

Indonesian Hoax News Detection Using IndoBERT and Knowledge Graph

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Abstract

The spread of hoax news in Indonesian online media has become an increasing concern, highlighting the need for accurate automatic detection systems. This study proposes an integrated hoax detection approach that combines IndoBERT, which captures semantic context in Indonesian text, with a Knowledge Graph that verifies relationships between entities. IndoBERT's performance is also compared with SVM+TF-IDF, FastText, 1D-CNN, and LSTM. Experimental results show that IndoBERT achieves the highest performance, reaching 98.05% accuracy on headline data and 96.35% on narrative data using a dataset of 8,433 news articles. Although the Knowledge Graph alone produces lower accuracy, it enhances information verification by validating entity relationships. Integrating IndoBERT and the Knowledge Graph using a 90:10 weighting scheme further improves overall performance, achieving 98.00% accuracy on headline data and 96.20% on narrative data. The proposed approach provides a more accurate and comprehensive solution for Indonesian hoax detection.

A. Introduction

The development of information technology has significantly increased the dissemination of information through online media in Indonesia. The high penetration of the internet and social media usage has led to a growing public reliance on digital platforms as their primary source of information [1]. However, this condition is also accompanied by the rising spread of hoax news, which can cause disinformation, erode public trust, and impact social and political stability [2], [3].

The spread of hoax news presents a serious challenge because the public often faces difficulties in distinguishing between valid and invalid information. Manual verification processes are considered ineffective in dealing with the rapid flow of information; therefore, an automated system based on artificial intelligence is required to accurately detect and classify news [4].

Various studies have proposed hoax detection methods using machine learning and deep learning approaches, such as Support Vector Machine (SVM), FastText, Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) [2], [5]. Although these methods demonstrate relatively good performance, most approaches still focus on analyzing text patterns and have limitations in deeply understanding semantic context, while also lacking the capability to verify the factual truth of the information [4].

Transformer-based models like IndoBERT can significantly enhance the understanding of the Indonesian language context [6]. However, this model is still limited to text-based analysis and lacks a mechanism to verify the relationships between entities within the news. On the other hand, Knowledge Graphs are capable of representing entities and relations in a structured manner, allowing them to support fact-checking, yet they are less effective in understanding complex linguistic contexts [7], [8].

Based on these issues, this research proposes an integrated approach by combining IndoBERT and Knowledge Graph. This approach aims to leverage IndoBERT's strengths in understanding semantic context and the Knowledge Graph's ability to verify entity relationships, thereby producing a more accurate and comprehensive hoax detection system.

Although IndoBERT and Knowledge Graph have been widely used independently, there is still limited research that integrates both approaches for Indonesian hoax detection. This study introduces a hybrid framework that combines semantic understanding from IndoBERT with factual verification from a Knowledge Graph, enabling the system to not only classify text but also validate entity relationships.

B. Research Method

1. System Design

The proposed system consists of two primary components: a text-based classification model using IndoBERT and a relation-based verification system using Knowledge Graph. The system workflow begins with an input of news text (either headlines or narrative), followed by preprocessing to clean the data. Subsequently, the text is processed by the IndoBERT model to generate a classification prediction.

In parallel, entity extraction is performed on the text to establish relations within the Knowledge Graph. This graph is utilized to verify the relationships

between entities in the news. The outputs from both IndoBERT and the Knowledge Graph are then combined using a weighting scheme to produce the final decision. The architecture of this system is illustrated in Fig. 1.

