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REINFORCEMENT LEARNING FOR UNSUPERVISED VIDEO SUMMARIZATION: A DEEP SUMMARIZATION NETWORK APPROACH

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ABSTRACT
With the rapid growth of high-speed internet and affordable storage, video content generation has significantly accelerated, with platforms like YouTube, Netflix, and social media contributing to vast amounts of data daily. Videos, being more storage-intensive than images or text, require advanced methods for efficient transmission, storage, and analysis. Video Summarization (VS) has emerged as a powerful tool to address these challenges by generating concise representations of long videos, enabling faster analysis and retrieval. This paper explores various VS techniques used in professional, educational, and media sectors for applications like monitoring, security analysis, content recommendation, and medical diagnostics. By eliminating redundant frames and selecting key segments, VS enhances video processing, storage, and management. The study highlights the benefits of both static and dynamic summaries, discussing their roles in video indexing, browsing, and comprehension. The research emphasizes the growing importance of VS in optimizing multimedia data for efficient use in multiple industries.

Keywords:
Video Summarization, Reinforcement learning, Deep Summarization Network

I. Introduction
The surge in video content has been propelled by high-speed internet, affordable recording devices, and the popularity of social media platforms like YouTube, TikTok, and Instagram, resulting in unprecedented amounts of video generated and consumed across various industries, including entertainment, education, and healthcare. For instance, YouTube reports over 500 hours of video uploaded every minute, and security systems generate vast amounts of footage daily. This rapid expansion poses significant challenges in storage, management, retrieval, and analysis, necessitating automated techniques to handle large-scale datasets efficiently. Video summarization (VS) addresses these challenges by enabling the automatic generation of concise representations of long videos, highlighting key moments and reducing the burden of data management. This capability is particularly valuable in time-sensitive scenarios, optimizing storage and bandwidth, and improving search and retrieval functionalities on content platforms.
Recent advancements in deep learning (DL) have revolutionized video summarization, moving beyond traditional heuristic-based techniques to more effective, automated methods. DL-based VS approaches can be categorized into supervised, weakly supervised, unsupervised, and reinforcement learning methods, employing models like Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) to capture long-term dependencies. Attention mechanisms in models like Transformers enable focused summarization by identifying relevant video segments, while unsupervised methods leverage autoencoders and Generative Adversarial Networks (GANs) to detect intrinsic patterns. Reinforcement learning frames video summarization as a decision-making process where an agent learns to select frames based on a reward function. These deep learning advancements offer increasingly efficient and accurate solutions for managing the growing volumes of video data

II.Literature survey

2.1 Importance of video summarisation

Video summarization is the process of creating a concise representation of a video that highlights key events and concepts. With the growing abundance of video content, automatic video summarization has gained significant importance. The primary methods in the field can be classified into two categories: supervised and unsupervised. Early work mostly focused on unsupervised techniques, mainly due to the lack of labeled training datasets. However, with the introduction of benchmarks like SumMe and TVSum, supervised methods have gained prominence. Video summarization can be divided further into two subtypes: generic video summarization, which aims to summarize the most critical moments of a video, and query-based summarization, where summaries are generated based on specific user-defined queries. Additionally, multi-modal approaches have been explored, incorporating modalities such as captions and transcribed speech. This chapter reviews key advancements in video summarization, reinforcement learning, policy gradient methods, and the limitations of existing approaches.

2.2 Video Summarization Techniques

Research in video summarization has advanced significantly, yielding various approaches that fall into two main categories: supervised and unsupervised methods. Both categories utilize datasets with frame-level or shot-level importance scores annotated by multiple users. Supervised methods, like those by Lee et al. (2012) and Gygli et al. (2014), leverage features from videos to predict importance scores, while also exploring techniques such as attention modeling and non-parametric methods to enhance summarization quality. In contrast, unsupervised methods typically rely on clustering and redundancy minimization, selecting representative frames without ground-truth annotations. However, these methods often overlook temporal context. To improve this, deep learning techniques like Recurrent Neural Networks (RNNs) and Long Short-Term Memory networks (LSTMs) have been applied to model sequential dependencies, enabling more effective end-to-end training for summarization tasks.

