Matrix: Jurnal Manajemen Teknologi dan Informatika
Volume 15 Issue 2 Year 2025 Pages 50-59
DOI: http://dx.doi.org/10.31940/matrix.v15i2.50-59
URL: http://ojs2.pnb.ac.id/index.php/matrix

Classification of public complaint report types on social crimes using a chatbot for law enforcement agencies

***Luh Putu Ary Purwanthi* [1]*, I Made Agus Dwi Suarjaya* [2], I Nyoman Prayana Trisna* [3]**

[1, 2, 3] *Information Technology Department, Universitas Udayana, Indonesia*

*Corresponding Author: *arypurwanthi@gmail.com*

Abstract: Social crime is a complex problem that occurs every day and requires a quick response. The large number of reports with language variations makes the manual classification process difficult. This research aims to develop an AI-based chatbot to classify types of social crime reports automatically using the IndoBERT model. Data was obtained from East Denpasar Police, LAPOR website, and X social media. The initial data set of 250 reports was augmented to 6,250 data using synonym augmentation technique. The data was then divided into 70:20:10 training scenarios to produce the best model. The evaluation showed high performance with accuracy 0.999200, precision 0.999203, recall 0.999200, and F1-score 0.999200. Validation was also done through confusion matrix and accuracy-loss graph. The chatbot is able to receive reports from the public and classify them into five main categories, namely theft, maltreatment, embezzlement, domestic violence, and murder. The results show that IndoBERT is effective in understanding and classifying Indonesian text reports accurately. The system is expected to assist law enforcement agencies in improving efficiency and speed in handling community reports as well as supporting the digitisation of the social crime complaint process.

Keywords: AI, chatbot, complaint report classification, indobert, social crime

History Article: Submitted 16 April 2025 | Revised 5 May 2025 | Accepted 16 May 2025

How to Cite: L. P. A. Purwanthi, I. M. A. D. Suarjaya, and I. N. P. Trisna, "Classification of public complaint report types on social crimes using a chatbot for law enforcement agencies", *Matrix : Jurnal Manajemen Teknologi dan Informatika*, vol. 15, no. 2, pp. 50–59, 2025. doi.org/10.31940/matrix.v15i2.50-59.

Introduction

Social crimes refer to actions that violate the rules and norms upheld within a society, such as theft, assault, murder, and other forms of social crime [1]. The police institution serves as the primary the initial point of contact within Indonesia's criminal justice process [2]. One of the biggest obstacles encountered by law enforcement institutions is the high number of public complaints related to social crimes, including theft, violence, fraud, and other violations.

Based on statistics gathered by Indonesia's Central Bureau of Statistics (BPS) in 2024, a total of 584,991 criminal cases were recorded nationwide, with crimes such as theft, fraud, assault, and domestic violence dominating the reports received by the police [3]. Currently, the reporting process for public complaints is still frequently conducted manually, requiring individuals to visit police stations in person, which often takes time and necessitates direct interaction with officers. The public often faces difficulties in reporting crimes, and once a report is submitted, the classification and follow-up process can be time-consuming [4]. This situation presents a significant challenge, especially in the digital era, where the public expects faster, easier, and more responsive services. The existing manual process not only hampers efficiency but also complicates the classification of reports due to variations in language, writing structure, and narrative from the complainants, making the system prone to recording errors. Such data irregularities lead to delays in follow-up actions and impose additional workload on officers. Therefore, there is a need for a monitoring system that can assist law enforcement agencies (the police) in classifying public complaints efficiently and accurately. Advancements in information and communication technology present a great opportunity to improve the complaint system. One potential innovation is the use of chatbots. Chatbots can serve as interactive tools that allow the public to report crimes quickly and easily, while also assisting in the classification of complaint reports [5]. Prior studies have explored the application of chatbot systems in legal and governmental service contexts, showing their potential to improve accessibility and efficiency in handling public complaints [6].