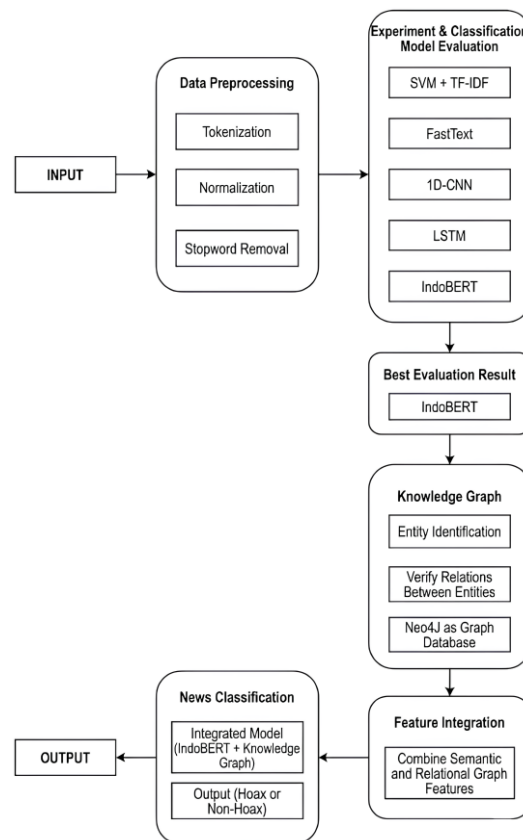


Figure 1. System Design

2. Dataset

The dataset used in this research consists of Indonesian news classified into two categories: valid news and hoax news. . The dataset was compiled from both publicly available datasets and self-collected data. Publicly available datasets were obtained from Kaggle, while additional news articles were collected by the authors through web scraping from several Indonesian online news portals to ensure source diversity and information quality. The labeling process is conducted manually based on verified sources. Valid news was obtained from Kompas and Detik, while hoax news was gathered from the TurnBackHoax platform. Additionally, a portion of the data from CNN Indonesia and Tempo was utilized as external test data to evaluate the model's generalization capabilities.

The average token length ranges from 10–20 tokens for headlines and 150–300 tokens for narrative content. This variation enables evaluation across different text complexities. The selected data sources are chosen due to their credibility, diversity, and relevance, ensuring that the dataset reflects real-world information distribution.

The dataset reflects real-world conditions, where hoax news tends to dominate in certain scenarios. The third dataset is intentionally imbalanced to

simulate real-world hoax distribution, while the fourth dataset represents large-scale balanced data for generalization evaluation. To comprehensively evaluate the model's performance, this study employs four dataset variations with different sizes and class distributions. These datasets are designed to test the model's ability under small, medium, and large data conditions, as well as on balanced and imbalanced class distributions. A summary of the characteristics of the datasets used in this study is shown in Table I.

Table 1. Dataset that Used

Dataset	Data Total	Valid News	Hoax News
1 st Dataset	1,269	767	502
2 nd Dataset	8,433	4,217	4,216
3 rd Dataset	16,864	4,217	12,467
4 th Dataset	18,066	8,967	9,099

Based on the data distribution, the 1st dataset and 2nd dataset have relatively balanced class compositions between valid and hoax news, thus they are used to evaluate the initial performance and stability of the model under ideal conditions. The 3rd dataset has an imbalanced distribution with a dominant number of hoax news, aiming to simulate real-world conditions where the proliferation of hoaxes is more prevalent than valid news. Meanwhile, the 4th dataset is the largest dataset with a balanced distribution, serving as the primary evaluation to measure the model's performance at scale. Regarding the objective, the 1st dataset serves as the initial baseline to observe the model's fundamental capabilities. The 2nd Dataset is used to test performance on a medium scale with a stable distribution. The 3rd dataset evaluates the model's robustness against data imbalance, while the 4th dataset assesses the model's generalization capability on a large dataset with a more representative distribution. These four datasets provide sufficient variation to evaluate the stability and generalization of the proposed models.

3. Preprocessing

The preprocessing steps include removing elements irrelevant to the classification process, such as URLs, mentions, and hashtags, which generally do not contribute to the semantic meaning of the text. Additionally, numbers, symbols, and non-alphabetic characters are removed to reduce noise and simplify text representation.

Following the cleaning process, whitespace normalization is performed to eliminate excessive spaces, ensuring text consistency. Subsequently, all text is converted to lowercase to avoid redundant representations of the same word. The output of this stage consists of cleaned and normalized text, which is then used as input for the classification models. The result of preprocessing is shown in Table II.

Table 2. Preprocessing

Before	After
Letter number 20198/HRD/PT Pertamina â€ ???	letter number hrd pt pertamina persero vi regarding an invitation to the recruitment selection process.

