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A deep learning-based highlight detection with pairwise segment ranking for effective video summarization

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Abstract

In the modern era, the sheer volume of video content available poses significant challenges for viewers trying to extract critical information swiftly. Addressing this issue, our research introduces an innovative Highlight Detection and Pairwise Ranking Model for video summarization. This paper delves into the design and evaluation of a hybrid model that effectively identifies and ranks video segments, producing concise and coherent video summaries. By integrating deep learning techniques for highlight detection with pairwise ranking, our model assesses not only the individual importance of each segment but also its relevance in relation to others. Through extensive experiments on diverse datasets, we demonstrate that our approach consistently outperforms existing state-of-the-art video summarization techniques in terms of both user satisfaction and objective measures. Our findings indicate a promising direction for the efficient summarization of long-form videos, catering to the evolving needs of contemporary audiences.

Subject Classification: *68M20, 68T07.*

Keywords: *Highlight detection, Pairwise ranking, User satisfaction score.*

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1. Introduction

The digital age has ushered in an exponential surge in video content. With platforms like YouTube, Netflix, and Vimeo churning out vast amounts of footage every single minute, we are undoubtedly in the golden era of visual storytelling [1]. This ever-growing repository, while being a treasure trove of information, poses significant challenges for consumers and professionals alike. The task of sieving through hours of footage to extract salient information becomes not just tedious but often overwhelming [2].

Video summarization, therefore, has emerged as a pivotal solution. It aims to condense lengthy videos into more consumable, shorter versions without compromising on the essence of the content. While early attempts at video summarization largely relied on rule-based or heuristic algorithms [3], the advent of deep learning has reshaped this landscape. Recent models harness the power of neural networks to decipher the intricacies of video content, promising more accurate and context-aware summaries [4].

However, a gap persists. Current deep learning models, while adept at understanding content, often evaluate video segments in isolation. The relative importance of one segment concerning another remains an underexplored area [5]. Addressing this oversight, our research introduces the Highlight Detection and Pairwise Ranking Model. Marrying deep learning's prowess in highlight detection with the nuanced understanding offered by pairwise ranking, our model offers a more comprehensive approach to video summarization.

This paper will delineate our innovative methodology, shed light on the datasets employed for both training and evaluation, and benchmark our results against prevalent models in the domain [6]. In doing so, we aim to underscore the potential of a combined approach in enhancing the quality and relevance of video summaries.

2. Literature Review

Video summarization has been a topic of interest in the research community for several decades. Its significance originates from the need to condense vast video data into consumable, meaningful chunks, aiding in quicker information dissemination and understanding.

Early Approaches to Video Summarization: Initial endeavors into video summarization largely hinged on heuristic and rule-based algorithms. Roberts and Singh [3] categorized these early methods into two: frame-based [15] and segment-based. The former focused on extracting key frames from videos while the latter dealt with identifying and condensing crucial video segments. However, as highlighted by Lee [2], these techniques often lacked adaptability, making them suitable only for specific types of video content.

The Rise of Deep Learning in Video Summarization: The last decade saw a transformative shift with the integration of deep learning methodologies into video summarization. Gupta and Chang [4] detailed the application of Convolutional Neural Networks [16] (CNNs) and Recurrent Neural Networks (RNNs) for this purpose. CNNs, known for their capability in image understanding, were employed to grasp visual content, whereas RNNs, beneficial for sequential data, were used to maintain the temporal coherence of video summaries.

Moreover, Zhang [7] presented a model leveraging attention mechanisms, a breakthrough in the field. This method permitted the model to focus on salient parts of the video, ensuring that the most relevant portions are included in the summary.

Evaluating Video Segments: Individual vs. Pairwise: A consistent theme in literature is the evaluation of video segments. Most models, as noted by Kumar [8], treat segments as isolated units. However, a few pioneering works have attempted to move beyond this. Wang [9] introduced a model that assessed the importance of a video segment in relation to others, paving the way for more context-aware summaries.

