VIDEO SUMMARISATION

MAJOR PROJECT-I

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Chapter 1 : Introduction

1.1 Abstract

With the ever-increasing popularity and decreasing cost of video capture devices, the amount of video data has increased drastically in the past few years. Video has become one of the most important form of visual data. Due to the sheer amount of video data, it is unrealistic for humans to watch these videos and identify useful information. It is estimated that it will take around 5 million years for an individual to watch all the videos that are uploaded on the Internet each month in 2021! It is therefore becoming increasingly important to develop computer vision techniques that can enable efficient browsing of the enormous video data. In particular, video summarization has emerged as a promising tool to help cope with the overwhelming amount of video data.

1.2 Problem Statement

Given an input video, the goal of video summarization is to create a shorter video that captures the important information of the input video. Video summarization can be useful in many real-world applications. For example, in video surveillance, it is tedious and time-consuming for humans to browse through many hours of videos captured by surveillance cameras. If we can provide a short summary video that captures the important information from a long video, it will greatly reduce human efforts required in video surveillance. Video summarization can also provide better user experience in video search, retrieval, and understanding. Since short videos are easier to store and transfer, they can be useful for mobile applications. The summary videos can also help in many downstream video analysis tasks. For example, it is faster to run any other analysis algorithms (e.g. action recognition) on short videos.

1.3 Significance of the problem

The aim of video summarization is to speed up browsing of a large collection of video data and achieve efficient access and representation of video content. By watching the summary users can make quick decisions on the usefulness of the videos. Dependent on application and the target audience, the evaluation of summary often involves usability studies to measure the content informativeness and quality of the summary.

1.4 Empirical Study

We studied the literature pertaining to the various video summarization techniques by going through the existing research papers. We then tried reproducing the results of a few authors from the above mentioned papers. We analyzed different data sets used for video summarization techniques , the most popularly used being TVSum and SumMe and found the

ground truth summaries corresponding the data sets for training the model. More details about both the datasets have been mentioned further in the report.
As a part of the existing tools survey we studied the unsupervised and supervised methods for video summarization. Also for deep learning we will be using NeuralNetworks and Convolutional Neural Networks. This requires agood amount of computational power and GPU power to do the required MLtasks quickly and efficiently.

1.5 Brief description of the solution approach

Our proposed solution is to first divide the video into video frames and then extract features from these frames. These extracted features will be fed to the LSTM network, to determine time-based importance of these frames. Finally they will be classified into a yes or no, whether they will be included in the final summary or not by computing their Temporal Intersection over Union with the ground truth. The data sets used for this approach will be SumMe and TVSum. The detailed overview of the solution approach is mentioned further in the report.

1.6 Comparison of existing approaches the problem faced

Most relevant to our approach is the work of online video summarization, which compiles the most salient and informative portion of a video by automatically scanning through the video stream, in an online fashion, to remove repetitive and uninteresting content. Various strategies have been studied, including Gaussian mixture model, online dictionary learning and submodular optimization. Our approach significantly differs from these methods in that it only processes a subset of frames instead of the entire video. To the best of our knowledge, this is the first work to address video summarization by using convolutional neural networks in generating an informative summary from a video.

Chapter 2: Literature Survey

2.1 Summary of papers studied

We studied and analyzed the following research papers as a part of a literature survey.

1. Attentive and Adversarial Learning for Video Summarization
   By Tsu-Jui Fu, Shao-Heng Tai, Hwann-Tzong Chen
   Link to paper: ReseachPaper 1

   Summary:

   This paper aims to address the video summarization problem via attention-aware and adversarial training. The authors formulated the problem as a sequence-to-sequence task, where the input sequence is an original video and the output sequence is its summarization. They proposed a GAN-based training framework, which combines the merits of unsupervised and supervised video summarization approaches. The generator is an attention-aware Ptr-Net that generates the cutting points of summarization fragments. The discriminator is a 3D CNN classifier to judge whether a fragment is from a ground-truth or a generated summarization. The experiments show that the method achieves state-of-the-art results on SumMe, TVSum, YouTube, and LoL datasets with 1.5% to 5.6% improvements. The Ptr-Net generator can overcome the unbalanced training-test length in the seq2seq problem, and the discriminator is effective in leveraging unpaired summaries to achieve better performance. [1]

Data Sets used: SumMe, TVSum, YouTube, and LoL datasets.

Limitations: During inference, they only performed the generation part, which includes visual feature extraction and ptr-generation, to process the input video. Furthermore, when performing inference, they did not adopt teacher forcing as they have done during training, and therefore the output of predicted summarization fragments may be overlapped or out of order.

2. Unsupervised Video Summarization via Multi-source Features
By Hussain Kanafani, Junaid Ahmed Ghauri, SherzodHakimov, Ralph Ewerth
Link to paper: https://arxiv.org/pdf/2105.12532.pdf

Summary:

In this paper, the authors proposed a deep learning model for unsupervised video summarization called Multi-Source Chunk and Stride Fusion (MCSF), which investigates the impact of multiple visual representations extracted about visual objects and scene (i.e., places) content. It also uses two temporal constellations of the video features which give the model different perspectives of the video. Consequently, three fusion strategies are suggested and evaluated.For a comprehensive evaluation on the two benchmarks TVSum and SumMe, they comparedthe method with four state-of-the-art approaches. Two of these approaches were implemented by them to reproduce the reported results. Their evaluation shows that they obtain state-of-the-art results on both datasets, while also highlighting the shortcomings of previous work with regard to the evaluation methodology. Finally, they performed error analysis on videos for the two benchmark datasets to summarize and spot the factors that lead to misclassifications.

DataSets used: SumMe and TVSum. [2]

Limitations: Overall, results obtained from unsupervised methods on the original splits were close to the reported ones. Yet, the many videos that were from the test splits (and other videos evaluated twice) led to an unfair evaluation. The error analysis determined that existing methods have difficulties with videos filmed using moving camera settings. These difficulties can be attributed to two main reasons. First, the evaluated methods are basically trained using only object based features that process only frame-level information. Second, those methods create a representative summary that has a similar distribution to the original video without considering the relationships between video segments. Their approach addressed the first issue and presents a corresponding solution but couldn't address the second issue.

3. AC-SUM-GAN: Connecting Actor-Critic and Generative Adversarial Networks for Unsupervised Video Summarization
   By E. Apostolidis, E. Adamantidou, A. I. Metsai, V. Mezaris and I. Patras.
   Link to paper: https://doi.org/10.1109/TCSVT.2020.3037883

   Summary:
   The proposed architecture embeds an Actor-Critic model into a Generative Adversarial Network and formulates the selection of important video fragments (that will be used to form the summary) as a sequence generation task. The Actor and the Critic take part in a game that incrementally leads to the selection of the video key-fragments, and their choices at each step of the game result in a set of rewards from the Discriminator. The designed training workflow allows the Actor and Critic to discover a space of actions and automatically learn a policy for key-fragment selection. Moreover, the introduced criterion for choosing the best model after the training ends, enables the automatic selection of proper values for parameters of the training process that are not learned from the data (such as the regularization factor σ). Experimental evaluation on two benchmark datasets (SumMe and TVSum) demonstrates that the proposed AC-SUM-GAN model performs consistently well and gives SoA results in comparison to unsupervised methods, that are also competitive with respect to supervised methods. [3]

   DataSets: SumMe and TVSum

4. DSNet: A Flexible Detect-to-Summarize Network for Video Summarization
   By Wencheng Zhu; Jiwen Lu; Jiahao Li; Jie Zhou
   Link to paper: https://ieeexplore.ieee.org/document/9275314
   Summary:
   In this paper the authors have proposed a Detect-to-Summarize network (DSNet) framework for supervised video summarization.TheDSNet contains anchor-based and anchor-free counterparts. The anchor-based method generates temporal interest proposals to determine and localize the representative contents of video sequences, while the anchor-free method eliminates the pre-defined temporal proposals and directly predicts the importance scores and segment locations. Different from existing supervised video summarization methods which formulate video summarization as a regression problem without temporal consistency and integrity constraints, their

interest detection framework is the first attempt to leverage temporal consistency via the temporal interest detection formulation. [4]

Data sets: TVSum, SumMe,Youtube,Lol.

