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Automatic Issue Classification Feature and Generative Standard Operating Procedure in IT Helpdesk Application PKG V2 at PT. Petrokimia Gresik

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Abstract

Effective Information Technology (IT) incident management is a crucial need in large-scale enterprise environments such as PT Petrokimia Gresik. Therefore, this final project develops an automated issue prioritization classification feature and an AI-based generative solution mechanism within the Helpdesk TI PKG V2 application. By utilizing the Naïve Bayes algorithm for issue classification and integrating the ChatGPT API for automated SOP-based solution generation, the system aims to overcome the limitations of previous manual processes. The expected outcomes include improved efficiency in incident handling, higher accuracy in prioritization, and faster responses through relevant and informative solutions. During testing, the incident classification model demonstrated satisfactory performance, particularly in identifying extreme urgency levels. Additionally, the automatically generated SOP solutions proved to be relevant and aligned with internal handling procedures. The system is evaluated through functional testing and user acceptance testing to ensure its optimal implementation in a dynamic and complex work environment.

I. INTRODUCTION

In today's rapidly evolving technological landscape, organizations are increasingly reliant on digital systems to manage various operational processes. PT Petrokimia Gresik, a prominent industrial company in Indonesia, has recognized the importance of optimizing its internal IT services to effectively manage and resolve incident reports from its Business Service Departments [1]. This necessity led to the development and deployment of the Helpdesk TI PKG application, a platform designed to streamline incident reporting and tracking [2]. Despite the implementation of the first version, several limitations were identified, including inefficiencies in incident classification, limited scalability, and the absence of advanced data

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processing capabilities. These issues have hindered the overall effectiveness of the system, particularly in handling large volumes of incident data and providing accurate and timely responses.

However, To address these challenges, the second version of the Helpdesk TI PKG application (V2) was developed with a focus on backend optimization. The primary objective of this research is to enhance the backend infrastructure by integrating advanced data processing techniques, specifically the Naïve Bayes algorithm, to automate the classification of incident reports [3], [4]. Additionally, the integration of artificial intelligence and ChatGPT aims to further optimize incident handling processes by providing automated responses and recommendations [5], [6], [7]. This study not only discusses the architectural improvements made to the backend system but also evaluates the impact of these enhancements on overall system performance and user satisfaction. By implementing a more robust and scalable backend structure, the Helpdesk TI PKG V2 application seeks to provide a more efficient, reliable, and user-friendly platform for managing IT incidents and service requests [8], [9].

II. RELATED WORKS

Several studies have investigated the application of AI and machine learning in incident management systems [10], [11], [12]. Proposed a cognitive system that leverages AI for automated helpdesk email ticket assignment, emphasizing the potential of AI to streamline incident handling processes in complex enterprise environments [13]. Similarly, explored AIOps solutions for incident management, identifying the importance of AI-driven classification and response mechanisms in enhancing operational efficiency [14] Furthermore, examined the applications of generative AI in various sectors, including incident management, highlighting the potential of AI to provide SOP-based solutions automatically [15]. Their findings align with the objectives of this research, which focuses on integrating ChatGPT to generate automated responses based on predefined SOPs for each incident type. In contrast to existing literature, this study specifically targets backend optimization through the implementation of a Naïve Bayes classifier for incident prioritization, coupled with ChatGPT for generative SOP recommendations [16], [17]. By integrating these AI-driven components, the proposed system aims to enhance the overall efficiency, accuracy, and response time in incident management processes within the Helpdesk TI PKG V2 application [18].

III. METHODS

The Helpdesk TI PKG V2 system is designed to support the automation of IT incident management and request handling at PT Petrokimia Gresik through the integration of artificial intelligence technologies [19]. This section explains the architecture of the system, divided into multiple interrelated component.

