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Original Article

Automatic Text Summarization Using Deep Learning

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Abstract: *Text summarising is a method for taking the most crucial information from various texts, compressing it, and keeping the text's overall meaning. Rarely does one need to read reams of documentation to get the gist of a topic; frequently, a brief synopsis is adequate. Automatic Text Summarization (ATS) can be useful in this situation by compressing the text and gathering important information in one place. Only the important sentences from the original document are recognized by the extraction techniques and extracted from the text. As a result, it is more difficult when using abstractive summarization approaches, which create the summary after reading the original text. In this paper, we implemented text summarization using the t5 algorithm and evaluated it based on different criteria, such as the amount of compression or summarization, the amount of meaning lost, and the number of grammatical errors. We also made sure that the information we got from the output was accurate and useful.*

Keywords: *Natural Language Processing, T5 Model, Feature Extraction.*

I. INTRODUCTION

It is frequently important for a machine learning model to parse text in a way that permits downstream learning when training the model to execute natural language processing (NLP) tasks. This might be interpreted as the model acquiring all-purpose information that enables text comprehension. Using this information, a low-level equal contribution to an equal high-level contribution can be made. The core tenet of our work is to treat text processing as a text-to-text issue: to accept the existing text as input and output new text. This method was motivated by earlier unifying frameworks for NLP jobs, for tasks for span extraction, language modeling, or treating all text problems as questions.

With the text-to-text architecture, we can use the same model, aim, training procedure, and decoding strategy for every problem we face. Using a unified approach to NLP research, we may compare the efficacy of various transfer learning targets, unlabeled datasets, and other elements. By scaling up models and datasets beyond what has been previously taken into consideration, we may additionally investigate the limitations of transfer learning for NLP.

A summary is a text that has been created from several texts and condenses the most important information from the source material. The objective of automatic text summarising is to provide consumers with a condensed, semantically rich version of the original material that is easier to read and comprehend. The reduction in reading time is the main advantage of text summarization. Using an extractive summarising technique, significant sentences, paragraphs, and other portions of a material are taken out and combined into a condensed version. Understanding the key ideas in a paper and then articulating them in plain words constitutes an abstract summary.

A sort of information retrieval application called text summarization involves reducing the length of the supplied text. It strives to keep its general meaning and informational content. The process of gathering the required data involves a variety of technologies, giving rise to the summarizing technique. A text constructed from one or more texts and includes a sizable amount of the original material is called a summary. An extracted document is the end result of text summarization. Automatic text summarization is the term used when a computer performs this task automatically.

II. LITERATURE SURVEY

Extracting the most instructive sentences, developed a variety of query-oriented text summarizing techniques. In this, a variety of features are taken from the sentences, each of which assesses the significance of the sentences from a different angle. More precise selection of the most instructive sentences results in a better-quality summary that is generated. In this case, the ROUGE criterion has been applied to extract the 11 best features from each of the sentences and use them to generate more appropriate features that result in improved summaries [1].

Building a single neural network that can be cooperatively changed to improve translation performance is the goal of neural machine translation. A member of the encoder-decoder family uses an encoder to transform a phrase into a vector of a predetermined length; a decoder then uses this vector to provide a translation. To better handle unfamiliar or uncommon terms is one of the problems still ahead. This will be necessary for the model to be more widely applied and to function on with modern, cutting-edge machine translation systems in all scenarios [2].

A machine learning, deep learning and statistical models were utilized in constructing the framework for the AI text summarization system they developed. Also evaluated how well the performance of the three models was. Artificial intelligence deep learning models are trained using deep learning models, and candidate essay titles are produced using these trained models. Following this, ROUGE evaluates these possible titles based on the performance of the three models [3].

The strategy uses an extractive heading-wise text summarizer with automatic feature-based extraction to increase coherence and as a result, understandability. Two different methodologies are possible for extrinsic and intrinsic evaluation respectively. An automated extractive text summarizer that goes by the name heading wise summarizer is the instrument that we utilize. When one-third of the sentences from each heading are included in the summary paragraph, the paragraph has a considerably stronger sense of cohesion. According to a computer program for reading comprehension and vocabulary developed by the United States National Institute of Education (NIE), [4] the coherence of the summary improves the overall quality of the assessment.

