Scientific Journal of Informatics
Vol. 13, No. 4, November 2026
p-ISSN 2407-7658 http://journal.unnes.ac.id/nju/index.php/sji e-ISSN 2460-0040

Integrating Fine-Tuned IndoBERT into a Conversational Chatbot for Automated Ticket Categorization

Yulio Ferdinand[1], Muharman Lubis[2*], Oktariani Nurul Pratiwi[3]
[1,2,3]Department of Information Systems, School of Industrial Engineering, Telkom University, Indonesia

Abstract.
Purpose: University IT service desks frequently face operational bottlenecks due to manual ticket classification and high incident volumes. This study aims to develop an automated ticket categorization workflow by fine-tuning the IndoBERT model and embedding it into an interactive chatbot for real-time ticket categorization.
Methods: A dataset of 6,192 Indonesian-language service desk tickets was divided into training (70%), validation (15%), and test (15%) sets. Class-weighted training was applied to address class imbalance, while grid search was performed to optimize the learning rate, batch size, and number of training epochs. The optimal model was then integrated into the Rasa conversational framework via custom actions and connected to the existing web-based service desk through a REST API, with Telegram serving as the user interface.
Result: Fine-tuned IndoBERT achieved a test accuracy of 92.03% and a macro- and weighted-average F1-score of approximately 0.92, outperforming SVM (89.67%), Logistic Regression (88.37%), Random Forest (87.84%), and Naïve Bayes (81.27%). The integrated Telegram chatbot successfully provided automated initial guidance and submitted categorized tickets to the existing service desk platform.
Novelty: While many reviewed higher education chatbots focus on FAQ retrieval or intent recognition, this study establishes an end-to-end framework integrating deep learning contextual text classification with an open-source conversational agent and a web-based IT helpdesk system, supporting automated ticket categorization and submission for academic IT service management.

Keywords: IndoBERT, IT service desk, NLP, Ticket categorization, Chatbot
Received August 2026 / **Revised** October 2026 / **Accepted** October 2026

This work is licensed under a Creative Commons Attribution 4.0 International License.

INTRODUCTION

The development of information technology in universities is increasingly complex [1]. The use of information technology in educational institutions aims to improve information literacy, develop intellectual capacity, expand opportunities for learning new technologies, and facilitate access to various digital resources and services. Furthermore, this technology supports flexible knowledge acquisition without the constraints of space and time, while fostering a strong information culture [2]. A study analyzing 184 digital transformation initiatives across 39 universities found that 24% of the initiatives focused on improving educational quality and competitiveness. The most frequently adopted technologies were advanced analytics 23%, cloud computing 20%, and artificial intelligence 16% [3]. In the education sector, technology is utilized to bring innovation to the learning and teaching process, while expanding access to education for people of all ages and backgrounds [4]. Supporting these technological needs requires effective IT Service Management (ITSM), which is guided by established standards [5]. To comply with these standards, universities typically provide a dedicated service known as Service Desk. The service desk is a crucial function within an organization, acting as the primary gateway to facilitate communication and collaboration for users, which in the university context includes both employees and students [6]. This service plays a role in assisting with individual technical issues and facilitating interaction with the IT team. Furthermore, the service desk also provides various benefits, such as aligning IT business processes across units, improving the management of hardware and organizational assets, driving business process efficiency, and supporting data collection and analysis for more optimal strategic planning and monitoring [7].

*Corresponding author.
Email addresses: muharmanlubis@telkomuniversity.ac.id (Lubis), yulioferdinand@gmail.com (Ferdinand), onurulp@telkomuniversity.ac.id (Pratiwi)
DOI: 10.15294/sji.v13i4.63341

However, implementing Service Desk services still faces several challenges, particularly in incident management. Problems such as increasing incidents, recurring issues, and unresolved IT operational disruptions continue to affect organizational performance [8]. To overcome these issues, various studies have developed web-based service desk systems. For example, the Faculty of Information Technology at Tarumanagara University developed a helpdesk system using the Agile Scrum method, replacing manual Excel-based management with features such as ticket creation, status updates, history tracking, and monitoring, which improved user satisfaction [9]. Communication systems have also evolved from platforms like WhatsApp and Telegram to integrated web-based chat applications. At the University of Benin, a React.js, Node.js, and Firebase-based communication system improved efficiency through real-time notifications, group dialogue, and administrative controls [10]. Furthermore, the rise of automation has introduced chatbot-based virtual agents. One study implemented a bilingual AI chatbot using IBM Watson at Sultan Qaboos University, achieving intent recognition accuracy of 84.9% in supporting university services [11]. These developments demonstrate the growing adoption of digital service platforms and conversational technologies in higher education.

