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Optimizing Online News Understanding: Abstractive Summarization Approach with T5 for Comprehend Content

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***Abstract*— *In this modern era, news articles now usually come in the form of digital newspapers. Despite the change of form from physical form to digital one, the problem that is faced by the reader persists which is the boredom that struck the reader when the article contains a lot of information with a lot of data. To face this problem, this research proposes an abstractive summarization approach toward online news articles. Abstractive summarization provides a way for the reader to easily obtain the information from an online news article where abstractive summarization can shorten an online news article by understanding the main ideas of the article and generate a summary containing those main ideas with hints of novel new words. To achieve this, a fine-tuning method is used on a T5-small model and the ROUGE score metrics are used for evaluating the model's performance. Fine-tuning involves training the T5-small model on a dataset containing online news articles to prepare the language model for an abstractive summarization task. The methods for fine-tuning the language model in this research are divided into several phases which are: environment preparation, dataset preparation, model preparation, training and evaluation, and inference. This research successfully implemented the T5-small model to generate abstractive summary from online news articles.*

***Keywords*— *Abstractive summarization, Fine-tuning, Machine learning, Natural Language Processing, T5-small.*

I. INTRODUCTION

The internet has played a vital role to provide a wide variety of content for many people across the world. As technology keeps advancing throughout time, along with the need for information from many people has resulted in a massive flow of information that affects people through those contents that are available on the internet. Among those contents, one of them is news articles. News articles have traditionally been found in newspapers, but nowadays, people can access these articles through digital newspapers available online.

Newspapers contain so much information to the point it might overwhelm the readers, making them gradually lose interest in the article as they read and to find the main idea of the article itself might be time consuming [1]. To address these issues, a method of summarization is proposed.

Summarization can be considered as a process to form a summary of a given document that includes the important information in it with the aim to ease the reader by not reading the entire document page by page to understand it, saving the time and energy of the reader [2]. Summarization can be divided into two approaches, which are extractive approach and abstractive approach. Extractive summarization combines important sentences from a document based on the extracted features without any modifications whatsoever applied on the chosen text [3] while abstractive summarization generates novel words that are different from the original document [4].

As technology advances throughout time, nowadays machines are able to understand human language where the field that discussed this matter is Natural Language Processing (NLP). NLP involves the automatic processing of text in natural language and has been used in various fields, including summarization [5]. To leverage NLP, language models are often used and customized to the specific tasks they need to perform.

Language models are machine learning models that are commonly used in NLP due to their ability to provide probabilistic predictions for the next sentence in a word sequence [6]. These models can also be considered as artificial intelligence systems trained on extensive textual data, earning them the label of large language models [7] which enable them to understand languages and excel in text generation tasks.

There are various language models that have been used for summarization task, one of them is the Text-to-Text Transfer Transformer (T5) model. The way this language model is prepared for the summarization task is by fine-tuned the language model on a dataset, enabling it to extract information, learn patterns, and build internal representation that allow it to generate coherent summaries [8]. To measure the performance of the fine-tuned language model, a metric often used where ROUGE scores being the common metric for summarization task.

In a study where the T5 language model was utilized to generate abstractive summaries of Wikipedia pages in Short Message Service (SMS) format. Fine-tuning of the model are done by applying the Adam optimizer along with initializing the learning rate to 0.0001, the input batch size for training and testing to 2, the epochs to 2, and the datasets are splitted to 80% for the training set and 20% for the test set. The dataset used to train the model is the Wikipedia summary section. The fine-tuned model is able to provide satisfactory results both in the generated abstractive summaries and the ROUGE scores [9]. Another study also uses the T5 language model to prove the effectiveness of the T5 language model for large-scale Indonesian online news data. This study also uses a fine-tuning approach to train the model. The dataset used for fine-tuning the model is IndoSum, an Indonesian language news corpus which contains news from various Indonesian news portals and their summaries, where they only use half of the entire dataset due to limitations faced when conducting the research. The dataset then splitted into 90% for the training set and 10% for the test set. The fine-tuned language model succeeds in generating an abstractive summary of the news and achieves average results on the ROUGE scores [10]. Furthermore, another study also uses the T5 language model by fine-tuning the model with a mixture of summarization and text similarity tasks using summary-article and title-article training pairs, respectively. The aim of this research is to improve the quality of summaries produced by the language model for news in Ukrainian. The dataset comprised articles from Ukrainian news media, and ROUGE scores were used for evaluation. The model exhibited improved performance in generating abstractive summaries in Ukrainian [11].

