

Abstractive Text Summarization of Training Review on Learning Management System Using Text-to-Text Transfer Transformers

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Abstract. Many Learning Management Systems (LMS) provide user reviews for training programs, yet these reviews often lack concise summaries, making it difficult for users to evaluate training quality effectively. Therefore, this research purposes to generate abstractive summary insights from large volumes of LMS training reviews. The method used in this research is the Text-to-text Transfer Transformers (T5) algorithm with the T5-Base variant, which is capable of transforming lengthy textual inputs into shorter, coherent summaries. Data collection is scraped from 60 training modules on the LMS and results in over 30,000 review data. The T5-Base model was trained and evaluated using Recall-Oriented Understudy for Gisting Evaluation (ROUGE) metrics, yielding scores of ROUGE-1 is 0.4809, ROUGE-2 is 0.2816, and ROUGE-L is 0.3773, with an overall model accuracy of 75%. These performance indicators confirm that the model is able to capture essential information and produce summaries that effectively reflect the core content of the original reviews. Overall results demonstrate that the T5-Base model effectively produces relevant abstractive summaries, offering a practical solution for improving LMS content transparency and assisting users in selecting suitable training programs. By providing clear and concise summaries, the system improves content transparency and assists users in making informed decisions when selecting training programs. This research highlights the potential of abstractive text summarization to support better information management within modern digital learning environments.

Keywords: *Abstractive Summarization; Natural Language Processing; Review Comment; ROUGE; T5 Algorithm*

Abbreviations: Abstractive Text Summarization (ATS); Learning Management Systems (LMS); Recall-Oriented Understudy for Gisting Evaluation (ROUGE); Text-to-text Transfer Transformers (T5)

INTRODUCTION

Digital learning has become a core component of contemporary education and professional training. After the expansion of online and blended learning, many institutions adopted LMS platforms to organize content, manage learning activities, and support remote or flexible participation [1], [2]. In this ecosystem, LMS platforms are not only repositories for learning materials but also decision-support spaces where users evaluate training quality through ratings, comments, and experiential feedback [3]. For learners, these reviews can indicate whether a course is relevant, easy to understand, practical, and worth completing. For training providers, reviews can reveal learner satisfaction and areas for improvement.

Despite their value, review comments are often long, repetitive, informal, and scattered across many training modules. Users who need to choose suitable training may need to read hundreds or thousands of comments manually, while providers may overlook review content because it is not presented as concise insight. In educational settings, this creates an information-management problem: the review data exist, but they are not always transformed into a form that improves learning decisions. Automatic text summarization is therefore relevant because it can condense large textual collections into shorter representations while preserving important information [4], [5], [6].

Various studies indicate that the T5 model and its variants have been widely used to generate abstractive summaries for scientific articles, Wikipedia entries, video transcripts, research journals, diverse document types, and reviews; results generally demonstrate T5's capability to produce concise and meaningful summaries [7], [8], [9], [10], [11], [12]. Research has also compared T5 with other models (such as BERT and ChatGPT) and combined it with Seq2Seq, LSTM, and RNN architectures to enhance summary quality, revealing that model performance is significantly influenced by the architecture, dataset, fine-tuning process, and evaluation methods employed [13], [14], [15], [16]. Beyond T5, approaches such as Automatic Text Summarization (ATS), Seq2Seq, LLMs, ConSeq, and graph-based methods have been utilized to summarize text and video while preserving key information, improving factual consistency, and

supporting the quality and efficiency of the summarization process [5], [6], [16], [17], [18], [19], [20], [21]. In the context of recommendation systems, RankT5 has been used to generate summaries that support course recommendations, while other studies have employed T5 and ChatGPT to summarize restaurant reviews [14]. Based on this literature, research specifically utilizing T5-Base to summarize training reviews as a basis for recommendations remains limited. Therefore, this study employs T5-Base to generate summaries of training reviews to support training recommendations and evaluates summary quality using ROUGE, aiming to provide a more quantifiable approach to optimizing the T5-Base model for recommendation purposes.

Recent advances in transformer-based NLP have significantly improved the quality of automatic summarization. Transformer architectures support contextual representation and have been applied to many deep learning tasks [22]. Among them, T5 is particularly suitable for summarization because it frames every NLP task as a text-to-text problem, allowing both input and output to be expressed as natural language sequences. Previous studies have shown that T5 can produce meaningful summaries in different domains, including general documents, news, research papers, and multilingual text [7], [8], [13], [23], [24], [25]. However, the use of T5 to summarize LMS training reviews remains limited, especially for Indonesian training review data.