4. Classification Models

The selected models represent different approaches to text classification, including traditional machine learning (SVM + TF-IDF), embedding-based models (FastText), deep learning models (CNN and LSTM), and transformer-based models (IndoBERT).

SVM with TF-IDF is used as a baseline due to its stable performance in text classification. TF-IDF is configured with 5,000 features and unigram–bigram combinations. The model uses LinearSVC with probability calibration. Data is split 80:20 with stratification, and evaluated using accuracy, precision, recall, and F1-score. The trained model is saved for reuse.

FastText is used as a comparative model because it can handle sub-word information, making it robust to vocabulary variations and OOV words. The data is formatted into FastText labels and trained with supervised learning using 25 epochs and word n-grams up to bigrams. The embedding size is set to 100 with softmax loss for classification.

1D-CNN is applied to capture local patterns such as phrases commonly found in hoax news. The model consists of an embedding layer, Conv1D, global max pooling, and dense layers with dropout. Training is done with early stopping and checkpointing to avoid overfitting, and both model and tokenizer are saved.

LSTM is used to capture sequential context in text. The model uses a bidirectional LSTM to understand both forward and backward dependencies, followed by dropout and dense layers. Training is performed with stratified data splitting, early stopping, and Adam optimizer. Training is conducted for up to 10 epochs with a batch size of 64, supported by EarlyStopping and ModelCheckpoint. Both the model and tokenizer are saved for subsequent use.

As the primary model, IndoBERT, a pre-trained BERT-based model specifically designed for the Indonesian language. Several challenges are encountered during training, including class imbalance, token truncation due to the maximum sequence length (512 tokens), and potential overfitting. To address these issues, class weighting, early stopping, dropout, and gradient clipping are applied to stabilize the training process. The dataset is partitioned with an 80:20 ratio, where headlines and news content are concatenated to enrich the context. The model is trained using a fine-tuning approach with the AdamW optimizer (learning rate $2e-5$, weight decay 0.01), supported by a cosine scheduler, warmup steps, and gradient clipping. Training is conducted with a batch size of 8 for 1 to 5 epochs, incorporating early stopping. Evaluation is performed using accuracy, precision, recall, and F1-score, as well as a confusion matrix. The best-performing model and its tokenizer are serialized for future use.

5. Knowledge Graph

In this research, a Knowledge Graph (KG) is used to support fact verification by modeling relationships between entities in news text. The KG is stored in Neo4J, where entities are nodes and relations are edges, enabling relation-based verification to enhance hoax detection performance. Entities such as person, organization, location, and date are extracted using IndoBERT-based NER, with chunking applied for long texts. The extracted entities serve as the foundation for constructing the Knowledge Graph. Each identified entity is represented as a node, while the entity category assigned by the Named Entity Recognition (NER) model is used as the node label. In this study, the identified entities include Person (PER), Organization (ORG), Geopolitical Entity (GPE), Location (LOC), Date (DAT), Event (EVT), Product (PRD), and several other categories. These entities are subsequently used to establish semantic relationships during the entity relationship verification stage.

Table 3. Extracted Entities

id_berita	entity	label_ner	Meaning
0	<i>Selasa Maret</i>	DAT	Date
0	<i>Amerika Serikat</i>	GPE	Location
1	<i>Jim Chalmers</i>	PER	Person
1	<i>Pemilu</i>	EVT	Event

After the entity nodes have been constructed, the next step is entity relationship verification. This process aims to identify semantic relationships between pairs of entities extracted from the same news article. The relationships are generated using a combination of spaCy dependency parsing and manually defined rule-based patterns. Once identified, each relationship is stored in Neo4j as an edge connecting two corresponding nodes.