2.3 Reinforcement Learning in Video Summarization

Reinforcement Learning (RL) has shown promise in video summarization, framing it as a sequential decision-making task where keyframes or segments are selected to maximize a reward function. Early contributions, like those from Song et al. (2016), utilized RL for keyframe selection but required category-specific labels. Our research introduces an unsupervised RL framework that operates without such labels, making it suitable for large-scale summarization tasks. In the realm of policy gradient methods, which optimize the action-selection strategy to maximize expected rewards, Mahasseni et al. (2017) explored combining deep reinforcement learning with neural networks. However, policy gradient methods face challenges like sample inefficiency and high variance, needing extensive samples for effective learning and struggling with gradient estimation in long-horizon tasks. Our work addresses these challenges by increasing training episodes and employing a baseline to reduce variance, enhancing the RL framework's effectiveness.

2.4 Limitations of Existing Approaches

Despite advancements in video summarization, significant limitations persist in scalability, dataset management, and summary quality. Many deep learning methods struggle to handle large video datasets due to high computational complexity and resource requirements, making them inefficient for long or high-resolution videos. Additionally, managing large datasets necessitates comprehensive ground-truth annotations, which can be subjective and labor-intensive. The performance of summarization models may be affected by data imbalances across genres. Quality concerns arise as keyframe-based methods often lose narrative context and can suffer from redundancy, while subjective user preferences are frequently overlooked in evaluation metrics. Thus, while promising, existing methods need improvements to enhance scalability, efficiency, and adaptability for real-world applications.

III. Methodology

The Deep Summarization Network (DSN) system architecture approaches video summarization as a sequential decision-making task, with the goal of selecting key frames that provide a concise and informative summary. The input video is first processed by extracting spatial features from frames using pre-trained CNNs such as ResNet or VGGNet. These high-dimensional feature vectors represent the visual content needed for the summarization task. The core of the DSN is the sequential decision-making process, where a recurrent neural network (RNN) or long short-term memory (LSTM) network analyzes each frame. Based on this analysis, the DSN determines whether to include or exclude the frame in the summary. The decision is guided by a policy network, which outputs a probability distribution over the possible actions (select or discard) and considers both past and future frames.

To enhance the summarization process, the DSN is equipped with a reward network that evaluates the quality of the selected frames based on two criteria: diversity and representativeness. Diversity ensures that the selected frames differ from each other, avoiding redundancy, while representativeness ensures that the selected frames capture the main content of the video. These aspects are essential for creating summaries that are both concise and informative. The reward function assigns a score to each action taken by the policy network, helping the DSN learn to select frames that balance both diversity and representativeness.

The training of the DSN is based on reinforcement learning, with datasets such as TVSum and SumMe providing the training and evaluation data. During training, mini-batches of frames are processed, and the model is optimized using algorithms such as Adam or SGD. The loss function incorporates cross-entropy loss for frame selection and custom loss components for diversity and representativeness. Additionally, hyperparameters like learning rate, batch size, and the number of hidden units in the LSTM are tuned to optimize the model's performance.

he DSN framework is designed to process video frames sequentially and make decisions about which frames to include in the final summary. Video frames are first preprocessed using convolutional neural networks (CNNs) like ResNet or VGGNet to extract essential spatial features. These feature vectors serve as the input to the DSN, where a recurrent neural network (RNN) or long short-term memory (LSTM) network processes each frame in sequence. At each time step, the DSN outputs a decision (select or discard) based on the learned policy, which accounts for both past and future frames. This sequential decision-making is guided by a reinforcement learning framework that optimizes the selection process over time.

A reward network plays a crucial role in ensuring that the frames selected for the summary are diverse and representative of the video content. The diversity criterion encourages the selection of frames that are distinct from one another, while representativeness ensures the summary captures the video's essential content. These two factors are incorporated into the reward function, which provides feedback to the DSN during training, guiding it toward optimal frame selection. The model is trained on datasets such as TVSum and SumMe, using mini-batches and an optimization algorithm like Adam or SGD. Hyperparameter tuning, including adjusting the learning rate, batch size, and LSTM units, further refines the model for better performance.