This study addresses that gap by developing an abstractive review summarization model for LMS training reviews using the T5-Base model. The study focuses on review data from an Indonesian public training LMS and evaluates model performance using accuracy and ROUGE metrics. The objective is to determine how T5 can be applied to summarize LMS training reviews and how well the model performs under different training-test split and learning-rate scenarios. The expected contribution is a model-based approach that can help learners understand the general quality of training programs more efficiently and help LMS providers improve the transparency of review-based information.

METHODS

Study Area and Data Source

This study used training review data from the Kemenkeu Learning Center (KLC), an LMS for financial training. The data source was selected because it provides multiple training modules with user ratings and textual comments that can be used to represent learner feedback. The collected fields included training title, organizer, description, review time, rating, and review text. The web scraping process extracted review data from 60 training contents, consisting of ten training contents from each of six training centers. The raw scraping process produced 34,316 review rows. For supervised summarization, the data were organized into paired instances in which the input text combined training title, description, and accumulated reviews, while the target text represented the reference review summary. After tokenization and split preparation, the paired dataset consisted of 165 text-summary instances used across the training and testing scenarios.

T5 Architecture

T5 is a Transformer model used to perform various tasks using a text-to-text format for both input and output. It employs an encoder-decoder architecture identical to the standard Transformer architecture [23]. To handle multiple tasks without altering the core architecture, T5 utilizes a simplified scheme; this approach streamlines computation and reduces complexity while remaining effective at conveying information. T5 also implements dropout to enhance model generalization and prevent overfitting across various network components. A key distinction from standard Transformers lies in the application of dropout. T5 applies it throughout the entire network, including weights and feed-forward layers, whereas standard Transformers apply it only to the feed-forward layers [23].

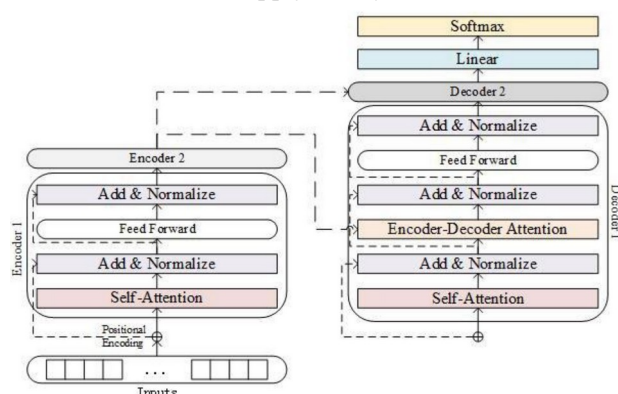


Figure 1. T5 Architecture [26]

The model architecture in Figure 1 employed in this study is as follows [24]:

1. **Input layer:** In this stage, long reviews from the LMS are ingested and tokenized using the T5 tokenizer, yielding tokens such as ``input_ids``, ``attention masks``, and ``labels`` for the encoder and decoder training processes.
2. **Encoder:** The encoder receives ``input_ids`` and ``attention masks`` as input; it comprises multiple layers made up of sub-layers that implement residual connections and layer normalization.
3. **Decoder:** The decoder receives ``labels`` (reference summaries) as input; unlike the encoder, it consists of three layers, one of which differs from those in the encoder.
4. **Output layer:** This stage represents the model's final output, where the output layer generates the summary prediction produced by the decoder based on the training, utilizing test data processed with the labels previously received by the decoder.

Research Procedure

The research procedure followed the CRISP-DM framework, which is commonly used for data mining and data science projects [27], [28]. The first phase, business understanding, defined the problem as the lack of concise information from training reviews and the need for automatic review summarization to support training selection. The second phase, data understanding, examined the structure and availability of review data collected from the LMS.

The third phase, data preparation, normalized the textual data by converting selected text columns to lowercase and removing line-break artifacts. The prepared input was constructed in the format: title, description, and reviews. The target summary was stored as the target text. Tokenization was then performed using the T5 tokenizer to produce input identifiers, attention masks, and labels required for training. Data splitting used 90:10, 80:20, and 70:30 train-test ratios to observe model behavior under different data allocation strategies [29].

