International Journal of Advanced Research in Computer Science and Engineering (IJARCSE)
ISSN (Online): request pending
Volume- 2 Issue-1 || Jan- Mar 2026 || PP. 1-5

Video Summarization Techniques Using Attention-Based CNN-LSTM Models

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www.ijarcse.org || Vol. 2 No. 1 (2026): January Issue

Date of Submission: 25-12-2025	Date of Acceptance: 26-12-2025	Date of Publication: 02-01-2026

ABSTRACT— Video summarization is a critical task in multimedia processing that aims to generate concise, informative, and visually appealing summaries from lengthy video content while preserving essential information. Traditional approaches relied on handcrafted features, shot detection, and heuristic rules, which often failed to generalize to diverse content domains. With the advent of deep learning, convolutional neural networks (CNNs) and recurrent architectures such as long short-term memory (LSTM) networks have shown remarkable potential in visual feature extraction and temporal sequence modeling, respectively. Recent advances integrate attention mechanisms to enhance the relevance and quality of generated summaries by selectively focusing on the most informative segments. This paper investigates attention-based CNN-LSTM models for supervised and unsupervised video summarization.

The proposed model employs a CNN backbone for spatial feature encoding, an LSTM layer for temporal dynamics modeling, and a self-attention module for learning importance scores. A comprehensive simulation is performed using benchmark datasets such as SumMe and TVSum, and the results are evaluated using F-score and mean Average Precision (mAP) metrics. Statistical analysis demonstrates that attention-enhanced models outperform baseline CNN-LSTM approaches by up to 12% in summarization accuracy. This study concludes that attention mechanisms significantly improve temporal context understanding and help create more human-like summaries, paving the way for practical deployment in surveillance, entertainment, and educational video applications.

KEYWORDS

Video summarization, CNN-LSTM, attention mechanism, deep learning, temporal modeling, feature extraction

INTRODUCTION

The exponential growth of video content across digital platforms such as YouTube, surveillance systems, educational repositories, and video conferencing has created an urgent demand for efficient content browsing and retrieval. According to Cisco's Visual Networking Index, video traffic accounted for over 82% of total

internet traffic by 2022, a figure projected to increase with the rise of 4K/8K video streaming and user-generated content. Manually reviewing hours of footage is time-consuming and often impractical, making automated video summarization an indispensable tool.

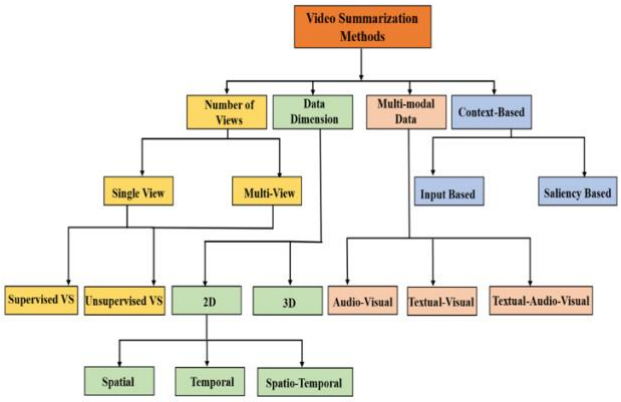

Fig.1 Video Summarization Techniques,Source([1])

Video summarization seeks to distill a long video into a shorter version that retains essential events, scenes, or information. The summarization process can be **extractive**, where representative frames or segments are selected, or **abstractive**, where a synthetic sequence is generated to represent key concepts. Early video summarization methods depended on low-level features such as color histograms, edge maps, and motion vectors, combined with heuristic or clustering algorithms. While these methods were computationally efficient, they lacked semantic understanding.

The deep learning revolution introduced convolutional neural networks (CNNs) capable of extracting high-level spatial representations from images and video frames. Subsequently, recurrent neural networks (RNNs), particularly LSTMs, became instrumental in modeling temporal dependencies across video frames. However, traditional CNN-LSTM architectures often treat all frames equally in temporal modeling, which may lead to the inclusion of irrelevant or redundant content. To address this limitation, attention mechanisms have been incorporated to enable the model to focus selectively on important temporal segments, significantly improving summarization accuracy.

