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# SummaGen: Next-Generation Seq-to-Seq Model for Summarizing Unstructured Text

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**Abstract:** In today's digital era large volume of textual data is generated every second, we can search anything on the web, and it never say "Sorry! Unable to find it on internet". It always come with plenty of suggestions and data, now practically it is impossible to go through all the data and reach the final decisions. Exponential growth of textual information, automatic text summarization has emerged as a crucial answer. Redundancy, coherence, co-reference, and semantic links between words and sentences are only a few examples of concerns that might be prioritized to strengthen the essential of a summary. In this research, we examine how to improve semantic link between words and sentences, it can help bring about a more accurate generated summary. The suggested technique generates summaries of texts using a pre-existing deep learning model based on a Seq-to-Seq LSTM encoder decoder. Sentence summaries and dictionaries are mapped against one another to see how close they are conceptually. The suggested method was tested on the CNN/Daily-Mail dataset, which is available for public use and contains unstructured text describing news items. Using Rouge scores (Rouge-1, Rouge-2, and Rouge-L), we evaluate how well our system performs in comparison to the current gold standard for extractive text summarization. With the Seq-to-Seq model, the proposed approach produced a 42.74 percent Rouge-1 score, a 12.46 percent Rouge-2 score, and a 43.01 percent Rouge-L score.

***Keywords:*** *Deep learning (DL), Automatic text summarization (ATS), LSTM, Rouge metric, Daily mail, Sequence to Sequence (Seq-to-Seq)*

## 1. Introduction

Since there is a wealth of data available online, it would be useful to provide users with a concise overview of the topic. Therefore, there is a growing interest in creating better techniques for automatically summarising literature among academics. The process of condensing a document's text into a more digestible format for readers is called "text summary." The study of automatic document summarization encompasses a wide range of disciplines, from computing to multimedia to statistics to cognitive psychology. Summarizing a big volume of articles by hand is a task that is incredibly challenging for humans [1][2].

Automatic document summarization has made significant strides in recent years, addressing the problem of information overload and radically altering the business as a result. By providing a concise description of each document, document summarization makes it easier for users to narrow down their search results and zero in on the one they need. Therefore, it is an essential and trustworthy component of information retrieval (IR). To reduce the amount of time spent reading and to introduce the key points of a longer work are the two primary goals of a summary [3][4]. It is important to differentiate between summarising a single item and summarising a collection of documents.

Multi-document summarization entails automatically creating a description that includes a plurality of information material regarding an explicit main topic or implied one of a large collection of documents, while document summarization entails automatically creating a reduced text of useful and necessary information for the user from the original text. Researchers have been looking into the topic of text summarization since the 1950s. The term "text" is used here in a generic sense, so it could refer to anything from a simple written document to a multimedia file, a voice recording, a hypertext link, etc. Summary can have a wide variety of interpretations, depending on the researcher [5][6][7][8].

One of these definitions states, "A summary can be loosely described as a text constructed from one or more texts that provides essential information in the original text(s) and that is no longer than half of the original text(s) and generally significantly less than that." No matter how much study is done in this area, no machine will ever be able to provide "gold summaries," or summaries as accurate as those produced by humans [9]. The primary problem in summarising is determining which parts of a document are most relevant, given that information in documents is typically presented in a rapid-fire sequence of gunshots. As a result, it is crucial to differentiate these perceptive passages from the rest of the text, as the overview would be less

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accurate if all material was of comparable importance. Thus, text summary is a method for condensing a lengthy piece of writing into an easy-to-read description while keeping the most important points intact [10]. Summarizing text is the process of reducing the length of one or more texts to create a more concise version. When searching through enormous text archives or the Internet, automatic text summarization has proven to be a beneficial tool.

By utilising an algorithm, "extractive summarization" can glean the most relevant sentences from a large body of text. In order to generate brief sentences from a large body of material, abstractive summarization employs an algorithm. This is far closer to the way individuals take in information. Text summarising approaches differ depending on the quantity of input documents (single or numerous), the intent (generic, domain-specific, or query-based), and the performance (extractive or abstractive) (extractive or abstractive) [11][12].

