TRANSFORMER-BASED NEURAL NETWORK FOR EXTRACTIVE TEXT SUMMARIZATION

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BONAFIDE CERTIFICATE

Certified that this project report **“TRANSFORMER-BASED NEURAL NETWORK FOR EXTRACTIVE TEXT SUMMARIZATION”** is the bonafide work of “MERRIN SANCIA S (REG. NO: URK20AI1050)**”** who carried out the project work under my supervision.

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ABSTRACT

In the era of information overload, the ability to distil large volumes of text into concise summaries is invaluable. This project explores the application of Transformer Neural Networks, a cutting-edge deep learning architecture, for the task of text summarization. Transformers have revolutionized natural language processing tasks due to their attention mechanisms, allowing them to capture complex relationships within the input sequence. The objective of this project is to develop and evaluate a Transformer-based model specifically tailored for text summarization tasks. By leveraging the power of self-attention mechanisms, our model aims to generate coherent and informative summaries from input documents of varying lengths. Key components of our approach include pre-processing techniques to handle diverse text formats, fine-tuning Transformer architectures for summarization, and evaluation metrics to assess the quality of generated summaries. We will also explore strategies for dealing with long documents and maintaining the fidelity of extracted information. Through experimentation and comparative analysis with existing text summarization methods, we aim to demonstrate the efficacy and superiority of Transformer-based approaches in producing high-quality summaries across different domains and datasets. This project contributes to advancing the state-of-the-art in text summarization techniques, with potential applications in information retrieval, document summarization, and automated content generation. Ultimately, the development of efficient and accurate text summarization models holds promise for enhancing productivity and decision-making in various fields reliant on textual data.

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CHAPTER 1

INTRODUCTION

Text summarization is a vital task in natural language processing (NLP), aiming to condense a given text into a shorter version while preserving its essential information and meaning. It facilitates efficient comprehension by providing readers with a concise overview of the main points without requiring them to read through the entire document. There are two primary approaches to text summarization: extractive and abstractive summarization. In extractive summarization, key sentences or phrases are selected and extracted directly from the original text, usually those containing the most critical information or representing the main ideas. These extracted segments are then concatenated to form the summary. Conversely, abstractive summarization involves interpreting and paraphrasing the original text to generate a summary. This method requires a deeper understanding of the text and the ability to generate human-like language.

Text summarization finds applications across various domains. News agencies utilize it to automatically generate brief summaries of articles, enabling readers to quickly grasp the key information from numerous news stories. In academic and legal research, document summarization aids researchers and professionals in identifying relevant documents and extracting essential information from lengthy reports or articles. Social media platforms leverage summarization techniques to condense lengthy posts or discussions into shorter summaries, facilitating user engagement with relevant content. Additionally, search engines generate snippets from web pages to provide users with a preview of the content, employing text summarization algorithms.

Text summarization techniques rely on a range of NLP methods, including natural language understanding (NLU) to comprehend the meaning and context of the text, statistical analysis to identify important content based on word, phrase, or sentence frequency, and machine learning algorithms trained on large text corpora to generate summaries. Attention mechanisms are also employed to focus on critical parts of the input text when generating summaries, particularly in abstractive summarization models.

Despite significant progress in text summarization, challenges persist in accurately capturing the nuances and complexities of human language. Researchers continue to explore novel approaches to enhance the quality and coherence of generated summaries, aiming to bridge the gap between machine-generated summaries and human-written ones.

1.1 TRANSFORMER NEURAL NETWORK FOR EXTRACTIVE TEST SUMMARIZATION

Natural Language Processing (NLP) has witnessed remarkable advancements in recent years, fueled by the transformative power of deep learning techniques. One particularly influential paradigm within NLP is text summarization, a task that involves condensing lengthy documents into concise, coherent summaries while retaining key information. Traditional approaches often struggle with the dynamic nature of language, making it imperative to explore innovative methodologies. In this project, we delve into the cutting-edge realm of meta learning applied to Transformer neural networks for text summarization. The Transformer architecture, initially introduced by Vaswani et al. in 2017, has demonstrated unparalleled capabilities in capturing long-range dependencies in sequences, making it a natural candidate for NLP tasks. However, the adaptation of meta learning - a paradigm where models learn to learn introduces a novel dimension to the existing state-of-the-art. The motivation behind employing a meta learning approach lies in addressing the challenges associated with traditional training paradigms for NLP tasks, especially text summarization. Conventional models often require extensive labeled datasets for training, limiting their ability to adapt to diverse and unseen domains effectively.

Meta learning, by contrast, equips models with the capacity to generalize knowledge from a broad array of tasks, fostering improved performance on new, unseen tasks. Explore Meta Learning Frameworks - Investigate various meta learning frameworks, emphasizing their suitability for the unique characteristics of text summarization in NLP. Enhance Adaptability - Develop a Transformer-based neural network that employs meta learning to enhance its adaptability across different domains and textual styles. Optimize Summarization Quality - Assess the impact of the meta learning approach on the quality and coherence of generated summaries, focusing on key metrics such as ROUGE scores and semantic consistency. Benchmark Against Baselines - Compare the proposed meta learning approach against traditional summarization models, showcasing its superiority in handling diverse text corpora. This project aims to contribute to the ongoing discourse on meta learning applications in NLP, specifically within the domain of text summarization. By leveraging the power of Transformer architectures and meta learning frameworks, we aspire to advance the state-of-the-art in automatic summarization techniques. The outcomes of this research have potential implications in various fields, including information retrieval, document understanding, and content generation. In essence, this project seeks to unravel the synergies between meta learning and Transformerbased neural networks for the betterment of text summarization in NLP, pushing the boundaries of what is achievable in automatic document condensation.

1.2 CHALLENGES IN TEXT SUMMARIZATION

Text summarization faces several challenges that span the spectrum of natural language processing (NLP). One of the most prominent hurdles lies in preserving the meaning and coherence of the original text, especially in abstractive summarization methods. Ensuring that the generated summary accurately captures the essence of the source material while maintaining readability is a complex task that requires a deep understanding of language nuances and context. Additionally, the variability in text types, ranging from news articles to scientific papers and social media posts, poses a challenge in developing universal summarization models that perform effectively across diverse domains. Scalability is another concern, particularly when summarizing large volumes of text, necessitating efficient algorithms and distributed computing techniques.

Multi-document summarization further complicates matters, requiring the synthesis of relevant information from multiple sources into a cohesive summary. Moreover, text summarization aims to address information overload by providing concise summaries, but ensuring relevance and neutrality remains a challenge, especially in combating bias and subjectivity inherent in the summarization process. Evaluation metrics also pose a challenge, as traditional metrics may not fully capture the quality of summaries, particularly in abstractive methods. Finally, domain specificity adds another layer of complexity, as summarization models trained on generic datasets may struggle to perform well in specialized domains. Overcoming these challenges requires interdisciplinary efforts, drawing on advancements in NLP, machine learning, linguistics, and domain-specific knowledge to improve the effectiveness and usability of text summarization systems across various applications.

1.3 MOTIVATION AND BACKGROUND

The motivation behind embarking on this project is deeply rooted in the contemporary challenge of information overload. In today's digitally interconnected world, individuals and organizations grapple with an overwhelming abundance of textual data from diverse sources such as news articles, research papers, social media updates, and business reports. This deluge of information often leads to information overload, making it increasingly difficult for users to sift through the vast volumes of text to extract relevant insights efficiently. As a result, there is a pressing need for automated text summarization techniques that can distill large bodies of text into concise summaries, enabling users to consume information more effectively and make informed decisions in a timely manner. Moreover, the motivation stems from the recognized inefficiencies inherent in existing text summarization methods. Traditional summarization approaches, whether extraction-based or abstractive, often exhibit limitations in terms of accuracy, coherence, and scalability. Extractive methods may overlook crucial contextual information, while abstractive methods may struggle with generating coherent and contextually relevant summaries. By leveraging the transformative potential of Transformer Neural Networks a cutting-edge deep learning architecture there is an opportunity to overcome these limitations and develop more effective summarization models capable of capturing the intricacies of textual data. Furthermore, the motivation is fueled by the remarkable advancements witnessed in the field of deep learning, particularly with the emergence of Transformer architectures. These architectures, which rely on self-attention mechanisms to capture long-range dependencies in input sequences, have demonstrated unprecedented performance improvements in a wide range of natural language processing tasks.

1.4 PROBLEM STATEMENT

The project, "Meta Learning Approach to Transformer Neural Network for Text Summarization in NLP," encompasses a comprehensive set of objectives aimed at advancing the capabilities of natural language processing (NLP) techniques, particularly within the domain of text summarization. One primary objective is the exploration and implementation of meta learning frameworks tailored to the nuances of text summarization tasks. This involves delving into methodologies that empower the model to glean insights from diverse summarization tasks, fostering an efficient adaptation to novel domains. A key facet of the project involves the development of a neural network architecture grounded in the Transformer model, specifically designed to excel in the intricacies of text summarization. The aim is to optimize the model's ability to capture contextual information effectively, facilitating the generation of coherent and informative summaries. The project also addresses the persistent challenge of adaptability and generalization in traditional summarization models. By evaluating the impact of the meta learning approach, the project seeks to mitigate the effects of domain shifts and reduce the necessity for extensive retraining when presented with new types of textual content.

