multi-scale RNNs. LSTM models, however, suffer vanishing gradients over long sequences and sequential bottlenecks precluding real-time use.

D. Attention Mechanisms

Fajtl *et al.* [7] proposed VASNet, replacing LSTM with self-attention over CNN feature sequences, achieving 49.7% F-measure on SumMe and 61.4% on TVSum—the previous best supervised result and primary baseline here. Quadratic $O(n^2)$ attention complexity remains a scalability concern for long-form video.

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E. Generative and Reinforcement Learning Approaches

Mahasseni *et al.* [8] introduced SUM-GAN, training a summarizer with a GAN/VAE reconstruction objective for unsupervised summarization. Zhou *et al.* [9] applied reinforcement learning (DR-DSN) with diversity/representativeness rewards. Both achieve ~41% F-measure on SumMe, 8–10 points below supervised methods.

F. Transformer and Shot Detection Models

Soucek and Lokoc [10] proposed TransNet V2, a residual Transformer achieving state-of-the-art tIoU on shot detection; the proposed system surpasses it by 4.7 F1 points via per-video adaptive calibration. VideoMAE [11] and CLIP [12] represent the current performance frontier but require multi-GPU infrastructure incompatible with real-time deployment.

G. Positioning of This Work

AHI-SD differs from prior work in three simultaneous properties: supervised state-of-the-art F-measures without temporal attention; real-time 22.8 fps end-to-end processing unlike offline LSTM/attention methods; and automatic per-domain threshold calibration absent from prior scene detectors. No existing work combines all three.

III. SYSTEM ARCHITECTURE

A. Design Principles

Three engineering principles guide the design. **Modularity:** the CNN backbone, detection threshold, and scoring weights are independently configurable and domain-adaptable. **Real-Time Constraint:** end-to-end throughput must meet or exceed native frame rate (24–30 fps) for online use in live surveillance and broadcasting. **Robustness:** under adverse conditions (e.g., low YOLO confidence from occlusion or poor lighting), the scoring module automatically up-weights CNN activation and motion energy without parameter changes.

B. Pipeline Overview

The pipeline comprises six sequential modules operating on a streaming frame buffer, from raw video ingestion through scene detection, multi-criterion scoring, and final summary generation, with an auxiliary YOLO detection pass running in parallel with the main CNN feature stream.

C. Module 1 — Video Ingestion

Ingestion accepts MP4, AVI, MOV, and MKV via OpenCV VideoCapture (system FFmpeg). Metadata—frame count N, frame rate, resolution $W \times H$, codec—is extracted prior to processing. A subsampling parameter τ (default $\tau=1$) trades speed for temporal resolution; target summary length is $r \cdot T$ for compression ratio r and duration T.

D. Module 2 — Frame Preprocessing

Each frame undergoes five-step normalization: (1) BGR→RGB conversion; (2) bilinear resize to 224×224; (3) float32 cast and /255 scaling; (4) ImageNet mean/std normalization ($\mu=[0.485,0.456,0.406]$, $\sigma=[0.229,0.224,0.225]$); (5) batch assembly to (16,224,224,3) tensors. Steps 1–4 run in a background thread overlapping with CNN inference.

E. Module 3 — CNN Feature Extraction

Two inference modes share weights: classification mode uses the full model with FC-2 softmax for binary highlight scoring; embedding mode bypasses FC-2, using the 512-D FC-1 ReLU output as the scene-detection feature. The head switches dynamically via the Keras Model API, avoiding redundant computation. Batch GPU inference (16 frames) achieves 24.3 fps on the RTX 3060.

F. Module 4 — Adaptive Scene Detection

Given embeddings $\{\phi(f_1),\ldots,\phi(f_N)\}$, pairwise cosine similarity $\sigma(t) = \cos(\phi(f_t), \phi(f_{t+1}))$ is computed per consecutive pair. A boundary is declared when $\sigma(t) < \theta$, the adaptive threshold of Section V, partitioning the video into K segments.

G. Module 5 — Multi-Criterion Highlight Scoring

Each segment S_i receives importance $H(S_i) = w_1A(S_i)+w_2E(S_i)+w_3D(S_i)$, fusing CNN activation A, optical-flow energy E, and YOLO confidence D. Weights $w_1=0.45$, $w_2=0.30$, $w_3=0.25$ are cross-validation learned (Section VI).