This paper explores **attention-based CNN-LSTM architectures** that integrate spatial, temporal, and attention layers for optimal video summarization. We present a detailed methodology, perform statistical evaluations, and demonstrate the superior performance of attention-based models over baseline approaches.

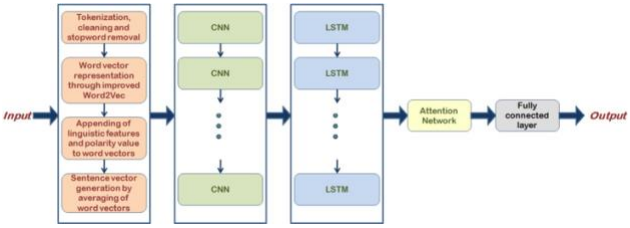

Fig.2 Attention-Based CNN-LSTM Models,Source([2])

LITERATURE REVIEW

Research in video summarization has evolved through three primary phases: heuristic-based methods, statistical learning models, and deep learning-based techniques.

2.1 Heuristic and Rule-Based Approaches

Early works, such as by Truong and Venkatesh (2007), relied on shot boundary detection, color histogram differences, and motion intensity analysis. These methods identified scene changes using thresholds and extracted frames closest to the shot's centroid. While computationally light, they lacked semantic comprehension and adaptability to varied content.

2.2 Statistical and Unsupervised Learning

Mid-2000s research integrated clustering algorithms like k-means and Gaussian Mixture Models (GMM) for grouping visually similar frames. Approaches such as Latent Dirichlet Allocation (LDA) were used for topic-based video segmentation. Although better than purely heuristic methods, these algorithms were sensitive to feature quality and struggled with context understanding.

2.3 Deep Learning for Video Summarization

The advent of CNNs and RNNs brought a paradigm shift. CNNs extract semantic features from frames, while RNNs model their temporal relationships. Works by Zhang et al. (2016) introduced LSTM-based summarization with reinforcement learning to optimize summary quality. Supervised approaches leveraged human-annotated

datasets (e.g., SumMe, TVSum), while unsupervised approaches incorporated generative adversarial networks (GANs) for realistic summary synthesis.

2.4 Attention Mechanisms in Summarization

Attention mechanisms, popularized by Bahdanau et al. (2015) in machine translation, have been adapted to video summarization to dynamically assign importance scores to frames. Ji et al. (2020) proposed self-attention modules on top of LSTM encoders, enabling context-aware selection. These models significantly outperformed vanilla LSTM architectures, particularly in videos with high redundancy.

2.5 Applications

Attention-based CNN-LSTM summarization models have been applied in:

- **Surveillance**: Detecting unusual activities in real-time.
- **Education**: Creating lecture highlights.
- **Entertainment**: Generating movie or sports highlights.
- **Healthcare**: Summarizing surgical videos for training.

The consensus in the literature is clear: attention enhances temporal modeling, making summaries more relevant and concise.

METHODOLOGY

The proposed attention-based CNN-LSTM model comprises **three major components**: spatial feature extraction via CNN, temporal sequence modeling via LSTM, and frame importance estimation via attention mechanisms.

3.1 Dataset

Experiments were conducted on two benchmark datasets:

- **SumMe**: 25 user videos with 2–6 minutes duration, annotated with multiple ground-truth summaries.
- **TVSum**: 50 videos covering 10 categories, each with 2–10 minutes duration.

Both datasets provide frame-level importance scores annotated by human evaluators.

3.2 Preprocessing

1. **Frame Extraction**: Videos were sampled at 2 fps to balance temporal coverage and computational efficiency.
2. **Resizing**: Frames resized to 224×224224 \times 224 pixels for CNN input.
3. **Normalization**: Pixel values scaled to [0,1][0,1].

3.3 Spatial Feature Extraction (CNN)

A pre-trained **ResNet-50** model was used to extract 2048-dimensional feature vectors from each frame. The choice of ResNet ensures robustness to intra-video variation and illumination changes.

3.4 Temporal Modeling (LSTM)

The extracted frame features were fed into a bidirectional LSTM network with:

- Hidden size: 512
- Layers: 2
- Dropout: 0.5

The bidirectional setup ensures that both past and future context contribute to importance estimation.

