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PROJECT PRESENTATION

Guide

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Group 4

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Problem Definition

The project addresses the challenge of making visual content more accessible to the blind by automating the generation of audio descriptions, using deep learning to produce synchronized, non-overlapping descriptions.



To develop a project that automates the generation of Audio Descriptions (AD) for Blind visually impaired (BVI) people, making visual content more accessible.

The **need** arises because manually creating AD is time-consuming, costly, and not widely available.



The objectives of this project are:

 Use deep learning to develop a system to automatically generate AD.

 Ensure that the AD is synchronized with the video's scene change without overlapping, allowing for smooth integration.



This project introduces an assistive system that automatically generates scene descriptions, enabling visually impaired individuals to experience rich, contextual storytelling.

By integrating deep learning models it ensures real-time, meaningful narration beyond traditional audio descriptions.

Literature Survey

Title	Dataset	Methodology	Result	Advantages	Disadvantages
Machine	ImageNet	Applies	Generates	Automates	May miss nuances
Generation of	(ILSVRC)	machine	automated	audio	important for full
Audio	12333	learning to	audio	descriptions,	understanding
Description		automate	descriptions	making content	500.50
(2023)		audio	for videos	more	
		descriptions		accessible	
STAT: Spatial-	MSVD,	Enhances	Automatically	Reduces	Computationally
Temporal	MSR-	video	generates	errors,	heavy, Depends
Attention	VTT-10	captioning by	natural	Captures fine	on object
Mechanism		jointly	language	details	detection
for Video		modelling	description		accuracy, Limited
Captioning		spatial	for video		gains on MSR-
(2020)		(object-level)			VTT-10K
		and temporal			Company and Company and Company
		(frame-level)			
		attention in			
		an encoder-			
		decoder			
		framework			
A Video	MSRVTT	Uses semantic	Context-based	Provides	Requires high-
Captioning		topic	captions	context-based	quality input data
Method by		modeling to	enhance user	captions,	for effective
Semantic		guide caption	understanding	enhancing	results
Topic-Guided		generation	8	comprehension	of the Arms Constitution of the Arms and the
(2024)					
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					0

Fine-Grained	MS-COCO	Proposed a	Outperformed	Generates	Tends to generate
Image		global-local	baseline	more fine-	captions that may
Captioning		discriminative	methods	grained and	not match ground
with Global-		objective with	significantly,	discriminative	truth; challenges
Local		global and	achieving	captions;	with adaptive
Discriminative		local	competitive	addresses	threshold settings
Objective		constraints to	performance	uneven word	for local
(2020)		improve	on MS-COCO	distribution	constraints
		image	with a notable	issues;	
		captioning	increase in	enhances the	
		accuracy and	CIDErscores	quality of	
		detail.		descriptions	
TimeChat: A	TimeIT	Combines	Improves user	Integrates	Complexity can
Time-		multiple	experience	multiple data	hinder
sensitive		modalities	using diverse	types for better	accessibility for
Multimodal		and time-	data types	user	some users

experience

sensitive

analysis

Large

Language

Model (2024)

Proposed Method

- 1. Scene Change and Language Identification.
- 2.Frame Extraction.
- 3. Scene description generation.
- 4. .srt file formation
- 5. Audio file generation and synchronization.

Proposed Method (Contd.)

1.Scene Change Detection

- The Scene Change Detection module identifies significant visual transitions in the video.
- It determines when a major scene change occurs, ensuring that descriptions are added only when a new scene begins and the corresponding frames extracted.
- This improves contextual accuracy by preventing redundant or unnecessary descriptions.

2.Frame Extraction

- The Frame Extraction module captures the first frame of each detected scene.
- This snapshot represents the visual state of the scene and serves as input for caption generation and object detection.
- By anchoring the description to a single frame, it maintains consistency and focuses on the most relevant visual content.

3. Scene Description generation

- This module generates a detailed textual description of each scene.
- It first analyzes the scene to identify key visual elements and their spatial positions. The initial description is then refined using advanced language processing techniques to ensure clarity and coherence.
- The final output is an informative caption that enhances understanding of the visual content.