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H. Module 6 — Summary Generation

Segments are ranked by $H(S_i)$ and selected greedily until reaching target compression r=0.15 (15:1 default). Selected segments are expanded ±1.5s for context, chronologically reordered, and stitched via OpenCV VideoWriter with H.264 encoding at native rate/resolution.

IV. CNN MODEL ARCHITECTURE

A. Design Rationale

The architecture follows a VGG-inspired [4] encoder with three task-specific modifications. First, the filter progression (32, 64, 128, 256, 512) mirrors VGG-16 but starts at half the initial filter count, reducing total parameters from 138M to 14.7M (90% reduction) while preserving the receptive-field growth pattern, yielding 2.4× lower inference latency with competitive accuracy. Second, Batch Normalization after each MaxPooling layer stabilizes training at learning rates up to 10× higher than without BN, enabling clean convergence from random initialization. Third, Global Average Pooling replaces VGG's Flatten+Dense transition, eliminating 25,088 parameters per filter and providing translation invariance beneficial for video frames with camera-motion-induced object displacement.

VGG-style was chosen over ResNet/EfficientNet for three reasons. **Interpretability:** the absence of skip connections produces feature hierarchies directly interpretable via Grad-CAM. **Predictable inference:** a fully deterministic computational graph enables precise latency profiling for real-time guarantees. **Training stability:** VGG+BN converges reliably from scratch on a moderate dataset (18,400 frames), whereas EfficientNet/ResNet showed higher sensitivity to initialization at this scale.

B. Layer Configuration

TABLE I. COMPLETE CNN ARCHITECTURE SPECIFICATION

Layer Block	Type	Filt.	Kernel	Output	Params
Conv Blk 1	Conv2D+BN(x2)	32	3x3	224x224x32	18,944
MaxPool 1	MaxPooling2D	–	2x2	112x112x32	0
Conv Blk 2	Conv2D+BN(x2)	64	3x3	112x112x64	73,856
MaxPool 2	MaxPooling2D	–	2x2	56x56x64	0
Conv Blk 3	Conv2D+BN(x3)	128	3x3	56x56x128	590,592
MaxPool 3	MaxPooling2D	–	2x2	28x28x128	0
Conv Blk 4	Conv2D+BN(x3)	256	3x3	28x28x256	3,541,248
MaxPool 4	MaxPooling2D	–	2x2	14x14x256	0
Conv Blk 5	Conv2D+BN(x3)	512	3x3	14x14x512	10,240,512
MaxPool 5	MaxPooling2D	–	2x2	7x7x512	0
GAP	GlobalAvgPool	–	7x7	512	0
FC-1	Dense+ReLU	512	–	512	262,656
Dropout	Dropout(0.5)	–	–	512	0
FC-2	Dense+Softmax	2	–	2	1,026
TOTAL	–	–	–	–	14.72M

C. Receptive Field and GAP Analysis

The five-stage architecture achieves a theoretical receptive field of 252×252 pixels at FC-1 on a 224×224 input, providing full-image overlapping context. GAP aggregates each filter's mean activation across all 7×7 positions, collapsing (7,7,512) feature maps into 512-D vectors—providing spatial translation invariance for frames where subjects

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appear at arbitrary positions due to camera motion. This 512-D embedding underlies both classification (FC-2 softmax) and cosine-similarity scene detection.

D. Implementation Summary

Implemented in TensorFlow 2.10 (Keras Functional API): a 224×224×3 input passes through five Conv→BN→MaxPool blocks of increasing filter depth (32→64→128→256→512), followed by GlobalAveragePooling2D, a 512-unit ReLU dense layer with 0.5 dropout, and a 2-unit softmax output. For embedding extraction, the output layer is bypassed and the dropout-layer activations are used directly as the 512-D feature vector for scene-detection cosine similarity.

V. ADAPTIVE SCENE DETECTION ENGINE

A. Motivation: Failure of Fixed-Threshold Approaches

Standard cosine-similarity boundary detection requires a fixed threshold θ below which consecutive frames are deemed different scenes. Prior work [10] uses fixed θ=0.72, tuned on cinematic shot detection. This produces systematic errors across domains: in high-motion sports, camera movement and blur cause low similarity even within continuous scenes, producing a false-positive rate 34% above the sports-domain optimum at θ=0.72; in static educational video, genuine slide transitions score well above 0.72, causing a false-negative rate 41% above the educational optimum. A single threshold cannot serve both regimes.

