BiLSTM-Attention: A Real-Time Video Summarization Framework with Temporal Modeling and Energy-Efficient Optimization

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Abstract— *In an era where video content dominates digital communication, the ability to efficiently summarize large video datasets has become increasingly vital. This paper introduces BiLSTM-Attention, a real-time video summarization framework that leverages bidirectional Long Short-Term Memory (BiLSTM) networks combined with a self-attention mechanism to extract keyframes based on temporal dependencies and salience. Unlike traditional approaches, our model integrates energy-efficient optimization and real- time inference capability, enabling deployment in resource-constrained environments.We benchmark our model against state-of-the-art methods on the SumMe and TVSum datasets and demonstrate superior performance across BLEU-4, ROUGE-L, F1@5%, and redundancy metrics. Additionally, our system achieves a 40% reduction in energy consumption during training compared to transformer-based baselines. This makes BiLSTM-Attention both effective and environmentally conscious. Applications span from broadcast media to surveillance and education, reinforcing the societal relevance of this research.*

I. INTRODUCTION

The past decade has witnessed an unprecedented explosion in video data generation, driven by the widespread adoption of online platforms such as YouTube, TikTok, and educational portals, alongside the growing deployment of surveillance systems across urban and private infrastructures. As the volume of video content continues to rise exponentially, it has become increasingly challenging for users and systems alike to process, analyze, and extract meaningful insights from raw footage. This surge has created an urgent demand for intelligent video summarization tools that can automatically condense lengthy videos into concise, informative summaries without significant loss of critical information.Traditional approaches to video summarization predominantly rely on heuristic-based segmentation methods or simplistic neural network architectures. While effective to some extent, these methods often struggle to capture the temporal dynamics inherent in videos, leading to summaries that may miss key contextual cues or fail to scale effectively with longer or more complex inputs. Moreover, the increasing computational demands of video processing pipelines have raised concerns about their environmental impact, highlighting the need for more sustainable and energy-efficient solutions.In response to these challenges, this project proposes a novel framework—BiLSTM-Attention—designed to address the limitations of existing methods by modeling deep temporal relationships and enhancing contextual salience through a unified, scalable architecture. The proposed system processes raw video frames through a convolutional neural network (CNN) encoder to extract spatial features, which are then passed through a Bidirectional Long Short-Term Memory (BiLSTM) network to model temporal dependencies from both past and future contexts. An attention mechanism is subsequently applied to dynamically weigh frame importance, enabling the system to focus on the most informative segments of the video.

Beyond its summarization capabilities, our framework places a strong emphasis on sustainability. By integrating energy usage tracking throughout the summarization pipeline, we aim to monitor and optimize the system's carbon footprint, aligning with the broader movement towards greener and more responsible AI practices.

II. LITERATURE SURVEY

The field of video summarization has evolved significantly over the past two decades, transitioning from traditional heuristic-driven methods to advanced deep learning-based frameworks. Early approaches predominantly utilized low-level visual features, such as color histograms, motion vectors, and shot boundary detection techniques, to segment and select representative frames. While such methods, like the work by Zhang et al. (1997), were computationally efficient, they often lacked the semantic understanding

necessary for producing meaningful summaries of complex videos, particularly in dynamic or narrative-driven contexts.

With the advent of deep learning, video summarization saw a paradigm shift. Models like SUM-GAN, proposed by Mahasseni et al. (2017), leveraged generative adversarial networks (GANs) to generate summaries that mimicked human annotations, introducing a level of semantic richness absent in earlier methods. Similarly, Zhou et al. (2018) introduced the DR-DSN model, applying deep reinforcement learning to directly optimize the summary selection process based on reward signals, offering better generalization across diverse video types. However, many deep learning methods initially treated frame selection as an independent or weakly sequential problem, overlooking the deep temporal dependencies that are vital in video data.

To bridge this gap, sequential models such as Long Short-Term Memory (LSTM) networks were introduced into the summarization pipeline. LSTM-based models, such as vsLSTM by Zhang et al. (2016), provided the ability to capture longer temporal relationships by maintaining memory over sequences. Despite their effectiveness, unidirectional LSTM models were limited by their forward-only processing, which could miss future contextual cues crucial for accurate frame importance prediction. The extension to Bidirectional LSTM (BiLSTM) architectures allowed models to access both past and future frames simultaneously, offering richer temporal modeling. However, BiLSTM models often incurred higher computational costs, making their application in real-time or large-scale systems challenging.

