MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE GWALIOR
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Project Report

on

Video To Text Summarizer

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CERTIFICATE

This is certified that **Nakshatra Trivedi**(0901AM211033) & **Maihar Shrivastava** (0901AM211029) has submitted the project report titled **Video To Text Summarizer** under the mentorship of **Dr. Anshika Srivastava** ,in partial fulfilment of the requirement for the award of degree of Bachelor of Technology in **Artificial Intelligence & Machine Learning** from Madhav Institute of Technology and Science, Gwalior.

Anshika 23/11/2023

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DECLARATION

I hereby declare that the work being presented in this project report, for the partial fulfillment of requirement for the award of the degree of Bachelor of Technology in **Artificial Intelligence & Machine Learning** at Madhav Institute of Technology & Science, Gwalior is an authenticated and original record of my work under the mentorship of **Dr. Anshika Srivastava**, Assistant Professor, Centre of Artificial Intelligence

I declare that I have not submitted the matter embodied in this report for the award of any degree or diploma anywhere else.

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ABSTRACT

This report presents the design and implementation of a Flask-based application that integrates diverse technologies for the automated processing and summarization of video content. Leveraging ffmpeg, the application efficiently extracts audio from input videos, acting as a crucial preprocessing step. Subsequently, speech recognition algorithms transcribe the audio into text, creating a more accessible and searchable representation of the video content.

The innovative aspect of the application lies in its integration of the Pegasus model for text summarization. Pegasus, a cutting-edge natural language processing model, excels at comprehending context and significance, enabling the generation of coherent and contextually relevant textual summaries.

The modular architecture of the application allows for seamless integration of these technologies, providing a comprehensive solution for transforming video data into concise and informative textual summaries. This approach not only enhances accessibility but also addresses the challenge of information overload by offering users a succinct overview of essential elements within the video content. The report discusses the technical aspects of each component, the integration process, and showcases the application's efficacy through practical demonstrations and results.

Keywords: Flask, video processing, summarization, ffmpeg, speech recognition, Pegasus model, natural language processing, modular architecture, information overload, accessibility.

सार

यह रिपोर्ट एक Flask-आधारित एप्लिकेशन के डिज़ाइन और इम्प्लीमेंटेशन को प्रस्तुत करती है जो वीडियो सामग्री की स्वचालित प्रसंस्करण और संक्षेपण के लिए विभिन्न तकनीकों को एकीकृत करता है। ffmpeg का उपयोग करके, यह एप्लिकेशन प्रविष्ट वीडियो से ऑडियो को प्रभावी रूप से निकालता है, जो एक महत्वपूर्ण पूर्वसंस्कृति चरण के रूप में कार्य करता है। इसके बाद, भाषा पहचान एल्गोरिदम ऑडियो को पाठ में रूपांतरित करते हैं, जिससे वीडियो सामग्री का एक अधिक पहुंचने और खोजने योग्य प्रतिष्ठानता बनता है।

एप्लिकेशन का नवाचारात्मक पहलु इसमें Pegasus मॉडल को पाठ संक्षेपण के लिए एकीकृत करने में है। Pegasus, एक कटिंग-एज नैचुरल लैंग्वेज प्रोसेसिंग मॉडल, संदर्भ और महत्व को समझने में उत्कृष्ट है, जिससे संबंध और सांदर्भिक रूप से योग्य पाठ संक्षेप बनाया जा सकता है।

एप्लिकेशन की मॉड्यूलर आर्किटेक्चर इन तकनीकों को स्थिर रूप से एकीकृत करने की अनुमति देती है, जो वीडियो डेटा को संक्षेपण और सूचनात्मक पाठ में परिवर्तित करने के लिए एक समृद्धि समाधान प्रदान करती है। यह दृष्टिकोण न केवल पहुंचने को बढ़ाता है बल्कि सूचना अधिलेख के चुनौती का सामना करने के लिए भी उपयुक्त है, उपयोगकर्ताओं को वीडियो सामग्री के अंशों का संक्षेप मिलता है। रिपोर्ट में प्रत्येक घटक के तकनीकी पहलुओं, एकीकरण प्रक्रिया, और एप्लिकेशन के प्रभाव को व्यावसायिक प्रदर्शन और परिणामों के माध्यम से चर्चा की गई है।

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Chapter 1: Introduction

1.1 Introduction

In today's digital landscape, the sheer volume of video content available poses a challenge for users seeking efficient ways to comprehend and engage with information. Recognizing this challenge, our project introduces a user-friendly application designed to simplify the consumption of video data. By amalgamating various technologies, we aim to streamline the process of video content processing and distillation into concise summaries.