The major topic of Natural Language Processing research that is being used continuously in the context of programmed libraries. A process called as automated text summarization is used to generate a concise and accurate summary of the text that is fed into it. However, it may be argued that the summaries were appropriate when examining the results using recognized measures in the field [5].

The most common ways are word-based, sentence-based, and graph-based. Among them, sentence relationships are used to create summaries using graph-based algorithms for automatic text summarising. The development of a number of text-processing applications, including extractive and abstractive summaries, question-and-answer systems, and information retrieval systems, among others, may also be supported by these linkages. This was done on the CNN corpus using the Text Rank algorithm and the suggested methodology. The outcomes demonstrate that the model put out here outperforms the existing methods in both quantitative and qualitative terms [6].

Presented extensive applications for Natural Language Processing in augmentative and alternative communication (especially). Our method is unsupervised and not domain-specific. The suggested strategy has been applied to many types of documents. Each time, our programme produced a logical summary. For summarizing a single document, our model performs fairly well [7].

To remove the most critical information from given text and deliver to the users, utilize a text summarizing method. The system generates an extractive text summary to recognize text characteristics and grade the sentences according to the articles fed into the system. Tokenizing and stemming procedures are done on the text. Utilizing in-text citations and finding synonyms are two innovative strategies. These qualities, in addition to more traditional methods of analysis, are used to provide a score to the sentences. The scores are used in conjunction with neural networks to classify the texts into the appropriate categories [8].

Text summary condenses the original text into a shorter form while maintaining the informational values and all-inclusive targets. Text summarization is a difficult problem that is becoming increasingly important. There is an information overload as a result of the fast progress of technology and internet use. Strong text summarizers that create a summary of papers for consumers can assist in overcoming this problem. This text's substance calls for sophisticated natural language processing tools, such as grammar and lexicons, for generation and parsing [9].

The ROUGE summary assessment package contains four different ROUGE measures and their evaluations. Additionally, three content-based evaluation techniques that gauge summary similarity were presented. These techniques include unit overlap (such as a bigram or a unigram) and the longest common subsequence. There is frequently a contradiction between the wants of users and the extracted opinionated statements because most existing algorithms cannot discern between the meaning of a review phrase and a user's inquiry when both have the same bag of words. However, the QMOS summarization phase can prevent extracting a review phrase that has a high degree of similarity to the user's question but a different meaning [10].

Recent results from study indicate that there is no association between match and non-match similarity scores. This is due to the fact that there is no detectable underlying distribution function. Because of the many forms that these distribution functions take, it is vital to use a method that is not parametric while researching fingerprint similarity scores. It is feasible to generate an accurate Receiver Operating Characteristic (ROC) curve even without making any assumptions about the operating thresholds or the shape of the distribution functions. This is because the ROC curve is used to describe the receiver's performance. [11] This study used the match similarity scores and the false acceptance rate (FAR) of the non-match similarity ratings.

Using Attentional Encoder-Decoder Recurrent Neural Networks to summarize text, we demonstrate that they perform at the cutting edge on two independent corpora. We propose a number of unique models that tackle important summarizing issues that the basic architecture does not fully address, these include modelling keywords, and capturing the hierarchy of sentence-to-word structure. We propose a number of unique models that tackle important summarizing issues that the basic architecture does not fully address. We also develop future study performance goals and suggest a new dataset made up of multi-sentence summaries [12].

A cutting-edge method for verifying the accuracy of summarize produced by abstract neural models. In contrast to previously proposed sentence-based approaches, the models are taught to examine the factual consistency of documents on a sentence-by-sentence basis, which allows them to handle a greater variety of mistakes. In order to trained models, weakly supervised artificial data is constructed based on perception from the examination of mistakes made by progressive summarization methods. According on the results of perceptible studies, this technique performs better than previous models on available textual entailment and fact-checking data on less abstract domains, such as CNN/Daily Mail news items, which motivated our use of weak-supervision over transfer learning from related domains. Experiments with human annotators demonstrated that our suggested strategy, which includes a model for explaining factual consistency checks, is sound [13].