The advancement of natural language processing (NLP) has also enabled the development of contextual text classification models, including IndoBERT, a pre-trained language model designed to capture the linguistic characteristics of the Indonesian language [12]. A study applied IndoBERT to analyze public sentiment toward IndiHome services using 3,307 Indonesian-language tweets categorized into positive, neutral, and negative sentiments. The model achieved its best performance in detecting negative sentiment, with an accuracy of 80% and an F1-score of 91%, while the neutral and positive categories obtained F1-scores of 53% and 43%, respectively [13]. Another study implemented an NLP-based chatbot using IndoBERT to automate 24/7 customer service on a housing website. Using Hugging Face Transformers, the study fine-tuned the model on 3,082 training samples augmented with typos and informal language. IndoBERT Base achieved the best intent classification performance, with 95.85% accuracy and a 95.87% F1-score, outperforming Indonesian RoBERTa, IndoBERTweet, and XLM-RoBERTa [14]. Another study applied IndoBERT Large to classify economic census listings of enterprises in Indonesia. The results showed that IndoBERT Large outperformed CatBoost, DistilBERT, and IndoBERT Base, achieving an F1-score of 96.82%, balanced accuracy of 96.10%, and recall of 96.96% [15]. These findings demonstrate the effectiveness of IndoBERT across different Indonesian-language classification tasks. However, the reviewed studies primarily evaluated classification performance within their respective application domains, providing limited evidence of its integration into an operational IT service desk workflow for automated ticket categorization.

One implementation of ITSM in improving communication between services and users is the use of chatbots as automated helpdesk systems. The Tayseer chatbot was implemented in higher education at the Technical College for Girls in Najran (TCGN), Saudi Arabia, as an automated helpdesk for admission, registration, and FAQ services. The system was developed using the Rasa framework with the DIET Classifier model for NLP, supported by web technologies and cloud services. Evaluation results showed approximately 90% accuracy in intent and entity recognition, with response times of less than one second [16]. Another study implemented a chatbot for government IT helpdesk services at the Department of Communication and Informatics of Mojokerto Regency using the Rasa framework and Telegram Bot API. The system utilized the DIET Classifier model for intent recognition and entity extraction, achieving 82.5% accuracy with an average response time of 2.15 seconds [17]. Another study developed the College Enquiry (MPSTME Bot) as a higher education information service chatbot at NMIMS MPSTME, Mumbai, to assist students, staff, and parents in accessing academic and campus-related information. The system utilized NLP and machine learning for intent recognition and entity extraction, achieving 95% accuracy, outperforming rule-based chatbots (65%) and Rasa-NLU models (70%) [18]. These studies demonstrate the applicability of conversational AI in educational and helpdesk environments. Nevertheless, their reported performance cannot be directly compared because of differences in datasets, classification tasks, and evaluation settings. Moreover, the reviewed chatbot implementations primarily emphasize information retrieval, FAQ automation, or intent recognition rather than integrating contextual ticket classification with automated ticket creation in an existing service desk system.

Telkom University is currently in the process of digitizing towards a smart campus concept, adapting to developments in digital transformation [19]. Telkom University already has a service desk system managed by the Information Technology Center Directorate. This system is based on a web application that students, employees, and lecturers use to report incidents. Its features include ticket creation, ticket monitoring, ticket

approval, and a dashboard. Currently, the service desk system does not have an AI-based chatbot and still relies on ticket creation through the website or WhatsApp communication. This creates an opportunity to integrate automated ticket categorization into the existing service desk workflow. Based on the reviewed studies, existing research has demonstrated the effectiveness of IndoBERT for Indonesian-language text classification and conversational AI for automated information services. However, these approaches have generally been evaluated separately, with limited evidence of end-to-end integration between a fine-tuned Indonesian-language classification model, a conversational chatbot, and an operational web-based service desk. In addition, some chatbot implementations depend on platform-specific services, whereas open-source frameworks such as Rasa offer greater flexibility for customization and integration with external applications. Therefore, this study aims to develop an integrated university service desk chatbot by combining fine-tuned IndoBERT for automated ticket categorization with the Rasa conversational framework and REST API integration. The main contribution of this study is an end-to-end implementation that enables users to report incidents through Telegram, receive initial assistance, and automatically create categorized tickets in the existing service desk system. This integration demonstrates the feasibility of combining contextual text classification and conversational AI to support incident management in higher education.

METHODS

This research focused on fine-tuning IndoBERT to classify service desk tickets into multiple service categories. The methodology consisted of several stages, including data collection, preprocessing, model fine-tuning, grid search, and performance evaluation, as illustrated in Figure 1.

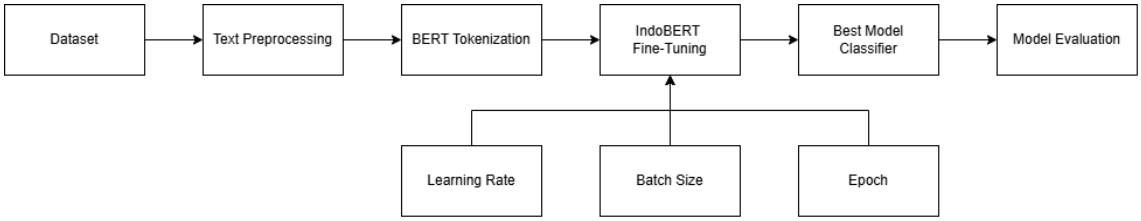


Figure 1. Research flow diagram

Dataset

The dataset employed in this study was sourced from the Service Desk application database managed by the Directorate of Information Technology Center at Telkom University. This application functions as an official platform for submitting service requests and issue reports from employees, lecturers, and students. The use of the dataset for academic research was formally authorized by the institution under Non-Disclosure Agreement (NDA) No. 578/NDI/0.0/0.0/PuTI/2025, which specifies the approved research purpose and establishes data confidentiality obligations. To minimize the use of personal information, usernames were excluded from model training, while only ticket descriptions and service category labels were utilized. The original ticket descriptions were retained to preserve relevant contextual information and were not fully anonymized. The dataset was used in accordance with the institutional authorization and confidentiality requirements established under the agreement.

