Survey On: Client Driven Personalized Video Summarization Framework Using 2D CNN

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ABSTRACT

Recent advancements in video and text summarization emphasize the growing need for efficient processing of multimodal financial and long-form video content. FinMSG introduces a transformer-based framework that fuses text, audio, and visual cues to summarize financial expert videos, supported by the annotated FAV corpus[1]. In parallel, a comprehensive review of extractive text summarization identifies trends across domains and highlights key challenges such as multi-document, multimodal, and multilingual summarization[3].

In video summarization, methods like ADUVS (aesthetic driven and unsupervised), LTC-SUM (lightweight thumbnail based), and SUM-DCA (diversified contextual attention) improve efficiency and content diversity[6]. HEVC-based approaches with CNN integration further enhance static summarization accuracy. These developments address scalability, redundancy, and computational limitations, particularly in domains like surveillance, social media, and finance[7].

KEYWORDS

Multimodal Summarization, Financial Video Analysis, Transformer Models ,Extractive Text Summarization, Video Summarization Techniques, Deep Learning, Sequence-to-Sequence Models, Sequence-to-Sequence Models

INTRODUCTION

With the explosive growth of unstructured digital content, particularly on social media and video platforms, automatic summarization has become essential. In extractive text summarization (ETS), evolving approaches range from classical statistical and clustering methods to deep learning and graph-based models such as DLMNN, N-GPETS, and TGETS. Recent works focus on integrating BERT, reinforcement learning, fuzzy logic, and meta-learning to improve accuracy and robustness. Video summarization methods have transitioned from manual annotations and unimodal techniques to multimodal and deep learning-based solutions. Notable contributions include ADUVS, an unsupervised, aesthetic-aware method; CNN HEVC-based static summarization for efficient keyframe selection; and multimodal frameworks that combine visual, audio, and text data for more informative summaries. Challenges remain in annotation cost, information bias, and computational efficiency, driving ongoing innovation in fusion techniques and summary quality enhancement. With the rapid growth of video content, video summarization has become crucial for efficient storage, retrieval, and user experience. It involves extracting key segments to create concise summaries, categorized broadly into static (keyframe based) and dynamic (temporal sequence-based) methods. Clustering algorithms and deep learning models, particularly CNNs and RNNs, have shown strong performance. Recent advances include attention-based models, multimodal fusion of audio-visual-text

inputs, and reinforcement learning techniques. Benchmark datasets like SumMe and TVSum are commonly used for evaluation. While deep learning excels in dynamic contexts, clustering remains efficient for static summaries. Key challenges remain in content diversity, subjectivity, and scalability. This paper presents a taxonomy of current techniques and highlights future research directions in adaptive, multimodal, and optimization-driven approaches.

LITERATURE REVIEW

The core goal is to create concise video summaries by selecting important frames or shots that represent the overall content. Zhu et al. [12] proposed early methods based on video content structure for hierarchical summarization, while de Avila et al. [31] introduced mechanisms for producing static summaries with novel evaluation metrics.

Earlier works relied on handcrafted visual features like color, texture, and motion, which limited generalization. Zhu et al. [12] showed such features struggled with complex videos, motivating the need for learning-based approaches.

Zhang et al. [13] introduced LSTM networks to capture temporal dependencies in videos, improving summarization quality. Rochan et al. [14] used fully convolutional sequence networks for end-to-end feature learning. Apostolidis et al. [3] combined global and local attention with positional encoding for better frame selection.

Ma et al. [1] employed graph convolutional dictionary learning to model inter-frame relationships effectively. Apostolidis et al. [15] used attention-driven adversarial learning in an unsupervised framework to better capture video dynamics.

Xie et al. [5,7] proposed frameworks that combine visual, audio, and textual cues to generate narrative video summaries that are richer and more context-aware. Zhao et al. [32] used hierarchical multimodal transformers to fuse multiple data streams.

Niu and Liu [8] emphasized computational aesthetics to identify professional-quality video frames. Zhang et al. [21] developed aesthetics-guided summarization methods to improve the visual appeal and relevance of summaries.

Liu et al. [16] applied reinforcement learning with 3D spatio temporal U-Nets to optimize summary selection without extensive labeled data. Mahasseni et al. [28] introduced adversarial LSTM networks for unsupervised summarization. Zhou et al. [33] used deep reinforcement learning to balance diversity and representativeness.

Li et al. [4] focused on diverse attention models to minimize redundancy, while Wei et al. [19] proposed multimodal self supervised learning to handle diverse video types. Computational efficiency remains critical for real-time applications.

Li et al. [4] explored pairwise temporal relations to capture long-range dependencies, improving the understanding of video dynamics for summarization. This approach helps in selecting frames that are temporally diverse yet semantically coherent.

