International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

# Pretraining-Based Natural Language Generation for Text Summarization with Machine Learning

Dr. Navneet Kaur Sandhu
Assistant Professor
Desh Bhagat University

Er. Harwinder Singh
Assistant Professor
Desh Bhagat University

***Abstract:***

This paper presents a novel approach to text summarization using pretraining-based natural language generation (NLG) with machine learning. Utilizing transformer models like BERT and GPT, the study develops an encoder-decoder framework to generate concise and coherent summaries from input text. The methodology encompasses data collection, preprocessing, and the implementation of pretraining techniques to enhance language understanding and summary generation. Evaluation using metrics such as ROUGE scores demonstrates the framework's effectiveness in producing high-quality summaries. The research contributes to advancing NLG applications by focusing on the development and evaluation of a robust summarization system. It highlights the benefits of leveraging pretraining methods to improve the efficiency and accuracy of text summarization tasks. By refining the summarization process through advanced NLP techniques, this study aims to provide a comprehensive framework for generating informative summaries across various text domains.

***Index Terms*** **- Natural Language Generation, Text Summarization, Machine Learning, Transformers, BERT, GPT, ROUGE Scores, Encoder-Decoder Models, Pretraining Techniques.**

## I INTRODUCTION

Natural language generation, or text generation, has become one of the most critical and significant challenges in natural language processing. Its objective is to produce human-readable and credible text based on input data (including keywords and a sequence)(Gatt & Krahmer, 2018). Natural Language Generation (NLG) is an indispensable constituent of summarization systems, chatbots, and other text-based applications. Non-linear grammar recognition (NLG) has made significant strides, particularly in the domain of text summarization, since the advent of pretraining methods. NLG models that rely on pretraining, including Bidirectional Encoder Representations from Transformers (BERT) and Generative Pretrained Transformer (GPT), have demonstrated remarkable proficiency in both understanding and generating coherent text(W. Li et al., 2012). By leveraging extensive text corpora, these models amass detailed language representations, which enable them to generate concise yet perceptive synopses of incoming content. The purpose of this research is to enhance the quality and efficiency of a novel encoder-decoder system for text summarization based on pretraining(Ray, 2023). Utilising NLP techniques like Bidirectional Encoder Representations from Transformers (BERT), the framework enhances output sequence generation and context representation. It undertakes a two-stage process of refining prototype outputs, guaranteeing an improved summary(Rezaeipourfarsangi, 2023). This research paper examines the performance of natural language processing (NLP) on diverse datasets and delves into the broader consequences of integrating NLP into text generation tasks. By doing so, it potentially establishes new benchmarks for applications involving natural language processing(Al-Maleh & Desouki, 2020).

### 1.1 Natural language generation

Natural language generation (NLG) is the production of spoken or written narratives from a data set through the implementation of artificial intelligence (AI) code. Computational linguistics, natural language processing (NLP), and

natural language understanding (NLU) are related to NLG in terms of human-machine and machine-human interaction(AJALA, 2021). Frequently, NLG research centres on the development of computer programmes that supply context to data points. Advanced NLG software is capable of extracting valuable insights from vast amounts of numerical data, discerning patterns, and presenting this knowledge in a comprehensible format for human users(Manu Madhavan, 2013).

Natural Language Generation (NLG) is a Natural Language Processing (NLP) activity in which sentences are generated based on word knowledge and logically represented data. NLG is a rapidly developing technology and a fascinating area of research with a wide range of real-world uses. An abstract thought or idea is represented by a phrase(Khatter, 2021).

A system's capacity to produce a coherent sentence is a good indicator of its idea generation intelligence(Reiter & Dale, 1997). The opposite of natural language understanding (NLU) is natural language generation. NLU maps from text to meaning, while NLG maps from meaning to text. The NLG system's input varies greatly depending on the application. However, all of the pieces in NLU follow a rather standard grammar. NLU has been identified by unclear, under-specified, and improperly formatted information. However, the non-linguistic input to the NLG system is mostly clear-cut, precisely defined, and well-formed(Dethlefs, 2014).

### 1.1.1 Stages of NLG


**Fig 1: Natural Language Generation in six steps**(Leopold et al., 2016)

**1. Examine the content:**

To determine which elements should be incorporated into the final content, data is filtered. A component of this phase entails the identification of the source document's principal themes and affiliations.

**2. Data comprehension:**

Patterns are identified within the data, and the information is contextualized. Presently, machine learning is implemented frequently.

**3. Document structuring:**

An identified narrative structure is selected and a documented plan is formulated in accordance with the type of data being analysed.

**4. Sentence aggregation:**

It is a method of sentence combination. Sentences or segments thereof that are pertinent to the matter are interspersed in manners that precisely encapsulate the subject matter.

**5. Grammatical organization:**

In order to produce writing that appears intuitive, grammatical principles are utilised. The software infers the syntactical structure of the sentence. Subsequently, the statement is rewritten with grammatical accuracy by utilising the data given(Naber et al., 2003).

**6. Presentation of the language:**

The final output is generated using a template or format chosen by the user or programmer.

**1.2 Evolution of Pretraining Techniques in Natural Language Processing**

The expansion of pretraining methodologies in natural language processing (NLP) has been marked by a multitude of advancements, each of which has made a distinct contribution to the enhancement of language comprehension and generation(Khatter, 2021). At the outset, natural language processing (NLP) was revolutionized by word embedding's such as Word2Vec and Glove, which represented words as dense vectors in continuous space capable of capturing semantic associations and similarities(Dharma et al., 2022). Nevertheless, the absence of context awareness in these embedding's led to the generation of contextualized word representations. Natural Language Processing (NLP) entered the era of contextual embedding's with the introduction of models such as ELMo (Embedding's from Language Models) and ULMFiT (Universal Language Model Fine-tuning), in which words are embedded within a phrase based on their context. This approach significantly enhances the performance of subsequent natural language processing tasks through the incorporation of contextual information(Khurana et al., 2022). The significant development took place when transformer-based architectures were implemented, specifically BERT (Bidirectional Encoder Representations from Transformers)(Gorenstein et al., 2024). These architectures allowed for pretraining to be performed at the phrase and sentence-pair levels. BERT achieved exceptional performance across a range of natural language processing (NLP) benchmarks due to its ability to obtain comprehensive contextual information from both the left and right contexts via its bidirectional attention mechanism. Following that, models such as GPT (Generative Pertained Transformer) demonstrated the effectiveness of large-scale unsupervised learning in capturing intricate linguistic patterns, thereby expanding the boundaries of pretraining. The progress made in self-supervised learning and multimodal models is driving the evolution of pretraining methodologies, which hold the potential for further improvements in language generation and interpretation.

**1.3 Text Summarization**

The term "text summary" denotes reducing a lengthy text to a more succinct and meaningful version, wherein the most vital information is retained while extraneous or superfluous particulars are eliminated. Although text summarization can be accomplished manually, the process is typically laborious and time-consuming. By identifying the most important information in a document and analyzing it, text summarization algorithms automate the process and produce a more concise and manageable summary that retains the essential details(Radev & McKeown, 2002). In this method, we construct programmes or algorithms that summarise our text data and decrease its size. In the field of machine learning, this is known as automated text summarization.Shortening lengthy texts while preserving their meaning is known as text summarization.

