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Development of an Intent-Classification Chatbot to Support Operational Services at Kadin Indonesia

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ABSTRACT

The digital transformation era demands business membership organizations such as the Indonesian Chamber of Commerce and Industry (Kadin) to provide responsive and scalable services. Operational inquiries related to the Certificate of Origin (COO), membership information (KTA), activity agendas, and administrative correspondence are still predominantly handled manually, resulting in service queues and limited operating hours. This study develops an intelligent text-based chatbot using Natural Language Processing (NLP) with an intent classification approach implemented through a Long Short-Term Memory (LSTM) model to automate initial responses to user queries. A labeled dataset consisting of more than 90 intents was constructed from Frequently Asked Questions (FAQ), Kadin service data, and data augmentation to increase text variation. The preprocessing pipeline includes normalization, tokenization, padding, and 300 dimensional FastText embeddings. The LSTM model, configured with 128 units, was trained using categorical cross-entropy with a label smoothing factor of 0.05, the Adam optimizer, a batch size of 20, and 80 epochs, and integrated into the backend for real-time inference. Evaluation on the test set achieved an accuracy of 92.08% and a Top-3 Accuracy of 96.23%. Visual analyses using the confusion matrix and accuracy–loss curves indicate strong generalization capability. These findings demonstrate that a properly configured LSTM model can effectively recognize service-related intents for Kadin.

INTRODUCTION

Based on the background and related research previously described, the Indonesian Chamber of Commerce and Industry (Kadin), as a public service organization, faces challenges in maintaining high-quality interactions with service users. Much of the information delivery process related to operational services such as inquiries on the Certificate of Origin (COO), membership status (KTA), and organizational activities still relies heavily on staff, limiting the speed, consistency, and availability of responses, especially during increased demand or outside formal working hours. This condition highlights a gap between the public's need for responsive services and the organization's current capacity to meet those expectations (Johnston et al., n.d.).

Meanwhile, the growing adoption of digital technologies has shifted public expectations toward services that are accessible at any time, interactive, and capable of providing context-appropriate responses. One potential solution is the implementation of Natural Language Processing (NLP) technologies through a chatbot system employing an intent classification approach. NLP enables machines to interpret human language despite substantial variations in vocabulary, structure, and usage patterns across user groups, making computational techniques essential for reliable text understanding (McRoy, 2021).

Given this context, the objective of this research is to design and implement a chatbot prototype powered by NLP with an intent classification approach using a Long Short-Term Memory (LSTM) model to support Kadin's operational services. The system is intended to automatically identify user intents, deliver relevant responses to recurring inquiries, and provide access to service information without time limitations. This research aims to enhance the efficiency of service information delivery, improve responsiveness, and strengthen the consistency of user interactions.

Beyond its practical benefits for the organization, this study is expected to contribute academically by reinforcing the literature on LSTM-based intent classification within public service contexts and by serving as a foundation for future developments in the application of artificial intelligence across various public service sectors in Indonesia.

LITERATURE REVIEW

Previous studies have demonstrated the widespread adoption of NLP-based chatbots across various public service and institutional domains, although each approach offers distinct strengths and limitations. A study on an LSTM-based customer service chatbot for PLN, for example, achieved an accuracy of 82.71%, indicating its potential to improve service efficiency (Rokhayadi et al., 2025). However, its scope remains limited to basic customer inquiries

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and does not fully address the complexity of operational services within large membership-based organizations.

Several other studies highlight the strong performance of LSTM in intent classification. Within university helpdesk environments, LSTM achieved perfect accuracy for Indonesian-language text due to its ability to retain long-term contextual information (Al Farisi et al., 2024). Similar results were found in the banking sector, where LSTM attained 100% accuracy in categorizing customer complaints at Bank Sumut (Pangaribuan et al., 2025). The combination of FastText and LSTM in student admission chatbots further demonstrated robust performance, reaching 90% accuracy (Yusron & Komarudin, n.d.). Nevertheless, these findings typically arise from relatively structured domains with narrower intent coverage, and therefore may not directly reflect the challenges present in large-scale public service organizations such as Kadin.