Depending on the tone of the performance, a summary might be either indicative or informative. Overviews of the text in the form of indicative summaries. Information about the document is provided. Even though they cover the same ground as other summaries, informative summaries provide a more thorough presentation of the material. Summaries can be either multilingual (covering more than one language) or monolingual (covering just one) or cross-lingual (covering more than two languages) [13]. When both the source and target papers are written in the same language, this technique is known as mono-lingual summarising. To summarise a text written in many languages, such as English, Hindi, and Punjabi, a multi-lingual summarising approach is used. If the original document is written in English but the summary is written in Hindi or some other language, then the system is said to be cross-lingual.

## 2. Literature Review

The proliferation of information thanks to the World Wide Web. Readers are put through unnecessary stress by reading lengthy documents when a condensed version would serve. All computer users, whether seasoned pros or complete newcomers, should find this scenario extremely alarming. There is an immediate requirement for research into digital documents containing hidden information. Because of the tremendous expansion in textual content, text summarization has become a major topic in recent years. As a document summary, accurate and relevant material can be retrieved using several already proven ways. Automatic summarization based on a combination of conventional sentence extraction and a trainable classifier based on support vector machines was proposed by [14]. The study provides a sentence segmentation approach for lowering the size of the extraction unit from the first sentence extraction. To facilitate summarization, the Sentence Reduction System use an automated process to remove unnecessary phrases from sentences taken from a text [15]. To identify the terms in an extracted sentence can be removed, the system leverages a range of sources of information, including syntactic awareness, context information, and statistics computed from a corpus of instances authored by human professionals. By eliminating unnecessary information, automated summaries become much more concise. It was looked at how to create a description of an original text using a different [16]. The system generates many solutions to the problem, all of which are of high quality. The model is comprised of four distinct steps. The process of preprocessing takes unstructured text and makes it more organised. In the first stage, the system filters out unnecessary words, parses the text, and gives each word a POS (tag), all of which is subsequently saved in a database. The next step involves implementing a new algorithm to rank candidate terms so that relevant key phrases can be extracted from the text. On the basis of the keywords that were collected, the system chooses the most crucial statement. Each sentence was given a ranking based on a number of criteria, such as how frequently the target keyword appeared, how closely the sentence related to the title, and so on. In the last phase of the proposed approach, the highest-rated sentences are retrieved. The fourth phase is the filtering process. To produce a qualitative description using KFIDF computation, this step eliminated potential summary sentence candidates.

Some researchers have published a review of Text Summarization Extractive Methods [3]. Extractive summarising is a method whereby relevant sentences, paragraphs, and other pieces from the original text are selected and combined into a shorter version. Sentence importance is calculated by analysing their statistical and linguistic features. Several automated text summarization methods are considered text mining jobs since they provide a description or abstract from a single or numerous input text sources [17]. Many different heuristic and semi-supervised learning strategies have been investigated. They investigate the efficiency of popular summarization heuristics when applied to the creation of variable-length extracts from a single document. To determine the quality of the summaries, both the original text documents and their summaries were scored by separate human reviewers using a variety of subjective metrics, including subject coverage, relative coherence, novelty, and information substance. The assumption that the quality of the summary created by combining sentence scoring systems is influenced by the text topic is supported by A Context Based Text Summarization System [18]. A hypothesis like this can be tested in three settings: headlines, news articles, and online content. The results back up the theory put out and indicate which methods fare better in each of the settings examined.

Some researchers also recommend Clustering-based methods to be used to summarize the text. Such methods work best for multi-document and query based. In such type of clustering process semantic and syntactic similarities were considered. From each cluster important sentence selected and set of selected sentences were sorted in main document and constitute the final summary [19].

Some researchers have used seven types of features for feature vector generation namely word frequency , title similarity, sentence stop words, part of speech tag, sentence pronouns, sentence length and sentence position.[20].

