

Abstractive Document Summarization Using Machine Learning Approach

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ABSTRACT: We present a novel divide-and-conquer strategy for the neural summary of large documents. Our solution makes use of the document's discourse structure and sentence similarity. Divide the task into smaller summarization challenges. We divide a lengthy document and its summary into numerous source-target pairs, which are then used to train a model. learns to sum up each section of the document individually After The partial summaries are then combined to form a final comprehensive summary. In contrast to the conventional approach, we may break down the challenge of long document summaries into smaller pieces and simpler problems, reducing computational complexity and increasing the number of training examples while also reducing There is noise in the target summaries. There are two publicly available datasets.

KEYWORDS: Complexity, Contrast, Summarization, Machine Learning, Classification, NLP(Natural Language Processing).

I. INTRODUCTION

In this present era, where huge quantity of information is generating on the internet day by day. So, it is necessary to provide a better mechanism to extract useful information fast and effectively. Text summarization is one of the methods of identifying the important meaningful information in a document or set of related documents and compressing them into a shorter version preserving its overall meaning. It reduces the time required for reading whole documents and also it is a space problem that is needed for storing a large amount of data. The automatic text summarization problem has two sub-problems that is a single document and multiple documents. In the single document, the single document is taken as the input and summarized information is extracted from that particular single document. In Multiple documents, the multiple documents of the single topic are taken as input and the output which is generated should be related to that topic.

Automatic Text summarization has two approaches 1) Abstractive text summarization and 2) Extractive text summarization. An extractive text summarization means important information or sentence are extracted from the given text file or original document. An extractive text summarization approach uses linguistic or statistical features for selecting useful informative sentences. An Abstractive text summarization will try to understand the input file or original file and re-generate the output in a few words by identifying the main concept of the input file. In many research papers, they have mentioned that extractive text summarization is sentence ranking. Extractive text summarization is divided into two phases: 1) Pre-processing and 2) Processing. In this paper, we are explaining extractive text summarization on a single document.

This thesis aims to replicate and extend knowledge of automatic text summarizing. The success of sequence-to-sequence (seq2seq) modelling in NLP has pushed rapid and significant growth in this field. However, the focus of the study has been on developing frameworks for short, single-document summarizing, rather than extended and multi-document summarization. The ultimate goal of this topic is to provide a framework that can produce high-quality summaries regardless of the length of the source documents, whether it's a single or multi-document assignment and irrespective of domain or language.

Given the recent impressive progress in a short document summarizing, the next challenge will be to reproduce the results using longer documents. The goal of this thesis is to contribute to the knowledge of expertise in the field of long document summaries. The evaluation of summaries and systems for Abstractive document summarizing are two particularly relevant areas that we identify as core issues in this thesis.

II. RELATED WORK

1. Paper name: Text Summarization using Sentiment Analysis for DUCData.

Author: Nidhika Yadav, Niladri Chatterjee

Abstract: The basic purpose of this study is to see if sentiments can be used to summarize material effectively. We describe a text summarization technique based on the emotions associated with key phrases that is computationally efficient. Sentiment analysis is already in use for large-scale text data interpretation and opinion mining in a variety of fields. The current research shows that sentiment analysis can be utilized to summarize text as well. Our findings were compared to those of the conventional DUC2002 datasets. A text summary is a technique for determining a text's main points. In the literature, various strategies have been presented, and many of these are currently in use in commercial systems

The work in this paper is divided into two stages. 1) Text- Detection 2) Inpainting. Text detection is done by applying morphological open-close and close-open filters and combining the images. Thereafter, the gradient is applied to detect the edges followed by thresholding and morphological dilation, erosion operation. Then, connected component labelling is performed to label each object separately. Finally, the set of selection criteria is applied to filter out non-text regions. After text detection, text inpainting is accomplished by using exemplar based Inpainting algorithm.

2. Paper name: Multi-document Summarization by using Text Rank and Maximal Marginal Relevance for Text in Bahasa Indonesia.

Author: Multi-document Summarization by using Text Rank and Maximal Marginal Relevance for Text in Bahasa Indonesia

Abstract: The text summarizer eliminates unnecessary information by selecting the most important sentences. There's a chance that two or more crucial statements in a multi-document summary will contain the same information. If those sentences are included in the summary result, the information will be redundant. The goal of this research is to condense similar lines from a variety of sources containing similar information into a more concise text summary. This study divides a variety of internet news articles into six groups to achieve its goal. The articles are concatenated and pre-processed to create clean text. Following the acquisition of clean text, the Text Rank algorithm is used to extract the important sentences based on similarity measurement. This procedure produced the summary text.