Conversely, BERT-based models have shown superior contextual understanding through bidirectional encoding and achieved high accuracy, including 98.7% in academic chatbot applications (Syallya et al., 2025). Despite these advantages, BERT requires substantial computational resources, making it less feasible for organizations with limited infrastructure (Peyton & Unnikrishnan, 2023). Traditional RNNs are also used for sequential data processing; however, they suffer from vanishing gradients and are less reliable when handling long sentences (Jiao, 2020).

Comparative studies involving SVM, CNN, LSTM, and other methods indicate that deep learning models generally outperform classical machine learning techniques such as Naïve Bayes and Random Forest (Assayed et al., 2023; Larson et al., 2019). However, many of these studies remain generic and do not focus specifically on the demands of public service environments, which require rapid, consistent, and 24/7 responsiveness. Approaches integrating NER, sentiment analysis, and intent classification also demonstrate promising results (Fairoose Abedin et al., 2021), yet these models require large and diverse datasets, which may not always be available in governmental or membership-based organizations.

Other literature highlights how NLP and deep learning have been successfully applied to structure large-scale conversational data, such as Facebook posts (TURBAN et al., 2021), while the evolution of chatbots from ELIZA to modern AI conversational systems illustrates significant advancements in conversational capabilities (Jurafsky & Martin, n.d.). Studies on LSTM-based cultural education chatbots achieved high accuracy up to 100% (Yuniati & Gurning, 2024), though the domain differs substantially from public operational services. Research on LSTM-based QnA chatbots similarly reports strong performance, yet results may vary depending on cross-validation techniques (Khatib Sulaiman Dalam No et al., n.d.). While BiLSTM models achieved 84.64% accuracy in government-related applications, their computational overhead may not align with Kadin's infrastructural constraints (Cahyadi et al., 2025).

Overall, the literature indicates that although various NLP approaches have demonstrated strong performance, there remains a notable gap in applying LSTM specifically to operational public services within organizations such as Kadin. This gap underscores the need for a chatbot solution that can accurately classify service-related intents, operate efficiently under limited computational resources, and support continuous service availability. Accordingly, this study positions LSTM as an optimal balance between high accuracy and operational feasibility for public service environments.

METHOD

This research adopts a combination of a naturalistic qualitative-descriptive approach, the Waterfall software development method, intent classification techniques, and the Long Short-Term Memory (LSTM) algorithm as the primary learning model. The qualitative approach is employed to understand Kadin's service interaction patterns in depth, while the Waterfall model is used to structure the system development stages sequentially. Intent classification is applied to categorize users' underlying question intents, and LSTM functions as a sequence-based predictive model.