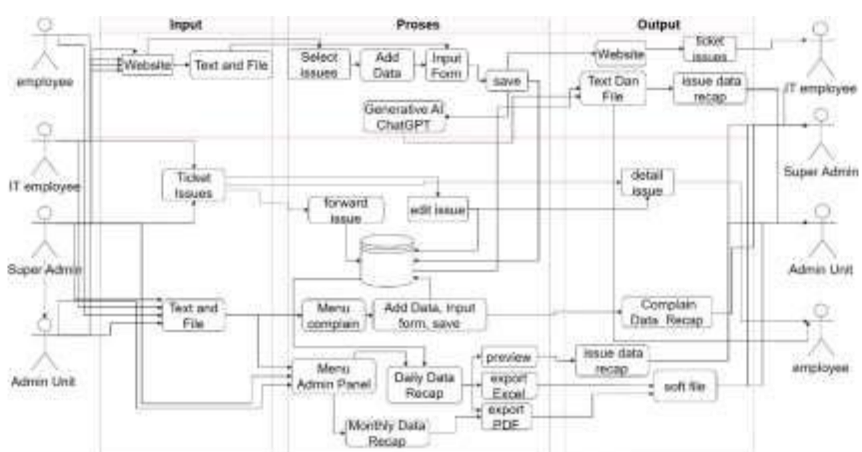

Figure 1. General System Architecture

The Helpdesk TI PKG V2 application's general architecture, as depicted in Figure 1, is designed to streamline IT incident and request handling within the enterprise environment of PT Petrokimia Gresik. This architecture is structured into three primary segments: Input, Process, and Output. Each segment represents a core phase of the system's operational workflow, ensuring a seamless flow of data from user interaction to automated AI-driven decision-making and final system response.

Users interact with the Helpdesk TI PKG V2 system primarily through a web-based platform. This interface accommodates various roles, such as employees, IT staff, field administrators, and super administrators, enabling them to perform specific tasks based on their access levels. The main input is the issue report form, where users provide structured information including the issue category, service type, subject, and description. Users also have the option to attach supporting documents or screenshots to clarify the reported issue. This input stage serves as the initial data acquisition point for the system and is crucial for initiating the incident management process.

The processing layer is responsible for handling all submitted input and managing the flow of data within the system. Once an issue is reported, the system stores the data in a centralized PostgreSQL database. Role-based access controls dictate how each type of user can process and interact with the reported issues. For instance, IT staff can update issue statuses, forward reports to relevant departments, and add comments or supporting details, while administrators can generate recapitulation data, assign responsibilities, or escalate cases. This stage also incorporates background processes such as logging, status tracking, and report preparation to support effective service management. The system's outputs are tailored to each user's role. Employees can track the status of their submitted reports, receive system-generated responses, and view the resolution timeline. IT staff and administrators are provided with detailed dashboards containing aggregated issue data, allowing them to monitor performance metrics, generate reports, and analyze trends. Additionally, the system supports exporting daily or monthly summaries in commonly used formats like Excel or PDF. These outputs contribute to transparency, operational efficiency, and informed decision-making across departments.

A. Feature Architecture

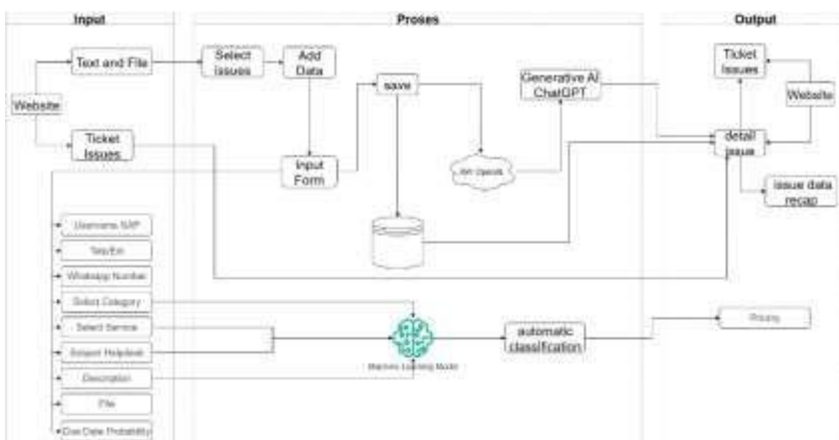

Figure 2. Feature Architecture

The AI and Machine Learning architecture integrated within the Helpdesk TI PKG V2 system aims to enhance the efficiency, accuracy, and consistency of issue management. This intelligent layer supports two core features: Automatic Issue Classification and Generative SOP Solutions. Both components operate concurrently to reduce reliance on manual analysis and accelerate the overall resolution process.

The AI pipeline initiates at the point of issue submission. When a user submits a report through the Helpdesk TI PKG V2 web interface, the input includes structured data fields such as category, service type, subject, and description, along with optional attachments. This structured textual data serves as the input for both the classification model and the generative solution engine, requiring no additional input from the user to ensure a frictionless experience. Upon receiving this input, the system performs two parallel processing operations. The classification module preprocesses the input text using tokenization and feature extraction before feeding it into a Naïve Bayes model hosted on a Flask API, which then returns a predicted priority level [20]. Simultaneously, the same input is formatted into a prompt for the ChatGPT API, which processes the request and returns a context-specific SOP recommendation [21]. These operations are fully automated and seamlessly integrated into the system's backend, ensuring minimal delay and eliminating the need for manual intervention.

