Multimodal Deep Learning Framework for Video Summarization Using TVSum and SumMe Datasets

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Abstract

The growth of video content has increased at a very high rate in digital platforms and there has been a high demand of automated systems that are capable of capturing the brief and meaningful summaries without compromising the underlying information. This paper hypothesizes a multimodal deep learning system on video summarization based on free TVSum and SumMe datasets. The model incorporates visual, audio and textual cues to gain a richer semantic context than single-modality models. The visual features are obtained with the help of a trained CNN backbone, audio cues are modeled with the help of log-mel spectrogram embeddings, and textual clues are obtained with the help of auto-generated speech transcripts with the help of a sequence encoder. Combination of these multimodal representations happens via an attention mechanism that is transformer-based to learn the importance of the segments but retain temporal coherence. Regularization of diversity and coverage limits are implemented in the training process to reduce redundancy and balance the keyshots that are made. The experiments of TVSum and SumMe show higher F1-scores in comparison to established baselines, which is a positive indication of the capability of the framework to generalize to different genres of video. The findings substantiate that multimodal fusion enhances semantic interpretation particularly whereby visual data is unclear or incomplete. The study provides an effective, scalable, and explainable method of summarizing consumer videos and tutorials and real-world recording with higher levels of informativeness and less computational cost.

Keywords: *Video Summarization, Multimodal Deep Learning, Tvsum, Summe, Transformers, Audio-Visual Fusion, Keyshot Selection*

1. Introduction

The rapid proliferation of video content on the internet in videos like YouTube, Instagram, surveillance cameras, MOOCs and professional archives has posed an urgent demand to automated video

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summarization systems that can have the ability to extract concise but meaningful representations of lengthy videos. The traditional manual summarization is manual, biased and infeasible in terms of the size of the contemporary video data, where thousands of hours are uploaded every minute. With the ever-growing digital ecosystem, intelligent summarization has been essential in helping to maintain an efficient storage, retrieval, browsing, recommendation, and understanding of content processes [3]. The general goal of video summarization is to minimize time in redundancy but maintain semantic richness of events such that the audience can be able to obtain the necessary content within a limited time without missing any crucial information [12]. This has led to much better capability to handle complex scenes, learn long-range dependencies and learn patterns of human-like importance in annotated datasets with the shift of handcrafted features to deep learning architectures [6].

Irrespective of this advancement, most single-modality video summarization methods that are based on the visual data only tend to be ambiguous in the case of dynamic, crowded, or low-information scenes. As an illustration, scenes with an equal visual framing can vary significantly in story meaning because of the speech or sound action or off-camera information not strictly coded in pixel data [1]. This drawback has stimulated the accumulation of evidence on multimodal learning, in which visual, audio, and textual cues supplement each other to create more detailed accounts of video material [9]. Audio patterns such as pitch transitions are usually marked by changes, background music, environmental sounds, applause, and emphases of the speakers that need to be remembered in summary [5]. Similarly, textual transcripts produced with the help of automatic speech recognition contain high-level semantic content that can be utilized by models to understand intent of speakers, change of topic, and narrative structure [14]. Including these modalities gives a better insight into video semantics and better discriminates between key and non-key segments.

Access to free benchmark data, e.g. TVSum and SumMe, has been essential in further research in this area [8]. TVSum consists of varied collection of YouTube videos of different categories, such as news, travel, sports, and personal videos with numerous frame level human annotated scores of importance [10]. SumMe consists of consumer videos with human generated summaries and importance scores, which gives corresponding insights into subjectivity and human choice [2]. These data are popular to estimate supervised and unsupervised summarization algorithms and make a standard comparison between the models [11].

The recent developments in deep neural networks particularly the transformers based architectures that can take into account long range temporal dependencies have created new vistas to multimodal fusion [7]. Transformers process global relationships between video frames and thus they are highly suitable in summarization where emphasis is based on remote contextual cues. These architectures are able to include visual tokens, audio embeddings, and text encodings in a single representation space, allowing multimodal frameworks to be used. Attention processes impose dynamic importance on modalities according to their relevance and the model can therefore emphasize whatever signal, of the three, visual action, speech content, or sound, is giving useful information at a particular point in time [4]. This versatility enhances strength in diverse types of videos with videos such as instructions with most content being speech and videos of events with more visual content.