The data were collected over a three-year period, spanning 2023 to 2025, and subsequently converted into Excel format to serve as the raw dataset. All records within the dataset had been pre-labeled and formally validated by the Service Desk unit to ensure accuracy and consistency. Prior to analysis, the authors designed a data template to identify and extract the specific attributes required for this research. Table 1 provides a detailed overview of the Excel columns utilized in the study. The dataset consisted of 6,192 service desk tickets, divided into training (70%), validation (15%), and testing (15%) subsets. A two-stage stratified random splitting procedure was applied to preserve the distribution of the six service categories. First, 70% of the data was allocated to training, while the remaining 30% was equally divided into validation and testing subsets. A fixed random seed of 42 was used to ensure reproducibility. To minimize potential data leakage, ticket descriptions were checked for exact duplicates, and no identical descriptions were found across the subsets. Furthermore, class weights were calculated exclusively from the training labels. Hyperparameter tuning was performed using the validation set, while the test set was reserved for the final evaluation of the selected model.

Table 1. Service desk dataset

Columns	Ticket Example	Counts
Bug Fixes	I would like to inform you that there are two students who need to print their thesis approval letter. However, when accessing the "Manage SK" menu and attempting to save the data before printing, an "Error Happened" notification appears.	1462
WordPress Website	Good afternoon, kindly check the domain pascasarjana.telkomuniversity.ac.id, as it is experiencing a CSS-related error that prevents users from logging in. Thank you.	1230
Request Data	Request for student supervision data for the Master's Program in Industrial Engineering for the Odd and Even Semesters of the 2023–2024 academic year.	1142
Internet Access	The Tel-U Connect internet access in GKU 04–06 cannot be accessed. I have tried using both a mobile phone and a laptop, but it does not work at all.	1026
License	Kindly assist in providing an Adobe license for the following email address. Thank you for your attention and support. Thank you for your attention and support.	783
Application Development	Dear digi-TRAIN Team, Kindly assist in adding an EVALUATOR column to the task download data, as it is needed for manual reminders through the respective unit or faculty leadership. Thank you.	549
	Total	**6192**

Preprocessing

Data preprocessing was carried out through several steps to improve the quality of the complaint texts by implementing suitable text pre-processing strategies that not only avoid degrading the model's performance but instead contribute to improving the overall quality of the classification results [20]. First, all HTML elements that might appear in the ticket descriptions were removed using a regular expression (re.sub(r'<.*?>', ' ', text)) to eliminate tags that carry no semantic meaning and could interfere with feature extraction. Next, non-alphanumeric characters considered irrelevant for natural language analysis were cleaned using re.sub(r'[^0-9A-Za-zÀ-ÿ\u00f1\u00d1.,?!]+', ' ', text). This step retains only letters, numbers, and common punctuation marks, reducing noise from special symbols that might affect model accuracy. Next, excessive whitespace was removed through re.sub(r'\s+', ' ', text).strip(), ensuring consistency in word spacing. All text was then converted to lowercase (text.lower()) to maintain uniform word representation and prevent meaning variations caused by capitalization differences such as "Error" vs. "error". Finally, entries containing missing values were removed using data.dropna(), preventing potential bias or disturbances during model training due to incomplete information.

To address class imbalance within the dataset, class weights were computed using the compute_class_weight function with the balanced weighting scheme. This function calculates proportional weights based on the distribution of categorical labels, ensuring that minority classes receive greater emphasis during model training. The resulting weights were converted into a PyTorch tensor and used in the cross-entropy loss function. Additionally, the total number of unique labels was derived from the categorical field, enabling the model to correctly configure its output layer [21].

IndoBERT Tokenizer

The BertTokenizer class was used to tokenize the ticket descriptions, while a customized BertForSequenceClassification model was employed for classification with class-weighted cross-entropy loss [22]. In this study, tokenization was performed using the IndoBERT tokenizer provided by the indobenchmark/indobert-base-p1 model. The maximum sequence length was set to 128 tokens to accommodate ticket descriptions while maintaining computational efficiency during model encoding. A custom tokenization function was implemented to convert each input text into token IDs while applying padding and truncation based on the predefined maximum length. The function also attaches the corresponding class label to each tokenized instance, preparing the data for supervised learning. Subsequently, the training and testing datasets were constructed using the Dataset.from_dict() method, which organizes the raw text and label pairs into a structured format. Each dataset was then processed through the tokenization function using batched mapping, enabling efficient transformation of all samples into the numerical representations required for downstream model training and evaluation.

IndoBERT Classifier

BERT is trained in two main phases: pre-training and fine-tuning. During pre-training, the model learns general language patterns from large amounts of unlabeled text by predicting masked words based on context. In the fine-tuning phase, BERT is further trained on labeled data for a specific downstream task, allowing it to adapt its learned representations to the task's requirements [23].