The fourth phase, modeling, fine-tuned T5-Base using six scenarios. Each scenario used three epochs and a batch size of eight, while the learning rate was set to either 1e-4 or 3e-4. The learning rate was varied because it affects model convergence and the balance between faster learning and training stability [12]. Model configuration summary available in Table 1. The fifth phase, evaluation, measured accuracy, precision, recall, F1-score, and ROUGE. The deployment phase was limited to model saving and readiness verification; the trained model was stored for later use and could be connected to a user interface such as Gradio.

[illegible]

Component

Description

Data source

Training reviews from Kemenkeu Learning Center

Raw data

34,316 review rows from 60 training contents

Prepared paired data

165 input-summary instances

Input fields

Training title, training description, and review text

Target field

Reference summary of training reviews

Model

T5-Base for abstractive summarization

Train-test splits

90:10, 80:20, and 70:30

Learning rates

1e-4 and 3e-4

Epoch and batch size

3 epochs and batch size of 8

Evaluation

Accuracy, precision, recall, F1-score, ROUGE-1, ROUGE-2, and ROUGE-L

Data Analysis

Model performance was analyzed from two perspectives. First, the final-epoch classification-like metrics produced during training were used to observe model convergence and prediction consistency. Second, Recall-Oriented Understudy for Gisting Evaluation (ROUGE) was used to evaluate textual similarity between generated summaries and reference summaries. ROUGE is an evaluation metric used in NLP for the development of summarization models. It operates by comparing the model-generated summary against a reference summary, which may be produced manually or with the assistance of AI tools like ChatGPT. Specific ROUGE variants include ROUGE-1, which focuses on unigrams (individual words); ROUGE-2, which focuses on bigrams (word pairs); and ROUGE-L, which measures the longest common sequence of words between the model's summary and the reference to assess structural similarity [30], [31]. ROUGE-1 measured unigram overlap, ROUGE-2 measured bigram overlap, and ROUGE-L measured the longest common subsequence. A higher ROUGE score indicates that the generated summary is closer to the reference summary.

RESULTS AND DISCUSSION

Dataset Preparation and Training Results

The LMS review data contained short expressions such as positive appreciation, practical comments about training usefulness, and repeated responses such as acknowledgements. These characteristics are typical of user-generated educational reviews, where useful information is mixed with repetitive and informal comments. After normalizing the text and preparing the paired dataset, the model was trained in six scenarios. Figure 2 shows the stages of the process T5 undergoes to build a summarization model, beginning with data pre-processing that involves cleaning and splitting the data. Ideally, training utilizes an 80/20 split to ensure balance during the model training process and to prevent data overlap. The experiments were also conducted using 90/10, 80/20, and 70/30 training-to-testing splits to evaluate performance under different scenarios beyond the standard 80/20 split. The data from these three scenarios serve as input for the encoder, while the testing set is used to measure evaluation metrics based on the decoder's predictions. Then, the tokenization process with T5-Tokenizer that used in conjunction with the pre-trained T5-Base model from Hugging Face to generate specific input tokens, attention masks, and labels, thereby enhancing utility for the modeling task.

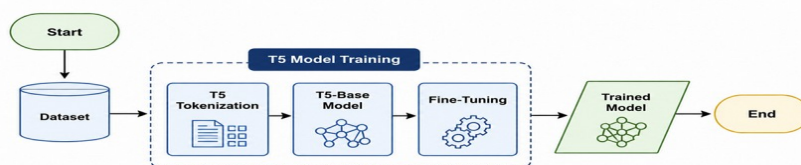


Figure 2. Training Process

Implementation is conducted after tokenization with the pre-trained T5-Base model. The T5-Base algorithm is implemented for the summarization model training process, incorporating hyperparameters such as learning rate, batch size, and epochs. T5-Base offers advantages over other variants due to its ability to capture keywords within sentences; it possesses a larger parameter capacity and delivers optimal results for text processing tasks, such as NLP-based summarization [25]. Lastly, the fine-tuning process produces the final summarization model by fine-tuning the pre-trained T5-Base model using the tokenized inputs (input tokens, attention masks, and labels), enabling the model to learn how to generate summaries. The fine-tuned summarization model outputs training loss, model accuracy, and evaluation metrics

calculated using ROUGE (specifically recall, precision, and F1-score). Table 2 presents the final epoch results for each scenario.