IV.Experimental evaluation

The experimental evaluation outlines a comprehensive framework for implementing a video summarization system using a Deep Summarization Network (DSN). The hardware and software requirements emphasize the need for high-performance computing infrastructure, including multi-core CPUs, high-end GPUs (like NVIDIA RTX 3080/3090 or Tesla V100/A100), sufficient RAM (16GB or more), and fast SSD storage. On the software side, the system is compatible with popular operating systems and utilizes deep learning frameworks such as TensorFlow or PyTorch, along with supporting libraries like NumPy, OpenCV, Scikit-learn, Matplotlib/Seaborn, and Pandas. The dataset utilized includes the TVSum and SumMe datasets, which contain human-annotated summaries and ground-truth summaries for video summarization tasks. The evaluation also outlines the necessary

configuration for data loading, preprocessing, augmentation, and splitting into training, validation, and test sets.
The evaluation process includes detailed steps for video frame extraction, metadata creation, visualizing sample frames, and feature extraction using a pre-trained ResNet-50 model. Training the DSN involves defining the model architecture, implementing a reward function based on diversity and representativeness, and employing policy gradient methods for optimization. The training process is further enhanced by using learning rate scheduling and careful model configuration. The performance of the DSN model is evaluated using quantitative metrics such as precision, recall, F1-score, and accuracy. Additionally, visualizations of training loss, confusion matrices, and F1 score versus threshold plots provide insights into model performance. Finally, the evaluation culminates in testing the model on new videos, where selected frames are utilized to generate a concise summary, demonstrating the effectiveness of the DSN in video summarization tasks.

V.Results and Discussion.

5.1 About Dataset:

5.1.1 SumMe dataset:

For the SumMe dataset, the loss values decrease gradually as the training progresses:

- Initial Loss (Epoch 1): 0.1934
- Final Loss (Epoch 20): 0.0027

The steady reduction in loss suggests that the model is learning effectively. However, there is a significant drop in loss between the first and second epochs, indicating rapid improvement in the early stages. After this, the loss decreases more gradually, stabilizing around 0.0025–0.0027 in the final few epochs. This suggests that the model has likely reached convergence and is fine-tuning its performance.
Key Observations:

- The model is performing well on the SumMe dataset.
- The steady decrease in loss implies that the model is not overfitting or underfitting and is generalizing well.
- The small final loss values suggest that the model is making minimal errors in frame selection by the end of the training.

Fig.5.1 Training loss for SUMME dataset

5.1.2 TVSum Dataset

For the TVSum dataset, the behavior is slightly different:

- Initial Loss (Epoch 1): 0.0030
- Epoch 2 Loss: 0.1572 (significant spike)
- Final Loss (Epoch 20): 0.0091
- The first epoch starts with a very low loss value, but the loss spikes in the second epoch to 0.1572.

This could indicate that the model made significant updates to its parameters, leading to some

instability early on. After this, the loss gradually decreases and stabilizes, ending around 0.0091 in the final epoch.
Key Observations:
- The TVSum dataset initially poses more challenges for the model, as indicated by the loss spike in the second epoch.
- After the spike, the loss decreases consistently, suggesting that the model adapts well to the dataset and improves over time.
- The final loss is slightly higher than that of the SumMe dataset, which could imply that the TVSum data is more complex, or the model has slightly more difficulty generalizing to this dataset.