3. Paper name: Automatic Text Summarization by Local Scoring and Ranking for Improving Coherence

Author: P. Krishnaveni, Dr. S. R. Balasundaram.

Abstract: Due to a large amount of textual material available on the internet, machine-generated summarization has received a lot of attention. Manually summarizing these online text documents is difficult for most people. As a result, we will require an automatic text summarizer. Automatic Text Summarization (ATS) is defined as "shortening the original text while preserving its information value and overall meaning." Despite the fact that automatic text summarization has been studied since the 1950s, more cohesive and meaningful summaries still exist. The proposed technique generates an automatic feature-based extractive heading-wise text summarizer that improves the summary text's coherence and, as a result, its understandability. It just summarizes the input document using local scoring and ranking, and that's it.

4. Paper name: A Divide-and-Conquer Approach to the Summarization of Long Documents.

Author: Alexios Gidiotis and Grigorios Tsoumakas

Abstract: We propose a novel divide-and-conquer strategy for the neural summarization of large documents. Our solution takes advantage of the document's discourse structure and divides the challenge into smaller summarization problems using sentence similarity. We divide a lengthy text and its summary into numerous source-target pairs, which are then used to train a model that learns to summarize each section of the document separately. The partial summaries are then combined to create a final full summary.

III. METHODOLOGY

- TEST CASES

1. GUI TESTING

GUI Testing:	
Test case	Login Screen- Sign up
Objective	Click on sign up button then check all required mandatory fields with leaving all fields blank
Expected Result	All required/ mandatory fields should display with symbol "**". Instruction line "** field(s) are mandatory" should be displayed
Test case	Create a Password >>Text Box Confirm Password >>Text Box
Objective	Check the validation message for Password and Confirm Password field
Expected Result	Correct validation message should be displayed accordingly or "Password and confirm password should be same" in place of "Password mismatch".

Figure 1: GUI Test Case

2. LOGIN TEST CASE

Login test case					
Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test case criteria(P/F)
001	Enter The Wrong username or password click on submit button	Username or password	Error comes	Error Should come	P
002	Enter the correct username and password click on submit button	Username and password	Accept	Accept	P

Figure 2: Login Test Case

3. Registration Test Case

Registration test case					
Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test case criteria(P/F)
001	Enter the number in username, middle name, last name field	Number	Error Comes	Error Should Comes	P
001	Enter the character in username, middle name, last name field	Character	Accept	Accept	P
002	Enter the invalid email id format in email id field	kkemail.com	Error comes	Error Should Comes	P
002	Enter the valid email id format in email id field	kk@gmail.com	Accept	Accept	P
003	Enter the invalid digit no in phone no field	99999	Error comes	Error Should Comes	P
003	Enter the 10 digit no in phone no field	9999999999	Accept	Accept	P

Figure 3: Registration Test Case

4. System Test Cases

System Test Cases:					
Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test case criteria(P/F)
001	Store Xml File	Xml file	Xml file store	Error Should come	P
002	Parse the xml file for conversion	parsing	File get parse	Accept	P
003	Attribute identification	Check individual Attribute	Identify Attributes	Accepted	P
004	Weight Analysis	Check Weight	Analyze Weight of individual Attribute	Accepted	P
005	Tree formation	Form them-Tree	Formation	Accepted	P
006	Cluster Evaluation	Check Evaluation	Should check Cluster	Accepted	P
007	Algorithm Performance	Check Evaluation	Should work Algorithm Properly	Accepted	P
008	Query Formation	Check Query Correction	Should check Query	Accepted	P