Compare the value of one summary with that of other (ideal) summaries written by people and have the comparison done automatically. The metrics evaluate the level of similarity between the ideal summaries generated by people and those generated by computers by counting the number of overlapping units, such as n-grams. It introduces four various The ROUGE summary evaluation package and their assessments comprise the ROUGE measures. In this Document Understanding Conference, it is a sizable summary review that NIST sponsored, three of them were employed. Using bootstrap resampling, we calculated confidence intervals for the correlations to assess the significance of the data [14].

A technique for summarizing material that focuses on the problem at hand. An optimum and efficient method for producing text summaries is outlined here, and it makes use of lexical chains and theorems derived from WordNet. We are able to generate a text summary with our approaches by first adopting a model of topic development in the text. This allows us to avoid the need of doing an in-depth semantic analysis of the text [15].

The discovery of new concepts that can enhance the outcomes of a certain framework for a particular problem is the main goal of the theoretical work that is common in this area of research on rough sets. While the experimental analysis has its own parallel significance for determining how well a certain technique works on a particular dataset. Furthermore, in this particular field, experimental analysis has become even more important than theoretical attempts in order to obtain the learnt parameters for a given situation [16].

Recent neural network summarizing methods primarily use generation-based abstraction or selection-based extraction. In this article, we build a neural model for syntactic Compression and joint extraction to summarize a single text. According to the results of our experiments using the CNN/Daily Mail and New York Times datasets, our model performs admirably (at the same level as systems at the forefront of their fields), as evaluated by ROUGE [17].

Deep learning approach used to handle the automated extractive text summarizing jobs. This method makes use of self-critical sequence training (SCST) for optimization and the convolutional sequence-to-sequence (ConvS2S) model to contain the important subject information. Our method can enhance the integrity, diversity, and informativeness of generated summaries using a statistical term which means a systematic deviation from the actual value by jointly focusing on topics and word-level alignment. For the purpose of abstract text summarization, we propose using a topic-aware ConvS2S model trained using reinforcement learning. It has been shown that the novel topic-aware attention approach incorporates some amount of contextual information into the process of text summarization. The effectiveness of suggest model improves cutting-edge techniques on numerous benchmark datasets. Our model can also generate summaries that are more informative, coherent, and diverse [18].

Introducing the first sizable MDS news dataset, multi-News. We also suggest an end-to-end model that, when applied to MDS datasets, delivers competitive performance by combining a conventional extractive summarization approach with a typical SDS model. A useful tool as the quantity of online publications increases quickly is the automatic compilation of summaries from a variety of news pieces. Due to the accessibility of big datasets, single document summarization (SDS) system has profited from developments into neural encoder-decoder models. In the first comprehensive multi-document news summary, Multi -News, is presented in this study [19].

The ATS framework (ATSDL), which is built on LSTM-CNN, has the potential to generate new sentences by focusing on fragments of a smaller size than sentences, particularly semantic phrases. A text summarization technique called ATSDL consists of two fundamental steps: the first extracts terms from source sentences, and the second employs deep learning to generate text summaries. This sets it apart from currently used abstraction-based methodologies [20].

This paper has concentrated explicitly on deep learning technology to manage time and improve the illustration of text summarision. Moreover, the input sentence provides reliable results. The redundancy issue is being actively addressed by researchers who are also actively pursuing a more accurate rendering of the text's content and, more intriguingly, are currently attempting to provide summaries that are specifically catered to user needs. Another area of research that is very active is sentence compression. Sentence compression seeks to keep only the important and interesting portions of the original papers' sentences instead of simply choosing the most pertinent sentences. The improvement in readability and summarization quality brought about by this method still needs assessment. Given state of the art in parsing, many sentence compression approaches require a precise analysis of the input text in order to produce trustworthy results, which is not always possible. Sentence compression is a potential source of improvement, but its effectiveness needs to be confirmed. One of their fundamental drawbacks is the inability of the text produced by extractive technologies to be read.