Table 4. Entity Relationships

a.name	type (r)	b.name	r.methods
<i>Indonesia</i>	<i>RELATED TO</i>	<i>Directorate General of Hajj and Umrah</i>	rule-based
<i>Jim Chalmers</i>	<i>WORKS_AT</i>	<i>Adelaide</i>	rule-based
<i>HAM</i>	<i>HAS_MEMBER</i>	<i>Erick</i>	rule-based
<i>Xiang Qiu</i>	<i>FROM</i>	<i>China</i>	rule-based

Table 3. presents a sample of entities extracted from the news dataset. The results indicate that a single news article may contain multiple entities belonging to different categories, such as persons, organizations, locations, and dates. Table 4 presents examples of entity relationships generated during the relationship verification process. The Source Entity and Target Entity columns indicate the connected nodes, while the Relationship column specifies the semantic relation identified using the rule-based approach.

C. Result and Discussion

1. Model Performance Comparison

This section evaluates the performance of several classification models, specifically SVM + TF-IDF, FastText, 1D-CNN, LSTM, and IndoBERT. Testing was

conducted across four dataset variations with different sizes and distributions, targeting both news headlines and narrative data. The performance comparison results for the headline data are presented in Table V.

Table 5. Model Performance Comparison on The News Headline Dataset
(Accuracy/F1-Score)

Model	1 st Dataset (%)	2 nd Dataset (%)	3 rd Dataset (%)	4 th Dataset (%)
<i>SVM + TF-IDF</i>	49.65 / 49.74	59.90 / 61.47	51.75 / 51.35	51.80 / 51.35
<i>FastText</i>	75.95 / 71.70	42.70 / 43.69	57.65 / 56.05	50.00 / 50.00
<i>1D-CNN</i>	48.45 / 48.80	50.60 / 65.50	48.40 / 44.68	50.90 / 52.32
<i>LSTM</i>	50.00 / 50.00	80.55 / 76.06	50.00 / 50.00	50.00 / 50.00
<i>IndoBERT</i>	64.30 / 61.88	98.05 / 99.02	66.30 / 79.74	25.50 / 27.80

Generally, IndoBERT demonstrates the most superior and consistent performance, achieving a peak accuracy of approximately 98.05% on headline data. This underscores its capability to understand semantic context with greater depth. The results of the model comparison are illustrated in Figure 2.

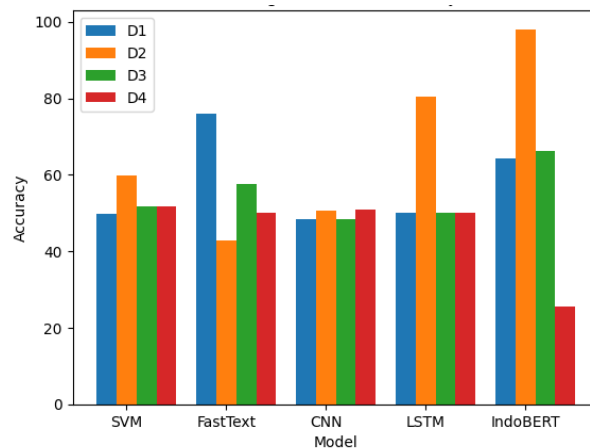


Figure 2. Comparison of Models in News Headline

Subsequently, the performance comparison results for the narrative data are presented in Table IV. Table VI indicates that the more comprehensive information contained within the narrative assists the models in understanding textual patterns more accurately.

Table 6. Model Performance Comparison on The News Narrative Dataset
(Accuracy / F1-Score)

Model	1 st Dataset (%)	2 nd Dataset (%)	3 rd Dataset (%)	4 th Dataset (%)
<i>SVM + TF-IDF</i>	52.10 / 51.58	69.90 / 82.03	96.95 / 94.60	69.20 / 81.71
<i>FastText</i>	53.90 / 52.97	79.40 / 88.25	94.05 / 96.20	97.15 / 95.86
<i>1D-CNN</i>	75.45 / 72.47	48.95 / 21.52	67.85 / 80.22	50.30 / 50.23
<i>LSTM</i>	56.40 / 54.87	86.90 / 82.89	49.45 / 0.00	88.35 / 84.57
<i>IndoBERT</i>	46.70 / 47.46	96.35 / 97.28	97.85 / 96.85	69.20 / 81.71

Generally, IndoBERT demonstrates the most superior and consistent performance, achieving a peak accuracy of approximately 96.35% on narrative data. This underscores its capability to understand semantic context with greater depth. The results of the model comparison are illustrated in Figure 3.

