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Development of MyCare AI: A Dual-AI Mental Health Chatbot for Personalized Emotional Support

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ABSTRACT — Access to mental health services remains a critical challenge in Indonesia, primarily due to societal stigma and limited availability of professional support. In response to this issue, this study introduces MyCare AI. This web-based mental health chatbot platform combines a Bi-LSTM-based emotion classification model with a generative conversational model provided by Google Vertex AI. This Dual-AI architecture enables the system to detect user emotions from Indonesian text inputs and deliver real-time, contextually appropriate, and empathetic responses. The emotion classification model is trained on a balanced English-language dataset representing four key emotional states: sadness, suicidal ideation, fear, and anger. The system employs a translation mechanism to convert Indonesian input into English before classification and then uses the detected emotion to condition the response generation process dynamically. The model achieved a classification accuracy of 95%, outperforming comparable models based on BERT-SVM and conventional LSTM architecture. This platform is intended for individuals who require immediate, anonymous, and continuous emotional support, including users in underserved or remote communities. MyCare AI represents a scalable and practical solution for digital emotional assistance and lays the groundwork for future integration with professional mental health services and native-language support frameworks. Key limitations include the system's reliance on real-time translation and an English-based dataset, highlighting the need for future development of culturally specific models.

KEYWORDS — MyCare AI, Empathetic Chatbot, Emotion Detection, Generative AI, Mental Health, Natural Language Processing, Bi-LSTM, Google Vertex AI.

1. INTRODUCTION

Mental health is a fundamental pillar of individual well-being, yet it is often overlooked due to various social and economic factors [1], [2]. In Indonesia, the prevalence of mental health disorders is significant, with estimates showing that approximately 2% to 9.8% of the population aged 15 and over experience them [3], [4], [5]. Specifically, adolescents and young adults in Indonesia represent a demographic with high vulnerability to mental health challenges due to academic pressures, career uncertainty, and the pervasive influence of social media. This group is also the most dominant and active user of digital technology, making them an ideal target audience for interventions delivered through platforms like chatbots. Therefore, developing a solution tailored to their needs is critical in leveraging technology for public mental health improvement.

This challenge is exacerbated by the very low ratio of mental health professionals compared to WHO standards [6]. Amidst this situation, artificial intelligence (AI) technology, particularly chatbots and social media data analysis, offers a potential innovative solution to provide private, easily accessible, and round-the-clock psychological support [7], [8]. Digital solutions that are private and accessible have great potential to bridge this gap.

Previous research has extensively explored sentiment analysis regarding mental health using machine learning. Many early studies applied traditional classification methods, such as the Naïve Bayes Classifier [2], [9] and Support Vector Machine (SVM). Several performance comparisons indicate that SVM is often superior, achieving accuracies ranging from 86.11% to 91% in various sentiment analysis scenarios [10], [11]. Furthermore, specific challenges like imbalanced data have been effectively addressed using the ADASYN oversampling technique, which significantly boosted the accuracy of a Naïve Bayes model to 93% [5].

As technology evolved, deep learning approaches were adopted to handle more complex data. Models like Long Short-Term Memory (LSTM) and its variant, Bidirectional LSTM (Bi-LSTM), have proven effective for detecting specific conditions such as depression and cyberbullying [12], as well as classifying the public's basic emotions during a crisis like the pandemic [13]. Further advancements are shown through the use of transformer models. Research integrating BERT for feature extraction with SVM for classification has achieved a very high accuracy of 93.49% in detecting indicators of anxiety and depression [4].

Specifically in the domain of intervention, the development of deep learning-based chatbots has become a primary focus. Research has demonstrated the feasibility of LSTM architecture for building mental health consultation chatbots, with evaluation results showing an F1-score of 77% after various hyperparameter testing scenarios [14]. Other studies also emphasize the importance of developing chatbots that are not only functional but also empathetic, often adopting sequence-to-sequence architectures equipped with mechanisms like stage-awareness [15], [16]. As reviewed in previous studies [17], deep learning-based architectures are now the de facto standard for modern chatbots. However, their implementation in Indonesia still faces challenges such

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as limited empathy, cultural sensitivity, and data privacy issues.