The outputs from both AI modules are directly displayed in the issue detail view, accessible to IT staff and administrators. The predicted urgency level is applied to the ticket, influencing the queueing and escalation logic. Concurrently, the AI-generated SOP is displayed in a dedicated text box under the issue details. This dual output ensures that each reported issue is appropriately prioritized and accompanied by an actionable response, thereby enhancing the system's responsiveness and reducing the burden on human operators [22].

B. Machine Learning Models

The automatic classification system in the Helpdesk TI PKG V2 application adopts a supervised learning approach to categorize the priority levels of incident reports based on historical data. The dataset used consists of 1,000 records, each containing four key attributes:

- Category
- Service
- Subject (a brief summary of the issue)
- Priority (used as the classification label)

The dataset is divided into 80% for training (800 records) and 20% for testing (200 records). The primary objective of this architecture is to develop a classification model capable of predicting the priority level of incident reports automatically based on the content of these attributes [23]. The classification process begins with text preprocessing, which includes tokenization, stopword removal, and stemming. After preprocessing, the textual data is converted into numerical representations using TF-IDF (Term Frequency-Inverse Document Frequency) to emphasize the most relevant terms in the dataset.

To enable automatic classification of issues based on priority levels, the Helpdesk TI PKG V2 application leverages the Multinomial Naïve Bayes method, implemented in Python [24]. This process utilizes a Natural Language Processing (NLP) approach, with text representation based on Term Frequency-Inverse Document Frequency (TF-IDF), which converts the text into weighted numerical vectors. The dataset used consists of historical incident reports with four parameters: Category, Service, Subject, and Priority, where the first three parameters are used as input features, and Priority serves as the label (target). The text from the three columns is combined into a combined_text, cleaned of missing values, and the label is encoded using LabelEncoder. The data is then split into 80% training data and 20% test data.

The TF-IDF transformation is calculated using the formula:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \text{IDF}(t) \tag{1}$$

Where $\text{TF}(t, d)$ is the term frequency of term t in document d, and

$$\text{IDF}(t) = \log\left(\frac{N}{\text{df}(t)}\right) \tag{2}$$

where N is the total number of documents, and $df(t)$ is the number of documents containing the term t. Classification is carried out using the Multinomial Naïve Bayes, which calculates the probability of class C_k from features x using the following formula:

$$P(C_k \mid x) = \frac{P(C_k) \prod_{i=1}^{n} P(x_i \mid C_k)}{P(x)} \quad (3)$$

Since $P(x)$ is constant across all classes, the prediction is made by selecting the class C_k that maximizes:

$$\hat{y} = \arg\max_{C_k} (\log P(C_k) + \sum_{i=1}^{n} x_i \log P(x_i \mid C_k)) \quad (4)$$

Once the model is trained, it is integrated into the backend of the application through a REST API built using Flask. The /predict endpoint receives input for Category Name, Service Name, and Subject Name, processes them through the classification pipeline to automatically generate the priority label. The predicted result is returned in JSON format and can be directly utilized by the system to support real-time decision-making processes, eliminating the need for manual analysis and improving operational efficiency.

C. Generative AI Architecture

The generative Standard Operating Procedure (SOP) feature in the Helpdesk TI PKG V2 application was implemented by integrating OpenAI's ChatGPT API (version 3.5) into the Laravel backend [25], [26]. This integration was designed to automate the generation of relevant solutions and recommendations for incoming incident reports, enhancing the efficiency and accuracy of incident management. To begin the integration process, developers registered on OpenAI’s platform to obtain an API key, which serves as an authentication mechanism for each request made to the OpenAI server [27]. The API key is securely stored in the backend, typically within environment variables, to ensure confidentiality. Once the API key was obtained, the next step involved preparing the prompt templates. These templates incorporated essential contextual information from the incident report, such as category, service type, subject, and detailed description. By structuring the input in this manner, the queries sent to ChatGPT were made comprehensive and context-specific, ensuring that the responses generated would be relevant and tailored to the reported issue .