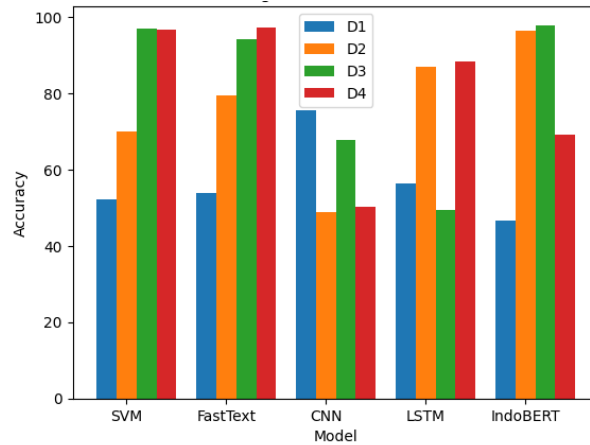


Figure 3. Comparison of Models in News Headline

2. Confusion Matrix Analysis

To provide a deeper evaluation, confusion matrix analysis is conducted. For narrative data, the model correctly classifies 983 valid news (True Negative) and 944 hoax news (True Positive), with only 17 False Positives and 56 False Negatives. These results indicate that the model achieves strong performance, with only a small number of misclassifications occurring in complex narrative cases.

Table 7. Confusion Matrix for IndoBERT (Headline Data)

	Predicted	
	Valid	Hoax
<i>Actual Valid</i>	1000	0
<i>Actual Hoax</i>	38	961

Table 8. Confusion Matrix for IndoBERT (Narrative Data)

	Predicted	
	Valid	Hoax
<i>Actual Valid</i>	983	17
<i>Actual Hoax</i>	56	944

These results indicate that the model achieves strong performance in distinguishing between hoax and valid news, with only a small number of misclassifications occurring in complex narrative cases.

3. Knowledge Graph Results

An evaluation of the Knowledge Graph is conducted to measure its capability in verifying entity relationships within the news. Testing was performed using several threshold values to determine the classification boundaries.

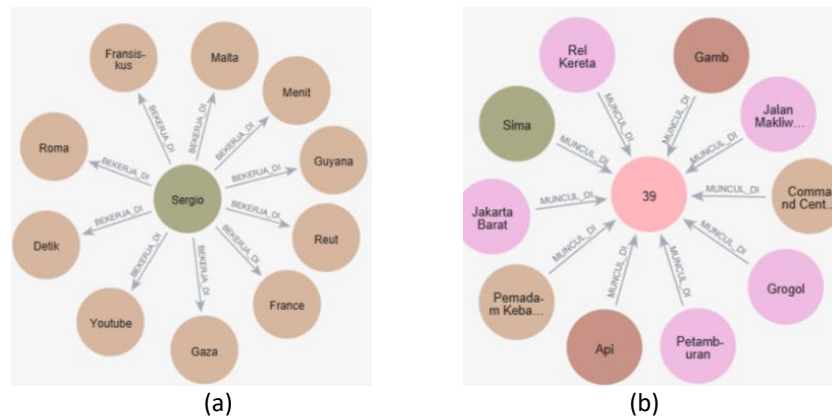


Figure 4. Knowledge Graph in Neo4J

As shown in Fig. 4, the Knowledge Graph represents entities (Person, Organization, Location, Date) as nodes and their relationships as edges. A rule-based approach is used to validate these relations, where inconsistencies increase the likelihood of hoax classification. The results in Table IX show that performance on headline data is relatively low, while narrative data achieves better results.

Table 9. Confusion Matrix for IndoBERT (Narrative Data)

Threshold	News Headlines		News Narrative	
	Accuracy	F1-Score	Accuracy	F1-Score
70	53.15	52.59	50.45	49.46
60	48.70	48.89	52.80	52.32
50	43.85	44.09	55.35	55.02
40	45.05	43.62	61.20	63.89
30	48.70	46.28	57.65	66.09

The results show that the threshold value strongly affects Knowledge Graph performance. A lower threshold improves hoax detection (higher recall) but can reduce overall accuracy, mainly due to limited entity extraction and difficulty capturing implicit relationships. In contrast, a higher threshold increases accuracy but lowers sensitivity to hoaxes. Therefore, selecting an appropriate threshold is crucial for balancing performance.