									Table 2. Final-epoch model performance for each training scenario.

Sc.

Split

LR

Train loss

Val. loss

Acc.

Prec.

Recall

F1

Training Loss and Accuracy Curve

1

90:10

1e-4

1.4148

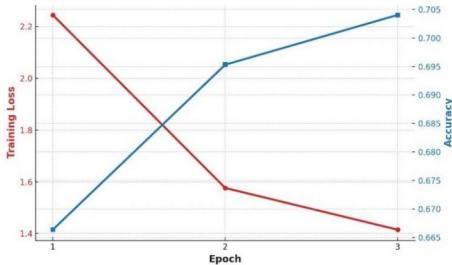
1.4012

0.7040

0.5829

0.5294

0.5318



2

90:10

3e-4

1.0160

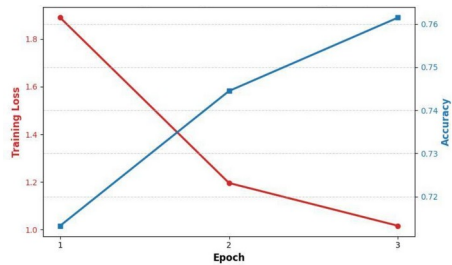
1.0823

0.7614

0.6511

0.6150

0.6184



3

80:20

1e-4

1.4708

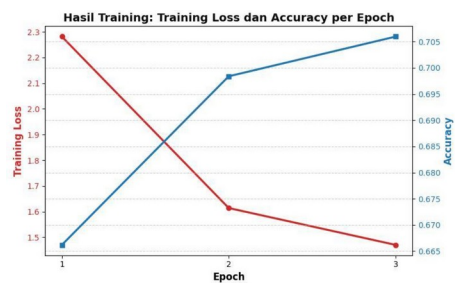
1.3760

0.7059

0.6225

0.5640

0.5688



4

80:20

3e-4

1.0795

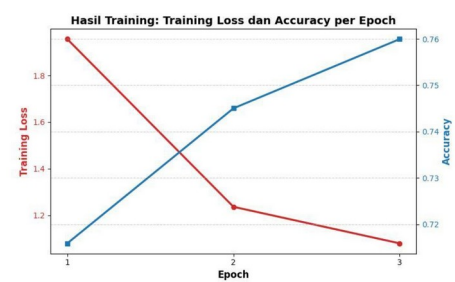
1.0804

0.7599

0.6704

0.6157

0.6214



5

70:30

1e-4

1.5522

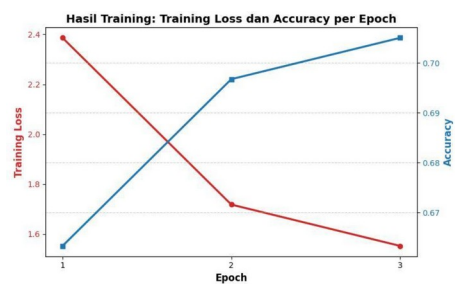
1.3935

0.7050

0.6083

0.5558

0.5589

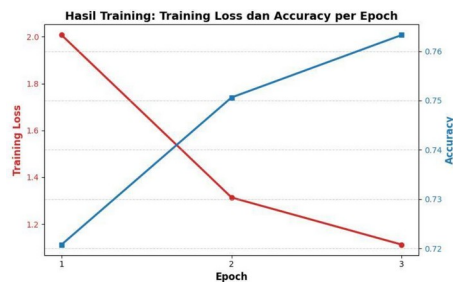


6

70:30

3e-4

1.1129
1.0676
0.7632
0.6762
0.6231
0.6275



The training results show that the $3e-4$ learning rate consistently produced stronger accuracy, precision, recall, and F1-score than the $1e-4$ learning rate across the three split ratios. The highest final accuracy was obtained by the 70:30 split with a $3e-4$ learning rate, reaching 0.7632. However, accuracy alone does not fully represent summarization quality because abstractive summarization must also be evaluated by the similarity and informativeness of generated text.

ROUGE Evaluation

ROUGE evaluation was used to compare generated summaries with reference summaries. Table 3 shows that the best ROUGE-1 and ROUGE-L scores were achieved by the 80:20 split with a $3e-4$ learning rate, while the highest ROUGE-2 score was achieved by the 90:10 split with a $3e-4$ learning rate. Because ROUGE-1 and ROUGE-L were strongest in the 80:20 scenario, this configuration was considered the best overall summarization configuration.