One applicable methodological approach is the use of IndoBERT. By utilizing IndoBERT, chatbots can categorize reports based on specific categories, enabling law enforcement agencies to respond and resolve cases more swiftly. IndoBERT is a machine learning model known for its high effectiveness in understanding the context of natural language [7]. Using this model, chatbots can classify reports according to the types of social crimes reported Research on text classification has been widely conducted, particularly in the areas of news, general text, and academic publications. Studies such as Abri et al. [8], Fitrianto and Editya [9], Latifah et al. [10], Khairani et al. [11], Supriyadi and Sibaroni [12], Prabowo and Indra [13] employed fine-tuned IndoBERT models and revealed that IndoBERT achieved high accuracy levels. Additionally, studies by Juarto [14], Nabiilah et al. [15], Rizky and Hidayat [16] explored text classification using IndoBERT combined with other methods and found that IndoBERT consistently outperformed alternative approaches in terms of accuracy. However, previous research using IndoBERT has generally been limited to experimental applications in text classification and has yet to be integrated directly into interactive chatbot systems. One potential innovation is the use of chatbots which could enhance the accessibility and practical benefits of IndoBERT technology by enabling direct interaction with the public [17]. As a result, the public has not had direct access to such technology, and its practical benefits have not yet been fully realized.

This study focuses on developing a chatbot designed to classify public complaint reports related to social crimes. The system is built to identify and categorize reports into five main categories: theft, assault, embezzlement, domestic violence (DV), and murder. The selection of these five classes is based on the most frequently handled case types by local police units *(Polsek)*, as well as on authentic data collected directly from *Polsek* offices as the primary data source for model training and testing. These crime types are considered to represent the most common social problems in communities and require urgent response due to their direct impact on public safety and order. By focusing the classification on these five types of cases, the chatbot system is expected to serve as an interactive tool that streamlines the digital recording and classification of reports. Moreover, the system is also expected to reduce the workload of police officers in sorting reports, thereby allowing time and resources to be allocated more effectively to more complex cases. Through systematic and data-driven classification, law enforcement authorities will also find it easier to identify crime patterns and formulate more targeted countermeasures.

Methodology

This study employs a quantitative approach using an experimental method based on text classification to develop a chatbot system for classifying public complaint reports related to social crimes. The object of this study is public complaint report data collected directly from the East Denpasar Police Sector *(Polsek Denpasar Timur)*, along with secondary data obtained through web scraping techniques from the LAPOR website and social media platform X. The initial dataset consisted of 250 reports, which was expanded to 6,250 reports using synonym-based data augmentation techniques to enrich sentence variation.

The research process involves several key stages: data collection, text cleaning and preprocessing (including normalization, punctuation removal, stopword removal, and case folding), manual labeling based on five crime categories (theft, assault, fraud, domestic violence, and murder), and tokenization using the IndoBERT tokenizer. The data was divided into several training scenarios, namely 60:20:20 and 70:20:10 used in the phases of training, validation, and evaluation respectively. The model used is IndoBERT, fine-tuned using the Hugging Face Transformers library.

IndoBERT is a Transformer-based language model that has undergone a pre-training phase using a large Indonesian text corpus from multiple sources such as news articles, social media, and encyclopedias. During the pre-training stage, IndoBERT was trained in an unsupervised manner with objectives like masked language modeling (MLM) and next sentence prediction (NSP), based on the BERT model architecture introduced by Devlin et al. [18] and utilizing the Transformer mechanism proposed by Vaswani et al. [19]. This approach enables IndoBERT to learn general language representations specific to Indonesian. In this study, the pre-trained

IndoBERT model was then fine-tuned on a labeled dataset consisting of public complaint reports related to social crimes. Fine-tuning involved supervised learning where the model parameters were updated using a smaller, task-specific dataset categorized into theft, assault, embezzlement, domestic violence, and murder. This adaptation process allows IndoBERT to specialize in understanding the linguistic characteristics and context patterns present in community crime reports, improving its performance in the classification task within the chatbot system. The dataset consisted of complaint reports written in Indonesian, each represented as a single paragraph of natural language text. Each report was manually labeled with one or more crime categories depending on its content. The five categories used were theft, assault, embezzlement, domestic violence, and murder. Each record in the dataset includes the report text and a list of target labels, enabling the use of multi-label classification methods. This approach aligns with recent studies that highlight the effectiveness of multi-label classification models, particularly for classifying complaint data involving overlapping categories [20].

Evaluation was conducted using including metrics like accuracy, precision, recall, F1-score, and the confusion matrix. An additional evaluation was conducted an evaluation was conducted to measure the model's effectiveness for each individual category and detect potential misclassifications. The most accurate model was subsequently implemented within a Telegram-based chatbot, developed using Python and the python-telegram-bot library, and tested for its ability to classify text-based reports in real time. The research workflow is illustrated in Figure 1.