Nevertheless, this review identifies a research gap. Many studies focus on one aspect, either the accuracy of emotion classification [4], [12], [13] or the quality of empathetic conversation [14], [15], [16] but few systematically integrate both within a single architecture. Often, empathetic chatbots rely solely on the implicit emotional understanding of a Large Language Model (LLM), without a transparent and measurable classification module to provide deeper context.

Therefore, the novelty of this research lies in the design and implementation of a **Dual-AI architecture**. This architecture explicitly combines the conversational fluency of a Generative AI (Google Vertex AI) as the "heart" of the conversation, with the accuracy of a custom TensorFlow-based emotion classification model acting as the analytical "brain." By providing measurable and specific emotional context, this architecture is expected to deliver more personalized, relevant, and targeted mental health support, addressing the identified research gap in integrating analytical and empathetic capabilities in psychological support technology.

2. METHODOLOGY

This research employed a structured system development methodology, encompassing dataset selection and processing, architectural design, model development, software implementation, and deployment to a cloud environment. Methodology we can see in **Figure 1.**

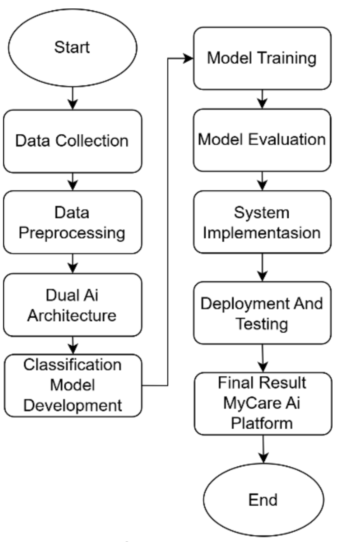

Figure 1. Research Methodology Stages

2.1 Dataset

The dataset used in this study combines two public, English-language sources obtained from the Kaggle platform.

1. **General Emotions Dataset:** The first source is the "Emotions" dataset published by S. A. Nelgiri on Kaggle [18]. We extracted three relevant emotion classes from this source: **sadness**, **anger**, and **fear**.
2. **Mental Health Context Dataset:** To supplement the dataset with a crisis-specific context, we used a second source, "Sentiment Analysis for Mental Health" by S. Sarkar [19]. From this dataset, we specifically extracted data labeled as indicative of being **suicidal**.

After merging, cleaning duplicates, and data balancing, the final dataset used to train the model consisted of four target classes. The total processed dataset comprised **40.000** text samples.

The selection of these four emotion categories was based on several strategic considerations. First, they represent core negative affective states and a critical crisis indicator (suicidal ideation) most relevant for a first-line support system. Second, these categories are well-represented in public datasets, ensuring sufficient data for robust model training. By focusing on these key emotions, this study prioritizes high accuracy and specialization in detecting critical conditions, rather than building a generalist model that might have lower performance across a broader spectrum of emotions.

These were then split into training and testing data with an 80:20 ratio. This study uses two publicly available datasets: the Emotions dataset for classification and a mental health sentiment dataset for contextual adaptation (see **Appendix B** for links).

2.2 Text Data Preprocessing

Before feeding into the model, the text data preprocessing phase is critical in preparing raw text for classification, according to Zucco et al. [20]. This process is necessary because online data is often noisy, incomplete, or inconsistent, which can negatively impact model performance. The primary goal of these meticulous steps is to clean and standardize the data to improve the quality of the features fed into the model. The process employed in this study involved the following sequential steps:

1. **Case Folding:** All text in the dataset was converted to lowercase.
2. **Punctuation and Noise Removal:** All punctuation, numbers, and other non-alphabetic characters were removed.
3. **Stopword Removal:** Common English words with no significant emotional meaning (e.g., 'the', 'is', 'in') were removed.
4. **Tokenization:** The cleaned text was split into individual word units, or 'tokens'.
5. **Sequencing & Padding:** The Keras Tokenizer mapped Each unique token to an integer index. All text sequences were then standardized to a uniform length of **150** tokens via post-padding.

2.3 System Architecture and Inference Flow

The MyCare AI system was designed using a microservices architecture (an approach where the application is built as a collection of independently deployable services). The inference flow for each user message is as follows.