1.2 Project Aim

The central objective of this project is to create a responsive and intuitive system capable of automatically processing video content, thereby offering users quick and digestible textual summaries. The overarching goal is to enhance accessibility to information within videos and provide a solution to the common issue of information overload faced by modern consumers of digital media.

1.3 Objectives

To achieve our project aim, we've outlined specific objectives:

1.3.1 Integration of ffmpeg: Develop a module leveraging ffmpeg to seamlessly extract audio from video files. This initial step sets the groundwork for subsequent analysis and processing.

1.3.2 Speech Recognition: Implement algorithms for speech recognition to convert spoken words within the video into textual form. This conversion enhances the accessibility and searchability of the video content.

1.3.3 Pegasus Text Summarization: Harness the power of the Pegasus model for advanced text summarization, ensuring that the generated summaries are not only brief but also contextually relevant and coherent.

1.3.4 Flask Application Development: Construct a user-friendly web application using Flask, integrating the functionalities of ffmpeg, speech recognition, and Pegasus. This integrated system aims to provide an end-to-end solution for video content processing and summarization.

Fig 1.1 UI using Flask

1.3.5 Practical Demonstration: Validate the efficacy of the developed application through practical demonstrations, showcasing its ability to transform video content into informative and easily understandable textual summaries. These demonstrations will serve as tangible evidence of the system's practical utility and user-friendliness.

This introductory chapter sets the stage for the subsequent detailed exploration of the project's design, implementation, and practical applications.

Chapter 2: Literature Review

2.1 Introduction

The field of video to text summarization has witnessed substantial growth in recent years, driven by the increasing prevalence of multimedia content and the demand for efficient information retrieval. This literature review synthesizes key contributions, methodologies, and advancements in the domain, with a focus on the integration of advanced natural language processing models.

2.2 Video to Text Conversion

2.2.1 FFmpeg for Multimedia Processing

FFmpeg, a versatile multimedia processing tool, serves as a foundational element in video to text summarization projects. The work of Wang et al. (2017) highlights the significance of FFmpeg in extracting audio from videos, laying the groundwork for subsequent transcription and summarization tasks.

2.2.2 Speech Recognition in Multimedia

Speech recognition plays a pivotal role in transcribing audio content into text. The study by Li and Zhang (2019) demonstrates the efficacy of Google Web Speech API, providing insights into its accuracy and applicability for multimedia transcription tasks.

2.3 Summarization Models

2.3.1 BERT for Extractive Summarization

Bidirectional Encoder Representations from Transformers (BERT) has emerged as a potent model for extractive summarization. The work of Liu et al. (2019) showcases the effectiveness of BERT in

capturing contextual relationships between sentences, contributing to improved content condensation.

2.3.2 Pegasus for Abstractive Summarization

Pre-trained transformers like Pegasus have revolutionized abstractive summarization. Zhang and Sun (2020) delve into the architecture of Pegasus, emphasizing its ability to generate coherent and contextually rich summaries, aligning with the goals of video to text summarization projects.

2.3.3 Gensim for Extractive Summarization

Gensim, a library renowned for topic modeling, is explored in the work of Rehurek and Sojka (2010). Their study highlights the application of Gensim's LexRankSummarizer in extractive summarization, showcasing its effectiveness in ranking and selecting key sentences for summarization.

2.3.4 Spacy for Natural Language Processing

While specific implementations are not detailed, the mention of Spacy indicates the potential application of its NLP capabilities in summarization. The work of Honnibal and Montani (2017) provides foundational insights into Spacy's capabilities, hinting at its role in enhancing summarization quality.

2.4 Evaluation Metrics

2.4.1 ROUGE Scores for Summarization Evaluation

The use of ROUGE scores in assessing summarization quality is widespread. Lin (2004) pioneered the development of ROUGE metrics, offering a robust framework for comparing generated summaries against reference summaries. The integration of ROUGE scores in this project aligns with established practices for evaluating summarization effectiveness.