III. METHODOLOGY

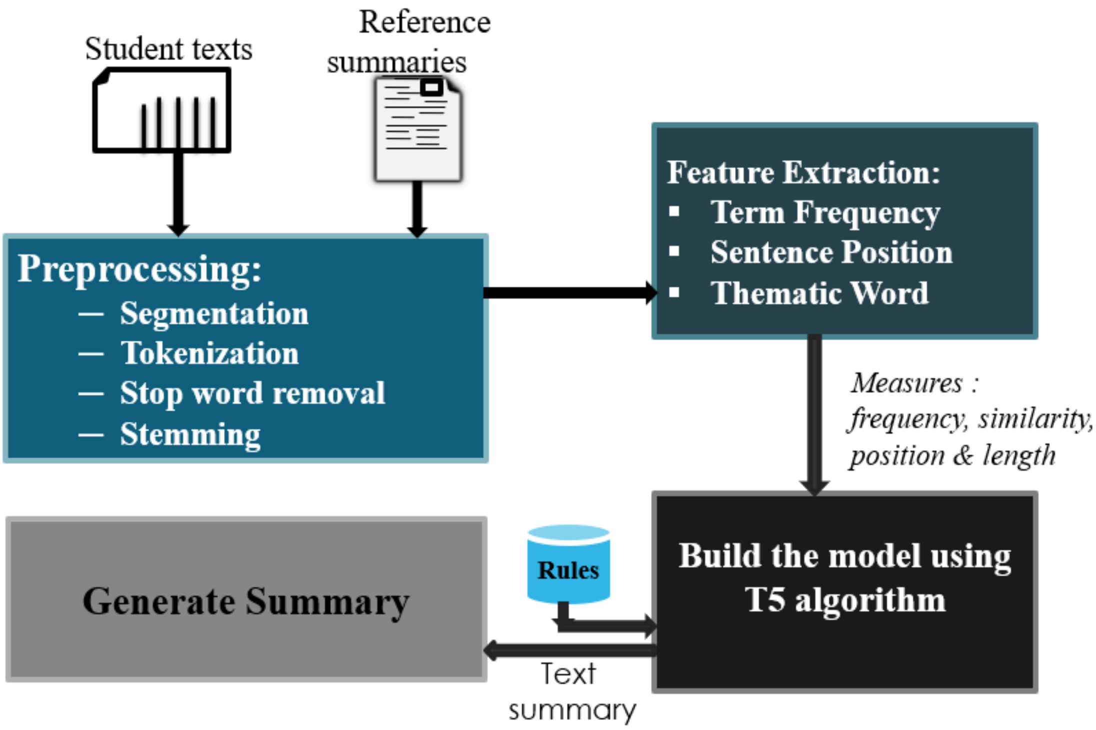

Figure 1: Proposed System

A. Preprocessing:

Preprocessing is a crucial step in Automatic Text Summarization since it helps to reduce the amount of text that needs to be represented. In the initial preprocessing stage, segmentation, tokenization, and stop-word elimination are all included. Sentence structure, sentence length, numerical information, an inverted comma, and keywords are some of the factors taken into account in this step. In order to determine if a specific statement should be added to the final summary or not, a machine-learning model is finally deployed. Preprocessing the text is necessary. The text must be divided into sentences, all words must be lowercase, stop words (such as is, an, and the) must be eliminated, and additional duties must be completed. The technique described in this paper initially preprocesses the input text by removing any stop words. The word stem is then identified, and its (POS) is labeled.

a) Segmentation:

The process of dividing text into pertinent chunks is known as text segmentation. These chunks may be made up of words, phrases, or subjects. In this article, we'll take a closer look at a particular kind of text segmentation task called topic segmentation, which separates a lengthy text into chunks that each belong to a different topic or subtopic.

b) Tokenization:

Splitting a text entity into tokens, or tiny pieces of text, is the process of tokenization. Tokens can be anything from words to characters to numbers, symbols to n-grams.

c) Stop Word Removal:

By using SpaCy, we can quickly and efficiently remove stop words from the text that has been submitted. The stop words included inside the spacy.lang.en.stop words class are included on the list of words it has as its own and may be imported as STOP WORDS. He made the decision to immediately re-file his claims against the wood-cutting and fisheries rights and end his legal dispute with the monastery.

d) Stemming:

Lemmatization and stemming have traditionally been employed in Automatic Text Summarization to normalize words. However, the curse of dimensionality can impair the performance of summarizers even when normalization is used on huge texts. In order to further shrink the space of representation, this work offers a new technique for normalizing words. We suggest using a technique known as Ultra-stemming to reduce each word to its basic components. The findings demonstrate that Ultra-stemming maintains the substance of summaries generated by this representation and can frequently significantly enhance system performance. Fresa was used to analyse summaries on trilingual corpora automatically. Results show that performance has improved, irrespective of the summarizer system employed.