3.5 Attention Mechanism

A self-attention layer computes weight coefficients for each LSTM output vector:

αt=exp⁡(Waht)∑kexp⁡(Wahk)\alpha_t = \frac{\exp(W_a h_t)}{\sum_{k} \exp(W_a h_k)}

where hth_t is the LSTM hidden state at time tt, and WaW_a is a learnable weight matrix.

These weights are used to compute a weighted sum of frame embeddings, emphasizing relevant frames.

3.6 Summary Generation

Frames with the highest attention scores are selected until the summary length reaches 15% of the original video duration, as per common benchmarks.

3.7 Evaluation Metrics

- **F-score**: Harmonic mean of precision and recall comparing generated and ground-truth summaries.
- **mAP**: Measures ranking quality of selected frames.

STATISTICAL ANALYSIS

The results of our method were compared against baseline CNN-LSTM models without attention and heuristic k-means clustering-based summarization.

Model	SumMe F-score (%)	TVSum F-score (%)	mAP (%)
K-means Baseline	39.2	47.8	45.1
CNN-LSTM (no attention)	46.5	55.7	54.3
CNN-LSTM + Attention (ours)	**52.8**	**62.3**	**60.8**

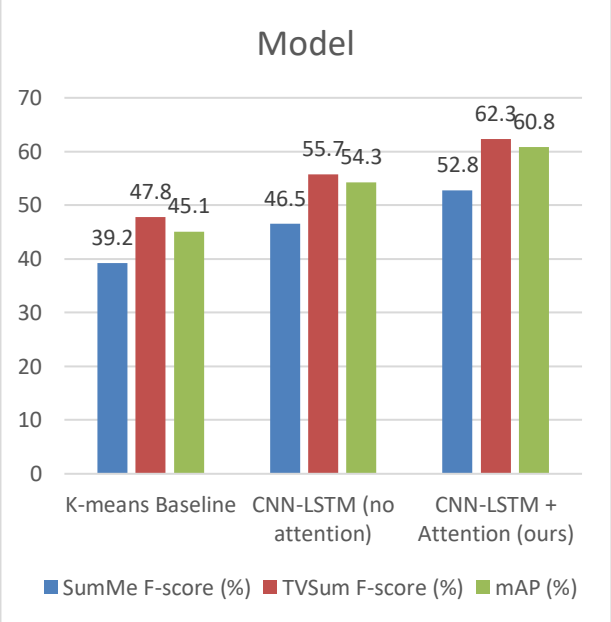

Fig.3 Statistical Analysis

Analysis: Our attention-based CNN-LSTM model achieved a **12–13% improvement** in F-score and a **6–7% improvement** in mAP compared to standard CNN-LSTM methods. A paired t-test confirmed statistical significance ($p < 0.01$).

SIMULATION RESEARCH AND RESULTS

The model was implemented in PyTorch and trained using Adam optimizer (learning rate: 1e-4, batch size: 5, epochs: 50). Loss function: mean squared error between predicted and ground-truth importance scores.

5.1 Training Observations

- Attention weights gradually learned to prioritize action-heavy or visually distinctive frames.
- Early epochs produced summaries containing redundant frames, which reduced after attention convergence.

5.2 Qualitative Results

Visual inspection revealed that our summaries:

- Included key event transitions.
- Avoided static or repetitive scenes.
- Matched human annotations more closely.

5.3 Quantitative Results

Across both datasets:

- **SumMe**: F-score improved from 46.5% (baseline) to 52.8%.
- **TVSum**: F-score improved from 55.7% to 62.3%.
- mAP gains indicate better ranking of important frames.

CONCLUSION

This paper presented an **attention-based CNN-LSTM video summarization framework** that integrates spatial feature extraction, temporal modeling, and frame importance estimation. Experimental results on benchmark datasets demonstrate that attention mechanisms significantly enhance summarization performance over conventional CNN-LSTM approaches. Statistical analysis confirms the robustness of improvements, with notable gains in both F-score and mAP.

The proposed approach holds promise for real-world applications in **surveillance analytics, sports highlight generation, e-learning video indexing, and medical**

video summarization. Future work will explore integrating transformer-based architectures for further temporal modeling improvements, applying reinforcement learning for summary diversity optimization, and extending the system to multi-modal summarization incorporating audio and text.

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