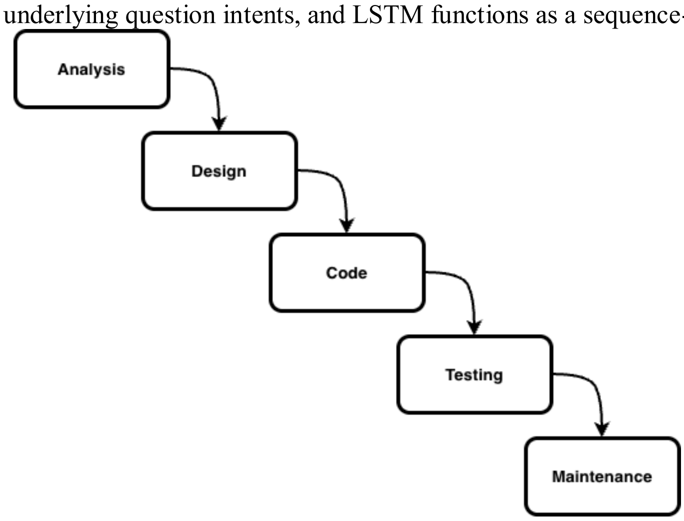

Fig. 1 Waterfall Method

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Figure 1 illustrates the Waterfall development model used as the methodological framework. The Waterfall method consists of sequential phases including requirements analysis, system design, implementation, testing, and maintenance, each of which must be completed and validated before progressing to the next stage (Li et al., 2022). As a conventional Software Development Life Cycle (SDLC) model, Waterfall is widely applied due to its sequential and predictive nature, emphasizing comprehensive documentation and strict process control (TURBAN et al., 2021). These characteristics ensure phase-to-phase consistency, structured risk management, and well-defined deliverables for each development stage (Pengembangan & Hartono MKom, n.d.).

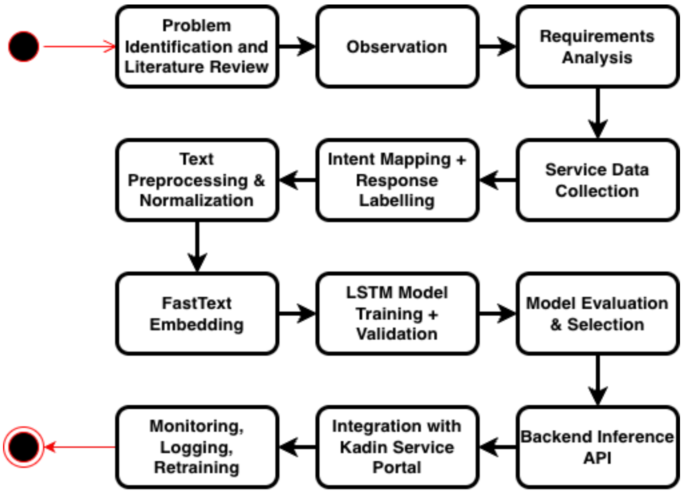

Fig. 2 Chatbot Development Pipeline

The pipeline illustrated in Figure 2 describes the customized chatbot development flow. The process begins with Problem Identification supported by literature review and direct observation to strengthen the Requirements Analysis. This is followed by Service Data Collection, Intent Mapping, and Response Labelling to construct the dataset. The dataset then undergoes Text Preprocessing and Normalization, followed by Word Representation using FastText Embedding. The LSTM model is subsequently trained and validated, followed by Evaluation and Selection of the Best Model. The selected model is integrated into the Backend Inference API and further deployed within Kadin's Service Portal. The final stage includes Monitoring, Logging, and Model Retraining to ensure long-term performance and improvement.

RESULT

Service Analysis and Scope Definition

The preliminary stage produced findings related to the identification of key service flows frequently accessed by Kadin users. Based on workflow observations and interviews with operational staff, data were collected on processes such as Certificate of Origin (COO) issuance, KTA membership, document legalization, and general inquiries regarding the Kadin portal. The needs analysis resulted in the identification of more than 90 primary intents, covering categories such as greetings, service fees, membership status, procedural guidance, and other operational details.

The system scope was limited to automated intent-based information delivery, excluding sensitive transactions such as payments and identity verification. This stage also finalized the integration direction with the LSTM inference API to enable real-time responses.

Intent - Response Dataset Construction and Labeling

Following the definition of classification as the process of assigning appropriate category labels to input data (Bird et al., 2009), the intent–response dataset was constructed using service information from FAQs, official documents, and expert interviews. The preparation process followed stages including solution identification, intent categorization, scope and abstraction definition, and lifecycle-based category maintenance (Li et al., 2022).