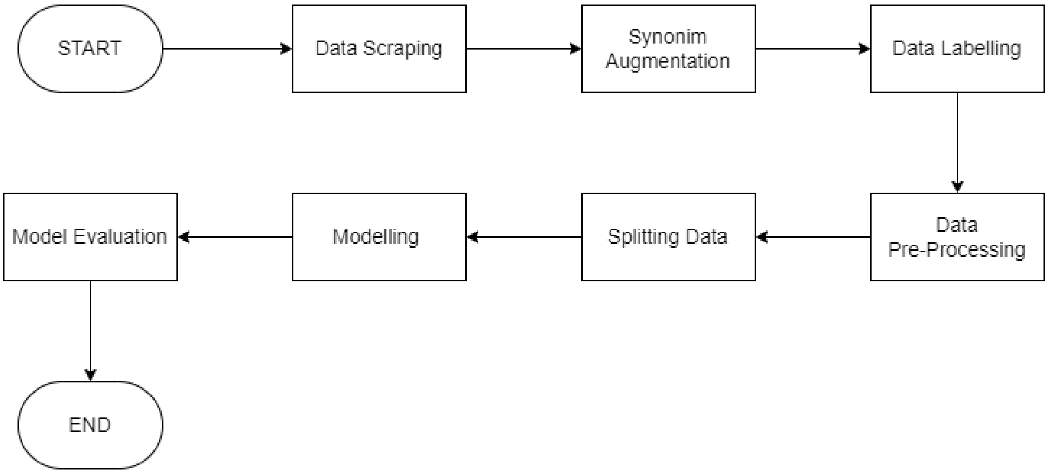


Figure 1. Research Workflow

Data collection is the initial stage carried out to obtain relevant and high-quality information from various sources for the purposes of analysis, decision-making, or research. This is followed by the synonym augmentation process, which increases the number of public report datasets. After the synonym augmentation process, the data is then subjected to labeling. Dataset labeling is the process of assigning labels or categories to each collected report dataset based on specific characteristics, to help the model understand the patterns and relationships between the input data and the corresponding expected outcomes. The labeled data then undergoes data preprocessing was carried out to cleanse, reformat, and ready the data for subsequent analysis. After preprocessing, the dataset was split into training, validation, and testing segments. The model is built and optimized using the training dataset so that it can learn and identify patterns in order to perform classification tasks Validation data serves the purpose of utilized to fine-tune the model and ensure proper learning in the process is valid, clean, and appropriate. The testing dataset serves to measure the model's ability to generalize to new, previously unobserved data, to determine how well it can classify data it has never seen before. Next, modeling is carried out using the IndoBERT algorithm, and finally, the model was assessed using standard evaluation metrics such as accuracy, precision, recall, and the F1-score. The modeling workflow of this study is illustrated Figure 2 below.