The system’s backend was then configured to send these structured prompts via HTTPS requests to the ChatGPT API, leveraging secure communication protocols. Upon receiving the response from the API, the system was designed to efficiently parse and integrate the generated SOP recommendations [28]. These recommendations were prominently displayed within the Issue Detail View of the Helpdesk application, labeled as "Solusi Cepat" (Quick Solution). This seamless integration facilitated the standardization of solutions, significantly reducing response times by providing instant, AI-generated solutions based on predefined SOPs. The ChatGPT model, based on the Transformer architecture, utilizes self-attention and multi-head attention mechanisms to fully understand the context of the input and generate highly accurate responses [29]. The model processes the incident report’s details, which are structured as a prompt containing four main parameters: category, service, subject, and description. For example, if a user reports an issue with VPN access, the model is prompted to identify the cause and provide appropriate troubleshooting steps.

This approach leverages the Transformer model's capability to compute the following attention mechanism:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \quad (5)$$

Where:

- Q is the Query,
- K is the Key,
- V is the Value,
- d_k is the dimension of the Key.

This equation allows the model to determine the relevance of words in a given context, ensuring that the responses generated are contextually accurate and targeted. The integration of this technology enables the Helpdesk TI PKG V2 application to automatically provide solutions without needing to retrain the model, thereby accelerating development, enhancing operational efficiency, and improving service quality [30]. This implementation of AI-generated SOPs not only reduces manual intervention but also ensures that the solutions provided are consistent and aligned with internal standards, ultimately improving the overall helpdesk workflow.

IV. RESULTS AND DISCUSSIONS

This chapter presents the experimental results obtained after implementing and testing the Helpdesk TI PKG V2 application. The experiments aim to evaluate the functionality, accuracy, responsiveness, and practicality of the newly developed features, especially the automatic issue classification and AI-generated SOP modules.

A. Experiment Parameters

The experiments were primarily conducted to assess two main features: Automatic Issue Priority Classification and Generative SOP Recommendations. The Automatic Issue Priority Classification feature evaluated the system's ability to classify issue urgency levels based on textual input using a trained Naïve Bayes model. Concurrently, the Generative SOP Recommendations feature assessed the relevance and usability of AI-generated standard operating procedures (SOP) for submitted issues, leveraging OpenAI's ChatGPT. Beyond these core features, the evaluation also measured system response time, classification accuracy, the relevance of AI-generated responses, and the impact on helpdesk workflow and admin workload.

B. Results of Generative Standard Operating Procedure Feature

Figure 3 shows the output of the Generative AI for feature integrated into the Helpdesk TI PKG V2 system. Based on the issue submitted by the user, the AI automatically generates a contextual quick solution. In this example, the system correctly identifies that the issue relates to a forgotten SAP application password and suggests a step-by-step procedure to resolve it, including user identification, policy checks, performing the reset, and confirming with the user.

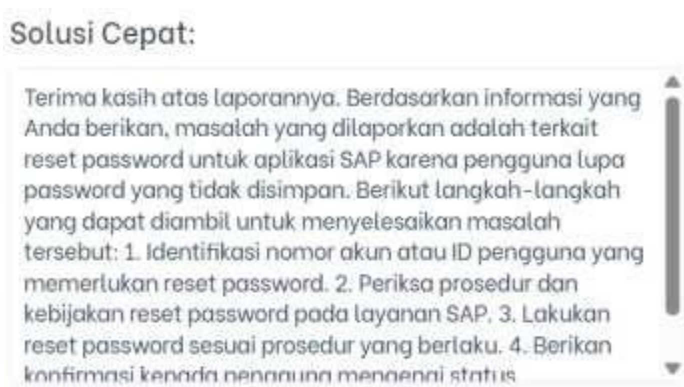

Figure 3. Results of Generative Standard Operating Procedure Feature

This result highlights the effectiveness of generative AI in providing immediate, relevant guidance to helpdesk staff, thus streamlining issue resolution and enhancing user support efficiency.

