Analysis of the Effectiveness of Iterative Prompts in the Integration of Classification and Summarization of User Reports Based on NLP

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Abstract. User reports submitted through feedback features or ticketing systems provide valuable insights for improving mobile applications. However, the high volume of reports creates challenges for review and decision-making. Effective classification and summarization are therefore essential to manage this information efficiently, allowing developers to quickly identify recurring issues and support data-driven development strategies. This study automates large-scale user feedback processing using Natural Language Processing (NLP) and evaluates multiple language models. The Bigbird-Small model achieved the highest agreement with the majority (81.51%) due to its ability to process long-text contexts. XLM-R-Base performed competitively (78.08%), while BERT-Base and Roberta-Base showed stable performance (75.68% and 74.32%). Distilbert-Base, though more computationally efficient, had slightly lower accuracy (74.32%). For summarization, Simple Prompt and Iterative Prompt approaches were compared. The Iterative Prompt with four iterations performed best, achieving similarity 0.911, compression 0.846, keyword overlap 0.624, and redundancy 0.070. These results demonstrate that combining automated classification with iterative summarization can significantly improve both efficiency and accuracy in managing user reports, supporting better decision-making and enhanced mobile app development.

Keyword: Classification, Natural Language Processing (NLP), Summarization, User Reports

1. Introduction

Mobile devices have undergone rapid development and have become versatile tools used for a variety of activities, from communication and entertainment to navigation, to professional activities such as field surveys, data management, financial transactions, and online learning. In this context, mobile application development is crucial to ensure application quality is maintained and continuously improved. Therefore, development teams need to actively gather user feedback to continuously adapt applications to user needs and provide an optimal user experience. One invaluable source of feedback that cannot be ignored is user reports submitted through the reporting feature or ticketing system. These reports provide crucial insights into issues that may not be detected during the internal testing phase. By leveraging the information from these reports, developers can understand real-world user experiences and respond to issues such as bugs, crashes, or malfunctions more quickly and appropriately. Thus, user reports not only aid in identifying and resolving technical issues but also serve as a valuable basis for future application improvement and development.

For policymakers, both at the organizational and institutional levels, user reports play a crucial role as a data source for decision-making based on real-world needs. Through these reports, they can understand application usage patterns, the types of complaints that frequently arise, and the features that users most need. This information can be used to develop development strategies, allocate resources more efficiently, and formulate policies that support improving the quality of digital services. Thus, user reports serve not only as a technical tool but also as an important reference in policy development and evaluating the overall success of application implementation.

However, in practice, challenges arise when a large number of user reports arrive in close succession. This can cause delays in the report review process and increase the risk of missing important issues. To address this, it is necessary to group or classify reports into specific categories—such as bug reports, feature requests, performance complaints, or general feedback. This grouping process not only helps the development team prioritize improvements and development but also makes it easier for policymakers to identify trends and understand user needs in a more structured way.

However, report classification alone is not enough. Within a single category, such as bugs or feature requests, there can be dozens or even hundreds of reports with similar content. Therefore, it is necessary to summarize or combine information from reports in the same category into a single, concise summary that still captures the key points raised by users. This summary allows the development team to more easily understand the core issues or needs raised without having to read through the entire report individually. Furthermore, it helps policymakers gain an overview of user needs, make faster and more targeted decisions, and allocate resources based on clearer priorities.

Rapid advances in Natural Language Processing (NLP) offer promising solutions to challenges in user report management, particularly in classification and summarization. Transformer-based and large-scale language models have enabled deep contextual understanding of natural language, allowing systems to automatically group reports into relevant categories and generate concise, coherent summaries. Prompt-based learning further enhances this capability by reducing task-specific training while improving adaptability across multiple NLP tasks [2]. Recent studies have shown that GPT-based and prompt-engineered summarization models can produce factually consistent summaries across diverse domains [18], [20]. However, empirical evidence remains limited regarding their effectiveness in combined classification–summarization workflows, especially for non-English or domain-specific datasets, highlighting the need for further exploration in real-world applications.

This iterative approach has also been applied in other fields, such as radiology. One study introduced ImpressionGPT, a framework that leverages ChatGPT's capabilities to automatically generate the impressions section of radiology reports [1]. Using dynamic prompts, the system is able to refine summaries without requiring additional training. The research results show that this approach is effective and adaptable to various natural language processing needs, including managing user reports in digital applications. This technology enables faster, more efficient, and consistent report review, supporting timely, data-driven decision-making by development teams and policymakers [1].

This research aims to design and implement an automated approach to managing user reports based on natural language processing, with a focus on the classification and summarization processes. Leveraging modern language models and ChatGPT, a system was developed to accurately group reports into relevant categories and generate concise and informative summaries from a collection of similar reports. The classification phase was evaluated using a model agreement approach using a majority vote method to objectively assess model performance. In the summarization phase, the summary quality of the simple prompt and iterative prompt approaches was compared using automated evaluation metrics. Specifically, the iterative prompt approach was tested at the 2nd, 3rd, and 4th iterations to evaluate the effect of increasing the number of iterations on summary quality.