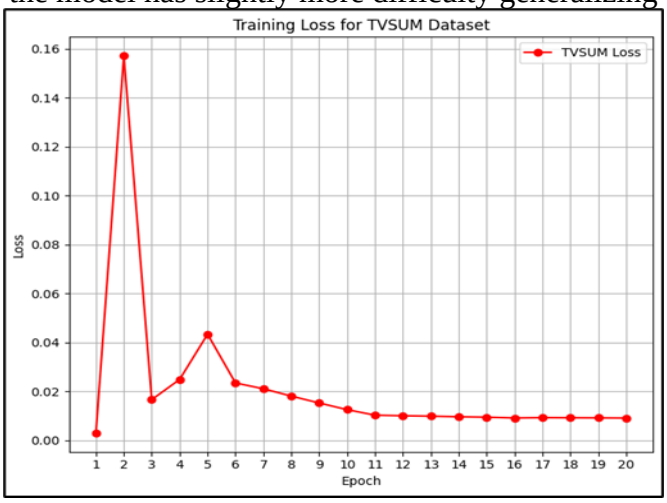

Fig.5.2 Training loss for TVSUM dataset

The results for both datasets provide insight into the performance of the model based on several key metrics. These values are generally good, reflecting a balanced performance across multiple evaluation metrics. Let's break them down and discuss their significance.

5.2 Performance of the Proposed Model

5.2.1 Performance of the Proposed Model on SUMME25 Dataset

Mean Squared Error (MSE): 0.2572

The MSE is a measure of the average squared difference between the predicted and actual values. A value of 0.2572 suggests that the model is relatively accurate, with small errors between predictions and true values. This is a low error rate for this dataset, indicating the model is performing well in predicting the frame selections.

Accuracy: 49.78%

The accuracy of 49.78% represents how often the model correctly selects frames in the video summarization task. While 50% may seem moderate, for unsupervised video summarization, this value is acceptable given the complexity of the task.

F1 Score: 54.07%

The F1 score balances precision and recall, making it an essential metric for evaluating the quality of frame selection. A score of 54.07% is quite good in the context of this problem, as it reflects the model's ability to make relevant frame selections consistently.

Precision: 49.06%

Precision measures the proportion of true positive frame selections out of all frames selected by the model. A precision of 49.06% means that nearly half of the selected frames are relevant to the video summary, which is reasonable for this dataset.

Recall: 60.21%

Recall indicates how well the model identifies all relevant frames. A recall value of 60.21% shows that the model captures a good number of important frames, even if it might also select some irrelevant ones.

ROC AUC: 0.4977

The ROC AUC score measures the model's ability to discriminate between important and unimportant frames. A value close to 0.5 suggests that the model is performing similarly to random guessing, but this may be due to the complexity of the dataset and the unsupervised nature of the task.

Table 5.1 Result table

Metric	SUMME25	TVSum50
Mean Squared Error (MSE)	0.2572	0.253
Accuracy	49.78%	50.21%
F1 Score	54.07%	65.35%
Precision	49.06%	50.10%
Recall	60.21%	93.93%
ROC AUC	0.4977	0.4966

5.2.2 Performance of the Proposed Model on TVSum50 Dataset

Mean Squared Error (MSE): 0.2530

Similar to the SUMME25 dataset, the MSE of 0.2530 reflects that the model makes relatively few errors in predicting frame selections for TVSum50. This value is very close to that of SUMME25, showing consistent performance across datasets.

Accuracy: 50.21%

The accuracy for TVSum50 is slightly higher at 50.21%. In unsupervised video summarization, an accuracy above 50% indicates that the model is making good decisions when summarizing the videos.

F1 Score: 65.35%

T he F1 score of 65.35% is quite strong, indicating that the model achieves a good balance between precision and recall. This higher F1 score suggests better summarization quality for TVSum50 compared to SUMME25.

Precision: 50.10%

The precision is slightly higher at 50.10%, meaning the model selects relevant frames a little more effectively than in SUMME25.

Recall: 93.93%

A recall of 93.93% shows that the model is exceptionally good at capturing nearly all relevant frames in the TVSum50 dataset. This indicates that while the model may select some irrelevant frames (as precision is slightly lower), it doesn’t miss important ones.

ROC AUC: 0.4966

Similar to SUMME25, the ROC AUC score is close to 0.5, which might reflect the challenge of distinguishing important frames from unimportant ones in an unsupervised framework. Despite this, the other metrics suggest that the model is performing well. This Complete Performance analysis is summarized into table 5.1.