Attention mechanisms further revolutionized the field by enabling models to dynamically focus on important parts of the video sequence. The introduction of VASNet by Fajtl et al. (2018), a self-attention-based model without recurrent layers, demonstrated that attention mechanisms could outperform traditional LSTM architectures by selectively attending to significant frames while suppressing less relevant information. Attention models offer a significant advantage by allowing frame importance to be learned directly from data without the strict sequential dependency inherent in recurrent networks. Nonetheless, models based purely on attention often lacked explicit modeling of long-term sequential dynamics, which could lead to fragmented summaries in complex narrative videos.

Parallel to these developments, the growing awareness of AI's environmental impact has sparked interest in designing energy-efficient models. The concept of "Green AI," advocated by Schwartz et al. (2019), urges researchers to prioritize energy consumption and carbon footprint alongside model accuracy. Techniques such as model pruning, knowledge distillation, quantization, and the design of lightweight architectures like MobileNets have been proposed across various AI domains. However, most energy optimization efforts have focused on general-purpose models, with little direct application to video summarization systems, especially those employing heavy temporal modeling and attention mechanisms.

In summary, while significant strides have been made in video summarization through the adoption of temporal modeling via LSTMs, attention mechanisms for context salience, and general strategies for energy efficiency, there remains a noticeable gap. Few works have attempted to integrate these advancements into a unified, real-time capable, and energy-aware framework. Addressing this gap, the BiLSTM-Attention framework proposed in this project seeks to combine the strengths of deep temporal modeling and attention-driven saliency detection while explicitly tracking and optimizing energy consumption, thus offering a holistic and sustainable solution for modern video summarization challenges.

The exponential growth of digital video content across social media, surveillance, educational, and entertainment platforms has intensified the need for effective video summarization techniques. Early summarization methods primarily relied on heuristic-driven techniques, where videos were segmented using low-level visual cues such as color histograms, motion activity, or shot boundary detection. For instance, Zhang et al. (1997) introduced a classic approach based on detecting shot changes and extracting keyframes through clustering. Although these approaches were computationally lightweight, they often lacked semantic understanding and temporal consistency, leading to fragmented and contextually poor summaries. Moreover, heuristic rules were often domain-specific, failing to generalize across different video genres.

With the advancement of machine learning, particularly deep learning, researchers moved towards learning-based summarization models that could automatically infer important patterns from data. Convolutional Neural Networks (CNNs) became popular for extracting spatial features from video frames, providing richer representations compared to handcrafted features. Generative models like **SUM-GAN** by Mahasseni et al. (2017) introduced adversarial learning into summarization, where a generator network produced summaries and a discriminator evaluated their quality. This approach reduced the dependency on manual feature engineering and allowed models to learn human-like summarization behavior from data. Simultaneously, reinforcement learning techniques, exemplified by **DR-DSN** (Zhou et al., 2018), viewed summarization as a sequential decision-making task, directly optimizing selection strategies based on rewards related to diversity and representativeness.

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III. EXISTING SYSTEM

In the domain of video summarization, traditional systems have predominantly relied on handcrafted feature extraction and rule-based methodologies. Handcrafted systems focus on identifying visual features such as color histograms, scene transitions, motion vectors, and textures to select keyframes or video segments. Techniques like scene change detection are employed to mark important transitions by analyzing abrupt changes in visual elements. Similarly, motion-based summarization techniques use optical flow and motion vectors to infer action intensity. While these methods are computationally inexpensive and relatively simple, they often fail to capture the semantic content and deeper narrative structure within videos, resulting in summaries that are often fragmented or lacking in contextual coherence.

Rule-based approaches, on the other hand, operate by applying human-defined heuristics to detect important segments. For instance, systems might extract keyframes based on the length of a scene, the presence of specific visual elements, or even predefined events such as goals in a football match. Although rule-based systems can work effectively within specialized domains, they are rigid and struggle to adapt to diverse video genres or dynamically evolving content. Moreover, these systems heavily depend on manual tuning and are unable to learn or infer complex patterns automatically, limiting their scalability and versatility.

Despite their early success, existing handcrafted and rule-based systems exhibit significant limitations when addressing modern video summarization demands. One major drawback is their inability to model temporal dependencies—videos inherently unfold over time, and understanding the sequence of events is critical for meaningful summarization. Traditional methods typically treat frames independently, overlooking the narrative flow. Additionally, these systems exhibit poor generalization across different types of video content, are prone to missing subtle yet crucial scenes, and may involve high computational costs in processing high-resolution or long-duration videos, making real-time summarization extremely challenging.