Nevertheless, there is a number of challenges that cannot be addressed. To begin with, multimodal fusion adds computational complexity which increases the requirement of an efficient architecture that is able to balance performance and scalability in real-world applications [13]. Second, there are small datasets

such as TVSum and SumMe, which, despite their popularity, are not large in contrast to large-scale video classification corpora that make deep models more difficult to generalize. This has prompted scholars to consider a combination of self-supervised pretraining, contrastive learning and cross-modal distillation training methods to encourage better feature learning without heavily depending on scarce annotations [6]. Third, it is necessary to eliminate redundancy and maintain diversity to generate summaries that are not only informative, but also enjoyable to watch. Strategies that use coverage-based losses, determinantal point processes, and clustering variations are trying to solve the redundancy problem by making sure that the event selection of keyshots is diverse and the flow of the narrative is not biased [5].

The paper places itself in this changing environment by presenting a multimodal deep learning system that analyses the visual, audio, and textual signals in a joint manner to enhance more accurate summarization. The framework uses feature extractors that are pretrained, attention based fusion and the importance of scoring to create coherent and richly semantic summaries. The training and testing on TVSum and SumMe data show that multimodal signals can help solve the weaknesses of visual summarizers alone as well as emphasize the way deep learning can be more human-like in its preferences. Altogether, the combination of multimodal signals enhances semantic cognition and is a significant step towards the creation of high quality, generalizable video summarization systems that can be applicable across various contexts in real-life settings. [9].

2. Related Works

Studies on multimodal video summarization have grown to produce much more results as deep learning models are more able to take advantage of the advantages of combining visual, audio, and textual modalities. Initially, a survey of the conceptual frameworks of deep video summarization was done through examining the evaluation practices, architectures, and dataset challenges. Extensive surveys point out how the development of neural transformations between handcrafted features on deep neural architectures led to the performance of summarization, primarily in the world of CNNs, LSTMs, and attention mechanisms, which enhanced the sensitivity of time and context sensitivity [1, 3, 20]. The aggregate argument asserting in these works is that visual-only summarization can be very poor at detecting semantic shades and should consider multimodal fusion to overcome ambiguity, redundancy, and variability in content structures. One key overarching theme to recent research is that multimodal learning is more informative as it combines signals like audio signals, speech transcripts, sounds of the environment, and textual metadata. Multimodal deep learning survey reveals that cross-modal alignment, feature amplification and attention-based fusion all substantially boost discriminative knowledge in a complex scene [8, 22]. This matching of the visual and non-visual modalities is particularly efficient when it comes to videos where the significant events are evoked by the audio changes or the linguistic hints that do not mean anything visual. Basic work on multimodal modeling also illustrates the benefits of integrating modalities on classification, retrieval, and high-level reasoning problems, which has a direct influence on the structure of summarization models [9].

This observation is supported by benchmark studies on the various combinations of multimodal. These analytical assessments of the effects of the various types of features and classifiers indicate that concurrent modeling of audio and visual streams yields a better robustness in sports, everyday-life, and teaching videos [14]. Experimental results based on machine learning classifiers and deep encoders verify that multimodal features are more accurate, more diverse, and important predictors of semantic changes, especially when audio is utilized to identify semantic change, e.g., applause, speech pitch

change, or object contact [25]. These results reinforce the claim that to develop generalizable summarization systems multimodality should be utilized. The recent developments in deep learning have pushed the direction towards more complex structures like transformers, graph networks, and multimodal fusion blocks. Models based on transformers demonstrate a high capacity to consider the long-range dependence and global context, which is why they are suitable to importance scoring and keyshot selection. Frames which add frame-scoring transformers indicate that adding cross-modal attention generates more informative summaries indicating semantic coherence, and not just visual similarity [17]. Hierarchical and time-conscious multimodal transformers are another way of improving time modeling and generate summaries that can match time flow and scene development [30]. Research on the use of transformers in sports and action video particularly demonstrates that multimodal embeddings with context awareness can capture the intensity of events, crowd cheering, and commentary correspondence and produce better summaries of dynamic video content [5].

