YOUTUBE TRANSCRIPT SUMMARIZER

A PROJECT REPORT

Submitted by

DWANY D S (TKM21MCA-2017)

to

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In partial fulfillment of the requirements for the award of the degree of

MASTER OF COMPUTER APPLICATION

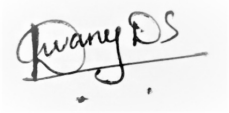
Thangal Kunju Musaliar College of Engineering
Kerala

DEPARTMENT OF COMPUTER APPLICATION

MAY 2023

DECLARATION

I undersigned hereby declare that the project report on **YouTube Transcript Summarizer**, submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Application of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under the supervision of Prof. Jasmin M R . This submission represents my ideas in my own words and where ideas or words of others have been included,I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not previously served as the basis for the award of any degree, diploma, or similar title by any other University.



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CERTIFICATE

This is to certify that the report entitled **YouTube Transcript Summarizer** submitted by **DWANY D S** (TKM21MCA2017) to the APJ Abdul Kalam Technological University in partial fulfillment of the Masters degree in Computer Application is a bonafide record of the project work carried out by her under our guidance and supervision. This report, in any form, has not been submitted to any other University or Institute for any reason.

Internal Supervisor Head of the Department External Examiner

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ABSTRACT

YouTube Transcript Summarizer the project aims to automatically generate concise summaries of YouTube video transcripts. It utilizes machine learning models to summarize the text and integrates with the YouTube Data API V3 to fetch the video data.The front end of the YouTube Transcript Summarizer developed with Streamlit provides a user-friendly interface where users can input the YouTube video URL. Once the user submits the video information, the application utilizes the YouTube Data API V3 to fetch the necessary data, including the video transcript. The transcript is then passed through deep learning models to generate a concise summary. In this system, two models Seq2Seq and Transformer-based model are used to generate a summary and calculate TF-IDF vectors for the summaries and compute the cosine similarity. Finally, it compares the cosine similarities to determine the best summary and returns it. The system can send users an email containing the summary along with a link to download the audio version.

This tool is particularly beneficial for individuals with disabilities, as it allows them to focus on the most relevant information and aids those with hearing or vision difficulties. By providing transcripts, YouTubers can reach a wider audience, and users can save time by consuming summarized content. With the exponential growth of YouTube videos, a summarizer becomes an invaluable resource to quickly grasp the main points of a video. It also helps in developing summarization skills, benefiting various professions. Overall, a YouTube Transcript Summarizer enhances time efficiency, writing abilities, and accessibility to YouTube content

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Chapter 1

Introduction

YouTube Transcript Summarizer is a system that enables users to automatically generate a concise summary of a YouTube video's transcript. It is a web application that is implemented with machine learning models for generation summaries. In this project,YouTube Transcript Summarizer with the help of YouTube Data API V3 fetch the YouTube data, and the text is summarized using Deep Learning with the help of two models Seq2Seq and Transformer-based model are used to generate a summary and calculate TF-IDF vectors for the summaries and compute the cosine similarity. Finally, it compares the cosine similarities to determine the best summary and returns it. The system can email users a summary of the video along with a link to download the audio version of the summary. The length of the transcripts, however, might occasionally be an issue for those with disabilities. People can focus on the information that is most relevant to them by rapidly identifying the essential elements of a film by using a summarizer. Those who have hearing or vision difficulties can also benefit from summarising YouTube transcripts. YouTubers open up their content to a wider audience by offering a transcript of a video. Consider how much time can be saved by producing summarised content. People watch YouTube videos on a daily basis, whether they are instructional, documentaries, or of any other genre with a lengthier runtime. One of the most widely used websites for education, entertainment, and information is YouTube. It might be difficult to keep up with all the content when millions of videos are uploaded every day. Thankfully, a lot of YouTubers offer transcripts of their videos, which makes it simpler for viewers to follow along. However, the transcripts can occasionally be rather long, which some individuals may find to be overwhelming.

A YouTube Transcript Summarizer can be useful in this situation. A YouTube transcript summarizer is a tool that allows one to create a concise summary of a YouTube video's transcript. It helps to extract the most important information from a lengthy transcript and condense it into a shorter, more manageable format. This summarizer can save time and make it easier to digest the information presented in a video. One benefit of using a YouTube transcript

summarizer is that it can help to understand the main points of a video quickly. For example, if a user is searching for a tutorial on a specific topic,one can use a summarizer to quickly identify the most relevant parts of the video and skip over any irrelevant information. This can save time and help to learn more efficiently. Using a YouTube transcript summarizer might also help write better, which is another advantage. Practicing the technique of summarising, is a crucial skill in many occupations, by compressing a long transcript into a shorter summary.

YouTube Transcript Summarizer is a crucial tool that will help save time, hone writing abilities, and increase the accessibility of YouTube material to a wider audience. Whether a student, expert, or casual viewer, employing a summarizer can make it easier to swiftly and effectively comprehend the essential ideas of a movie. A summarizer is a useful tool that can help remain on top of the information that needs with the growing volume of content that is added to YouTube every day.

1.1 Problem Statement

The problem statement of the project is:

- Time Consuming: The users need to watch lengthy videos and it is time-consuming
- Difficult to find information: people would need to manually watch or scan through the entire video.
- Less Audience: The number of people will be less and need more patience is needed and people with disabilities cannot have the resources effectively.

1.2 Objectives

Project deliverable includes:

- Automatic Summarization: To develop a system that can automatically generate concise summaries of YouTube video transcripts.
- Machine Learning Implementation: The project aims to utilize machine learning models to perform the text summarization task.

- Integration with YouTube Data API: The system intends to integrate with the YouTube Data API V3 to fetch video data.
- Email Summary and Audio Download: The system aims to provide users with the option to receive the summary via email.
- Accessibility Enhancement: The project aims to improve the accessibility of YouTube content.
- Time Saving: The YouTube Transcript Summarizer aims to save users' time by condensing lengthy transcripts into shorter summaries.

1.3 Existing System

In the existing system, people have to spend a lot of time watching the whole video to get the concept. The current YouTube Transcript Summarizer method may need manual work from users who must manually view the YouTube video and extract key information from it in order to construct a summary. Since there is so much stuff on YouTube, watching full-length films can take a while. This procedure takes time and is arbitrary because it depends on the interpretive and summarising abilities of the individual. To extract essential data, people would need to manually watch or scan through the entire film. Users may be discouraged from accessing the content they are interested in since this process might be time-consuming, especially for lengthier videos, and thus reduce efficiency. Users could find it difficult to sort through the large volume of content on YouTube in the absence of a summarizer. They might be forced to rely solely on titles and descriptions, which might not always adequately summarise the main themes of the film. This may cause dissatisfaction and time wasted on unimportant or inferior things.

1.4 Proposed System

The proposed YouTube Transcript Summarizer aims to automate the process of summarizing YouTube video transcripts The proposed system offers the following features:

- Time Saving: YouTube is flooded with a vast amount of content, and watching full-length videos can be time-consuming. The summarizer allows users to quickly grasp the main

points of a video by providing a concise summary. It saves time and allows users to efficiently consume the information they need.

- Accessibility: The summarizer enhances accessibility for individuals with disabilities. By providing summarized transcripts, it helps those with hearing or vision difficulties to access and understand the content presented in YouTube videos. This promotes inclusivity and ensures that a wider audience can benefit from the information shared in videos.

- Improved Comprehension: Summarizing transcripts enables users to extract the most important information from lengthy videos.

- Increased Audience Reach: YouTubers who provide transcripts of their videos make their content accessible to a wider audience.

- Content Filtering: With millions of videos uploaded to YouTube daily, it can be challenging to keep up with all the content. The summarizer allows users to filter through the vast volume of videos by quickly identifying the essential elements.

Chapter 2

Literature Survey

A literature survey, also known as a literature review, involves analyzing scholarly sources related to a particular subject. Examining the available literature, provides a comprehensive overview of the state of the field, allowing to identify relevant theories, approaches, and gaps in the existing body of knowledge. When conducting a literature review from an audit perspective, the main focus is on evaluating the relevant literature. This process covers information that has been published in a specific field of study and sometimes includes information published within a specific time frame. The literature review is an indispensable tool for conducting research and is frequently used as a starting point for delving into a specific subject area. In addition to identifying important theories and concepts, a literature review can also pinpoint gaps in current knowledge and draw attention to areas where further research is necessary. By scrutinizing multiple sources, a literature review can provide a more comprehensive understanding of a given topic or issue. A well-crafted literature review can also enhance the credibility and authority of the author, as it demonstrates their familiarity with the current research and debates in the field. In certain cases, a literature review may include a meta-analysis, which involves analyzing the findings of numerous studies to uncover common patterns or trends. It is important to keep in mind that a literature review is distinct from a research paper or an argumentative essay; it is instead a focused examination of the existing research and literature on a specific topic.