It is suggested that karci entropy be used for automatic text summarization, and this is where karci summarization comes in [5]. It's a completely new programme that can glean broad overviews from text files. For the first time, Karci Entropy was applied in a text summarising process as part of a revolutionary strategy. The proposed system has the advantage of not requiring any kind of information source or training data. Selecting the most effective, generic, and instructive sentences within a paragraph or unit of text is the focus of a method based on the Karci Entropy [21] propose a novel mechanism for detecting novelty that can be integrated with preexisting web crawlers. The ontology is used to provide a summary of the text, and then word net 3.0 is used to provide a quantitative measure of semantic similarity. The hash value is then evaluated with the help of the winnowing method. The Dice coefficient is used to compare the hash value of a document to those of other files to determine the similarity index. The paper is classed as novel or not novel depending on the similarity criteria selected. The backend for this suggested system is SQL, and the frontend is Visual Studio 2012. The results demonstrate that the proposed method not only conserves memory but also minimises the number of final records, meaning the user can spend less time sifting through the accumulated results in search of relevant data.

## 3. Research Gaps

A work on multi-document extractive text summarising was proposed by [22]. Multi-document summarization feature vectors were generated as part of this study's foundational research. Key sentences are analysed across several documents and extracted using the function vector. Difficulties arise because the feature generating process is carried out by hand. Construct a fully automated system for generating features from raw data using deep learning techniques.

SummCoder was proposed by [23] as an unsupervised method for extracting text summarization using deep auto-encoders. In this paper, we present a novel approach to extracting text summarization of individual documents. This approach generates a description based on three criteria: sentence material relevance, sentence novelty, and sentence place relevance. Using auto-encoder networks for multi-document text summarising is crucial for the summarization process.

The necessity for text summary has developed because of the rise in online publishing, enormous numbers of internet users, and the rapid growth of electronic government (e-government) (e-government). Rapid progress in IT has led to an explosion of online papers, and users are having a hard time sifting through the noise to locate the information they need. In addition, the advent of the World Wide Web has facilitated the accessibility of voluminous collections of written material covering a wide range of subjects. This explains why there is so much repetition in the online writings. When people have to read a lot of text, they get fatigued and may miss important information. As a result, in this generation, a robust text summarising system is needed [12].

Informational breadth, depth, significance, and redundancy, as well as textual cohesiveness and management. The majority of newspaper readers don't even bother to read past the headline when it comes to articles. If they read your one-sentence headline, they might also read your five-sentence summary. People will receive more insight on the storey as a result of this summary, allowing them to be better educated.

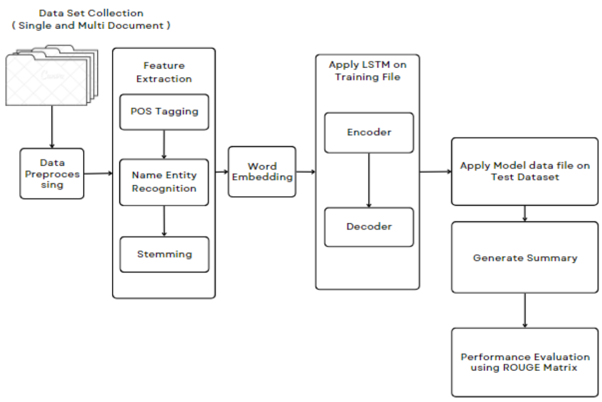


**Fig. 1:** Overall approach for Extractive text summarization

## 4. Proposed Methodology

Different phases for text summary are shown in fig.1, which also presents the overall recommended approach. The data used in the trials is obtained from a dataset compiled from CNN and Daily-Mail news articles. The Seq-to-Seq model takes as input word tokens that have been produced from the source and summary texts. This model, based on the idea of a many-to-many relation between input and output, is used to construct a summary of product reviews in the first presented technique. It accepts a string of words as input and returns a summary of many words as output. Both the training and inference stages of the Seq-to-Seq model are detailed below:

Training and inference phases of the Seq-to-Seq model are utilised to produce the summary. In both the training and inference phases, the encoder-decoder architecture is utilised to first encode the data and then generate the necessary context before being decoded into a summary text. Scores in the range of 0 to 100 are assigned to each of the three factors (precision, recall, and F-score) to assess the quality of the generated projected summary. Associating semantic characteristics with WordNet further improves this model's performance. This predicted summary is then post-processed by searching for and replacing any words or sentences that are semantically similar. Repeat the summary generation and Rouge score evaluation after post-processing is complete. Next, we will use a voting method to determine which predicted summary of the identical source text is the best by comparing the rogue ratings of the two. The best score from these two approaches is used to determine which summary is chosen as the result in a voting procedure.