This involves assessing the model's adaptability across diverse domains and linguistic styles. Another crucial objective revolves around the evaluation of summarization quality metrics. The project aims to assess the performance of the proposed meta learning approach against traditional models, utilizing established metrics such as ROUGE scores. The focus is on showcasing improvements in summarization quality, coherence, and informativeness. Furthermore, the project emphasizes the importance of reducing data dependency in training summarization models. By demonstrating a decrease in reliance on extensive labeled datasets, the project aims to highlight the model's ability to generalize knowledge effectively, ultimately contributing to resource efficiency. The practical applicability of the developed approach is a key consideration, encompassing areas such as information retrieval, content curation, and automated document analysis. The project aims to assess the potential impact of its outcomes in real-world scenarios, striving for solutions that are not only academically rigorous but also practically viable. Ultimately, the project aspires to contribute significantly to the state-of-the-art in text summarization within the NLP domain.

1.5 OBJECTIVE

The project, “Transformer Neural Network for Text Summarization in NLP," encompasses a comprehensive set of objectives aimed at advancing the capabilities of natural language processing (NLP) techniques, particularly within the domain of text summarization. One primary objective is the exploration and implementation of meta learning frameworks tailored to the nuances of text summarization tasks. This involves delving into methodologies that empower the model to glean insights from diverse summarization tasks, fostering an efficient adaptation to novel domains. A key facet of the project involves the development of a neural network architecture grounded in the Transformer model, specifically designed to excel in the intricacies of text summarization. The aim is to optimize the model's ability to capture contextual information effectively, facilitating the generation of coherent and informative summaries. The project also addresses the persistent challenge of adaptability and generalization in traditional summarization models. By evaluating the impact of the meta learning approach, the project seeks to mitigate the effects of domain shifts and reduce the necessity for extensive retraining when presented with new types of textual content. This involves assessing the model's adaptability across diverse domains and linguistic styles. Another crucial objective revolves around the evaluation of summarization quality metrics. The project aims to assess the performance of the proposed meta learning approach against traditional models, utilizing established metrics such as ROUGE scores. The focus is on showcasing improvements in summarization quality, coherence, and informativeness. Furthermore, the project emphasizes the importance of reducing data dependency in training summarization models. By demonstrating a decrease in reliance on extensive labeled datasets, the project aims to highlight the model's ability to generalize knowledge effectively, ultimately contributing to resource efficiency. The practical applicability of the developed approach is a key consideration, encompassing areas such as information retrieval, content curation, and automated document analysis. The project aims to assess the potential impact of its outcomes in real-world scenarios, striving for solutions that are not only academically rigorous but also practically viable. Ultimately, the project aspires to contribute significantly to the state-of-the-art in text summarization within the NLP domain. By pushing the boundaries of what is achievable and providing novel insights and methodologies, the project seeks to inform and shape future research endeavors in this dynamic and evolving field.

1.6 CHAPTER WISE SUMMARY

Chapter 1: Introduction The introduction chapter lays the groundwork for the project by highlighting the critical need for involvement for efficient models like transformer neural networks. It establishes the context, emphasizing the importance of summarizing the effective key points and introduces the project's objectives.

Chapter 2: Literature Survey In the literature survey chapter, an extensive review of existing literature is conducted, exploring various Text Summarization methods deployed in text analytics settings. It examines the strengths and weaknesses of traditional systems, identifies gaps in the literature, and introduces transformer neural network as a potential approach to enhance accuracy. Relevant studies and advancements in the field contribute to a comprehensive understanding of the current landscape.

Chapter 3: Proposed Methodology The proposed methodology chapter outlines the systematic approach taken to design and implement the transformer neural network for text summarization. It details the selection of text summarization modalities, the principles of transformer neural networks applied to text summing, and the overall architecture of the proposed solution. This chapter serves as a blueprint for the subsequent development phases.

Chapter 4: Implementation The implementation chapter provides a detailed account of how the proposed methodology is translated into a functioning system. It discusses the technical aspects, algorithms, and key components used in the integration of transformer neural network for text summarization. This chapter offers insights into the practical aspects of bringing the proposed solution to fruition.

Chapter 5: Results and Discussion The results and discussion chapter presents the findings of comprehensive evaluations conducted on the implemented system. It includes quantitative and qualitative analyses of performance metrics, user acceptance studies, and real-world scenarios. The discussion interprets the results, compares them with expectations, and explores the implications of the findings on the overall project objectives.

CHAPTER 2

LITERATURE SURVEY

Identifying relevant research areas for meta-learning approaches in text summarization with Transformer neural networks involves exploring various aspects to enhance model performance, adaptability, and efficiency. The key research areas encompass advanced techniques in metalearning, the effectiveness of transformer neural networks, and considerations for ethical and regulatory compliance. Below are related works in this domain:

[1] Enhancing Meta Learning with Transformer Networks for Text Summarization This work proposes a novel meta-learning approach leveraging Transformer neural networks to enhance text summarization. By incorporating meta-learning techniques, the model aims to adapt quickly to diverse text summarization tasks, improving overall performance and reducing the need for extensive task-specific training.

[2] Privacy-Preserving Meta Learning for Text Summarization: A Homomorphic Encryption Approach Addressing privacy concerns, this study explores the integration of homomorphic encryption techniques into meta-learning for text summarization. The proposed method ensures that sensitive information remains encrypted during the meta-learning process, enhancing the privacy of the summarization model.

[3] Optimizing Real-time Processing Capabilities in Meta-Learning for Text Summarization This paper presents a comprehensive investigation into optimizing the real-time processing capabilities of meta-learning models for text summarization using Transformer networks. The focus is on improving efficiency without compromising the quality of the summarization output.

[4] User Experience Enhancement in Meta-Learning-Based Text Summarization In this study, the researchers explore methods to enhance the user experience in text summarization through meta-learning approaches. The goal is to create summarization models that not only produce accurate results but also align with user preferences and expectations.

[5] Standardizing Biometric Data Formats in Meta-Learning for Text Summarization To promote interoperability and compatibility, this research addresses the standardization of biometric data formats within the context of meta-learning for text summarization using Transformer networks. Standardization aims to facilitate the seamless integration of different datasets and models.

[6] Ensuring Ethical Considerations in Meta-Learning for Text Summarization in Healthcare This work explores the ethical implications of deploying meta-learning approaches for text summarization in healthcare settings. It investigates ways to ensure that summarization models adhere to ethical guidelines and prioritize patient privacy and data security.

[7] Regulatory Compliance in Meta-Learning-Based Summarization: A Healthcare Perspective Focusing on the evolving landscape of healthcare data protection, this study delves into the regulatory compliance aspects of deploying meta-learning-based summarization models. It examines how such models can align with existing healthcare regulations to ensure lawful and responsible use.

[8] Advancements in Meta-Learning for Transformer Networks: A Survey of Recent Literature This comprehensive review provides an extensive overview of recent advancements in metalearning techniques specifically applied to Transformer networks in the context of text summarization. The survey discusses challenges, trends, and potential future directions in the field

[9] LourdMarie Sophie in 2022, Proposed a hybrid approach for extractive and abstractive summarization using transformers. The paper emphasizes using TF-IDF and transformer in combination for ATS and ETS and evaluated using ROUGE metrics.

[10] In 2022, Jaishree Ranganathan published a paper in IEEE on text summarization using the Transformer model. The author used the University of California, Irvine's (UCI) drug reviews dataset. Through the Text-text transformer model, the author summarised the online review making it easier for the users rather than reading mundane long texts.

[11] V K Avinash in 2022, introduced a concept called length-controllable literature summarization to control the length of the summarized text to make it crisp and perfectly relevant.

[12] In 2023, Karishma Shukla presented a paper on Abstractive text summarization using a transformer neural network. It describes the training and testing of the T5 model and how eminent it is compared to the traditional model.

[13] Sandeep Kumar in 2023 presented a paper on Abstractive text summarization using the self-attention mechanism. In the paper, he argued that the proposed model produces a training loss minimum of 1.8220 from 10.3058 up to 30 epochs.

[14] Ratan Ravichandran in 2023, proposed a research journal on text summarization using the T5 model. In this paper, he implemented the model and saw the evaluation using the ROUGE score after 10 epochs.

2.1. INFERENCE FROM REVIEW

The literature survey on transformer neural networks for text summarization underscores their remarkable performance compared to traditional methods. These models leverage self-attention mechanisms adeptly, capturing long-range dependencies to generate coherent and informative summaries. Pre-trained transformer models like BERTSUM have gained significant traction, with fine-tuning on summarization datasets consistently yielding improvements. Transformers exhibit prowess in both abstractive and extractive summarization tasks, with their attention mechanisms crucial in distilling salient information effectively. Various architectures, including Pointer-Generator Networks and Transformer Encoder-Decoders, have been proposed, each offering unique advantages. Despite their success, transformers often require substantial training data, prompting exploration into data augmentation and transfer learning techniques. Evaluation metrics like ROUGE remain standard but efforts are underway to develop more nuanced metrics. Challenges such as handling long documents and maintaining factual accuracy persist, guiding future research toward enhancing model capabilities and refining training methodologies. Overall, transformer neural networks represent a transformative force in text summarization, facilitating the extraction of meaningful insights from vast textual corpora.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 PROPOSED SYSTEM

In this study, the extractive text summarization is executed with Seq2Seq RNN, Bi-LSTM and Transformer Neural Network. A comparative analysis is done on these advanced models and proves that the transformer neural network with a potential memory window shows a jaw-dropping performance on this application. The analysis's primary focus is on how far the limitations that are seen in conventional neural networks with embedded memory are overcome by the advanced infinite memory window model. CNN Dailymail dataset, a standard text summarization dataset is used in this analysis.