IndoBERT is a monolingual BERT-based language model specifically designed for the Indonesian language. It was pre-trained on a large-scale Indonesian text corpus and has demonstrated state-of-the-art performance across various NLP tasks in the IndoLEM benchmark, including sentiment analysis, named-entity recognition, and morpho-syntactic analysis. Its results surpass those of multilingual BERT and several other baseline models [24]. Following preprocessing and tokenization, the IndoBERT transformer was fine-tuned for service-category classification. Built on the PyTorch framework, the IndoBERT tokenizer converts raw text into token IDs, which are subsequently processed by the IndoBERT model to generate contextual representations for ticket classification. The model was then fine-tuned for improved ticket classification performance. Hyperparameter tuning was conducted using grid search by varying the learning rate, batch size, and number of training epochs, while the maximum sequence length was fixed at 128 tokens throughout all experiments.

Evaluation

For comparative evaluation, four traditional machine learning algorithms, namely Naïve Bayes, Random Forest, Logistic Regression, and Support Vector Machine (SVM), were employed as baseline models. Ticket descriptions were represented using TF-IDF with a maximum of 5,000 features. The models were trained on the 70% training subset and evaluated on the 15% test subset, using the same stratified splitting configuration as IndoBERT. The TF-IDF vectorizer was fitted exclusively on the training data to prevent data leakage. Classification accuracy was used to compare model performance. The model was evaluated using accuracy, precision, recall, and F1-score. These metrics were derived from the confusion matrix based on true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each class. Together, these metrics provide a comprehensive assessment of overall classification performance and class-specific prediction quality [25], [26].

RESULT AND DISCUSSION

The experiments were conducted on a Windows 11 (64-bit) system with an Intel Core i5-8265U processor. This approach systematically assessed the impact of different parameter combinations on performance. Variations in learning rate influenced training stability and convergence, batch size affected gradient estimation and efficiency, and different epoch values helped identify the optimal training duration to avoid underfitting or overfitting. The grid search configuration and evaluated parameters are presented in Table 2.

Table 2. Hyperparameter tuning results for fine-tuned IndoBERT

Learning Rate (LR)	Batch Size (BS)	Epoch	Training Loss	Validation Loss	Validation Accuracy (%)
3e-05	16	10	0.0026	0.5990	90.20
3e-05	16	15	0.0019	0.6550	90.63
3e-05	32	10	0.0037	0.5063	90.63
3e-05	32	15	0.0023	0.5850	90.41
3e-05	64	10	0.0046	0.4589	91.17
3e-05	64	15	0.0025	0.5061	90.31
5e-05	16	10	0.0040	0.5809	91.38
5e-05	16	15	0.0042	0.7485	90.63
5e-05	32	10	0.0031	0.5475	90.63
5e-05	32	15	0.0020	0.6238	90.20
5e-05	**64**	**10**	**0.0040**	**0.5028**	**91.50**
5e-05	64	15	0.0022	0.5363	90.63

Table 2 presents the hyperparameter tuning results for the fine-tuned IndoBERT model. Increasing the training duration to 15 epochs generally led to higher validation loss across configurations, signaling overfitting. Overall, models trained for 10 epochs with a batch size of 64 showed better generalization. The configuration with a learning rate of 5e-05, a batch size of 64, and 10 epochs achieved the optimal performance, yielding the highest validation accuracy of 91.50% with a validation loss of 0.5028.

Table 3. Model performance comparison

Method	Test Accuracy (%)
Naïve Bayes	81.27
Random Forest	87.84
Logistic Regression	88.37
Support Vector Machine	89.67
Fine-tuned IndoBERT	**92.03**

To evaluate the effectiveness of the proposed approach, the fine-tuned IndoBERT model was benchmarked against several traditional machine learning baselines, including Naïve Bayes, Logistic Regression, Random Forest, and Support Vector Machine (SVM). As summarized in Table 3, the fine-tuned IndoBERT achieved the highest classification accuracy of 92.03%, outperforming all baseline models. Among the traditional algorithms, SVM demonstrated the strongest performance with an accuracy of 89.67%, whereas Naïve Bayes yielded the lowest at 81.27%. These results highlight the superior capability of the transformer-based architecture in capturing contextual semantic representations compared to conventional machine learning techniques. These results demonstrate the effectiveness of IndoBERT in performing multiclass classification on Indonesian-language data [27].

Table 4. The classification report

Class	Precision	Recall	F1-Score	Support
Bug Fixes	0.91	0.92	0.91	220
WordPress Website	0.94	0.96	0.95	185
Request Data	0.87	0.82	0.85	171
Internet Access	0.99	0.96	0.97	154
License	0.89	0.96	0.92	117
Application Development	0.94	0.90	0.92	82

The classification report in Table 4 summarizes performance on the 929-sample test set, achieving an overall accuracy of 92%, with macro- and weighted-average F1-scores also reaching 0.92. The model exhibits exceptional discrimination for the Internet Access class, with the highest precision (0.99) and F1-score (0.97), followed by the WordPress Website category (F1-score: 0.95). High recall values for License (0.96) and WordPress Website (0.96) indicate relatively few false negatives in these categories. Conversely, the Request Data class recorded the lowest metrics across the dataset precision 0.87, recall 0.82, F1-score 0.85, suggesting potential semantic overlap with other request-oriented tickets. Overall, all six classes maintain an F1-score of 0.85 or higher, confirming robust generalization across heterogeneous service categories. The results further demonstrate that fine-tuned IndoBERT achieves higher test accuracy than the evaluated traditional machine learning baseline [28].