Figure 4: System Test Cases

IV. RESULT

1. GUI MAIN PAGE

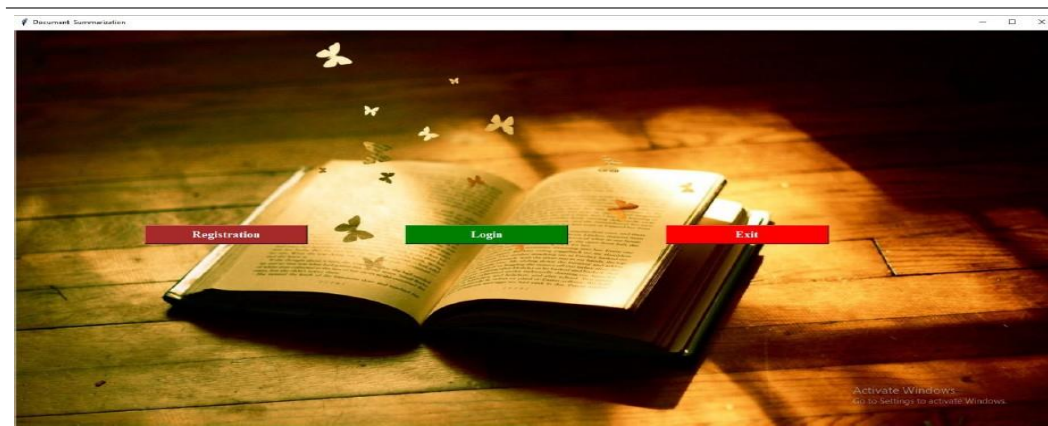


Figure 5: GUI Main Page

2. REGISTRATION



Figure 6: Registration

3. LOGIN PAGE

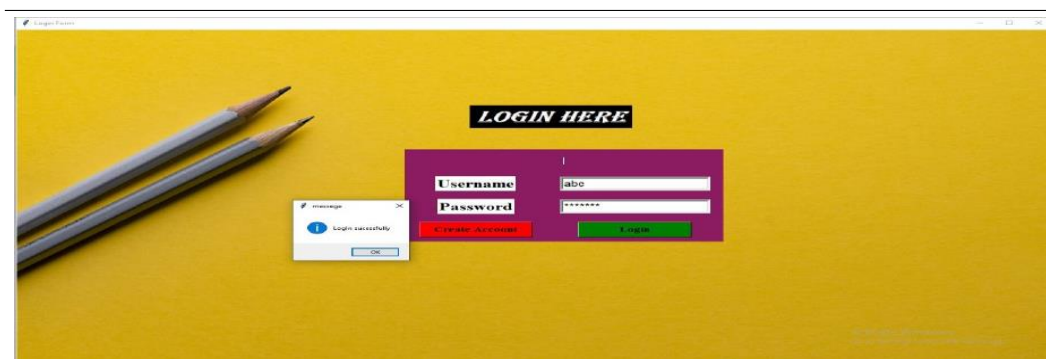


Figure 7: Login Page

4. FINAL OUTPUT

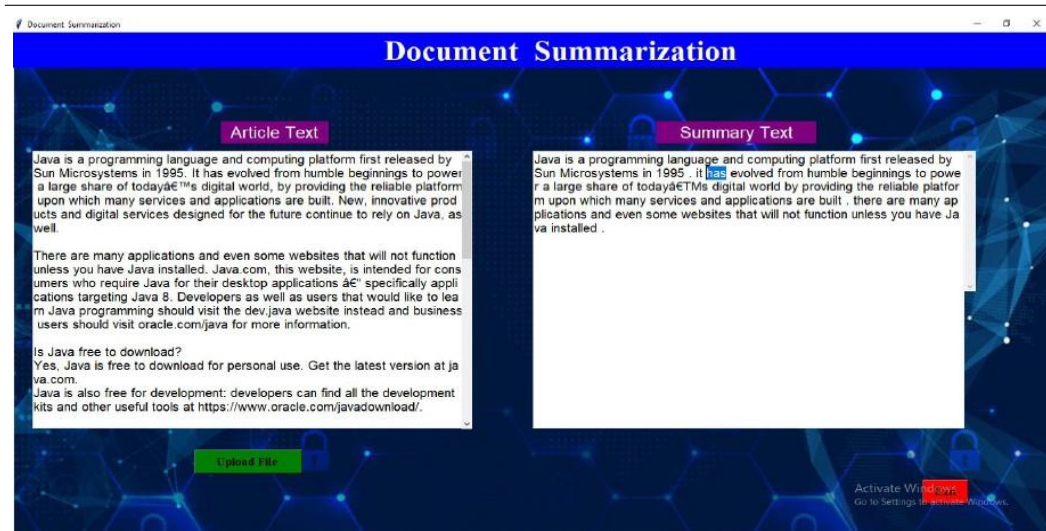


Figure 8: Result

V. CONCLUSION

Autonomy abstracted Document summarizing is a multi-step process with several sub-tasks. Every subtask has the ability to generate high-quality summaries. Abstractive document summarization requires identifying necessary paragraphs from a given document. We suggested an abstractive based text summary in this research, based on a statistical new approach based on sentence ranking, in which the summarizer selects phrases based on their rating. Abstract sentences are created as a summarized text that is then turned into audio. The proposed model outperforms the old technique in terms of accuracy.

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