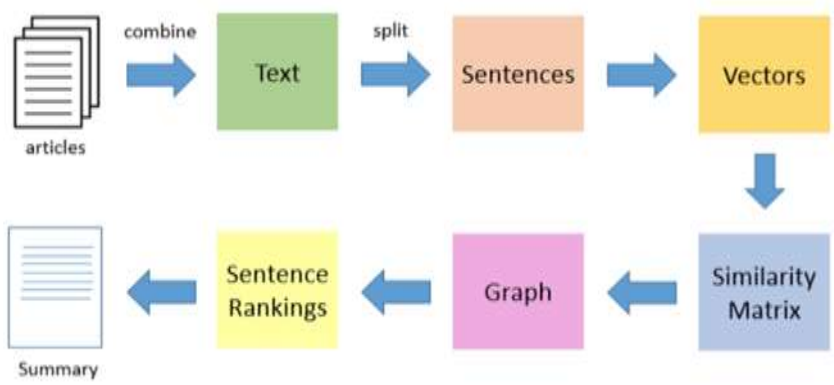



**Fig: .2 Text Summarization**(El-Kassas et al., 2021)

Two varieties of text summarization exist: informative and indicative. Informative summarization provides succinct information in 20-30% of the length of the text, whereas inductive summarization presents the text's main idea in 5-10% of its length.

**1.3.2 Significance of text summarization in data processing.**

Text summarization is an essential component of data processing, helping to organise and comprehend large volumes of data in an effective manner. In a time when the amount of data being generated is greater than ever, people and organisations must find a way to sort through massive amounts of text in order to derive valuable insights(Sharma & Sharma, 2023). One such approach is text summarising, which preserves the spirit of the original material while providing shorter, more comprehensible summaries of the information. This procedure not only saves time but also improves the information's usefulness and accessibility, making it invaluable in a variety of fields, such as business, academia, media, and more(Y. K. Dwivedi et al., 2021).

Text summary is essentially the process of condensing a lengthy text content into a shorter form. There are two main methods to do this: extractive and abstractive summarization. The process of extractive summarising involves locating and removing essential lines or phrases from the original text, then assembling them into a summary. This approach, which is often simpler to use, depends on the intrinsic significance of certain textual passages. Conversely, abstractive summarising is creating new sentences that encapsulate the primary concepts of the source material in a manner akin to that of a human summary writer. This approach is more involved and calls for a thorough comprehension of the subject matter as well as the ability to speak in natural language, but it often yields summaries that are more logical and succinct(Taye, 2023). Text summarising has several applications in data processing. It starts by addressing the issue of too much information. As digital material grows at an exponential rate, people are inundated with more knowledge than they can possibly comprehend. By breaking down large volumes of material into digestible chunks, summarization enables readers to rapidly understand the essential ideas without having to peruse whole publications. This is especially helpful in professions like research, where it's important yet time-consuming to remain current with studies and publications(Grewal et al., 2016).

Text summary improves decision-making and efficiency in the business sector. To make well-informed judgements, executives and managers often need to go through lengthy studies, market evaluations, and other materials. They can quickly assimilate important information from condensed versions of these materials, which expedites the decision-making process. Furthermore, social media postings, user-generated material, and customer feedback can all be tracked and analysed with the use of summarising tools(Deep, 2023). This helps companies get valuable insights and enhance their interactions with customers. Summarising texts is also very beneficial to the media and journalism sectors. Journalists may generate accurate and timely news pieces by using summarising techniques to swiftly extract the most important information from long press releases, reports, and other sources. Furthermore, summaries are used by news aggregation services to provide users brief summaries of the most important items, saving them time and effort by

avoiding the need to read several lengthy pieces. Text summary helps researchers and students in academics. To comprehend and remember material from textbooks, articles, and lecture notes more effectively, students may make use of summarising tools. On the other hand, researchers may use these tools to stay up to date with the large volume of papers in their area, making sure they don't miss any significant advancements and are able to efficiently synthesise material from several sources. Text summarising also improves information retrieval systems, increasing their effectiveness and user-friendliness(Spirgel & Delaney, 2014). Users may quickly ascertain if a document is relevant to their inquiry by using the summarised versions of search results that search engines and digital libraries can provide. This enhances the user experience while also cutting down on the time and effort needed to locate relevant information. Text summarization has greatly improved with the combination of machine learning and natural language processing (NLP) technology. Pretrained language models—like BERT, GPT, and T5 have shown an amazing level of competence in producing and comprehending human language. By using big datasets, these models may be optimized for summarization tasks, resulting in increased efficiency. By recognising patterns and significant details in the text, machine learning algorithms make it possible to create summaries that are more precise and logical(Taye, 2023).

### 1.4 Advancements in Machine Learning for NLG

Advancements in machine learning have catalyzed significant progress in natural language generation (NLG) tasks. Traditional rule-based and template-based approaches have been superseded by neural network-based models, offering enhanced flexibility and performance. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM)(Ji et al., 2020) and Gated Recurrent Unit (GRU), revolutionized NLG by capturing sequential dependencies in text data. Convolutional Neural Networks (CNNs) brought advancements in tasks like image captioning and text generation from structured data(R. Zhang et al., 2016). Nevertheless, the most significant advancement occurred when transformer-based architectures were implemented. In NLG, cutting-edge outcomes were attained by models such as GPT (Generative pertained Transformer) and BERT (Bidirectional Encoder Representations from Transformers) through the utilisation of self-attention mechanisms and extensive pretraining on enormous text corpora. These developments have enabled the development of text generation systems that are more precise, contextually aware, and fluent, thereby transforming numerous natural language processing (NLP) applications, such as Chatbots, language translation, and content creation(Basha et al., 2023).


**Fig : 3 NLP and Machine Learning**(Harrison & Sidey-Gibbons, 2021)

### 1.5 Emergence of Pretraining-based Natural Language Generation

**Shift from Rule-Based to Data-Driven Approaches:**

Pretraining-based NLG marks a departure from rule-based approaches towards data-driven methodologies.

**Utilization of Large-Scale Text Corpora:** Models like BERT and GPT are pretrained on massive text corpora, enabling them to learn rich linguistic representations from unlabeled data.

**Capture of Deep Linguistic Patterns:**

Pertained models encode deep semantic understanding of language, capturing intricate linguistic patterns and semantic relationships.

**Enhanced Contextual Understanding:**
By pretraining on diverse text sources, models gain a nuanced understanding of context, facilitating more accurate and contextually relevant text generation.
**Flexibility and Adaptability:**

pertained models exhibit flexibility and adaptability across various NLP tasks, including text summarization, translation, and question answering(Soliman et al., 2024).

**Efficiency in Downstream Tasks:**

Fine-tuning pretrained models on specific tasks, such as text summarization, results in improved efficiency and performance compared to training from scratch.

**Democratization of Advanced NLP:**
The emergence of pretraining-based NLG democratizes access to advanced NLP capabilities, empowering researchers and practitioners to develop state-of-the-art solutions for a wide range of applications.

**Advancements in Summarization Quality:**
Pretraining-based NLG promises advancements in summarization quality by leveraging deep contextual understanding and semantic representation(H. Zhang, Gong, et al., 2019).

**Addressing Challenges in Traditional Approaches:**

Pretraining-based NLG addresses inherent challenges in traditional summarization methods, such as producing concise and informative summaries from large and diverse datasets.

## II. LITERATURE REVIEW

### 2.1 Pretraining-Based Approaches for Natural Language Generation

Text summarization extracts important information from source materials and summarises it into summaries. This is a significant job that has several practical applications. Numerous approaches have been put out to address the issue of summary of texts.The two primary methods for summarising texts are extracting and abstractive. While abstractive techniques modify and reorganise words to create the overview, extractive summarising creates the summary by picking out important lines or phrases from the original text. In this study, we concentrate on abstractive summarising since it is more versatile and can provide a wider range of summaries(Sharma & Sharma, 2023).