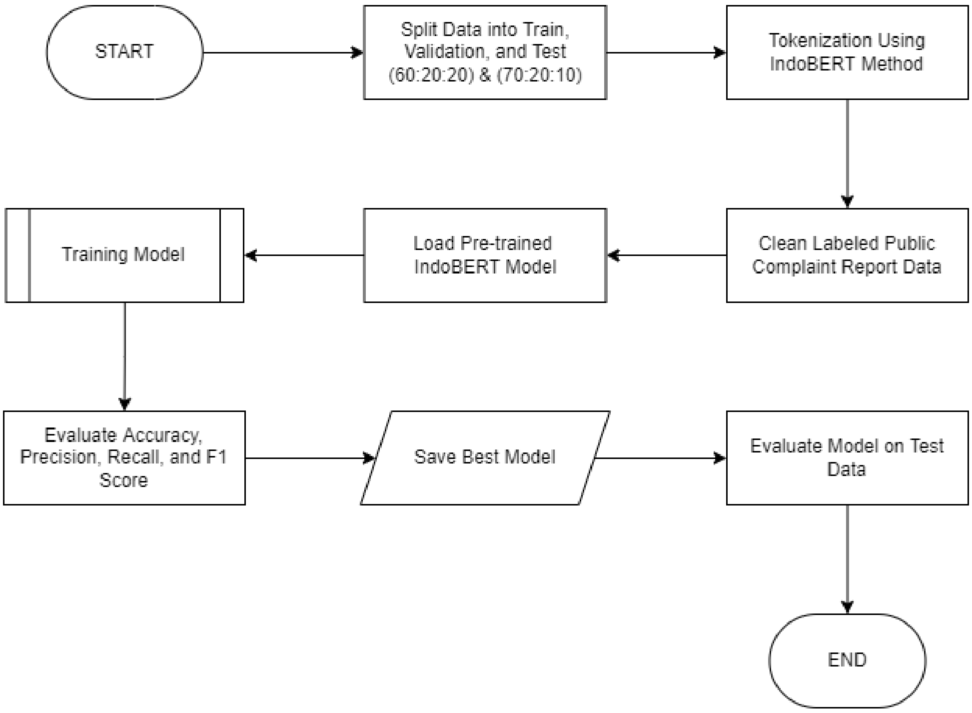


Figure 2. Modeling Workflow

Results and Discussions

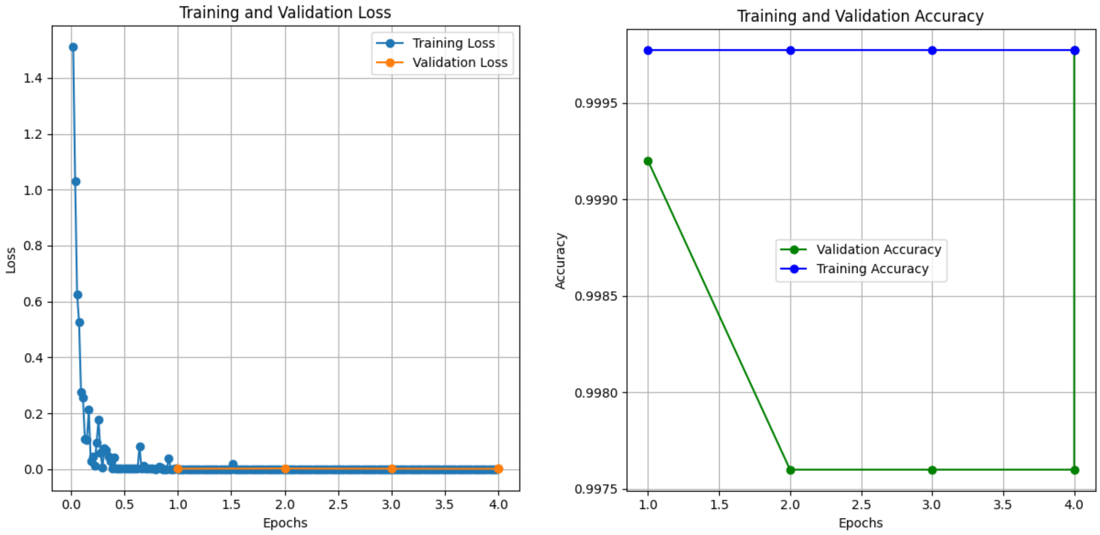
Results

The training outcomes suggest that the best-performing model was obtained through data augmentation techniques, the dataset was partitioned into 70% for training, 20% for validation, and 10% for testing. This proportion combination yielded optimal model performance, allowing the model to efficiently extract patterns from the training data, adjust its parameters through validation, and evaluate its accuracy using previously unseen test data. A summary of the training outcomes can be found in Table 1.

Table 1. Evaluation metrics results of the IndoBERT Model 70:20:10 scenario

Epoch	Training Loss	Validation Loss	Accuracy	Precision	Recall	F1
1	0.0015	0.001824	0.9992	0.999203	0.9992	0.9992
2	0.0002	0.002654	0.9992	0.999203	0.9992	0.9992
3	0.0001	0.001763	0.9992	0.999203	0.9992	0.9992
4	0.0001	0.001591	0.9992	0.999203	0.9992	0.9992

The results through the adaptation phase of IndoBERT to the specific task using the 70:20:10 scenario demonstrate the best performance. The training results table shows that the training loss remained within two decimal places and consistently decreased, it shows that the model performs well in recognizing and sorting different types of data. Meanwhile, the validation loss also remained stable at a relatively low value. A modest gain was recorded during epoch two, the validation loss continued to decrease consistently afterward. These outcomes demonstrate that the model is effective in differentiating among types of reports namely theft, assault, fraud, domestic violence, and murder with performance metrics as follows: accuracy 0.999200, precision 0.999203, recall 0.999200, and F1-score 0.999200.