This iterative approach has also been examined in hybrid frameworks that combine classification and summarization. An iterative optimization method using ChatGPT has been introduced to enhance summary quality through dynamic prompt refinement without requiring additional fine-tuning [1]. Another study demonstrated that integrating ChatGPT with BERT can improve both sentiment classification and summarization accuracy across diverse textual domains [17]. Despite these advancements, limited research has explored how iterative prompt refinement affects the joint performance of classification and summarization tasks within a unified model. Therefore, this study contributes by empirically evaluating the effectiveness of iterative prompt strategies for integrated classification–summarization processes, aiming to improve coherence, accuracy, and overall efficiency in automated user report management.

2. Related Works

2.1. *Classification*

BERT-based models continue to demonstrate superior performance in various text classification tasks, particularly when further enhanced through domain-specific fine-tuning and semantic enrichment [2]. Taye et al. enhanced BERT with ontology augmentation for multilingual sentiment classification on Twitter data, achieving 91.6% accuracy, demonstrating that semantic enrichment aids cross-language generalization [3]. In fake review detection, Roja et al. applied BERT to a hotel review dataset and achieved 93.3% accuracy, outperforming the BiLSTM method [4]. Lilli et al. introduced MISTIC, a BERT model for Italian medical records, which achieved an AUC of 0.93 in cancer metastasis classification, outperforming conventional logistic regression [5]. Alsobhi et al. combined BERT with CNNs to distinguish between human- and AI-generated text, increasing precision to 87.1% [6]. Albladi et al. developed TWSSenti, a topic-based sentiment classification model for Arabic Twitter, which improved the macro F1-score to 88.7%, better than standard BERT [7]. For restricted languages, Rizvi et al. fine-tuned BERT on mixed Sinhala-English data and achieved 86.2% accuracy [8]. Sivakaran inserted conditional mutual information into BERT representation, improving accuracy to 3.7% on the GLUE task [9]. Maasaoui et al. demonstrated the effectiveness of BERT for real-time log classification with 94% recall and sub-second latency [10]. Chapagain and Rus used DistilBERT to assess student code explanations with a correlation of 0.88 to human judgment [11]. Finally, Qaffas introduced an ensemble model combining TextBlob, ChatGPT, and BERT for student sentiment classification with 90.4% accuracy [12].

2.2. *Summarization*

ChatGPT and other large language models are increasingly demonstrating their effectiveness in various text simplification tasks, particularly in domains where readability, coherence, and cross-language adaptation are important. In medical contexts, several studies have explored the ability of GPT-like models to summarize clinical reports with results approaching the standards of human experts [13], [14]. In scientific writing and education, the use of GPT-based models has been shown to accelerate the process of simplifying and rewriting text, while improving comprehension for multilingual users [15], [16]. Social media analytics also utilize hybrid models that combine GPT with traditional NLP techniques for more accurate classification and summarization [17]. Comparisons between ChatGPT and other summarization models such as BART and Pegasus indicate that GPT is superior in language fluency, although sometimes less informatively dense [18], [19]. Improved summary quality can also be achieved through appropriate prompt engineering, as demonstrated in several studies that optimize prompt structure to maintain factual consistency and improve coherence [20], [21]. These findings underscore the importance of model selection and prompt design in AI-based summarization applications.

A similar approach has been applied in radiology, as described by Zhang et al. [1] in their study of ImpressionGPT, a framework that automates the generation of the “Impression” section of radiology

reports using ChatGPT. This section is crucial for communication between radiologists and medical professionals, but the manual process is time-consuming and error-prone. ImpressionGPT leverages the in-context learning capabilities of large language models like ChatGPT through dynamic prompts and an iterative optimization algorithm. The system uses a small amount of domain-specific data to generate prompts that capture relevant semantic information and then iteratively improves the quality of the summary without the need for model retraining. Evaluation results on the MIMIC-CXR and OpenI datasets demonstrated superior performance in automated summarization tasks. This research demonstrates the potential of LLM in understanding domain-specific technical language and opens up opportunities for similar applications in managing user reports for digital applications.

2.3. Data augmentation

Various data augmentation techniques such as synonym replacement, back-translation, and random insertion have been studied in various NLP contexts. Şahin and Steedman showed that augmentation techniques improve the performance of dependency parsing and POS tagging in resource-constrained languages. However, their effectiveness is highly dependent on the technique and language used [2]. Jin et al. introduced the AdMix method, which mixes original and augmented samples in machine translation training, resulting in a BLEU gain of approximately 1.0–2.7 points, with additional improvement when combined with back-translation [18]. Furthermore, an adaptation of augmentation for Indonesian—combining synonym replacement, random insertion, and back-translation—has been shown to improve accuracy in paraphrase identification [16]. Meanwhile, the integration of ChatGPT into a hybrid model for sentiment analysis and social media summarization showed an increase in classification accuracy of up to 90.4% [12]. Overall, the effectiveness of augmentation is strongly influenced by the context, language, and goal of the NLP task.

2.4. Model Agreement

Evaluation of data without reference labels (ground truth) can be done using a model agreement approach, where predictions from multiple models are combined to obtain more reliable results. For example, in studies of sentiment classification and security logs, the use of ensemble methods or model combinations has been shown to improve the accuracy and stability of the results [6], [10], [12]. Approaches such as majority voting or prediction consensus calculations are often applied when manual annotation is not available, because consistent predictions among multiple models have a higher probability of reflecting the correct label.