1. **Input (Indonesian):** The user enters text through the Frontend (React) interface.
2. **Real-time Translation:** The API Gateway (Node.js) forwards the text to the ML Service (Python/Flask), where the Indonesian text is first translated into English using the googletrans library.
3. **Emotion Classification:** The resulting English text is fed into the TensorFlow model for classification.
4. **Contextual Conversation:** The classification result is returned to the API Gateway. This emotion information is used as additional context when calling **Google Vertex AI** to generate an empathetic and relevant chat response.

5. **Output:** The response from Vertex AI is displayed to the user on the frontend.

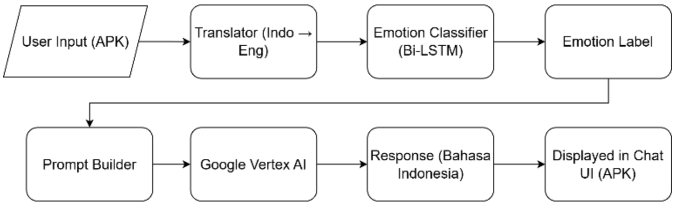

Figure 2. End-to-End Architecture of My\Care AI combining Bi-LSTM classifier and Vertex AI for personalized response generation.

Figure 2 illustrates the end-to-end architecture of the MyCare AI platform. It begins with user input through the mobile/web-based interface, which is translated from Indonesian to English. The translated text is passed to a Bi-LSTM-based emotion classifier. The resulting emotion label is used to construct a personalized prompt sent to Google Vertex AI, which generates a context-aware, empathetic response. This response is then delivered back to the user interface in real time.

2.4 Vertex AI

Vertex AI is an AutoML platform developed by Google Cloud [21], designed to simplify the training and deployment of machine learning models across various data types, including images, videos, text, and tabular data. The platform offers a unified interface through APIs, client libraries, and a web UI, enabling users to manage the entire model development lifecycle efficiently. For model performance evaluation, Vertex AI employs metrics such as Area under the Precision–Recall Curve (AuPRC), log-loss, and the confusion matrix, and it also supports conversion to mean Average Precision (mAP) for object detection tasks. Vertex AI utilizes Bayesian optimization for automated hyperparameter tuning, allowing users to configure parameters manually. Although the platform is supported by comprehensive documentation, much of its internal implementation remains hidden from users. In this implementation, the generative component utilized Google's llama-4-maverick-17b-128e-instruct-maas model deployed through Vertex AI's Model Garden API. The system interacts with the model via REST API using text prompts enriched with contextual emotion information from the classifier.

2.5 BI-LSTM

Bidirectional LSTM (Bi-LSTM) is derived from bidirectional recurrent neural networks (RNNs), which process sequential data in both forward and backward directions using two separate hidden layers. In Bi-LSTM, these two hidden layers are connected to a single output layer. Bidirectional networks have been shown to significantly outperform unidirectional ones in various tasks, such as phoneme classification and speech recognition [22] The architectural design of the Bi-LSTM model used in this study is illustrated in **Figure 3**. However, based on our literature review, Bi-LSTM has not yet been widely applied to traffic prediction problems.

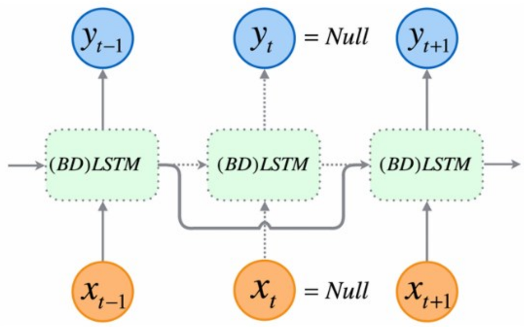

Figure 3. Architecture BI-LSTM

2.6 Model Development and Hyperparameters

The emotion classification model was built using TensorFlow and Keras with a Bidirectional Long Short-Term Memory (Bi-LSTM) based architecture. Bi-LSTM was chosen for its proven effectiveness in capturing sequential dependencies from both forward and backward directions in text data, which is crucial for understanding emotional context. For the conversational component, Google's Vertex AI was utilized to generate coherent and supportive dialogue based on the context provided by our classification model. The system was configured to prioritize safe and empathetic conversational outputs. The training process involved fine-tuning with the hyperparameters set as shown in Table 1. The training and evaluation of the Bi-LSTM model were performed using a Colab notebook in a cloud-based environment. Full implementation details can be accessed via **Appendix A**.