(a) (b)

Figure 3. (a) Training and validation loss (b) Training and validation accuracy

Figure 3 (a) illustrates the changes in training loss and validation loss throughout the refinement phase of the model IndoBERT model using the 70:20:10 data split scenario. The visualization reveals a notable decrease in loss during the early stages of training, followed by a gradual stabilization at a lower value. This indicates that the model successfully Was able to extract meaningful features from the data and did not experience excessive overfitting.

Figure 3 (b) presents the graph of changes in training accuracy and as well as performance on validation samples during the increasing number of epochs. This graph depicts the improvement in model performance during training, where the accuracy values gradually increased and eventually stabilized. The stability of the high accuracy values demonstrates that the fine-tuned model using the 70:20:10 split scenario is capable of demonstrating effectiveness in handling data not seen during training.

The model's effectiveness was assessed using several evaluation indicators, including commonly used metrics like accuracy, precision, recall, and the F1-score. Accuracy is not sufficient to test the classification accuracy. Therefore, precision, recall, and F1-score offer more comprehensive insights additional information for classifying report types. Precision refers to The proportion of correctly predicted positives relative to all instances predicted as positive within a specific class, recall measures how well the model detects the correct class, and the F1-score serves as a harmonic mean that balances both precision and recall. Table 2 summarizes the results derived from these performance indicators.

Table 2. Evaluation metrics results of the IndoBERT Model for the 70:20:10 scenario

Class	Precision	Recall	F1-score
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00

Through the Confusion Matrix, it is possible to observe how the model classifies each category in the dataset, including the number of correct predictions and classification errors that occur. The high performance of IndoBERT in classifying community crime reports is attributed to several factors. First, IndoBERT is a Transformer model that has been specifically trained using a large and diverse Indonesian-language text corpus, making it more contextual in understanding local sentence structures. Second, the fine-tuning technique used in this study was tailored to the specific context of crime reports, including the selection of an appropriate tokenizer. Third, The use of synonym-based augmentation contributes to enhancing the variety within the training dataset without altering its meaning, thus improving the model's capability to generalize when processing unseen or novel reports.