### 4.1. Seq-to-Seq Model

***Training Phase:***

During this stage, the model is constructed based on the information found in the training dataset. News (xi, yi) represents the pair consisting of the original news article xi and its summary yi, where I is the index number of the news article in the collection. The word sequences from the original news story and the summary are represented in (1) and (2), where Lx and Ly represent the total number of words in the original and condensed versions of the article, respectively. You can see in figure 2 that the Seq-to-Seq model uses an encoder and a decoder that are based on long short-term memory circuits.

$$\boldsymbol{x^i} = \{\boldsymbol{x^i_1}, \boldsymbol{x^i_2} \ldots\ldots\ldots \boldsymbol{x^i_{Lx}}\} \quad (1)$$

$$\boldsymbol{y^i} = \{\boldsymbol{y^i_1}, \boldsymbol{y^i_2} \ldots\ldots\ldots \boldsymbol{y^i_{Ly}}\} \quad (2)$$

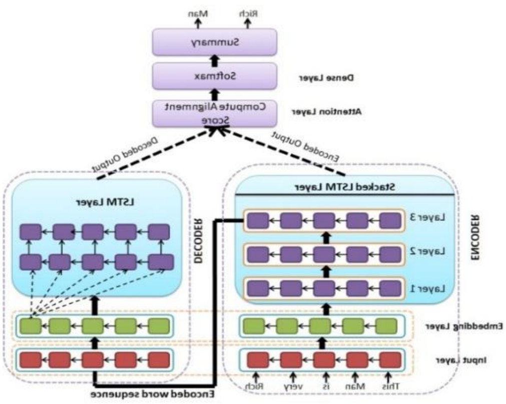

**Fig. 2:** Sequence to sequence LSTM based encoder decoder model

***Encoder :***

The document is encoded into a vector format by the encoder. The LSTM-based encoder has three layers: an input layer, an embedding layer, and a stacked LSTM layer. At each time step, the encoder receives a single token from the tokenizer, so the input layer receives the full document's word sequence. Before being sent into the encoder, each phrase has the unique token "eos>" attached to its conclusion. The embedding layer maps input words to dense vectors of a predetermined size, also known as the embedding weights matrix. Hidden states and cell states are generated at each time step using an LSTM layer. The sequence is more accurately represented using three-layer Stacked LSTM in the proposed approach. By tracking the input sequence, LSTM layers' hidden states are able to gather contextual data. The encoder receives the news article (1) as input and produces the hidden states (3). Once the word encoder has received the "eos>" token, it will use the last concealed state as the embedding representation of the sentence.

$$\mathbf{he} = \{\mathbf{he_1}, \mathbf{he_2} \ldots\ldots\ldots, \mathbf{he_{Lx}}\} \quad (3)$$

***Decoder:***

The decoder also employs the LSTM network, which accepts the whole target sequence of words one by one and predicts the next word according to the specified preceding word at one time step. The target sequence is supplemented with the special tokens "sos>" and "eos>" before being given into the decoder. During the decoding of the test sequence, the target sequence is unknown, that's why start predicting the target sequence by feeding the decoder with the first word, which is always the “<sos>” token. A mathematical description of the entire process of decoding a given word sequence is illustrated in (4). The decoder's initial state and the encoder's final state, the sequence of words (h (j, k-1)), is fed into the decoder's input layer. The embedding layer creates the embedding of previously generated word which is indicated as 〖(e〗 (j.k-1)). LSTM layer predicts the word sequences and concatenates with context vector. The end-of-sentence token "eos>" signals that this sentence is complete.

$$\boldsymbol{h_{j,k}} = \boldsymbol{LSTM}\{\ \boldsymbol{h_{j,k-1}}, \boldsymbol{e_{j.k-1}}\} \quad (4)$$

***Inference Phase:***

After training, the LSTM encoder decoder model is put to the test on the remaining 10% of news stories where the target sequence is undefined. It is necessary to have an encoder and a decoder to decode a test sequence during the inference phase. The encoder stores the entire input word sequence in a concealed internal state, and the decoder is set up based on the encoder's output. The "sos>" token is passed to the decoder at the outset, and the internal states are used to process each word in turn at the same time. Next word is chosen based on the decoder's probability prediction. The present state of the decoder will be altered at the next time step based on the input of the selected word. The decoder is fed words one at a time until it finds "eos>."