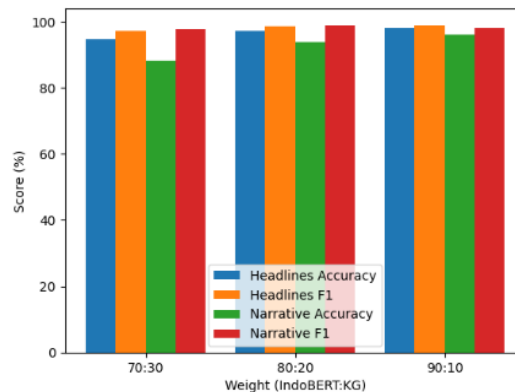


Figure 5. Knowledge Graph in Neo4J

Experimental results in Figure 5. show that KG performance is heavily influenced by the threshold value. For headline data, the highest accuracy was achieved at a threshold of 70, reaching 53.15%, with performance declining at lower thresholds. Conversely, on narrative data, the performance improved, with peak accuracy reaching 61.20% at a threshold of 40 and the best F1-score of 66.09% at a threshold of 30. This suggests that a lower threshold tends to enhance hoax detection capability (recall) but may compromise overall accuracy.

4. Integration Results of IndoBERT and Knowledge Graph

IndoBERT and the Knowledge Graph are integrated to enhance hoax detection accuracy by combining semantic and relational information. The Knowledge Graph score is calculated based on the number of successfully verified entity relationships, where a higher number of formed relations results in a higher score. Subsequently, the IndoBERT and Knowledge Graph scores are combined using a weighting method across three scenarios: 70:30, 80:20, and 90:10. The final score is obtained through a linear combination of both components. The evaluation results on headline and narrative data in Table VIII. demonstrate that all combinations yield high performance, with IndoBERT acting as the dominant component and the Knowledge Graph serving as a supporting element that helps improve accuracy.

Table 10. Integration Results of IndoBERT and Knowledge Graph

Weight (IndoBERT : KG)	News Headlines		News Narrative	
	Accuracy	F1-Score	Accuracy	F1-Score
70 : 30	94.75	97.30	88.20	97.73
80 : 20	97.20	98.58	93.85	98.83
90 : 10	98.00	98.99	96.20	98.06

Experimental results indicate that the integration of IndoBERT and Knowledge Graph effectively enhances system performance compared to using each method independently. IndoBERT plays a primary role in understanding the semantic context of the text, while the Knowledge Graph functions as an additional verification mechanism through entity relationships. Higher Knowledge Graph contributions tend to reduce overall accuracy due to its limited capability in handling complex linguistic structures. These results are illustrated in Figure 6.

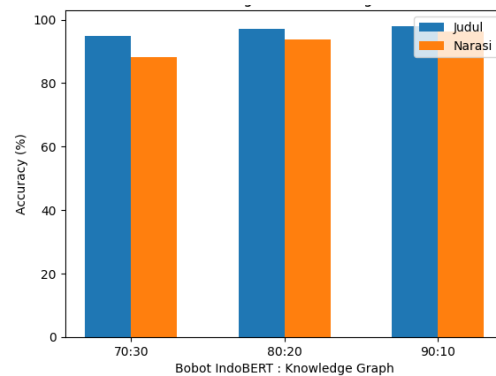


Figure 5. Knowledge Graph in Neo4J

5. Application

The implementation of the proposed system is realized as an Android-based mobile application. The application processes user input in the form of text, URL, or OCR-based images through a backend API. The input undergoes preprocessing before being analyzed using IndoBERT for semantic classification and a Knowledge Graph for relation-based verification. The final decision is obtained by combining both outputs using a 90:10 weighting scheme. The system then returns the classification result along with a confidence score to the user. The main interface of the application is shown in Figure 5, which serves as a navigation hub for users to access news detection features. An example of the news classification process using text input and its corresponding output is illustrated in Figure 6.