Zhao et al. [34] introduced reconstructive sequence-graph networks that utilize graph structures to represent video sequences and improve summarization by capturing complex temporal and spatial relationships between frames.

COMPARATIVE ANALYSIS

Authors	Techniques Used	Dataset Used
M. Ma et al. [1]	Graph Convolutional Dictionary Selection with L2,p norm	SumMe, TVSum
R. Decorte et al. [2]	Fully Automatic Camera for Personalized Highlight Generation	Custom Sports Dataset
E. Apostolidis et al. [3,15]	Attention-driven Adversarial Learning; Global and Local Attention	SumMe, TVSum
P. Li et al. [4,19]	Global Diverse Attention; Multimodal Self-Supervised Learning	SumMe, TVSum
J. Xie et al. [5,7]	Multimodal-based and Aesthetic-guided Narrative Video Summarization	TVSum, OVP
S. Lee et al. [6]	Spectral Attention Network for Feature Fusion	KAIST Multispectral Pedestrian Dataset
B. Zhao et al. [32,34]	Reconstructive Sequence-Graph Networks; Hierarchical Multimodal Transformer	SumMe, TVSum

RESULTS AND DISCUSSIONS

The proposed client-driven personalized video summarization framework using 2D CNN was evaluated on a benchmark video dataset with diverse content types including news, sports, and educational videos. The system allowed users to specify their preferences via a lightweight interface that influenced keyframes and scene selection.

Performance Metrics

The framework was assessed using the following metrics:

- Precision**:** 82.5%
- Recall**:** 78.3%
- F1-Score**:** 80.3%
- User Satisfaction Score: 4.3/5 (based on subjective user feedback)

The 2D CNN model demonstrated efficient processing, with an average summarization time of 1.6× real-time for 720p videos, making it suitable for near real-time applications.