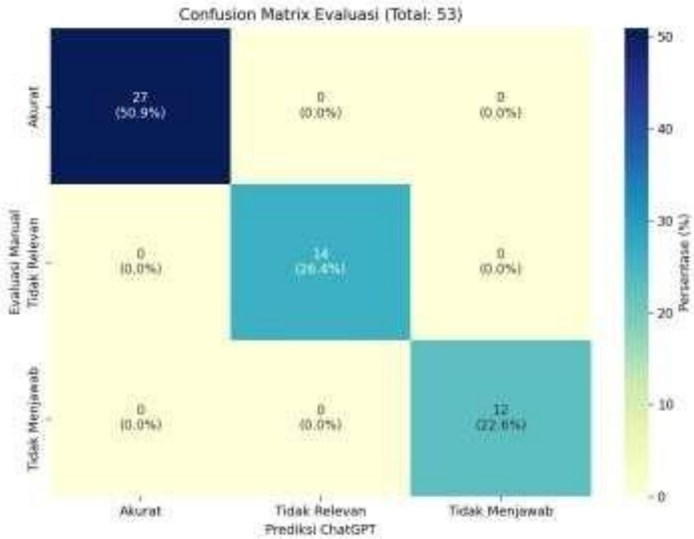

Figure 4. Confusion Matrix Evaluation

In Figure 4 show the performance evaluation of the generative SOP feature was conducted using a confusion matrix and classification evaluation metrics such as accuracy, precision, recall, and F1-score. Based on the confusion matrix in the figure above, out of the total 53 evaluation data, the system successfully generated accurate SOP responses for 27 instances (50.9%). A total of 14 instances (26.4%) were categorized as "Not Relevant," where the system generated answers that did not align with the context of the reported issue. Additionally, 12 instances (22.6%) were classified as "Did Not Answer," indicating cases where the system failed to generate an SOP or provide a response. These results indicate that the system achieved an accuracy rate of 50.9%, suggesting room for improvement, particularly through the development of prompt engineering techniques and dataset adjustments to produce more consistent and relevant SOP outputs.

```
=== Classification Report ===
                precision    recall  f1-score   support

        Akurat       1.00      1.00      1.00        27
 Tidak Relevan       1.00      1.00      1.00        12
Tidak Menjawab       1.00      1.00      1.00        14

      accuracy                           1.00        53
     macro avg       1.00      1.00      1.00        53
  weighted avg       1.00      1.00      1.00        53

=== Accuracy Overall: 100.00% ===
=== Akurasi Jawaban Akurat: 50.94% ===
```

Figure 5. Evaluation Report

The performance of the generative SOP feature was evaluated using a confusion matrix and classification report to measure the system's accuracy in generating SOP recommendations. The evaluation was conducted on 53 incident report data representing various real-world cases. The accuracy for generating correct SOPs was calculated as:

$$\text{Accuracy (Correct)} = \frac{\text{Number of Correct Responses}}{\text{Total Data}} \times 100\%$$
$$= \frac{27}{53} \times 100 = 50.94\% \quad (6)$$

Further evaluation using the classification report showed that the system achieved perfect precision, recall, and F1-score (1.00) across all three categories (Correct, Not Relevant, Did Not Answer), indicating accurate classification according to manual labels. The overall accuracy was 100%, with macro and weighted average precision, recall, and F1-scores also reaching 1.00. However, while the classification labels were accurate, the "Correct" category only accounted for 50.9% of the total cases, representing the relevance of the generated SOPs. This suggests that although the system effectively classified data, further improvements in prompt engineering and model optimization are needed to increase the proportion of truly relevant SOP responses.

C. Results of Automatic Issue Classification Feature

In Figure 6 shows the result of the system's prediction based on a submitted helpdesk ticket. The system processes the category, service, and subject to determine the appropriate priority and estimated resolution time using the Naïve Bayes model.

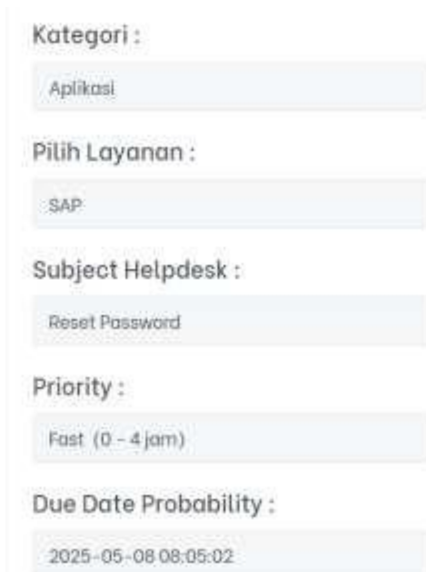

Figure 6. Results of Automatic Issue Classification Feature

As shown in the image, the system successfully classified the ticket with the subject "Reset Password" as having a "Fast (0 – 4 hours)" priority, with a specific predicted resolution time. This demonstrates how the integration of a classification model into the application helps provide quick responses to high-urgency tickets.