				Table 3. ROUGE scores for T5-Base summarization scenarios.

Split

Learning rate

ROUGE-1

ROUGE-2

ROUGE-L

90:10

$1e-4$

0.4435

0.2471

0.3625

90:10

$3e-4$

0.4775

0.2828

0.3650

80:20

$1e-4$

0.4590

0.2747

0.3644

80:20
 3e-4
 0.4809
 0.2816
 0.3773
 70:30
 1e-4
 0.4474
 0.2686
 0.3491
 70:30
 3e-4
 0.4721
 0.2533
 0.3638

Generated Summary Quality

Qualitative analysis of the generated summaries indicates that T5-Base was able to capture common review themes, such as usefulness, ease of understanding, and the relevance of training materials. In one training sample, the input contained a course title, a description of learning objectives, and many repeated positive comments. The generated summary retained the main learning objective and condensed repeated review expressions into a coherent statement about the usefulness and clarity of the training. This result demonstrates the advantage of abstractive summarization: the model does not simply copy review fragments but attempts to compose a new summary that represents the main review content. The example of generated summary result is available in Table 4 in Indonesian language.

1st Comment

2nd Comment

Reference Summary

Generated Summary

judul: microlearning estimasi kebutuhan biaya rincian output (ro) (open access) deskripsi: selamat datang pada microlearning estimasi kebutuhan biaya rincian output (ro). setelah mengikuti pelatihan ini, peserta diharapkan mampu memahami perhitungan estimasi kebutuhan biaya untuk suatu output (rincian output) yang bersifat sederhana dengan menggunakan teknik analisis biaya. selamat belajar. ulasan: bermanfaat sangat bermanfaat bagus materi dan pelatihannya sangat menarik sangat membantu terima kasih terima kasih menambah ilmu pengetahuan baru sangat bermanfaat bagus memberikan pencerahan sangat bermanfaat pelatihan singkat, sangat menarik. belajar di klc kayak scroll reels ig... singkat, seru, bermanfaat... tapi dapet lencana. terimakasih sangat bermanfaatttt. terima kasihh baik baik bagus sangat membantu materinya sangat bermanfaat sangat bermanfaat sangat baik, terima kasih sangat bermanfaat

(Title: Microlearning on Estimating Cost Requirements for Output Details (RO) (Open Access). Description: Welcome to the microlearning course on estimating cost requirements for Output Details (RO). Upon completing this training, participants are expected to understand how to calculate estimated cost requirements for a simple output (output detail) using cost analysis techniques. Happy learning. Reviews: Useful; very useful; great; the material and training are very engaging; very helpful; thank you; gained new knowledge; very useful; great; provided valuable insights; very useful; short training, very engaging. Learning on KLC is like scrolling through IG Reels... short, fun, useful... but you get a badge. Thank you, very useful. Thank you; good; great; very helpful; the material is very useful; very useful; excellent; thank you; very useful.)
menambah wawasan dan meningkatkan kompetensi sangat bermanfaat sangat baik bagus terima kasih sangat berguna informasinya seruuuu sangat informatif terima kasih aset pengetahuan ---- sangat bagus terima kasih baik "terima kasih sangat bermanfaat" baaik nice sangat bermanfaat sekali sangat membantu dan manfaat terimakasih bagus good terima kasih sangat bermanfaat mantap sekali mantappu menarik dan penting mencerahkan sesuai tupoksi baik good sangat membantu peningkatan pemahaman sangat bermanfaat sangat membantu bagus.

(Broadens horizons and enhances competence; very beneficial; excellent; great; thank you; the information is very useful; exciting; highly informative; thank you; a knowledge asset; very good; thank you; good; "thank you, very beneficial"; good; nice; extremely beneficial; very helpful and useful; thank you; great; good; thank you; very beneficial; fantastic; awesome; interesting and important; enlightening; relevant to core duties; good; very helpful for improving understanding; very beneficial; very helpful; great.)

selamat datang di microlearning estimasi kebutuhan biaya rincian output (ro). setelah pelatihan ini, peserta diharapkan dapat memahami perhitungan estimasi biaya untuk output sederhana menggunakan teknik analisis biaya. pelatihan ini sangat bermanfaat, membantu, menarik, informatif, dan menambah ilmu pengetahuan serta wawasan. banyak peserta menyebut materi bagus, mantap, seru, mencerahkan, dan relevan dengan tupoksi. disukai karena singkat, seperti scroll reels ig tapi tetap dapat lencana. komentar seperti 'terima kasih', 'baik', 'good', 'nice', 'mantappu', dan 'kelas' menunjukkan antusiasme tinggi. terima kasih atas pelatihannya.