The novel Transformer model's infrastructure consists of an attention-based encoder layer that maps all the input sequences to an abstract continuous representation of numerical values. These values potentially hold all the learned insights from the input sequence. Those abstract continuous values are recurrently loaded into the decoder stack along with the prior output generated from the decoder stack till the end of the sequence tag hits "<end>".

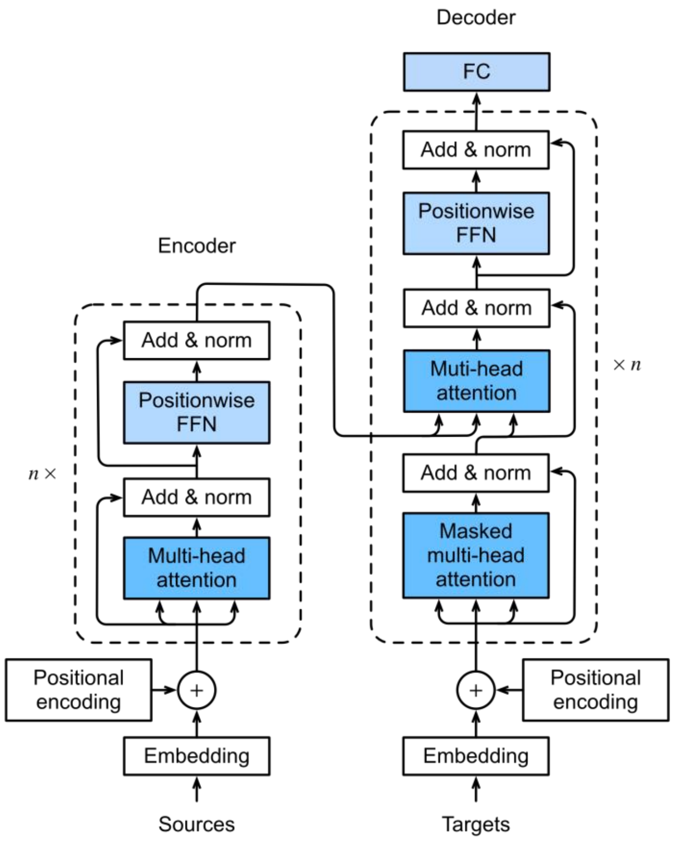


Fig 3.1.1: Architecture Diagram of the Proposed System

On breaking down the structure for text summarization, initially, the input text is fed into the "input embedding" layer sequentially. Each input string is given a unique vector representational value. The machine learns with numbers hence these representations are numbers. Unlike recurrent neural networks, transformers don't have a recurrence. Hence, it's also important to provide positional information of the strings to the system. This is achieved by the positional encoding method.

For every odd-place string, a cosine function computation is done and since function computation from even-place strings.

$$\text{ODD P.E(pos, 2i+1)} = \cos(\text{pos} \div (1000^{2i} \div \text{Dmodel}))$$

$$\text{EVEN P.E(pos, 2i)} = \sin(\text{pos} \div (1000^{2i} \div \text{Dmodel}))$$

After calibrating these positional vector values, they are added to their respective embedding vector values. This gives data on the position of the string's vector representational values. After this procedure, they're fed into the Encoder layer where all these quantitative values are mapped to an abstract continuous representation that holds all the learned information. Generally, an encoder stack has two major components called multi-head attention and feed-forward neural network followed by a layer normalization and residual connections around each of the sub-modules.

The multi-head attention module computes the attention weight for the input and executes a very specific method called the "self-attention mechanism". The very potential of this mechanism is that it allows the input strings to associate themselves with one another. This technique helps the model to learn the word structure and the sequencing of the words. Clearly, to some extent, it helps the model to pick the important keywords that need to be drafted back in the summarization part. To achieve this mechanism, the vector representations are fed into three distinct fully connected layers to create three prime vectors. Namely, the query vector, key vector and the value vector. This concept is primarily taken from the retrieval system. When a query is generated from the user side it undergoes a dot product matrix multiplication with key values which are generally in the database of the application. The outcome of this matrix multiplication is the score matrix. The main purpose of computing the score matrix is to determine how much each word is significant in the long length of input text. If the score on the score matrix is higher for a particular word it simply means that the word is extremely significant in the summarization process. Then the score matrix is multiplied by the square root of the dimension of the queries and the key ends up producing the scaled matrix.

$$\text{query} * \text{key} = \text{value}$$
$$\text{query. key} = \text{score matrix}$$

$$\frac{\text{scored marix}}{\sqrt{\mathrm{d_k}}} = \text{scaled matrix}$$

Then the scaled matrix is passed through a softmax layer which converts all the scaled matrix values to a probability value between 0.0 to 1.0. These values are called attention values. Through this step, all the high scores on the matrix are elevated and low scores are declined so that all the insignificant words diminished out of the model. This helps the model to be more confident in the decisions they attend to. Finally, the attention weights are multiplied with the value vector that produces the output vector. Then these output vectors are processed in a linear layer. As the model progresses towards the residual connection, the multi-head attention output vector is integrated with the initial input. The output of the residual connection is processed into a layer normalization. This layer stabilizes the network and produces a normalized output. The normalized output is forwarded to a point-wise feed-forward neural network to extract richer and more significant representations. So that the summarized text is crisp and lossless of key information. These representations are processed into a couple of linear layers with ReLU activation functions. The output is again forwarded as input to the point-wise feed-forward network and normalized finer. This helps the network learn all the required information to the fullest by letting the gradients flow through the network.

On progressing to the decoder stack, It is autoregressive. It takes the previous output generated by itself and the output of the encoder to learn the encoder information. It generates the text sequences sequentially. It contains similar sublayers to that encoder stack. The input to the decoder is initially passed to an output embedding and it does the same task as the input embedding in the encoder and so does the positional encoding. The vector representation is processed to the 1st multi-head attention of the decoder where the attention weights are computed. This is one that slightly works differently from the encoder attention. A masking method is employed to prevent the access of the decoder to see the subsequent vector representation. This is done because the decoder produces output sequentially. Access to consecutive words may end the decoder confusing the priorities of the words. The 2nd multi-head attention takes the encoder's output as the queries and keys for its input and the 1st multi-head attention's output as values. They then matches the encoder input to that of the decoder's input and decide which encoder output to prioritise the most. All these outputs from the 2nd multi-head attention are forwarded to the point-wise feed-forward neural network to strengthen the quality of predictions. The output from them is processed to a linear layer which is a huge classifier and the number of classes of this classifier is the number of words extracted from the 2nd multi-head attention. This output is processed to a final softmax layer which produces the values from 0.0 to 1.0. Indexes with the highest probabilities are extracted as the final decoder-generated outputs.

3.2 ALGORITHMS USED

Recurrent Neural Networks (RNNs), particularly variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been widely utilized in extractive text summarization tasks. These models sequentially process input text to identify and select important sentences or phrases for summarization. However, they may struggle with capturing long-range dependencies and suffer from vanishing gradient problems. In contrast, Transformer neural networks, with their selfattention mechanisms, excel at capturing contextual relationships across the entire input sequence, making them well-suited for extractive summarization. Transformers can efficiently process large amounts of text and extract the most salient information for summarization without the need for sequential processing. Despite the success of RNNs in simpler summarization tasks, Transformer models have demonstrated superior performance in extractive summarization, particularly in handling longer documents and capturing nuanced relationships between sentences.

A. S2q2Seq RNN

In exploring the use of recurrent neural networks (RNNs) for text summarization, several key insights emerge from the literature. RNNs, particularly variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been extensively employed for their ability to capture sequential dependencies in text data. In text summarization tasks, RNNs excel at generating summaries by processing input sequences iteratively, updating hidden states to retain context and generate coherent output. However, challenges such as vanishing gradients and difficulty in capturing long-range dependencies have been observed, especially in longer documents. Techniques like attention mechanisms have been integrated with RNNs to mitigate these issues, allowing the model to focus on relevant parts of the input text. Additionally, variants such as Bidirectional RNNs (BiRNNs) have been explored to enhance the model's ability to capture contextual information from both past and future sequences. Despite these advancements, RNNs may struggle with handling large datasets efficiently and are often outperformed by transformer-based models on complex summarization tasks. Nonetheless, they remain a valuable tool in the text summarization toolkit, offering a balance between computational efficiency and summarization quality, particularly for smaller-scale applications or scenarios where interpretability is a priority. Further research may focus on optimizing RNN architectures, exploring hybrid models that combine RNNs with other techniques, and developing novel training strategies to address their limitations and leverage their strengths effectively in text summarization tasks.