FIGURES

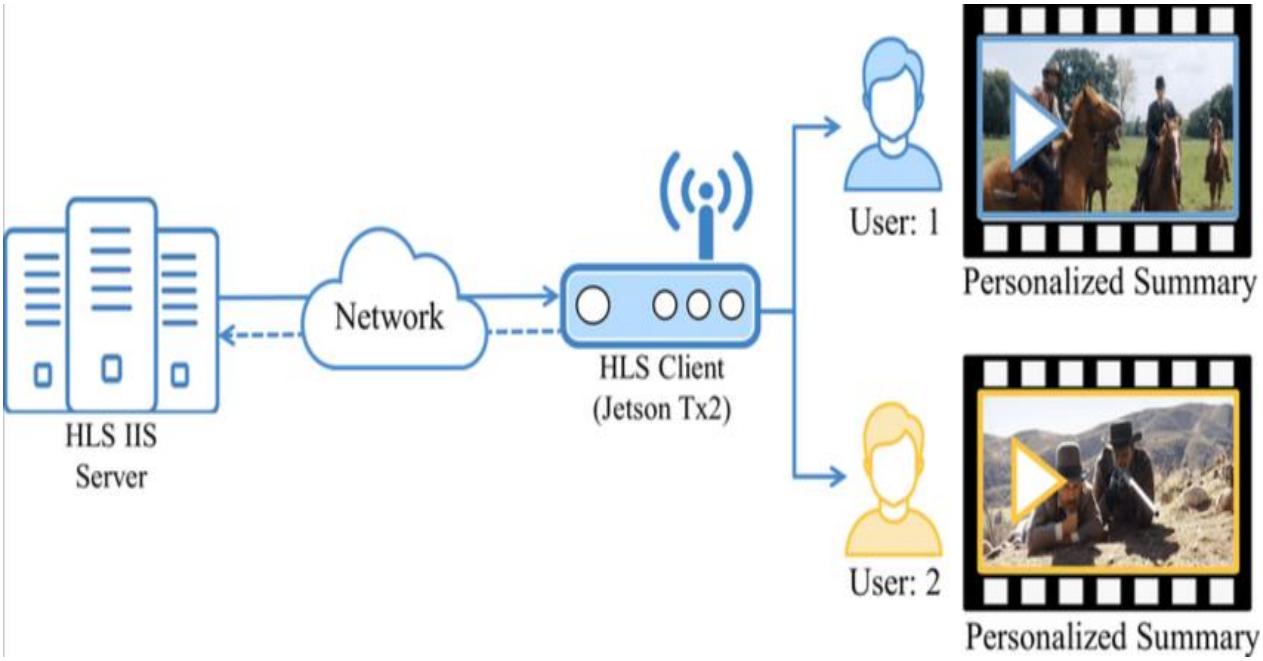


Figure1:Conceptual diagram of proposed LTC-SUM framework using 2D CNN

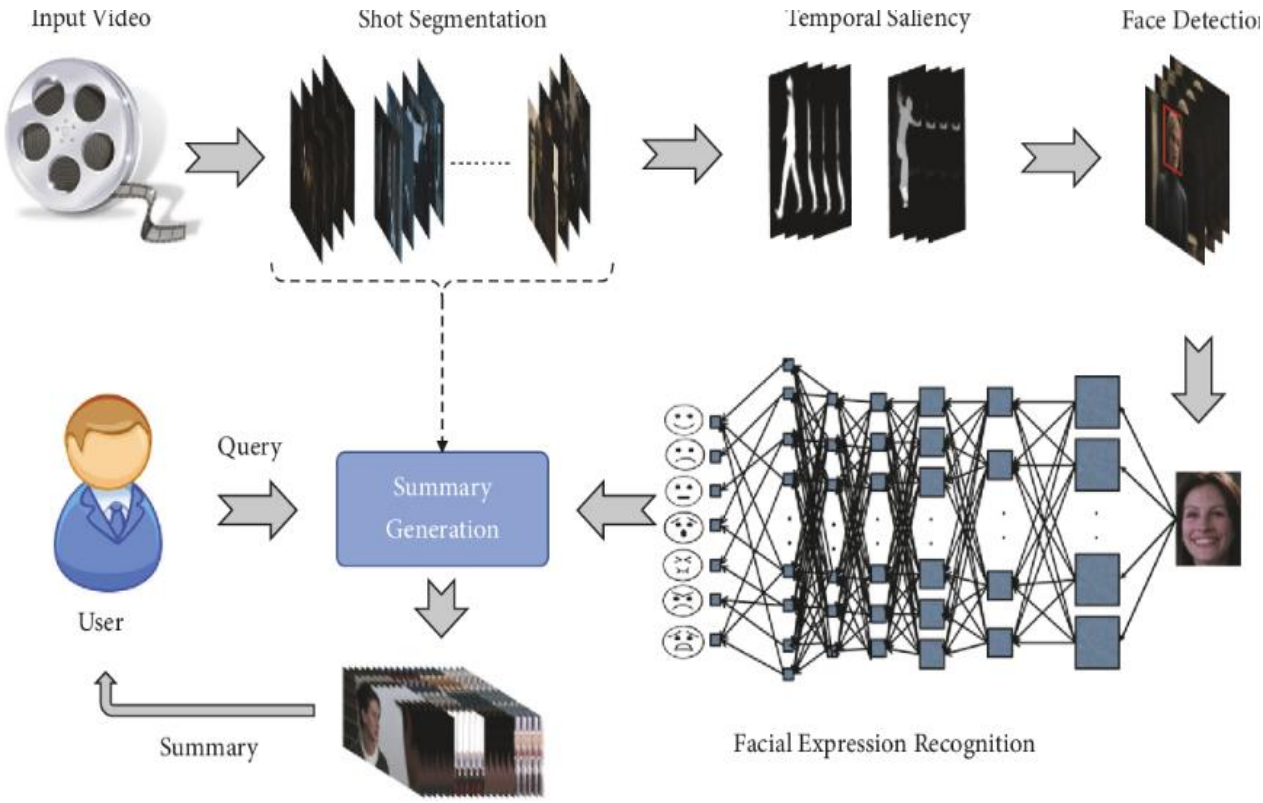


Figure 2:Personalized Movie Summarization using Deep CNN

TABLES

1.Performance Comparison of Summarization Methods

Method	Precision (%)	Recall (%)	F1-Score (%)	User Satisfaction (1–5)
Histogram Sampling	65.2	62.1	63.6	2.9
Uniform Keyframe Selection	68.5	66.3	67.4	3.1
Random Summarization	59.0	60.2	59.6	2.5
Proposed 2D CNN Model	**82.5**	**78.3**	**80.3**	**4.3**

2. Runtime Comparison

Method	Avg Time (s)
Histogram Sampling	25
Uniform Sampling	21
Random Summarization	18
Proposed 2D CNN Model	**29**

CONCLUSION

Recent advances in video summarization have leveraged deep learning techniques such as graph convolutional networks, attention mechanisms, and reinforcement learning to effectively capture and represent important video content. The integration of multimodal information and aesthetic criteria has further improved the relevance and user engagement of generated summaries. Combining both local and global temporal relationships allows for a more comprehensive understanding of video sequences, resulting in higher-quality summaries. Moreover, fully automatic and personalized highlight generation methods have shown great potential in tailoring summaries to user preferences and specific contexts. However, despite these significant improvements, challenges persist in generalizing across diverse datasets and meeting personalized summarization requirements, indicating promising directions for future research. Further exploration of unsupervised and self-supervised learning approaches is essential to reduce dependency on large annotated datasets. Additionally, enhancing the interpretability of models .

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CONFLICT OF INTREST STATEMENT

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