Based on the studies described earlier, fine-tuning a T5 language model is a common approach to prepare the language model for an abstractive summarization task with ROUGE scores as its metric to measure the performance. The T5 language model also demonstrates promising performance in generating abstractive summaries which are shown from the ROUGE scores achieved and the summary that generated.

II. RESEARCH METHOD

2.1. Problem Analysis

The amount of information contained in a news article might be too much for the reader to the point it might cause the reader to become bored of the article and consume the reader's time for them to find the main idea of the said article. Thus, the aim of this research is to leverage a language model by fine-tuned it with a news dataset. This approach has a purpose to generate an abstractive summarization with the aim to make the reader easily grasp what the article is trying to convey.

Furthermore, several similar research studies were reviewed, where language models were developed to perform abstractive summarization. The results of these studies suggest that fine-tuning a language model is sufficient to enable it to perform abstractive summarization tasks.

In this research, the process of fine-tuning the language model is divided into several phases, which are: environment preparation, dataset preparation, model preparation, training and evaluation, and inference.

2.2. Environment Preparation

In this stage, the preparation before training the language model is initialized. The preparation in this phase consists of installing the required libraries, configuring both the parameters and hyperparameters for fine-tuning, and importing some modules that are necessary for the process of fine-tuning.

This research is carried out on the Google Colab. Google Colab is chosen since it provides the necessary resources for this research such as the pre-installed libraries and the GPU for training the language model.

The libraries used in this research include Transformers, KerasNLP, Datasets, NLTK, ROUGE score, TensorFlow, and NumPy. These libraries are installed into the environment through the Python package manager available on Google Colab.

Next step is to define the parameters and hyperparameters. Hyperparameters are directly affecting the training of the language model, while parameters are not [12]. The defined hyperparameters in this research are the maximum input length, minimum and maximum target length, size of the batch, and maximum epochs.

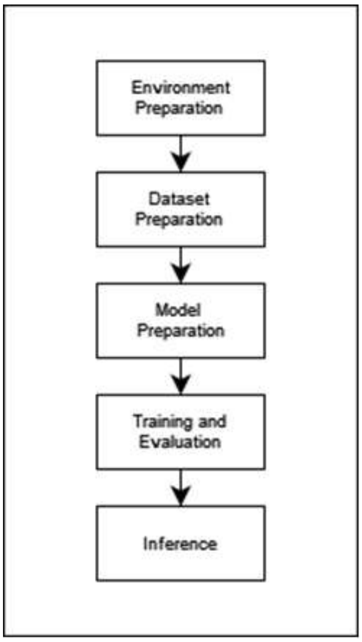

Fig. 1. Fine-tuning Phases.

The maximum input length is a hyperparameter that controls the length of the input accepted by the model during training. In this research, the value is set to 1024, indicating that the model can accept inputs of up to 1024 tokens, with longer inputs being truncated.

Minimum and maximum target length are hyperparameters that determine the minimum and maximum length of the generated summaries. In this research, these values are set to 5 and 128, respectively.

The value of the batch size in this research is set to 4. Batch size is responsible for how many samples are used in one epoch [13] and tend to result in out of memory when the value is set to a bigger number, thus the value that is set in this research are is safe value to avoid out of memory issues.

Learning rate in this research is used to obtain the appropriate results by adjusting the weight used in the training [14]. The value of the learning rate is set to 2e-5, which is 0.00002 in the decimal form.

The maximum number of epochs is set to 1, determining how many iterations the model will undergo during training, with each epoch representing a complete pass through the training dataset [15].

The parameters primarily affect the dataset and specify the language model's name as the checkpoint. The dataset parameter specifies the splitter, with a split ratio of 10%, indicating that only 10% of the entire dataset is used for both

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the training and test sets. The language model's name checkpoint parameter sets the name of the language model used in this research, which is the t5-small model. This parameter is responsible for loading the language model and the tokenizer from the HuggingFace hub.

The final step in this phase involves importing the modules that have been installed in the environment. Key modules imported into the environment include NLTK, NumPy, and TensorFlow, along with additional modules such as OS, logging, modules for loading and concatenating datasets, auto tokenizer, auto model for sequence-to-sequence, data collator for sequence-to-sequence, Keras module, and pipeline for inference.

2.3. Dataset Preparation

A dataset is needed to fine-tune the language model, thus there are several steps to preparing said dataset. These steps consist of loading the dataset, dataset concatenation, data preprocessing, and data conversion.