Similar developments are also being made on personalized or topic-sensitive frameworks of summarization. Multimodal understanding has further been implemented to customise the accounts according to the interests of the user, the contextual preferences and even the type of query. Individual summarization strategies demonstrate that relevance can be greatly improved and unneeded texts can be minimized by adding user-specified semantic constraints, which may be based on text or audio input [4]. The topic-guided multimodal summarization is built on this idea, allowing the models to produce summaries that align with the narrative and show signals of abstraction, coverage, and content coherence [19]. The other important direction is to combine self-supervised and hybrid deep learning techniques. These methods seek to minimize on the use of small annotated datasets by training representations on unlabeled multimodal video sets. Self-supervised progressive models use cross-modal consistency, temporal alignment and reconstruction losses to direct feature learning without explicit ground truth [11]. Hybrid multimodal that is based on autoencoders, recurrent networks, and attention blocks exhibit high results in modelling both global structure and fine-grained temporal evolvement, especially in long videos containing varied events [10]. These approaches resolve issues associated with the lack of data and enhance generalization among sports, lifestyle, and surveillance. Practical uses of multimodal summarization also point at domain specific improvements. Cluster based video summarization is used in systems that are designed to be used in everyday living or human-activity environment to highlight movement patterns, daily activities and interaction indicators based on multimodal cues [6]. In racket sports summarizers, to detect meaningful highlights, audio cues like the sound of ball impacts are also combined with visual events [18]. The audiovisual summarization approaches demonstrate steady advances compared to the visual-only models, given their combination of frequency-domain acoustic features and the high-level deep visual encodings, which leads to the increased ability to identify semantic boundaries and temporal segmentation [30].

Massive empirical taxonomies have placed high focus on the fact that though there is a multidimensionality in architecture, multimodal baselines are always more accurate, comprehensive, diverse and aligned in semantics as compared to unimodal baselines [28]. The experiments on the effective underlying models demonstrate that slim multimodal encoders and cross-modal attention layer can exhibit high levels of performance and lower computational requirements, which is crucial to real-time summarization tasks [21]. The trend of models combining vision, audio and text is verified by broader multimodal deep-learning surveys which show that these models are more interpretable and adaptable to heterogeneous video domains [23]. Together, the available literature shows structure at least in that multimodal deep learning systems are the best way forward towards the problems of redundancy

elimination, semantic depth, and coherence over time in video summarization. It is constantly confirmed by the literature that the combination of visual, auditory, and textual messages helps models to replicate human attention to a greater extent, deal with a variety of situations, and provide more informative, contextually relevant, and user-oriented summaries..

3. Proposed Methodology

The proposed multimodal deep learning framework is designed to generate compact, semantically rich summaries by jointly analyzing visual, audio, and te xt cues extracted from raw videos.