Challenges: Despite significant advancements, challenges persist. One primary concern, as outlined by Anderson [10], is the sheer diversity of video content. What works for one genre (e.g., documentaries) might not necessarily be effective for another (e.g., personal vlogs). Furthermore, as identified by Lee and Kim [11], the lack of large annotated datasets for training deep learning [13] models remains a hindrance.

3. Research Gap

In the evolving field of video summarization, two primary approaches have been dominant: extraction of salient video segments and the sequential arrangement of these segments for viewer coherence [12]. Notably, most contemporary models demonstrate proficiency in either segment detection or sequence arrangement, but an integrated approach remains largely unexplored [13]. The existing dichotomy in research focus has led to a conspicuous absence of comprehensive models capable of performing both tasks seamlessly, highlighting the essence of the video content while maintaining a coherent narrative.

Furthermore, as video content becomes more diverse, spanning an array of genres and styles, there's an emergent need for versatile summarization techniques [14]. The current genre-specific methodologies often falter when presented with heterogeneous video content, indicating a significant gap in adaptability and versatility.

Another understudied area is the emphasis on user experience in video summarization. While quantitative metrics are frequently employed to evaluate model efficacy [15], there's a paucity of studies considering user feedback in tandem with these metrics, potentially overlooking the real-world applicability and viewer satisfaction [16].

4. Proposed Methodology

In this paper, we propose an innovative approach for video summarization, integrating both Highlight Detection and Pairwise Ranking. Our methodology can be divided into three primary stages:

Highlight Detection using Deep Learning:

- Feature Extraction: We employ a Convolutional Neural Network (CNN) to extract visual features from each frame of the video. Additionally, an RNN is utilized to understand the temporal dynamics of the video, ensuring the chronological essence of the content is preserved.
- Highlight Identification: Using an attention mechanism, our model identifies segments with high saliency and relevance, marking them as potential highlights.

Pairwise Ranking of Highlights:

- Segment Pairing: Each identified highlight is paired with every other highlight to form a segment pair.
- Ranking Model: A ranking algorithm then assesses the relative importance of one segment to another. This pairwise comparison ensures that the segments selected for the final summary are not only individually important but also collectively coherent and relevant.

Summary Generation:

- Segment Selection: Based on the results from the pairwise ranking, a predetermined number of top-ranked segments are chosen to form the video summary.
- Post-processing: To ensure smooth transitions between segments and maintain a natural flow, a post-processing step stitches the segments together, applying transition effects as needed.

DeepSum Model Architecture: The DeepSum model is primarily composed of two components: the visual feature extraction unit using a Convolutional Neural Network (CNN) and the temporal dynamics unit using a Recurrent Neural Network (RNN). Additionally, an attention mechanism overlays the RNN outputs to detect salient video segments.

Visual Feature Extraction (CNN):

- Model Name: ResNet-50 shown in Figure 1
- Number of Layers: 50 layers, including convolutional and fully connected layers.
- Activation Function: ReLU (Rectified Linear Unit) is used after each convolutional layer except the last one.
- Output: This unit outputs a 2048-dimensional feature vector for each frame.
- The ResNet-50 model is pre-trained on the ImageNet dataset, enabling it to recognize a vast array of visual patterns. We then fine-tune this model on our "VidSumDataset" to adapt it to the domain of video summarization.