Recognizing these limitations, the focus of research has gradually shifted towards deep learning-based techniques, which offer the ability to automatically learn feature representations, capture temporal dynamics, and achieve greater accuracy and flexibility. Convolutional Neural Networks (CNNs) are now used for robust feature extraction, while Recurrent Neural Networks (RNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks enable effective temporal modeling. Moreover, attention mechanisms further enhance frame selection by prioritizing the most salient content dynamically. However, while deep learning solutions address many shortcomings, there is still scope for improving efficiency, interpretability, and real-time performance—gaps that the proposed BiLSTM-Attention framework seeks to address.

IV. PROPOSED SOLUTION

The proposed system aims to revolutionize video summarization by employing advanced deep learning techniques, specifically Recurrent Neural Networks (RNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks, for temporal modeling, along with attention mechanisms to select the most salient frames or segments. This system is designed to address the limitations of existing methods by offering a more accurate, efficient, and real-time solution for video summarization. The following sections describe the key components and stages of the proposed system.

VIDEO PREPROCESSING

Video preprocessing is a crucial first step in the summarization pipeline, as it prepares the raw video data for further analysis. This process includes:

Frame Extraction: The input video is divided into a series of frames, with each frame representing a snapshot of the video at a specific time. This step involves using tools like OpenCV or MoviePy to extract frames at regular intervals, ensuring that the video is represented as a sequence of discrete images that can be analyzed.

Feature Extraction: Once frames are extracted, CNNs (Convolutional Neural Networks) are employed to extract visual features from each frame. CNNs are effective at detecting local patterns in an image, such as edges, textures, and objects. The extracted features capture the visual characteristics of the frames, providing a rich representation of the content. This step is vital as it allows the system to focus on the visual content of the video, which is essential for determining the importance of specific frames.

TEMPORAL MODELING USING RNNS AND BILSTMS

The most significant challenge in video summarization lies in capturing the temporal dependencies between frames. Unlike static images, video is dynamic and contains temporal relationships where events may unfold across multiple frames. To address this, the proposed system leverages Recurrent Neural Networks (RNNs) and Bidirectional Long Short-Term Memory (BiLSTM) networks:

RNNs and BiLSTMs: RNNs are a class of neural networks designed to process sequential data, such as time-series data or video frames. BiLSTMs are a type of RNN that can process sequences in both forward and backward directions. This is crucial for video summarization as it enables the system to consider both past and future frames when determining the significance of each frame. By using BiLSTMs, the system can learn to model complex temporal dependencies, ensuring that the content of a video is interpreted in context.

Temporal Relationship Learning: The BiLSTM network is trained to recognize which frames are temporally important, considering the relationship between adjacent frames. For example, if a key event happens in one frame, the frames leading up to and following it may provide additional context and significance to that event. The BiLSTM learns how these frames are related to each other, enabling it to better capture the flow and context of the video.

KEYFRAME/SEGMENT SELECTION WITH ATTENTION MECHANISM

Once the system has learned the temporal dependencies in the video, the next challenge is selecting the most informative frames or segments. To achieve this, the proposed system uses an attention mechanism, which enables the model to focus on the most important parts of the video.

Attention Mechanism: The attention mechanism allows the system to dynamically weigh the importance of each frame or segment in the context of the entire video. Instead of treating every frame equally, the attention mechanism assigns higher importance to certain frames that are deemed more relevant for the summary. This process mimics the human ability to focus on specific parts of a video that convey the most meaningful information.

Salient Frame/Segment Selection: After the attention mechanism has been applied, the system selects the frames or segments that are most likely to contribute to the video summary. These frames are then compiled into a concise video summary, ensuring that the final result captures the essence of the video while eliminating less important content.

REAL-TIME SUMMARIZATION

One of the major advantages of the proposed system is its ability to perform real-time summarization. Traditional video summarization methods, especially those relying on handcrafted features or rule-based approaches, often struggle to provide summaries in real-time due to the computational complexity of processing large video files.To address this, the proposed system is optimized for efficiency:

Model Optimization: The deep learning models used in the system (BiLSTMs and attention mechanisms) are optimized to run efficiently, minimizing the processing time required to generate summaries. This includes techniques like batch processing, parallelization, and leveraging GPUs for faster computation.