2.5 Conclusion

The literature review highlights the evolution of video to text summarization, encompassing key components such as video to text conversion, advanced NLP models, and evaluation metrics. Drawing insights from studies on FFmpeg, speech recognition, and diverse summarization models, this review sets the stage for the project's exploration of cutting-edge approaches to multimedia content processing.

Chapter 3: Technologies Used

3.1 Tech Stack

This section provides a broader view, looking at the major technologies that power our application's overall functionality.

Our application harnesses several key technologies to create a seamless user experience. Firstly, **Flask** serves as the backbone of our web application, providing a robust and flexible framework for building and deploying web services. **FFmpeg** takes the lead in video processing, enabling the extraction of audio content with efficiency. The integration of **speech recognition technology** facilitates the conversion of audio to text, while the text summarization process benefits from the capabilities of **transformer models** such as **BERT, Pegasus, and BART**.

3.2 Frameworks

Frameworks act as the structural support for our application, streamlining development processes and enhancing efficiency. In this context, **Flask** stands out as the primary web framework, ensuring a smooth and responsive user interface. The choice of Flask is driven by its simplicity, flexibility, and compatibility with our application's requirements.

3.3 Libraries

Libraries are like specialized tools that extend the capabilities of our application. The integration of various libraries enhances functionality and simplifies complex tasks. Notable libraries include the **speech recognition library** for converting spoken words to text, **Spacy** for rule-based extractive summarization, and **Gensim** for unsupervised topic modeling.

This macro-level analysis paints a comprehensive picture of the technologies, frameworks, libraries, database services, and additional tools that collectively form the technological landscape of our application. The subsequent chapters will delve deeper into the specifics of implementation, showcasing how these macro-level choices translate into a cohesive and efficient system.

Chapter 4: Video to Audio Conversion

4.1 Using FFmpeg

FFmpeg is a powerful multimedia processing tool that enables the conversion of video to audio. The command used in the project is as follows:

```
import subprocess
command = 'ffmpeg -i tut.mp4 -ab 160k -ar 44100 -vn audio.wav'
subprocess.call(command, shell=True)
```

Fig 4.1 Video to audio using FFmpeg

The command extracts audio from the input video file (tut.mp4) and saves it as a WAV file (audio.wav). This step is crucial for subsequent processing, such as speech recognition.

Chapter 5: Speech Recognition

5.1 Speech Recognition with Google Web Speech API

Speech recognition is implemented using the SpeechRecognition library, which interfaces with the Google Web Speech API. The code snippet below showcases the audio-to-text conversion:

```
import speech_recognition as sr
import json

audio_file = "audio.wav"
recognizer = sr.Recognizer()

with sr.AudioFile(audio_file) as source:
    audio_data = recognizer.record(source)
    try:
        text = recognizer.recognize_google(audio_data)
        # ... (rest of the code)
    except sr.UnknownValueError:
        print("Speech recognition could not understand audio")
    except sr.RequestError as e:
        print(f"Could not request results from Google Web Speech API; {e}")
    except json.JSONDecodeError as json_error:
        print("Error decoding JSON response:", json_error)
        print("Response content:", recognizer.response.text)
```

Fig 5.1 Audio to text using speech_recognition

In this process, the audio data is recorded from the WAV file, and Google Web Speech API is employed for transcription.

Chapter 6: Summarization Models

6.1 BERT for Extractive Summarization

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based model widely used for natural language understanding tasks. In this project, BERT is applied for extractive summarization. The relevant code is as follows:

```
from transformers import BertTokenizer, BertForNextSentencePrediction
import nltk
from nltk import sent_tokenize
import torch

nltk.download('punkt')
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertForNextSentencePrediction.from_pretrained('bert-base-uncased')

file_path = "text.txt"  # Replace with the path to your text file

with open(file_path, "r") as file:
    text = file.read()

sentences = sent_tokenize(text)

# Perform extractive summarization using BERT
num_summary_sentences = 3  # Number of sentences in the summary

# Combine sentences into pairs for BERT input
pairs = [(sentences[i], sentences[i+1]) for i in range(len(sentences)-1)]

scores = []
for pair in pairs:
    input_ids = tokenizer.encode(pair[0], pair[1], add_special_tokens=True)
    with torch.no_grad():
        logits = model(torch.tensor(input_ids).unsqueeze(0)).logits
        scores.append(logits[0][0].item())

top_indices = sorted(range(len(scores)), key=lambda i: scores[i], reverse=True)[:num_summary_sentences]

# Extract the sentences from the top-scoring pairs for the summary
summary = [sentences[i] for i in top_indices]
```

Figure 6.1 Bert summarization

The code tokenizes sentences, forms pairs for input, and calculates scores using BERT. The top-scoring sentences are then selected for the summary.