Limitations: The existing supervised methodonly learns the importance score of each frame, our anchor-based DSNet approach and formulates video summarization as an interest detection problem and simultaneously learns importance scores and location offsets of generated interest proposals, handling incorrect and incomplete segments.

Future Scope: To eliminate the drawbacks of interest proposals, one can further propose the anchor-free DSNet approach to directly predict the importance scores and segment boundaries. The proposed anchor-based and anchor-free DSNet approaches outperform most state-of-the-art supervised methods on the widely-used SumMe and TVSum datasets. In the future, one can attempt to incorporate key shot selection into a unified framework.

5. FFNet: Video Fast-Forwarding via Reinforcement Learning
   By Shuyue Lan, Rameswar Panda, Qi Zhu, Amit K. Roy-Chowdhury.
   Link to paper:
   https://openaccess.thecvf.com/content_cvpr_2018/papers/Lan_FFNet_Video_Fast-Forwarding_CVPR_2018_paper.pdf

   Summary:
   In this paper, the authors presented a supervised framework (FFNet) for fast-forwarding videos in an online fashion, by modeling the fast-forwarding operation as an Markov decision process and solving it with a Q-learning method. Quantitative and qualitative results demonstrate that FFNet outperforms multiple baseline methods in both performance and efficiency. It provides an informative subset of video frames that have better coverage of the important content in original video. At the same time, it only processes a small percentage of video frames, which improves computation efficiency and reduces requirements on various resources. In the future, we plan to work on integrating this method with practical system constraints like energy and available bandwidth. [5]

   Limitations: In average, it only processes 18.67% of the video frames, which could greatly improve computation efficiency, reduce resource requirement, and lower energy consumption. Note that the requirements on storage and communication are also reduced, but not as much. This is because the neighboring windows of the processed frames are also considered as important for users, and should be stored and transmitted (if needed).

   Future scope: It would be interesting to extend our approach by introducing memory in the form of LSTMs–we leave this as part of the future work.

6. Unsupervised video summarization with deep reinforcement learning.
   By Kaiyang Zhou, Yu Qiao, Tao Xiang.
   Link to paper: https://arxiv.org/abs/1801.00054

   Summary:
   In this paper, the authors formulated video summarization as a sequential decision-making process and develop a deep summarization network (DSN) to summarize videos. DSN predicts for each video frame a probability, which indicates how likely a frame is selected, and then takes actions based on the probability distributions to select frames, forming video summaries. To train their DSN, they proposed an end-to-end, reinforcement learning-based framework, where they designed a novel reward function that jointly accounts for diversity and representativeness of generated summaries and does not rely on labels or user interactions at all. During training, the reward function judges how diverse and representative the generated summaries are, while DSN strives for earning higher rewards by learning to produce more diverse and more representative summaries. Since labels are not required, our method can be fully unsupervised. Extensive experiments on two benchmark datasets show that our unsupervised method not only outperforms other state-of-the-art unsupervised methods, but also is comparable to or even superior than most of published supervised approaches. [6]

   Data Sets: TVSum and SumMe.

7. Movie Summarization via Sparse Graph Construction
   By PinelopiPapalampidi Frank Keller Mirella Lapata
   Link to paper: https://arxiv.org/pdf/2012.07536v1.pdf

   Summary:
   In this paper the authorssummarized full-length movies by creating shorter videos containing their most informative scenes. They explored the hypothesis that a summary can be created by assembling scenes which are turning points (TPs), i.e., key events in a movie that describe its storyline.They proposed a model that identifies TP scenes by building a sparse movie graph that represents relations between scenes and is constructed using multimodal information1 . According to human judges, the summaries created by their approach are more informative and complete, and receive higher ratings, than the outputs of sequence-based models and general-purpose summarization algorithms. The induced graphs are interpretable, displaying different topology for different movie genres. [7]

   Future scope: In the future, one can explore ways to further exploit the graph structure and definitions of TPs in order to produce personalized summaries.

8. Summarizing Entertainment Video Using Color and Dialogue

By Fred Hohman, Sandeep Soni, Ian Stewart, John Stasko
Link to the paper: https://fredhohman.com/a-viz-of-ice-and-fire/
Summary:
Color quantization is a process that reduces the number of distinct colors used in an image, usually with the intention that the new image should be as visually similar as possible to the original image. They used the well-studied median cut quantization clustering algorithm from computer graphics on the data in order to extract the top ten most dominant colors in an image.
Similar to the color extraction, they first segmented each episode into 60 equal-sized time slices and group all dialogue within each slice. We then annotate the dialogue for words that fall into one of the following categories: anger, death, family, home, humans, negative affect, positive affect, religion, swearing, and sexual. [8]

9. Query-adaptive Video Summarization via Quality-aware Relevance Estimation.
By Arun Balajee Vasudevan, Michael Gygli, Anna Volokitin, Luc Van Gool
Link to paper: https://arxiv.org/pdf/1705.00581.pdf
Summary:
In this paper the authors introduced a new method for query-adaptive video summarization. At its core lies a textual-visual embedding, which let them select frames relevant to a query. In contrast to earlier works, this model allowed them to handle unconstrained queries and even full sentences. They proposed and empirically evaluated different improvementsfor learning a relevance model. Their empirical evaluation showed a better training objective, a more sophisticated text model, and explicitly modelling quality leads to significant performance gains. In particular, they showed that quality plays an important role in the absence of high-quality relevance information, such as queries, i.e. when only the title can be used. Finally, they introduced a new dataset for thumbnail selection which comes with query-relevance labels and a grouping of the frames according to visual and semantic similarity. On this data, they tested our full summarization framework and showed that it compares favorably to strong baselines. [9]

Limitations: The reader should be aware that differences in the variance of the objectives can affect the weights learned. Thus, they should be taken with a grain of salt and only be considered tendencies.

10. Video Summarization Using Fully Convolutional Sequence Networks
By MrigankRochan, Linwei Ye and Yang Wang
Link to paper:
https://openaccess.thecvf.com/content_ECCV_2018/papers/Mrigank_Rochan_Video_Summarization_Using_ECCV_2018_paper.pdf

Summary:
This paper addresses the problem of video summarization. Given an input video, the goal is to select a subset of the frames to create a summary video that optimally

captures the important information of the input video. With the large amount of videos available online, video summarization provides a useful tool that assists video search, retrieval, browsing, etc. In this paper, the authors formulated video summarization as a sequence labeling problem. Unlike existing approaches that use recurrent models, we propose fully convolutional sequence models to solve video summarization. They firstly establish a novel connection between semantic segmentation and video summarization, and then adapt popular semantic segmentation networks for video summarization. Extensive experiments and analysis on two benchmark datasets demonstrate the effectiveness of their models. [10]

Data Sets: TVSum and SumMe.