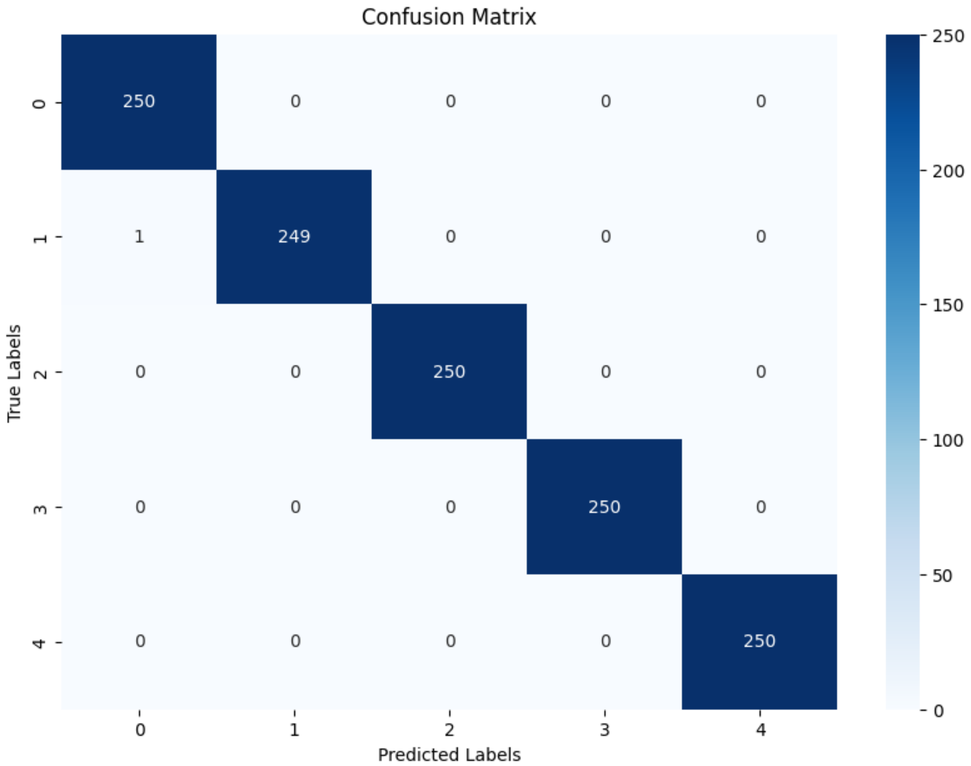


Figure 4. Confusion matrix

The Confusion Matrix derived from the fine-tuning evaluation stage IndoBERT model using a data partitioning scheme consisting of 70% for training purposes, 20% for validation, and the remaining 10% for testing. The distribution of predicted versus actual classes is visualized through the Confusion Matrix, where the True Labels axis represents the true classes of the data, and the Predicted Labels axis shows the predictions made by the model. Elevated values along the matrix diagonal signify that the model achieved reliable classification performance, while values outside the diagonal show the number of classification errors that occurred.

Based on the Confusion Matrix displayed in Figure 4, the model demonstrates a very accurate prediction distribution with perfect diagonal values, indicating no classification errors in the test data. However, when tested with new, more varied data (such as reports written in informal language styles or reports that do not explicitly mention the crime object), there were some cases where the model could only recognize one class, even though the report should belong to two classes. This suggests that the model is still sensitive to sentence structures or certain terms that are dominantly present in the training data. For example, reports containing words like "attacked" and "lost wallet" were sometimes classified only as abuse, without detecting the theft component. This highlights the importance of further training with multi-label reports and more diverse language variations. However, the dataset used in this study has limitations in covering the complexity of sentence structures and more diverse report contexts, which impacts classification accuracy in certain cases involving more than one type of crime. Table 3 below provides two examples of the public complaint reports used in this study, along with their corresponding crime category labels.

Table 3. Examples of the public complaint reports used in this study

Epoch	Training Loss
I was attacked and my phone was taken while walking home.	Theft, Assault
My neighbor secretly took the TV when I wasn't home.	Theft, Embezzlement

These samples illustrate the type of natural language input typically processed by the chatbot, consisting of narrative complaint reports submitted by the public. The classification system utilizes a multi-label approach to account for the possibility of overlapping or co-occurring crime categories within a single report. This allows the model to accurately reflect the complexity of real-world complaints, where one incident may involve more than one type of crime.

(a) (b)

Figure 5. (a) Complete report (b) Incomplete report

Figure 5 (a) above shows the interface of the crime complaint chatbot developed in this study. The user starts the interaction with the chatbot by pressing the 'Start Bot' or 'Help' button. After that, the chatbot provides instructions to the user to submit a complaint related to the crime they experienced. The user then sends a report in the form of a narrative that includes important information such as the time of the incident, location, perpetrator's identity (if known), and the modus operandi of the crime. After receiving the report, the chatbot asks for confirmation from the user regarding the completeness of the information provided, with options 'Complete' or 'Incomplete.' If the user confirms that the report is complete, the chatbot will process the report and classify it into the appropriate category based on natural language processing (NLP) analysis. In this example, the chatbot successfully identified the report as a 'Theft' case. After the classification process, the chatbot displays a confirmation message that the report has been successfully recorded and provides the contact information of the police officer responsible for the case.

Figure 5 (b) above shows the interface of the crime complaint chatbot developed in this study. The user starts the interaction with the chatbot by greeting or directly submitting a complaint related to the crime they experienced. In this example, the user reports a theft case that occurred at an electronics store on March 11, 2024, providing a detailed chronology of the incident, including the identity of the perpetrator and the modus operandi used. After receiving the report, the chatbot asks the user if the information provided is complete or if there is additional information that needs to be submitted. The user is given the option to select 'Complete' or 'Incomplete.' If the user selects the incomplete option, they are prompted to add additional information, and the chatbot will record it to improve the accuracy of the report. Once the report is confirmed to be complete, the chatbot classifies the reported crime type using natural language processing (NLP) technology. In this example, the chatbot identifies the report as both a 'Theft' and 'Embezzlement' case.