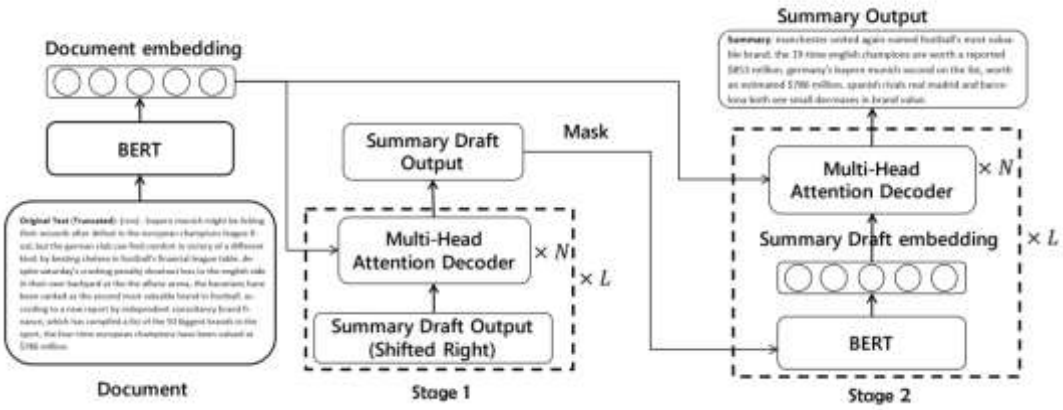



**Fig: 4 Model Overview, N represents the decoder layer number and L represents summary length.**(Nguyen et al., 2023)

**Haifeng Wang et.al (2023),** provides a comprehensive review of pre-trained language models (PTMs) in natural language processing (NLP), elucidating their impact, challenges, and future directions. PTMs, based on pre-training followed by fine-tuning, have revolutionized NLP, significantly enhancing downstream task performance. Despite their success, challenges such as interpretability and multimodal understanding persist. Future research directions include improving interpretability, unifying multimodal and multilingual pre-training, and incorporating prior knowledge to enhance reasoning abilities. While PTMs have demonstrated strong generalization capabilities, efficient deployment and model compression remain open questions. Nevertheless, the continuous evolution of PTMs in real-world applications promises to address new challenges and propel advancements in pre-trained methods for AI(H. Wang et al., 2023).

**Angelina Yang et.al (2022)** One subject of machine learning is known as natural language generation, and its primary objective is to develop computer programmes that are capable of producing documents in human language that can be understood by humans. In addition to the fields of journalism and online Chatbots, it is applicable to all other fields that deal with reporting and the development of information. In spite of the fact that natural language generation is classified as a subfield, it encompasses a wide variety of subjects that are well outside the scope of this work. Word Embedding, Long Short-Term Memory (LSTM), and Encoder-Decoder Architecture are the three subjects that will be discussed in this research paper. The purpose of this study is to present an overview of these issues specifically within the realm of natural language creation. In spite of the fact that the subject matter is quite vast, the writers have analysed and reinterpreted the material in order to provide the audience with a better grasp of natural language production(Yang & Halim, 2022).

**Sheetal Patil et.al (2022),** explores the frequency-based approach for text summarization, aiming to condense multiple papers into concise summaries. The study highlights the usefulness of text summaries in various natural language processing tasks and computer science fields like text classification and data retrieval. By enhancing access time for information search and minimizing bias, text summarization systems offer significant benefits. Future extensions of this study include expanding summarization strategies to different domains and incorporating machine-dependent methods. Overall, this research underscores the importance of automated summarization in improving information processing and outlines potential avenues for future exploration(Patil et al., 2022).

**Haoyu Zhang et.al (2019).** provide a new encoder-decoder architecture that relies on pretraining to produce the output sequence from the input sequence in a two-stage process. Our model's encoder makes use of BERT to convert the input sequence into text representations. We use a Transformer-based decoder to provide a preliminary output sequence in the first of our two-stage decoder model. In the second step, we give BERT the draft sequence with each word mask applied. Then, we utilise a decoder based on Transformers to forecast the refined word for each masked place by merging the input sequence with BERT's draft representation. As far as we are aware, our technique is the first to

include the BERT into activities involving text creation. To kick things off, we test our suggested approach on the text summarising job. On the CNN/Daily Mail dataset as well as the New York Times dataset, our model outperforms the state-of-the-art, according to experimental findings(H. Zhang, Gong, et al., 2019).

**Ms.G. 46.Khan, B., Shah et.al (2022),** Text summarization has become indispensable in today's data-rich environment, where long articles and documents abound across various platforms. This review paper explores diverse approaches to generating summaries from extensive texts, encompassing both abstractive and extractive techniques, as well as query-based summarization methods. Structured and semantic-based approaches are examined, drawing insights from studies on datasets like CNN, DUC2000, and others. Despite advancements, the accuracy and relevance of summaries remain challenging, with evaluation metrics like ROGUE and TF-IDF scores commonly employed. The ongoing research in text summarization reflects its vital role in saving time and resources for users. While no single model stands out as the best, continuous exploration and experimentation drive progress in this field(Khan et al., 2023).

**Aakash srivastava et.al (2022),** The proliferation of online information on the World Wide Web necessitates efficient access and processing methods. Automated summarization has emerged as a solution to handle the escalating volume of electronic data, condensing multiple documents into concise summaries. This report explores a frequency-based approach for text summarization, emphasizing its utility in various natural language processing tasks and computer science domains like text classification and data retrieval. Summaries not only enhance information search efficiency but also mitigate human bias. Commercial capture services leverage text summarization systems to increase text processing capabilities. Overall, automated text summarization holds significant promise for improving information retrieval and processing in an era of abundant online information(Saklecha & Uplavdiya, 2023).

### 2.2 Machine Learning Techniques for Text Summarization

Machine learning techniques for text summarization advantage algorithms like Extractive and Abstractive models. Extractive methods identify key sentences to form a summary, using techniques like TF-IDF, clustering, and neural networks. Abstractive methods, more advanced, generate new sentences to capture the text's essence, utilizing sequence-to-sequence models and transformers such as BERT and GPT. These approaches enhance summarization by understanding context and semantics, producing coherent and concise summaries suitable for various applications.

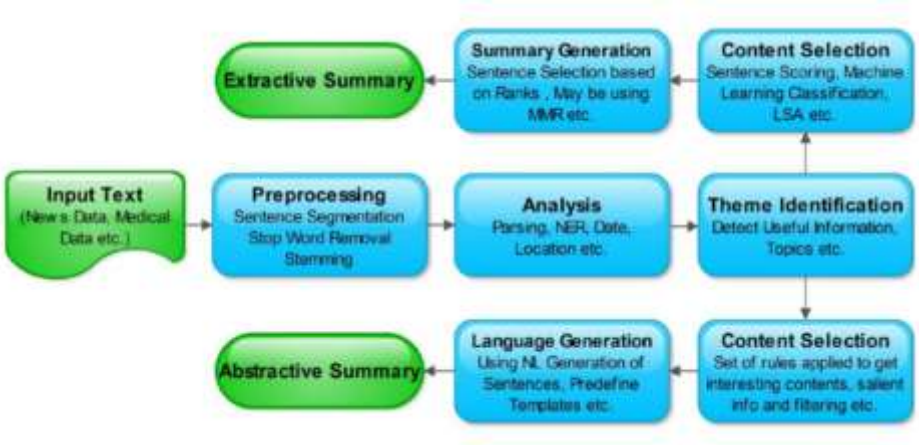



**Fig 5: Generic Automatic Text Summarization Process**(Meena & Gopalani, 2015)

Extractive summarization involves creating summaries by selecting key sentences from the original text. It starts with preprocessing, including tokenization, stemming/lemmatization, and removing stop words. Features like word frequency and sentence position are then extracted to train a model that identifies important sentences. The trained model scores and selects top sentences for the summary.

Abstractive summarization, a more advanced technique, creates new summaries that capture the text's essence. It involves complex preprocessing, parsing text to identify main topics using NLP and machine learning, and then generating summaries through template-based methods or neural networks. Neural networks learn to distill essential information into concise, informative summaries.