## 5. Experimental Work

### 5.1. Datasets

Data used for the automated summarising of texts comes from sources like CNN and DailyMail. Here we have a dataset comprised of two sources of news articles: CNN, with 90,266 items, and DailyMail, with 1,96,961 stories. In the study being proposed, the two datasets are joined to create a larger dataset of 287,227 documents. Dataset is split into train and test in the ratio of 90:10, 90% data is used to train the model and 10% data is used to the test the model.

### 5.2. Evaluation Metric

The ROUGE performance metric is used to automatically evaluate the effectiveness of the summary generation approach. Other available automatic metrics include BLEU, METEOR, and ATEC [24]. ROUGE, which stands for "Recall-oriented Understudy for Gisting Evaluation," is an abbreviation [25]. Specifically, it evaluates the accuracy of the predicted summary by contrasting it with the accuracy of a reference summary, which is a summary created by a human. Precision, recall, and the F1 score are all utilised in the determination of rouge. The colour red is instantly evoked while reading the whole name. The proportion of correctly predicted summary sentences to all reference summary sentences is a measure of recall. Accuracy is measured by comparing the number of right predictions to the total number of predictions made for a given summary phrase. The sum of your recall and accuracy harmonics is your F1 score. Because recall in rouge scores is so important in finding the right matched results, it receives a lot of attention. Very lengthy sentences, which are not part of the reference summary, are sometimes produced by the anticipated summary. Thus, accuracy is also vital, since it can distinguish between useful and superfluous terms in the projected summary and the reference summary. Therefore, it is recommended to first measure precision and recall before calculating F-Measure.

Many traditional approaches to assessing summary quality rely on Rouge. The major objective of Rouge is to determine the degree to which the anticipated summary and other reference summaries share common text units. Multiple Rouge ideas, such Rouge-N and Rouge-L, are bundled together here. Rouge N compares the reference summary and the anticipated summary based on the amount of overlap between unigrams, bigrams, and higher-order n-grams. It's a unigram in Rouge 1, a bigram in Rouge 2, and so on. A key idea behind Rouge-L is the LCS (longest common subsequence), which evaluates the length of the longest matching word sequences. A length of n-grams that has been predetermined is not necessary to mention. as a result of its inherent ability to detect longest in-sequence common n-grams. In order to display the facility with which one may render summaries or translations, Rouge-1 is combined with Rouge-2. It is presumed that the flow of the summary will improve if the word orders of the reference summary are adhered to.

## 6. Results and Discussions

The accuracy, recall, and F score of Rouge 1, Rouge 2, and Rouge L are used to assess the suggested approach. The outcomes of proposed methods 1 and 2 on the CNN/Daily Mail dataset are displayed in Table 1. To generate summaries, approach one employs a Seq-to-Seq model with three LSTM layers and an attention mechanism, yielding optimal results for Rouge 1 and Rouge L but an inappropriate value for Rouge 2. To prove that the summary is of high quality, Rouge 1 uses unigram matching on the correctly matched terms. The function of Rouge 2 is to execute the matching of two-word bigrams that fail to match adequately since the summary also contains unnecessary words in between. With a lower precision setting, the summary may contain some unmatched words. The longest matched sequence is provided by Rouge L, which also achieved a high recall rating. The accuracy number indicates that, between the longest sequences that do not match the reference summary, there are few further words accessible. The second approach incorporates a post-processing stage comprised of the WordNet Metathesaurus and a Seq-to-Seq model comprised of three layers of long short-term memory and an attention mechanism. Seq-to-Seq's execution can replace words with semantically comparable ones, hence raising the summary's quality. There is a 0.7 percentage point improvement in precision for Rouge 1, 2.12% for Rouge 2, and 1.91% for Rouge L. The recall values of Rouge 1 (1.75%), Rouge 2 (7.56%), and Rouge L (0.9%) are all improved. Though Rouge 2 has a higher recall value, it still takes more work to get accurate bigram matches. Table 2 displays a comparison between Method 1 Seq-to-Seq (Three LSTM layer encoder) and Method 2 Seq-to-Seq (Three LSTM layer encoder + Attention), where M1 represents Method 1 and M2 represents Method 2, and R1, R2, and RL values are displayed for both Methods 1 and 2. The greatest Rouge1 score for method 2 indicates a good match between the unigrams and the reference summary.