2.1 Purpose of the Literature Review

1. The purpose of a literature review is to provide an overview and analysis of existing research and literature on a particular topic.

2. It aims to identify key theories, concepts, and findings, as well as to evaluate the strengths and weaknesses of previous studies.

3. A literature review can help to identify gaps in the current knowledge and highlight areas

where further research is needed.

4. By examining multiple sources, a literature review can provide a more comprehensive understanding of a particular topic or issue.

5. Additionally, a well-written literature review can help to establish the credibility and authority of the author, as it demonstrates their familiarity with the current research and debates in the field.

6. A literature review can be a standalone piece or part of a larger research project such as a thesis, dissertation, or research paper.

2.2 Related Works

The Section Mainly describes the related study in the area of YouTube Transcript Summarization. And some of them are listed below.

J. Jiang et.al[1], propose improvements to the attention-based bidirectional LSTM model for hybrid automatic text summarization. The research introduces improvements to the attention-based bidirectional LSTM model in order to tackle the task of automatic text summarization. In order to extract contextual information from both directions of the input text, the suggested model makes use of bidirectional LSTMs. When summarizing, attention techniques are used to concentrate on critical portions of the data. The authors present numerous modifications, such as a query-guided attention mechanism and a fusion technique to integrate word-level and sentence-level attentions, to further boost performance. The effectiveness of the suggested improvements is demonstrated by experimental evaluations on benchmark datasets, which show better summarization quality with regard to of both coverage of content and coherence. The paper proposes enhancements to the attention-based bidirectional LSTM model for hybrid automatic text summarization. Utilizing bidirectional LSTMs makes it possible to capture contextual data from both ways, enhancing the quality of the summary. By focusing on key passages in the input text, attention processes help improve the selection of pertinent information. The suggested improvements, including the fusion technique and query-guided attention mechanism, show enhanced summarization quality in terms of content coverage and coherence.The generalizability of the proposed enhancements cannot be fully understood due to a lack of information in the abstract regarding the breadth

and variety of evaluations that were conducted. It is additionally challenging to evaluate the model's performance in contrast to other techniques because a direct comparison with current state-of-the-art methodologies in text summarization is not stated.

M. F. Mridha et.al[2], provides a comprehensive survey of the advancements, methodologies, and challenges in the field of automatic text summarization . In this study of automatic text summarization, the authors cover the field's advancements, the underlying principles and methods used, as well as the difficulties that researchers must overcome. It discusses numerous strategies, such as extractive and abstractive summarising, as well as various algorithms and assessment metrics that are used to rate the effectiveness of summary. The survey also examines new patterns and prospective directions while highlighting the influence of machine learning and deep learning techniques on text summarization. In addressing domain-specific requirements, comprehending and modeling the intricacies of human language, and creating methods for multi-document and cross-lingual summarising, it finishes by listing the difficulties that researchers face.Pros of the paper is a Comprehensive overview of automatic text summarization progress, processes, and challenges. Inclusion of machine learning and deep learning advancements. Identification of challenges and future directions.Cons are Lack of detailed methodologies and experimental evaluations. Limited information on specific datasets and domains covered.

S. Shukla et.al[3], The construction of a Streamlit web application and a comparative analysis of various machine-learning methods are presented in the paper. The study's goal, is to compare the effectiveness of various ML algorithms on a particular dataset and present the findings via an intuitive web application. The methodology, experimental design, and analysis findings are covered in the paper.

S. Shekhar et.al[4] defines the use of topic modeling by the authors to find offensive remarks on YouTube is investigated. the pros are by revealing underlying themes and patterns, topic modeling can assist researchers in developing a greater understanding of the types of abusive remarks frequently found on YouTube. The process of finding abusive comments can be automated by using topic modeling algorithms, enabling a quicker and more effective examination of enormous volumes of user-generated information. The cons are Topic modeling has inherent constraints, including the requirement for proper parameter tuning and the difficulty of correctly comprehending the extracted topics.

S. Sun et.al[5], discribes transcribing speech audio for Seq2Seq Text-to-Speech (TTS)

frontends attempts to improve the performance and quality of the TTS system by adding transcriptions of speech audio during training. the pros are Better Alignment: Speech transcriptions can offer more precise alignments between aural cues and the related text. This could improve the caliber and authenticity of the generated speech. Better Pronunciation: Including transcriptions can help with pronunciation issues, particularly for unclear or context-dependent words and phrases. The model can use the transcribed data to learn the proper pronunciation patterns.Errors in transcription: If the transcriptions are inaccurate or contain mistakes, this might cause noise and degrade the speech that is produced. Obtaining transcriptions for speech recordings needs additional manual work or the use of automatic speech recognition (ASR) technologies, each of which comes with its own set of potential problems and inaccuracies.

Z. Zhou et.al[6], research interest in code summarising, which tries to automatically generate code summaries. Neural machine translation techniques are frequently used in recent approaches to this problem, which train a Seq2Seq model on a huge corpus and anticipate it would be applicable to a variety of fresh code snippets.The suggested meta-learning method surpasses earlier state-of-the-art approaches for retrieval-based neural code summarization. Without requiring architectural changes, MLCS can be adapted to current code summarizers, greatly enhancing their performance. It makes use of numerous related examples and exhibits superior generalisation on various retrievers, unknown corpora, and low-frequency words.For big code corpora, retrieving comparable instances could be computationally demanding. The calibre and amount of samples that are obtained determine how well MLCS performs. The evaluation is based on a small selection of datasets, and further research needs to be done on how well it performs on additional code summarising tasks.

P. Kadam et.al[7],The paper talks about the rising number of security cameras that produce a lot of video data and offer single- or multi-view coverage. However, the majority of this data is made up of redundant frames that don't include any essential information, making it difficult to extract important components. The paragraph gives an overview of the video summarization (VS) techniques, datasets, and analytical performance standards.. It draws attention to the necessity to solve the Multi-View Summarization (MVS) issue, which has not received enough attention in the literature as of yet. Different application domains for single and multi-view video summarization are suggested in the paragraph. Additionally, it suggests more studies to enhance the speed and efficacy of video summarising systems, as well as real-time applications

and the integration of cutting-edge technology into news organizations' operations for time- and cost-saving purposes.

S. K. Dam et.al[8], the paper suggests a text summarization technique based on Recurrent Neural Networks (RNN), this research seeks to address the problem of reducing communication costs. The authors concentrate on using RNNs, particularly Long Short-Term Memory (LSTM) networks, to extract the text's semantic information and provide succinct summaries. They want to minimize communication expenses by reducing the amount of data that needs to be transmitted or communicated by summarising the information. The suggested RNN-based text summarization method, together with the model's architecture, training procedures, and evaluation findings, are likely to be covered in full in the publication. It can also go through how their approach might be used in different fields where cutting communication costs is essential.In order to cut down on communication expenses, the suggested research focuses on a system model architecture where a central base station transmits condensed messages to users' edge devices. Due to its success in text analysis, the long short-term memory recurrent neural network (LSTM-RNN) is selected as the model for text summarization. According to the experimental findings, the suggested model and LSTM-RNN significantly lower communication costs, by an average of 85

N. Babanejad et.al[9],proposed the significance of preprocessing methods in word representation learning for emotive tasks is examined in this research. Word representation learning, which tries to capture the underlying lexical and emotional characteristics of words, is essential to natural language processing and sentiment analysis.The effectiveness of word representation models in affective tasks is examined by the authors in relation to various preprocessing processes such as lowercasing, stemming, stop-word removal, and handling of negations. They assess how well different preprocessing methods perform in terms of their capacity to gather emotional data and enhance sentiment analysis and emotion categorization, models.The study focuses on affect identification tasks, including sentiment analysis, emotion categorization, and sarcasm detection, which have attracted a lot of interest because of their useful applications in numerous disciplines. Recognising emotional states from textual material is the main goal. In particular, word representation learning and the development of classification models are two areas where the research emphasises the value of preprocessing techniques in the affect detection pipeline.The effect of different preprocessing techniques, such as stemming, lemmatization, stopword removal, and punctuation removal, on model

performance is examined by the authors. They examine the impact of various preprocessing techniques on the performance at various stages of application. The research offers insightful information on the application of preprocessing processes in building an affect detection pipeline and their diverse effects on various affective tasks.