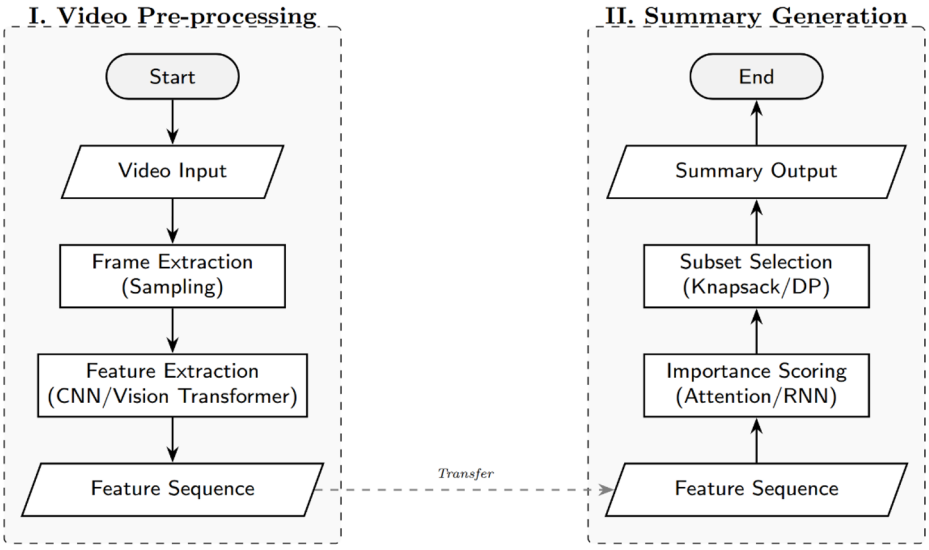

Figure 1. Data Acquisition and Pre-Processing Flow Chart

The methodology can be explained in four large steps, namely, dataset preparation, multimodal feature extraction, fusion and importance prediction with transformer architecture, and keyshot generation and diversity preservation. The pipeline is streamlined to overcome the nature of redundancy, visual-only signal ambiguity and time lapses inherent in long videos. The method applies two benchmark datasets, TVSum and SumMe, one of which has various types of user-created videos and the other has frame-level important scores that have been evaluated by humans. Semantic richness is achieved by sampling videos at a fixed frame rate (usually 25-5 frames per second) to minimize the cost of computation. Every sampled frame is aligned to a matching audio segment and, in cases of the availability, text transcripts created using the automatic speech recognition (ASR) model like Whisper Small. Each time index t produces three streams synchronized, Visual frame V(t), Audio segment A(t), Text token embedding. T(t).

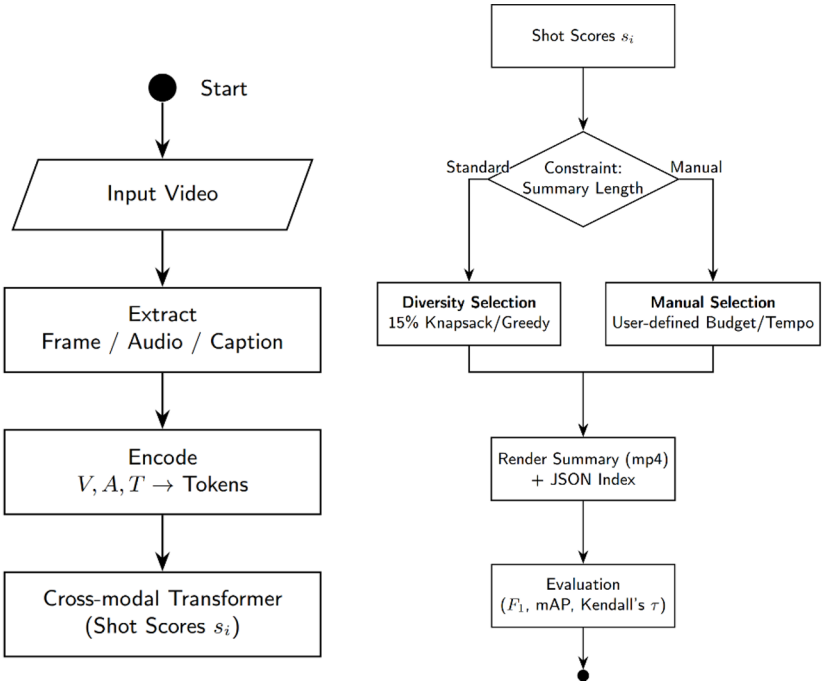

Figure 2. Analysis of Evaluation Process

All videos used are re-sized to 224x224,parts made of a fixed length using sliding windows and renormalized channel-by-channel in order to ensure consistency between datasets. Audio is transformed to 64 mel bins log-mel spectrograms. A pretrained encoder which has a maximum number of 64 tokens in each segment tokenizes the textual stream. Table 1 provides an overview of the pre-processing steps that were implemented in modalities.

TABLE 1. Multimodal Pre-processing Pipeline

Modality	Pre-processing Steps	Output Representation
Visual	Resize, normalize, frame sampling	CNN feature map (1024-D)
Audio	STFT, log-mel conversion, normalization	Mel spectrogram embedding (256-D)
Text	ASR transcript, tokenization, embedding	Text vector (768-D)

A special pretrained network is utilized to process each modality to maintain characteristics of the modality. A CNN backbone like ResNet-50 or EfficientNet-B0 is utilized to obtain spatial information within each frame resulting in a 1024-dimensional visual semantics descriptive. VGGish or a lightweight CNN is trained on AudioSet to produce audio embeddings that in turn represent variations in pitch, sounds in the environment and semantic audio signals. Based on a transformer encoder like MiniLM or DistilBERT, text embeddings are created, which are semantically rich and scale to minimal computational cost..