B. Feature Extraction

The feature computation phase aims to extract and compute the sentence similarity values across different sentences and the titles of those phrases. The ratings given to each phrase are used to determine where it falls in the overall rankings. Sentences with higher rankings have been included in the summary.

a) Term Frequency:

The term frequency (TF) indicator provides information on the frequency with which a specific word occurs in a particular report in relation to its significance. The phrase "TF" might refer to a term that frequently appears in the report. Now, each phrase receives a score calculated based on the components, and the rundown will only contain those sentences with extremely high scores. The word count of larger sentences has a tendency to grow when using this strategy, which is a downside of the method.

b) Sentence Position:

The position of the sentence (in reverse order) is utilised to establish its relevance because it is known that the beginning sentences of the text are more significant than the remainder of the text (this heuristic is known as baseline). As a result, the last phrases have very no chance of being chosen.

c) Thematic Word:

The weight of words in a text is computed using a formula based on the combined word recognition algorithm, taking into account word frequency, word part of speech, word location, and word length in order to provide high-quality automatic text summarization. The final summarization is formed by thoroughly examining the similarity of candidate phrases, eliminating information redundancy, and is weighted according to a sentence's content and location, the cue words in it, and the user's preference using the suggested formula. After that we can build the model using T5 Algorithm as given below with the help of measures which are "frequency," "similarity," "position," and "length."

C. T5 Algorithm:

This approach is used by a Transformer-based architecture that is often referred to as T5, which stands for "Text-to-Text Transfer Transformer." In order to generate some target text, the model text is used as input in each task, such as translation, question answering, and classification, and then trained to produce some text. As a result, we can employ the same model, loss function, hyperparameters, and so on for a range of different applications. The modifications from BERT include:

- Using a variety of different pre-training tasks in place of the fill-in-the-blank cloze activity.
- Expanding the bidirectional design with a causal decoder.

Transfer learning has become a potent method in natural language processing, where a model is pre-trained on a task with lots of data before being refined on a job downstream (NLP).