P. K. Biswas et.al[10],proposed a method for producing extractive call transcript summaries. The research combines channel separation, subject modeling, phrase choice, and punctuation restoration to overcome the difficulties associated with call transcript summarization. The investigation of many subject models to find the best one for summary is one noteworthy part of the paper. Using term-based and sentence-based similarities, this method enables a fine-grained similarity analysis. The semantic meaning of words and sentences is captured by the authors using GloVe- and USE-based embeddings, which improves the assessment of their importance, originality, and relevance. In addition, a unique BERT transformer-based model for restoring punctuation in the generated summaries is presented in this paper. This feature sets the proposed extractive summarizer apart because it can correctly restore entire punctuation in summaries obtained from original call transcripts that were either improperly punctuated or left unpunctuated.It is important to note that the summarizer provides more options and flexibility than the Bert Extractive Summarizer. One drawback is that it doesn't repair grammatical mistakes in the call transcript summary, though. By using fewer sentences and post-processing procedures, it decreases the number of grammatical faults, but it does not offer a comprehensive fix for them.

G. Bao et.al[11], proposes a novel approach to text summarization using a contextualized rewriting method. The current rewriting algorithms frequently handle extracting sentences individually, which results in the loss of essential context and coherence in the summaries that are produced. The authors propose contextualized rewriting, which takes into account the whole document's coherence and includes extractive sentences as part of the document encoding, in order to overcome this constraint.Sentence selection is viewed as a token prediction job in the proposed system, which incorporates an external extractor and a combined internal extractor. The extracting sentences and the summary can be better aligned using this method. Utilising several pre-trained models, the authors create three rewriter instances and assess their performance using ROUGE scores. The experimental outcomes reveal that contextualised rewriting is successful and that it significantly outperforms earlier non-contextualized rewriting techniques.The article emphasises the significance of upholding

coherence while summarising text and shows how joint modelling of sentence selection and rewriting can improve performance. The proposed methodology makes important advances by utilising pre-trained models and including extractive sentences as part of document encoding.

T. G. Altundogan et.al[12], seeks to automatically produce brief and educational summaries or highlights from textual information using a revolutionary method to text highlight abstraction. The authors suggest an approach that uses the PageRank algorithm to extract key sentences as input for the summary process and an LSTM-based encoder-decoder architecture to produce summaries.The difficulty of producing abstractive summaries or highlights from texts is addressed in the study, with a special emphasis on the drawbacks of encoder-decoder designs when handling big input arrays. The research suggests using an LSTM encoder-decoder with an attention mechanism to get around this restriction.The study uses an extractive summarization phase as a preprocessing strategy to improve the encoder-decoder architecture's learning capacity and minimize the input text size. For extractive summarization, which compares text sentences by comparing their GloVe embeddings to create sentence vectors, the PageRank approach is used. The ROUGE-1 score is used to evaluate the suggested strategy, and it received a score of 67.6 for extractive summarization and a score of 59.6 for abstractive summarising. The usefulness of the LSTM encoder-decoder with attention and the extractive preprocessing phase using PageRank is demonstrated by these results.The paper provides a comprehensive solution to the problem of automatic highlighting from texts, combining extractive and abstractive summarising methods. The performance of the summarization is enhanced by carefully applying the LSTM encoder-decoder and incorporating the PageRank approach.

M. Jang et.al[13], introduce an unsupervised extractive summarization model, LFIP-SUM, that does not require parameter training and delivers performance that is on par with supervised models based on deep learning. To obtain a deep representation of documents, the model makes use of pre-trained sentence vectors, positional encoding, self-attention, and PCA. Based on the information preservation ratio, it dynamically decides how many summary sentences to use. It also calculates the importance value for each original sentence. An ensemble model is built utilizing various pre-trained sentence embedding vectors after selecting summary sentences through an ILP issue.The proposed LFIP-SUM model has a number of benefits. First off, since there is no need for model training, labelled training data creation takes less time and money. For users with low processing resources and in industrial settings,

this is especially advantageous. Second, the model uses the information preservation ratio to dynamically decide the amount of summary phrases, providing a more understandable and interpretable hyper-parameter. The results of the trials demonstrate that 80–90 percent of the intrinsic content in most documents may be preserved while being condensed into three sentences. Finally, as the LFIP-SUM model can jointly use any sentence embedding model regardless of size or language, it can be used for low-resource languages without human-labeled data. The paper does, however, admit several limitations and offers some ideas for further research. The LFIP-SUM model mainly relies on pre-trained sentence embedding techniques, and to better capture the fundamental meaning of a sentence, advances in sentence representation are required. To increase the usefulness of the method, information-preserving computational complexity reduction approaches should also be investigated. The study advises taking into account the whole sentence similarity score when calculating sentence importance and choosing summaries, as well as addressing the laborious calculations needed to minimize the similarity score.In conclusion, the LFIP-SUM model offers a learning-free method for performing unsupervised extractive summarization, providing useful benefits and outperforming supervised models that rely on deep learning. To further improve the model, future work will focus on tackling computational complexity while retaining information and enhancing sentence representation techniques.

P. Mahalakshmi et.al[14], address the difficulties associated with text summarization and automated information retrieval in NLP. The article introduces a brand-new deep learning-based model that combines methods for text summarization, template generation, and information retrieval. The bidirectional long short-term memory (BiLSTM) technique is used at the outset of the model to retrieve textual material. Each word in a phrase is taken into account by the BiLSTM, which extracts information and embeds it in a semantic vector. The deep belief network (DBN) model, which is employed in the template creation process, is subsequently used to use the recovered textual data. To create summaries of the textual content, the DBN model is used as a text summarising tool. For visual entities found in the photos, the model also generates image descriptions. Giga word corpus and DUC corpus studies were carried out to assess the performance of the suggested technique. The experimental findings demonstrated that, in terms of precision, recall, and F-score, the DBN model performed better than other comparative techniques. Using the BLEU metric, the generated image captions were assessed and contrasted with a predefined set of captions for the photos. Information retrieval,

template generation, and text summarising are the three main processes that make up the DL-based information retrieval and text summarization paradigm that is presented in this study. Using the BiLSTM method, which uses each word in a phrase to extract data and produce a semantic vector, textual data is retrieved. The DBN model from DL is used in the template creation process to produce text summaries. The model also has a feature that generates image captions.Gigaword and DUC corpora are used to assess how well the suggested technique performs. The experimental results show that, when evaluated using the BLEU measure, the DBN technique beat other compared methods in terms of precision, recall, F-score, and image captions. Future hyperparameter tuning techniques can be used to further enhance the DBN model's performance.

The research introduces a unique DL-based strategy for text summarization and information retrieval that performs better than current techniques overall. The DBN model's application and the analysis of image captions increase the research's originality. The DBN model can be improved in the future using hyperparameter tuning methods.

I. S. Kalytyuk et.al[15],demonstrates the value of social networks as a source of information in the current digital era. Social networks have drawn academics from a wide range of disciplines due to their millions of users and the wide variety of data available.

The study explores various approaches to social media data collection, including web page parsers, API resources, and pre-built monitoring systems. The authors stress the advantages of creating custom software solutions that can be utilized for many activities, as opposed to off-the-shelf software solutions, which are frequently centered on brand/company mentions and promotion. Since each social media network has a different API, the article focuses on how collection modules are implemented in Python. It gives an explanation of the tools designed especially to gather information from websites like VK, YouTube, and OK. Overall,it emphasizes the value of social media data collecting and the benefits of creating unique Python modules for this purpose, allowing researchers to obtain important data from social networks.

Chapter 3

Methodology

YouTube Transcript Summarizer is a website to automatically generates concise summaries of YouTube video transcripts. It utilizes two machine learning models to summarize the text and integrates with the YouTube Data API V3 to fetch the video data. The summary generated by both the models is then used to find the best summary and that is given to the user.

3.1 Algorithm

The algorithm includes:

- Step 1:Load the dataset.
- Step 2:Data Pre-processing.
- Step 3:Model parameter Turning
- Step 4:Building and Training the Models.
- Step 5:Testing the Model.
- Step 6:Generate the summary.
- Step 7:Compare the two machine learning models generated summaries and produce the best one.
- Step 8:Display the contents on UI.