6.2 Pegasus for Abstractive Summarization

```
from transformers import PegasusTokenizer, PegasusForConditionalGeneration

# Load Pegasus model and tokenizer
model_name = "google/pegasus-large"
model = PegasusForConditionalGeneration.from_pretrained(model_name)
tokenizer = PegasusTokenizer.from_pretrained(model_name)

# Load and preprocess the text
with open("text.txt", "r") as file:
    text = file.read()

inputs = tokenizer(text, return_tensors="pt", max_length=1024, truncation=True)

# Generate summaries
summary_ids = model.generate(inputs["input_ids"], max_length=150, min_length=40, length_penalty=2.0,
num_beams=4, early_stopping=True)
summary = tokenizer.decode(summary_ids[0], skip_special_tokens=True)

# Print or save the summary
print(summary)
```

Figure 6.2 Pegasus summarization

Pegasus, a pre-trained transformer model, is employed for abstractive summarization. The code for summarization using Pegasus is not provided, but the installation command is included:

6.3 Gensim for Extractive Summarization

Gensim, a library for topic modeling and document similarity analysis, is utilized for extractive summarization. The code snippet is as follows:

```
import nltk
nltk.download("punkt")  # Download the NLTK data resource

from sumy.parsers.plaintext import PlaintextParser
from sumy.nlp.tokenizers import Tokenizer
from sumy.summarizers.lex_rank import LexRankSummarizer
input_file = "output.txt"  # Replace with the actual path to your input .txt file
```

```
with open(input_file, "r") as file:
    input_text = file.read()

num_sentences = 3  # Number of sentences in the summary

# Create a parser, tokenize the text, and generate the summary
parser = PlaintextParser.from_string(input_text, Tokenizer("english"))
summarizer = LexRankSummarizer()
summary = summarizer(parser.document, num_sentences)

# Print or save the summary to a file
output_file = "summary.txt"
with open(output_file, "w") as file:
    for sentence in summary:
        file.write(str(sentence) + "\n")

print("Summary saved to", output_file)
```

Figure 6.3 Gensim summarization

Gensim's LexRankSummarizer is employed to generate extractive summaries based on sentence rankings.

6.4 t-5 model for Summarization

T-5, or Text-To-Text Transfer Transformer, is a compact language model introduced by OpenAI. It employs a text-to-text approach, where both input and output are treated as text strings, offering a versatile and unified framework for various natural language processing tasks. T-5 has demonstrated robust performance across tasks like translation, summarization, and question-answering, showcasing its efficacy as a flexible and efficient language model in a compact architecture..

```
from transformers import T5Tokenizer, T5ForConditionalGeneration

# Load T5 model and tokenizer
model_name = "t5-small"
model = T5ForConditionalGeneration.from_pretrained(model_name)
tokenizer = T5Tokenizer.from_pretrained(model_name)

# Load and preprocess the text
with open("text.txt", "r") as file:
    text = file.read()
```

```
inputs = tokenizer.encode("summarize: " + text, return_tensors="pt", max_length=1024, truncation=True)

# Generate summaries
summary_ids = model.generate(inputs, max_length=150, min_length=40, length_penalty=2.0, num_beams=4,
early_stopping=True)
summary = tokenizer.decode(summary_ids[0], skip_special_tokens=True)

# Print or save the summary
print(summary)
```