Table 1. Model Hyperparameter Settings

Parameter	Description
Optimizer	Adam
Embedding Dimension	128
Loss Function	Sparse Categorical Cross-entropy
Batch Size	64
Bi(LSTM) Units	64
Dropout Rate	0.5
L2 Regularization	0.001
Epochs	10 with Early Stopping)

2.7 Evaluation

This study includes an evaluation to determine how well the classification model performs for sentiment analysis in this mental health research[23]. The model's performance is measured quantitatively using several metrics, including Accuracy, Precision, Recall, and F1-Score, all calculated based on the Confusion Matrix. A Confusion Matrix is a table that summarizes the prediction results of a model against the test data. These are calculated using the confusion matrix, as shown in (1). Accuracy is computed using (2), Precision and Recall are defined in (3) and (4), and the F1-score, as the harmonic mean of Precision and Recall, is given in (5).

$$\text{Confusion Matrix} = \begin{pmatrix} TF & \text{FN} \\ FP & TN \end{pmatrix} \tag{1}$$

Where:

1. TP (True Positive): The number of positive samples correctly predicted as positive.

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2. TN (True Negative): The number of negative samples correctly predicted as negative.
3. FP (False Positive): The number of negative samples incorrectly predicted as positive.
4. FN (False Negative): The number of positive samples incorrectly predicted as negative.

From this matrix, the other evaluation metrics are calculated as follows:

Accuracy measures the proportion of total correct predictions out of all samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Precision measures the proportion of true positives among all positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

Recall measures the model's ability to identify all actual positive samples.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The F1-Score is the harmonic mean of Precision and Recall, providing a single score that balances both metrics.

$$F1-score = 2\,x\,\frac{Precission+Recall}{Precission+Recall} \quad (5)$$

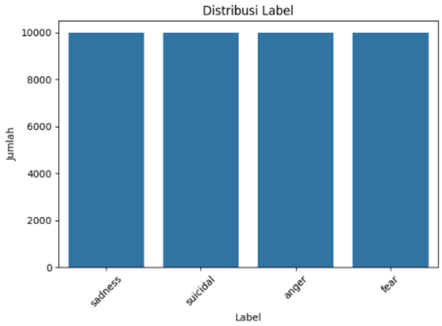
3. RESULTS AND DISCUSSION

The evaluation process in this study is divided into two key stages: exploratory analysis of the dataset and performance assessment of the emotion classification model. The first stage involves understanding the structure and characteristics of the input data through various visualizations, such as label distribution, word frequency, text length, and lexical patterns via word clouds. This exploratory phase is crucial for ensuring the data is representative and suitable for training a robust deep learning model.

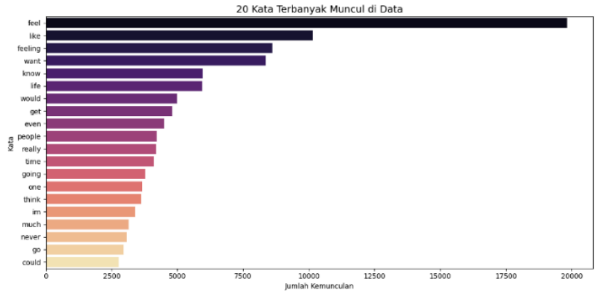
Following the data analysis, the second stage focuses on evaluating the performance of the Bidirectional LSTM model using standard classification metrics, including accuracy, precision, recall, and F1-score. The evaluation results are then discussed in relation to the system's overall architecture, particularly the integration of the emotion classifier into the Dual-AI conversational framework of the MyCare AI platform. This section also compares the findings to previous studies and outlines the proposed system's practical implications, strengths, and limitations.