The figure illustrates that the model is able to classifies based on the text input by the user. The model performs classification using the previously trained IndoBERT model, as shown in the first report. For example, words like 'secretly,' 'without permission,' and 'checked' become strong indicators for classifying the report into the 'Embezzlement' class. The report also contains terms such as 'lost' and 'took the phone' which help the model identify that the input report should be classified under the 'Theft' class. Therefore, in this case, the report is classified into two classes: theft and embezzlement. The report is classified into two classes because the probability values generated from the classification process show that these two classes have the highest probability values, while the next class has a 10% probability difference from the highest class, thus the report is classified into both classes.

Discussions

The Telegram-based chatbot developed in this study is designed to automatically classify various types of community crime complaint reports. The classification model based on natural language processing (NLP) enables the chatbot to understand and automatically group reports into predetermined crime categories exhibiting exceptional accuracy in its predictions. The application of this technology is intended to improve the efficiency of handling complaints and to support law enforcement agencies in analyzing patterns of social crimes. Evaluation results show that the chatbot is able to respond quickly and accurately, achieve a strong level of precision when categorizing the reports. The interface of the developed chatbot is displayed in the figure above, showing how users can submit reports and receive classification results automatically.

For comparison, previous research conducted by Nanda et al. [21] on text classification using Support Vector Machine (SVM) achieved a model accuracy of 88%. Meanwhile, the fine-tuned IndoBERT model in this study achieved an accuracy of up to 0.9992. By utilizing a natural language processing (NLP)-based classification model, the chatbot is able to understand and group reports according to the predefined categories. Evaluation results show that the chatbot is able to respond quickly and accurately, with a high level of accuracy in classifying reports. These results align with the findings from Nanda et al. [21] which show that Transformer-based models provide more stable results in the context of non-English text classification compared to conventional machine learning-based models.

Moreover, while IndoBERT has proven to be highly effective in processing the given dataset, future enhancements should focus on refining the model to handle more complex or ambiguous sentence structures that may emerge in real-world applications. This could be achieved by training the model with a broader range of text data, ensuring that it is equipped to manage a variety of language styles and tones that are commonly used in informal crime reports. Additionally, the integration of real-time language models and dynamic updates to the system can further enhance the chatbot's capability to remain relevant as language and crime reporting evolve.

Conclusion

This study successfully developed a chatbot using the IndoBERT model to classify public complaint reports into five crime categories. The system achieved excellent performance metrics, with accuracy, precision, recall, and F1-score reaching 0.9992. By integrating NLP and data augmentation, the chatbot can automate the classification process and support law enforcement agencies in handling social crime reports efficiently. Future improvements include expanding the dataset, improving multi-label capabilities, and integrating with official police systems.

Acknowledgments
The author gratefully acknowledges the support and contributions from all parties involved in the completion of this article. Particular thanks are expressed to Dr. Eng I Made Agus Dwi Suarjaya, S.T., M.Eng., and I Nyoman Prayana Trisna, S.Kom., M.Cs., for their guidance and input throughout the research process.