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```json
{
  "tag": "about_kadin",
  "patterns": ["Apa itu Kadin?","What is KADIN?","Kadin Indonesia organization info","Fungsi utama Kadin","Peran Kadin Indonesia",
  "Apa itu Kadin? kak","kak Fungsi utama Kadin","maaf mau tanya What is KADIN?","Kadin Indonesia organization info??","What is KADIN? ya",
  "Apa itu Kadin","halo Kadin Indonesia organization info","Peran Kadin Indonesia??"
  ],
  "responses": [
    "Kadin Indonesia adalah organisasi payung dunia usaha (besar-kecil; BUMN, swasta, koperasi) yang menjembatani kepentingan pengusaha dan
    pemerintah serta menyediakan layanan perdagangan dan dukungan bisnis."
  ]
}
```

Fig. 3 JSON Dataset Format

The dataset consists of user question patterns grouped under specific intents and paired with relevant responses. The final dataset contains more than 90 intents, each with 5–30 pattern variations. Several dataset files were produced:

- dataset_kadin_final.json (initial curated version),
- dataset_kadin_final_augmented.json (final version after augmentation).

All datasets were validated manually to ensure balanced intent distribution and the absence of duplicates.

Text Preprocessing, Normalization, and Augmentation

The preprocessing stage produced standardized text through lowercasing, symbol removal, and normalization. Tokenization was performed with an 8,000-word vocabulary limit and the addition of an <OOV> token for unknown words. Each pattern was converted into an indexed sequence with a maximum length of 20 tokens using padding and truncation.

Intent labels were transformed into one-hot representations, while class imbalance was addressed through oversampling and class weighting. The output files included condensed input sequences, tokenizer.json, and label_encoder_classes.npy as the encoded representation of final preprocessing results.

Word Representation and FastText Embedding

This stage produced a 300-dimensional embedding matrix generated using the pre-trained FastText model. Each token in the tokenized dataset was mapped into its corresponding FastText vector. FastText was selected due to its subword-based representation, which handles spelling variations and rare-word occurrences effectively.

Out-of-vocabulary tokens were initialized with random vectors, and the embedding matrix was set as trainable to allow adaptation to the Kadin service domain during training. The resulting output from this stage is an embedding matrix of size *(vocabulary_size, 300)*, which serves as the input to the LSTM layer.

LSTM Modeling for Intent Classification

The modeling stage produced an LSTM architecture designed to capture long-range dependencies in textual data, leveraging its gating mechanism to mitigate the vanishing gradient problem (Kulkarni & Shivananda, 2019). The model components include the input gate, forget gate, output gate, and memory cell, which regulate information updates and outputs at each time step.