There are two datasets used in this research, which are the Extreme Summarization Dataset (XSUM) and the CNN/Daily Mail dataset. Both datasets are commonly used to train language models for summarization task. The XSUM dataset comprises 226,711 news articles along with its summary, while the CNN/Daily Mail dataset comprises more than 300,000 news articles along with its summary.

Despite both XSUM and CNN/Daily Mail being a dataset composed of news articles, there are some differences between them. The most striking difference between them is the summary of their respective news articles. In XSUM, the summary is formed into a single sentence while in CNN/Daily Mail, the summary is formed into multiple sentences. Therefore, this concatenation of both dataset is to seek whether the differences in the summary might affect the performance of the language model to generate an abstractive summary.

The preprocessing stage comprises several steps, which are: dataset splitting, load the tokenizer, and preprocessing the data for model's input. Due to the limitations faced in this research, only 10% of the entire dataset is used and this portion of the dataset is then splitted into for training and for testing. The tokenizer used is the tokenizer for the T5-small model.

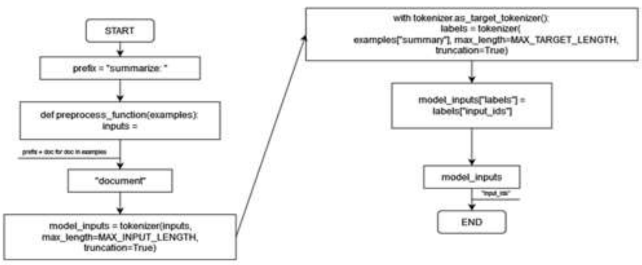

Fig. 2. Preprocessing Flowchart.

From Fig. 2, the preprocessing starts with applying a prefix into the inputs. This prefix is essential for the language model to understand what it should do. Tokenization is done towards the appended inputs and the target for the summary by using the declared tokenizer. The whole purpose of preprocessing is to apply changes for the dataset using the mapping function, creating a pre-processed dataset in the form of a dictionary which can be used by the language model to train with.

The purpose of converting the pre-processed dataset into the TensorFlow dataset structure is because the process of fine-tuning the language model is done with the TensorFlow framework, thus this conversion is important. From this dataset, a train set, a test set, and a generation set are defined.

2.4. Model Preparation

The language model used in this research is the T5-small model. There are other T5 variants, but this variant is chosen due to the resource's efficiency. This model is then paired with Adam optimizer where this optimizer is used for efficient stochastic optimization that requires a minimum amount of memory [16] during training.

The evaluation metric used is the ROUGE metric. ROUGE metric is the metric used to evaluate the language model's performance. In this research, ROUGE-N and ROUGE-L are the metrics used.

ROUGE-N is used to evaluate the overlap of n-grams between the generated summary and the reference summary.

Equation below shows how to generally calculate ROUGE-N.

$$ROUGE-N = \frac{\sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{gram_n \in S} Count(gram_n)}$$

ROUGE-N has several metrics itself, namely precision, recall, and F1 score.

$$Precision = \frac{C}{P}$$

$$Recall = \frac{C}{G}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Equations above show how to calculate each metric of ROUGE-N, which are precision, recall, and F1 score. Precision measured by dividing the number of common n-grams between the prediction and the ground truth with the number of n-grams in the prediction. Recall is measured by dividing the number of common n-grams between the prediction and the ground truth with the number of n-grams in the ground truth.

$$Precision = \frac{LCS(P,G)}{len(P)}$$

$$Recall = \frac{LCS(P,G)}{len(G)}$$

$$F1\ Score = \frac{(1+\beta^2) \times Precision \times Recall}{Recall + \beta^2 Precision}$$

Equations above show how to calculate each metric of ROUGE-L, which are the same as the metrics for ROUGE-N. Precision is measured by dividing the longest common subsequences of prediction and ground truth with the length of prediction. Recall is measured by dividing the longest common subsequences of prediction and ground truth with the length of ground truth.

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2.5. Training and Evaluation

The evaluation metrics that have been defined are used as callbacks during training. Callbacks is a Keras class that utilizes the evaluation metrics for assessing the model's performance. Once the callbacks are properly defined, the training is then initiated.

2.6. Inference

The result of the training phase is the fine-tuned language model which can be used to generate an abstractive summary from a news article. A pipeline module then used to utilize the trained model and the tokenizer to generate a summary.

III. RESULTS AND DISCUSSION

3.1. ROUGE Scores

During training, the language model's performance was evaluated with ROUGE scores as its metric. Once the training is done, the ROUGE scores can be viewed.