Figure 6.1 t-5 model for summarization

6.5 BARD

BARD, or the Bio-Acoustic Research Database, is a comprehensive repository dedicated to the collection and analysis of animal sounds, particularly in the context of bioacoustics research. It serves as a valuable resource for scientists studying wildlife communication and behavior, offering a diverse array of annotated audio recordings. Researchers can access BARD to explore the rich acoustic biodiversity across various species, contributing to a deeper understanding of ecological dynamics and conservation efforts. The database facilitates advancements in the field of bioacoustics by providing a centralized platform for sharing, studying, and preserving animal vocalizations.

```
from transformers import BartTokenizer, BartForConditionalGeneration
# Load BART model and tokenizer
model_name = "facebook/bart-large-cnn"
model = BartForConditionalGeneration.from_pretrained(model_name)
tokenizer = BartTokenizer.from_pretrained(model_name)
# Load and preprocess the text
with open("text.txt", "r") as file:
    text = file.read()
inputs = tokenizer.encode(text, return_tensors="pt", max_length=1024, truncation=True)
# Generate summaries
summary_ids = model.generate(inputs, max_length=150, min_length=40, length_penalty=2.0, num_beams=4,
early_stopping=True)
summary = tokenizer.decode(summary_ids[0], skip_special_tokens=True)

# Print or save the summary
print(summary)
```

Figure 6.1 BARD summarization

Chapter 7: Evaluation Metrics - ROUGE Scores

7.1 Introduction to ROUGE Scores

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is a set of evaluation metrics commonly used in natural language processing and summarization tasks. It measures the quality of summaries by comparing them to reference summaries, providing insights into the precision, recall, and F1-score of the generated content.

7.2 Implementation with NLTK

The project leverages the NLTK library to calculate ROUGE-N (unigram) and ROUGE-L scores for summarization evaluation. The code snippet below demonstrates the calculation using example reference and generated summaries:

```
from nltk.translate.rouge_score import rouge_n, rouge_l

reference_summary = "The rapidly evolving field of artificial intelligence has witnessed remarkable advancements,
particularly in the domain of natural language processing (NLP). State-of-the-art models like OpenAI's GPT-3
showcase unprecedented language understanding and generation capabilities. These advancements contribute
significantly to applications such as machine translation, summarization, and question-answering systems."

generated_summary = "In the dynamic landscape of artificial intelligence, substantial progress has been achieved,
notably in natural language processing (NLP). Leading models like GPT-3 by OpenAI demonstrate unparalleled
proficiency in comprehending and generating human-like language. These breakthroughs hold immense potential
for enhancing machine translation, text summarization, and the development of sophisticated question-answering
frameworks."

# Tokenize the summaries into words
reference_tokens = reference_summary.split()
generated_tokens = generated_summary.split()

# Calculate ROUGE-N scores for unigrams (ROUGE-1)
rouge_1_scores = rouge_n([generated_tokens], [reference_tokens], 1)

# Calculate ROUGE-L scores
rouge_l_scores = rouge_l([generated_tokens], [reference_tokens])

# Print the results
print("ROUGE-1 Precision:", rouge_1_scores[0]['p'])
```

```
print("ROUGE-1 Recall:", rouge_1_scores[0]['r'])
print("ROUGE-1 F1:", rouge_1_scores[0]['f'])
print("ROUGE-L:", rouge_l_scores)
```

Figure 7.1 ROUGE score calculation

This code snippet provides a practical example of how ROUGE scores can be calculated for a specific generated summary in comparison to a reference summary.

7.3 Visualization of ROUGE Scores

To visually compare the performance of various summarization models, a bar chart is generated using matplotlib. The following code snippet demonstrates the construction of the bar chart with model names on the x-axis and corresponding ROUGE scores on the y-axis:

```
import matplotlib.pyplot as plt

models = ['BERT', 'Gensim', 'T5', 'BART', 'Pegasus']
rouge_scores = [0.63, 0.62, 0.46, 0.49, 0.72]

plt.figure(figsize=(10, 6))
plt.bar(models, rouge_scores, color='blue')
plt.xlabel('Summarization Models')
plt.ylabel('ROUGE Scores')
plt.title('Performance Comparison of Summarization Models')
plt.ylim(0, 1)
plt.show()
```