The implemented architecture consists of a FastText 300-dimensional embedding layer, a single LSTM layer with 128 units, a pooling mechanism, and several ReLU-activated Dense layers, followed by a softmax output layer with neurons matching the number of intent classes. The model was trained using categorical crossentropy with label smoothing (0.05), the Adam optimizer with an initial learning rate of 0.001, and gradient clipping (5.0) to maintain training stability.

Training was conducted for 80 epochs with a batch size of 20, using early stopping and ReduceLROnPlateau to prevent overfitting.

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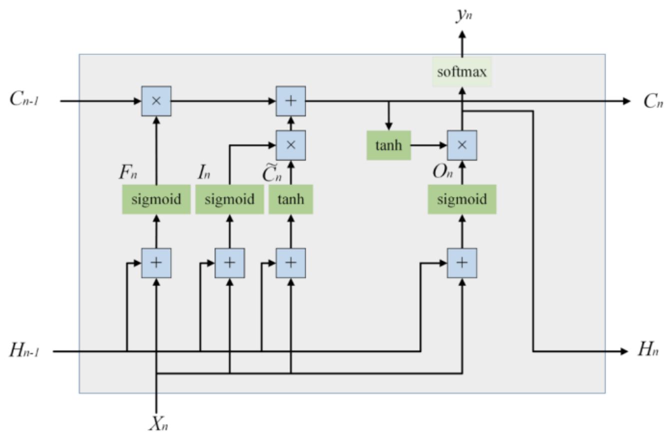

Fig. 4 LSTM Structure (Liu et al., 2021)

The LSTM cell mechanism (Figure 4) produced internal computations involving the forget gate, input gate, and output gate, which determine the update of the cell state (C_t) and hidden state (h_t) through nonlinear sigmoid and tanh transformations (Goodfellow et al., n.d.). These mechanisms allow the model to retain relevant contextual information while discarding less important content.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$
$$C_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$
$$C_t = f_t * C_{t-1} + i_t * C_t \quad (4)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$
$$h_t = o_t * tanh\,(C_t) \quad (6)$$

Table 1. Hyperparameter Configuration

Parameter	Values
Hidden Layer Unit	128
Window Size	20
Batch Size	20
Epoch	80
Learning Rate	0,001
Dropout	0,25 - 0.45
Optimizer	Adam (clipnorm=5,0)
Loss Function	Categorical Crossentropy (Label Smoothing 0.05)
Embedding	FastText 300-dim
Class Weight	Balanced

Table 1 presents the hyperparameter configuration. The LSTM layer size (128 units) was selected due to its proven effectiveness in text classification (Cahyadi et al., 2025). The batch size of 20 follows common practices in deep learning–based intent classification studies (Al Farisi et al., 2024; Pangaribuan et al., 2025). Adam with clipnorm 5.0 was chosen for its convergence efficiency and stability (Jiao, 2020; Yusron & Komarudin, n.d.), while the initial learning rate of 0.001 follows recommended settings for this task (Yuniati & Gurning, 2024). Dropout values between 0.25–0.45 were applied as a regularization strategy to reduce overfitting (Rokhayadi et al., 2025).

The 300-dimensional FastText embeddings were selected due to their robustness in handling OOV terms and Indonesian morphological variations, which has been validated in similar FastText-LSTM chatbot applications (Fairoose Abedin et al., 2021; Larson et al., 2019). These combined configurations enabled the LSTM model to identify user intents within Kadin's operational services with high consistency and accuracy.

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Model Evaluation and Selection

Table 2. LSTM Model Evaluation Results

Relationships	Values
Test Accuracy	92.08%
Top-3 Accuracy	96.23%
Coverage (Threshold = 0.5)	92.83%
Accuracy within Coverage (0.5)	97.15%
Learning Rate	0.001
Dropout	0.25 - 0.45
Optimizer	Adam (clipnorm = 5.0)
Loss Function	Categorical Crossentropy (Label Smoothing 0.05)
Embedding	FastText 300-dim
Class Weight	Balanced