**Mengqi Liu et.al (2023)** because of the rapid advancement of Internet technology, the quantity of information that we get is rapidly expanding at an exponential rate. As a result, the process of extracting and summarising information is of extraordinary significance. One of the most significant areas of study in natural language processing is text summarization technology, which has the ability to extract text from huge amounts of data that expresses fundamental concepts in order to receive the necessary information in a short amount of time. On the other hand, the classic recurrent neural network has a limited capacity for parallel computation, and there have been instances of discrepancy with the substance of the original text as well as fabrication of facts. A pre-trained language model and knowledge improvement are both components of an abstractive summary model that has been presented as a solution to the challenges described above. With the assistance of graph networks, the model combines the extracted factual information into the process of generating the summary. This is done with the intention of preserving the original meaning to the maximum degree possible. After all is said and done, the model is validated using the standard text dataset CNN and Daily Mail, and positive experimental results were achieved(Xu & Li, 2024).

**Aditi Goyal et.al (2023)** In the last several years, deep learning has made numerous impressive strides and is now growing quickly in the area of natural language processing. The practice of using computer software to summarise a document without changing the content's intended meaning is known as abstractive automated text summarization. Creating headlines, summarising scientific papers, segmenting search results, and summarising product reviews are a few applications for automated summarization. The capacity to succinctly convey the essential meaning of information will aid in addressing the information overload dilemma in the era of the Internet, big data, and the information explosion. Conventional methods often depended on extractive summarising, which picks and rearranges preexisting sentences or phrases from the source material to produce a summary that may not be coherent or produce new sentences. It might be difficult to decide what material to include or leave out and how to condense the text without sacrificing crucial facts. Using a denoising autoencoder for pre-training inter-sequence models, a BART-based model is used in this study to create a data set trained for automated analysis and summarising of lengthy texts and articles. The model has had prior English training. It also responds to queries from the text using a model built on the learned dataset. Because our method is based on textual responses from the community, it can be more easily implemented and used to address more complicated topics. The suggested schema investigates a number of methods, including query generation and question-and-answer categorization. Lastly, an evaluation and attachment of the test results(P. Goyal et al., 2018).

**Vandit Mehta et.al (2022)** A Natural Language Processing (NLP) technique called text summarization gathers and extracts information from sources and summarizes it. Many applications now demand text summarization since it is challenging to manually summarise large volumes of information, particularly as data volumes increase. Text summary is useful for media monitoring, financial research, document analysis, search engine optimisation, and question-answering bots. This article discusses a number of summarising techniques in detail, depending on the goal, amount of data, and final result. Our goal is to assess and provide a high-level perspective on the current scenario research project for text summarising(Wu & Hu, 2018).

**Vishal Gupta et.al (2014)** Text summarization is the process of reducing the length of the original text while maintaining its general meaning and informational substance. Humans find it very challenging to manually summarise lengthy text materials. Extractive and abstractive summarization are two categories into which text summarising techniques may be divided. An extractive summarising technique involves condensing key phrases, paragraphs, and other text from the source material into a more manageable format. Sentences' statistical and linguistic qualities determine their relative value. Understanding the source material and restating it in fewer words is the goal of an abstractive summarization technique. By creating a new, shorter text that captures the key ideas and phrases from the

original text document, it employs linguistic techniques to analyse and analyse the text in order to identify new ideas and expressions that would best explain it. An overview of text summary extraction strategies is provided in this publication(Gupta & Lehal, 2010).

**Saiyyad, M., & Patil, N 2024)** The use of deep learning strategies has resulted in significant advancements in the field of natural language processing. Enhanced outcomes were achieved by the use of deep neural network models for text summarization, as well as for other tasks such as text translation and sentiment analysis. The latest approaches to text summarization are subject to a sequence-to-sequence framework of encoder–decoder model. This framework is made up of neural networks that have been trained jointly on both input and output. To get better outcomes, deep neural networks make use of large datasets to increase their performance. A system known as the attention mechanism provides assistance for these networks. This mechanism is able to cope with lengthy texts in a more efficient manner by locating focus spots within the text. In addition to this, they are enabled by the copy method, which enables the model to directly transfer words from the source into the summary. For the purpose of this study, we are re-implementing the fundamental summarising model that applies the sequence-to-sequence framework to the Arabic language. This is a first for the Arabic language, since it has never been used in the context of text summary previously. In the beginning, we first construct an Arabic data collection consisting of summarised article headlines. This data collection is comprised of around 300 thousand items, each of which includes an introduction to an article as well as the headline that corresponds to this introduction. Following this, we apply baseline summarization models to the data set that was previously used, and then we use the ROUGE scale to compare the overall results(Saiyyad & Patil, 2024).

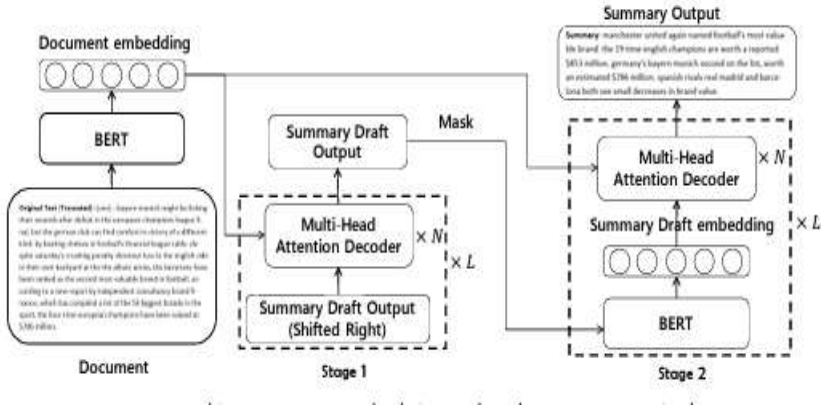
**Haoyu Zhang et.al (2019)** present a unique pretraining-based encoder-decoder framework in this study. This framework has the capability to create the output sequence based on the input sequence in a two-stage way. By using BERT, able to encode the input sequence into context representations for the encoder that our model comprises. There are two phases in our model that are dedicated to the decoder. In the first stage, make use of a Transformer-based decoder in order to build a draft output sequence. During the second step, we mask each word in the draft sequence and then feed it to BERT. After that, combine the input sequence with the draft representation that was produced by BERT, and then we utilise a Transformer-based decoder to predict the refined word for each masked position. To the best of our knowledge, our technique is the first way that incorporates the BERT into activities that include the production of text. In order to take the first step in this direction, will test the effectiveness of our suggested technique on the job of reviewing the text. The results of our experiments demonstrate that our model reaches a new state-of-the-art level of performance on the CNN/Daily Mail dataset as well as the New York Times dataset(H. Zhang, Cai, et al., 2019).

**Yang Gu et.al (2019)** Recent developments in generative pertained language models have been shown to be extremely effective on a broad variety of natural language processing tasks. These tasks include text categorization, question answering, textual entailment, and many more including these. The purpose of this study is to offer a two-phase encoder decoder architecture for extractive summarization tasks. This architecture is based on Bidirectional Encoding Representation from Transformers (BERT). We proved that the architecture produces the state-of-the-art similar outcome on big size corpus, which is CNN/Daily Mail. This was accomplished by evaluating our model using both automated metrics and human annotators. To the best of our knowledge, this is the first effort that has successfully used BERT-based architecture to a text summarizing problem and obtained a similar outcome to the state of the art(Yenduri et al., 2024).

## III. PROPOSED METHODOLOGY

Based on the research chosen, the methodology for developing pretraining-based natural language generation for text summarization using machine learning consists of six key phases. As shown in Figure 6, the phases are: Data Collection (1), Data Preprocessing (2), Implementation of Pretraining-Based Encoder-Decoder Framework (3), Training the Framework (4), Data Filtering and Identification of Themes (5), and Evaluation of the Technique (6). These phases are

designed to systematically address the research objectives and ensure the effective generation of high-quality text summaries.