Future Scope: . As future work, one can explore more recent semantic segmentation models and develop their counterpart models in video summarization.

11. Summarizing Videos with Attention
    By Jiri Fajtl, Hajar Sadeghi Sokeh, Vasileios Argyriou, Dorothy Monekosso and Paolo Remagnino
    Link to paper: https://arxiv.org/pdf/1812.01969v2.pdf

    Summary: . In this work the authors proposed a novel method for supervised, keyshots based video summarization by applying a conceptually simple and computationally efficient soft, self-attention mechanism. Current state of the art methods leverage bi-directional recurrent networks such as BiLSTM combined with attention. These networks are complex to implement and computationally demanding compared to fully connected networks. To that end we propose a simple, self-attention based network for video summarization which performs the entire sequence to sequence transformation in a single feed forward pass and single backward pass during training. Our method sets a new state of the art results on two benchmarks TvSum and SumMe, commonly used in this domain. [11]

    Data Sets: TVSum and SumMe.

    Future Scope: The model is based on a single, global, self-attention layer followed by two, fully connected network layers. The authors intentionally designed and tested the simplest architecture with global attention, and without positional encoding to establish a baseline method for such architectures. Limiting the aperture of the attention to a local region as well as adding the positional encoding are simple modifications that are likely to further improve.

12. Unsupervised video summarization framework using keyframe extraction and video skimming
    By Shruti Jadon, Mahmood Jasim.
    Link to paper: https://arxiv.org/pdf/1910.04792v2.pdf

Summary:
From what the baseline has been given in SumMe Dataset, the chose the average human baseline as true, as they would like to consider all perspectives. After testing with all different forms of videos, one can conclude that Gaussian Clustering along with Convolutional Networks can give better performance than other methods with moving point camera videos. In fact, the SIFT algorithm seems to perform well on videos with high motion, the reason behind it is that we used deep layered features, thus they consists of important points inside image, followed by Gaussian Clustering, which is specifically made for mixture based components. We have also observed that, even Uniform Sampling is giving better result for videos which have stable camera view point and very less motion. One can conclude that one single algorithm can't be solution of video summarization, it is dependent of the type of video, the motion inside video. [12]
Data Set : SumMe Dataset

Limitations: Video Summarization is one of the hardest task because it depends on person's perception. So, we can never have a good baseline to understand whether our algorithm is working or not. Sometimes, Humans just want 1-2 second of video as summary, whereas machine looks for slightest difference in image intensity and might give us 10 seconds of video.

13. ILS-SUMM: Iterated local search for unsupervised video summarization.
    By Yair Shemer, Daniel Rotmanand Nahum Shimkin.
    Link to paper: https://arxiv.org/pdf/1912.03650v1.pdf

    Summary:
    In this paper, the authors developed ILS-SUMM, a novel video summarization algorithm to solve the subset selection problem under the knapsack constraint. Their algorithm is based on the well-known metaheuristic optimization framework – Iterated Local Search (ILS), known for its ability to avoid weak local minima and obtain a good near-global minimum. Extensive experiments show that their method finds solutions with significantly better total distance than previous methods. Moreover, to indicate the high scalability of ILS-SUMM, they introduced a new dataset consisting of videos of various lengths.[13]

    Limitations: Since the question of what is a right evaluation of video summarization is still an open question, there is no solid evidence for an advantage in using deep features rather than color histogram features for this task.
    Future Scope: Future research may examine the integration of deep and color histogram features.
14. Query-controllable Video Summarization
    By Jia-Hong Huang, Marcel Worring
    Link to paper: https://arxiv.org/pdf/2004.03661v1.pdf

Summary:
The authors treat a query-controllable video summarization task as a supervised learning problem in this work. To tackle this problem, they proposed an end-to-end deep learning based approach to generate a query-dependent video summary. The proposed method contains a video summary controller, video summary generator, and video summary output module. To foster the query-controllable video summarization research and conduct their experiments, they proposed a new dataset. Each video in the proposed dataset is annotated by frame-based relevance score labels. Their experimental results show that the text-based query not only helps control video summary, but also improves the model performance with +5.83% in the sense of accuracy. [14]

Limitations: Because of the limited space, one is only able to show some frames to represent the original video and the corresponding generated video summary in time order.

Future Scope: Based on the experiment, the authors know that the multi-modal feature fusion method is crucial, so developing a new fusion approach will be interesting future work.

15. Multi-stream dynamic video Summarization
By Mohamed Elfeki, Liqiang Wang, and Ali Borji
Link to paper: https://arxiv.org/pdf/1812.00108v4.pdf
Summary:
In this work, the authors proposed the problem of multi-view video summarization for dynamically moving cameras that often do not share the same field-of-view.The formulation provides the first supervised solution to multi-stream summarization in addition to an unsupervised adaptation. Unlike previous work in multi-view video summarization, they presented a generic approach that can be trained in a supervised or unsupervised setting to generate a comprehensive summary for all views with no prior assumptions on camera placement nor labels. It identifies important events across all views and selects the view(s) best illustrating each event. They also introduced a new dataset, recorded in uncontrolled environments including a variety of real-life activities. When evaluating the approach on the collected benchmark and additional three standard multi-view benchmark datasets, the framework outperformed all baselines of state-of-the-art supervised, reinforcement and unsupervised single- and multi-view summarization methods. [15]

2.2 Integrated summary of research papers

Given an input video, video summarization aims to produce a shortened version that captures the important information in the video. There are various representations proposed for this problem including video synopsis, time-lapses montages and storyboards. Early work in video summarization mainly relies on hand-crafted heuristics. Most of these approaches are unsupervised. They define various heuristics to represent the importance or representativeness of the frames and use the importance scores to select representative frames to form the summary video. Recent work has explored supervised learning approaches for video summarization. These approaches use training data consisting of videos and their ground-truth summaries generated by humans. These supervised learning approaches tend to outperform early work on unsupervised methods, since they can implicitly learn high-level semantic knowledge that is used by humans to generate summaries. Recently deep learning methods are gaining popularity for video summarization.

Chapter 3: Requirement Analysis and Solution Approach

3.1 Requirement Analysis

For Video Summarization, we will be using Deep Learning. And so for that NeuralNetworks and Convolutional Neural Networks will be used. This requires agood amount of computational power and GPU power to do the required MLtasks quickly and efficiently.

We require the following for the project:-

- A laptop or computer running Windows 10 or macOS Sierra or above or
Linux, or Ubuntu 16.04 LTS
- A dual core processor 2 GHz or more
- 8GB of RAM or more
- NVidia GPU 1000 series or above
- Jupyter Notebook
- Google Colab

We also require these things:-

- For training our model we need training data. For this we need video files along with human created ground truth summaries for the video files. We need this, so that the model can learn from it and then be able to identify which frames are important in a video and also for checking Temporal Intersection over Union of the proposed frames with the ground truth frames.
- For validation purposes, we also need testing data, so that we can check
the performance of our model and see how well it can propose summary frames and create a temporally coherent summary.