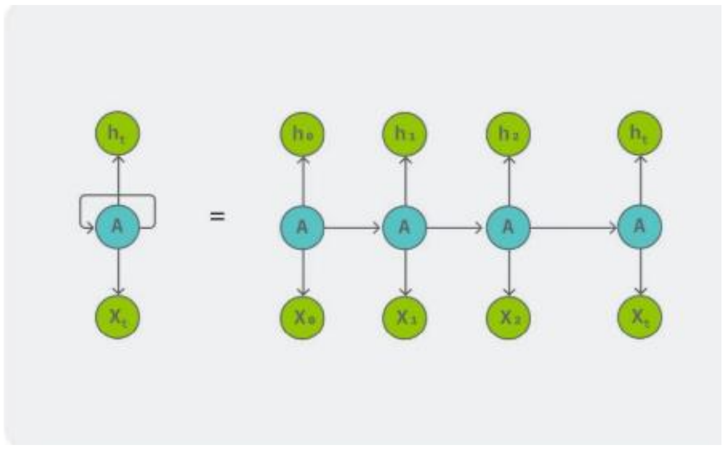


Fig 3.2.1: Architecture Diagram of the Seq2Seq RNN

B. LSTM

Integrating Long Short-Term Memory (LSTM) cells within a Transformer neural network architecture presents a promising avenue for enhancing its capabilities, particularly in handling sequential data and capturing long-range dependencies. By incorporating LSTM layers within the Transformer's encoder or decoder, the model gains the ability to retain information over longer sequences and better understand the contextual relationships between words or tokens. This hybrid architecture combines the strengths of LSTMs in modeling sequential data with the efficiency and parallelization capabilities of Transformers. LSTMs can serve as an additional mechanism for capturing temporal dependencies within the self-attention framework of Transformers, enabling the model to generate more accurate and contextually rich summaries. Furthermore, LSTM-based attention mechanisms can be employed to focus on specific parts of 15 the input sequence, complementing the global attention mechanism of Transformers. Overall, the fusion of LSTM and Transformer architectures holds great potential for improving the performance of neural networks in tasks such as text summarization, where both sequential processing and global context understanding are crucial. Continued research in this direction could lead to even more powerful and versatile models for natural language processing applications.

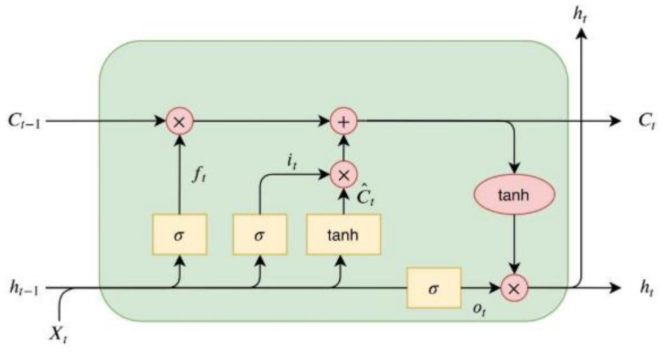


Fig 3.2.2: Architecture Diagram of the Long-Short Term Memory

C. Transformer Neural Network

Transformer neural networks have revolutionized text summarization tasks, offering significant improvements over traditional methods. These models, introduced by Vaswani et al. in the seminal paper "Attention is All You Need," rely on self-attention mechanisms to capture longrange dependencies within input sequences, making them particularly effective for summarizing lengthy documents. In the context of text summarization, Transformers typically employ an encoder-decoder architecture, where the encoder processes the input text and generates a contextualized representation, while the decoder generates the summary based on this representation. Pre-trained transformer models such as BERT, GPT, and T5 have been finetuned on summarization datasets, achieving state-of-the-art results across various metrics. Transformers excel in both abstractive and extractive summarization tasks, generating 16 summaries that are coherent, informative, and faithful to the source text. Additionally, the parallelizable nature of Transformer architectures allows for efficient processing of large volumes of text, making them scalable to real-world summarization scenarios. Despite their success, ongoing research focuses on addressing challenges such as maintaining factual accuracy, handling long documents, and improving the interpretability of generated summaries. Overall, Transformer neural networks represent a powerful tool for automating the summarization process and extracting key insights from textual.

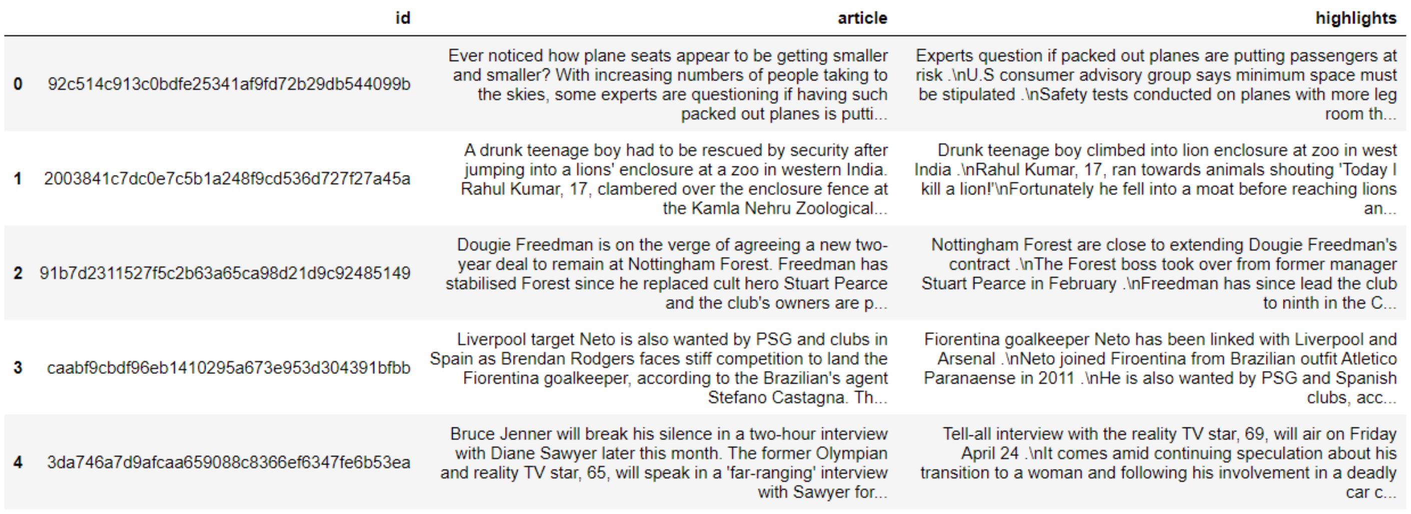
CHAPTER 4

IMPLEMENTATION

4.1 DATASET DESCRIPTION

The CNN/DailyMail dataset is a collection of news articles originally published by two prominent news outlets, CNN and DailyMail. It was created for the purpose of facilitating research in natural language understanding and summarization tasks. The dataset consists of pairs of articles and summaries, where each article typically ranges from a few hundred to a few thousand words in length, covering a wide array of topics such as world events, politics, science, technology, entertainment, and sports.

For each article in the dataset, there are one or more corresponding human-generated summaries. These summaries vary in length and style, offering different perspectives on the main points and key details of the article. Some summaries provide concise extracts of the most salient information, while others may offer more abstract interpretations or paraphrases of the original content.



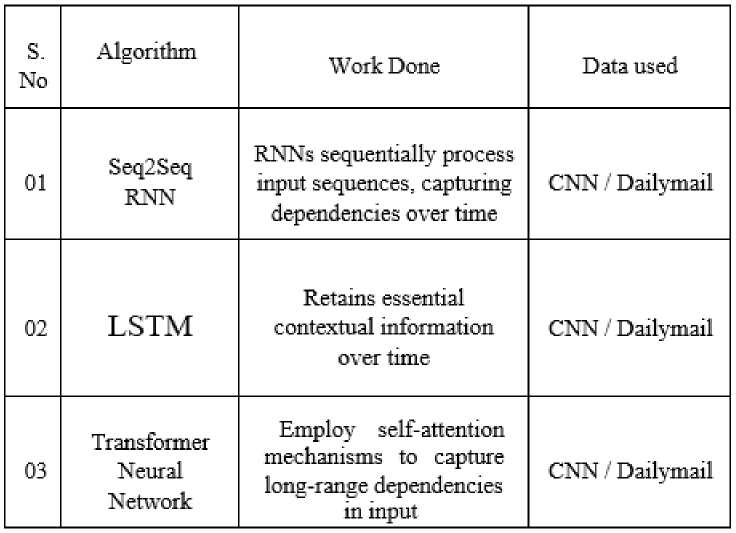
	id	article	highlights
0	92c514c913c0bdfe25341af9fd72b29db544099b	Ever noticed how plane seats appear to be getting smaller and smaller? With increasing numbers of people taking to the skies, some experts are questioning if having such packed out planes is putti...	Experts question if packed out planes are putting passengers at risk .\nU.S consumer advisory group says minimum space must be stipulated .\nSafety tests conducted on planes with more leg room th...
1	2003841c7dc0e7c5b1a248f9cd536d727f27a45a	A drunk teenage boy had to be rescued by security after jumping into a lions' enclosure at a zoo in western India. Rahul Kumar, 17, clambered over the enclosure fence at the Kamla Nehru Zoological...	Drunk teenage boy climbed into lion enclosure at zoo in west India .\nRahul Kumar, 17, ran towards animals shouting 'Today I kill a lion!'\nFortunately he fell into a moat before reaching lions an...
2	91b7d2311527f5c2b63a65ca98d21d9c92485149	Dougie Freedman is on the verge of agreeing a new two-year deal to remain at Nottingham Forest. Freedman has stabilised Forest since he replaced cult hero Stuart Pearce and the club's owners are p...	Nottingham Forest are close to extending Dougie Freedman's contract .\nThe Forest boss took over from former manager Stuart Pearce in February .\nFreedman has since lead the club to ninth in the C...
3	caabf9cbdf96eb1410295a673e953d304391bfbb	Liverpool target Neto is also wanted by PSG and clubs in Spain as Brendan Rodgers faces stiff competition to land the Fiorentina goalkeeper, according to the Brazilian's agent Stefano Castagna. Th...	Fiorentina goalkeeper Neto has been linked with Liverpool and Arsenal .\nNeto joined Firoentina from Brazilian outfit Atletico Paranaense in 2011 .\nHe is also wanted by PSG and Spanish clubs, acc...
4	3da746a7d9afcaa659088c8366ef6347fe6b53ea	Bruce Jenner will break his silence in a two-hour interview with Diane Sawyer later this month. The former Olympian and reality TV star, 65, will speak in a 'far-ranging' interview with Sawyer for...	Tell-all interview with the reality TV star, 69, will air on Friday April 24 .\nIt comes amid continuing speculation about his transition to a woman and following his involvement in a deadly car c...