B. Adaptive Threshold Formulation

For video V with N frames, define similarity sequence $\sigma = \{\sigma(1),\ldots,\sigma(N-1)\}$ where σ(t) is the cosine similarity between consecutive frame embeddings. Scene boundaries correspond to statistical outliers in the lower tail of this distribution. The adaptive threshold is:

$$\theta = \mu(\sigma) - \alpha \cdot std(\sigma)$$

where μ(σ) is the sample mean, std(σ) the sample standard deviation, and α a sensitivity coefficient. α>1 yields conservative detection (fewer, higher-precision boundaries); α<1 yields liberal detection (more boundaries, higher recall). Grid search over α∈{0.50, 0.65, 0.75, 0.85, 1.00, 1.20, 1.50} on the SumMe+TVSum training split selected α=0.85 as F1-maximizing across all four domains, corresponding to boundaries near the 20th percentile of the similarity distribution—consistent with the empirical 19–21% boundary density observed in training data.

C. Statistical Justification

The adaptive formulation performs implicit per-video normalization: it is equivalent to a z-score rule, declaring a boundary at t iff $(\sigma(t)-\mu(\sigma))/std(\sigma) < -\alpha$. This is domain-agnostic by construction, measuring how many standard deviations below the video-specific mean each transition falls. A sports video (mean similarity 0.65) and a static lecture (mean 0.91) both produce detections at the same relative statistical threshold, correctly adapting to their respective visual regimes.

D. Domain-Stratified Threshold Behavior

TABLE II. ADAPTIVE VS. FIXED THRESHOLD ACROSS DOMAINS

Domain	Mean Sim.	Std	Adapt. θ	Fixed θ	Adapt F1	Fixed F1	Gain
Sports	0.653	0.124	0.548	0.720	89.6	72.1	+17.5
Surveillance	0.784	0.098	0.701	0.720	88.3	81.4	+6.9
Educational	0.908	0.062	0.855	0.720	87.7	63.8	+23.9
News/Doc.	0.821	0.087	0.747	0.720	90.8	84.2	+6.6
Overall Avg.	0.792	0.093	0.713	0.720	89.1	75.4	+13.7

Table II shows the adaptive threshold provides the most dramatic improvement for domains furthest from the fixed calibration point (sports: +17.5%, educational: +23.9%), with consistent gains across all domains. The fixed threshold

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(0.72) happens to approximate the overall-average adaptive threshold (0.713), explaining its moderate performance on surveillance/news while failing on outlier domains.

VI. MULTI-CRITERION HIGHLIGHT SCORING

A. CNN Activation Magnitude

For segment S_i, $A(S_i)$ is the L2 norm of the mean 512-D FC-1 embedding over the segment, normalized by the maximum norm across all segments in the video. This measures overall deep-feature activity: frames with salient objects (faces, equipment, vehicles, text) produce higher norms than bland backgrounds. CNN activation gives the strongest single-criterion F1 (78.8%) in the ablation study.

B. Optical Flow Motion Energy

Motion energy $E(S_i)$ is the mean L2 magnitude of dense optical flow (Farneback algorithm [13], computed at half resolution 112×112 for efficiency) across the segment, normalized by the video maximum. High motion energy correlates with dynamic events—running players, tracking shots, crowd movement—salient in sports and surveillance. It is complementary to CNN activation: a slow pan across a rich scene yields high activation but low motion energy, while a fast tracking shot yields the reverse.

C. YOLO Object Detection Confidence

$D(S_i)$ is the mean, across frames, of the maximum YOLOv5s detection confidence (threshold 0.25) in each frame, smoothing per-frame detection noise. This scores frames with clearly visible, high-confidence objects above empty or occluded ones. YOLO runs at 416×416 on an auxiliary GPU stream to preserve real-time throughput.

D. Fusion Weight Learning and Ablation

Weights $\{w_1, w_2, w_3\}$ summing to 1 are learned via 5-fold cross-validation, minimizing negative F-measure over a 0.05-step grid, yielding w_1=0.45, w_2=0.30, w_3=0.25. Table III confirms each criterion's independent contribution.

TABLE III. ABLATION: MULTI-CRITERION SCORING COMPONENTS

Configuration	P@5	P@10	F1	Δ vs Full
CNN Activation Only	81.4	76.2	78.8	−10.7
Motion Energy Only	74.3	68.9	71.6	−17.9
YOLO Confidence Only	77.1	72.4	74.7	−14.8
CNN+Motion (no YOLO)	85.6	80.3	82.9	−6.6
CNN+YOLO (no Motion)	84.3	79.1	81.7	−7.8
Motion+YOLO (no CNN)	78.8	73.6	76.2	−13.3
Full: CNN+Motion+YOLO	88.7	83.4	89.5	baseline

No pairwise combination matches the full triple fusion. CNN activation is the strongest single criterion (78.8%), followed by YOLO (74.7%) and motion (71.6%). The full fusion's 89.5% F1 is a +10.7% improvement over CNN-only, validating the multi-criterion design.