References
[1] Nurfadilah Syawal Ibraya, Sam'un Mukramin, and Fatimah Azis, "Penanggulangan Kriminalitas di Desa Cikoang Kec. Mangarabombang Kab.Takalar," *TOBA: Journal of Tourism, Hospitality and Destination*, vol. 2, no. 2, pp. 24–29, May 2023, doi: 10.55123/toba.v2i2.2259.
[2] M. Sochib, S. Setiyono, and I. Indrawati, "Penanganan Laporan Pengaduan Masyarakat terhadap Proses Penyidikan Polri di Tingkat Polres dan Polsek," *MLJ Merdeka Law Journal*, vol. 1, no. 1, pp. 40–50, Mar. 2020, doi: 10.26905/mlj.v1i1.4292.
[3] S. S. M. I. K. D. P. P. SST. , M. E. K. K. R. D. S. ST. N. S. S. Tr. S. Hendry Syaputra, "statistik-kriminal-2024," 2024.
[4] Ahkmad Pancarudin, "Pengaruh Citra Kepolisian Dan Pelayanan Terhadap Kepuasan Masyarakat Pada Polres Metro," 2019.
[5] H. Daniel, R. Sarwono, A. B. Gunawan, and B. Pratama, "Arsitektur Sistem Chatbot untuk Penyelesaian Sengketa Daring pada Divisi Profesi dan Pengamanan Kepolisian Negara Republik Indonesia," vol. 20, no. 1, pp. 270–277, 2022.
[6] Swapna Marrivagu and Aruna Rao S, "Artificial Intelligence For Legal Chatbot," 2024.
[7] M. N. Hidayat and R. Pramudita, "Analisis Sentimen Terhadap Pembelajaran Secara Daring Pasca Pandemi Covid-19 Menggunakan Metode IndoBERT," *Information Management for Educators and Professionals*, vol. 8, no. 2, pp. 161–170, 2023.
[8] I. Abri Oktariansyah, F. Rakhmat Umbara, and F. Kasyidi, "Klasifikasi Sentimen Untuk Mengetahui Kecenderungan Politik Pengguna X Pada Calon Presiden Indonesia 2024 Menggunakan Metode IndoBert," *Technology and Science (BITS)*, vol. 6, no. 2, 2024, doi: 10.47065/bits.v6i2.5435.
[9] R. A. Fitrianto and A. S. Editya, "Klasifikasi Tweet Sarkasme Pada Platform X Menggunakan Bidirectional Encoder Representations from Transformers," *Jurnal Teknologi Dan Sistem Informasi Bisnis*, vol. 6, no. 3, pp. 366–371, Jul. 2024, doi: 10.47233/jteksis.v6i3.1344.
[10] N. Latifah, R. Dwiyansaputra, and G. S. Nugraha, "Multiclass Text Classification of Indonesian Short Message Service (SMS) Spam using Deep Learning Method and Easy Data Augmentation," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 23, no. 3, pp. 663–676, Jun. 2024, doi: 10.30812/matrik.v23i3.3835.
[11] U. Khairani, V. Mutiawani, and H. Ahmadian, "Pengaruh Tahapan Preprocessing Terhadap Model Indobert Dan Indobertweet Untuk Mendeteksi Emosi Pada Komentar Akun Berita Instagram," *Jurnal Teknologi Informasi dan Ilmu Komputer*, vol. 11, no. 4, pp. 887–894, Aug. 2024, doi: 10.25126/jtiik.1148315.
[12] P. F. Supriyadi and Y. Sibaroni, "Xiaomi Smartphone Sentiment Analysis on Twitter Social Media Using IndoBERT," *Jurnal Riset Komputer)*, vol. 10, no. 1, pp. 2407–389, 2023, doi: 10.30865/jurikom.v10i1.5540.
[13] A. Prabowo and F. Indra Sanjaya, "Penerapan Metode Transfer Learning Pada Indobert Untuk Analisis Sentimen Teks Bahasa Jawa Ngoko Lugu," *Simkom*, vol. 9, no. 2, pp. 205–217, Jul. 2024, doi: 10.51717/simkom.v9i2.478.
[14] B. Juarto, "International Journal of Intelligent Systems And Applications In Engineering Indonesian News Classification Using IndoBert," Feb. 2023. [Online]. Available: www.ijisae.org
[15] G. Z. Nabiilah, I. N. Alam, E. S. Purwanto, and M. F. Hidayat, "Indonesian multilabel classification using IndoBERT embedding and MBERT classification," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 1, pp. 1071–1078, Feb. 2024, doi: 10.11591/ijece.v14i1.pp1071-1078.

[16] A. S. Rizky and E. Y. Hidayat, "Emotion Classification in Indonesian Text Using IndoBERT," Feb. 2025.

[17] I. M. A. D. S. I. M. S. R. I Made Adhiarta Wikantyasaa, "Design and Building Mikrotik Based Billing System and Chatbot as Media Transaction Online I Made Adhiarta Wikantyasa a1 , I Made Agus Dwi Suarjaya a2 , I Made Sunia Raharja a3," 2021.

[18] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," Oct. 2018, [Online]. Available: http://arxiv.org/abs/1810.04805

[19] A. Vaswani *et al.*, "Attention Is All You Need," Jun. 2017, [Online]. Available: http://arxiv.org/abs/1706.03762

[20] N. K. Nissa and E. Yulianti, "Multi-label text classification of Indonesian customer reviews using bidirectional encoder representations from transformers language model," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 5, pp. 5641–5652, Oct. 2023, doi: 10.11591/ijece.v13i5.pp5641-5652.

[21] R. Nanda, E. Haerani, S. K. Gusti, and S. Ramadhani, "Klasifikasi Berita Menggunakan Metode Support Vector Machine," *Jurnal Nasional Komputasi dan Teknologi Informasi*, vol. 5, no. 2, 2022.