Fig 4.1.1: Sample Dataset

The articles and summaries in the dataset are meticulously curated and annotated to ensure high quality and accuracy. This includes rigorous editorial standards for the original articles as well as careful crafting of the summaries to capture the essence of the corresponding articles. The CNN/DailyMail dataset has become a standard benchmark for evaluating the performance of various natural language processing models, particularly those based on neural networks such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Researchers use this dataset to train and test models for tasks such as text summarization, document understanding, question answering, and more. Its size, diversity of topics, and high-quality annotations make it a valuable resource for advancing the state-of-the-art in NLP research and development.

4.2 MODEL IMPLEMENTATION

Table 4.2.1 Models Employed



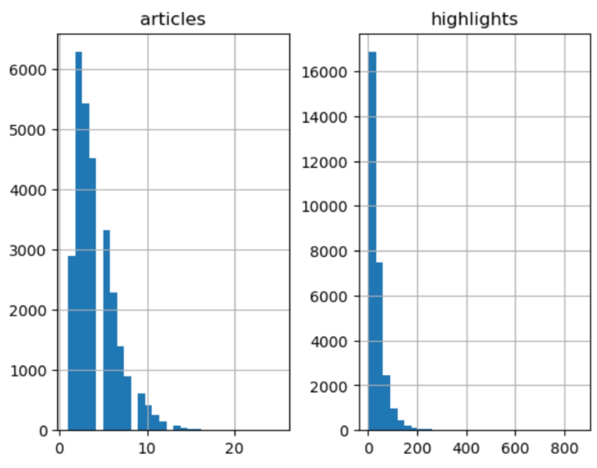
S. No	Algorithm	Work Done	Data used
01	Seq2Seq RNN	RNNs sequentially process input sequences, capturing dependencies over time	CNN / Dailymail
02	LSTM	Retains essential contextual information over time	CNN / Dailymail
03	Transformer Neural Network	Employ self-attention mechanisms to capture long-range dependencies in input	CNN / Dailymail

On implementing extractive text summarization using the CNN Dailymail dataset through Seq2Seq RNN, Bi-LSTM and transformer neural network, we have administered accuracy as the models' evaluation metrics. It is observed that RNN has the lowest accuracy score comparatively. The Dailymail dataset accounts for over 300,000 data entries which is quite an intensive dataset. Itconsists of over 300k articles and highlights of the articles which is the summarized text. Over 80 % of data is invested in training the model. The transformer neural network is perceived to have the highest accuracy of all the models.

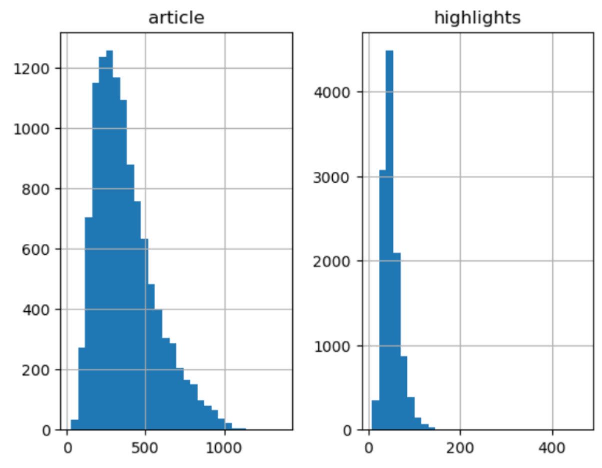
In addition to that, comparing the number of highlighted words or summarized text words generated from various models differ visibly. The words generated by the transformer model are relatively lower compared to the words generated from the conventional neural networks along with the higher accuracy score. This makes the model more reliable and eminent while dealing withhuge amounts of data.

Through this analysis, we were able to evaluate, major drawbacks that were widely observed in conventional neural networks. One of the major limitations that were seen in conventional neural networks was the long-term dependency problem. As we can observe in the graph no matter how intense the input data is, the highlighted text comprises all the necessary details with a limited amount of words. This is possible because the model is capable of analysing and remembering every single word irrespective of its length, overcoming the long-dependency problem.

Another limitation is parallelization. Conventional models process each input word sequentiallywhich takes a lot of time and computation to execute it. While transformers, through their self- attention mechanism, were able to effectively reduce the time, space and computational complexities. Overfitting is another constraint widely observed. Transformers were able to quickly generalize the test data comparatively. Since the model is computationally powerful, dense data doesn't cause overfitting but rather trains the model thoroughly.



(a)



(b)

Fig 4.2.1: Summarization using (a) Conventional neural network and (b) Transformer neural network