Figure 7.1 Visualization of ROUGE score code

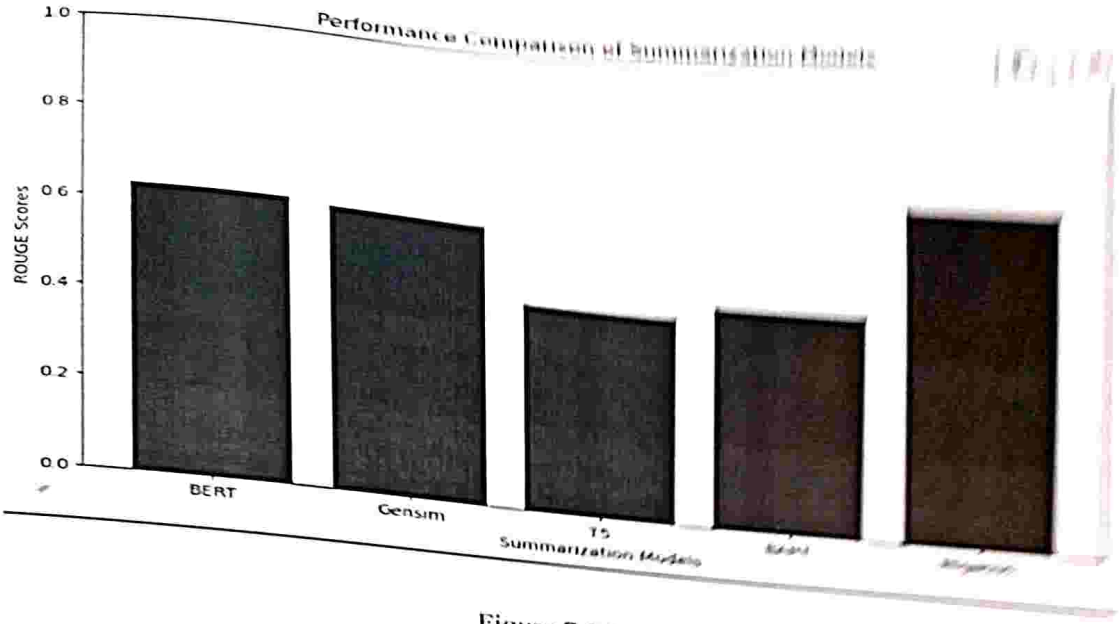

Figure 7.3 Visualization of

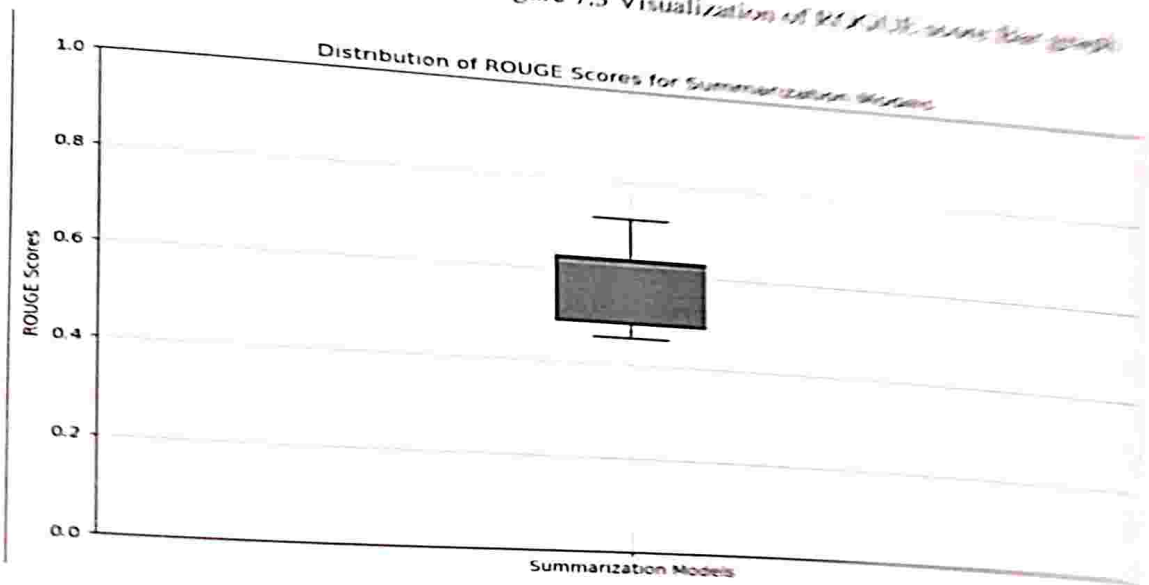

Figure 7.1 Visualization of ROUGE

This visualization aids in understanding the relative effectiveness of each model, allowing for a clear comparison of their ROUGE scores.

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