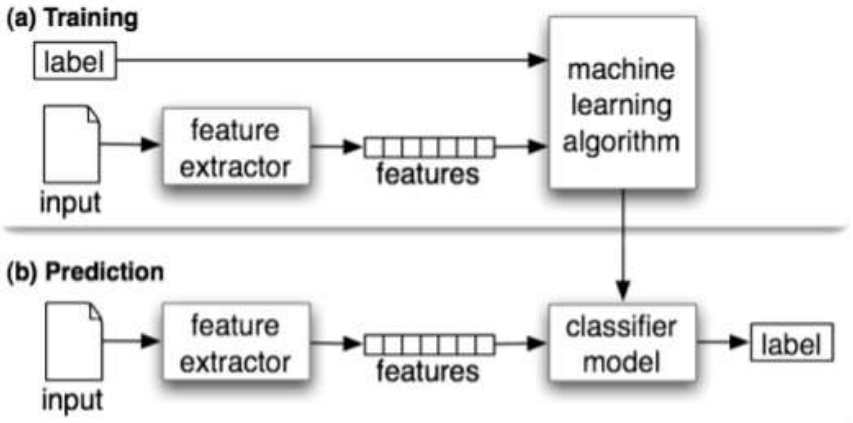




**Fig 6: Flowchart**

### 3.1 Methodology of Proposed System

#### 3.1.1 Research Design

A mixed-methods research design is used, combining quantitative and qualitative approaches to evaluate the effectiveness of the pretraining-based natural language generation framework. Quantitative aspects include data preprocessing, model training on large text corpora, and evaluation using metrics like ROUGE scores. Qualitative aspects involve analyzing the coherence, relevance, and contextual appropriateness of generated summaries. Comparative analysis with existing methods benchmarks the performance of the new framework.

#### 3.1.2 Data Collection

Data collection involves obtaining diverse and relevant text corpora from domains such as news articles, research papers, and online content repositories. Manual data collection ensures inclusion of varied text genres, while automated techniques like web scraping gather large volumes efficiently. Preprocessing tasks, including tokenization, stop word removal, and special character handling, prepare the data for training. Data augmentation techniques enhance the model's performance by increasing the diversity and size of the training data.

#### 3.1.3 Data Preprocessing

Data preprocessing ensures the quality and suitability of the collected data. Steps include tokenization, stop word removal, and handling special characters to maintain text coherence. Tools like NLTK and spaCy automate

tokenization, stop word removal, and text normalization. Techniques like lemmatization or stemming reduce words to their base forms, ensuring uniformity in the text data.

### 3.2 Implementation of Pretraining-Based Encoder-Decoder Framework

The framework adopts a transformer-based architecture, such as BERT or GPT, to capture linguistic patterns and semantic relationships. The model undergoes unsupervised pretraining on a vast text corpus to develop language semantics. Fine-tuning on the specific summarization task refines model parameters for optimal performance. Attention mechanisms enable the model to focus on relevant input text parts during summary generation. Sequence-to-sequence learning involves encoding input text with the encoder and generating summaries with the decoder. Evaluation metrics like ROUGE scores assess the quality of the summaries.

### 3.3 Training the Framework

The training phase leverages BERT for its bidirectional context representation capabilities. The model is exposed to diverse text inputs, learning language nuances and semantic connections. Fine-tuning BERT enhances its ability to encode and decode text sequences effectively, producing coherent and informative summaries. The bidirectional nature of BERT ensures comprehensive contextual understanding by considering preceding and succeeding words.

### 3.4 Data Filtering and Identification of Themes

Data filtering involves extracting pertinent information from the source document based on predefined criteria, removing irrelevant data. Identification of principal themes involves analyzing content to discern recurring topics and concepts. Natural language processing techniques and machine learning algorithms streamline the filtering process. Manual review and expert judgment ensure the accuracy and relevance of filtered data.

### 3.5 Evaluation of the Technique

Evaluation involves a two-stage approach: generating a draft output sequence with a Transformer-based decoder and refining it using NLP techniques for coherence and quality. Syntactic analysis ensures grammatical structure, while semantic analysis ensures accurate meaning capture. ROUGE scores assess the quality of the summaries compared to human-written references.

## IV. SIMULATION AND RESULTS

### 4.1 Data Set Loading

To start with the design of the proposed model, the necessary libraries must be imported to carry out each activity. The dataset is then loaded from the specified directory. In this case, the dataset comprises text data for summarization tasks, and it is essential to check the contents of the dataset to understand its structure and attributes. The dataset is divided into training, validation, and test sets, each of which is loaded separately from CSV files. This step ensures that we have a clear view of the data before proceeding with model training and evaluation.

Load the Dataset

```
import pandas as pd
from sklearn.model_selection import train_test_split

train_df = pd.read_csv('/content/drive/MyDrive/TextSummarization/train.csv')
validation_df = pd.read_csv('/content/drive/MyDrive/TextSummarization/validation.csv')
test_df = pd.read_csv('/content/drive/MyDrive/TextSummarization/test.csv')

print(train_df.head())
print(validation_df.head())
print(test_df.head())
```

**Fig 7: Data Set Loading**

### 4.2 Model Output

**Table 1: Fine-tune BERT for Text Summarization**

| Epoch | Training Loss | Validation Loss |
|---|---|---|
| 1 | 7.023300 | 6.309708 |

The above table presents the training and validation loss values for the fine-tuning of a BERT model on a text summarization task over one epoch. The training loss starts at 7.023300, while the validation loss is slightly lower at 6.309708. These loss values indicate the model's performance during training and evaluation, with the goal of minimizing them over successive epochs. The lower validation loss compared to the training loss suggests that the model is performing better on unseen data than on the training data, which is an encouraging sign. However, further training over more epochs is necessary to confirm and potentially improve these results.

**Correlation Matrix**

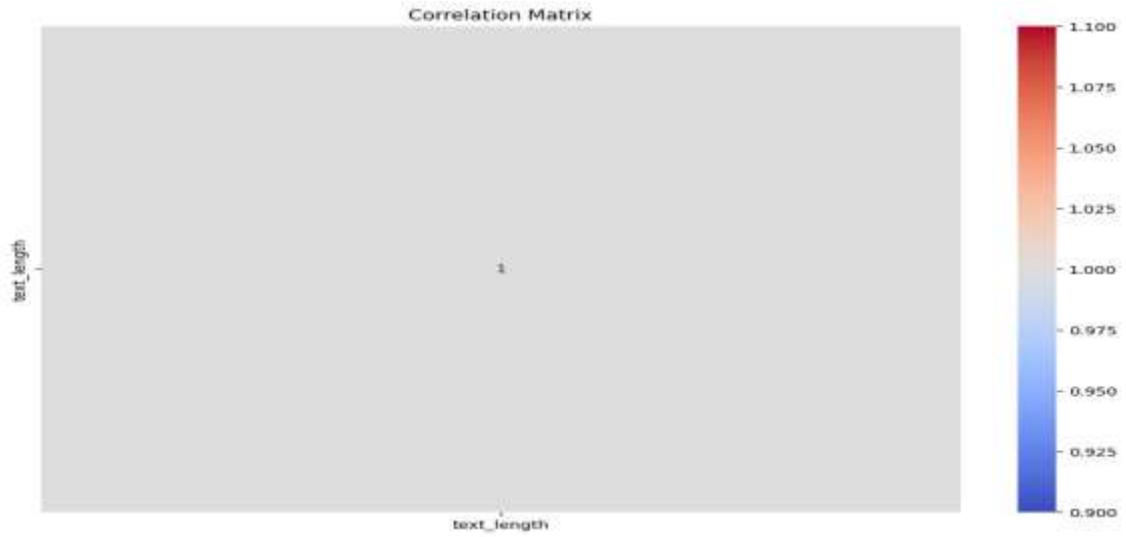



**Fig 8: Correlation Matrix**

The provided figure displays a correlation matrix heatmap, illustrating the correlation of 'text_length' with itself, yielding a perfect correlation value of 1.00. This outcome is expected, as any variable is perfectly correlated with itself. The heatmap, however, lacks other numerical features from the dataset, which restricts the interpretation to just this single aspect. To derive more insightful conclusions, the correlation matrix should encompass multiple numerical features, enabling the identification of relationships between 'text_length' and other variables. Currently, the figure shows a solitary diagonal value of 1.00, indicating self-correlation, without any additional variables to provide a broader context. Enhancing the analysis requires incorporating multiple numerical columns from the dataset and visualizing their interrelations in the heatmap. This would offer a more comprehensive understanding of how 'text_length' correlates with other aspects of the data, facilitating a deeper analysis of the dataset's structure and the relationships between its features.