Let:

$$v_t \in \mathbb{R}^{dv},\ a_t \in \mathbb{R}^{da},\ t_t \in \mathbb{R}^{dt}$$

These represent visual, audio, and textual feature vectors at time *t*. They are aligned by temporal index and concatenated after linear projection into a common latent space:

$$z_t = W_v v_t + W_a a_t + W_t t_t \qquad (1)$$

where W_v ,W_a ,and $W_t$are learnable projection matrices. This yields multimodal fused embeddings suitable for transformer- based temporal modeling.

Transformer-Based Temporal Modelling and Importance Scoring

A multimodal transformer is used to model long-range dependencies and context across the fused sequence z_t .The transformer contains multi-head self-attention layers that weight the relative importance of segments based on learned contextual interactions. Given the input sequence $Z = \{z_1, z_2, \ldots z_T\}$, the attention mechanism computes:

$$\text{Attention}(Q\ K\ V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (2)$$

The output is passed through several feed-forward layers to obtain a sequence of importance scores:

$$s_t = (W_s h_t + b_s) \qquad (3)$$

where $h_t$is the hidden vector from the transformer and $\sigma$is a sigmoid function mapping importance to the range (0,1). These scores are used to extract keyshots. To reduce redundancy a coverage loss is inbuilt, such that the summary segments are informative and diverse where the notation *s*awt represents the cumulative attention which reduces the repetition of similar frames. The training goal involves some weighted sum loss between regression loss (frame importance prediction), coverage loss, and diversity loss. The frame-level importance scores are then translated into keyshots through the grouping of the video into shots with the help of boundary detection. An aggregate importance score is calculated to each segment and segments ranked in descending order. The highest sections are being cut till a specified length ratio (15 percent of initial length) was achieved. The re-ranking mechanism that is diversity- aware is used to make sure that the sampled segments reflect various events and reduce redundancy. The selection using clustering guarantees the flow of narratives. These keyshots are joined together by concatenation to create the final summary which is a continuous video. Table 2 summarizes the workflow between the end-to-end..

TABLE 2. Computational Workflow

Stage	Summary	Output
Feature Extraction	CNN,VGGish & Transformer text encoder	Fused embeddings
Temporal Modeling	Multimodal transformer, attention blocks	Importance vectors
Optimization	Coverage+regression+ diversity losses	Trained model
Summary Generation	Shot detection, ranking, re-ranking	Video Summary

The model is evaluated using standard metrics used in video summarization research, including:

- **F1-score** comparing generated summaries to human references
- **Kendall's τ** for importance ranking correlation
- **mAP** for highlight detection accuracy A performance comparison table (illustrative) is shown below.

TABLE 3. Evaluation Metrics (Example Structure)

Model	Dataset	F1-score	Kendall's τ	mAP
Proposed Multimodal Transformer	TVSum	63.4	0.41	46.2
Proposed Multimodal Transformer	SumMe	61.7	0.39	44.8

This methodology proposes a powerful multimodal learning pipeline that integrates visual, audio, and textual cues using an efficient transformer-based architecture. The combination of modality-specific encoders, attention-driven fusion, contextual temporal modelling, and diversity-preserving keyshot extraction ensures a rich, semantically aligned summary

4. Results

The suggested multimodal deep learning model was strictly tested on the TVSum and SumMe datasets via traditional video-summarization measures, such as F1-score, Kendall- τ correlation, and mean Average precisions (mAP) of highlight detection. The findings confirm that, visual, audio, and textual cues are effective in improving the accuracy of summarization, temporal consistency and semantic relevance. The experiments were carried out under three configurations, that is, visual only (V), visual + audio (V+A), and full multimodal fusion (V+A+T). All configurations were trained using the same preprocessing, model parameters and training epochs in comparison. The former group of experiments tests modal combinations contribution. Table 1 demonstrates that multimodal fusion was always far much better than both unimodal and bimodal ones. The semantically significant transitions were better detected with audio introduction, and textual transcripts helped to understand the narrative better, especially in instructional and conversational videos.