3.1 Data Distribution and Preprocessing

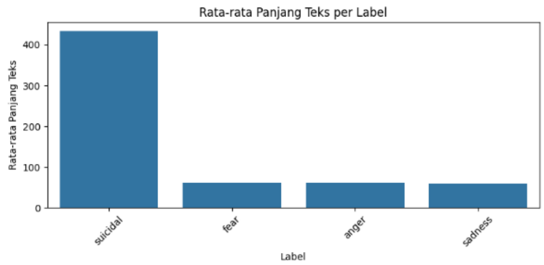
An initial analysis was conducted on the distribution and characteristics of the dataset to ensure quality inputs for the model. As shown in Figure 4(a), the emotional categories sadness, suicidal, anger, and fear were evenly distributed, with approximately 10,000 samples per class. A balanced dataset is essential to prevent classification bias and ensure fair representation across emotional categories.



(a)



(b)



(c)

Figure 4. (a) Distribution Label, (b) 20 words appear frequently, (c) Avg text length

The frequency analysis of words, Figure 4(b), revealed that terms like feel, like, feeling, want, and know were among the most frequently occurring in the corpus. This reflects that the textual data primarily consists of personal emotional expressions, making it highly relevant for mental health classification.

Figure 4(c) illustrates the average text length per label. The suicidal category had a significantly higher average length compared to the others, indicating that users expressing suicidal thoughts tend to write longer and more complex narratives. This highlights the deeper and more serious content associated with this emotional state.

Figure 5. Wordcloud for each label

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Further, WordCloud visualizations, as shown in Figure 5, for each label reveal distinct linguistic patterns. For instance, the sadness class is dominated by words such as lost, missed, and alone, while the suicidal category frequently includes die, tired, kill, and enough. The anger class shows terms like mad, offended, and insulted, whereas fear prominently features afraid, scared, and threatened. These observations affirm that each class is linguistically distinct, providing strong indicators for the classifier.

3.2 Model Evaluation

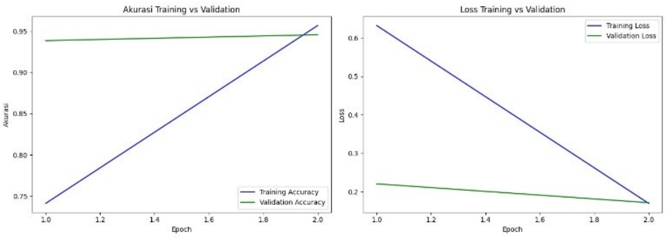

Figure 6. Training and Validation Accuracy and Loss Across Epochs

Model performance was evaluated using accuracy, precision, recall, and F1-score, as shown in **Figure 6** and summarized in Table 2. The graph on the left shows a significant increase in training accuracy across epochs, with validation accuracy above 94%. The graph on the right displays a steady decrease in training and validation loss, indicating that the model was effectively trained without signs of overfitting. These patterns suggest that the model generalizes well and benefits from balanced data and robust preprocessing.

Table 2. Model Evaluation Metrics

Emotion	Precision	Recall	F1-score
Sadness	0.96	0.93	0.94
Suicidal	0.98	0.97	0.98
Fear	0.90	0.96	0.93
Anger	0.95	0.93	0.94

As seen in the classification report and confusion matrix **Table 2**, the model achieved an overall accuracy of 95%, with the highest F1-score observed in the suicidal category (0.98). All four classes achieved strong metrics, with both macro and weighted F1-scores averaging at 0.95. This indicates that the model is accurate and balanced across all emotional categories.