3.1.1 Datasets used:

TvSum:

Title-based Video Summarization (TVSum) dataset is used as a benchmark to validate video summarization techniques. It contains 50 videos of various genres (e.g., news, how-to, documentary, vlog, egocentric) and 1,000 annotations of shot-level importance scores obtained via crowdsourcing (20 per video). The video and annotation data permits an automatic evaluation of various video summarization techniques, without having to conduct a user study.

Contents:
GrounTruth/ : folder containing the human summary selections
Videos/ : folder with the videos themselves in mp4 (H.264) format

SumMe:

The SumMe dataset is a video summarization dataset consisting of 25 videos, each annotated with at least 15 human summaries (390 in total).

Contents:
GrounTruth/: folder containing the human summary selections
Videos/ : folder with the videos themselves in mp4 (H.264) format

3.1.2 Technologies Used:

1. Programming Language: Python

2. Programming Framework
a. PyTorch
b. Tensorflow

3. Neural Networks
a. Convolutional Neural Network (CNN)
b. Long Short Term Memory(LSTM)

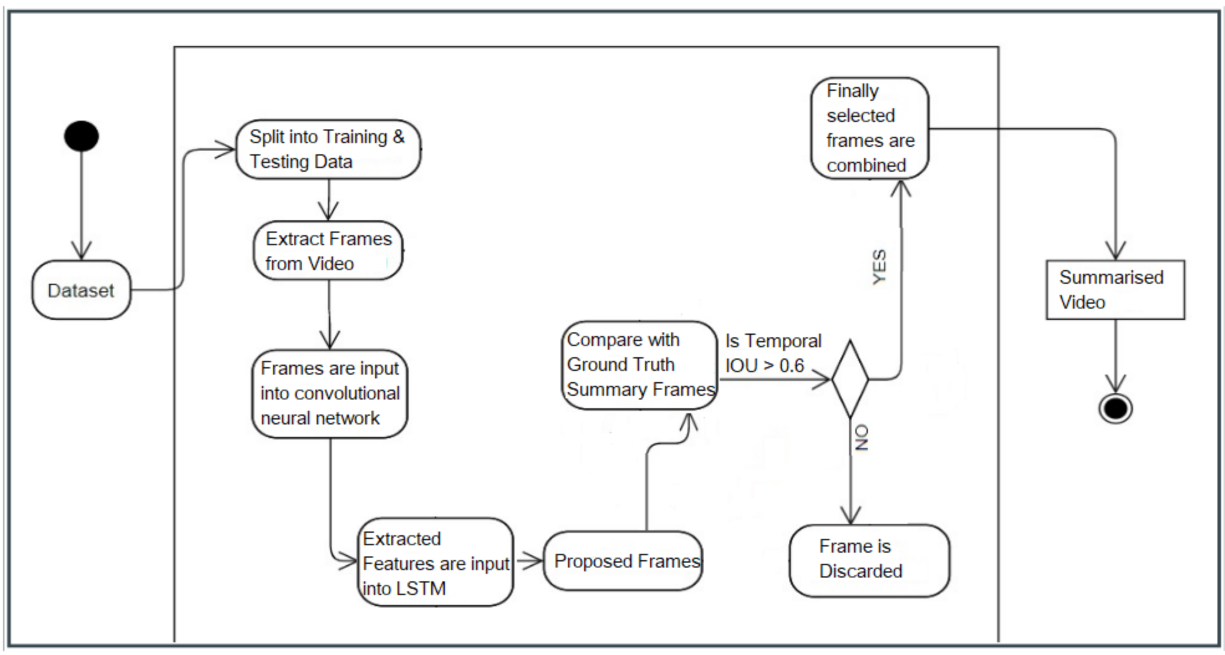
5. IDE
a. Google Colab
b. Jupyter Notebook

3.2 Solution Approach | Proposed Solution

Overall Description of Proposed Solution:

Our proposed solution is to first divide the video into video frames and then extract features from these frames. These extracted features will be fed to the LSTM network, to determine time-based importance of these frames. Finally they will be classified into a yes or no, whether they will be included in the final summary or not by computing their Temporal Intersection over Union with the ground truth.

Video Summarization using Deep Learning: Proposed Approach-

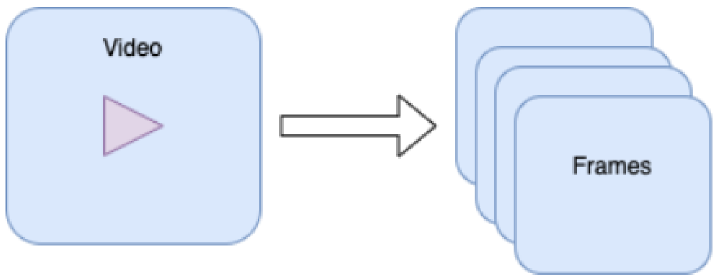


Detailed Description of Proposed Solution:

Our proposed solution consists of 5 steps:

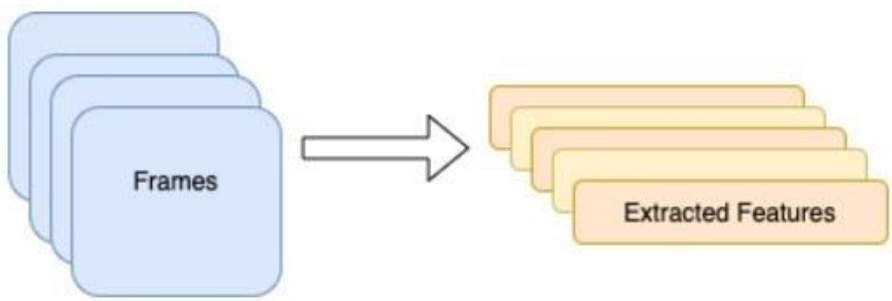
1. **Extracting Frames from video file:**

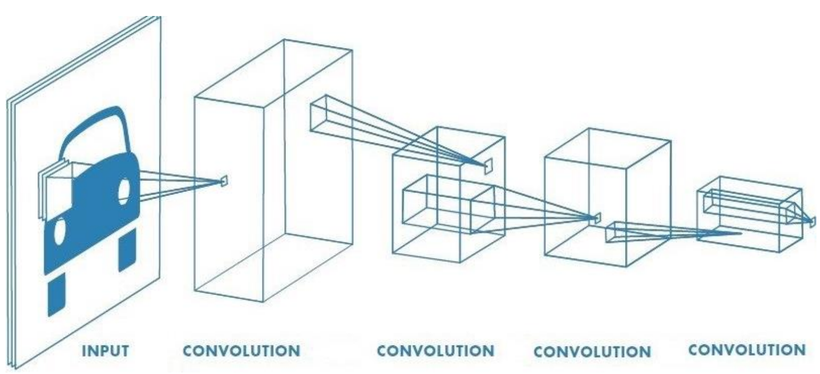
Any given video consists of a number of video sequences and each video sequence consists of a number of video frames. So we first divide the video into sequences. Then we extract image frames from the video. Thus, we get an image representation of a video in the form of all the frames, which the video is made up of. For this we use the OpenCV library from python.