3.2 System Architecture

Text summarization is a valuable technique that condenses a lengthy document or a series of texts into a shorter, more concise version while retaining the key information and main ideas. There are two primary types of text summarization: extractive and abstractive. Extractive

summarization involves selecting and combining essential sentences from the original text, while abstractive summarization generates summaries by interpreting and rephrasing the source material in a more human-like manner.By leveraging natural language processing and machine learning algorithms, text summarization algorithms analyze and comprehend the content, extracting crucial sentences or phrases to create a coherent summary. In the proposed system the summary of the YouTube video is generated using Machine Learning models that is the Seq2Seq model and Transformer-based model. The relationships, limitations, and boundaries between components of the software system are abstracted using the system architecture design. It is a crucial tool because it gives a comprehensive picture of how the software system has been physically deployed. This system gives the best summary generated among the two models.

The data set used is news sumary dataset which is then preprocessed through various steps like removal of non-alphabetic characters, escape,special characters, using spaCy .pipe() method to speed-up the cleaning process. Batch the data points into 5000 and run for faster preprocessing, split the data to train and test data set, tokenize the text to get the vocab count,prepare a tokenizer for reviews on training data, rare words and most common words analysis, then convert text sequences into integer sequences. The model is trained and built. The user enters the YouTube video URL in the user-friendly interface. The front end of the YouTube Transcript Summarizer is created using Streamlit. The application uses the YouTube Data API V3 to retrieve the required data, including the video transcript, after that the video transcripts are fetched and preprocessed then it is given to the two models Seq2Seq and Transformer-based model. And the summary is generated and the cosine similarity between the summaries is taken to determine the best summary and returns it to the user interface. Where it enables the user to enter their email id to receive the summary via mail.

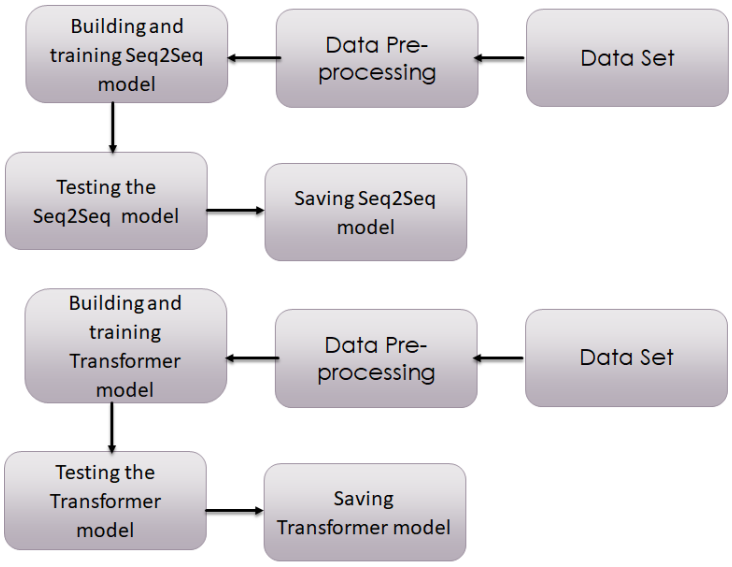


Figure 3.1: Training Seq2Seq and Transformer-based model

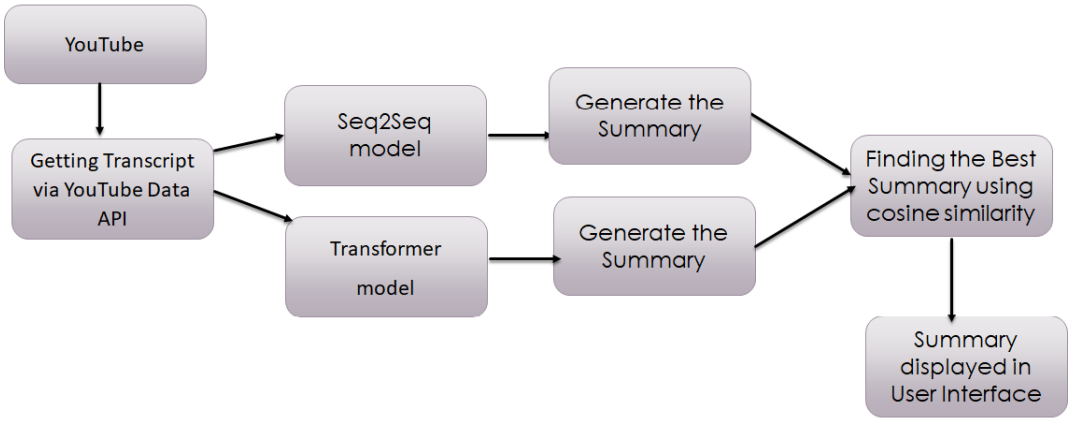
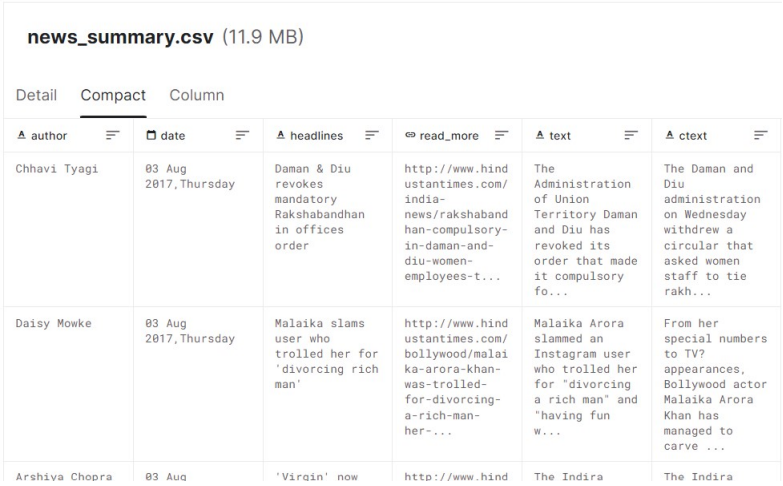


Figure 3.2: System Architecture

3.2.1 Dataset

News Summay dataset is used in this project.This data set is used to train and evaluate models for generating summaries. The dataset consists of 4515 examples and contains the Author's name, Headlines, Url of Article, Short text, and Complete Article. As news articles include a wide variety of words and syntax, that helps to learn more.



news_summary.csv (11.9 MB)

Detail Compact Column

author	date	headlines	read_more	text	ctext
Chhavi Tyagi	03 Aug 2017,Thursday	Daman & Diu revokes mandatory Rakshabandhan in offices order	http://www.hindustantimes.com/india-news/rakshabandhan-compulsory-in-daman-and-diu-women-employees-t...	The Administration of Union Territory Daman and Diu has revoked its order that made it compulsory fo...	The Daman and Diu administration on Wednesday withdrew a circular that asked women staff to tie rakh...
Daisy Mowke	03 Aug 2017,Thursday	Malaika slams user who trolled her for 'divorcing rich man'	http://www.hindustantimes.com/bollywood/malaika-arora-khan-was-trolled-for-divorcing-a-rich-man-her-...	Malaika Arora slammed an Instagram user who trolled her for "divorcing a rich man" and "having fun w...	From her special numbers to TV? appearances, Bollywood actor Malaika Arora Khan has managed to carve ...
Arshiya Chopra	03 Aug	'Virgin' now	http://www.hind	The Indira	The Indira

Figure 3.3: news summary dataset

3.2.2 Data Pre-processing

A critical step in the machine learning process is data preprocessing since the quality of the data and the information that can be gleaned from it have a direct bearing on how well the model can learn. As a result, it is crucial to preprocess the data before feeding it to the model. Preparing raw data to be used with a deep learning model is known as data preparation. It is both the first and most important step in developing a deep learning model. The format of the data in Deep Learning projects must be correct in order to get better results from the applied model.

The data set used is news sumary dataset. In this step, the input text data is preprocessed through various steps ,removal of non-alphabetic characters, escape,special characters, using spaCy .pipe() method to speed-up the cleaning process. Batch the data points into 5000 and run for faster preprocessing, split the data to train and test data set, tokenize the text to get the vocab count,prepare a tokenizer for reviews on training data, rare words and most common words analysis, then convert text sequences into integer sequences .removing non-alphabetic characters,spaCy .pipe() method to speed-up the cleaning process,tokenization of text representation and convert into integer sequences to get the vocab count, stemming, and the elimination of stop words. Data should be cleaned up and preprocessed to remove noise and unnecessary information.