4.srt File Formation

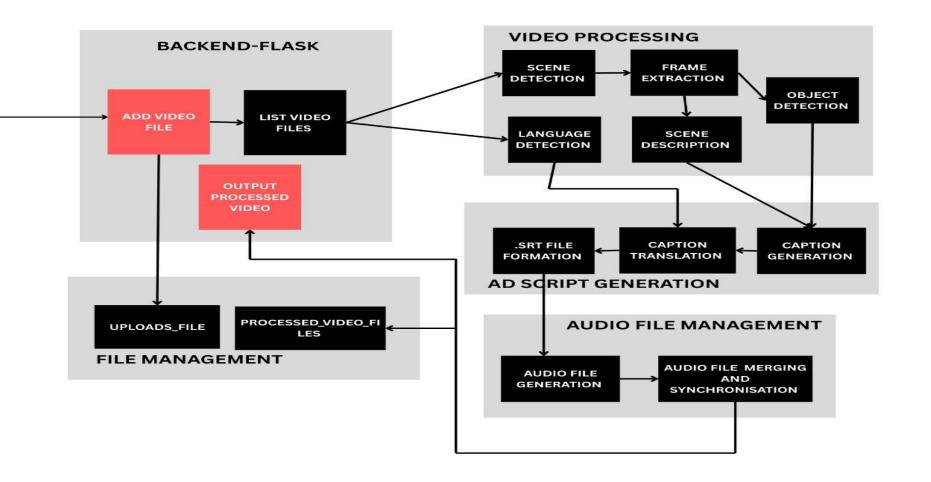
- The Subtitle Generation module timestamps each scene's description and formats it into a standard .srt file.
- Each entry includes a start time, end time, and the corresponding description.
- This allows the captions to be viewed as text alongside the video, improving accessibility and comprehension.

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5. Audio file generation and synchronization.

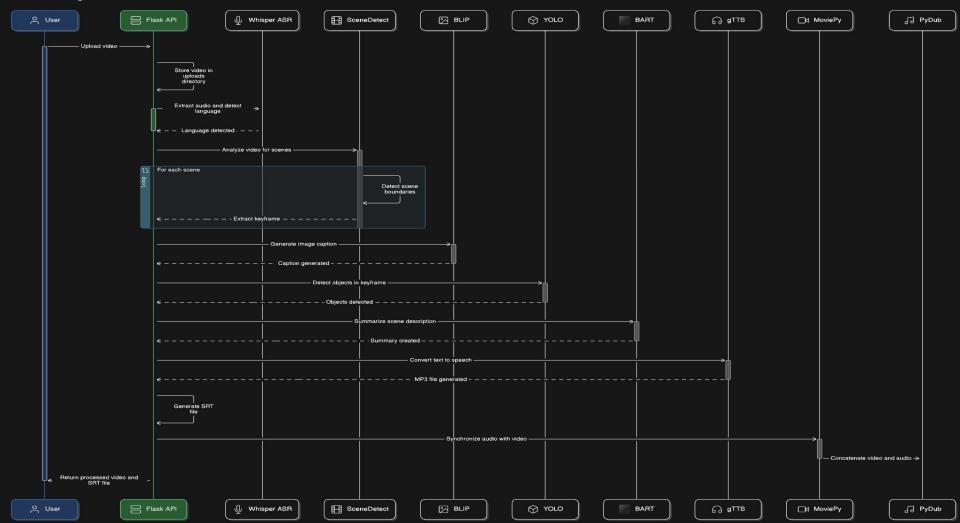
- This module translates the text descriptions into speech using text-to-speech (gTTS) in the appropriate language.
- Each audio clip is synchronized with its corresponding video segment, including both freeze-frames and original scenes.
- This creates a seamless audio description experience, making the video accessible to visually impaired viewers.

ARCHITECTURE DIAGRAM

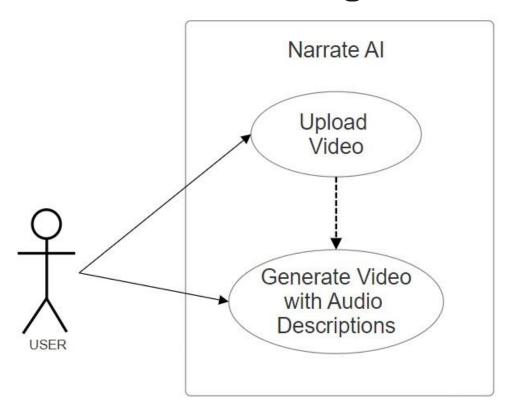


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SEQUENCE DIAGRAM



Use Case Diagram



Modules

- 1. Web Interface
- 2. Scene Change and Frame Extraction
- 3. Object Detection and Image Captioning
- 4. Scene-Level Caption Generation
- 5. SRT File Update
- 6. Audio Description Generation and Enhancement
- 7. Appending Audio to Video and Output Generation