**Table 1.** Evaluation of methods using rouge scores on CNN/Daily mail dataset

| *Method* | *Metrics* | *Rouge-1* | *Rouge-2* | *Rouge-L* |
|---|---|---|---|---|
| Seq-to-Seq (Three LSTM layer encoder ) | P | 39.54 | 11.08 | 37.89 |
| | R | 42.74 | 12.46 | 43.01 |
| | F | 40.78 | 11.62 | 39.98 |

| | | | | |
|---|---|---|---|---|
| Seq-to-Seq (Three LSTM layer encoder + Attention) | P | 40.24 | 13.20 | 39.80 |
| | R | 44.49 | 20.02 | 44.00 |
| | F | 42.26 | 15.92 | 41.79 |

The proposed methods are compared to previous work that has also processed the CNN/ DailyMail dataset and produced a quality report. There has been a lot of work done on extractive summarising, however this paper compares some of the most recent automatic text summary techniques that have produced better outcomes. Using the CNN/daily mail dataset, Table 2 compares the Rouge Score to state-of-the-art extractive summarization techniques. It has recently been applied (Liu and Lapata, 2019b) and has delivered the best result for Rouge 1, Rouge 2, and Rouge L compared to previous approaches. The BERTSumEXT approach emphasises the semantic representation of sentences. Method1, which employs a three-layer long short-term memory (LSTM) encoder model, outperformed the other offered approaches in terms of Rouge L score. When compared to other baseline systems, with the exception of BERTSumEXT, the Rouge 1score performs admirably, whereas the Rouge 2score does not. Second proposed technique uses WordNet to do semantic similarity identification, much like the first method, BERTSumEXT.

**Table 2.** Rouge score comparison against other systems of extractive text summarization on CNN/Daily Mail dataset

| ***Method*** | ***Rouge-1*** | ***Rouge-2*** | ***Rouge-L*** |
|---|---|---|---|
| Sumo | 41.00 | 18.40 | 37.20 |
| TransformerEXT | 40.90 | 18.02 | 37.17 |
| BERTSumEXT | 43.25 | 20.24 | 39.63 |
| Lead-3 baseline | 39.2 | 15.7 | 35.5 |

| ***Proposed Method*** | ***Rouge-1*** | ***Rouge-2*** | ***Rouge-L*** |
|---|---|---|---|
| Seq-to-Seq (Three LSTM layer encoder) | 42.74 | 12.46 | 43.01 |
| Seq-to-Seq (Tthree LSTM layer encoder + Attention) | 44.49 | 20.02 | 44.00 |

## 7. Conclusions

The goal of the proposed method is to improve the quality of text summarization by applying deep learning models and semantic characteristics. To build a summary context vector, this method first applies cleaned data from the CNN/Daily mail dataset to LSTM-based encoder decoder deep learning models. The effectiveness of the summary was assessed using the ROUGE score. After pre-processing on the Seq-to-Seq model, attention is found to correctly summarise 70% of the test data. In the future, hyper parameter tuning will be performed to do more experiments and confirm that which one is suitable to apply for performance [1] enhancement in text summarization. Comparisons will also be made using alternative performance matrices, such as BLEU, METEOR, and ATEC.

### Author Contributions

**Sachin Solanki:** He worked on design and development of system, analysis of results, writing manuscript.

**Suresh Jain:** He provides the supervision and results findings and reviewing of manuscript.

**Kailash Chandra Bandhu:** He worked on investigation, writing, reviewing and editing of manuscript.

### Conflicts of Interest

The authors do not have any conflicts of interest.

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