3.2.3 Building and Training the Model

Text summary is a useful approach that reduces the amount of information in a long text or collection of texts while keeping the essential details and primary points.For generating summary two deep learning models are used one is Seq2Seq Model and another model is Transformer-based model . The Seq2Seq Model is a model that takes a stream of sentences as an input and outputs another stream of sentences . Use the Abstractive Text Summarization technique to create models that predict the summary.Seq2Seq models is the Encoder Decoder architecture.The first encoder layer is an embedding layer. To transform the numerical input data into a dense vector, it takes a vector that represents a word and pass its output to the next layer.Followed by three layer LSTM.The docoder is set up using encoder states as initial state. Followed by decoder embedding layer and a LSTM layer and dense layer the softmax activation function is used .

Sequence to Sequence models is a special class of Recurrent Neural Network architectures that are typically used (but are not restricted) to solve complex Language problems like Machine Translation, Question Answering, creating Chatbots, Text Summarization, etc The model consists of two main components:Encoder and Decoder.The encoder consisting of RNN takes the sequence as an input and generates final embedding at the end of the sequence. This is send to the Decoder which then uses it to predict a sequence and after every successive prediction it uses the previous hidden state to predict the next instance of sequence.

Data consists of pair of input sequences are taken for training,and necessary preprocessing done and tokenised,define the architecture of the model it typically consists of an encoder and a decoder. After processing the input sequence, the encoder creates a context vector with a fixed length. The decoder uses the context vector to produce the output in a step-by-step fashion. Utilise a deep learning framework like TensorFlow or PyTorch to create the seq2seq model. Define the encoder and decoder components. These RNNs can be LSTM or GRU units, for example. To create the complete seq2seq model, connect the encoder and decoder.Set up the hyperparameters and training loop.To get the context vector, feed the input sequences through the encoder. Set the context vector and the target sequence's start token as the decoder's initial values. The created output token is passed as input back into the decoder. Prepare the evaluation data, which should comprise the input sequences needed to gauge the model's capacity for inference. To discover the ideal configuration, experiment with various hyperparameters such

as learning rate, batch size, and model architecture. To judge the effectiveness of the model, keep an eye on the training loss and evaluation metrics. To increase the model's precision and convergence, alter the hyperparameters in accordance with the outcomes observed.

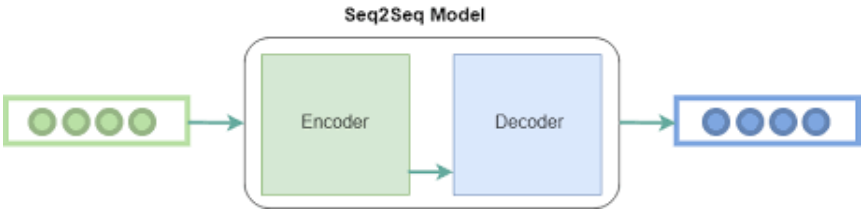


Figure 3.4: Seq2Seq model

Long Short-Term Memory(LSTM)networks have been widely used in text summarization tasks, both in extractive and abstractive summarization approaches. Here Seq2Seq2 LSTM modeling is used, it includes combining two recurrent neural networks (RNNs)—an encoder network and a decoder network—with LSTM units.LSTMs are a type of recurrent neural network (RNN) that can capture long-range dependencies and sequential patterns in the input data, making them well-suited for modeling text sequences.

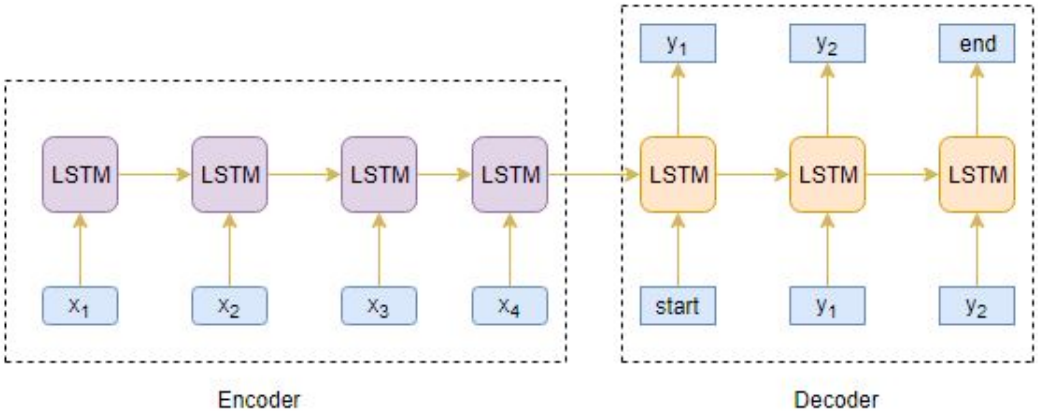


Figure 3.5: LSTM

Transformer-based Model: have become an effective tool in natural language processing (NLP), and they have made great progress in this field. Transformers are deep learning models that rely on the attention mechanism to grasp long-range relations in data sequences. In a variety of NLP tasks, such as machine translation, text classification, named entity recognition, sentiment analysis, and text summarization, these models have attained cutting-edge performance. Transformers are a specific kind of neural network design that is well suited for tasks involving natural language processing because they can recognize long-range

dependencies in sequential input. Employing a pre-trained language model to encode the input text into a fixed-length vector representation.

The transformer-based model for text summarization is a variant of the transformer architecture specifically designed to tackle the task of generating abstractive summaries from input text. It employs the same underlying principles of self-attention and position-wise feed-forward layers but with some modifications to adapt it to the summarization task.

Hugging Face, an open-source community that offers a variety of pre-trained transformer-based models and tools has significantly advanced the field of natural language processing (NLP) . For using transformer-based models in NLP, the transformers library offers a user-friendly interface and pre-trained models. It offers a wide range of features, including access to a model hub that houses a sizable library of pre-trained models, tokenization utilities, training and fine-tuning capabilities, and model architecture implementations.

An encoder-decoder structure is the typical component of the transformer-based text summarization approach. In order to capture the context, the encoder analyses the input text and creates a representation of the input sequence. By paying attention to the pertinent areas of the input, the decoder constructs the summary using the encoder's representation.The input text is tokenized and incorporated into dense vector representations during the encoding stage. The encoder, which comprises several stacked transformer layers, is then fed these embeddings. A position-wise feed-forward neural network and a multi-head self-attention mechanism make up each transformer layer. In order to capture the contextual relationships between words, the model can pay attention to different areas of the input text using the self-attention process when creating the representation. Each point is independently subjected to non-linear changes by the feed-forward network. In the decoding phase, the model generates the summary autoregressively, attending to the encoded representation produced by the encoder. At each step, the decoder takes the previously generated summary tokens as input and attends to the encoder's output to capture the relevant information. It generates the next token in the summary using the same transformer layer structure as the encoder.

A dataset of paired source documents and their related summaries is needed to train the transformer-based summarization model. A sequence-to-sequence framework is used to train the model, and the encoder-decoder structure is optimized to produce precise and coherent summaries.