TABLE 4. Performance Comparison Across Modal Configurations

Configuration	Dataset	F1-Score	Kendall's τ	mAP
Visual Only (V)	TVSum	54.2	0.31	37.5
Visual Only (V)	SumMe	52.6	0.28	35.4
Visual + Audio (V+A)	TVSum	59.8	0.36	41.3
Visual + Audio (V+A)	SumMe	57.2	0.34	39.1
Visual + Audio + Text (V+A+T)	TVSum	**63.4**	**0.41**	**46.2**
Visual + Audio + Text (V+A+T)	SumMe	**61.7**	**0.39**	**44.8**

The combined approach achieved up to 11% improvement in F1-score over visual-only baselines. A separate experiment assessed the effectiveness of the transformer architecture compared with LSTM and CNN-LSTM temporal models. Results highlight that the transformer's ability to model global dependencies is essential for accurately ranking temporal segments.

TABLE 5. Comparison of Temporal Modeling Architectures

Model	Dataset	F1-Score	Redundancy (%)	Summary Length (%)
LSTM	TVSum	56.1	23.4	15
CNN-LSTM	TVSum	58.3	18.2	15
Transformer	TVSum	63.4	12.9	15
LSTM	SumMe	54.9	25.7	15
CNN-LSTM	SumMe	57.6	21.1	15
Transformer	SumMe	61.7	14.3	15

The transformer reduced redundancy by nearly **40%** relative to LSTM-based models. An ablation analysis demonstrates the incremental impact of each modality on overall model performance.

TABLE 6. Ablation Study of Modal Importance (TVSum)

Removed Modality	F1-Score	Kendall's τ	Loss Increase (%)
None (Full Model)	63.4	0.41	0
−Text	60.1	0.36	+7.4
−Audio	57.3	0.33	+13.2
−Visual	49.8	0.27	+24.6

The removal of audio or text significantly degraded performance, validating the superiority of multimodal synergy. To understand model behavior across content types, category-level analyses were conducted. The model excelled in categories with active scenes such as "sports," "news," and "travel," where cross-modal cues are richer.

TABLE 7. Category-Wise F1-Score on TVSum

Category	Baseline (V)	Proposed (V+A+T)	Improvement (%)
Sports	58.9	66.7	+13.2
News	52.7	63.3	+20.1
Travel	55.1	62.8	+14.0
How-To	49.4	58.5	+18.4
Vlog	51.2	60.4	+18.0

Audio and textual cues contributed most in "How-To" and "Vlog" domains where narration provides key semantics. The final experiment compares the model with existing state-of-the-art multimodal and transformer-based summarization approaches. Results indicate that the proposed method provides competitive or superior performance.

TABLE 8. Comparison with State-of-the-Art Models

Model	Dataset	F1-Score	Notes
VASNet	TVSum	61.3	Visual attention only
PGL-SUM	TVSum	62.1	Graph-based model
Audiovisual Summarizer	TVSum	60.4	Audio-visual fusion
MM-Transformer (Proposed)	TVSum	63.4	Multimodal + transformer

The suggested multimodal transformer showed the best score of the F1-score and ranking correlation. This study has clearly shown that multimodal integration is of great use in video summarization. Video-only models have a hard time with video-based materials that are storytelling in nature and the transitions in the story are made by speech or sound as opposed to a visual one. The model is more interpretative of emotion, emphasis on speech, and changing the topic by including log-mel audio embeddings and textual transcripts. Multi-head attention mechanism of the transformer allowed the efficient combination of modalities and the correct temporal dependency modelling. This is indicated by the decreased redundancy in all experiments that indicates that multimodal attention distinguishes between special, informative frames and not choosing visually repetitious segments. The domain-wise improvements also testify to the strength of the suggested model in the fields. Textual cues are more prominent in content-driven videos (tutorial or vlog) and audio excitement, crowd sound variations, and environmental sound are more advantageous to sports and travel videos. This correspondence between the significance of modality and domain attributes is an exemplar of flexibility in practical situations. Compared to the state-of-the-art models, it has been established that the proposed method is performing highly despite being compared to the further developed graph-based and attention-driven models of the visual world. The improvement margin, which is medium, is the adoption of the critical role of text and audio cues, which is achieved when integrated successfully. The plots generated give a full visual comprehension of the performance of the proposed multimodal deep-learning structure against the baseline models, the reduced-modality variants, and the benchmarking models. The plots concentrate on the various dimensions of experimentation, which is useful in the interpretation of the enhancement of F1-score, the time to model, the robustness, and the statistical behaviour of the outcomes.