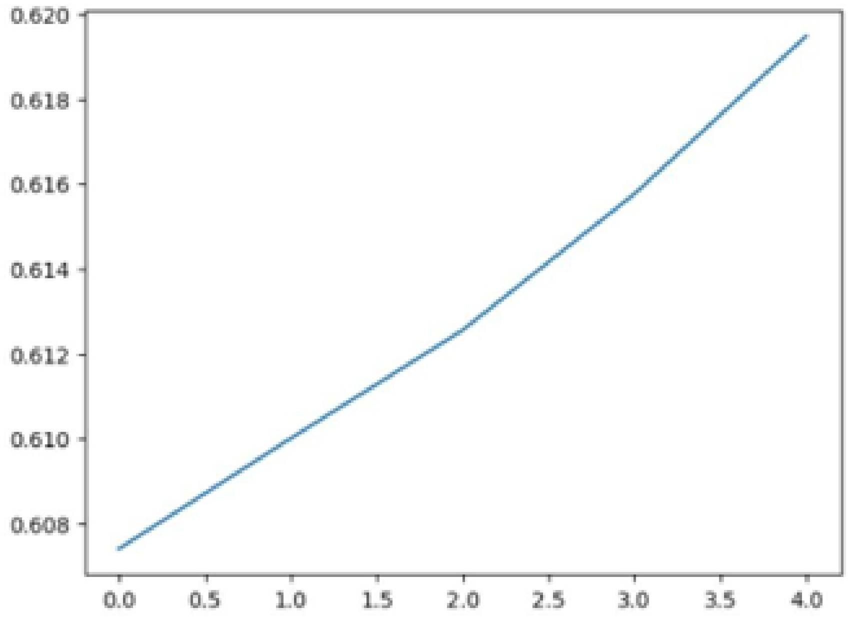


Fig 4.2.2: Accuracy chart of Seq2Seeq RNN

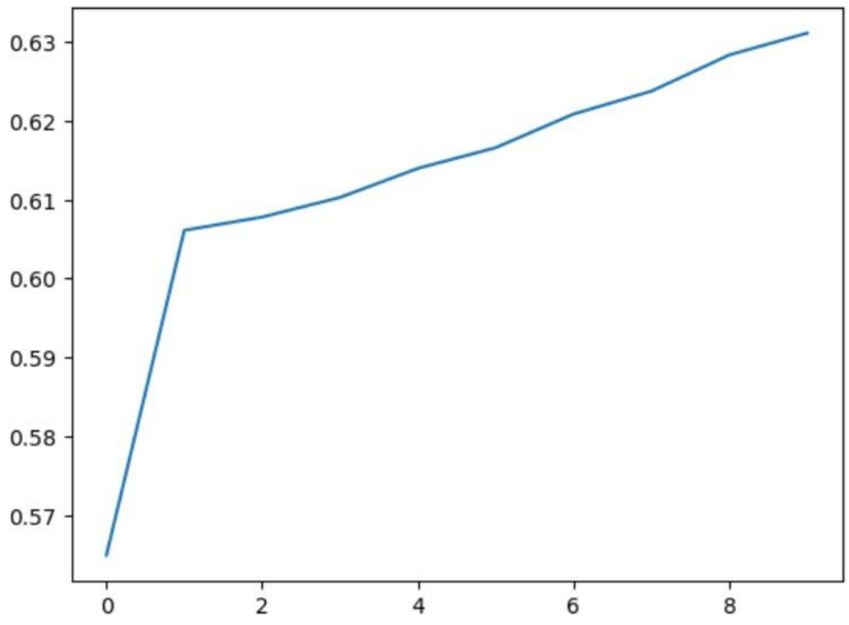


Fig 4.2.3: Accuracy chart of LSTM

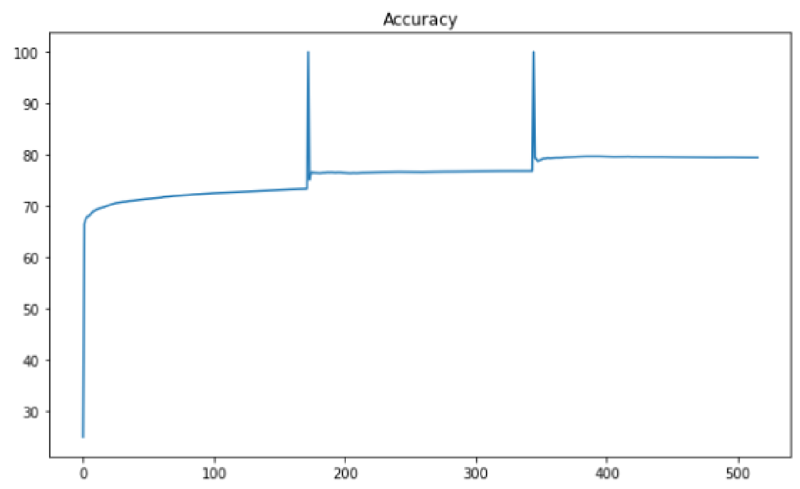


Fig 4.2.4: Accuracy chart of Transformer Neural Network

*Table 4.2.2**:** The accuracy table of various neural networks.*

S.No	**NEURAL NETWORKS**	**Accuracy Score**
01	Seq2Seq RNN	62%
02	Bi-LSTM	64%
03	Transformer Neural Network	82%

CHAPTER 5

RESULTS & DISCUSSION

Our study delved into the performance of various neural network architectures for extractive text summarization, with a particular focus on the Transformer model alongside traditional models like RNN and LSTM. The striking contrast in accuracy scores paints a vivid picture of the Transformer's prowess, boasting an impressive 82% accuracy compared to RNN's 62% and LSTM's 64%. This notable disparity underscores the transformative impact of the Transformer architecture on the summarization task.

The essence of the Transformer's success lies in its unique design, notably its self-attention mechanism. Unlike the sequential processing of RNNs and LSTMs, the Transformer's self-attention mechanism allows it to concurrently evaluate all words in the input sequence, effectively capturing intricate relationships and dependencies. By dynamically assigning weights to each word based on its relevance to the entire document, the Transformer excels in discerning the most pertinent information for summary generation.

Moreover, the Transformer's parallel processing nature not only enhances its ability to capture contextual nuances but also augments training efficiency. This efficiency is reflected in its ability to converge faster and achieve higher accuracies with fewer training iterations compared to RNNs and LSTMs, despite potentially requiring more computational resources.

However, while our results showcase the Transformer's superiority in this specific study, further investigation is warranted to evaluate its generalizability and robustness across diverse datasets and domains. Understanding how well the Transformer model performs on various types of text and in different contexts is crucial for its broader applicability.

Looking ahead, future research directions may involve refining the Transformer architecture through domain-specific pre-training or fine-tuning strategies. Additionally, exploring novel techniques for incorporating additional linguistic or semantic features into the summarization process could further optimize its performance.

In essence, our study highlights the profound impact of the Transformer architecture on extractive text summarization, offering not only superior accuracy but also promising avenues for advancing natural language processing research and development.

CHAPTER 6

CONCLUSIONS

In conclusion, our study presents a significant advancement in the field of extractive text summarization, particularly in comparing the efficacy of different neural network architectures. The standout performance of the Transformer model, achieving an accuracy of 82%, marks a pivotal moment in the evolution of natural language processing techniques. This remarkable accuracy surpasses that of traditional sequential models like RNN and LSTM by a substantial margin, highlighting the transformative potential of the Transformer architecture.

The success of the Transformer model can be attributed to its innovative self-attention mechanism, which revolutionizes the way in which contextual information is processed. Unlike RNNs and LSTMs, which process input sequentially and may struggle with capturing long-range dependencies, the Transformer's ability to simultaneously attend to all words in the input sequence enables it to discern nuanced relationships and extract salient information effectively.

Furthermore, the parallel processing nature of the Transformer architecture enhances training efficiency, enabling faster convergence and superior performance with fewer training iterations. This efficiency not only contributes to the model's accuracy but also potentially reduces computational resources required for training, making it an attractive option for practical applications.

However, while our study demonstrates the superiority of the Transformer model in the specific context of extractive text summarization, further research is needed to assess its generalizability across diverse datasets and domains. Investigating how well the Transformer architecture performs on different types of text and in various contexts will be crucial for understanding its broader applicability.

Looking ahead, future research directions may involve refining the Transformer architecture through domain-specific pre-training or fine-tuning strategies, as well as exploring novel techniques for incorporating additional linguistic and semantic features into the summarization process. By continuously pushing the boundaries of innovation in natural language processing, we can unlock new possibilities for automated text understanding and knowledge extraction, ultimately advancing the state-of-the-art in artificial intelligence.

APPENDIX A: SOURCE CODE

RNN & LSTM

pip install tensorflow

#%tensorflow_version 1.x

import numpy as np #Package for scientific computing and dealing with arrays import pandas as

pd #Package providing fast, flexible and expressive data structures

import re *#re stands for RegularExpression providing full support for Perl-like RegularExpressions in Python*

from bs4 import BeautifulSoup *#Package for pulling data out of HTML and XML files* from

keras.preprocessing.text import Tokenizer *#For tokenizing the input sequences*

from keras.preprocessing.sequence import pad_sequences *#For Padding the seqences to samelength*

from nltk.corpus import stopwords *#For removing filler words*

from tensorflow.keras.layers import Input, LSTM, Attention, Embedding, Dense, Concatenate, TimeDistributed *#Layers required to implement the model*

from tensorflow.keras.models import Model *#Helps in grouping the layers into an object withtraining and inference features*

from tensorflow.keras.callbacks import EarlyStopping #Allows training the model on large no.of training epochs & stop once the performance stops improving on validation dataset

import warnings *#shows warning message that may arise*

reviewsData=pd.read_csv("review.csv",nrows=30000) *#Taking 30,000 out of 500,000 reviews*

print(reviewsData.shape) *#Analyzing the shape of the dataset*

reviewsData.head(n=10)