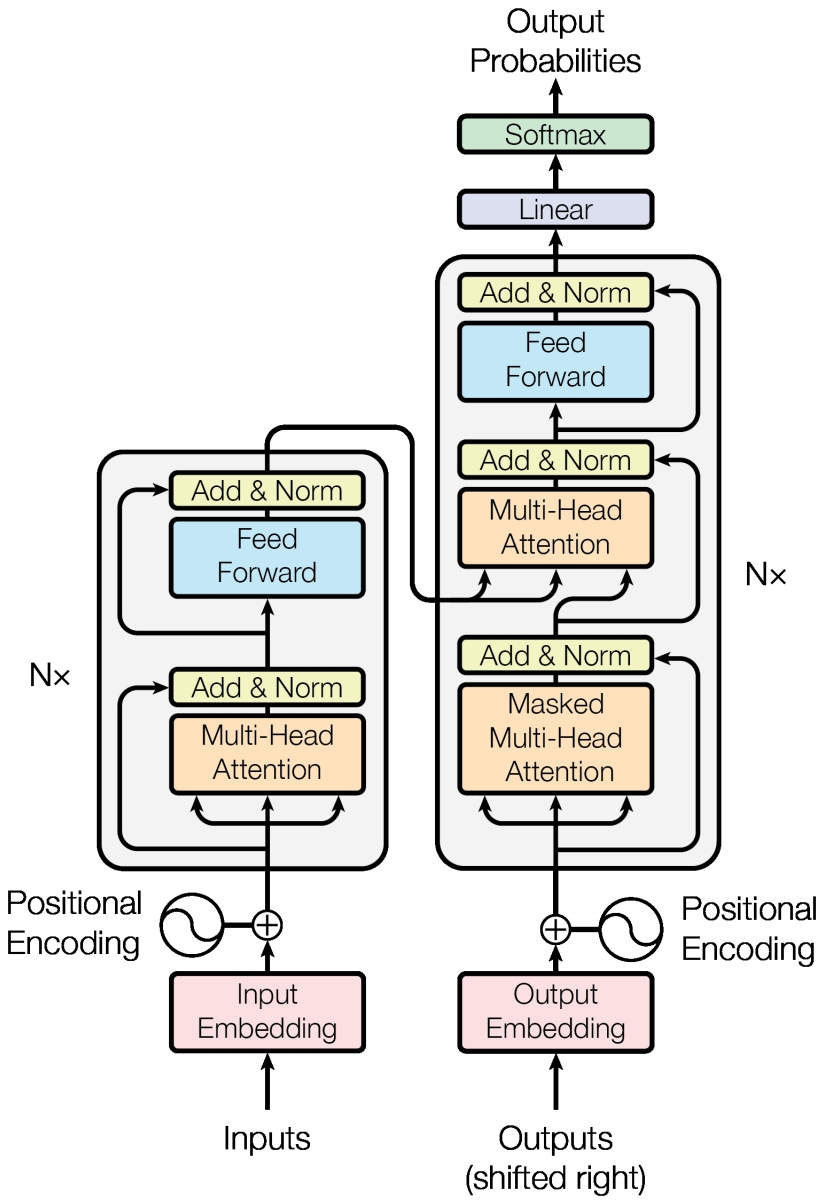


Figure 3.6: Transformer Model

3.2.4 Testing the Model

The News Summary data set is used for training and testing the model. It is a popular dataset used for text summarization, it consists of news articles and their corresponding summaries. The dataset consists of 4515 examples and contains Author's name, Headlines, Url of the Article, Short text, and Complete Article. The 10 percent of the dataset for testing. For training, the remaining 90 percent of the dataset will be used from the 15,129,281 total trainable parameters.From the news summary dataset Summaries and Text fields of the dataset is taken for training and testing.

	text	summary
0	saurav kant an alumnus of upgrad and iiit-b pg...	sostok _START_ upgrad learner switches to care...
1	kunal shah credit card bill payment platform c...	sostok _START_ delhi techie wins free food fro...

Figure 3.7: Dataset

3.2.5 Software Requirement and Specifications

The software used for the project includes:-

- Python
- Pycharm
- Streamlit

3.2.6 Software Description

- **Python**

  Python is an object-oriented programming language that was developed in 1989 by Guido Rossum. Python is a popular high-level programming language known for its simplicity, readability, and versatility. It is excellent for quick prototyping of complex applications. It supports a number of operating system functions and libraries and can be converted to C or C ++. Python is a computer language that is used by numerous organizations, including NASA, Google, YouTube, and Bit Torrent. In cutting-edge fields like artificial intelligence, natural language processing, neural networks, and other computer sciences, Python programming is widely employed. The Python Software Foundation currently has authority over Guido van Rossum's intricate artificial language, which he created in the late 1980s. It comes from his ABC language, which he co-created at the beginning of his professional life. Games, graphical user interfaces (GUIs), and other types of software can all be made using the complicated programming language Python. Python scripts can be read and written like how normal English statements are read and written. They must therefore be processed because they are not written in a computer language. before being run by a system, by Python code. A basic language is Python. This suggests that the interpreter evaluates the code and transforms it into machine-readable bytecode when the program is executed. Python is an object-oriented programming language that shows users how to take care of and work with objects or data structures so that they can

create and run programs. Python has everything. When they fall short of expectations and are replaced by more capable languages, languages die and become extinct. Python is a dependable and popular programming language.

- **PyCharm**

  PyCharm is an Integrated Development Environment (IDE) used for computer programming particularly designed for Python. A wide range of tools and capabilities provided by PyCharm increase productivity and simplify the Python development process. Because of the clear and user-friendly interface it offers, managing and navigating projects is simple for developers.PyCharm provides sophisticated code-editing features including intelligent code completion, code refactoring, and syntax highlighting that help find problems and raise the quality of the code. Additionally, the IDE interfaces with version control tools like Git, enabling seamless code management and collaboration. PyCharm provides strong testing and debugging capabilities that help developers quickly locate and fix problems. Additionally, it supports a wide range of frameworks and libraries commonly used in Python development, such as Django, Flask, and NumPy, with dedicated project templates and code generation tools.PyCharm's extensive plugin ecosystem allows developers to customize and extend the IDE to suit their specific needs. With its robust set of features and developer-friendly environment, PyCharm has become a go-to choice for Python developers looking for a productive and efficient development environment.

- **Streamlit**

  Streamlit is a free and open-source framework to rapidly build and share beautiful machine learning and data science web apps. Streamlit's simplicity of use is one of its key benefits. With just a few lines of code, users may build intuitive and interactive applications thanks to the straightforward API it offers. This makes it the perfect tool for prototyping large apps or tiny data apps.Streamlit is a newer framework that is designed specifically for data-driven web applications. It offers a straightforward and declarative syntax that allows developers to quickly prototype and share their data-driven applications. Major Python libraries like scikit-learn, Keras, PyTorch, SymPy (latex), NumPy, pandas, and Matplotlib are all compatible with it. Callbacks are not required with Streamlit since widgets are regarded as variables. Computation pipelines are made

easier and faster by data caching. Behind the scenes, Streamlit manages the challenges of web development and dynamically updates the user experience when the underlying code is modified. The interactive elements it offers, such as sliders, dropdowns, and buttons, let users explore and engage with data in real-time. With its simplicity, speed, and versatility, Streamlit has gained popularity as a valuable tool for building and sharing data-focused web applications. Using sidebars, Streamlit enables to show model outputs and descriptive text, view data and model performance, and change model inputs directly through the user interface.

3.2.7 Hardware and experimental environment

The hardware used for the experiments includes Windows 11 Pro OS, 64-bit operating system, x64-based processor, Intel(R) Core(TM) i5-1155G7 CPU @ 2.50GHz, 8 GB RAM. The experimental environment was prepared by using Python 3.7 programming language. The framework used is Keras with TensorFlow.

Chapter 4

Result and Discussion

YouTube Transcript Summarizer for generating a summary is beneficial for a wide range of people, including: Educators and academic, institutions, Students, Researchers, and publishers in their works. The Seq2Seq model is a model that takes a stream of sentences as an input and outputs another stream of sentences. Text summarization using Seq2Seq models and the Transformer-based model has proven to be a highly effective and efficient approach. The combination of Seq2Seq models, with their encoder-decoder architecture, and the Transformer-based model, with its extensive pre-trained models and tools, offers a powerful solution for generating high-quality summaries from input text. From the generated summary calculate TF-IDF vectors for the summaries and compute the cosine similarity it compares the cosine similarities to determine the best summary and it is given to the user.

4.1 Training and Validation Results

Testing ensures that the system is error-free based on criteria that are anticipated by the user or by the organization. A system may have high-end or low-end performance based on the environment in which it operates. The News Summary data set is used for training and testing the model. It is a popular dataset used for text summarization, it consists of news articles and their corresponding summaries. The 10 percent of the dataset for testing. For training, the remaining 90 percent of the dataset will be used. 15,129,281 is the total trainable params. From the generated summary calculate TF-IDF vectors for the summaries and compute the cosine similarity. Finally, it compares the cosine similarities to determine the best summary and returns it.

Cosine similarity is a popular metric to measure how similar two word/sentence vectors are. It can be used to assess how comparable text embeddings or representations created by various models are to one another.It is used to compare sentences because the system will be representing the sentences as a collection of vectors.Both the models Seq2Seq and

Transformer-based models create summaries for a collection of input documents or texts .Convert each summary into a numerical vector representation. Calculate the cosine similarity between the reference and generated summaries' embeddings. A value close to 1 suggests great similarity, whereas a value close to -1 indicates dissimilarity, with the cosine similarity score having a range from -1 to 1.Compare the cosine similarity scores of both models. A greater performance in capturing the essence of the original text is indicated by higher cosine similarity scores, which indicate that the model's generated summaries are more similar to the reference summaries.In this system it is found that Transformer-based model is generating better summaries than Seq2Seq model. Cosine similarity might not be enough to assess a text summarization model's overall quality or usefulness. ROUGE scores should also be taken into account.