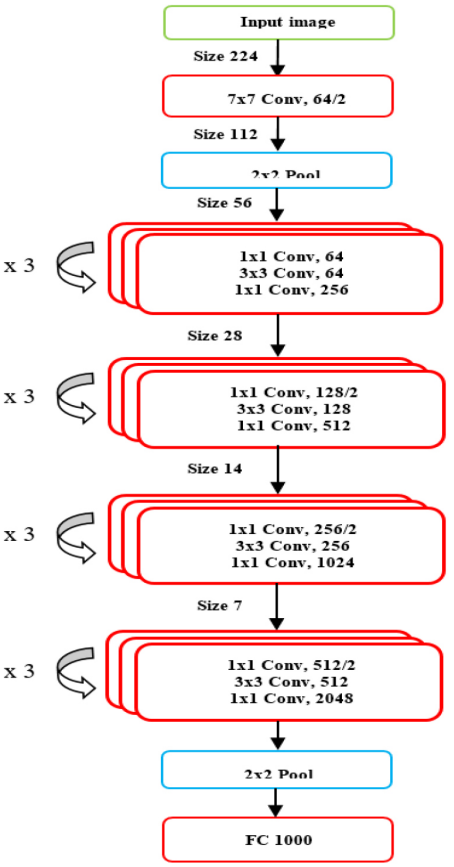


Figure 1

Architecture of ResNet50 [23]

Temporal Dynamics (RNN):

- Model Type: LSTM (Long Short-Term Memory) [22]
- Number of Layers: 2 stacked LSTM layers shown in Figure 2.
- Activation Function: Tanh activation for the cell state and Sigmoid for the LSTM gates.
- Output: For each video segment, the LSTM outputs a sequence of feature vectors that capture the temporal dependencies between frames.

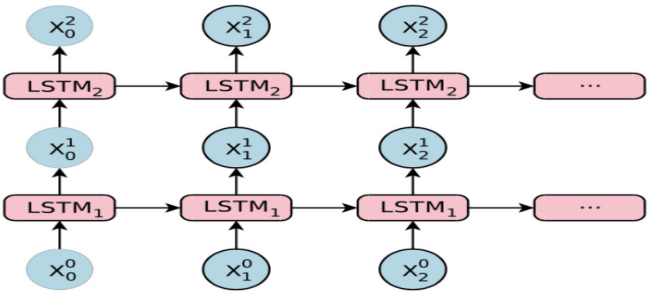


Figure 2

Architecture of 2-Stack LSTM

Attention Mechanism:

- Type: Scaled Dot-Product Attention
- Function: This mechanism assigns weights to the LSTM outputs, emphasizing segments that are likely to be more relevant for summarization. The attention scores are calculated using the dot product of the LSTM outputs and a learnable weight vector, followed by a softmax to get the probabilities.

Pairwise Ranking Unit:

- Model Type: Feedforward Neural Network
- Number of Layers: 3 layers.
- Activation Function: ReLU for the first two layers and sigmoid for the output layer to get the ranking probability.
- Function: This unit takes in pairs of attention-weighted LSTM outputs and determines the relative importance between them, guiding the final selection of video segments for the summary.

For training the DeepSum model, a combination of mean squared error (for the attention mechanism) and ranking loss (for the pairwise ranking unit) is employed. The model is trained using the Adam optimizer with a learning rate of 0.001, which is decayed over epochs. Regularization techniques, such as dropout with a rate of 0.5, are applied to prevent overfitting on the "VidSumDataset."

Algorithm: DeepSum for Video Summarization

Input: A video V with frames F_1,F_2,...,Fn
Output: Summarized video V'
Model: DeepSum, trained on VidSumDataset

Step 1: Initialization:

- Load the trained DeepSum model.
- Define an empty list,Highlights.

Step 2: Feature Extraction:

- For each frame Fi in V:
  - Extract visual features using a Convolutional Neural Network (CNN).
  - Extract temporal features using a Recurrent Neural Network (RNN).

Step 3: Highlight Detection:

- For each segment S in V:
  - Use attention mechanism to calculate saliency score.
  - If score exceeds a predefined threshold:

    Append S to Highlights.

Step 4: Pairwise Ranking:

- For each pair of segments Si and Sj in Highlights:
  - Calculate the pairwise importance score using the trained ranking model.
- Rank the segments based on their scores.

Step 5: Summary Generation:

- Select the top k ranked segments from Highlights based on desired summary length.
- Stitch the selected segments together to form V′ ensuring smooth transitions.