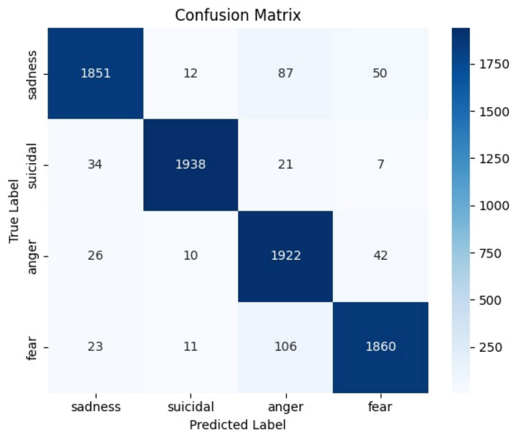

Figure 7. Confusion Matrix

The confusion matrix in Figure 7 further reinforces these results by providing a detailed visualization of the model's prediction distribution. The sadness class achieved 1,851 correct predictions, with some misclassifications into anger (87 instances) and fear (50 instances). The suicidal category showed the highest number of accurate predictions (1,938) and minimal misclassifications, indicating strong precision and recall. The anger class had 1,922 correct predictions, although some confusion occurred with sadness (26 instances) and fear (42 instances), likely due to overlapping emotional
recall. The anger class had 1,922 correct predictions, although some confusion occurred with sadness (26 instances) and fear (42 instances), likely due to overlapping emotional
expressions. The fear class also performed well, with 1,860 correct classifications and minor misclassifications into anger (106 instances) and sadness (23 instances).

3.3 System Integration and Dual-AI Architecture

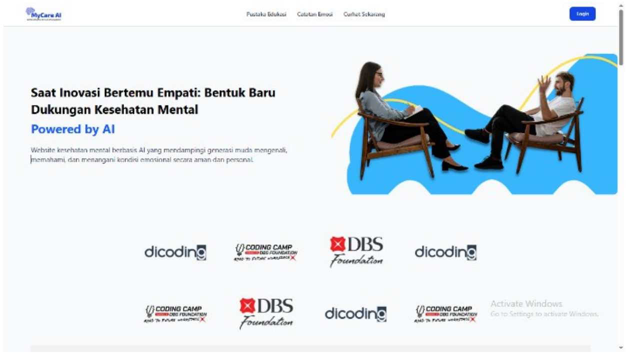

Figure 8. The landing page of MyCare AI highlights the empathetic AI support service.

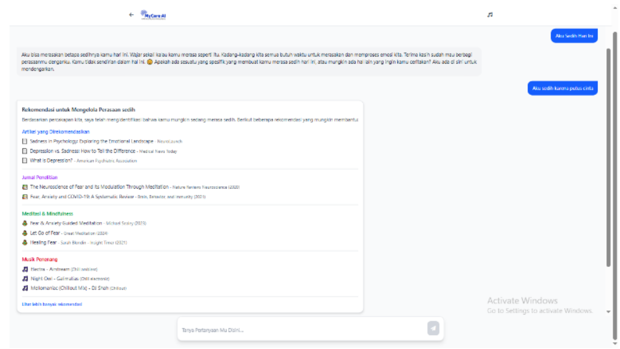

Figure 9. Chat interface showing a detected emotion (e.g., sadness) with personalized response and recommendations such as music or articles.

Figure 8 shows the main page of the MyCare AI web platform, which provides 24/7 mental health support using AI. Figure 9 displays the user interaction with the chatbot system, demonstrating how the system detects emotion and provides a customized response. The interface includes added-value features such as suggestions for meditation music and informative articles.

The trained Bi-LSTM emotion classification model was integrated into the MyCare AI chatbot using a Dual-AI system. The frontend (built with React) accepts Indonesian-language input, which is then translated to English using the googletrans library. The translated text is sent to the emotion classifier (TensorFlow model served on Google Cloud Run) for emotion detection. The predicted emotion is then sent as contextual input to Google Vertex AI, which generates an empathetic response tailored to the user's emotional state.

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In the response generation phase, MyCare AI leverages Google Vertex AI as a generative engine based on a large language model. The integration is handled through a Node.js backend, which bridges user input and the Vertex AI API. Upon receiving a message, the system first classifies the user's emotional state via a Python-based service using a Bi-LSTM model trained on emotional text. The resulting emotion (e.g., sadness, suicidal) is then passed to the backend as an active Emotion variable.

This emotion label is used to dynamically enrich the system prompt sent to Vertex AI, instructing it to tailor its language, tone, and content based on the user's inferred emotional condition. For instance, if the user is detected to be experiencing sadness, the prompt will explicitly request empathetic language and emotional validation in response to sadness-related concerns. The personalized prompt is constructed as follows:

"*Model frontend telah mendeteksi bahwa pengguna kemungkinan sedang merasakan kesedihan. Berikan perhatian khusus pada perasaan ini. Validasi emosi mereka, tawarkan dukungan yang lebih mendalam terkait kesedihan, dan tunjukkan empati ekstra*."