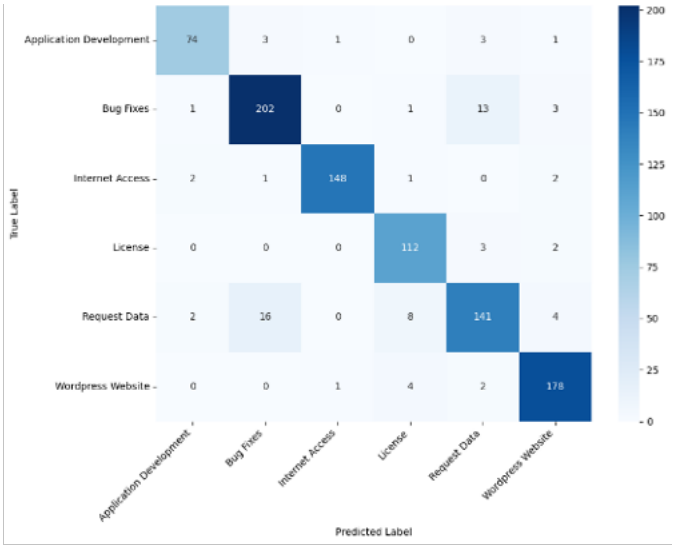


Figure 2. Confusion matrix

Figure 2 displays the confusion matrix on the test set, demonstrating strong classification performance alongside specific misclassifications caused by semantic overlap. The most notable confusion occurs between Request Data and Bug Fixes, where 16 Request Data instances were misclassified as Bug Fixes and 13 Bug Fixes instances were predicted as Request Data. This bidirectional error arises from shared technical phrasing regarding system errors and data retrieval failures. Additionally, 8 Request Data instances were misclassified as License, likely due to overlapping terminology around access rights and authorization permissions. In contrast, classes with distinct vocabularies, such as Internet Access and Application Development, exhibited minimal confusion.

System Integration

The proposed system integrates the trained IndoBERT classification model with the Rasa conversational framework to extend the existing service desk process. As illustrated in Figure 3, the integration enables users to report issues through Telegram and connect the chatbot to the Telkom University Service Desk web service through an API. Rasa serves as the conversational framework and integration bridge, using its default intent mechanism together with utter responses and rules/stories to support the chatbot dialogue.

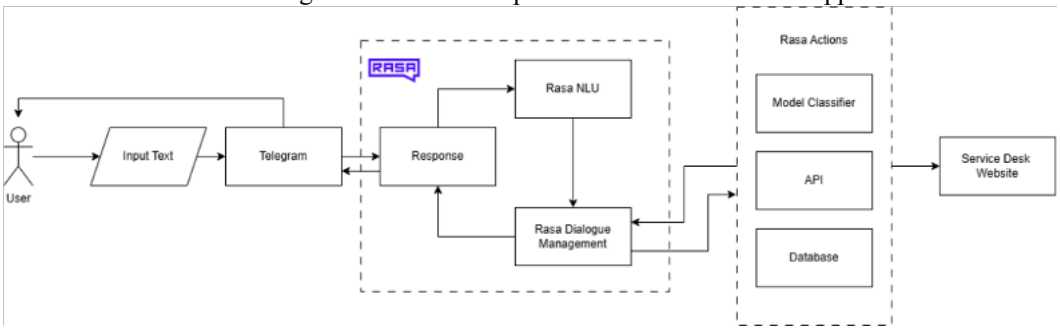
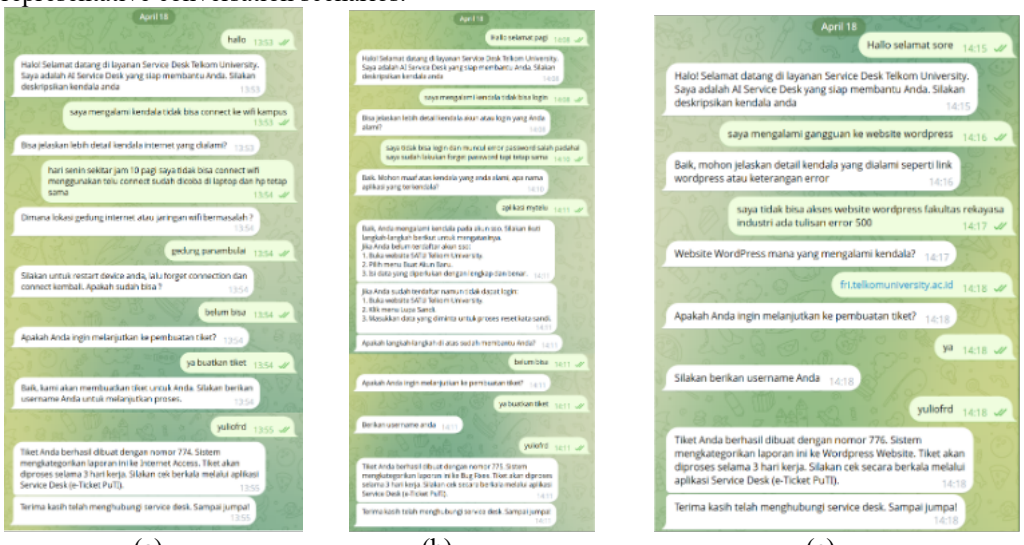


Figure 3. Proposed system integration

The process begins when a user initiates a conversation through Telegram. The user input is processed by Rasa NLU based on the predefined chatbot configuration. If the response generated by the dialogue manager is sufficient to address the user's request, the interaction is concluded. However, if the issue cannot be resolved and a ticket needs to be created, a Rasa custom action invokes the trained IndoBERT model to predict the ticket category. The classification result and ticket information are then transmitted through an API and stored in the service desk database. This integration adds an automated ticket categorization capability to the existing Telkom University Service Desk. By connecting the chatbot with the existing web-based service desk, users can report issues through Telegram while ticket categories are automatically determined using the trained IndoBERT model.