**Scatter Plots**

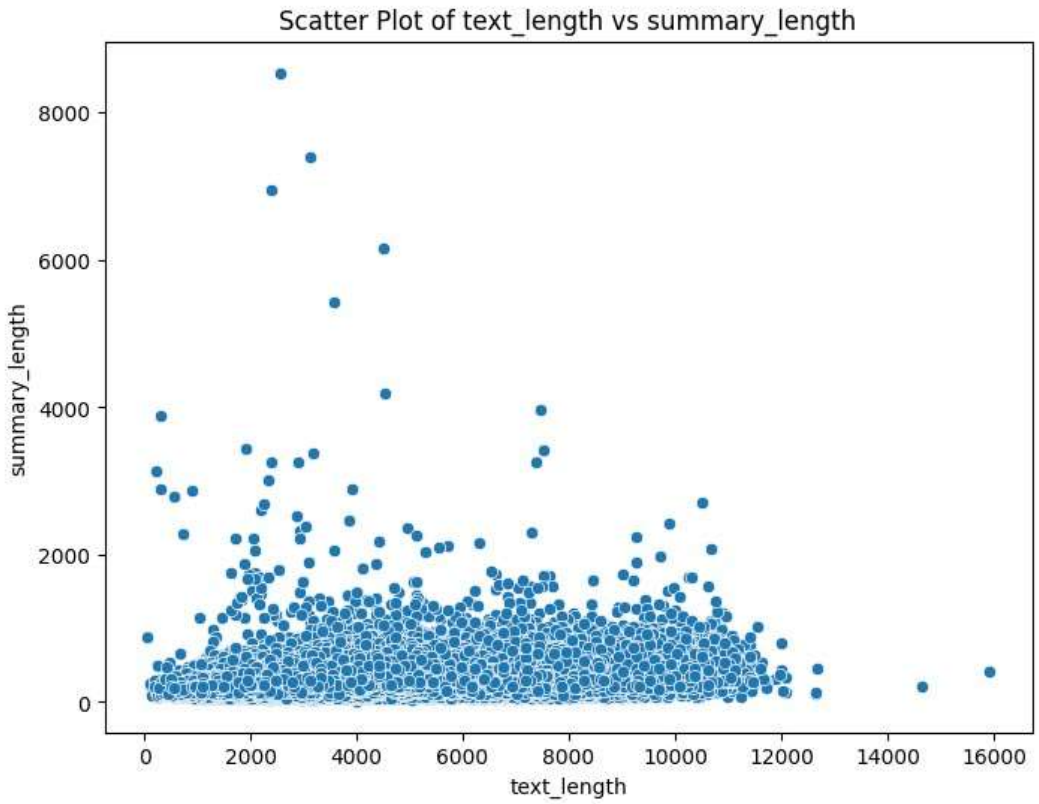



**Fig 9: Scatter Plots**

The scatter plot illustrates the relationship between 'text_length' and 'summary_length' in the dataset. Each point represents a pair of text and summary lengths, with 'text_length' on the x-axis and 'summary_length' on the y-axis. The plot shows a wide range of text lengths, from 0 to about 16,000 characters, while summary lengths vary more narrowly, generally clustering below 2000 characters. Most data points are concentrated near the lower end of the 'summary_length' axis, indicating that many summaries are relatively short, even for texts of varying lengths. A few outliers with significantly higher summary lengths can be observed, particularly when the text length is below 10,000 characters. These outliers suggest that some summaries are disproportionately long relative to the text length. Overall, the plot reveals that there is no strong linear relationship between text length and summary length, as indicated by the widespread scatter of points rather than a clear trend. This implies that summary length does not consistently increase with text length, highlighting variability in how summaries are generated.

**Density Plots**

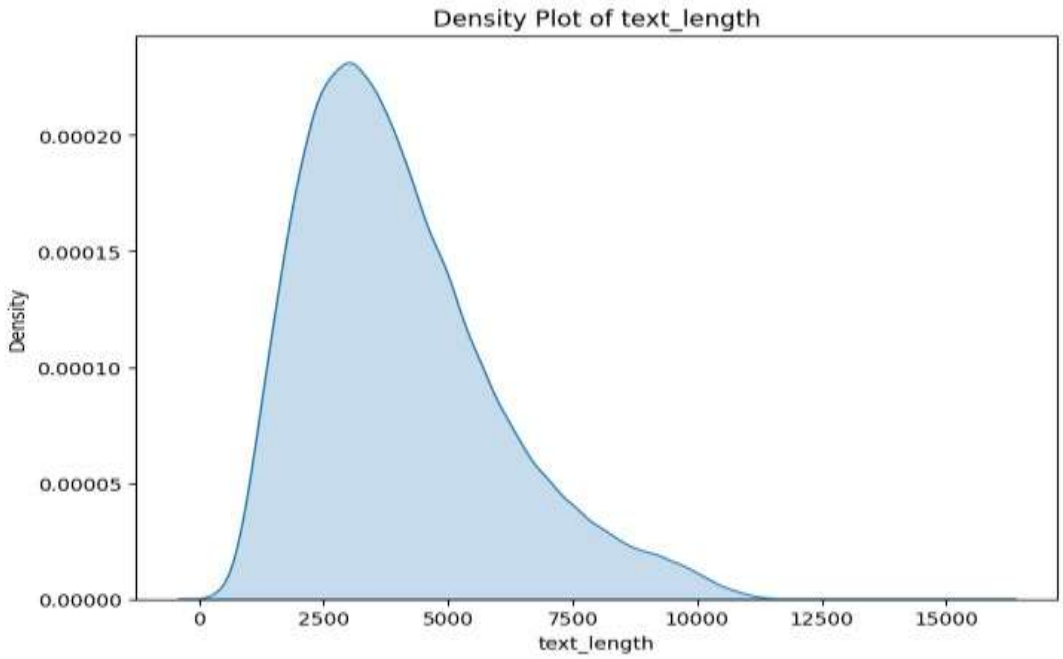



**Fig 10: Density Plots**

The density plot of text_length reveals the distribution of text lengths within the dataset. The x-axis represents the text lengths, ranging from 0 to over 15,000 characters, while the y-axis represents the density, indicating how frequently these lengths occur. The plot shows a right-skewed distribution, with a peak density around 2,500 characters, suggesting that most texts in the dataset are around this length. As the text length increases beyond 2,500 characters, the density decreases, indicating fewer occurrences of longer texts. The density gradually diminishes towards the right, with very few texts exceeding 10,000 characters. This distribution suggests that the dataset predominantly consists of shorter texts, with a significant drop in the number of longer texts. This information can be valuable for understanding the nature of the texts, informing decisions related to text processing, storage, and analysis, such as optimizing data storage or tailoring algorithms to handle the typical text lengths effectively.