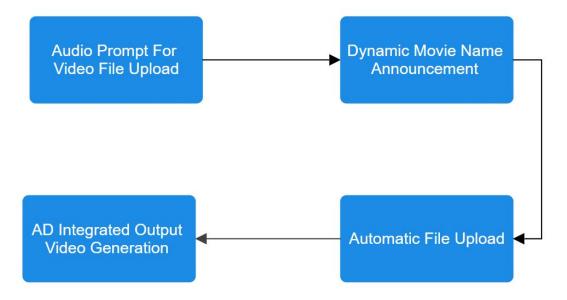
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Web Interface

- Frontend:
 - HTML/CSS for layout and styling.
 - JavaScript for interactivity and audio feedback using the Web Speech API.
- Backend:
 - Flask (Python) for handling file uploads and processing.

Web Interface(Contd.)

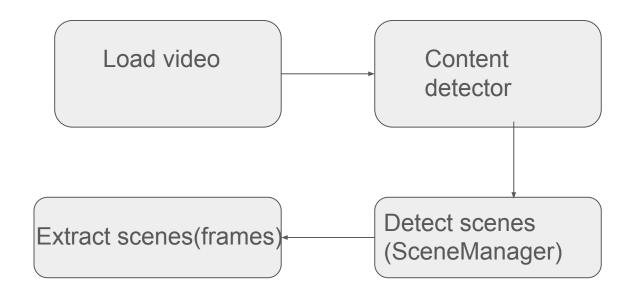
A web application that provides audio feedback for file uploads and movie selections, enhancing accessibility for visually impaired users.



Scene Change Detection and Frame Extraction

- It determines when a major scene change occurs, ensuring that descriptions are added only when a new scene begins.
- When a scene change is detected, the Frame Extraction module captures the first frame of the new scene.
- These frames serve as input for the object detection and caption generation models.
- A temporary storage system ensures efficient handling of extracted frames.

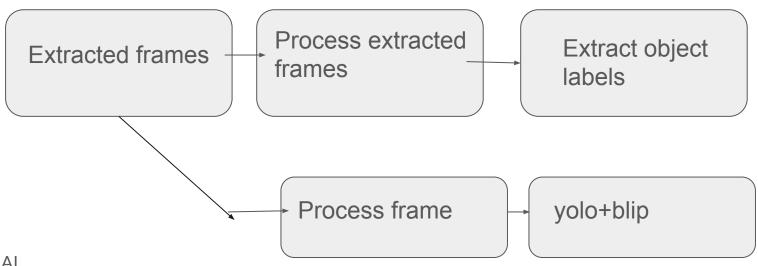
Scene Change Detection and Frame Extraction (Contd.)



Object Detection and Image Captioning

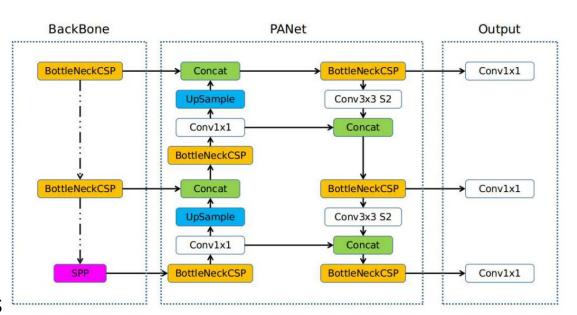
- Extracted frames are processed using a YOLOv5 (You Only Look Once) model to detect objects and visual elements.
- The detected objects are then fed into a BLIP (Bootstrapped Language Image Pretraining) model to generate preliminary image captions.
- By combining YOLOv5 and BLIP outputs, a detailed scene description is created.

Object Detection and Image Captioning



Object Detection(YOLOv5s)

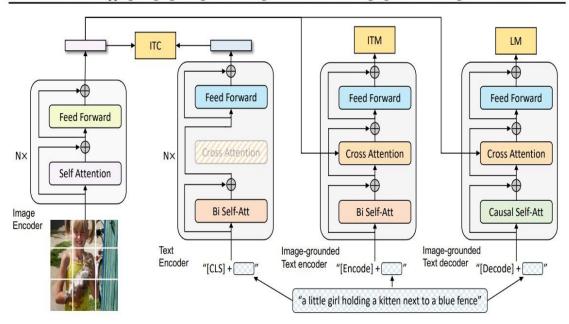
YOLOv5s is a fast and lightweight deep learning model for real-time object detection. It detects and labels multiple objects in images or videos using a single forward pass. It's built with PyTorch and widely used in applications like surveillance and robotics.