2.5. Evaluation Metrics for Summarization

The evaluation of summarization performance in this study adopts a reference-free approach, enabling assessment without the need for gold-standard summaries. Four primary metrics are employed to capture different dimensions of summary quality. Semantic similarity (avg_similarity) evaluates how effectively the generated summary preserves the meaning of the original text, following the semantic evaluation principles proposed by Zhang et al. [22]. Compression ratio (avg_compression) measures how efficiently information is condensed while maintaining essential content, consistent with the approaches discussed by Narayan et al. [23] and Paulus et al. [24]. Keyword overlap (avg_keyword_overlap) assesses lexical relevance by calculating the proportion of shared key terms between the summary and the source text, in line with Fabbri et al. [25]. This multi-metric framework integrates semantic, lexical, and structural aspects to provide a comprehensive and balanced evaluation of summary quality.

3. Research Method

This research flow consists of five main stages as shown in figure 1. **(1) Dataset Preparation**: ticket

data is collected and cleaned, then separated into labeled and unlabeled tickets. Labeled tickets are enriched using three data augmentation techniques, namely synonym replacement, back translation, and random insertion, to form a training dataset (80%) and a testing dataset (20%). **(2) Fine-tuning**: several pre-trained models (BERT-Base, Roberta-Base, BigBird-Base, XLM-R-Base, and Distilbert-Base) are trained using the dataset to produce a fine-tuned model. (3) **Model Agreement**: the ticket prediction results from each fine-tuned model are compared using a majority vote approach to determine the best model. **(4) Summarization**: the final data, consisting of the best model prediction results and labeled data, is then grouped by month and category to be summarized using two approaches, namely simple prompt and iterative prompt. **(5) Evaluation**: both summarization results are evaluated to determine the best approach.

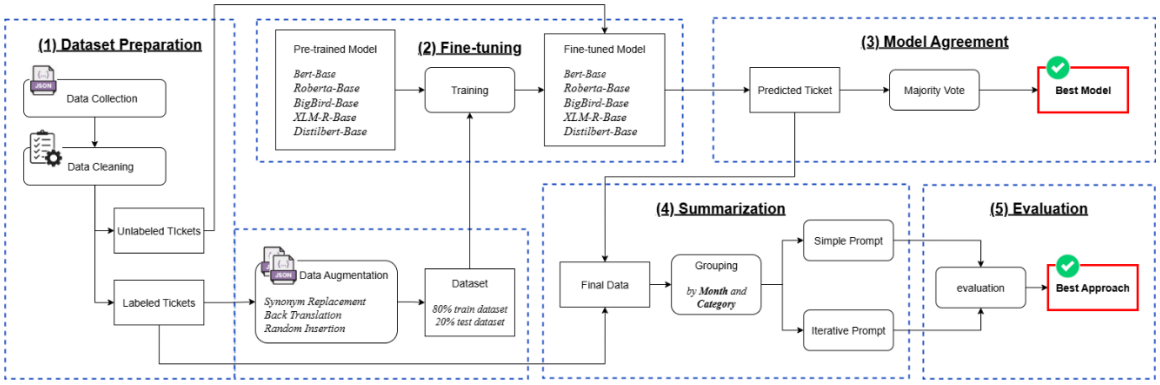

Figure 1. Research flow.

3.1. Dataset Preparation

3.1.1 Data Collection.

The dataset used in this study comes from the ticketing system in an Android-based data collection application called FASIH, developed by Badan Pusat Statistik(BPS - Statistics Indonesia). This application is used by enumerators in conducting surveys and censuses in the field. One of the FASIH application's key features is the ticketing menu, which allows enumerators to submit reports regarding technical difficulties or other issues during the data collection process.

```
ticket = {
    '_id': 'dcc7854a-14c7-4a46-ae0f-4ffc057dece4',
    'subject': 'muncul error tandai sls selesai',
    'content': 'muncul notifikasi error klik tandai sls selesai, solusinya? terima kasih',
    'createdAt': '2024-06-22 00:39:50.703000+00:00',
    'category': {'_id': 2, 'name': 'Pengisian Kuesioner', 'color': '#FFF4E6'},
    'category_id': 2.0,
    'category_name': 'Pengisian Kuesioner',
    'messages': [
        {
            '_id': '9e37cb39-7c6a-4803-b76a-1fc880f5efe8',
            'content': 'Selamat Pagii, Silahkan coba logout kemudian login kembali ya pak',
            'user': {
                'fullname': 'abc',
                'email': 'abc@gmail.com'
            },
            'dateCreated': {'$date': '2024-06-22T01:27:05.836Z'},
            'readAt': {'$date': '2024-06-22T01:35:04.669Z'}
        },
        {
            '_id': 'fc94242f-da69-4b3a-b66b-5b11b14ec506',
            'content': 'Baik terima kasih',
            'user': {
                'fullname': 'def',
                'email': 'def@gmail.com'
            },
            'dateCreated': {'$date': '2024-06-22T06:11:23.656Z'},
            'readAt': {'$date': '2024-06-22T06:38:36.920Z'}
        }
    ]
}
```

Figure 2. One example of a ticket obtained from the FASIH application.