Model evaluation was conducted by comparing predictions on the test dataset with the true labels using accuracy, precision, recall, and f1-score metrics. This stage is part of the *Model Evaluation and Best Model Selection* process within the development pipeline. In addition, *Top-k Accuracy* analysis (k = 3 and 5) and coverage metrics were performed to assess prediction reliability when considering results with high confidence levels.

The evaluation results show that the LSTM model achieved a test accuracy of 92.08%, with a Top-3 Accuracy of 96.23%. Furthermore, the coverage metrics at confidence thresholds of 0.5, 0.6, and 0.7 were 92.83%, 91.32%, and 88.30%, respectively, with in-coverage accuracies of 97.15%, 97.93%, and 98.72%. For visual analysis, the confusion matrix and accuracy–loss curves are included. Figure 4 illustrates the model's prediction distribution across intent classes, while Figures 5 and 6 show the trends in training and validation accuracy and loss across 80 training epochs.

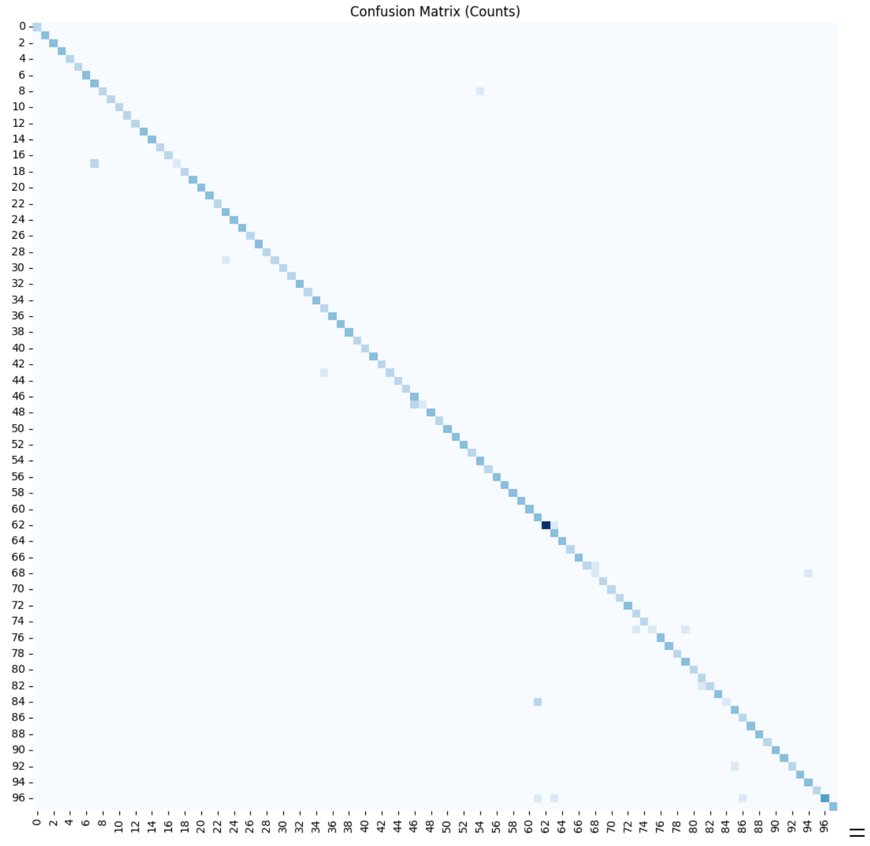

Fig. 5 Confusion Matrix LSTM

Figure 5 shows that most intent classes are correctly predicted by the model, as indicated by the dominance of diagonal values in the confusion matrix. However, several misclassifications are present, especially for intents with fewer training samples or those with patterns similar to other intents. This highlights the importance of maintaining balanced data distribution across intents and applying data augmentation to help the model better distinguish minor

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variations in sentence patterns. These observations serve as a reference for improving dataset strategies in future development.

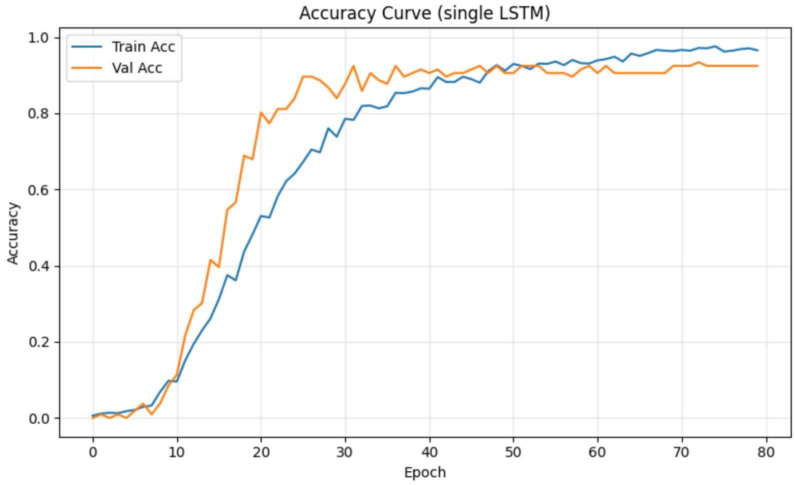

Fig. 6 Accuracy Curve LSTM

The accuracy curve in Figure 6 demonstrates that the model's performance increased significantly during the early training phase, with steady accuracy gains until around epoch 60. After this point, the curve plateaus, indicating the model has reached convergence. This trend suggests the effectiveness of training parameters such as learning rate, LSTM unit size, and early stopping in preventing overfitting. The analysis further indicates that the chosen hyperparameter configuration is sufficiently optimal to maintain a balance between accuracy and generalization.

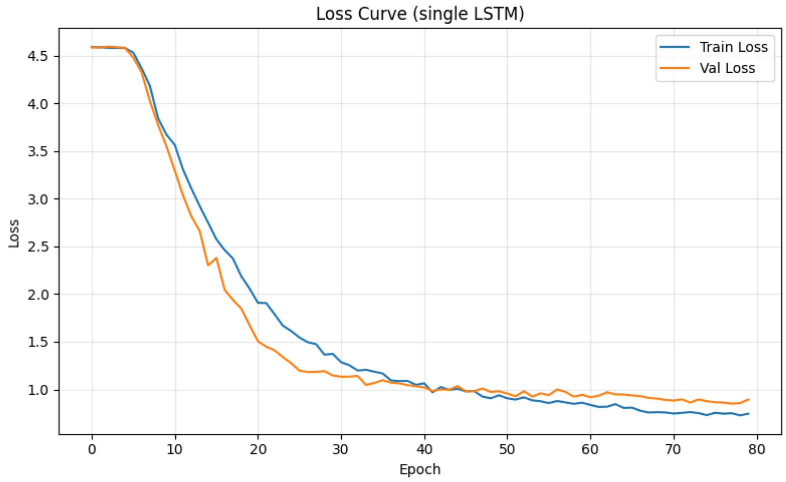

Fig. 7 Loss Curve LSTM

Figure 7 shows that the loss trend for both training and validation data decreases steadily as epochs progress, with a relatively small gap between the two curves. This indicates that the model does not suffer from significant overfitting, as its validation performance closely follows its training behavior. The *generalization gap* remains below the 15% threshold, suggesting that the model demonstrates good generalization capability. This pattern also reflects the success of regularization strategies such as dropout, label smoothing, and class weight balancing in preventing the model from becoming overly biased toward training data.

Chatbot Application Implementation