2. **Feature Extraction from the extracted frames:**

Our model needs to learn the features from these extracted frames. For this, we use convolutional neural networks to extract features from the video frames. Now, our model starts learning from the frames extracted from the video in the above step. Moreover, in order to stop overfitting, we have added dropout layers between the convolutional layers. The output of these layers gives us the features our model has extracted from the video frames

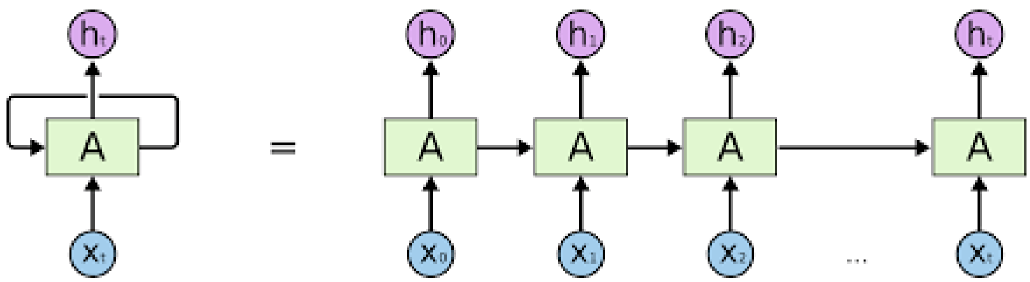


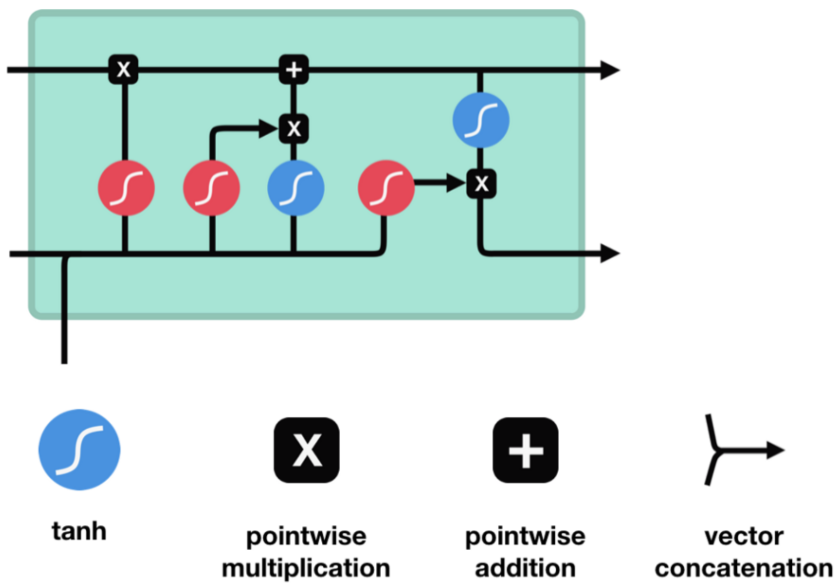


3. **Temporal interest proposals:**

Now we need to determine which video frames are the most important and need to be included in the summary. We use LSTM (Long Short Term Memory) cells in this case. We use

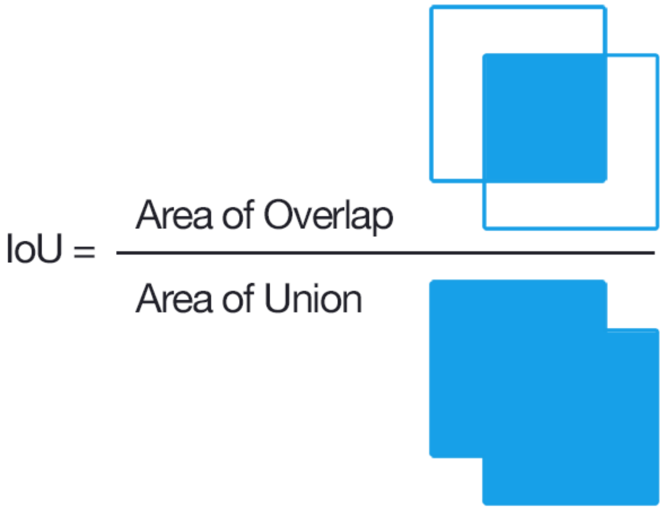
LSTM because they are able to pick up information from the previous LSTM cells also. This is important because in a video or movie, time-based interest video segments are very important. In order to determine whether a scene is important or not, we need to know what scene happened before that scene. Thus, we have used LSTM and so, our model has “attention” and can remember the previous scenes, so it can better determine which scenes have a higher interest value in the summary. The model then proposes which frames are interesting and important in a time-coherent manner with the help of LSTM.





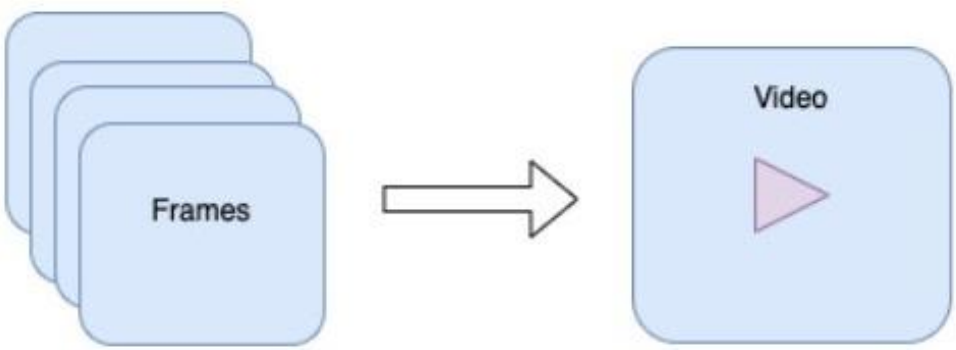
4. Classification on the basis of Temporal Intersection over Union:

Finally we classify if a frame is going to be put in the final summary or not. The above frames are compared with the Ground Truth summary frames and if their Temporal Intersection over Union (tIOU) is more than 0.6, then we consider that proposal to be positive and is given a score of 1 and thus gets included in the final summary. If the Temporal Intersection over Union is less than 0.6, then that frame is considered negative and is given a score of 0 and thus is not included in the final summary.



5. **Amalgamation of Frames:**

All the frames which are positive and given a score of 1, need to be combined to make the summary video. We use the OpenCV library to combine these frames together and thus the output is the final video summary.



Chapter 4:Modeling and Implementation Details

4.1 Implementation Details

These are the steps we did for implementing our proposed solution:

1. **Collecting the datasets:**

We collected the TVSum and SumMe Datasets. We sorted them in the correct order i.e. all the video files along with their human created ground truth user summaries. This is important to be done, so that the model can learn and get trained on the input videos.