The data used in this study are Indonesian language tickets for the 2023-2025 period. The initial dataset consists of 9,298 ticket entries, which contain information such as "_id", "content", "createdAt", "messages", "subject", "category", "category_name", and "category_id". One example ticket is shown in figure 2, while a list of ticket categories and their category_ids is shown in table 1.

Table 1. Category Reference Table in Ticket Data

Category_id	Category_name [Indonesian]	Category_name [English]
0	Assignment Petugas	User Assignment
1	Pengisian Kuesioner	Questionnaire Filling
2	MK ST2023	MK ST2023
3	SBR 2023	SBR 2023
4	UMKM 2023	UMKM 2023
5	PES ST2023	PES ST2023
6	Login & User	Login & User
7	Geotagging	Geotagging
8	Data Hilang	Missing Data

3.1.2 Data Cleaning.

The data cleaning phase was conducted to ensure consistency, remove irrelevant information, and prepare the data in an optimal format for analysis. This process focused on two main columns—subject and content—which are the core of user reports. After the cleaning phase, the available data consisted of 4,925 labeled tickets (with category information) and 292 unlabeled tickets (without category information). This dataset was then considered clean data ready for use in the next analysis phase. The cleaning steps included:

- Converts all text to lowercase.
- Removes irrelevant characters or symbols.
- Removes stop words in Indonesian such as "yang," "dan," "untuk," etc.
- Filters text that is too short or meaningless (less than 3 words).
- Removes duplicate entries based on subject and content.
- Separates tickets with and without categories.

3.1.3 Data Augmentation.

To enrich the data variety and improve the model's generalization capabilities, an augmentation process was performed on the labeled tickets by generating sentence variations from each available ticket. The goal of this step was to reduce the model's dependence on specific language structures or patterns in the original data. Three augmentation techniques were used to generate three new tickets from each original ticket, increasing the total data set to 18,445 tickets after augmentation. This resulted in a linguistically richer training dataset and is expected to improve model performance. Details of the augmented data are shown in table 2, while the three augmentation techniques used are explained below:

- Synonym Replacement:

Words in a sentence are replaced with synonyms that have a similar meaning.

Example:

- Original text:
  "The application cannot be opened after being updated."

  (*"Aplikasi tidak dapat dibuka setelah diperbarui."*)

- Augmented result:
  "The application cannot be opened after being updated.".

  (*"Aplikasi tidak bisa dibuka setelah di-update."*)

- Back Translation:
  The sentence is translated into a foreign language (e.g., English), then back into Indonesian to produce a paraphrase.

  Example:

  - Original text:
    "Data does not appear on the application's main page."

    (*"Data tidak muncul di halaman utama aplikasi."*)

  - Augmented result:
    "Information is not visible on the application's initial display."

    (*"Informasi tidak terlihat pada tampilan awal aplikasi."*)

- Random Insertion:
  Synonyms or additional words are randomly inserted into a sentence to create variation in sentence structure.

  Example:

  - Original text:
    "The report cannot be sent due to poor network connection."

    (*"Laporan tidak bisa dikirim karena jaringan buruk."*)

  - Augmented result:
    "The report cannot be sent due to poor network connection."

    (*"Laporan tidak bisa jaringan dikirim karena koneksi buruk."*)

Table 2. Details of FASIH ticket data

Stage	Tickets	Max Words	Avg Words	Categories	Missing Categories
Data Collection	11.164	361	14 - 15	10	779
Data Cleaning	4.925	162	11 - 12	10	292
Data Augmentation	18.445	187	12 - 13	10	292

3.2. *Fine-tuning*

The fine-tuning process for the classification model aims to handle user reports that lack category labels. Several previously trained classification models, as listed in table 3, will be retrained with augmented data. Model selection focused on Indonesian language models with different architectures to assess the architecture's impact on prediction results. The fine-tuning process begins with combining the subject and content columns as input, followed by tokenization using a tokenizer appropriate to the model architecture used. Performance evaluation is performed using the accuracy metric to assess the classification accuracy of the prediction results. Next, the prediction results from each model are compared to determine the best model.

Table 3. Classification Model

Model	Language	Architectures	Description
cahya/ **bert-base-**indonesian-1.5G	Indonesian	Bert For Masked LM	Based on the BERT architecture, this model captures bidirectional context by predicting masked words within a sentence, enabling strong understanding of Indonesian grammar and semantics.
cahya/ **roberta-base**-indonesian-1.5G	Indonesian	Roberta For Masked LM	An improved variant of BERT that uses larger training data, dynamic masking, and longer training time, resulting in better language understanding and generalization.
ilos-vigil/ **bigbird-small**-indonesian	Indonesian	Big Bird For Masked LM	A transformer model optimized for handling long documents efficiently by using sparse attention, making it suitable for processing lengthy Indonesian texts.
ashwani-tanwar/ Indo-Aryan-**XLM-R-Base**	Indonesian	XLMRoberta For Masked LM	A multilingual version of RoBERTa trained on over 100 languages, including Indonesian, designed to support cross-lingual understanding and transfer learning.
distilbert/ **distilbert-base-**multilingual-cased	Multilingual	DistilBert For Masked LM	A distilled and lighter version of BERT that retains most of its language comprehension ability while being faster and more resource-efficient for real-world applications.