(Welcome to the microlearning session on estimating cost requirements for Output Details (RO). Upon completing this training, participants are expected to understand how to calculate cost estimates for simple outputs using cost analysis techniques. The training is highly beneficial, helpful, engaging, and informative, while also expanding knowledge and insights. Many participants described the material as excellent, solid, exciting, enlightening, and relevant to their core duties. It is popular for being concise—akin to scrolling through Instagram Reels—yet still rewarding, as participants earn a badge. Comments such as "thank you," "great," "good," "nice," "awesome," and "top-notch" reflect a high level of enthusiasm. Thank you for the training.)

selamat datang di course e-learning jabatan fungsional analis anggaran ahli pertama dalam lingkup tugas selaku chief operational officer (coo). peserta membantu mantap materinya bagus dan sangat bermanfaat terima kasih atas, menambah pengetahuan, dan mudah dipahami.

(Welcome to the e-learning course for the First-Level Budget Analyst functional position. The material is excellent and highly beneficial; it has enhanced my knowledge and is easy to understand. Thank you.)

However, some generated outputs still showed limitations. In a few cases, the model included information from a different training context or produced generic positive expressions. This issue may occur because LMS reviews contain many repeated short phrases and because the final paired dataset was relatively small compared with the amount of raw review data. It may also be related to maximum input-length constraints during tokenization, where long review collections must be truncated before training. These limitations suggest that future systems should consider chunking, overlap strategies, or hierarchical summarization for very long review collections.

Discussion

The results support previous findings that transformer-based models, particularly T5 variants, are effective for abstractive summarization tasks [7], [13], [23], [24], [25]. The strongest ROUGE-1 score of 0.4809 shows that the model preserved many important unigrams from the reference summaries, while the ROUGE-L score of 0.3773 indicates that the generated summaries maintained a reasonable sequence structure. The lower ROUGE-2 score shows that bigram-level overlap remains more challenging, which is common in abstractive summarization because generated text may paraphrase reference text rather than reproduce identical phrases. Compared with prior Indonesian summarization studies, the result is competitive for a domain-specific dataset. Research on educational video transcript summarization using T5 reported lower ROUGE values for ROUGE-1, ROUGE-2, and ROUGE-L [32]. The current results also complement Indonesian extractive summarization research, where graph-based and sequential pattern mining methods rely on sentence selection rather than generating new text. In this study, the abstractive T5 model is more suitable for LMS review summarization because user comments are repetitive, informal, and often fragmented.

From an educational innovation perspective, the model can improve LMS transparency by transforming large review collections into concise summaries. Learners can use the summaries to understand whether a course is useful, clear, or relevant before enrolling. Providers can also use the summaries to identify general patterns of learner feedback. Thus, review summarization can support data-informed decision-making in digital education without requiring users to manually read large numbers of comments.

CONCLUSION

This study developed an abstractive text summarization model for LMS training reviews using the T5-Base model. The study collected 34,316 raw review rows from 60 KLC training contents and prepared paired input-summary data for supervised summarization. Among six training scenarios, the 80:20 train-test split with a learning rate of $3e-4$ produced the strongest overall summarization quality, with accuracy of 75.99%, ROUGE-1 of 0.4809, ROUGE-2 of 0.2816, and ROUGE-L of 0.3773. The findings show that T5-Base can generate concise and relevant summaries that represent the main ideas of training reviews, thereby supporting learners in selecting suitable training and helping LMS providers make review information more accessible. The study remains limited by the size of the prepared paired dataset, repeated review expressions, and token-length constraints during model training. Future work should expand the paired dataset, apply overlap or chunking strategies for long review inputs, compare larger T5 variants or multilingual models, and integrate the model into an operational LMS interface for user-centered evaluation.

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REFERENCES

- [1] Leny Dhianti, "Efektivitas Blended Learning Berbasis LMS dalam Pembelajaran Matematika," *Jurnal Riset Pembelajaran Matematika Sekolah*, vol. 5, no. 1, pp. 80–84, Mar. 2021, doi: 10.21009/jrpms.051.10.