2. **Preprocess the input video file:**

We wrote a python program to extract image frames from the video. We used OpenCV python library for this. This is done, so that the Convolutional Neural Network can learn from these extracted frames

3. **Detect and Extract Features:**

We wrote a custom Machine learning model made up of Convolutional layers and dropout layers in between them. The Convolutional Neural Network extracts spatial features from the images and trains on them, so that it can better predict the right frame to be selected for the summary video.

```
[2021/09/25 20:18:28] Epoch: 8/300 Loss: 0.7023/0.7250/1.4273 F-score cur/max: 0.6189/0.6285
[2021/09/25 20:18:31] Epoch: 9/300 Loss: 0.6874/0.7258/1.4132 F-score cur/max: 0.6037/0.6285
[2021/09/25 20:18:33] Epoch: 10/300 Loss: 0.6691/0.7211/1.3902 F-score cur/max: 0.6260/0.6285
[2021/09/25 20:18:35] Epoch: 11/300 Loss: 0.6643/0.6916/1.3558 F-score cur/max: 0.6154/0.6285
[2021/09/25 20:18:38] Epoch: 12/300 Loss: 0.6523/0.7220/1.3743 F-score cur/max: 0.6174/0.6285
[2021/09/25 20:18:40] Epoch: 13/300 Loss: 0.6333/0.6979/1.3312 F-score cur/max: 0.6140/0.6285
[2021/09/25 20:18:43] Epoch: 14/300 Loss: 0.6321/0.6748/1.3069 F-score cur/max: 0.6125/0.6285
[2021/09/25 20:18:45] Epoch: 15/300 Loss: 0.6221/0.6648/1.2869 F-score cur/max: 0.6305/0.6305
[2021/09/25 20:18:48] Epoch: 16/300 Loss: 0.6118/0.6553/1.2671 F-score cur/max: 0.6130/0.6305
[2021/09/25 20:18:50] Epoch: 17/300 Loss: 0.6026/0.6504/1.2530 F-score cur/max: 0.6077/0.6305
[2021/09/25 20:18:52] Epoch: 18/300 Loss: 0.6001/0.6685/1.2686 F-score cur/max: 0.6185/0.6305
[2021/09/25 20:18:55] Epoch: 19/300 Loss: 0.5809/0.6502/1.2311 F-score cur/max: 0.6128/0.6305
[2021/09/25 20:18:57] Epoch: 20/300 Loss: 0.5701/0.6431/1.2132 F-score cur/max: 0.6316/0.6316
[2021/09/25 20:19:00] Epoch: 21/300 Loss: 0.5741/0.6385/1.2127 F-score cur/max: 0.6312/0.6316
[2021/09/25 20:19:02] Epoch: 22/300 Loss: 0.5608/0.6241/1.1849 F-score cur/max: 0.6172/0.6316
[2021/09/25 20:19:05] Epoch: 23/300 Loss: 0.5562/0.6175/1.1737 F-score cur/max: 0.6195/0.6316
[2021/09/25 20:19:07] Epoch: 24/300 Loss: 0.5497/0.6143/1.1640 F-score cur/max: 0.6163/0.6316
[2021/09/25 20:19:09] Epoch: 25/300 Loss: 0.5456/0.5866/1.1322 F-score cur/max: 0.6209/0.6316
[2021/09/25 20:19:12] Epoch: 26/300 Loss: 0.5324/0.6024/1.1348 F-score cur/max: 0.6129/0.6316
[2021/09/25 20:19:14] Epoch: 27/300 Loss: 0.5167/0.6271/1.1438 F-score cur/max: 0.6076/0.6316
[2021/09/25 20:19:17] Epoch: 28/300 Loss: 0.5318/0.5948/1.1265 F-score cur/max: 0.6111/0.6316
[2021/09/25 20:19:19] Epoch: 29/300 Loss: 0.5243/0.6057/1.1300 F-score cur/max: 0.6090/0.6316
[2021/09/25 20:19:21] Epoch: 30/300 Loss: 0.5178/0.5773/1.0951 F-score cur/max: 0.6087/0.6316
[2021/09/25 20:19:24] Epoch: 31/300 Loss: 0.5020/0.5733/1.0753 F-score cur/max: 0.6096/0.6316
[2021/09/25 20:19:26] Epoch: 32/300 Loss: 0.4968/0.5636/1.0604 F-score cur/max: 0.6090/0.6316
[2021/09/25 20:19:28] Epoch: 33/300 Loss: 0.5022/0.5620/1.0641 F-score cur/max: 0.5916/0.6316
[2021/09/25 20:19:31] Epoch: 34/300 Loss: 0.4909/0.5665/1.0574 F-score cur/max: 0.6046/0.6316
[2021/09/25 20:19:33] Epoch: 35/300 Loss: 0.4924/0.5656/1.0579 F-score cur/max: 0.6057/0.6316
```

4. **Reducing Overfitting:**

We noticed that the model was overfitting, so we added dropout layers with chance of 0.5 in between the convolutional layers. This helps reduce overfitting.

5. **Feeding these frames into LSTM:**

After extracting Spatial Features via Convolutional layers, we have used LSTM to better understand which frames are temporally coherent. As LSTM has “Attention”, it will know which scene occurred before the current scene and will thus be able to determine whether the current frame is important or not. The LSTM layers give output frames which it thinks should be included in the video. These we call as temporal interest proposal frames

6. **Comparing with ground truth summary video frames:**

These proposed frames are compared with the frames from the grounds truth summary video, and their Temporal Intersection over union is calculated

7. **Classifying these frames on the basis of Temporal IOU:**

If the Temporal Intersection over Union of a frame is >0.6, then we label it as positive and it gets included in the final summary video. If the Temporal Intersection over Union of a frame is <0.6, then we label it as negative and it does not get included in the final summary video.

```
[2021/10/16 15:04:50] Epoch: 297/300 Loss: 0.3075/0.6518/0.9594 F-score cur/max: 0.9337/0.933
7
[2021/10/16 15:04:50] Epoch: 298/300 Loss: 0.3629/0.6322/0.9951 F-score cur/max: 0.9337/0.933
7
[2021/10/16 15:04:50] Epoch: 299/300 Loss: 0.3576/0.6959/1.0535 F-score cur/max: 0.9337/0.933
7
[2021/10/16 15:04:50] Training done on custom. F-score: 0.8446
        nishit@nishit-ubuntu:~/Downloads/DSNet/src$ python evaluate.py anchor-based --model-d
ir ../models/custom --splits ../custom_data/custom.yml
[2021/10/16 15:04:50] {'model': 'anchor-based', 'device': 'cuda', 'seed': 12345, 'splits': ['
../custom_data/custom.yml'], 'max_epoch': 300, 'model_dir': '../models/custom', 'log_file': '
log.txt', 'lr': 5e-05, 'weight_decay': 1e-05, 'lambda_reg': 1.0, 'nms_thresh': 0.5, 'ckpt_pat
h': None, 'sample_rate': 15, 'source': None, 'save_path': None, 'base_model': 'attention', 'n
um_head': 8, 'num_feature': 1024, 'num_hidden': 128, 'neg_sample_ratio': 2.0, 'incomplete_sam
ple_ratio': 1.0, 'pos_iou_thresh': 0.6, 'neg_iou_thresh': 0.0, 'incomplete_iou_thresh': 0.3,
'anchor_scales': [4, 8, 16, 32], 'lambda_ctr': 1.0, 'cls_loss': 'focal', 'reg_loss': 'soft-io
u'}
[2021/10/16 15:04:54] custom split 0: diversity: 0.7782, F-score: 0.9375
[2021/10/16 15:04:54] custom split 1: diversity: 0.5905, F-score: 0.9337
[2021/10/16 15:04:54] custom split 2: diversity: 0.6661, F-score: 0.8745
[2021/10/16 15:04:54] custom split 3: diversity: 0.6432, F-score: 0.5435
[2021/10/16 15:04:54] custom split 4: diversity: 0.5905, F-score: 0.9337
[2021/10/16 15:04:54] custom: diversity: 0.6537, F-score: 0.8446
        nishit@nishit-ubuntu:~/Downloads/DSNet/src$
```

8. Varying Temporal IOU Threshold:

We tested and changed the Temporal IOU Threshold from 0.6 to 0.5 and 0.4, but the summary video obtained in this case was not temporally coherent, and thus produced bad results.