3.3. *Model Agreement*

Because ground truth labels were not available, classifier model evaluation was conducted using a model agreement approach to assess the level of prediction agreement between models. This study used

the majority vote method, which determines ticket categories based on the most frequently selected predictions. The level of agreement of each model with the majority label reflects the consistency of its predictions for the same ticket. The model with the highest agreement was considered the most stable and representative and was therefore selected as the primary model for further analysis.

3.4. Summarization

In this research, two approaches were developed to generate automatic summaries from Indonesian-language ticket content. All content that shared the same month and category was concatenate and then used as input to the summarization model. These two approaches were designed to be evaluated and compared to determine which approach was most effective in producing concise, relevant, and high-quality summaries without the need for reference data (ground truth).

The first approach, called the simple prompt approach, was implemented in a single step. OpenAI's GPT-4 language model was used to generate summaries based on clear instructions: to keep the summary to 3–5 sentences, focus on the core issue, and be presented from the officer's perspective. The process began by combining the content and prompt into a single input, which was then processed by the model to generate a summary, as seen in figure 3(a).

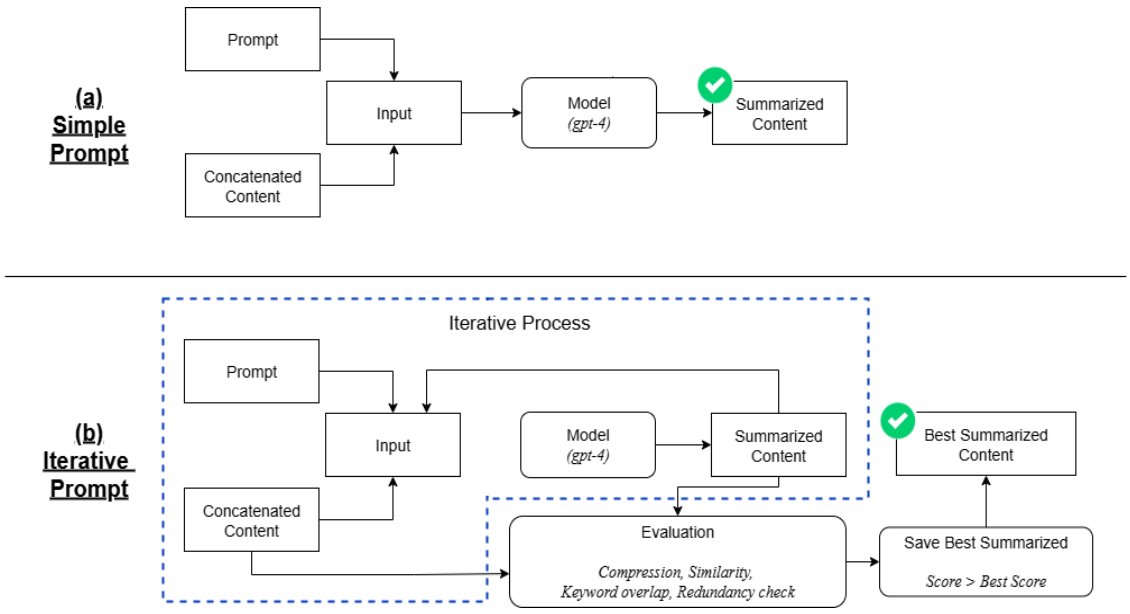

Figure 3. Workflow Summarization Using Simple Prompt and Iterative Prompt

The second approach uses an iterative prompt method. Unlike a simple prompt, which only generates a summary once, this approach involves an iterative process in which the summary is gradually refined based on the evaluation of previous results. The process begins by combining the content and the prompt into a single input, which is then processed by the GPT-4 model to generate an initial summary. This summary is evaluated using three key metrics: semantic similarity between the original text and the summary, the text compression ratio, and the degree of keyword overlap. These three metrics are combined into a final score to objectively assess the quality of the summary. Regardless of the score, the summary generated in each iteration is always reused as part of the input in the next iteration, allowing the model to continuously improve. If the score from an iteration is higher than the previous

best version, it is saved as the temporary best version. This process continues until an optimal summary is obtained or until a certain number of iterations is reached, as depicted in the bottom of figure 3(b).

3.5. Evaluation

To simplify the analysis process, each ticket will be grouped before being summarized. Grouping is done by month and ticket category, then each grouping result is applied to two summarization approaches: simple prompt and iterative prompt. For the iterative prompt approach, experiments will be conducted with 2, 3, and 4 iterations to observe the effect of the number of iterations on the quality of the resulting summary. This aims to evaluate the effectiveness of the incremental refinement process in increasing the relevance and density of the summary.

Next, the summary results from both approaches will be compared and analyzed to determine the most effective method in the context of IT ticket reporting, especially when truth labels are not available as a reference. The evaluation is conducted by calculating the average of four key metrics: avg_similarity (average semantic similarity), avg_compression (average compression ratio), and avg_keyword_overlap (average keyword overlap). These four metrics are used as a basis for objectively assessing and comparing the performance of each approach.