This research focused on ROUGE-1, ROUGE-2, and ROUGE-L scores from the fine-tuned language model. Table 1 below shows the ROUGE scores achieved by this fine-tuned language model and its comparison with some other fine-tuned language model.

From Table 1, ROUGE-1 score indicates that approximately 24% of the single words in the prediction overlap with the unigrams in the ground truth. The ROUGE-2 score indicates that approximately 9% of the consecutive pairs of words in the generated text overlap with the bigrams in the reference text. The ROUGE-L score indicates that about 19% of the longest common subsequences between the generated text and the reference text are captured.

TABLE 1. Fine-tuned Language Model ROUGE Scores.

Model	ROUGE Scores		
	ROUGE-1	**ROUGE-2**	**ROUGE-L**
T5-Small XSum/CNNDailyMail	0.24	0.09	0.19

TABLE 2. ROUGE Scores Comparison.

Model	ROUGE Scores		
	ROUGE-1	**ROUGE-2**	**ROUGE-L**
T5-Base-Indonesian IndoSum	0.68	0.61	0.65
T5-Base French Wikipedia Abstractive Summarizer	0.52	0.41	0.52
T5-Small XSum/CNNDailyMail	0.24	0.09	0.19

From Table 2, the fine-tuned model achieved the lowest scores when compared with other fine-tuned language models that this research referenced. But, these low scores might be caused by the language model used for this research. This research uses the T5-small language model while the other two use the T5-base language model. The T5-small model contains six layers of transformer blocks while T5-base has 12 layers, twice as much as the T5-small language model which limits this model's ability to capture complex relationships and nuances in the text. Thus, explain the low ROUGE scores achieved by this research's fine-tuned language model.

TABLE 3. Article and Summary.

Article	Summary
An Ohio sheriff has released 72 inmates because of budget cuts which he says are restricting his ability to safely run the jail. The move by Summit County Sheriff Steve Barry in Akron on Sunday reduces the county jail's overall capacity by 149 beds, from 671 to 522. Convicts, mostly with non-violent charges, beamed as they filed out of the now defunct wing to meet relatives and agencies outside the gates. Released: 72 inmates were released from Summit County Jail, Ohio, on Sunday after an entire wing was shut . Decision: Summit County Sherrif Steve Barry said he had no choice but to close the 150-bed wing . The jail has been reporting issues since the state cut local government funding by $1 billion in 2012. The sheriff's spokesman Bill Holland told the Akron Beacon Journal lowing staffing meant inamtes were being kept in their cells longer, with less recreational time, leading to heightened tensions and fights. To combat the issue, he said, staff had been refused holiday. A table was set up outside the jail with hats, gloves and scarves for the inmates as temperatures dropped to 24 degrees. Some were unaware they were being released until hours before. 'I ain't happy because I've got to go back to court,' one inmate, who was not named, told ABC News. Another said: 'I'm happy! I'm out!' Mixed feelings: One man (left) was delighted. Another (right) raged that he has to go back to court . 'Second chance': Antonio Spragling, jailed for drugs charges in November, said this is a second chance . Surprised: Many did not know they were going to be released until hours before the measure passed . Former inmate Antonio Spragling, 50, who was jailed for drug charges in November, told the Akron Beacon Journal: 'All I can do is thank God... I look at it as a second chance and I'm not going to let anyone down. No judge. The system. And more important, I'm not going to let myself down.' Most of the released men were taken home while some were transferred to alternative sentencing programs. The sheriff, who announced the planned measure last year, could not recall a similar release in the past. 'I don't want these people out,' Barry told the journal. 'I got no choice.' The next step: All inmates have been issued a court date to discuss the completion of their sentence . Barry, who began his sheriff's office career in 1979, said all the victims of the inmates have been contacted about the release. The jail received about 50 new inmates over the last two days, complicating Sunday's release. Cuts in state funding for local municipalities have squeezed the sheriff's budget, along with voters' November rejection of a county sales tax increase that would have generated about $20 million a year for 10 years.	Summit County Sheriff Steve Barry said he had no choice but to close 150-bed wing . Convicts, mostly with non-violent charges, beamed as they filed out of the now defunct wing to meet relatives and agencies outside the gates . The state cut local government funding by $1 billion in 2012.

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TABLE 4. Article and Summary.