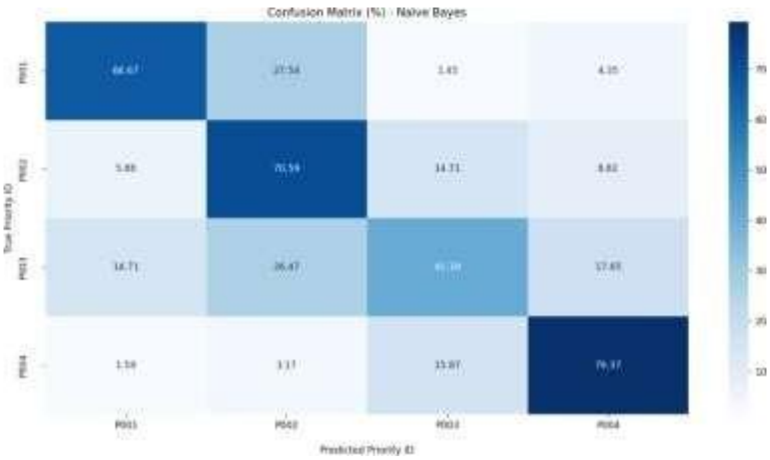

Figure 7. Confusion matrix

To evaluate the classification performance, a confusion matrix was used. The following image illustrates how the model's predictions are distributed across the actual labels for each priority class. From the confusion matrix above, it is evident that the model performed well in classifying tickets with extremely high (P001/Fast) and low (P004/Low) urgency levels, achieving 66.67% and 79.37% accuracy respectively. However, there was noticeable misclassification in mid-level priorities such as P002 and P003 (Medium and Normal), indicating reduced performance in distinguishing these categories.

```
=== Classification Report ===
                    precision    recall  f1-score   support

   Fast
(0 - 4 jam)       0.85      0.67      0.75        69
 Medium
(0 - 8 jam)       0.44      0.71      0.55        34
Normal
(0 - 2 hari)       0.47      0.41      0.44        34
   Low
(0 - 7 hari)       0.81      0.79      0.80        63

          accuracy                          0.67       200
         macro avg       0.64      0.64     0.63       200
      weighted avg       0.70      0.67     0.68       200
```

Figure 8. Classification Report

The evaluation of the Automatic Issue Classification feature involved rigorous testing of the trained Naïve Bayes model. The dataset, comprising 1000 tickets, was first split into training and testing sets, with 80% of the data allocated for training and 20% for testing (test_size=0.2). This split ensures that the model's performance is assessed on unseen data, reflecting its generalization capability. The model's predictions (y_pred) on the test set were then compared against the true labels (y_test) to compute performance metrics. A Confusion Matrix was generated to visualize the model's classification performance for each priority class. The matrix elements were then converted to percentages, calculated as percentage ×100%, where cmij represents the number of instances correctly (or incorrectly) classified from true class i to predicted class j. This percentage view provides a clear indication of classification accuracy per actual class.

V. CONCLUSIONS AND RECOMMENDATIONS

The development and successful implementation of the automatic issue priority classification and generative Standard Operating Procedure (SOP) features within the Helpdesk IT PKG V2 system have shown promising results. The Multinomial Naïve Bayes classification model achieved a 67% accuracy rate and a macro average F1-score of 0.63, demonstrating stable performance in classifying issue priorities. For the generative SOP feature, 50.9% of the generated answers were accurate, with the remaining categorized as irrelevant or unanswered. Despite perfect results in categorizing labels, the findings emphasize the need for optimization in prompt engineering to improve the content quality of SOP recommendations. Functional and usability testing indicated high user satisfaction, particularly regarding classification speed and SOP relevance. Thus, the Helpdesk IT PKG V2 system is deemed capable of supporting the IT incident management process efficiently, accurately, and responsively within PT Petrokimia Gresik, forming a solid foundation for future development.

Based on these findings, future improvements should focus on enhancing the prompt engineering techniques, as the structure and completeness of prompts greatly impact the relevance of generated SOP answers. Expanding the training dataset with diverse real-world cases is also crucial to increase the model's ability to handle complex issues effectively. Additionally, fine-tuning AI models using internal company data could provide deeper understanding and contextual accuracy for PT Petrokimia Gresik's operations. It is also recommended to regularly monitor system performance and integrate the Helpdesk IT PKG V2 system with other IT monitoring platforms to create a more responsive, proactive IT incident management ecosystem. Finally, re-evaluating supporting technologies, such as API integration and data pipeline management, and conducting more complex scenario testing, will provide valuable insights to enhance the system's stability, accuracy, and efficiency.

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