4. Result and Discussion

4.1. Finetuning

Each pretrained model in table 3 was retrained using augmented data, and the fine-tuned models were then used to predict unlabeled tickets. A sample prediction from each fine-tuned model is presented in table 4, where the displayed sample consists of the following:

- **Content**:
  "Data entry error. The submitted data can be deleted. What's the solution?"

  (*kesalahan pengisian data. data yg submit, hapus bisa. solusi,??*)

- **Subject**:
  "Deleting submitted data"

  (*menghapus data yg tersubmit.*)

Table 4. Example of prediction results from a fine tuned classifier model

Model	Predicted id	Predicted Category
Bert-Base	1	Questionnaire Filling
Roberta-Base	1	Questionnaire Filling
Bigbird-Small	1	Questionnaire Filling
XLM-R-Base	0	User Assignment
Distilbert-Base	1	Questionnaire Filling

4.2. Model Agreement

After all pretrained models were retrained and used to predict missing categories, evaluation was conducted using a model agreement approach with a majority vote technique. Out of 292 predicted

tickets, the performance of each model is summarized in table 5. The Bigbird-Small model achieved the highest agreement with the majority at 81.51%, highlighting its strength in processing long-text contexts through its sparse attention mechanism.

The XLM-R-Base model also performed competitively, reaching 78.08%, likely due to its multilingual design and robust cross-language representations. BERT-Base achieved 75.68%, slightly outperforming Roberta-Base and Distilbert-Base, which both reached 74.32%. This indicates that BERT/Roberta-based monolingual architectures maintain stable performance for Indonesian text, while Distilbert-Base, although lighter and more computationally efficient due to knowledge distillation, yielded slightly lower accuracy.

Table 5. Majority vote results

Model	Agrrement with the majority	%
Bert-Base	221	75.68
Roberta-Base	217	74.32
Bigbird-Small	**238**	**81.51**
XLM-R-Base	228	78.08
Distilbert-Base	217	74.32

Overall, these results confirm that model architecture plays a crucial role in predictive consistency. Bigbird-Small, with its ability to process long-text contexts, demonstrated superior agreement with the majority, while lighter models like Distilbert-Base offered computational efficiency at the cost of slightly lower accuracy. BERT-Base and Roberta-Base showed stable performance for Indonesian text, and XLM-R-Base delivered strong results thanks to its multilingual capabilities. Based on these findings, the prediction results from the Bigbird-Small model were subsequently used as the basis for the summarization stage.

4.3. Summarization

Before the summarization process is carried out, the labeled data and the predicted data from the ilos-vigil model are combined and then grouped by month and category. All content that shares the same month and category is concatenate and then used as input for the summarization model. This grouping aims to simplify the summarization process, allowing for more focused analysis on the available ticket categories. Table 6 presents an example of the results of grouping tickets by month and category.

Table 6. Example of summarization across four prompt configurations: one Simple Prompt baseline and three iterative refinements (Iterative 2, Iterative 3, Iterative 4).

Approach	Summarize	Content
Simple Prompt	Petugas menghadapi berbagai masalah teknis dengan aplikasi FASIH dalam pengelolaan tugas dan data. Isu-isu termasuk sinkronisasi yang berulang kali menghapus kegiatan yang sudah selesai,…	sync periode notif gangguan sync periode udpe 2 change log formgear muncul balasannya alamat url ditemukan mencoba menugaskan kues pendataan enum berhasil kendala, siang assign tugas enum muncul error gagal mengunduh daftar assignment download assigment error vrest umk.s kesalahan mendownload assigment sinkronisasi login gadget 2 3 pml 100 assignment, 120 gagal unduh asignment warning sinkronisasi assignment nya menghapus salah assignment kekeliruan menginput data. assignment submit masuk aplikasi fasih tdak sinkron mendownload daftar assignment keterangan gagal tulisan kesalahan mendownload assignment (1) kendalanya knapa ya? mohon solusiny data teruplоad statusnya pending, coba buka upload ulang muncul notifikasi code 500. failed to upload data assigment reject pkl masuk ppl pcl submit listing, ruta yg disubmit kunjung muncul pml pengecekan fasihsm, status listing ruta pml fasihsm bs submit 103 ruta, yg muncul pml 93 kejadian asignment runah tangga disubmit pcl terbaca fasih pml saa pengisian keluarga ruta baru, assignment disubmit rincian sls eror. rincian sls diperbaiki asigmen muncul, logout login sobat pencacahan prelist tersedia. gambar upload soraya laundry. mohon bantuannya terima kasih. …
Iterative Prompt 2	Petugas telah menerima tiket yang melaporkan sejumlah masalah dengan aplikasi survei "Fasih". Isu tersebut meliputi kesulitan dalam menyerahkan dan mengakses tugas survei, problem dalam mengunduh serta menampilkan daftar …	
Iterative Prompt 3	Petugas menghadapi berbagai masalah teknis pada aplikasi Fasih, yang meliputi kegagalan dalam submit assignment, masalah rendering questionnaire, dan rincian blok sensus kosong. Selain itu, petugas juga mengalami kesulitan dalam proses sinkronisasi dan pengunduhan template validasi. Terakhir, masalah juga muncul terkait akses ..	
Iterative Prompt 4	Petugas IT sedang menangani serangkaian masalah pada aplikasi Fasih yang telah dilaporkan oleh pengguna, termasuk error sinkronisasi, kesulitan mengunduh assignment, kegagalan pengajuan data, dan masalah login. Petugas juga akan mencari solusi untuk penundaan penyerahan data dan gangguan dalam penyerahan assignment.	