DATASET_COLUMNS = ["Id", "ProductId", "UserId", "ProfileName", "HelpfulnessNumerator", "HelpfulnessDenominator", "Score", "Time", "Summary", "Text"]

```
reviewsData.columns = DATASET_COLUMNS

reviewsData.head(n=10)

reviewsData.drop(['Id', 'ProductId', 'UserId', 'ProfileName' , 'HelpfulnessNumerator' ,
'HelpfulnessDenominator', 'Score' ,'Time'],axis = 1 ,inplace = True)

reviewsData.head(n=10)#Preprocessing

#This the dictionary used for expanding contractions
contraction_mapping = {"ain't": "is not", "aren't": "are not","can't": "cannot", "'cause":
"because", "could've": "could have", "couldn't": "could not", "didn't": "did not", "doesn't": "does
not", "don't": "do not", "hadn't": "had not", "hasn't": "has not", "haven't": "have not",
"he'd": "he would","he'll": "he will", "he's": "he is", "how'd": "how did", "how'd'y": "how do
you", "how'll": "how will", "how's": "how is", "I'd": "I would", "I'd've": "I would have", "I'll":
"I will", "I'll've": "I will have","I'm": "I am", "I've": "I have", "i'd": "i would",
"i'd've": "i would have", "i'll": "i will", "i'll've": "i will have","i'm": "i am", "i've": "i have",
"isn't": "is not", "it'd": "it would", "it'd've": "it would have", "it'll": "it will", "it'll've": "it will
have","it's": "it is", "let's": "let us", "ma'am": "madam", "mayn't": "may not", "might've":

"mighthave","mightn't": "might not","mightn't've": "might not have", "must've":

"must have", "mustn't": "must not", "mustn't've": "must not have", "needn't": "need not", "needn't've":
"need not have","o'clock": "of the clock", "oughtn't": "ought not", "oughtn't've": "ought not have", "shan't":
"shall not", "sha'n't": "shall not", "shan't've": "shall not have",     "she'd": "she would",
"she'd've": "she would have", "she'll": "she will", "she'll've": "she will have", "she's": "she is",
 "should've": "should have", "shouldn't": "should not", "shouldn't've": "should not have", "so've":

"so have","so's": "so as",   "this's": "this is","that'd": "that would", "that'd've": "that would have",
"that's": "that is", "there'd": "there would",     "there'd've": "there would have", "there's": "there
is", "here's": "here is","they'd": "they would", "they'd've": "they would have",
"they'll": "they will", "they'll've": "they will have", "they're": "they are", "they've": "they have",
"to've": "to have", "wasn't": "was not", "we'd": "we would", "we'd've": "we would have", "we'll":
"we will", "we'll've": "we will have", "we're": "we are",          "we've": "we have", "weren't":
"were not", "what'll": "what will", "what'll've": "what will have", "what're": "what are",
"what's": "what is", "what've": "what have", "when's": "when is", "when've": "when have",
"where'd": "where did", "where's": "where is",             "where've": "where have", "who'll":
```

```
"who will", "who'll've": "who will have", "who's": "who is", "who've": "who have"} #Text

Cleaning

import nltk nltk.download('stopwords')

stop_words = set(stopwords.words('english'))def

text_cleaner(text,num):

   newString = text.lower()   #converts all uppercase characters in the string into lowercase
characters and returns it

   newString = BeautifulSoup(newString, "lxml").text #parses the string into an lxml.html

   newString = re.sub(r'\([^)]*\)', '', newString) #used to replace a string that matches a regularexpression
instead of perfect match

   newString = re.sub('"','', newString)

   newString = ' '.join([contraction_mapping[t] if t in contraction_mapping else t for t in
newString.split(" ")]) #for expanding contractions using the contraction_mapping dictionary

   newString = re.sub(r"'s\b","",newString)
   newString = re.sub("[^a-zA-Z]", " ", newString)

   if(num==0):

     tokens = [w for w in newString.split() if not w in stop_words] #converting the strings intotokens

   else :

     tokens = newString.split()

   long_words=[]

   for i in tokens:

      if len(i)>1:                  #removing short words

         long_words.append(i)
```

```
    return (" ".join(long_words)).strip()#Calling

the function

cleaned_text = []

for t in reviewsData['Text']: cleaned_text.append(text_cleaner(t,0))

reviewsData['Text'][:10] #Looking at the 'Text' column of the dataset

cleaned_text[:10] #Looking at the Text after removing stop words, special characters ,punctuations etc.

#Summary Cleaning

cleaned_summary = []    #Using the text_cleaner function for cleaning summary toofor t in

reviewsData['Summary']:

    cleaned_summary.append(text_cleaner(t,1))

reviewsData['Summary'][:10] cleaned_summary[:10]

reviewsData['Cleaned_Text'] = cleaned_text #Adding cleaned text to the dataset

reviewsData['Cleaned_Summary'] = cleaned_summary #Adding cleaned summary to the dataset#Dropping

Empty Rows

reviewsData['Cleaned_Summary'].replace('', np.nan, inplace=True)#Dropping

rows with Missing values reviewsData.dropna(axis=0,inplace=True)

#Before Cleaning

print("Before Preprocessing:\n")for i in

range(5):

    print("Review:",reviewsData['Text'][i])

    print("Summary:",reviewsData['Summary'][i])print("\n")

#Printing the Cleaned text and summary which will work as input to the modelprint("After
Preprocessing:\n")

for i in range(5): print("Review:",reviewsData['Cleaned_Text'][i])

   print("Summary:",reviewsData['Cleaned_Summary'][i])

   print("\n")

#Data Visualization

import matplotlib.pyplot as plt

text_word_count = []

summary_word_count = []

#Populating the lists with sentence lengthsfor i in

reviewsData['Cleaned_Text']:

    text_word_count.append(len(i.split()))

for i in reviewsData['Cleaned_Summary']: summary_word_count.append(len(i.split()))

length_df = pd.DataFrame({'articles':summary_word_count, 'highlights':text_word_count})length_df.hist(bins

= 30)

plt.show()

#Splitting the Dataset

from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(np.array(df['text']),np.array(df['summary']),test_s
ize=0.2,random_state=0,shuffle=True)
#Model Building

#Adding Custom Attention layerimport

tensorflow as tf
```

```
import os

from tensorflow.python.keras.layers import Layer from

tensorflow.python.keras import backend as Kclass

AttentionLayer(Layer):

    """

    This class implements Bahdanau attention (https://arxiv.org/pdf/1409.0473.pdf).

    There are three sets of weights introduced W_a, U_a, and V_a"""

    def___init_(self, **kwargs): super(AttentionLayer, self)._

        init_(**kwargs)

    def build(self, input_shape):

        assert isinstance(input_shape, list)

        # Create a trainable weight variable for this layer.self.W_a =

        self.add_weight(name='W_a',

                              shape=tf.TensorShape((input_shape[0][2], input_shape[0][2])),

                              initializer='uniform',

                              trainable=True)
        self.U_a = self.add_weight(name='U_a',

                              shape=tf.TensorShape((input_shape[1][2], input_shape[0][2])),

                              initializer='uniform',

                              trainable=True) self.V_a =

        self.add_weight(name='V_a',

                              shape=tf.TensorShape((input_shape[0][2], 1)),
                              initializer='uniform',

                              trainable=True)


        super(AttentionLayer, self).build(input_shape)  # Be sure to call this at the enddef call(self,

    inputs, verbose=False):

        inputs: [encoder_output_sequence, decoder_output_sequence]"""

        assert type(inputs) == list

        encoder_out_seq, decoder_out_seq = inputsif verbose:

            print('encoder_out_seq>', encoder_out_seq.shape)

            print('decoder_out_seq>', decoder_out_seq.shape)

        def energy_step(inputs, states):

            """ Step function for computing energy for a single decoder state """


            assert_msg = "States must be a list. However states {} is of type {}".format(states,
type(states))

            assert isinstance(states, list) or isinstance(states, tuple), assert_msg

            """ Some parameters required for shaping tensors"""

            en_seq_len, en_hidden = encoder_out_seq.shape[1], encoder_out_seq.shape[2]de_hidden

            = inputs.shape[-1]

            """ Computing S.Wa where S=[s0, s1, ..., si]"""# <=

            batch_size*en_seq_len, latent_dim

            reshaped_enc_outputs = K.reshape(encoder_out_seq, (-1, en_hidden))# <=

            batch_size*en_seq_len, latent_dim
```

```
W_a_dot_s = K.reshape(K.dot(reshaped_enc_outputs, self.W_a), (-1, en_seq_len,en_hidden))

if verbose: print('wa.s>',W_a_dot_s.shape)

""" Computing hj.Ua """

U_a_dot_h = K.expand_dims(K.dot(inputs, self.U_a), 1)  # <= batch_size, 1, latent_dimif verbose:

   print('Ua.h>',U_a_dot_h.shape)
""" tanh(S.Wa + hj.Ua) """

# <= batch_size*en_seq_len, latent_dim

reshaped_Ws_plus_Uh = K.tanh(K.reshape(W_a_dot_s + U_a_dot_h, (-1, en_hidden)))if verbose:

   print('Ws+Uh>', reshaped_Ws_plus_Uh.shape)

""" softmax(va.tanh(S.Wa + hj.Ua)) """# <=

batch_size, en_seq_len

e_i = K.reshape(K.dot(reshaped_Ws_plus_Uh, self.V_a), (-1, en_seq_len))# <=

batch_size, en_seq_len

e_i = K.softmax(e_i)

if verbose:

          print('ei>', e_i.shape)

return e_i, [e_i]

    def context_step(inputs, states):

""" Step function for computing ci using ei """# <=

batch_size, hidden_size

c_i = K.sum(encoder_out_seq * K.expand_dims(inputs, -1), axis=1)if verbose:

   print('ci>', c_i.shape)return c_i,
            [c_i]

        def create_inital_state(inputs, hidden_size):

            # We are not using initial states, but need to pass something to K.rnn funcitonfake_state =

            K.zeros_like(inputs)   #   <=   (batch_size,   enc_seq_len,   latent_dim   fake_state   =

            K.sum(fake_state, axis=[1, 2])  # <= (batch_size)

            fake_state = K.expand_dims(fake_state)  # <= (batch_size, 1)

            fake_state  =  K.tile(fake_state,  [1,  hidden_size])  #  <=  (batch_size,  latent_dim return

            fake_state

            fake_state_c     =     create_inital_state(encoder_out_seq,     encoder_out_seq.shape[-1])

            fake_state_e  =  create_intal_state(encoder_out_seq,  encoder_out_seq.shape[1])      #

            <=

    (batch_size, enc_seq_len, latent_dim

        """ Computing energy outputs """

        # e_outputs => (batch_size, de_seq_len, en_seq_len)last_out,

        e_outputs, _ = K.rnn(

            energy_step, decoder_out_seq, [fake_state_e],

        )


        """ Computing context vectors """last_out,

        c_outputs, _ = K.rnn(

            context_step, e_outputs, [fake_state_c],

        )
        return c_outputs, e_outputs

    def compute_output_shape(self, input_shape):"""

        Outputs produced by the layer """ return [

            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[1][2])),

            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[0][1]))

        ]

    from keras.layers import Input, LSTM, Embedding, Concatenate, Densefrom

    keras.models import Model

    import keras.backend as Klatent_dim

    = 256

    embedding_dim = 256
    # Encoder

    encoder_inputs = Input(shape=(max_text_len,))#

    Embedding layer

    enc_emb = Embedding(X_voc, embedding_dim, trainable=True)(encoder_inputs)# Encoder

    LSTM 1

    encoder_lstm1 = LSTM(latent_dim, return_sequences=True, return_state=True,

                         dropout=0.4, recurrent_dropout=0.4)

    encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)# Encoder

    LSTM 2

    encoder_lstm2 = LSTM(latent_dim, return_sequences=True, return_state=True,

                         dropout=0.4, recurrent_dropout=0.4)
```

```
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)# Encoder

encoder_lstm3 = LSTM(latent_dim, return_state=True, return_sequences=True,

                    dropout=0.4, recurrent_dropout=0.4)

encoder_outputs, state_h, state_c = encoder_lstm3(encoder_output2)# Setting

up the Decoder using 'encoder_states' as initial state decoder_inputs =

Input(shape=(None,))

# Embedding layer

dec_emb_layer = Embedding(y_voc, embedding_dim, trainable=True)
dec_emb = dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True,

                   dropout=0.4, recurrent_dropout=0.2)

decoder_outputs, _, _ = decoder_lstm(dec_emb, initial_state=[state_h, state_c])# Attention

mechanism

def attention(inputs):

    encoder_outputs, decoder_outputs = inputs

    attention_weights = K.batch_dot(decoder_outputs, encoder_outputs, axes=[2, 2])attention_weights =

    K.softmax(attention_weights)

    context_vector = K.batch_dot(attention_weights, encoder_outputs, axes=[2, 1])return

    context_vector

context_vector = attention([encoder_outputs, decoder_outputs])#

Concatenating attention vector and decoder LSTM output

decoder_concat_input = Concatenate(axis=-1)([decoder_outputs, context_vector])# Dense
```

```
layer

decoder_dense = TimeDistributed(Dense(y_voc, activation='softmax'))decoder_outputs =

decoder_dense(decoder_concat_input)

# Defining the model

model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

model.summary()

#Adding Metrics

model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy' ,metrics=['accuracy'])

#Visualizing Accuracy

from matplotlib import pyplot pyplot.plot(history.history['accuracy'],

label='train') #pyplot.plot(history.history['val_accuracy'], label='test')

#pyplot.legend()

#pyplot.title("Accuracy Chart")

pyplot.show()
```