BLIP

BLIP (Bootstrapping Language-Image Pre-training) is a model for image captioning and vision-language tasks. It uses a Vision Transformer and a language decoder to generate natural, context-aware captions from images.

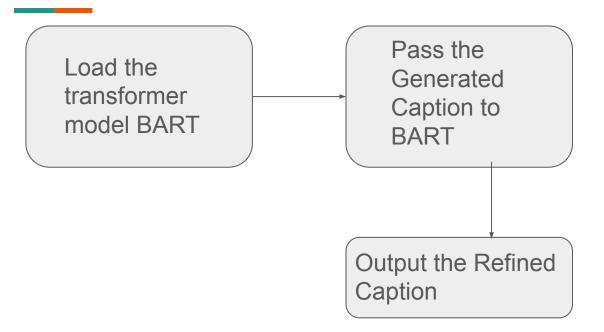
BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation



Scene-Level Caption Generation

- To improve temporal coherence, a BART (Bidirectional and Auto-Regressive Trans-
- former) model refines the captions by incorporating linguistic structure and scene context.
- This ensures that captions are not only accurate but also readable and natural.

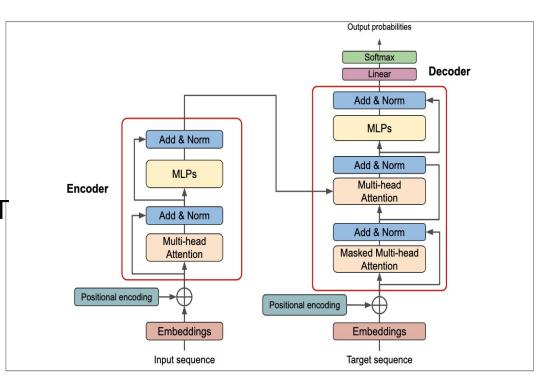
Scene-Level Caption Generation



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BART

BART (Bidirectional and **Auto-Regressive** Transformers) is a sequence-to-sequence language model. It combines the strengths of BERT and GPT . BART is commonly used for tasks like text summarization. translation, and caption generation.

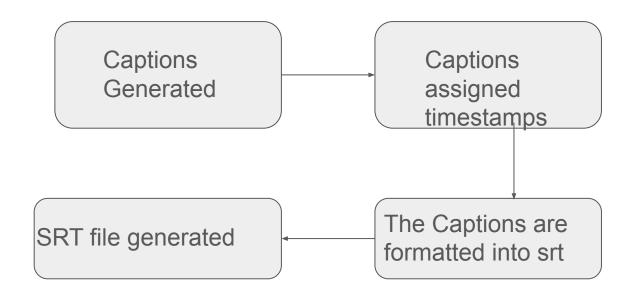


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SRT File Update

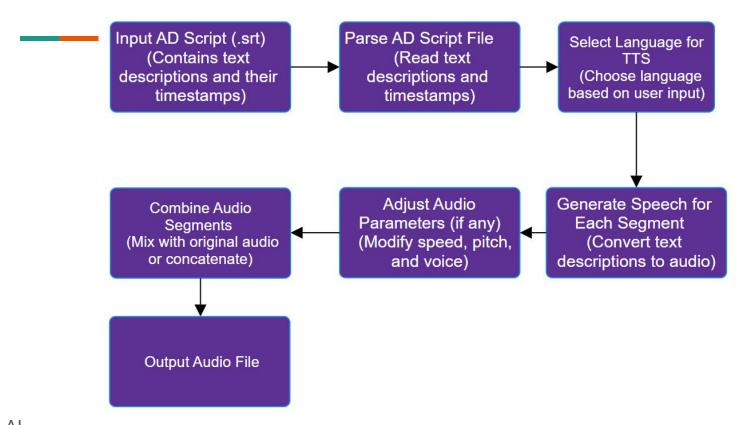
- The generated captions are converted into timestamped subtitles and integrated into an SRT (SubRip Subtitle) file
- This ensures that descriptions align properly with scene changes in the video.

SRT File Update



Audio Description Generation and Enhancement

- The finalized text descriptions are passed to a Text-to-Speech (TTS) engine, which synthesizes audio.
- The system takes into consideration the size ofthe description and speed to provide clear and engaging audio descriptions.