Chatbot Prototype and Ticket Classification

As illustrated in Figure 4, the conversation flow through Telegram demonstrates how the chatbot responds when a user reports an issue. Initially, the chatbot provides suggested solutions that the user can follow. If the issue remains unresolved, the interaction proceeds to the ticket creation process. The figure presents three representative conversation scenarios.



(a) (b) (c)

Figure 4. Example Telegram conversations: (a) slow internet connection, (b) account access issue, and (c) wordPress website issue

Table 5. Model inference and confidence scores for telegram conversation cases

Input Text Example	Predicted Category	Confidence Score
...hari senin sekitar jam 10 pagi saya tidak bisa connect wifi...	Internet Access (LABEL_2)	0.9995
...mytelu saya tidak bisa login dan muncul error password...	Bug Fixes (LABEL_1)	0.8267
..fri.telkomuniversity.ac.id saya tidak bisa akses website WordPress...	WordPress Website (LABEL_5)	0.9986

Within the integrated workflow shown in Figure 3, the embedded IndoBERT model performs real-time classification on the user's issue descriptions. Table 5 presents the corresponding technical inference results and confidence scores for each scenario. As detailed in the table, the model demonstrates high prediction confidence, achieving scores of 0.9995 for the internet access inquiry, 0.8267 for the account problem, and 0.9986 for the WordPress issue. If the chatbot fails to resolve the issue through automated suggestions, the predicted category and required user information are transmitted to the Service Desk API through an HTTP POST request to create a ticket in the service desk database. The user's single sign-on (SSO) username is used to retrieve the information required for ticket creation. The service category and ticket description are automatically populated based on information obtained from the chatbot conversation and the classification result generated by IndoBERT.

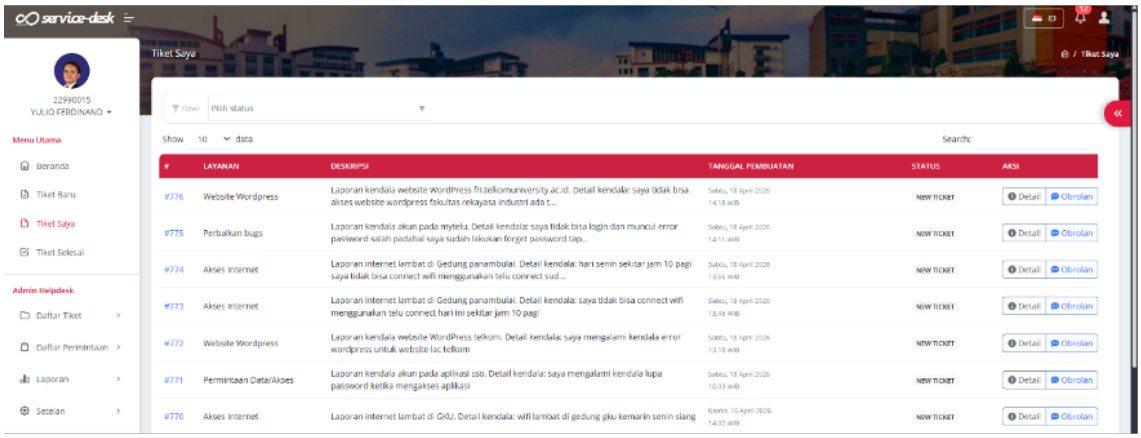


Figure 5. User ticket display on the service desk website through chatbot

The existing Service Desk follows an operational-level agreement (OLA) with a one-hour ticket escalation target during working hours. The proposed chatbot complements this workflow by automatically predicting service categories during ticket submission. However, the impact of this integration on actual ticket escalation times and OLA compliance was not evaluated in this study. Figure 5 shows an example of a ticket created through the chatbot and displayed on the Service Desk platform. After a ticket is created, users can monitor its status through the Service Desk website. As shown in the figure, incidents reported through the chatbot are automatically recorded in the dashboard along with their predicted ticket categories. Previous studies have demonstrated the use of Rasa for various educational and help desk applications. Sigdel et al. developed a college chatbot using Rasa for academic information and admission services [29], while Supreetha and Sandhya implemented a Rasa-based educational chatbot integrated with a web-based e-learning platform [30]. Mansoor et al. applied Rasa to help desk support for handling technical complaints [31], and Suasnawa et al. developed an Indonesian-language chatbot for student information services [32]. However, these studies primarily focused on conversational information services or complaint handling, with limited integration into dedicated web-based help desk systems and automated ticket categorization. In contrast, this study integrates Rasa with an IndoBERT-based ticket classification model to automatically determine service categories and connect the resulting classification to a web-based help desk through an API, enabling an end-to-end workflow from user interaction to ticket categorization and creation.