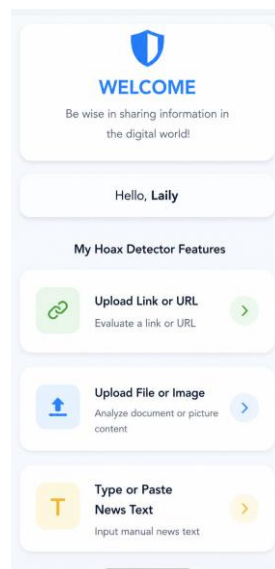


Figure 5. Application Home Page

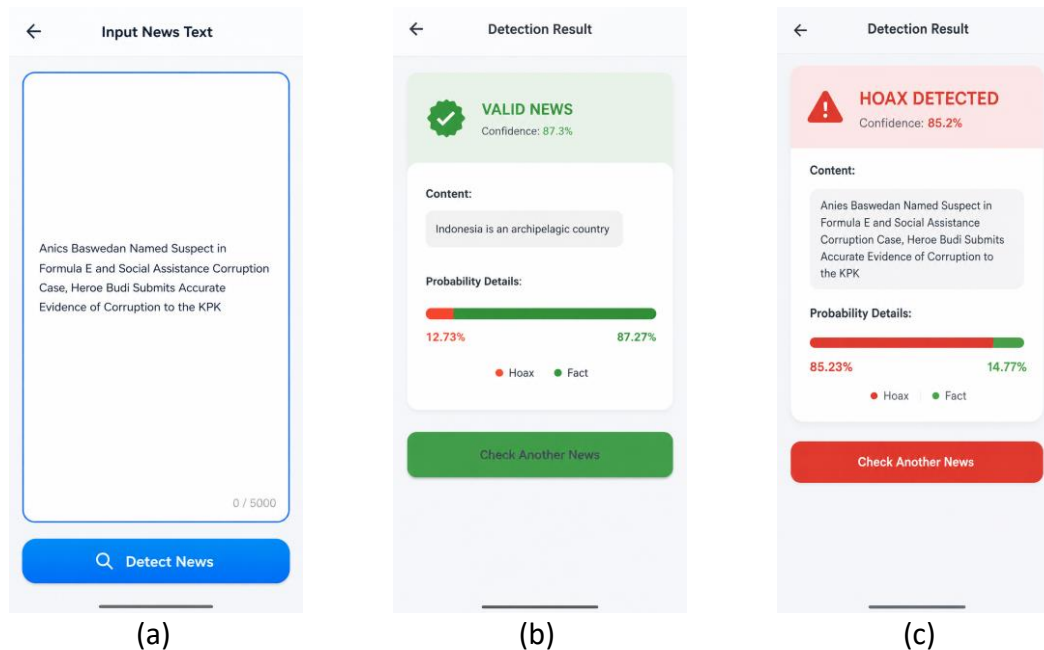


Figure 6. Input and Ouput Process in Appllication

D. Conclusion

This research demonstrates that the IndoBERT model provides the superior performance compared to other tested methods, such as SVM + TF-IDF, FastText, 1D-CNN, and LSTM. Its capability to comprehend the Indonesian language context in greater depth leads to more accurate classification results, in terms of both accuracy and F1-score. On the other hand, the constructed Knowledge Graph is also capable of verifying relationships between entities within news articles. Experimental results also show that Knowledge Graph performance is influenced by threshold values and data types, produce better results on data with clear information. When both approaches are integrated, the results show a performance improvement compared to using each method independently. IndoBERT plays a role in understanding the textual content, while the Knowledge Graph provides additional validation through entity relationships.

Future development could focus on enhancing the integration method between IndoBERT and the Knowledge Graph, for instance, by employing a more adaptive weighting approach to achieve optimal results. Furthermore, expanding the dataset and enriching the relations within the Knowledge Graph are essential to improve the system's ability to understand and verify information. Regarding implementation, the application can be further developed with more informative features to ensure that classification results are more easily understood by users.

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