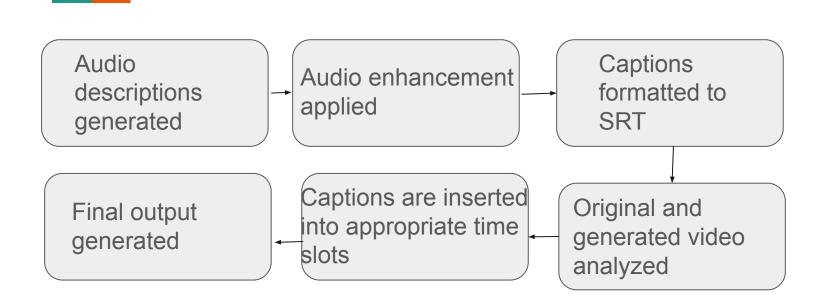
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Appending Audio to Video and Output Generation

- Audio descriptions are added without disrupting the original
- The system syncs them with scene transitions for smooth playback.
- The final video is optimized for accessibility and clarity.

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Appending Audio to Video and Output Generation



Assumptions

- The input videos are assumed to be of sufficient resolution to allow accurate object and scene recognition.
- It is assumed that the project operates within legal boundaries, and appropriate permissions for using video content for generating audio descriptions are in place.
- The videos provided are suitable for generating audio descriptions.

Work breakdown and responsibilities

1 Nandhana Suffin	2 Nikhil Stephen
Video Processing and Object Detection	Audio Description Script Generation
3 Niveditha B	4 Rachel Jacob

Hardware & Software requirements

Hardware:

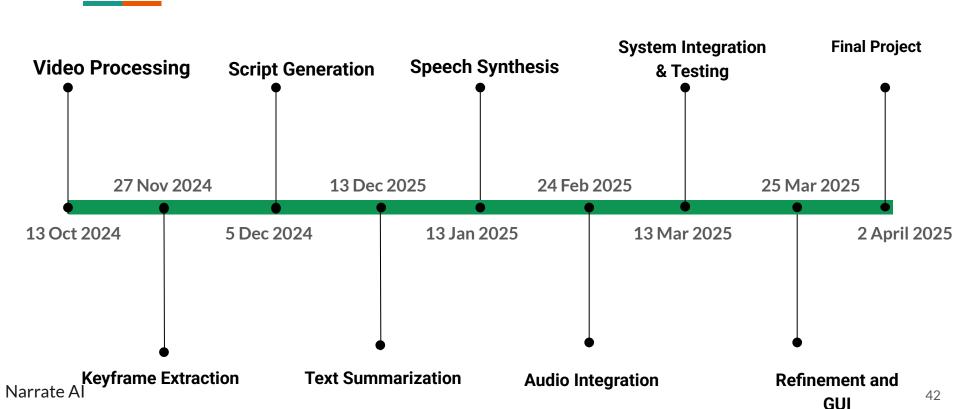
Minimum Specification:

- i5 or Ryzen 5 processor
- 16 GB RAM
- 512 SSD
- OS: Windows 1164-bit

Software:

- Development environment (Visual Studio Code)
- Framework : Flask,OpenCV,TensorFlow/ Pytorch ,YOLOv5
- Audio Processing: gTTS,PyDub,Speech Recognition

GANTT CHART



Risks & Challenges

Fitting Descriptions: ADs must be inserted during the scene Change of a video to avoid overlapping with dialogues or sound effects.

Performance and Scalability: Processing large amounts of video data efficiently and quickly to generate ADs could pose performance challenges, especially when dealing with diverse video types and lengths