This system prompt is combined with recent conversation history and submitted to the Vertex AI model named llama-4-maverick-17b-128e-instruct-maas. The model processes this information to generate a coherent, supportive, and emotionally intelligent response in Bahasa Indonesia. The response is then returned to the frontend and displayed in the chat interface with minimal latency.

This hybrid approach enables dynamic, personalized interactions and powers resource recommendations such as music, meditation content, and mental health articles aligned with the user's condition.

The MyCare AI system is deployed on a live web platform for public access and user testing. A working chatbot version can be accessed through the link in **Appendix C**.

3.4 Comparative Evaluation and Challenges

To evaluate the effectiveness of the proposed architecture, this study compares the Bi-LSTM approach with previous research that utilized more complex models such as BERT. While BERT offers high accuracy, it often requires substantial computational resources and extended training time. In contrast, the Bi-LSTM model used in MyCare AI achieves competitive accuracy with faster inference speed and lower computational cost, making it suitable for deployment in resource-constrained environments. Moreover, MyCare AI addresses the limitations of conventional LSTM-based chatbots by combining emotion classification with generative responses, enabling the system to deliver more personalized and context-aware interactions based on the user's emotional state.

Another advantage of this system lies in its use of a highly relevant dataset to emotional crisis and support contexts, unlike many previous studies that relied on social media data such as Twitter. The dataset in this study was curated to reflect more sensitive and emotionally rich expressions, enhancing the relevance and effectiveness of the chatbot's responses. By integrating emotional context into the generative process, MyCare AI offers a more adaptive and empathetic solution for delivering real-time mental health support.

Table 3. Performance Comparison of Mycare AI with Previous Mental Health Chatbot Models

Study	Model Used	Accuracy (%)	Notes
[3]	BERT + SVM	*93.49*	High accuracy, high resource requirement
[12]	Bi-LSTM	89.00	Used Twitter-based cyberbullying data
[14]	LSTM	77.00 (f1)	Basic chatbot, limited emotion coverage
This study	Bi-LSTM + Vertex AI	95	Real-time dual-ai; personalized responses

The studies compared in Table 3 demonstrate several methodological and contextual differences relevant to mental health chatbot development. A transformer-based architecture (BERT) combined with a Support Vector Machine for classification was proposed in [3], resulting in high accuracy and balanced performance metrics. However, this approach demands substantial computational resources and lacks support for real-time conversational applications, limiting its usability in practical deployments.

Another study [12]Implemented a Bi-LSTM model trained on Twitter data related to cyberbullying. Although the model achieved moderately strong results, the focus on social media data introduces a contextual gap when applied to clinical or emotional support scenarios, and the system was not integrated into an interactive chatbot.

In[14]A basic chatbot using an LSTM model was developed without incorporating an explicit emotion detection mechanism. As a result, the conversational responses were generic and lacked personalization based on user emotional state, leading to relatively low F1 performance.

In contrast, the system proposed in this study combines a deep learning-based Bi-LSTM emotion classifier with a generative conversational model (Vertex AI) to deliver contextualized and empathetic responses. With the highest performance metrics among the studies compared, the MyCare AI system is also designed for real-time deployment, personalization, and scalability. It is particularly suitable for addressing mental health service gaps in the Indonesian context.

3.5 Chat Response Simulation

In addition to quantitative model evaluation, a series of chat response simulations was conducted to assess the real-world behavior and empathy level of the MyCare AI system. These simulations demonstrate the system's ability to identify user emotions accurately and generate personalized, context-aware responses using its Dual-AI architecture.

Each scenario starts with a user input in Bahasa Indonesia, which is then translated, classified using the Bi-LSTM model, and forwarded as an emotional context to Google Vertex AI for generating an empathetic reply. The goal is to validate whether the system can not only classify emotions with high confidence but also respond appropriately to the user's emotional needs.

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Table 4. Inference Results and Response Simulation

Input Text (ID)	Translated (EN)	Predicted Emotion	Confidence
Aku merasa sangat sedih dan kesepian	I feel very sad and lonely.	*Sadness*	0.97
Aku ingin menyerah dan bosan hidup.	I want to give up and get tired of life	Suicidal	0.99
Aku ingin menyerah dan bosan hidup.	I'm afraid that my job is not finished.	Fear	0.86
Aku marah kepada teman-temanku karena mereka membohongiku.	I am angry with my friends because they lied to me.	Anger	0.96

Table 4 presents four sample inputs categorized under different emotional conditions: sadness, suicidal, fear, and anger. The emotion classifier consistently produced high-confidence predictions, with the suicidal category yielding the highest score of 0.99.