- [2] Z. Zainuddin, "Tinjauan Model Pembelajaran Blended Learning pada Perguruan Tinggi di Era New Normal Covid-19: Kebijakan dan Implementasi," *Asia-Pacific Journal of Public Policy*, pp. 34–45, Nov. 2021, doi: 10.52137/apjpp.v7i2.65.
- [3] R. Sugiarto and A. Musyafa, "Learning Management System (LMS) pada SMK 1 Barunawati Jakarta," *Jurnal Teknologi Informatika dan Komputer*, vol. 10, no. 2, pp. 768–789, Dec. 2024, doi: 10.37012/jtik.v10i2.2422.
- [4] R. Boorugu and G. Ramesh, "A Survey on NLP based Text Summarization for Summarizing Product Reviews," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, IEEE, Jul. 2020, pp. 352–356. doi: 10.1109/ICIRCA48905.2020.9183355.
- [5] G. Sharma and D. Sharma, "Automatic Text Summarization Methods: A Comprehensive Review," *SN Comput. Sci.*, vol. 4, no. 1, p. 33, Oct. 2022, doi: 10.1007/s42979-022-01446-w.
- [6] M. F. Mridha, A. A. Lima, K. Nur, S. C. Das, M. Hasan, and M. M. Kabir, "A Survey of Automatic Text Summarization: Progress, Process and Challenges," *IEEE Access*, vol. 9, pp. 156043–156070, 2021, doi: 10.1109/ACCESS.2021.3129786.
- [7] B. N. D. Kumari, B. N. M. N. S. K. P., and S. R. A., "Text Summarization using NLP Technique," in *2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER)*, IEEE, Oct. 2022, pp. 30–35. doi: 10.1109/DISCOVER55800.2022.9974823.
- [8] J. L. E. K. Fendji, D. M. Taira, M. Atemkeng, and A. M. Ali, "WATS-SMS: A T5-Based French Wikipedia Abstractive Text Summarizer for SMS," *Future Internet*, vol. 13, no. 9, p. 238, Sep. 2021, doi: 10.3390/fi13090238.
- [9] M. F. Fadlilah, A. R. Atmadja, and M. D. Firdaus, "Pemanfaatan Transformer untuk Peringkasan Teks: Studi Kasus pada Transkripsi Video Pembelajaran," *Building of Informatics, Technology and Science (BITS)*, vol. 6, no. 3, pp. 2111–2119, Dec. 2024, doi: 10.47065/bits.v6i3.6342.
- [10] V. K. Bhukya and U. Bhukya, "Abstractive Text Summarisation using T5 Transformer Architecture with analysis," Aug. 29, 2024. doi: 10.21203/rs.3.rs-4986903/v1.
- [11] S. Chaurasia, D. Dasgupta, and R. Regunathan, "T5LSTM-RNN based Text Summarization Model for Behavioral Biology Literature," *Procedia Comput. Sci.*, vol. 218, pp. 585–593, 2023, doi: 10.1016/j.procs.2023.01.040.
- [12] V. N. M. Abadi and F. Ghasemian, "Enhancing Persian text summarization through a three-phase fine-tuning and reinforcement learning approach with the mT5 transformer model," *Sci. Rep.*, vol. 15, no. 1, p. 80, Jan. 2025, doi: 10.1038/s41598-024-78235-3.
- [13] A. R. Lubis et al., "Enhancing Text Summarization with a T5 Model and Bayesian Optimization," *Revue d'Intelligence Artificielle*, vol. 37, no. 5, pp. 1213–1219, Oct. 2023, doi: 10.18280/ria.370513.
- [14] A. Gund, H.-C. Lo, C.-Y. Chiu, and C.-Y. Cheng, "Sentiment Analysis and Summarization of Restaurant Reviews Using T5 and ChatGPT," Available at SSRN 4963924, 2024.
- [15] M. Wang, P. Xie, Y. Du, and X. Hu, "T5-Based Model for Abstractive Summarization: A Semi-Supervised Learning Approach with Consistency Loss Functions," *Applied Sciences*, vol. 13, no. 12, p. 7111, Jun. 2023, doi: 10.3390/app13127111.
- [16] A. Gupta, D. Chugh, Anjum, and R. Katarya, "Automated News Summarization Using Transformers," 2022, pp. 249–259. doi: 10.1007/978-981-16-9012-9_21.