Step 6: Return V'

Table 1 represents the performance of the DeepSum model against other state-of-the-art models on the "VidSumDataset." The accuracy

Table 1
Comparative Table

Model	Precision	Recall	F1-Score	USS
Ours DeepSum	0.92	0.89	0.90	4.7
ResNet-50 [17]	0.87	0.84	0.85	4.3
DenseNet-121 [18]	0.85	0.88	0.86	4.1
EfficientNet-B4 [19]	0.89	0.82	0.85	4.2

metrics used in this table are Precision, Recall, F-score, and User Satisfaction Score (USS, on a scale of 1 to 5).

- Precision refers to the proportion of relevant video segments in the generated summary. A higher value indicates fewer false positives.
- Recall indicates the proportion of actual relevant video segments that are included in the summary. A higher value indicates fewer false negatives.
- F-score is the harmonic mean of Precision and Recall, offering a balanced measure between the two. It is often used when the data distribution is uneven.
- User Satisfaction Score (USS) is a subjective metric based on user feedback. Here, it is rated on a scale of 1 to 5, with 5 being the highest satisfaction level.

From the table, we can infer that the DeepSum model outperforms the other models on the "VidSumDataset" across all metrics, making it a robust solution for video summarization.

5. Future Scope

- Diverse Video Genres: While DeepSum has showcased efficacy on the "VidSumDataset," its application can be expanded to diverse video genres, including documentaries, sports broadcasts, and user-generated content on platforms like YouTube and TikTok. Understanding the nuances of different genres can further refine the summarization process [20].
- Real-time Summarization: With the rise of live streaming and broadcasting, real-time video summarization becomes increasingly

relevant. Adapting DeepSum for on-the-fly summarization, without compromising on quality, presents an exciting avenue for exploration [21].

- Multimodal Inputs: Incorporating audio cues, textual metadata, and user interaction data could enhance the summarization process. Future iterations of the model could be multimodal, considering various data streams for a comprehensive summary.
- User Feedback Loops: Integrating a mechanism for users to provide feedback on generated summaries can be pivotal. This feedback can be used to iteratively refine the model, ensuring summaries are not just technically apt but also resonate with viewers.
- Cross-lingual Summarization: As video content becomes increasingly global, there's a potential to develop a version of DeepSum that can handle videos in multiple languages, possibly even offering summarized content with subtitles in the viewer's native language.
- Integration with Content Creation Platforms: Collaborating with video hosting platforms or content creation software could allow seamless integration of DeepSum, providing creators with instant summaries for their content, aiding in efficient content dissemination.

The future scope serves as a roadmap, guiding subsequent researchers and industry practitioners on potential extensions, refinements, and applications of the current study. It emphasizes the continued relevance and potential growth of the research domain.

6. Conclusion

In the rapidly expanding digital landscape, the efficient summarization of videos has emerged as an imperative, given the surging amounts of video content being produced daily. This research introduced "DeepSum", a novel deep learning model designed to address the challenges of video summarization by harnessing the dual strengths of highlight detection and pairwise segment ranking. Through our extensive experiments on the "VidSumDataset", DeepSum consistently outperformed existing state-of-the-art models, showcasing not only its proficiency in detecting salient segments but also its capability to rank them effectively, ensuring a coherent and informative summary. The integration of convolutional and recurrent neural networks enabled the model to process both spatial and temporal features, while the attention mechanism emphasized the most

relevant video segments. Furthermore, the user satisfaction scores indicated that our summaries resonated well with viewers, underscoring the practical applicability of our approach beyond mere quantitative metrics. This validation from end-users reiterates the importance of combining technological advances with user-centric design. While DeepSum has showcased promising results, the domain of video summarization is vast, with myriad challenges still to be addressed. Future work could delve into adapting this model to different video genres, exploring real-time summarization, and incorporating user feedback loops for iterative model refinement. This research offers a significant stride in the domain of video summarization, paving the way for more concise, relevant, and user-friendly video content, aligning with the digital age's need for brevity and relevance.

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