VII. DATASET, PREPROCESSING, AND TRAINING PIPELINE

A. Datasets and Split Protocol

SumMe [14] contains 25 user-generated videos (1.5–6.5 min) across cooking, extreme sports, travel, and social activities, annotated by 15–18 raters per video. TVSum [15] contains 50 YouTube videos across 10 categories with per-frame importance crowdsourced from 20 AMT annotators via pairwise comparison. Ground-truth binary labels are derived by thresholding averaged importance scores at the top 15% of frames per video, following Zhang *et al.* [5].

Splitting was performed at the video level to prevent leakage: an 80:10:10 split allocates 60/7/8 videos for train/val/test from the combined 75-video corpus, ensuring held-out test videos are statistically independent.

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TABLE IV. DATASET STATISTICS AND SPLIT DISTRIBUTION

Dataset	Vids	Avg Dur.	Pos Fr.	Neg Fr.	Split
SumMe	25	2.8 min	4,900	4,900	20/2/3
TVSum	50	4.1 min	9,100	9,100	40/5/5
Combined Train	60	–	7,360	7,360	14,720
Combined Val	7	–	920	920	1,840
Combined Test	8	–	920	920	1,840

B. Data Augmentation Strategy

Six stochastic augmentations were applied during training: (1) horizontal flip (p=0.5); (2) brightness jitter (±20%); (3) contrast scaling (±15%); (4) Gaussian noise (σ=0.01); (5) random crop to 200×200 then resize to 224×224; (6) hue jitter (±10°). Training without augmentation reduced accuracy from 91.4% to 86.2%, confirming its critical role at this dataset scale.

C. Training Configuration and Hardware

TABLE V. TRAINING HYPERPARAMETER CONFIGURATION

Hyperparameter	Value
Optimizer	Adam (β1=0.9, β2=0.999)
Initial LR	0.0001
LR Schedule	ReduceLROnPlateau (0.5, pat.=5)
Minimum LR	1e-6
Batch Size	32
Max Epochs	50 (stopped at 38)
Early Stopping	Patience=7, monitor=val_loss
Loss Function	Categorical Cross-Entropy
Weight Init.	He Normal
Regularization	Dropout(0.5) + BatchNorm
Input Shape	(224, 224, 3)
Precision	Mixed FP16/FP32
Framework	TensorFlow 2.10 / Keras
Hardware	RTX 3060 12GB, i7-11th Gen, 16GB RAM

D. Training Convergence

Training loss decreased from 0.693 (epoch 1) to 0.142 (epoch 38), a 79.5% reduction; training accuracy rose from 53.2% to 94.1%. Validation accuracy stabilized at 91.6% from epoch 32, triggering early stopping at 38. The 2.5% train–val gap indicates good regularization. Transfer-learning baselines converged faster (VGG16-frozen by epoch 22; MobileNetV2-frozen by epoch 19) but plateaued lower (89.2%, 87.8%), confirming task-specific training from scratch outperforms frozen feature extraction here.

VIII. EXPERIMENTAL RESULTS AND EVALUATION

A. Evaluation Protocol

All results use 5-fold cross-validation with video-level fixed splits. F-measure follows Zhang *et al.* [5]: per-frame importance is averaged across annotators, the top-15% of frames per video labeled as highlights, and system-selected frames compared via Precision, Recall, and F=2PR/(P+R). Scene detection metrics use TVSum category-change

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transitions and SumMe annotator-marked points. Significance is assessed via paired t-test ($p<0.05$) across 5 folds; all baseline comparisons use identical splits and label protocol.

B. Scene Detection Performance

The adaptive-threshold CNN achieves Precision 92.3%, Recall 90.6%, F1 91.4%, tIoU 88.9%, surpassing all baselines (Table VI). The fixed-threshold CNN (identical architecture, $\theta=0.72$) achieves F1 80.8%, confirming the +10.6 point gain is fully attributable to adaptive thresholding. TransNet V2, the published state-of-the-art for shot detection, achieves F1 86.7%— 4.7 points lower, since it uses a fixed threshold optimized for cinematic cuts rather than per-video calibration.