4.4. Evaluation

Based on the evaluation results in table 7, Simple Prompt demonstrated the lowest performance compared to the iterative approach. The similarity value only reached 0.582 and the keyword overlap was 0.207, indicating that the summary was less able to represent the document's content and did not include important keywords. Furthermore, the compression value of 2.399 indicates that the resulting summary is relatively long and inefficient in reducing text. This condition confirms that Simple Prompt is only capable of producing basic summaries, but is not optimal for analytical purposes.

Table 7. Comparison of Simple Prompt and Iterative Prompt Performance Based on Evaluation Metrics

Metric (avg)	Simple Prompt	Iterative Prompt 2	Iterative Prompt 3	Iterative Prompt 4

similarity	0.582	0.910	0.909	0.911
compression	2.399	0.895	0.853	0.846
keyword_overlap	0.207	0.590	0.606	0.624

Furthermore, the Iterative Prompt 4 approach demonstrated the best performance compared to the other methods. Its similarity score reached 0.911, slightly higher than Iterative Prompt 2 (0.910) and Iterative Prompt 3 (0.909), indicating a better ability to maintain the summary's fidelity to the original text. In terms of compression, Iterative Prompt 4 produced a more compact summary with a score of 0.846, lower than Iterative Prompt 2 (0.895) and Iterative Prompt 3 (0.853), thus more efficiently summarizing text without compromising information quality. Furthermore, Iterative Prompt 4 had the highest keyword overlap (0.624), indicating a broader and more relevant coverage of important keywords.

Upon further analysis, increasing the number of iterations consistently improved summary quality. Initially, Simple Prompt produced a relatively low similarity (0.582) and minimal keyword overlap (0.207), indicating that the summary did not adequately represent the document's content. With the second iteration, there was a drastic increase in similarity (0.910) and keyword overlap (0.590), as well as an improvement in compression, which decreased to 0.895, resulting in a more concise and relevant summary. The third and fourth iterations further refined the results, indicated by a gradual increase in keyword overlap (from 0.606 to 0.624) and a slight improvement in compression. This demonstrates that the iterative process has a positive effect in producing increasingly concise and consistent summaries that cover important keywords, although the improvement from the third to the fourth iteration is relatively smaller than the jump from the first to the second iteration. Thus, the primary benefit of increasing iterations is strengthening the relevance and efficiency of the summary without sacrificing readability.

Table 8. Comparison of Simple Prompt and Iterative Prompt Performance Based on Evaluation Metrics

Prompt A	Prompt B	Metric	t-value	p-value	Significant
Simple	Iterative 2	Similarity	-40.16	7.9×10^{-83}	Yes
Simple	Iterative 2	Compression	5.17	7.2×10^{-7}	Yes
Simple	Iterative 2	Keyword Overlap	-19.20	1.8×10^{-42}	Yes
Simple	Iterative 3	Similarity	-38.79	9.9×10^{-81}	Yes
Simple	Iterative 3	Compression	5.30	3.9×10^{-7}	Yes
Simple	Iterative 3	Keyword Overlap	-21.94	5.9×10^{-49}	Yes

Prompt A	Prompt B	Metric	t-value	p-value	Significant
Simple	Iterative 4	Similarity	-37.53	9.3×10^{-79}	Yes
Simple	Iterative 4	Compression	5.30	3.9×10^{-7}	Yes
Simple	Iterative 4	Keyword Overlap	-22.91	3.7×10^{-51}	Yes
Iterative 2	Iterative 3	Similarity	0.36	0.72	No
Iterative 2	Iterative 3	Compression	2.51	0.013	No
Iterative 2	Iterative 3	Keyword Overlap	-1.06	0.29	No
Iterative 2	Iterative 4	Similarity	-0.18	0.86	No
Iterative 2	Iterative 4	Compression	2.82	0.005	No
Iterative 2	Iterative 4	Keyword Overlap	-2.31	0.022	No
Iterative 3	Iterative 4	Similarity	-0.46	0.65	No
Iterative 3	Iterative 4	Compression	0.45	0.65	No
Iterative 3	Iterative 4	Keyword Overlap	-1.18	0.24	No

The results of the paired t-tests (table 8) indicate that all iterative prompt methods (Iterative 2, 3, and 4) significantly outperformed the Simple Prompt approach across all three evaluation metrics—semantic similarity, compression, and keyword overlap—demonstrating clear improvements in summary quality. However, comparisons among the iterative variants themselves (Iterative 2 vs. 3, Iterative 2 vs. 4, and Iterative 3 vs. 4) revealed no statistically significant differences ($p \geq 0.05$) after correction for multiple comparisons. Although Iterative Prompt 4 achieved the highest mean scores in compression and keyword overlap, these gains were not statistically meaningful compared to Iterative 2 and 3, suggesting that performance improvements plateau after the second iteration. This finding indicates that most of the summarization enhancement occurs in the early stages of iteration, with subsequent iterations yielding only marginal benefits.