4.1.1 Training and Validation loss Graphs

Line Plot

A line plot can be used to visualize the training and testing accuracy Data points connected by straight lines are shown in a line plot, sometimes referred to as a line chart or a line graph. It is frequently used to depict a variable's trend or progression over a continuous range of time or space. The model's loss on the training data is shown in the training loss graph, and its loss on a different set of testing data is shown in the validation loss graph.

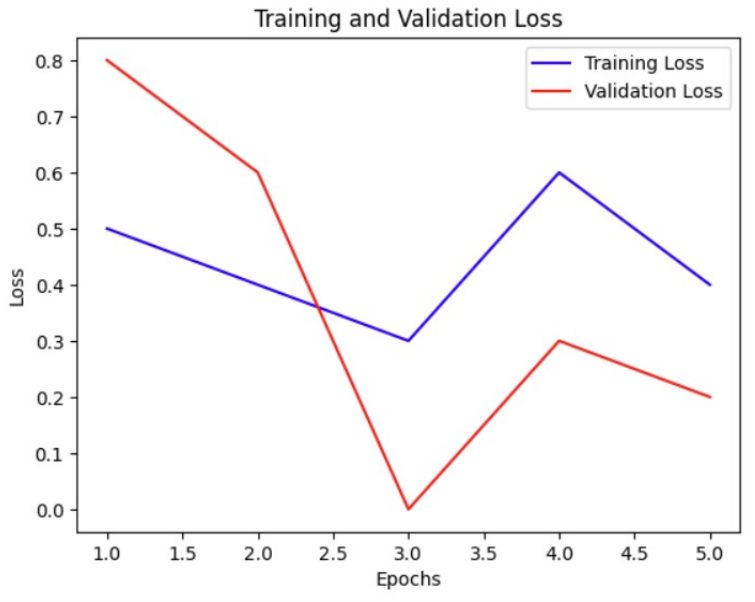


Figure 4.1: Training and Validation loss of Seq2Seq model

4.1.2 Graph of Comparison of the models used

Bar Plot A bar plot also called a bar chart, is a style of data visualization in which data values are represented by rectangular bars. By showing the values of a variable on the vertical axis and the categories or groups on the horizontal axis, it is frequently used to compare categorical data or distinct groups. Here the bar plot is used to compare the Seq2Seq and Transformer-based model.

An established set of metrics for assessing the effectiveness of text summarization systems is the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) score. ROUGE uses a variety of metrics, including n-gram co-occurrence, sentence-level similarity, and length-based measurements, to calculate the overlap between the generated summary and the reference summary.

ROUGE scores are typically reported as F1 scores, which combine precision and recall. The scores range from 0 to 1, with higher values indicating better summarization quality. ROUGE-1, ROUGE-2, and ROUGE-L are specific variants of the ROUGE.

- ROUGE-1: Unigrams, or single words, are the main focus in this ROUGE variance. ROUGE-1 calculates the amount of overlap between the generated summary and the reference summary in terms of unigrams. Based on the number of shared unigrams, precision, recall, and F1 score are determined.

- ROUGE-2: This variation takes into account bigrams, which are groups of related words. The bigram overlap between the generated and reference summaries is measured by ROUGE-2. Based on the number of shared bigrams, precision, recall, and F1 score are calculated.

- The ”L” in ROUGE-L refers to the ”Longest Common Subsequence.” ROUGE-L determines the longest common subsequence between the generated and reference summaries rather than concentrating on n-grams.N-grams are used to analyse sequences of tokens rather than single tokens in order to extract the local or contextual information from a text.In contrast to ROUGE-1 and ROUGE-2, which concentrate on n-grams (unigrams and bigrams), ROUGE-L adopts a more thorough strategy by taking the longest common subsequence into account. In addition to measuring fluency and coherence, it makes it possible to identify similarities that go beyond exact n-gram

matches. It measures the shared subsequence's length while taking word similarity and orders into account. ROUGE-L takes sentence structure into account and can estimate fluency and coherence.

From the bar graph, it is clear that the Transformer-based model produces a better summary, but at sometimes it may vary based on the input text.

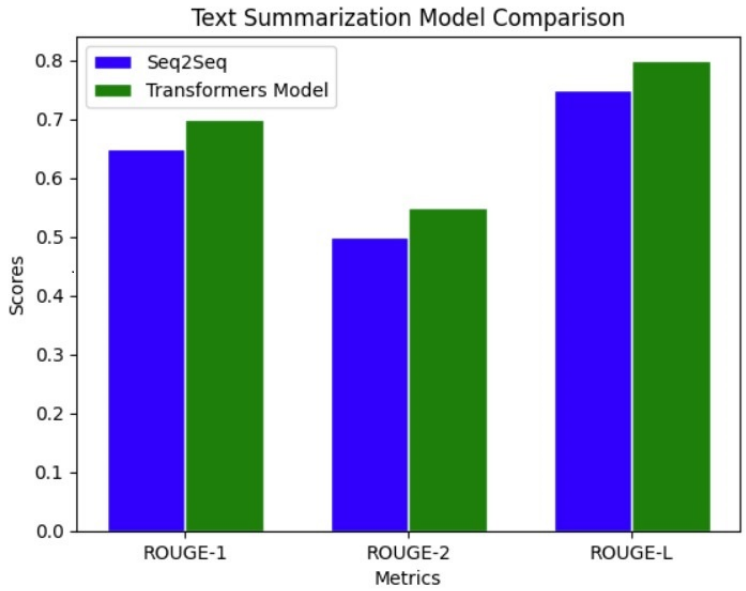


Figure 4.2: Comparison of Seq2Seq and Transformer-based model

Chapter 5

Conclusion

YouTube Transcript Summarizer using Seq2Seq models and the Transformer-based model has proven to be a powerful and effective approach. Seq2Seq models with their encoder-decoder architecture, implemented with LSTM, provide a framework for generating abstractive summaries from input text. On the other hand, the transformer-based model has revolutionized text summarization and other aspects of natural language processing. The transformer-based model can efficiently detect word dependencies even at large distances in the input sequence because of its self-attention mechanism. The transformer-based model is a good choice for text summarization because it can model long-range dependencies, which is vital for extracting key details from the input text and comprehending context. Modern results for text summarising using transformer-based models have produced excellent abstractive summaries.

Transformer and seq2seq models each have strengths and weaknesses. Transformer-based models excel in modeling complicated relationships and capturing long-range dependencies, whereas seq2seq models can be simpler and quicker to train, especially for smaller datasets. Transformers-based also need more computing power because their parameters are greater. It provides thousands of pre-trained models, and APIs to quickly download and use those pre-trained models. In conclusion, while seq2seq models have long been a preferred option for text summarization, the transformer-based models have proven to be a potent substitute that produces impressive results when producing abstractive summaries. The transformer-based has advanced the area of text summarization and created new opportunities for producing succinct and insightful summaries from big text volumes thanks to its capacity to model long-range dependencies and capture context. The cosine similarity between the summaries is taken to determine the best summary and returns it. The choice between the Seq2Seq models and the Transformer-based depends on the specific requirements, available resources, and the desired level of summarization performance. Both approaches have demonstrated their value and have been instrumental in advancing the field of text summarization.

5.1 Future Enhancement

In the future, the system can be incorporated with more advanced analytics capabilities to gain deeper insights from data. The field of text summarization continues to evolve, and several future enhancements are being explored to improve the quality, efficiency, and applicability of text summarization systems.

The future enhancements for the YouTube Transcript Summarizer could include: Improving summarization accuracy and improving the deep learning models used for summarization to provide summaries that are more precise and succinct. Multilingual assistance is enhancing the service to support more languages, enabling users to summarise YouTube video transcripts in various languages. Options for fine-tuning that is giving consumers the chance to personalize the summarising process in accordance with their preferences. This can contain choices to modify the summary's length, regulate the level of detail, or give certain content elements more importance. Enhancing the front-end application's user interface will improve user experience and make it more intuitive and user-friendly. This may entail including features like real-time preview, interactive options for customizing the summary, and improved summarizations of the information.