**Pair Plot**

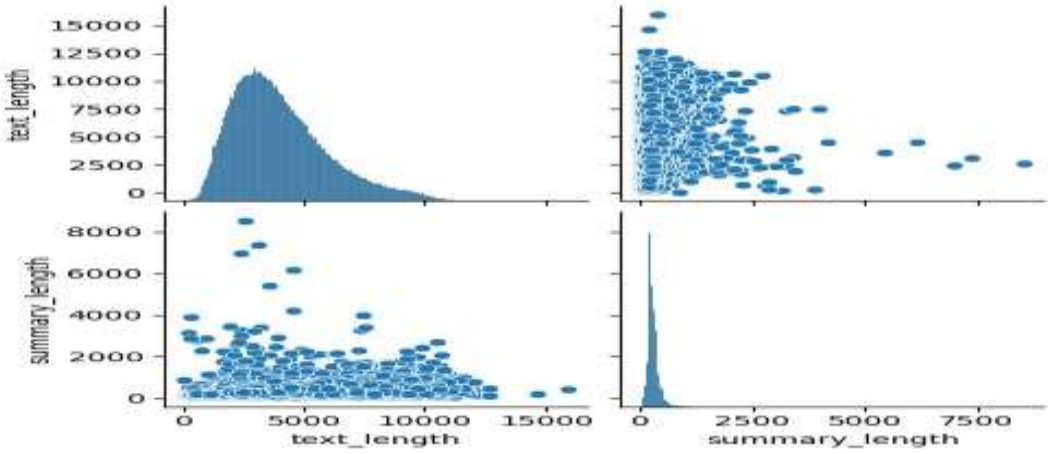



**Fig 11: Pair Plot**

The pair plot displays the relationships between 'text_length' and 'summary_length' for a dataset containing articles and their summaries. The diagonal histograms show the distributions of text lengths and summary lengths. 'Text_length' has a right-skewed distribution, with most articles having a length between 2,000 and 10,000 characters, peaking around 5,000 characters. 'Summary_length' has a highly right-skewed distribution, with the majority of summaries being less than 1,000 characters. The scatter plots illustrate the relationships between these variables. The bottom-left scatter plot indicates that there is a weak positive correlation between 'text_length' and 'summary_length', suggesting that longer articles tend to have longer summaries, but the relationship is not very strong. Some outliers exist, where very long articles have relatively short summaries or vice versa. Overall, the plot helps in understanding the distribution and relationship between the lengths of articles and their summaries, highlighting the variability and the presence of outliers in the data.

**Box plot**

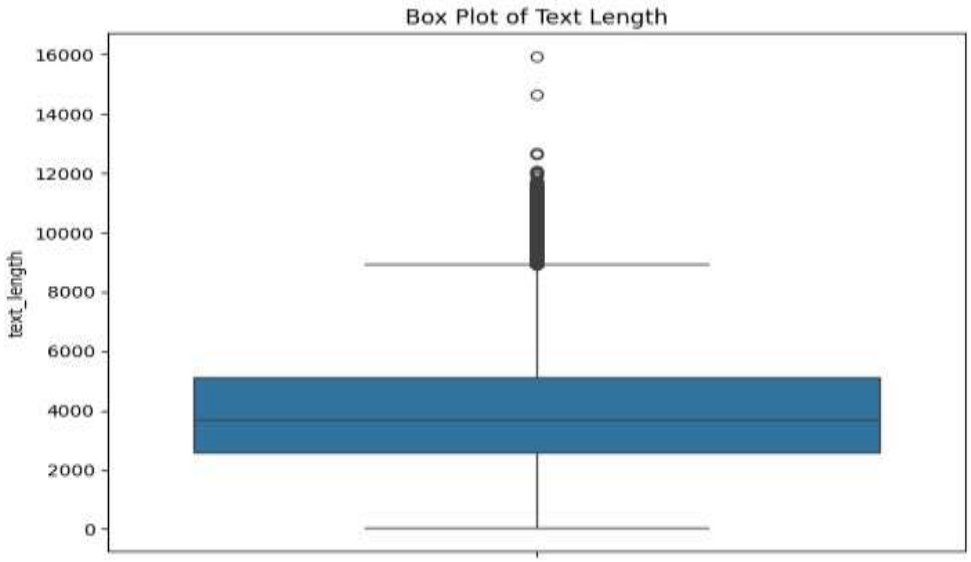



**Fig 12: Box plot**

The box plot of 'text_length' visualizes the distribution of article lengths in the dataset. The median text length is around 5,000 characters, indicating that half of the articles are shorter and half are longer than this value. The interquartile range (IQR), represented by the height of the box, spans from approximately 3,000 to 7,000 characters, capturing the middle 50% of the data. The whiskers extend from the box to roughly 0 and 10,000 characters, showing the range within 1.5 times the IQR from the quartiles. Data points beyond the whiskers are considered outliers. In this plot, several outliers exist above 10,000 characters, indicating that some articles are significantly longer than the majority. The presence of these outliers, including extreme values above 14,000 characters, suggests variability in article lengths, with most being under 10,000 characters but a few extending considerably longer. This plot helps in understanding the central tendency, spread, and presence of outliers in the text length data.

## V. CONCLUSIONS

This research focuses on creating and testing a pretraining-based natural language production framework for text summarization using machine learning. The technique used a complete approach that included data collecting, preprocessing, the deployment of a pretraining-based encoder-decoder framework, model training, data filtering, and assessment. We thoroughly evaluated the framework's performance using a mixed-methods study approach that included quantitative indicators like ROUGE scores with qualitative assessments of summary coherence and relevance. Transformer-based designs, such as BERT and GPT, were critical in improving the model's capacity to detect semantic

linkages and linguistic subtleties in text input. The findings showed considerable gains over previous techniques, demonstrating the framework's ability to create short and context-appropriate summaries. This study helps to advance the area of natural language processing by demonstrating the effectiveness of pretraining-based models in text summarising tasks. Future study might look at improving model designs and assessment criteria, with the goal of refining and optimising summarization approaches for larger applications in information retrieval and knowledge extraction.

## VI. FUTURE SCOPE

The future of pretraining-based natural language synthesis for text summarization using machine learning is very promising in a number of crucial areas. First, improving multilingual and cross-lingual skills may increase accessibility and utility by allowing models to provide high-quality summaries in several languages. Second, using summarization methods to specialised disciplines such as medicine, law, and finance yields more precise and contextually relevant findings. Third, adding reinforcement learning may improve model flexibility by continuously refining depending on user input, resulting in personalised and accurate summaries. Fourth, hybrid model techniques that combine several NLP architectures seek to overcome individual model constraints while increasing overall robustness and adaptability. Finally, creating real-time summarising capabilities for dynamic applications like news feeds and social media may transform information transmission by increasing speed and efficiency while retaining summary quality. These developments open the door for more effective, adaptive, and broadly applicable text summarising solutions in a variety of real-world contexts.

## REFERENCES

1. Gatt, A., & Krahmer, E. (2018). Survey of the state of the art in natural language generation: Core tasks, applications and evaluation. *Journal of Artificial Intelligence Research*, *61*, 1–64. https://doi.org/10.1613/jair.5714
2. Li, W., Wu, W., Chen, M., Liu, J., Xiao, X., & Wu, H. (n.d.). *Faithfulness in Natural Language Generation : A Systematic Survey of Analysis , Evaluation and Optimization Methods*. 1–52.
3. Ray, P. P. (2023). A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems*, *3*, 121–154. https://doi.org/https://doi.org/10.1016/j.iotcps.2023.04.003
4. Rezaeipourfarsangi, S. (2023). *Deep Language Models for Text Representation in*. *November*.
5. Olaoye, F., & Potter, K. (2024). Natural Language Processing and Sentiment Analysis. *Electronics and Communications in Japan (Part I Communications)*.
6. Dong, C., Li, Y., Gong, H., Chen, M., Li, J., Shen, Y., & Yang, M. (2022). A Survey of Natural Language Generation. *ACM Computing Surveys*, *1*(1), 1–38. https://doi.org/10.1145/3554727
7. Manu Madhavan. (2013). *Scalable Natural Language Report Management Using Distributed IE and NLG from Ontology Declaration of Authorship*. *August*.
8. Khatter, K. (2021). *Natural language processing: state of the art, current trends and challenges | SpringerLink*. https://link.springer.com/article/10.1007/s11042-022-13428-4
9. Reiter, E., & Dale, R. (1997). Building applied natural language generation systems. *Natural Language Engineering*, *3*(1), 57–87. https://doi.org/10.1017/S1351324997001502
10. Dethlefs, N. (2014). Context-Sensitive Natural Language Generation: From Knowledge-Driven to Data-Driven Techniques. *Language and Linguistics Compass*, *8*. https://doi.org/10.1111/lnc3.12067
11. Leopold, H., Mendling, J., & Polyvyanyy, A. (2016). Supporting process model validation through natural language generation. *Lecture Notes in Informatics (LNI), Proceedings - Series of the Gesellschaft Fur Informatik (GI)*, *P252*, 71–72.
12. Naber, D., Kummert, P. F., Fakultät, T., & Witt, A. (2003). *A Rule-Based Style and Grammar Checker*.