We found that the best summarized videos were produced when the Temporal IOU Threshold was set at 0.6

9. Combining the Frames:

After this we combine the frames. We combine the frames at the rate of 24 frames per second, the frame rate at which the videos were originally, so that the output summarized video looks best. We used OpenCV python library for this.

```
../models/custom/checkpoint/custom.yml.0.pt   --source ../custom_data/videos/St_Maarten_Landi
ng.mp4 --save-path ./output.mp4
Loading DSNet model ...
Preprocessing source video ...
Predicting summary ...
Writing summary video ...
        nishit@nishit-ubuntu:~/Downloads/DSNet/src$
```

10. Training the model:

We trained the model for 10,000 iterations for 30 hours. We made changes to the model multiple times and trained the model again to increase it's accuracy.

```
2021/09/25 20:59:50] Epoch: 286/300 Loss: 0.1905/0.2707/0.4612 F-score cur/max: 0.4242/0.4722
2021/09/25 20:59:51] Epoch: 287/300 Loss: 0.1690/0.2677/0.4367 F-score cur/max: 0.4399/0.4722
2021/09/25 20:59:52] Epoch: 288/300 Loss: 0.1680/0.2633/0.4313 F-score cur/max: 0.4267/0.4722
2021/09/25 20:59:52] Epoch: 289/300 Loss: 0.1717/0.2937/0.4654 F-score cur/max: 0.4138/0.4722
2021/09/25 20:59:53] Epoch: 290/300 Loss: 0.1757/0.2930/0.4688 F-score cur/max: 0.4133/0.4722
2021/09/25 20:59:54] Epoch: 291/300 Loss: 0.1601/0.2885/0.4486 F-score cur/max: 0.3978/0.4722
2021/09/25 20:59:55] Epoch: 292/300 Loss: 0.1754/0.2902/0.4656 F-score cur/max: 0.4264/0.4722
2021/09/25 20:59:56] Epoch: 293/300 Loss: 0.1806/0.2610/0.4417 F-score cur/max: 0.4198/0.4722
2021/09/25 20:59:57] Epoch: 294/300 Loss: 0.1637/0.2765/0.4402 F-score cur/max: 0.4020/0.4722
2021/09/25 20:59:58] Epoch: 295/300 Loss: 0.1562/0.2646/0.4208 F-score cur/max: 0.4392/0.4722
2021/09/25 20:59:58] Epoch: 296/300 Loss: 0.1679/0.3195/0.4874 F-score cur/max: 0.3818/0.4722
2021/09/25 20:59:59] Epoch: 297/300 Loss: 0.1641/0.2772/0.4414 F-score cur/max: 0.4443/0.4722
2021/09/25 21:00:00] Epoch: 298/300 Loss: 0.1668/0.2926/0.4594 F-score cur/max: 0.4032/0.4722
2021/09/25 21:00:01] Epoch: 299/300 Loss: 0.1558/0.2874/0.4432 F-score cur/max: 0.4045/0.4722
2021/09/25 21:00:01] Start training on summe: split 1
2021/09/25 21:00:02] Epoch: 0/300 Loss: 0.9570/1.1018/2.0588 F-score cur/max: 0.4446/0.4446
2021/09/25 21:00:03] Epoch: 1/300 Loss: 0.9430/0.9692/1.9122 F-score cur/max: 0.4458/0.4458
2021/09/25 21:00:04] Epoch: 2/300 Loss: 0.8813/0.8663/1.7475 F-score cur/max: 0.4368/0.4458
2021/09/25 21:00:04] Epoch: 3/300 Loss: 0.7956/0.8545/1.6501 F-score cur/max: 0.4257/0.4458
2021/09/25 21:00:05] Epoch: 4/300 Loss: 0.7778/0.8236/1.6014 F-score cur/max: 0.4153/0.4458
2021/09/25 21:00:06] Epoch: 5/300 Loss: 0.7550/0.8230/1.5780 F-score cur/max: 0.4402/0.4458
2021/09/25 21:00:07] Epoch: 6/300 Loss: 0.7383/0.7884/1.5267 F-score cur/max: 0.4359/0.4458
2021/09/25 21:00:08] Epoch: 7/300 Loss: 0.6949/0.8191/1.5140 F-score cur/max: 0.4802/0.4802
2021/09/25 21:00:09] Epoch: 8/300 Loss: 0.6799/0.7514/1.4313 F-score cur/max: 0.4714/0.4802
2021/09/25 21:00:10] Epoch: 9/300 Loss: 0.6589/0.7657/1.4246 F-score cur/max: 0.4529/0.4802
2021/09/25 21:00:11] Epoch: 10/300 Loss: 0.6636/0.8155/1.4791 F-score cur/max: 0.4501/0.4802
2021/09/25 21:00:11] Epoch: 11/300 Loss: 0.6349/0.7797/1.4147 F-score cur/max: 0.4281/0.4802
2021/09/25 21:00:12] Epoch: 12/300 Loss: 0.6767/0.7724/1.4491 F-score cur/max: 0.4224/0.4802
```

11. Testing the model:

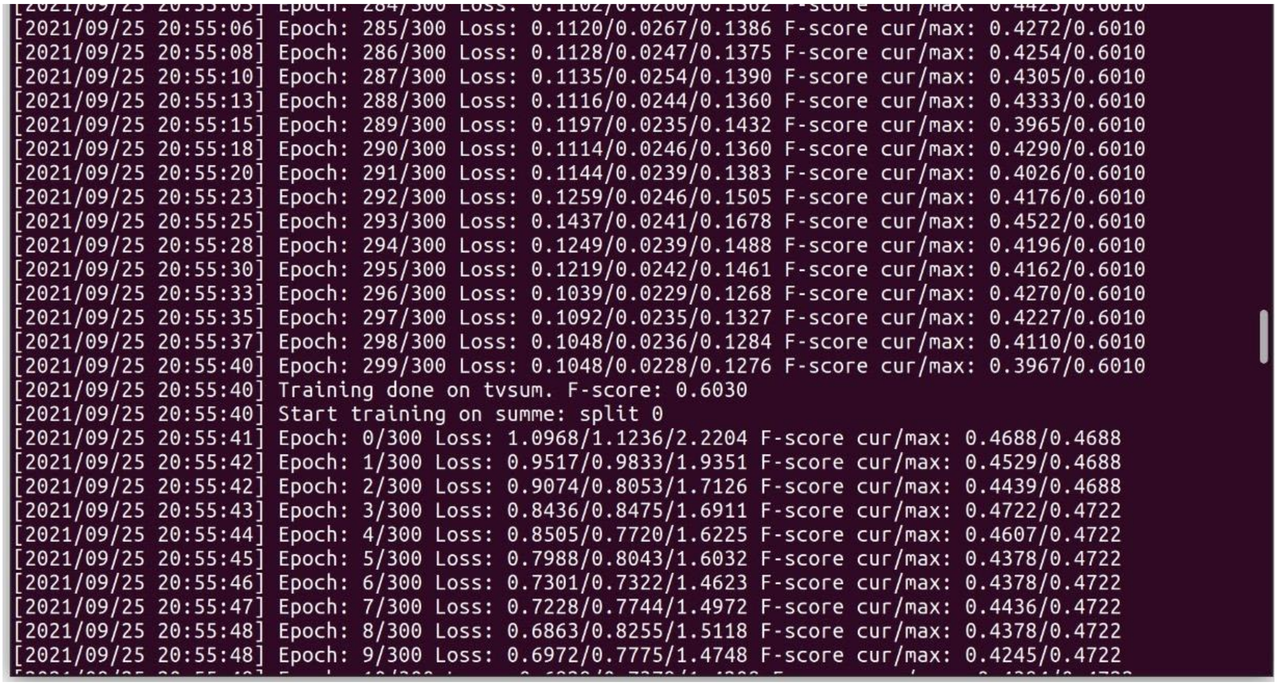
We originally split the TVSum and SumMe datasets for testing and training purposes, so now we evaluated the model by testing it against the testing dataset splits of the original datasets.