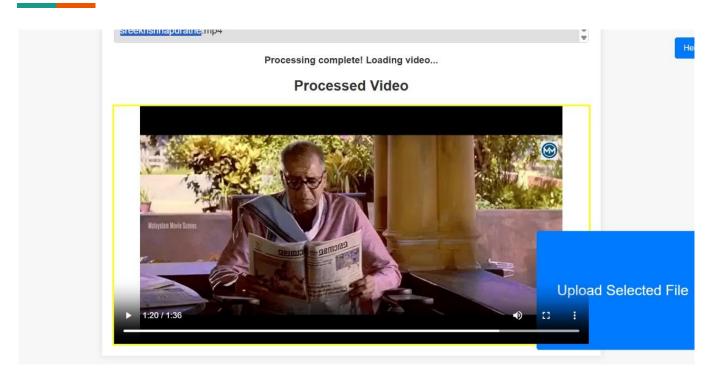
RESULTS

- BLIND FRIENDLY GUI
- AUDIO INTEGRATED OUTPUT VIDEO
- .srt FILE WITH CAPTIONS
- LANGUAGE DETECTED

BLIND FRIENDLY GUI



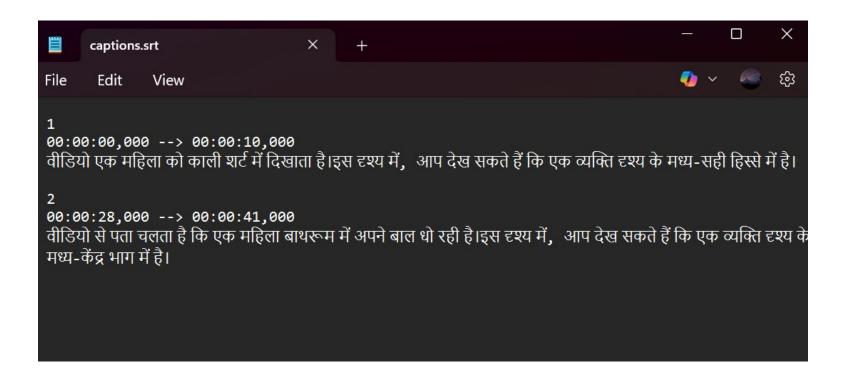
AUDIO INTEGRATED OUTPUT VIDEO



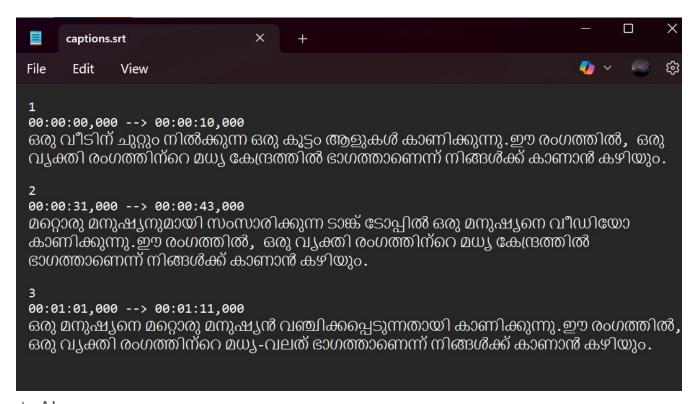
.srt FILE WITH CAPTIONS

```
1
00:00:00,000 --> 00:00:09,000
The video shows a man and woman playing with a baby. In this scene, you can see a person
is in the bottom-right part of the scene.
00:00:27,000 --> 00:00:36,000
The video shows a woman sitting on a couch eating food. In this scene, you can see a
person is in the middle-center part of the scene.
```

.srt FILE WITH CAPTIONS



.srt FILE WITH CAPTIONS





00:00:00,000 --> 00:00:10,000

The video shows a group of people standing in front of a house. In this scene, you can see A car is in the middle-left part of the scene.

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Language Detected

```
00:00:00,000 --> 00:00:10,000
The video shows a group of people standing in front of a house. In this scene, you can
see A car is in the middle-left part of the scene.
00:00:00,000 --> 00:00:10,000
ഒരു വീടിന് ചുറ്റും നിൽക്കുന്ന ഒരു കൂട്ടം ആളുകൾ കാണിക്കുന്നു.ഈ രംഗത്തിൽ, ഒരു
വ്യക്തി രംഗത്തിന്റെ മധ്യ കേന്ദ്രത്തിൽ ഭാഗത്താണെന്ന് നിങ്ങൾക്ക് കാണാൻ കഴിയും.
 00:00:00,000 --> 00:00:10,000
वीडियो एक महिला को काली शर्ट में दिखाता है।इस दृश्य में, आप देख सकते हैं कि एक व्यक्ति दृश्य के मध्य-सही हिस्से में है।
```

Conclusion

Our proposed system advances audio description generation by automating the process and generating accurate, synchronized descriptions directly from video content. It enhances accessibility for blind and visually impaired users by providing efficient and user-friendly audio descriptions, making visual media more inclusive compared to existing methods.

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FUTURE WORK

- Implement real-time processing so that live video streams (e.g., Zoom, YouTube Live) can be described on the go.
- A predefined character bank can be integrated into the system to recognize and consistently refer to recurring individuals by name.
- Allow users to choose the tone or type of narrator voice (e.g., calm, energetic, robotic, etc.). Accessibility meets personalization

THANK YOU