The chatbot workflow begins when a user inputs a question through the chatbot's user interface (UI). The input text is sent to the backend system integrated with the LSTM model. The backend carries out text preprocessing, intent classification using the model, and mapping the predicted intent to the appropriate response — whether static information, procedural guidance, or a fallback if the intent is not recognized.

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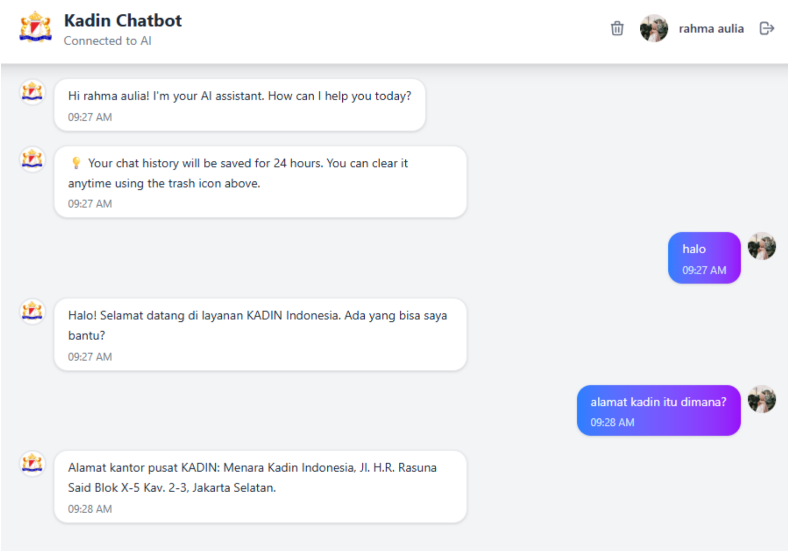

Fig. 8 Chatbot Interface

Figure 8 illustrates the chatbot interface designed to facilitate natural-language communication. Through this interface, users can interact directly with the system, receive responses within seconds, and access information related to Kadin services without navigating manual procedures. With a simple yet functional design, the chatbot aims to enhance service efficiency, shorten response times, and extend information accessibility beyond operational hours. This workflow demonstrates how the UI, backend API, and LSTM model integrate seamlessly to deliver an optimal user experience.

DISCUSSION

The experimental results demonstrate that the proposed LSTM-based intent classification model performs effectively in identifying user queries related to Kadin's operational services. An overall test accuracy of 92.08% and a Top-3 Accuracy of 96.23% indicate that the model can reliably distinguish among more than 90 intent classes with varying linguistic patterns. These results are consistent with findings from previous studies which show that LSTM architectures perform well on text classification tasks due to their ability to capture long-term dependencies in sequential data.

When evaluated using coverage metrics across confidence thresholds of 0.5, 0.6, and 0.7, the model maintained high accuracy within the covered predictions, reaching up to 98.72%. This suggests that the model is particularly reliable when its confidence score is high, making it suitable for real-time operational use where precision is essential. The confusion matrix also reflects strong diagonal dominance, indicating that most intent classes are predicted correctly. However, misclassifications remain present, especially in classes with limited training samples or overlapping linguistic structures. This aligns with known challenges in intent classification systems where data imbalance and semantic similarity often reduce model discriminability.

The training curves further support the model's stability. The accuracy curve shows consistent improvement until convergence, while the loss curve indicates no significant signs of overfitting. The narrow gap between training and validation loss reinforces the effectiveness of the adopted regularization strategy, including dropout, label smoothing, and class weight balancing. These techniques contributed to the model's ability to generalize beyond the training set.

Compared to simpler machine learning approaches often used for intent classification such as Naive Bayes, SVM, or shallow neural networks the LSTM model demonstrates superior performance in handling multi-intent, multi-pattern queries typical in public-service information systems. Although transformer-based models like BERT generally provide higher accuracy in many NLP benchmarks, the LSTM model offers a more lightweight and computationally efficient alternative that is easier to deploy within existing backend infrastructures.