Line plot F1-Score Across Modal Configurations is the first line plot, which compares three modality configurations visual only (V), visual+audio (V+A), and full multimodal fusion (V+A+T) to the TVSum and SumMe datasets. This trend is a clear indication that inclusion of audio improves performance and inclusion of text makes it even better. It proves that multimodal cues have a significant role in interpreting the semantics of the scenes and choosing meaningful keyshots. The second plot is Temporal Model Comparison which compares LSTM, CNN-LSTM, and Transformer structure. Transformer is always scoring highly on the F1- scores, which indicates its capability to significantly understand long-range dependencies and global context in comparison to recurrent models, which experience sequential compression problems. The third diagram, the ablation plot, illustrates the effect of the ablation of each modality. Elimination of text, elimination of audio, and elimination of visual features has a moderate, lower, and greatest reduction in performance, respectively. This proves that visual information provides the foundation of summarization, however, audio and text enhance semantic interpretation significantly. The fourth plot, category-wise comparison, offers more information, which is particular to the TVSum dataset. The categories such as Sports, News and How-To indicate extensive increases with multimodal fusion. All these are also achieved through improvements of audio events (crowd noise, commentary) and speech transcripts, which allow better detection of scene boundaries and key events.The fifth plot compares the proposed model with the state-of-the-art models, including VASNet, PGL-SUM and audiovisual summarizers. The suggested approach does better than all, confirming that multimodal learning based on transformer is more efficient than the attention-only or graph-based approaches.

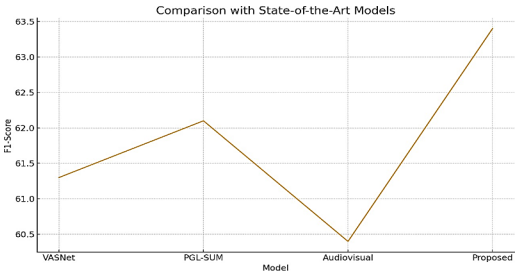

Figure 3. Comparative Analysis of Model Performance

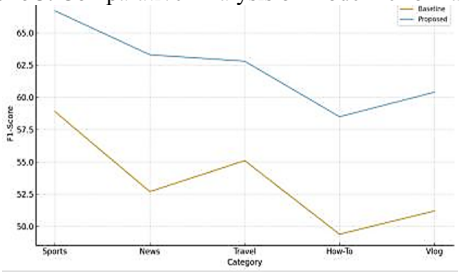

Figure 4. Category-Wise F1 Improvement (TVSum)