CONCLUSION

This study developed an integrated university helpdesk system by combining an IndoBERT-based text classification model with a Rasa chatbot for automated ticket categorization. The proposed model achieved an accuracy of 92.03%, outperforming conventional machine learning methods and demonstrating its effectiveness in classifying Indonesian-language helpdesk tickets. The integrated chatbot provides initial assistance, automatically classifying user complaints, and creating support tickets through API integration

with the service desk system. Overall, the findings demonstrate the feasibility of automating initial ticket categorization within an existing university service desk workflow. However, its impact on operational efficiency has not yet been quantitatively evaluated. Future work may focus on incorporating large language models (LLMs), multilingual support, and real-world user evaluations, including comparisons of manual and automated ticket categorization times and assessments of correction rates, to further enhance system performance and usability.

ACKNOWLEDGEMENTS
The authors acknowledge the use of ChatGPT as a writing assistance tool during the preparation of this manuscript, particularly for language refinement and clarity. The authors remain fully responsible for the scientific content, methodology, analysis, results, and conclusions.

REFERENCES

[1] M. Alenezi, S. Wardat, and M. Akour, "The Need of Integrating Digital Education in Higher Education: Challenges and Opportunities," *Sustainability (Switzerland)*, vol. 15, no. 6, Mar. 2023, doi: 10.3390/su15064782.

[2] S. Volodymyr, A. Vitalii, D. Hryhorii, H. Antonina, and M. Alla, "Information Technologies in Education: Current Realities and Development Trends," *IJCSNS International Journal of Computer Science and Network Security*, vol. 22, no. 3, p. 547, 2022, doi: 10.22937/IJCSNS.2022.22.3.70.

[3] A. Fernández, B. Gómez, K. Binjaku, and E. K. Meçe, "Digital transformation initiatives in higher education institutions: A multivocal literature review," *Educ. Inf. Technol. (Dordr).*, vol. 28, no. 10, pp. 12351–12382, Oct. 2023, doi: 10.1007/s10639-022-11544-0.

[4] S. Aithal and P. S. Aithal, "Effects of AI-Based ChatGPT on Higher Education Libraries," *SSRN Electronic Journal*, 2023, doi: 10.2139/ssrn.4453581.

[5] A. Widianto and A. P. Subriadi, "IT service management evaluation method based on content, context, and process approach: A literature review," in *Procedia Computer Science*, Elsevier B.V., 2021, pp. 410–419. doi: 10.1016/j.procs.2021.12.157.

[6] M. Dostál, "Complex Service Desk System for Incident Management Automation," *Computing Open*, vol. 03, Jan. 2025, doi: 10.1142/s2972370125500035.

[7] N. Hakiem, L. Kesuma Wardhani, F. Nugraha Wahyu, N. Anggraini, I. Marzuki Shofi, and Y. Setiadi, "Whistleblowing System Deployment using the Information Technology Infrastructure Library Framework: Evidence from a Public University in Indonesia," 2022. [Online]. Available: https://servicedesk.uinjkt.ac.id/.

[8] A. F. J. Nugroho and M. I. Fianty, "Streamlining IT Help Desk and Incident Management: Harnessing the Power of the ITIL Framework for Enhanced Efficiency in IT Services," *Journal of Information Systems and Informatics*, vol. 5, no. 2, pp. 683–695, May 2023, doi: 10.51519/journalisi.v5i2.496.

[9] A. N. Gunadi, D. Trisnawarman, and M. D. Lauro, "Design and Development of the HelpDesk Application for the Faculty of Information Technology, Tarumanagara University (FTI UNTAR) using the Agile Scrum Methodology," vol. 2, no. 02, 2024, doi: 10.54209/bios.v1i02.

[10] A. Obayuwana and A. Bundowa Mayowa, "Design and Implementation of a Client-Server Model for Campus Office Chat Systems," *Ilorin Journal of Computer Science and Information Technology*, vol. 7, no. 1, p. 76, 2024.

[11] Z. Nadir, H. M. Al Lawati, R. A. Mohammed, M. Al Subhi, and A. Hossen, "SQUbot: Enhancing Student Support Through a Personalized Chatbot System," *Technologies (Basel).*, vol. 13, no. 9, Sep. 2025, doi: 10.3390/technologies13090416.

[12] R. I. Perwira, V. A. Permadi, D. I. Purnamasari, and R. P. Agusdin, "Domain-Specific Fine-Tuning of IndoBERT for Aspect-Based Sentiment Analysis in Indonesian Travel User-Generated Content," *Journal of Information Systems Engineering and Business Intelligence*, vol. 11, no. 1, pp. 30–40, Feb. 2025, doi: 10.20473/jisebi.11.1.30-40.

[13] R. A. Siregar, F. Fitriyani, and L. S. Darfiansa, "Sentiment Analysis Of Indihome Service Based On Geo Location Using The Bert Model On Platform X," *Jurnal Teknik Informatika (Jutif)*, vol. 6, no. 5, pp. 2975–2990, Oct. 2025, doi: 10.52436/1.jutif.2025.6.5.4993.

[14] W. Sukma Jayawardhana, D. Rudiaman Sijabat, and M. Amien, "Implementation of IndoBERT-Based Chatbot for Information and Marketing Services on the Griya Alam Mandiri Website," *IC-ITECHS*, vol. 6, no. 1, pp. 114–124, Jul. 2026, doi: 10.32664/eqy3bv56.