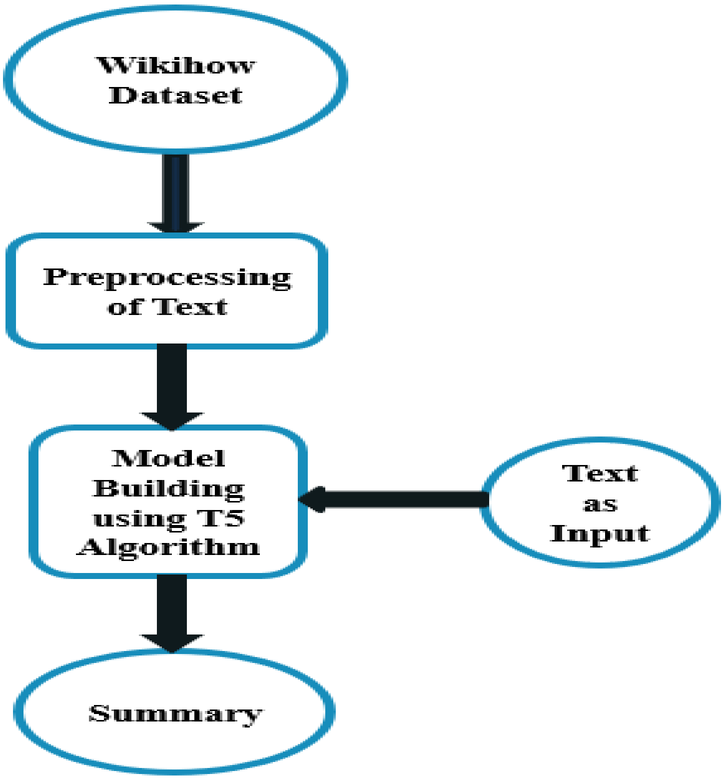

Figure 2: Architecture Diagram

Google's brand-new T5 transformer model takes in changed text for the training phase of its operation and produces unmodified text as the model's final output. It achieves cutting-edge performance on various natural language processing tasks, such as summarization, question answering, machine translation, and so on, with the assistance of a text-to-text transformer trained on a substantial text corpus. Today, we'll demonstrate how to leverage the library of transformers, from hugging faces to condensing any text. An algorithm for abstractive summarization is T5. It implies that rather than simply picking up sentences from the source text, it will rewrite them as necessary.

Using text as input and transformed text as output, Google's T5 model is a brand-new transformer that is trained from the beginning to end. The abstractive summarization algorithm T5 is used. It implies that it will modify phrases as necessary instead of just copying sentences verbatim from the source text. Encoder-decoder model known as T5 has been pre-trained on a number of supervised and unsupervised activities, with each task being translated into a text-to-text format. T5 was trained using a variety of unsupervised and supervised activities. By attaching a specific prefix to the input for each activity, T5 can manage a wide variety of responsibilities efficiently straight out of the box.

a) WikiHow Dataset:

More than 230,000 article and summary pairings were retrieved and assembled into the Wikihow dataset from an online knowledge base created by various human writers. The pieces cover a wide range of subjects and exhibit a great degree of stylistic diversity.

b) Text preprocessing:

It entails formatting text clearly and consistently so that it may be fed into a model for more research and education.

c) T5 Algorithm:

The T5 (Text-To-Text Transfer Transformer) model may be used for a broad range of jobs since it treats all tasks in the same manner by considering them to consist of receiving some input text and producing some output text.

d) Tokenizing:

The process of tokenizing a text involves slicing up the original text into "tokens," which are individual words and phrases. The tokens make understanding the circumstance or developing an NLP model easier. Tokenization is a method that helps readers grasp the meaning of a book by analyzing the sequence of the words in the text.

1. *Joining strings:* Concatenation is the process of one of the text functions joining two or more text strings into one string.

2. *Create tensor:* A set of algebraic objects connected to a vector space are described by a multi-linear relationship known as a tensor, an algebraic object.
3. *Summarizing:* It gives the most important sentences or facts about something or someone in a short and clear form.
4. *Decode:* Converts a coded message into understandable language.
5. *Display:* It displays the summary.

e) Text as Input:

After the text that was input by the user has been preprocessed using methods such as segmentation, tokenization, removal of stop words, stemming, and feature extraction using methods such as term frequency, sentence position, and thematic word to determine the text's length, similarity, position, and frequency, these results will be displayed to the user.

f) Summary: Summarize any text with a click of a button.

D. Analysis:

This phase involves the end-user's needs and converting the project objectives into the described. The requirement analysis will identify and consider any potential dangers that may arise due to the manner in which the new technology will be included in the standard operating procedures. The functional, system, user, and operational requirements of the business process will also be gathered through requirements analysis. In this section, we will use the transformers' implementation of the T5 model for this task. The software requirements include languages, libraries, packages, operating systems, and different project development tools.

a) For the implementation, we have been imported four packages to build the model using T5. These are following packages given below:

1. *Streamlit:* It is an open-source application framework that is written in Python. Previously, it manufactured web applications. It is compatible with the majority of the major Python libraries, including sci-kit-learn, keras, Pytorch, NumPy, pandas, and Matplotlib. It can launch a web server, create a web interface, it and create an HTML script automatically when we write Python i.e. This particular library can convert Python into HTML script, and HTML will launch on a webserver, which is run on streamlit.
2. *Transformers:* It is used to transfer the text into the summary.
3. *Torch:* It is used to check whether the GPU (Graphics Processing Unit) is available in a laptop or not. If it is available, it will take GPU or CPU (Control Processing Unit).
4. *Sentence Piece:* This API will offer Sentence Piece's encoding, decoding, and training. It will break the sentences into pieces.

b) To build the model using the T5 model, use the following steps:

1. Define the function summarization to summarize the text and next to check what device is available. If Cuda is available, it will enter Cuda or CPU.
2. Including a pre-trained T5 model by using T5 For Conditional Generator to know where the transformer model is generated or imported.
3. Initialize the tokenizer using T5Tokenizer to split the entire paragraph into different sentences than words, and these words are passed to the tokenizer.
4. Convert the data into string format, remove the newline, and replace with the empty code, i.e., there is space between in one paragraph to another, so we eliminate the space between the paragraph. We use the replace method and replace it with an empty code.
5. Converted data will split the text into different words. So, we join with a single quotation converted into a list format.
6. To tokenize the sentence, we tokenize the sentences into tensors. Tensors are a matrix representation of a different word, so these words are converted into a tensor, passing through the T5 model.
7. Passing the list to the tokenizer. Encode i.e., encoding into tensors, and words are converted into numerical arrays. So, we can convert input tokenized into a tensor, with the tensor size i.e., contains rows and columns.
8. Once the numerical arrays are created, we concatenate them into tensors by using the .cat method just convert them into tensors, and that tensor is passed to the model input_tokenized, and the dimension should be mins one which indicates rows and columns.
9. Defining the hyperparameters i.e. parameters, is used for training and testing the model. Hyper parameters are num_beams, no_repeat_ngram_size, length_penalty, min_length, max_length, early_stopping.
10. Next, we decode the value of the text by using the hyperparameters with T5_Tokenizer, which is a more understandable or readable form without grammatical errors.

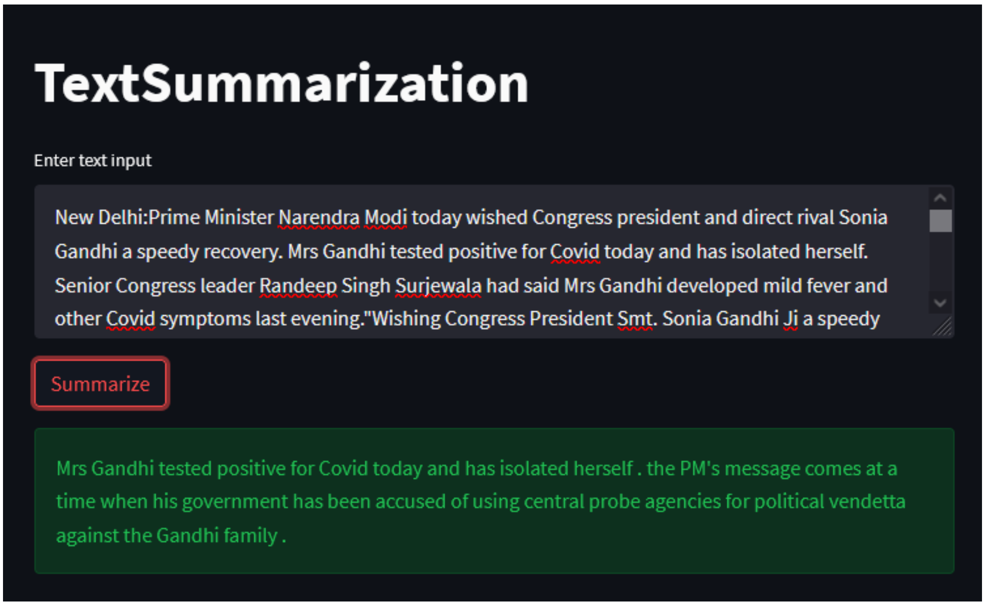

Figure 3: Output for Summarized Text

From the above figure, When we enter the text as input, it will tokenize into sentences and words, compare the most relevant words, and give the output as the summary for the relevant information.

IV. CONCLUSION

With the help of the transformer architecture, we built a pre-trained model for this article. Many algorithms and methods have been used to summarize texts in the past. When a number of different methods are used together, the resulting summaries lack coherence and accuracy and are presented in an illogical sequence. When we replace a sentence, it will pull from the copy rather than the original. We overcame this challenge by employing a text-to-text transfer transformer to pre-train the model. This Algorithm takes as input a model of a piece of text and, after training, produces a piece of text that matches certain specified criteria. There is no one model that reliably generates the best summaries. It is possible to make updates to the models that have been given in order to generate more accurate summaries in the future.

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