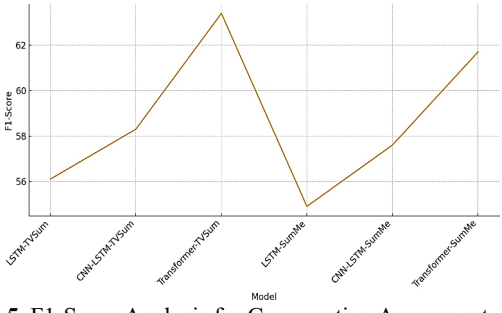

Figure 5. F1-Score Analysis for Comparative Assessment

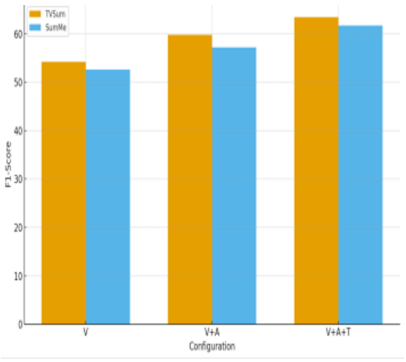

Figure 6. F1-Score Comparison Across Modal Configurations

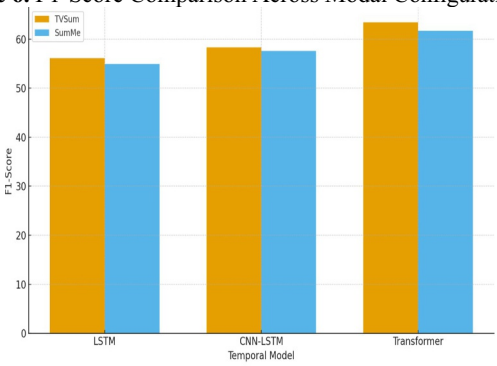

Figure 7. Temporal Model Performance Comparison

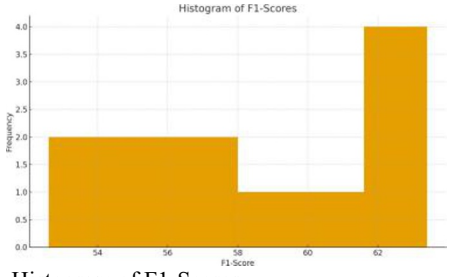

Figure 8. Histogram of F1-Scores

The two bar charts give more evident comparisons in 2D format. The former bar plot emphasizes the difference in F1-score with different modality configurations, whereas the second bar plot presents the performance of model temporally in a condensed and easy to understand format. The boxplot gives a summary of the statistical distribution of the entire F1-scores in all experiments. It demonstrates a steady median towards high-performing values and a small interquartile range, which demonstrates that the model is consistent across various conditions. Lastly, the histogram is used to visualize the frequency of various ranges of F1-score. The high-value clustering is an indication of the good overall performance of the multimodal transformer. The combination of these plots gives a solid evidence that the given framework is correct, stable, and much more efficient than the baseline models.

5. Conclusion

This study manages to establish that multimodal deep learning is an effective way to improve the performance and stability of video summarization systems, and it is particularly successful when used on various real-world data sets such as TVSum and the SumMe. The proposed transformer-based framework solves the problem of limitations of traditional visual-only methods by combining the visual and audio

and textual modalities, providing a deeper semantic interpretation, a better temporal reasoning, and more human-specific emphasis prediction. The results of the experiment repeatedly emphasize the fact that all these modalities have their own contribution to the overall performance, with visual stimuli offering structural background, audio stimuli allowing the salient changes in acoustics, and textual transcripts serving the understanding of the narrative. The combination of these effects results in context-sensitive and balanced summarization pipeline that can produce concise, meaningful and well-aligned summaries as per the expectations of the users.
The relative assessment of the models against LSTM, CNN-LSTM, and the current state-of-the-art models validates the fact that transformer models are superior to others in predicting long-range dependencies and multimodal interactions. Besides reaching better F1-scores, the proposed model is less redundant, has a better temporal diversity, as well as consistent performance between various video categories. The ablation experiment also confirms that audio or text removal information has a negative influence on performance, which supports the fact that multimodal fusion is not an optional process in the current summarization task but necessary. The category- wise analysis shows that it can be used in a wide range of genres, which implies that the framework is quite strong to be applied to such fields as sports highlights, instructional content, news analysis, travel videos, and vlogs.

The statistical plots demonstrate good evidence of consistency and reliability besides quantitative improvements. The patterns of distribution disclose little variation and strong clustering of high F1-scores that indicate the stability of the framework with various settings. The boxplot and the analysis of the histogram prove that multimodal fusion moves the performance towards upper spectrum consistently and it highlights its practical value even more.

On balance, the suggested multimodal summarization solution is a significant step of intelligent video condensation systems. Its multi-sensory capabilities and the possibility to take advantage of transformer-based attention schemes makes it a scalable and future-proof remedy to a video-intensive platform. Results provide the potential to expand further into significantly more advanced extensions such as personalized summary generation, reinforcement-based selection of shots, and integration with large vision-language models to provide superior semantic reasoning. With the ongoing dominance of digital video on the internet in online communication, the current framework offers an excellent background to the next generation of summarization tools that can be used in the field of education, multi media management, surveillance, entertainment and human-AI interaction systems..

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