These findings are consistent with previous research emphasizing the effectiveness of transformer-based architectures in improving summarization quality on long-text datasets [22], [23]. As observed by Ghosh and Sengupta [22], the BigBird-small model exhibits superior performance due to its sparse attention mechanism, which efficiently captures long-range dependencies while maintaining computational efficiency. This aligns with Zhou et al. [23], who demonstrated that prompt-based refinement enhances factual consistency and semantic coherence. However, the statistical analysis in this study revealed that, although iterative prompting consistently improved summarization metrics compared to the Simple Prompt approach, the differences among the iterative variants (Iterative Prompt 2–4) were not statistically significant ($p \geq 0.05$). This suggests that most performance gains occur in the early iterations, with subsequent refinements yielding only marginal improvements. Overall, the

superiority of BigBird-small reinforces prior evidence that transformer models optimized for long-sequence processing remain the most effective choice for large-context summarization tasks, while iterative prompting proves to be a practical and efficient strategy for enhancing summary relevance without requiring extensive computational overhead.

Limitation

This study relied exclusively on automated evaluation metrics, without validation against human-annotated ground truth data. Although automated metrics offer an efficient and objective way to assess model performance, they may not fully capture the contextual accuracy or semantic nuances of the output. Human evaluation was not employed in this study due to the extensive volume of data and the absence of pre-labeled references, which would require considerable time, cost, and expert involvement. Therefore, incorporating human evaluation in future research is recommended to provide a more comprehensive and reliable assessment of model quality.

In addition, the dataset used in this study was limited to a single application, FASIH, which may constrain the generalizability of the findings to other domains. However, the FASIH dataset represents a valuable real-world case of large-scale, domain-specific user feedback in the Indonesian language — a context that remains underexplored in current NLP research. It captures authentic operational interactions from a nationally deployed system, providing a rare opportunity to evaluate model performance in low-resource linguistic environments. Despite its domain specificity, this dataset contributes meaningful insights to the development of NLP models for practical, non-English applications.

5. Conclusion

The results of this study indicate that both model architecture and summarization strategy play crucial roles in enhancing prediction accuracy and summary relevance. In the prediction stage, the BigBird-small model demonstrated the highest agreement with the majority (81.51%), owing to its capacity to process long-text contexts through a sparse attention mechanism. XLM-R-base also showed competitive performance (78.08%) due to its multilingual design and cross-language representation capabilities. Monolingual models such as BERT-base and RoBERTa-base displayed stable performance on Indonesian text (75.68% and 74.32%, respectively), while lightweight models like DistilBERT-base offered computational efficiency but slightly lower accuracy (74.32%).

The superior performance of the BigBird-small model can be attributed to its architectural design, which employs a sparse attention mechanism combining global, local, and random attention patterns. This structure enables the model to capture long-range dependencies efficiently without incurring the quadratic computational cost associated with standard transformers. As a result, BigBird can process longer sequences, preserve contextual relationships across distant tokens, and maintain coherence in extended summaries. Furthermore, the smaller parameter size of the BigBird-small variant enables faster inference and better generalization when trained on limited data. These characteristics collectively explain its superior performance in long-text summarization tasks observed in this study.

A deeper analysis of classification errors revealed several underlying causes that affected model performance. Some misclassifications occurred in user reports containing overlapping topics, such as those discussing both technical issues and user-interface problems, which made it difficult for the model to assign a single dominant label. Other errors arose from the use of informal expressions, incomplete sentences, and ambiguous wording that obscured contextual meaning. These findings indicate that while the model performs effectively overall, its predictive accuracy is still influenced by linguistic variability and contextual overlap. Future research could improve this by applying more refined preprocessing

techniques, leveraging domain-adaptive embeddings, or expanding the labeled dataset to better capture nuanced language patterns.

In the summarization stage, the evaluation results confirmed that all iterative prompting approaches significantly outperformed the Simple Prompt method. The Simple Prompt approach produced only a basic summary with low similarity (0.582) and minimal keyword overlap (0.207), making it less representative of the document content. In contrast, iterative prompting—particularly from the second iteration onward—showed substantial improvements in similarity, compression, and keyword overlap, indicating more concise and contextually relevant summaries. However, statistical testing revealed that performance differences among Iterative Prompt 2, 3, and 4 were not significant ($p \geq 0.05$), suggesting that most improvements occur during the early iterations, while subsequent iterations provide only marginal gains.

Thus, this study highlights two key findings. First, the majority-vote evaluation confirms that model architecture directly influences ticket category prediction accuracy, with BigBird-small emerging as the superior model. Second, iterative prompting substantially enhances summarization quality compared to the Simple Prompt approach, though increasing iterations beyond the second yields diminishing returns. The two-iteration configuration therefore represents a balanced and efficient strategy for automated summarization in this context.

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