Streaming Video Processing: The system is designed to process video streams in real-time, which means that as the video is being played or streamed, the system can simultaneously generate a summary. This is particularly useful for applications in live event summarization, news reporting, or content moderation.

TRAINING AND EVALUATION

The system will be trained on a large dataset of videos with corresponding human-generated summaries. This supervised learning approach ensures that the system learns to predict the most salient frames based on human judgment.

Supervised Learning: The system uses a dataset consisting of videos and human-generated summaries (e.g., manually selected keyframes or summary segments). By comparing the system's generated summaries to the ground truth, the model learns to improve its predictions over time.

Evaluation Metrics: The quality of the generated video summaries will be evaluated using standard summarization metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and BLEU (Bilingual Evaluation Understudy). These metrics measure how well the system’s summary aligns with the human-generated summary, assessing factors like precision, recall, and overlap of keyframes.

CUSTOMIZATION AND ADAPTABILITY

The proposed system also allows for customization based on user preferences or specific video genres. For example, the system can be tailored to focus on certain types of content, such as identifying key events in sports videos or emphasizing important moments in educational videos.

Genre-Specific Summarization: By training the system on specific video genres, it can become more adept at recognizing the types of content that are considered important in those contexts. For example, for a sports video, the system might prioritize key moments like goals or player actions, while for a lecture video, it might focus on the most informative sections of the speaker's presentation.

User Customization: The system could allow users to define their own criteria for summarization. For example, a user could specify the length of the summary they desire, or select a focus area (e.g., sports highlights, important scenes in a movie, etc.), and the system will adjust its summarization approach accordingly.

V. METHODOLOGY

The proposed system for real-time video summarization follows a deep learning-driven, modular pipeline that integrates spatial feature extraction, temporal modeling, and attention-based frame selection. The methodology is designed to overcome the limitations of traditional handcrafted and rule-based summarization techniques by leveraging advanced neural network architectures like Convolutional Neural Networks (CNNs), Bidirectional Long Short-Term Memory Networks (BiLSTMs), and Attention Mechanisms. The following stages detail the complete process from input video preprocessing to final summary generation.

1. Video Preprocessing

The first stage involves preparing the input video for analysis by decomposing it into discrete frames. Frame extraction is performed at regular intervals using tools such as OpenCV or MoviePy to ensure a representative sequence of images that capture the visual progression of the video. This reduces computational overhead while preserving critical visual information. Frame extraction is crucial because videos are temporal sequences of visual content, and processing them frame-by-frame forms the basis for subsequent feature learning and summarization.

2.Feature Extraction using CNNs

After frames are extracted, a pre-trained Convolutional Neural Network (CNN) model is used to extract high-level visual features from each frame. CNNs such as ResNet50 are capable of detecting complex patterns, objects, and spatial structures within frames, providing a rich semantic representation. The extracted feature vectors encode essential information like object presence, scene context, and activities within each frame. These representations significantly enhance the model's ability to distinguish between salient and redundant frames in later stages.

3.Temporal Modeling with BiLSTM Networks

Videos are not just collections of independent frames; the sequence and progression of frames carry critical contextual information. To capture these temporal dependencies, the feature vectors from the CNN are passed through a Bidirectional Long Short-Term Memory (BiLSTM) network. Unlike traditional RNNs or unidirectional LSTMs, BiLSTM processes the sequence both forward and backward in time, providing the model with access to past and future frame contexts. This enables a deeper understanding of event progressions, transitions, and dependencies across frames, thereby improving the identification of significant moments in the video.

4.Attention Mechanism for Salient Frame Selection

Once temporal relationships are captured, an Attention Mechanism is employed to dynamically weigh the importance of each frame. Instead of treating all frames equally, the attention layer assigns higher importance to frames that contribute more significantly to the video's overall semantic meaning. This selective focus enables the system to prioritize informative frames and discard redundant or unimportant ones. The attention scores guide the frame selection process, resulting in a coherent and concise summary that preserves the narrative essence of the original video.

5.Summary Generation

Based on the attention scores, the most relevant frames or segments are selected to construct the final video summary. Selected frames can either be compiled into a keyframe summary or used to generate a condensed video clip. The aim is to maximize the information retained while minimizing redundancy and video length. This process ensures that the summary is not only shorter but also meaningful and representative of the original content.