The findings also highlight the practical significance of the proposed system. By automating recurring operational inquiries, the chatbot can reduce waiting times, alleviate manual workload, and extend access to Kadin services beyond standard office hours. Nonetheless, areas for improvement remain, including expanding the dataset for low-frequency intents, integrating semantic similarity checks to reduce misclassification, and exploring hybrid architectures that combine LSTM with attention mechanisms or transformer components.

Overall, the discussion confirms that the developed LSTM-based intent classification model is an effective and reliable solution for supporting Kadin's operational information services while also offering a solid foundation for further enhancements in future research.

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CONCLUSION

This study successfully developed a prototype of an operational service chatbot for the Indonesian Chamber of Commerce and Industry (Kadin) using an intent classification approach based on a Long Short-Term Memory (LSTM) model. The model demonstrated strong performance in identifying user intents, achieving a test accuracy of 92.08% and a Top-3 Accuracy of 96.23%. Further evaluation using a confusion matrix and accuracy-loss curves indicated that the model generalizes well and does not exhibit significant overfitting. The selected hyperparameter configuration including 128 LSTM units, the Adam optimizer with gradient clipping, label smoothing, class weight balancing, and dropout proved effective in maintaining model stability and reducing bias caused by imbalanced data.

The findings show that a well-optimized LSTM architecture can serve as an effective solution for automating text-based services, particularly in public service environments that require fast and accurate information delivery. The results highlight the practical benefits of the chatbot, such as reducing administrative workload, improving response time, and enhancing access to operational information.

Nevertheless, this research has several limitations, especially regarding the dataset's size and diversity. Some low-frequency intents remain challenging for the model, leading to occasional misclassifications. Future studies are recommended to expand and diversify the training dataset, explore the use of more advanced transformer-based models such as BERT or GPT, and strengthen integration with Kadin's real operational infrastructure. Additionally, implementing continuous monitoring, logging, and retraining mechanisms will be essential to ensure that the model can adapt to evolving user needs.

Overall, this research contributes meaningfully to the application of artificial intelligence in public service systems and provides a solid foundation for developing more intelligent, adaptive, and scalable chatbot solutions in the future.

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