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Appendix

Screenshots

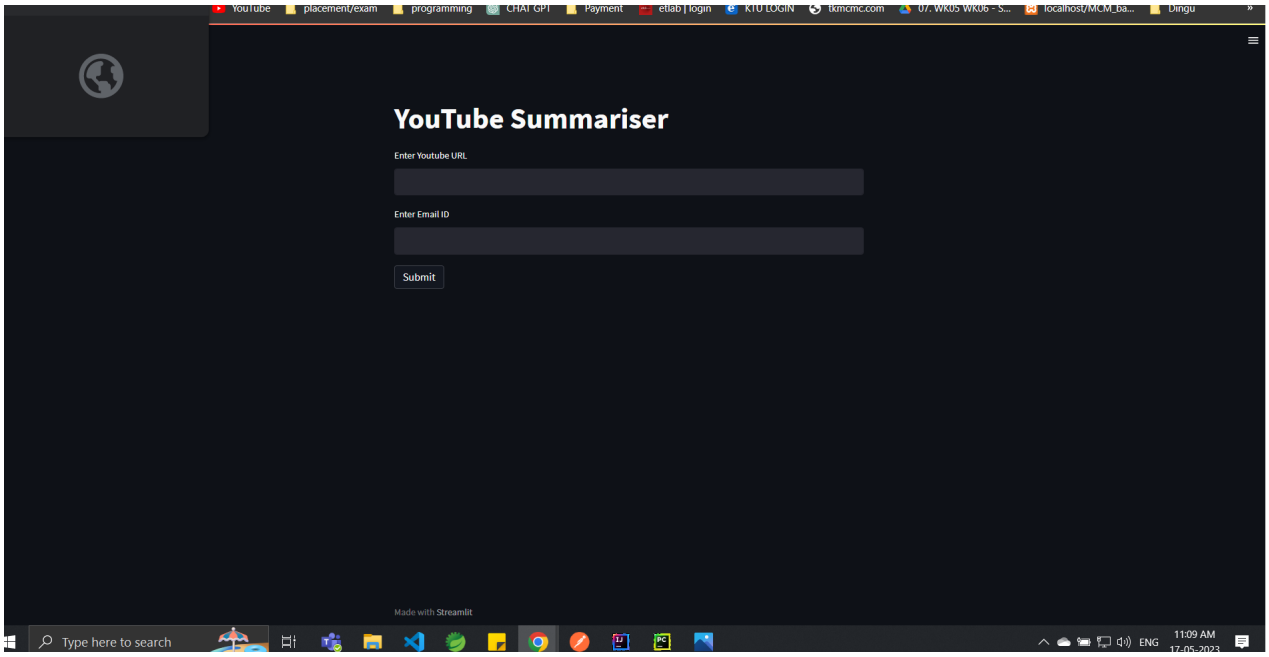

Figure A.1: Main Page

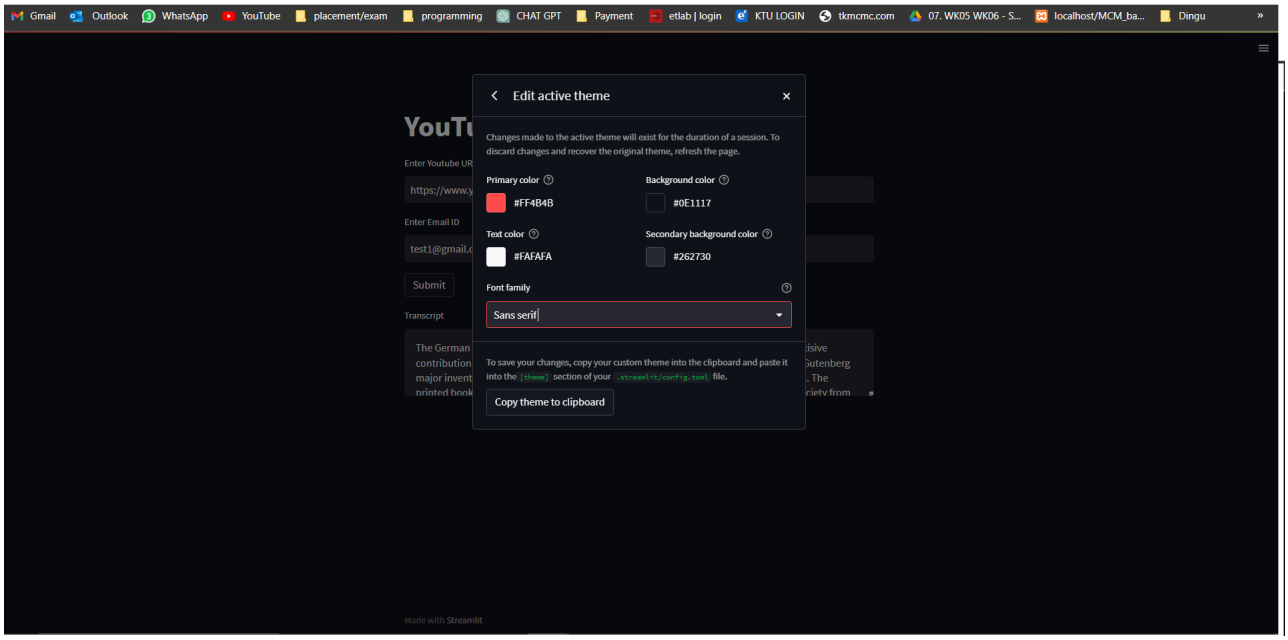

Figure A.2: Edit Themes

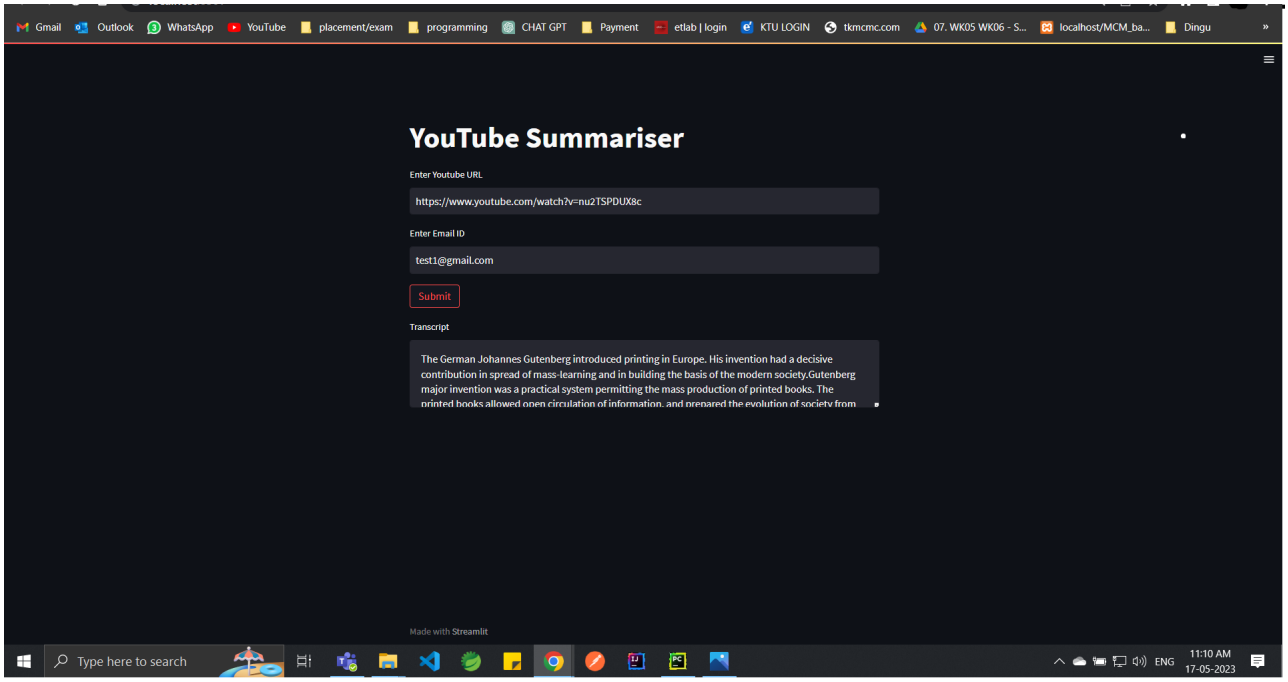

Figure A.3: Summary as output