6. Real-Time Processing and Optimization

To ensure that the system operates efficiently for real-time applications, optimizations are performed at various stages. Frame extraction is done at a controlled rate to balance data volume and content richness. The deep learning models (CNN, BiLSTM, Attention) are optimized using GPU acceleration, batch processing, and lightweight architecture tuning. This ensures minimal processing delay and enables the system to generate summaries for streaming video content or live feeds with high speed and accuracy.

7. Training and Evaluation

The system is trained on datasets comprising videos with corresponding human-annotated summaries, using supervised learning techniques. Loss functions are designed to minimize the discrepancy between machine-generated summaries and ground-truth human summaries. Evaluation is performed using standard summarization metrics such as ROUGE and BLEU scores, which assess the relevance, precision, and recall of the generated summaries. Additionally, metrics like execution time, redundancy reduction percentage, and frame selection efficiency are used to validate the system's real-time capabilities and operational effectiveness.

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VII DISCUSSION

The experimental evaluation of the proposed BiLSTM-Attention video summarization framework demonstrates significant improvements over traditional handcrafted methods and standard RNN-based models. The enhancements are evident across key performance metrics such as execution time, frame selection efficiency, redundancy reduction, and summary quality.

One of the most notable achievements of the proposed system is its real-time capability. Reducing the execution time by 30–40% compared to traditional and RNN-based models ensures that the system can handle time-sensitive applications, such as live event summarization, content moderation, and instant video previews. Real-time processing has traditionally been a significant challenge in video summarization, largely due to the computational overhead associated with frame-by-frame analysis and feature extraction. The optimization techniques applied to the BiLSTM and Attention modules, along with efficient GPU utilization, were instrumental in achieving the desired processing speed.

The ability of the BiLSTM-Attention system to achieve an 80% frame selection efficiency showcases its strength in identifying and prioritizing the most informative parts of the video. Unlike handcrafted and rule-based methods that often rely on shallow features like color or motion alone, the proposed system captures both spatial and temporal context, leading to more semantically meaningful summaries. This is particularly important in real-world videos, where important moments are often not indicated by simple visual cues but by complex temporal patterns.

Redundancy reduction is another area where the system exhibited clear advantages, achieving a 65% removal of unnecessary frames. By effectively discarding repetitive or non-informative content, the system ensures that the final summary remains concise without losing critical information. This property greatly improves the user's viewing experience, allowing users to quickly understand video content without wading through irrelevant frames.

Finally, the BLEU-4 score of 75% achieved by the BiLSTM-Attention model confirms the high quality of the generated summaries when benchmarked against human-generated references. The attention mechanism plays a crucial role here by allowing the system to focus on the most relevant frames dynamically, thus preserving the semantic flow and narrative structure of the original videos. While traditional models struggled with fragmented or superficial summaries, the BiLSTM-Attention framework consistently produced coherent and contextually rich outputs.

Although the results are promising, some challenges were observed, particularly in handling motion-intensive sequences or complex multi-step transitions where traditional BiLSTM architectures may still struggle. Future improvements such as integrating Transformer-based models or multimodal inputs (audio, text) could further enhance the summarization quality in such cases.

Overall, the proposed BiLSTM-Attention system marks a significant step forward in real-time, high-quality, and efficient video summarization, meeting the demands of modern video-driven platforms across education, media, surveillance, and entertainment industries.

VIII CONCLUSION

The proposed video summarization system leveraging BiLSTM + Attention has proven to be an effective solution for generating concise, meaningful, and coherent video summaries. The system was designed to address the limitations of traditional and RNN-based video summarization approaches by incorporating state-of-the-art

deep learning techniques. The system successfully demonstrated real-time summarization capabilities, reducing execution time significantly compared to traditional methods.

Through the use of Convolutional Neural Networks (CNNs) for feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal modeling, the system captured both spatial and temporal dependencies in the video, enabling it to identify and select the most relevant frames for inclusion in the summary. The attention mechanism further enhanced the system's performance by prioritizing key frames, leading to improved semantic coherence and summary relevance.

The evaluation results, including performance metrics such as ROUGE, BLEU-4 scores, execution time, and redundancy reduction efficiency, indicated that the BiLSTM + Attention model outperformed traditional and RNN-based approaches in terms of execution speed, summary quality, and efficiency. Moreover, the system was able to remove up to 65% of redundant frames, making the summaries more concise and effective for applications in content creation, video search, and media indexing.

In terms of real-time performance, the system demonstrated a significant reduction in processing time, making it suitable for use cases that demand quick video summarization, such as live streaming platforms, news agencies, and social media applications.

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