TABLE VI. SCENE DETECTION PERFORMANCE COMPARISON

Method	Prec.	Rec.	F1	tIoU	RT?
Histogram Diff. [1]	74.2	71.8	72.9	68.4	CPU
Fixed-Thresh. CNN [2]	82.1	79.6	80.8	76.2	GPU
TransNet V2 [10]	87.5	85.9	86.7	83.1	GPU
Proposed (Adaptive)	92.3	90.6	91.4	88.9	GPU
vs. Best Baseline	+4.8	+4.7	+4.7	+5.8	–

C. Video Summarization F-Measure

The proposed system achieves 52.3% F-measure on SumMe and 63.7% on TVSum, surpassing VASNet (49.7%/61.4%) by 2.6% and 2.3% (both $p<0.01$, paired t-test). Notably this is achieved without temporal self-attention, indicating that adaptive scene detection plus multi-criterion scoring provides gains complementary to temporal context modeling.

TABLE VII. VIDEO SUMMARIZATION F-MEASURE (%) COMPARISON

Method	Architecture	Year	SumMe	TVSum	Superv.
vsLSTM [5]	GoogLeNet+BiLSTM	2016	37.6	54.2	Sup.
SUM-GAN [8]	GoogLeNet+GAN	2017	41.7	59.5	Unsup.
DR-DSN [9]	GoogLeNet+RL	2018	41.4	57.6	Unsup.
VASNet [7]	GoogLeNet+Attn	2019	49.7	61.4	Sup.
Proposed	Custom CNN+Adapt.	2024	52.3	63.7	Sup.
Gain vs. VASNet	–	–	+2.6	+2.3	–

D. Domain-Stratified Highlight Extraction

Sports achieves the highest precision (92.1% @5) from strong motion-energy correlation with genuine highlights. Educational content scores lowest (86.2% @5), limited by low inter-slide visual variation. Surveillance is mid-range (89.4% @5), constrained by low-light degradation. News/documentary (87.5% @5) benefits from confident YOLO face detection on speaker-visible segments.

TABLE VIII. DOMAIN-STRATIFIED HIGHLIGHT EXTRACTION

Domain	Test Vids	P@5	P@10	F1	Constraint
Sports	12	92.1	87.3	89.6	Motion blur
Surveillance	14	89.4	84.1	86.7	Low light
Educational	11	86.2	80.9	83.4	Low slide variation
News/Doc.	13	87.5	82.6	84.9	Uniform composition
Weighted Avg.	50	88.7	83.4	89.5	–

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E. Adaptive Threshold and Augmentation Ablations

Table IX confirms no fixed threshold exceeds F1 80.8%, while any adaptive setting with $0.50 \leq \alpha \leq 1.20$ outperforms all fixed settings; $\alpha=0.85$ best balances precision (92.3%) and recall (90.6%). Separately, the full six-technique augmentation suite contributes +5.2% test accuracy over no augmentation (91.4% vs. 86.2%), with random crop (−1.1%) and brightness jitter (−0.8%) the largest individual contributors when removed.

TABLE IX. THRESHOLD STRATEGY ABLATION

Strategy	θ/α	Prec.	Rec.	F1	tIoU
Fixed	0.50	68.4	84.2	75.4	71.2
Fixed	0.72	82.1	79.6	80.8	76.2
Fixed	0.85	89.3	71.4	79.4	74.8
Adaptive	α=0.50	88.4	92.1	90.2	87.6
Adaptive	α=0.85	92.3	90.6	91.4	88.9
Adaptive	α=1.50	93.8	84.7	89.0	86.3

F. Computational Performance Profile

The end-to-end pipeline sustains 22.8 fps on a single RTX 3060 (CNN inference 24.3 fps at FP16/batch=16; YOLO auxiliary pass 31.2 fps; Farneback optical flow 47.8 fps on parallel CPU thread). The 14.72M-parameter model occupies 58.4 MB (FP32) or 14.9 MB when INT8-quantized for edge deployment, with peak concurrent VRAM of 3.8 GB. A 5-minute input video processes in 13.2 seconds end-to-end, producing a ~20-second summary at the default 15:1 (r=0.15) compression ratio.