12. Fine Tuning the Model:

We changed hyperparameters and finetuned the model in order to increase it's accuracy. Finally we achieved testing accuracy scores of 60.3 % on the TVSum Dataset and 48.9% on the SumMe Dataset.

Dataset	TVSum	SumMe
Accuracy of our Model	60.3	48.9

```
[2021/09/25 21:16:49] Epoch: 274/300 Loss: 0.1779/0.2996/0.4774 F-score cur/max: 0.3512/0.4167
[2021/09/25 21:16:49] Epoch: 275/300 Loss: 0.1653/0.3355/0.5007 F-score cur/max: 0.3529/0.4167
[2021/09/25 21:16:50] Epoch: 276/300 Loss: 0.1503/0.3011/0.4514 F-score cur/max: 0.3364/0.4167
[2021/09/25 21:16:51] Epoch: 277/300 Loss: 0.1457/0.3248/0.4706 F-score cur/max: 0.3364/0.4167
[2021/09/25 21:16:52] Epoch: 278/300 Loss: 0.1635/0.3065/0.4700 F-score cur/max: 0.3665/0.4167
[2021/09/25 21:16:53] Epoch: 279/300 Loss: 0.1520/0.3267/0.4786 F-score cur/max: 0.3604/0.4167
[2021/09/25 21:16:54] Epoch: 280/300 Loss: 0.1618/0.3262/0.4881 F-score cur/max: 0.3495/0.4167
[2021/09/25 21:16:55] Epoch: 281/300 Loss: 0.1560/0.2958/0.4519 F-score cur/max: 0.3826/0.4167
[2021/09/25 21:16:55] Epoch: 282/300 Loss: 0.1440/0.3111/0.4550 F-score cur/max: 0.3859/0.4167
[2021/09/25 21:16:56] Epoch: 283/300 Loss: 0.1584/0.3055/0.4639 F-score cur/max: 0.3850/0.4167
[2021/09/25 21:16:57] Epoch: 284/300 Loss: 0.1332/0.3256/0.4588 F-score cur/max: 0.3608/0.4167
[2021/09/25 21:16:58] Epoch: 285/300 Loss: 0.1483/0.2727/0.4210 F-score cur/max: 0.3587/0.4167
[2021/09/25 21:16:59] Epoch: 286/300 Loss: 0.1482/0.3167/0.4649 F-score cur/max: 0.3326/0.4167
[2021/09/25 21:17:00] Epoch: 287/300 Loss: 0.1486/0.2995/0.4481 F-score cur/max: 0.3435/0.4167
[2021/09/25 21:17:00] Epoch: 288/300 Loss: 0.1668/0.3013/0.4682 F-score cur/max: 0.3248/0.4167
[2021/09/25 21:17:01] Epoch: 289/300 Loss: 0.1498/0.2853/0.4351 F-score cur/max: 0.3289/0.4167
[2021/09/25 21:17:02] Epoch: 290/300 Loss: 0.1517/0.2907/0.4424 F-score cur/max: 0.3589/0.4167
[2021/09/25 21:17:03] Epoch: 291/300 Loss: 0.1404/0.3141/0.4545 F-score cur/max: 0.3497/0.4167
[2021/09/25 21:17:04] Epoch: 292/300 Loss: 0.1450/0.2959/0.4409 F-score cur/max: 0.3415/0.4167
[2021/09/25 21:17:05] Epoch: 293/300 Loss: 0.1614/0.2837/0.4451 F-score cur/max: 0.3285/0.4167
[2021/09/25 21:17:06] Epoch: 294/300 Loss: 0.1435/0.2835/0.4271 F-score cur/max: 0.3657/0.4167
[2021/09/25 21:17:07] Epoch: 295/300 Loss: 0.1562/0.2933/0.4494 F-score cur/max: 0.3614/0.4167
[2021/09/25 21:17:07] Epoch: 296/300 Loss: 0.1419/0.2966/0.4385 F-score cur/max: 0.3328/0.4167
[2021/09/25 21:17:08] Epoch: 297/300 Loss: 0.1567/0.3053/0.4620 F-score cur/max: 0.3422/0.4167
[2021/09/25 21:17:09] Epoch: 298/300 Loss: 0.1513/0.2942/0.4455 F-score cur/max: 0.3343/0.4167
[2021/09/25 21:17:10] Epoch: 299/300 Loss: 0.1346/0.2852/0.4198 F-score cur/max: 0.3438/0.4167
[2021/09/25 21:17:10] Training done on summe. F-score: 0.4890
        nishit@nishit-ubuntu:~/Downloads/DSNet/src$
```



4.2 Issues

Issues faced by us during the implementation were-

1. Some of the videos in the datasets were too hazy and of bad quality, which reduced the accuracy of the model. We had to manually remove these videos from training data.
2. Some of the human created ground truth summaries of the videos are not temporally coherent and thus are not good at all. Thus when comparing Temporal IOU, the results were not that good as the ground truth itself was not a very good summary.
3. As these are large videos and datasets we are dealing with, it requires a lot of resources and GPU Memory. Thus many times, while training the model, we ran out of GPU memory and had to start training the model from the start.

Chapter 5 : Gantt Chart

Try to increase the temporal coherence between the scenes	Increase the Temporal IOU by finding the most suitable value of Temporal IOU Threshold	Fine tune the model to increase the Test Accuracy of the model

23 October 8 November 23 November 8 December

Chapter 6: Future Plan and Conclusion -

In this report, we have proposed our idea to create a framework for video summarization. Unlike existing supervised methods which only learn the importance score of each frame, our approach will formulate video summarization as a temporal interest detection problem and will simultaneously help to learn temporal coherence between scenes in a video while handling incorrect and incomplete segments. In the future, we will attempt to incorporate more interest based coherence into our unified framework.

Chapter 7 : References

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