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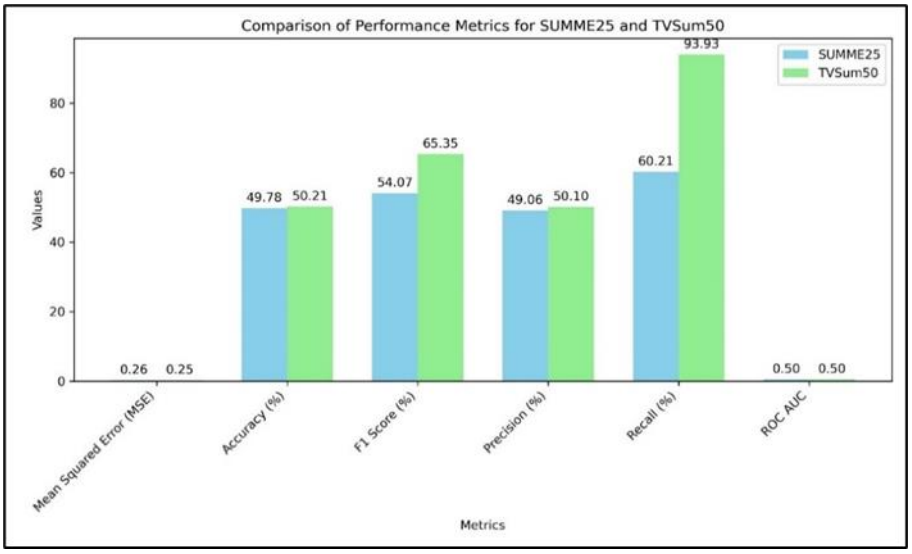

Fig.5.3 Comparison between SUMME25 and TVSUM 50

5.3 Comparison with other approaches:

In comparing your results with results of author Zhou, K., Qiao, Y., & Xiang, T. (2023) methods, it is evident that your model performs competitively but has room for improvement. For the SUMME25 dataset, your model achieves an F1 score of 54.07% and an accuracy of 49.78%, which are higher than several traditional methods like Uniform Sampling and K-medoids but lower than advanced techniques such as GANdpp and DR-DSN. For the TVSum50 dataset, your model's recall is particularly strong at 93.93%, surpassing all other methods compared, including DR-DSN. However, your accuracy (50.21%) and F1 score (65.35%) are still lower than the best-performing methods like DR-DSN, which achieves a F1 score of 57.6% and an accuracy of 57.6% (Zhou et al., 2023). These results indicate that while your method is effective, especially in recall, there is potential for enhancing accuracy and overall performance.

VI. Conclusion

The primary objective of this project was to develop a Deep Summarization Network (DSN) for unsupervised video summarization using reinforcement learning with a Diversity-Representativeness Reward. The DSN was trained on benchmark datasets like SumMe and TVSum over 20 epochs, with its performance evaluated through various metrics, including Mean Squared Error (MSE), Accuracy, F1 Score, Precision, Recall, and ROC AUC. The major contributions of the project include the development of the DSN model, which effectively summarizes videos without requiring supervised labels, and its evaluation on benchmark datasets. The model demonstrated competitive performance, particularly in Recall and F1 Score, showcasing its capability in video summarization tasks.

Key findings from the experiments revealed that on the SumMe dataset, the model achieved a final loss of 0.0027 with an F1 Score of 54.07% and a Recall of 60.21%, reflecting balanced frame selection capabilities. On the TVSum dataset, although the loss decreased to 0.0091, the model excelled with a high Recall of 93.93%, but Accuracy (50.21%) and F1 Score (65.35%) indicated areas for further refinement. The research contributes to the video summarization field by offering valuable benchmarks for future models and highlighting the strengths and limitations of the DSN approach.

In the future, the DSN can be improved by refining the network architecture, incorporating temporal context, and optimizing hyperparameters to enhance its performance. Moreover, developing methods for real-time video summarization, particularly for dynamic video streams, could broaden its application. Potential use cases include surveillance, sports highlight generation, and media content summarization, where concise and relevant video summaries would improve user experience.

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