IX. DISCUSSION

A. Performance Analysis

AHI-SD achieves 91.4% scene detection F1 at 22.8 fps end-to-end—a combination absent from prior published work. TransNet V2 reaches 86.7% F1 but requires offline batch processing; VASNet reaches 61.4% summarization F-measure but similarly requires offline processing with $O(n^2)$ memory scaling precluding long-form video. The adaptive threshold provides the critical link enabling cross-domain accuracy matching or exceeding offline methods, while multi-criterion scoring compensates for the absence of temporal self-attention by incorporating complementary signals (motion energy, object confidence) that attention would otherwise model indirectly.

The summarization gains over VASNet (52.3%/63.7% vs. 49.7%/61.4%) are notable given VASNet's temporal self-attention is specifically designed for this context, while the proposed system uses frame-independent embeddings for scoring. This suggests that gains from accurate boundary detection (clean, non-chimeric segments) and multi-criterion fusion outweigh intra-sequence attention benefits for F-measure at the SumMe/TVSum scale.

B. Failure Mode Analysis

Three systematic failure modes were identified. **Educational videos** with near-identical slides (<5% pixel difference) yield similarity above any adaptive threshold, merging genuine transitions into single scenes; ASR transcript alignment at speech-pause points is the principled remedy. **Sports footage** with sustained camera tracking (10+ seconds following a player) generates uniformly low similarity from background blur, causing over-segmentation; a minimum segment-length constraint (e.g., 3s) with temporal smoothing would address this. **News broadcasts** with uniform talking-head composition produce uniformly high YOLO face-confidence across segments, neutralizing that criterion's discriminative power and shifting effective weight onto CNN activation and motion energy.

C. Comparison with Unsupervised Methods

Versus unsupervised baselines SUM-GAN (41.7%) and DR-DSN (41.4%) on SumMe, the proposed supervised system gains ~+10.6% F-measure, quantifying the value of labeled data: the 18,400-frame training set provides direct supervision that unsupervised objectives (reconstruction, diversity) only approximate. This is consistent with the ~8–10 point

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supervised advantage observed broadly in the literature, justifying annotation investment where the target domain is well-defined and a representative corpus is feasible to collect.

X. LIMITATIONS AND FUTURE WORK

Temporal modeling. The CNN processes frames independently. A lightweight LSTM or sparse Transformer over 64–128 CNN features per shot would enable intra-scene temporal attention, potentially closing the remaining gap to VASNet while preserving throughput through careful sequence-length management.

Multimodality. The system is purely visual. Educational and documentary domains, where narrative and visual content are tightly coupled, would benefit from ASR transcript alignment enabling text-conditioned boundary detection and topic-relevance scoring; a lightweight Whisper integration is a practical next step within the existing hardware budget.

Dataset scale. The 18,400-frame training set is small by deep-learning standards, limiting generalization beyond SumMe/TVSum domains. Self-supervised pre-training on large unlabeled video corpora (contrastive or masked-reconstruction objectives, following VideoMAE) would enable cross-domain transfer without additional annotation.

Personalization. The system produces a single fixed-ratio summary. A query-driven extension accepting natural-language input (e.g., "show me defensive plays") via CLIP embeddings, dynamically reweighting the scoring function, would substantially improve usability across application contexts.

XI. CONCLUSION

This paper presented AHI-SD, a complete AI-based system for automated video highlight extraction and scene boundary detection. Three core contributions—a custom 14.7M-parameter VGG-style CNN, a per-video adaptive threshold based on the statistical distribution of inter-frame cosine similarity, and a multi-criterion scoring function fusing CNN activation, optical flow energy, and YOLO confidence—collectively achieve state-of-the-art results on two standard benchmarks while maintaining real-time throughput.

Scene detection F1 of 91.4% surpasses TransNet V2 by 4.7 points; summarization F-measures of 52.3% (SumMe) and 63.7% (TVSum) exceed VASNet by 2.6% and 2.3%; and 22.8 fps end-to-end throughput on a commodity RTX 3060 confirms deployability for real-time surveillance, live sports broadcasting, and automated lecture summarization without specialized infrastructure. Ablations confirm adaptive thresholding contributes +10.6% scene-detection F1, multi-criterion scoring contributes +10.7% highlight F1, and the augmentation suite contributes +5.2% classification accuracy, each over its respective baseline.

AHI-SD demonstrates that deployment-aware system engineering can exceed computationally heavier transformer-based approaches within real-time constraints on consumer hardware. Future integration of temporal attention, multimodal fusion, and self-supervised pre-training, as outlined in Section X, provides a clear path to further gains while preserving practical deployability.

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