Article	Summary
Crystal Palace have signed defender Brede Hangeland on a free transfer after being released by Fulham last season. The towering 33-year-old was released by Fulham via e-mail at the end of the season and has signed on a one-year deal at Selhurst Park. The Norwegian international, who has 91 caps for his country, played 214 Premier League games for the Cottagers since 2008. Capture: Brede Hangeland has signed for Crystal Palace on a one-year deal after his release from Fulham. Hangeland told the club's website: 'I'm absolutely delighted. All the things I've heard about this club – the manager, the players, the staff – it's all been good things and I've seen that for myself this morning. 'I'm delighted to be here. I look forward to helping out and doing the best I can for this club. 'I'm quite old school as a player, I just want to be part of a good group of players, working for a good manager, working really hard and driving something in the right direction,' he added. Target: Former Fulham defender Brede Hangeland is delighted to be a part of Tony Pulis' side . 'All the people I spoke to told me that's what's going on at Crystal Palace and I really wanted to be a part of that. 'It's a traditional club with a big following. I thought the atmosphere here was fantastic and obviously the fans had a lot to be happy about come the end of the season. 'If we can do something similar to that this season, that would be great. I'm really looking forward to playing in front of those fans as soon as possible.'	Brede Hangeland has signed for Crystal Palace on a one-year deal. The 33-year-old was released by Fulham via e-mail at the end of the season. Norwegian international played 214 Premier League games for the Cottagers since 2008.

TABLE 5. Article and Summary.

Article	Summary
CNN — Canadian Prime Minister Justin Trudeau and his wife Sophie Grégoire Trudeau are separating, Trudeau announced on his Instagram account Wednesday. Trudeau said after "many meaningful and difficult conversations" with Sophie, "we have made the decision to separate." "As always, we remain a close family with deep love and respect for each other and for everything we have built and will continue to build," he wrote. He asked that their privacy be respected for the well-being of their children. The prime minister's office said the pair have "have signed a legal separation agreement," in a Wednesday statement. "They have worked to ensure that all legal and ethical steps with regards to their decision to separate have been taken, and will continue to do so moving forward,' it said. After spending several years teaching in Vancouver, Trudeau returned to Montreal in 2002 where he met Grégoire, according to the Canadian Prime Minister's official biography. "In 2002, Justin returned home to Montréal, where he met Sophie Grégoire. They married in 2005 and are now the proud parents of Xavier, Ella-Grace, and Hadrien," it wrote. According to Trudeau's Liberal Party website, Grégoire Trudeau gained a degree in communications at the University of Montréal, later working in sales and advertising before becoming a television and radio reporter. In an Instagram post celebrating their wedding anniversary last year, Grégoire Trudeau said the pair had "navigated through sunny days, heavy storms, and everything in between and it ain't over." She added: "Long-term relationships are challenging in so many ways. They demand constant work, flexibility, compromise, sacrifice, devotion, patience, effort, and so much more. None of us are perfect and so there is no perfect relationship, but love is only true when it keeps you safe, sets you free, and makes you grow." The pair attended King Charles' coronation in London earlier in May, and also met with US President Joe Biden in March.	Justin Trudeau and his wife Sophie Grégoire are separating. The pair have signed a legal separation agreement. They are now the proud parents of Xavier, Ella-Grace and Hadrien.

Albeit the low scores achieved, the fine-tuned language model is still able to generate decent abstractive summaries from a news article. The summaries from tables above are able to identify the information of the main article, which can help the reader to quickly catch the main idea of the said article.

IV. CONCLUSION

This research has successfully fine-tuned a T5-small language model to generate abstractive summarizations from online news articles. The generated summaries can help readers to shorten their time in order to catch the main idea of a news article. The method used to develop the language model involves fine-tuning the T5-small language model with a combined dataset of the XSUM dataset and the CNN/DailyMail dataset. The language model's performance is evaluated using the ROUGE metrics.

The performance of the language model is assessed based on the ROUGE scores and the quality of the generated summaries. The model achieved low scores for ROUGE-1, ROUGE-2, and ROUGE-L. Despite the low ROUGE scores, the generated summaries effectively capture the important points of the articles.

There is still significant room for improvement in this research. A better environment with more robust hardware resources, such as GPU or TPU, might yield better results, as the hyperparameters in this research were limited to small values due to resource constraints. Exploring different datasets and approaches could also enhance the language model's performance in generating more informative summaries. Additionally, considering the use of other language models, such as the PEGASUS model, or another type of T5 based language model, such as T5-base or T5-large, presents an opportunity for comparative studies between the T5-small language model and alternative models.

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