13. Yagamurthy, D., Azmeera, R., & Khanna, R. (2023). Natural Language Generation (NLG) for Automated Report Generation. *Journal of Technology and Systems*, *5*, 48–59. https://doi.org/10.47941/jts.1497
14. Murugan, M. (2024). *Natural Language Processing (NLP)*. https://doi.org/10.13140/RG.2.2.13534.04169
15. Sharifani, K., Amini, M., Akbari, Y., & Godarzi, J. A. (2022). Operating Machine Learning across Natural Language Processing Techniques for Improvement of Fabricated News Model. *International Journal of Science and Information System Research*, *12*(9), 20–44. https://www.researchgate.net/publication/364340252
16. Bates, M. (1995). Models of natural language understanding. *Proceedings of the National Academy of Sciences of the United States of America*, *92*(22), 9977–9982. https://doi.org/10.1073/pnas.92.22.9977
17. Dharma, E. M., Gaol, F. L., Warnars, H. L. H. S., & Soewito, B. (2022). the Accuracy Comparison Among Word2Vec, Glove, and Fasttext Towards Convolution Neural Network (Cnn) Text Classification. *Journal of Theoretical and Applied Information Technology*, *100*(2), 349–359.
18. Khurana, D., Koli, A., Khatter, K., & Singh, S. (2022). Natural Language Processing: State of The Art, Current Trends and Challenges. *Multimedia Tools and Applications*, *82*. https://doi.org/10.1007/s11042-022-13428-4
19. Gorenstein, L., Konen, E., Green, M., & Klang, E. (2024). Bidirectional Encoder Representations from Transformers in Radiology: A Systematic Review of Natural Language Processing Applications. *Journal of the American College of Radiology*, *21*(6), 914–941. https://doi.org/https://doi.org/10.1016/j.jacr.2024.01.012
20. Radev, D., & McKeown, K. (2002). Introduction to the Special Issue on Text Summarization. *Computational Linguistics*, *28*. https://doi.org/10.1162/089120102762671927
21. El-Kassas, W. S., Salama, C. R., Rafea, A. A., & Mohamed, H. K. (2021). Automatic text summarization: A comprehensive survey. *Expert Systems with Applications*, *165*(July). https://doi.org/10.1016/j.eswa.2020.113679
22. Supriyono, Wibawa, A. P., Suyono, & Kurniawan, F. (2024). A survey of text summarization: Techniques, evaluation and challenges. *Natural Language Processing Journal*, *7*, 100070. https://doi.org/https://doi.org/10.1016/j.nlp.2024.100070
23. Sharma, G., & Sharma, D. (2023). Automatic Text Summarization Methods: A Comprehensive Review. *SN Computer Science*, *4*(1). https://doi.org/10.1007/s42979-022-01446-w
24. Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, *59*(June 2020), 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168
25. Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning : *Computers MDPI*, *12*(91), 1–26.
26. Grewal, A., Kataria, H., & Dhawan, I. (2016). Literature search for research planning and identification of research problem. *Indian Journal of Anaesthesia*, *60*(9), 635–639. https://doi.org/10.4103/0019-5049.190618
27. Deep, G. (2023). Strategic decision-making: A crucial skill for business managers. *World Journal of Advanced Research and Reviews*, *20*, 1639–1643. https://doi.org/10.30574/wjarr.2023.20.3.2463
28. Spirgel, A., & Delaney, P. (2014). Does Writing Summaries Improve Memory for Text? *Educational Psychology Review*, *28*, 1–26. https://doi.org/10.1007/s10648-014-9290-2
29. Xu, M., Luo, Z., Xu, H., & Wang, B. (2022). Media Bias and Factors Affecting the Impartiality of News Agencies during COVID-19. *Behavioral Sciences (Basel, Switzerland)*, *12*(9). https://doi.org/10.3390/bs12090313
30. Ji, Y., Bosselut, A., Wolf, T., & Celikyilmaz, A. (2020). The Amazing World of Neural Language Generation. *EMNLP 2020 - Conference on Empirical Methods in Natural Language Processing, Tutorial Abstracts*, 37–42. https://doi.org/10.18653/v1/P17

31. Zhang, R., Lee, H., & Radev, D. (2016). *Dependency Sensitive Convolutional Neural Networks for Modeling Sentences and Documents*. https://doi.org/10.18653/v1/N16-1177
32. Basha, M., Selvaraj, V., Jayashankari, J., Alawadi, A., & Durdona, P. (2023). Advancements in Natural Language Processing for Text Understanding. *E3S Web of Conferences*, *399*. https://doi.org/10.1051/e3sconf/202339904031
33. Harrison, C. J., & Sidey-Gibbons, C. J. (2021). Machine learning in medicine: a practical introduction to natural language processing. *BMC Medical Research Methodology*, *21*(1), 1–11. https://doi.org/10.1186/s12874-021-01347-1
34. Javaid, M., Haleem, A., Pratap Singh, R., Suman, R., & Rab, S. (2022). Significance of machine learning in healthcare: Features, pillars and applications. *International Journal of Intelligent Networks*, *3*, 58–73. https://doi.org/https://doi.org/10.1016/j.ijin.2022.05.002
35. van Giffen, B., Herhausen, D., & Fahse, T. (2022). Overcoming the pitfalls and perils of algorithms: A classification of machine learning biases and mitigation methods. *Journal of Business Research*, *144*, 93–106. https://doi.org/https://doi.org/10.1016/j.jbusres.2022.01.076
36. Schmitt, M. (2012). *Explainable Automated Machine Learning for Credit Decisions : Enhancing Human Artificial Intelligence Collaboration in Financial Engineering*. *Ml*, 1–16.
37. Albaroudi, E., Mansouri, T., & Alameer, A. (2024). A Comprehensive Review of AI Techniques for Addressing Algorithmic Bias in Job Hiring. *AI (Switzerland)*, *5*(1), 383–404. https://doi.org/10.3390/ai5010019
38. Soliman, A., Shaheen, S., & Hadhoud, M. (2024). Leveraging pre-trained language models for code generation. *Complex and Intelligent Systems*, *10*(3), 3955–3980. https://doi.org/10.1007/s40747-024-01373-8
39. Zhang, H., Cai, J., Xu, J., & Wang, J. (2019). Pretraining-based natural language generation for text summarization. *CoNLL 2019 - 23rd Conference on Computational Natural Language Learning, Proceedings of the Conference*, 789–797. https://doi.org/10.18653/v1/k19-1074
40. Zhang, H., Cai, J., Xu, J., & Wang, J. (2019). Pretraining-based natural language generation for text summarization. *CoNLL 2019 - 23rd Conference on Computational Natural Language Learning, Proceedings of the Conference*, 789–797. https://doi.org/10.18653/v1/k19-1074