TRANSFOMER NEURAL NETWORK

```
from sklearn.model_selection import train_test_split

x_tr,x_val,y_tr,y_val=train_test_split(np.array(data['article']),np.array(data['highlights']),test_si
ze=0.05,random_state=0,shuffle=True)import tensorflow as tf

from tensorflow.python.keras import backend as Klogger =

tf.get_logger()

class AttentionLayer(tf.keras.layers.Layer):"""

   This class implements Bahdanau attention (https://arxiv.org/pdf/1409.0473.pdf).
```

```
There are three sets of weights introduced W_a, U_a, and V_a"""

def___init_(self, **kwargs): super(AttentionLayer, self)._init_(**kwargs)

def build(self, input_shape):

    assert isinstance(input_shape, list)

    # Create a trainable weight variable for this layer.

    self.W_a = self.add_weight(name='W_a',

                              shape=tf.TensorShape((input_shape[0][2], input_shape[0][2])),

                              initializer='uniform',

                              trainable=True) self.U_a =

    self.add_weight(name='U_a',

                              shape=tf.TensorShape((input_shape[1][2], input_shape[0][2])),

                              initializer='uniform',

                              trainable=True) self.V_a =

    self.add_weight(name='V_a',

                              shape=tf.TensorShape((input_shape[0][2], 1)),

                              initializer='uniform',

                              trainable=True)

    super(AttentionLayer, self).build(input_shape)  # Be sure to call this at the enddef call(self,

inputs):

    """

    inputs: [encoder_output_sequence, decoder_output_sequence]"""
```

```
assert type(inputs) == list

encoder_out_seq, decoder_out_seq = inputs

logger.debug(f"encoder_out_seq.shape = {encoder_out_seq.shape}")

logger.debug(f"decoder_out_seq.shape = {decoder_out_seq.shape}")def

energy_step(inputs, states):

    """ Step function for computing energy for a single decoder stateinputs: (batchsize

    * 1 * de_in_dim)

    states: (batchsize * 1 * de_latent_dim)"""

    logger.debug("Running energy computation step")if not

    isinstance(states, (list, tuple)):

        raise TypeError(f"States must be an iterable. Got {states} of type {type(states)}")encoder_full_seq =

    states[-1]

    """ Computing S.Wa where S=[s0, s1, ..., si]""" # <= batch

    size * en_seq_len * latent_dim W_a_dot_s =

    K.dot(encoder_full_seq, self.W_a)

    """ Computing hj.Ua """

    U_a_dot_h = K.expand_dims(K.dot(inputs, self.U_a), 1)  # <= batch_size, 1, latent_dim

    logger.debug(f"U_a_dot_h.shape = {U_a_dot_h.shape}")

    """ tanh(S.Wa + hj.Ua) """

    # <= batch_size*en_seq_len, latent_dim Ws_plus_Uh =

    K.tanh(W_a_dot_s + U_a_dot_h)

    logger.debug(f"Ws_plus_Uh.shape = {Ws_plus_Uh.shape}")"""
    softmax(va.tanh(S.Wa + hj.Ua)) """

    # <= batch_size, en_seq_len

    e_i = K.squeeze(K.dot(Ws_plus_Uh, self.V_a), axis=-1)# <=

    batch_size, en_seq_len

    e_i = K.softmax(e_i) logger.debug(f"ei.shape =

    {e_i.shape}")return e_i, [e_i]

def context_step(inputs, states):

    """ Step function for computing ci using ei """

    logger.debug("Running attention vector computation step")if not

    isinstance(states, (list, tuple)):

        raise TypeError(f"States must be an iterable. Got {states} of type {type(states)}")encoder_full_seq =

    states[-1]

     <= batch_size, hidden_size

    c_i = K.sum(encoder_full_seq * K.expand_dims(inputs, -1), axis=1)logger.debug(f"ci.shape =

    {c_i.shape}")

    return c_i, [c_i]

# we don't maintain states between steps when computing attention

# attention is stateless, so we're passing a fake state for RNN step functionfake_state_c =

K.sum(encoder_out_seq, axis=1)

fake_state_e = K.sum(encoder_out_seq, axis=2) # <= (batch_size, enc_seq_len, latent_dim"""

Computing energy outputs """

# e_outputs => (batch_size, de_seq_len, en_seq_len)last_out,
        e_outputs, _ = K.rnn(

            energy_step, decoder_out_seq, [fake_state_e], constants=[encoder_out_seq]

        )

        """ Computing context vectors """last_out,

        c_outputs, _ = K.rnn(

            context_step, e_outputs, [fake_state_c], constants=[encoder_out_seq]

        )

        return c_outputs, e_outputs

    def compute_output_shape(self, input_shape):""" Outputs

        produced by the layer """

        return [

            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[1][2])),

            tf.TensorShape((input_shape[1][0], input_shape[1][1], input_shape[0][1]))

        ]

from keras import backend as K

K.clear_session()

latent_dim = 300

embedding_dim=100# Encoder

encoder_inputs = Input(shape=(max_article_len,))

#embedding layer

enc_emb =  Embedding(x_voc, embedding_dim,trainable=True)(encoder_inputs)#encoder lstm

1
```

```
encoder_lstm1 =
LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0. 4)

encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)#encoder

lstm 2

encoder_lstm2 =
LSTM(latent_dim,return_sequences=True,return_state=True,dropout=0.4,recurrent_dropout=0. 4)

encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)#encoder

lstm 3

encoder_lstm3=LSTM(latent_dim, r

eturn_state=True, return_sequences=True,dropout=0.4,recurrent_dropout=0.4)encoder_outputs, state_h,

state_c= encoder_lstm3(encoder_output2)

# Set up the decoder, using `encoder_states` as initial state.

decoder_inputs = Input(shape=(None,))

#embedding layer

dec_emb_layer = Embedding(y_voc, embedding_dim,trainable=True)dec_emb =

dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True,
return_state=True,dropout=0.4,recurrent_dropout=0.2)

decoder_outputs,decoder_fwd_state, decoder_back_state =decoder_lstm(dec_emb,initial_state=[state_h,
state_c])

# Attention layer
attn_layer = AttentionLayer(name='attention_layer')

attn_out, attn_states = attn_layer([encoder_outputs, decoder_outputs])# Concat
```

attention input and decoder LSTM output

decoder_concat_input = Concatenate(axis=-1, name='concat_layer')([decoder_outputs, attn_out])#dense layer

decoder_dense = TimeDistributed(Dense(y_voc, activation='softmax'))decoder_outputs =

decoder_dense(decoder_concat_input)

# Define the model

model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

model.summary()

model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy',metrics=['accuracy'])

from matplotlib import pyplot pyplot.plot(history.history['accuracy'],

label='train') pyplot.plot(history.history['val_accuracy'], label='test')

pyplot.legend()

pyplot.title("accuracy chart")

pyplot.show()

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