[15] M. R. Syazali and E. Yulianti, "Classification of Economic Activities in Indonesia Using IndoBERT Language Model," *Jurnal Ilmu Komputer dan Informasi*, vol. 18, no. 2, pp. 155–165, Jun. 2025, doi: 10.21609/jiki.v18i2.1446.
[16] A. Alabbas and K. Alomar, "Tayseer: A Novel AI-Powered Arabic Chatbot Framework for Technical and Vocational Student Helpdesk Services and Enhancing Student Interactions," *Applied Sciences (Switzerland)*, vol. 14, no. 6, Mar. 2024, doi: 10.3390/app14062547.
[17] W. M. H. Sasmita, S. Sumpeno, and R. F. Rachmadi, "Improving Government Helpdesk Service With an AI-Powered Chatbot Built on the Rasa Framework," *Jurnal RESTI*, vol. 9, no. 2, pp. 393–403, Apr. 2025, doi: 10.29207/resti.v9i2.6293.
[18] D. Patel, Ni. Shetty, P. Kapasi, and I. Kangriwala, "College Enquiry Chatbot using Conversational AI," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 11, no. 5, pp. 903–915, May 2023, doi: 10.22214/ijraset.2023.51324.
[19] A. Qurtubi, "Digital-Based Smart Campus at Telkom University," *The Asian Institute of Research Education Quarterly Reviews*, vol. 5, no. 3, pp. 259–269, 2022, doi: 10.31014/aior.1993.05.03.543.
[20] U. Naseem, I. Razzak, and P. W. Eklund, "A survey of pre-processing techniques to improve short-text quality: a case study on hate speech detection on twitter," *Multimed. Tools Appl.*, vol. 80, no. 28–29, pp. 35239–35266, Nov. 2021, doi: 10.1007/s11042-020-10082-6.
[21] F. Ashfaq, R. M. Ghoniem, N. Z. Jhanjhi, N. A. Khan, and A. D. Algarni, "Using Dual Attention BiLSTM to Predict Vehicle Lane Changing Maneuvers on Highway Dataset," *Systems*, vol. 11, no. 4, Apr. 2023, doi: 10.3390/systems11040196.
[22] I. A. Mannix and E. Yulianti, "Academic expert finding using BERT pre-trained language model," *International Journal of Advances in Intelligent Informatics*, vol. 10, no. 2, pp. 280–295, May 2024, doi: 10.26555/ijain.v10i2.1497.
[23] D. Vu, T. Nguyen, V. Tong, and S. Souihil, "Enhancing Multi-Label Vulnerability Detection of Smart Contract Using Language Model," in *2023 5th Conference on Blockchain Research & Applications for Innovative Networks and Services (BRAINS)*, IEEE, Oct. 2023, pp. 1–4. doi: 10.1109/BRAINS59668.2023.10316991.
[24] A. Pinkan Maretta and A. Meiriza, "Aspect-Based Sentiment Analysis of Hospital Service Reviews Using Fine-Tuned IndoBERT," 2025. [Online]. Available: http://jurnal.polibatam.ac.id/index.php/JAIC
[25] M. Abidin *et al.*, "Classification of Heart (Cardiovascular) Disease using the SVM Method," 2025. [Online]. Available: https://journal.abhinaya.co.id/index.php/IJMST
[26] A. D. Azman *et al.*, "Performance Analysis of Surface Defect Detection Algorithm of Aerospace Parts via Confusion Matrix Approach," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 55, no. 1, pp. 141–153, Oct. 2024, doi: 10.37934/araset.55.1.141153.
[27] F. K. Ihtada, R. Alfianita, and O. Q. Aziz, "Aspect-based Multilabel Classification of E-commerce Reviews Using Fine-tuned IndoBERT," *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, Jan. 2025, doi: 10.22219/kinetik.v10i1.2088.
[28] R. Budianoor, S. W. Saputro, F. Abadi, R. A. Nugroho, and A. Farmadi, "Quantifying the Impact of Text Preprocessing on IndoBERT Fine-Tuning for Indonesian Informal Culinary Sentiment Analysis," *Journal of Computing Theories and Applications*, vol. 3, no. 4, pp. 564–581, May 2026, doi: 10.62411/jcta.15980.
[29] Y. Sigdel, S. Shrestha, and N. Neupane, "College Chatbot Using RASA," 2024.
[30] S. H V and Dr. S. S, "Implementation of an Educational Chatbot using Rasa Framework," *International Journal of Innovative Technology and Exploring Engineering*, vol. 11, no. 9, pp. 29–35, Aug. 2022, doi: 10.35940/ijitee.G9189.0811922.
[31] F. Mansoor, S. Maham Batool, and M. Ahsan, "spectrum of engineering sciences issn (e) 3007-3138 (p) 3007-312x design and evaluation of a conversational ai bot for help desk support using the rasa framework and diet classifier", doi: 10.5281/zenodo.21371020.
[32] I. Suasnawa, I. Wiratama, I. Sudiartha, I. Caturbawa, A. Sapteka, and I. Indrayana, "Chatbot-Based Student Information Service in Indonesian Language," INSTICC, Dec. 2023, pp. 223–227. doi: 10.5220/0011753800003575.