- [17] C. Huang, Z. Zhang, B. Mao, and X. Yao, "An Overview of Artificial Intelligence Ethics," *IEEE Transactions on Artificial Intelligence*, vol. 4, no. 4, pp. 799–819, Aug. 2023, doi: 10.1109/TAI.2022.3194503.
- [18] F. Nan et al., "Improving Factual Consistency of Abstractive Summarization via Question Answering," in *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, Stroudsburg, PA, USA: Association for Computational Linguistics, 2021, pp. 6881–6894. doi: 10.18653/v1/2021.acl-long.536.
- [19] T. Shi, Y. Keneshloo, N. Ramakrishnan, and C. K. Reddy, "Neural Abstractive Text Summarization with Sequence-to-Sequence Models," *ACM/IMS Transactions on Data Science*, vol. 2, no. 1, pp. 1–37, Feb. 2021, doi: 10.1145/3419106.
- [20] E. Apostolidis, E. Adamantidou, A. I. Metsai, V. Mezaris, and I. Patras, "Video Summarization Using Deep Neural Networks: A Survey," *Proceedings of the IEEE*, vol. 109, no. 11, pp. 1838–1863, Nov. 2021, doi: 10.1109/JPROC.2021.3117472.
- [21] Y. Zhang, H. Jin, D. Meng, J. Wang, and J. Tan, "A Comprehensive Survey on Process-Oriented Automatic Text Summarization with Exploration of LLM-Based Methods," Oct. 2025.
- [22] S. Islam et al., "A comprehensive survey on applications of transformers for deep learning tasks," *Expert Syst. Appl.*, vol. 241, p. 122666, May 2024, doi: 10.1016/j.eswa.2023.122666.
- [23] D. Dharrao, M. Mishra, A. Kazi, M. Pangavhane, P. Pise, and A. M. Bongale, "Summarizing Business News: Evaluating BART, T5, and PEGASUS for Effective Information Extraction," *Revue d'Intelligence Artificielle*, vol. 38, no. 3, pp. 847–855, Jun. 2024, doi: 10.18280/ria.380311.
- [24] A. Bahari and K. E. Dewi, "Peringkasan Teks Otomatis Abstraktif Menggunakan Transformer Pada Teks Bahasa Indonesia," *Komputa : Jurnal Ilmiah Komputer dan Informatika*, vol. 13, no. 1, pp. 83–91, Apr. 2024, doi: 10.34010/komputa.v13i1.11197.
- [25] M. W. B. D. Satya, A. Luthfiarta, and M. N. Althoff, "Comparative Analysis of T5 Model Performance for Indonesian Abstractive Text Summarization," *Sistemasi: Jurnal Sistem Informasi*, vol. 14, no. 3, pp. 1092–1106, 2025.
- [26] C. Raffel et al., "Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer," *Journal of Machine Learning Research*, vol. 21, no. 140, pp. 1–67, 2020.
- [27] A. Rianti, N. W. A. Majid, and A. Fauzi, "CRISP-DM: Metodologi Proyek Data Science," in *Prosiding Seminar Nasional Teknologi Informasi dan Bisnis*, 2023, pp. 106–114.
- [28] C. Schröer, F. Kruse, and J. M. Gómez, "A Systematic Literature Review on Applying CRISP-DM Process Model," *Procedia Comput. Sci.*, vol. 181, pp. 526–534, 2021, doi: 10.1016/j.procs.2021.01.199.

- [29] T. Bijl, N. van Weeren, and S. Verberne, "Efficient course recommendations with T5-based ranking and summarization," Jun. 2024.
- [30] C.-Y. Lin, "Rouge: A package for automatic evaluation of summaries," in Text summarization branches out, 2004, pp. 74–81.
- [31] A. A. Khan, "Balanced Split: A new train-test data splitting strategy for imbalanced datasets," Dec. 2022.
- [32] D. S. Maylawati, Y. J. Kumar, and F. B. Kasmin, "Combination of Graph-based Approach and Sequential Pattern Mining for Extractive Text Summarization with Indonesian Language," *Khazanah Informatika : Jurnal Ilmu Komputer dan Informatika*, vol. 9, no. 2, pp. 132–145, Oct. 2023, doi: 10.23917/khif.v9i2.21495.