To further assess the system's ability to generate meaningful replies, the following are examples of actual responses generated by Vertex AI, guided by the predicted emotion class:

- Input: Aku merasa capek dan ingin menyerah.
  Output (suicidal): Saya mengerti betapa beratnya ini. Kamu tidak sendiri. Ada bantuan dan saya di sini untuk mendengarkan.
- Input: Aku marah hari ini, teman ku menjahiliku.
  Output (anger): Rasa marah karena merasa dijaili bisa sangat mengganggu... Aku ada di sini untuk mendengarkan.
- Input: Aku takut sekali jika sendirian di rumah.
  Output (fear): Rasa takut saat sendirian di rumah bisa membuatmu merasa tidak nyaman. Aku memahami itu dan aku di sini untuk mendengarkan.

These results indicate that the system detects emotional cues with high accuracy and adapts its response tone and content accordingly. The system uses a pre-engineered prompt structure that embeds the detected emotion (e.g., sadness, fear) to instruct Vertex AI. This allows for highly contextualized outputs that reflect empathy and support relevant to the user's emotional state.

In practice, this behavior is critical for building trust and emotional safety in users—especially those dealing with sensitive issues like loneliness, emotional distress, or suicidal ideation. The natural tone, comforting language, and reflective questions generated by the system position MyCare AI as a reliable entry point for mental health assistance, especially for users in remote or underserved communities.

3.6 Practical Implications

The MyCare AI platform is strategically developed to provide initial emotional support, particularly for individuals who may hesitate to access professional mental health services due to social stigma or limited infrastructure. This includes young adults and students coping with academic or social pressures, as well as individuals living in rural or remote areas where access to psychologists and mental health professionals is severely limited. The platform also aims to accommodate users who seek anonymous and empathetic emotional support accessible 24/7 through a web-based interface.

The system's Dual-AI architecture integrates emotion classification with generative conversation, creating personalized recommendations for relaxation content, music, or relevant articles. Beyond its standalone capabilities, the system supports potential integration with external mental health services. For example, users exhibiting signs of emotional crisis, such as those classified under the suicidal category, can be automatically directed to certified mental health professionals or emergency contact lines through in-app suggestions.

This design allows MyCare AI to serve as an immediate emotional aid and a gateway for further psychological intervention. Future development may include direct appointment booking with professionals and a secure referral system to enable a seamless continuum of care from digital to professional support services. The use of openly accessible tools and datasets, as seen in Appendix A–C, supports transparency and reproducibility for future mental health AI systems.

4 LIMITATIONS AND FUTURE WORK

While MyCare AI performs strongly in emotion detection and response generation, some limitations remain. First, the translation from Bahasa Indonesia to English introduces potential semantic drift, which may affect classification accuracy. Second, while the responses are generally empathetic, they have not yet been evaluated by a diverse group of native users in real-world settings. Finally, the current dataset is sourced from public English-language corpora, which limits cultural and linguistic specificity.

Future work will focus on:

- Building native Bahasa Indonesia emotional datasets.
- Incorporating direct feedback loops from users.
- Integrating referral systems with licensed professionals.

5 CONCLUSION

This study presented the development of MyCare AI. This web-based mental health support platform integrates a Dual-AI system: a Bi-LSTM-based emotion classifier and a generative response model powered by Vertex AI. The platform achieved an overall accuracy of 95% across four emotional classes: sadness, suicidal, fear, and anger, demonstrating its strong potential in accurately detecting emotional distress from text inputs.

The combination of emotion classification and real-time generative response represents a novel contribution, enabling the system to deliver empathetic, personalized support. Integrating translation modules and microservice architecture enhances its adaptability to Indonesian users, while supporting scalable and responsive interaction.

The proposed architecture offers a more lightweight, interpretable, and deployment-ready solution than prior research. The ability to tailor responses based on user emotion

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rather than generic replies positions MyCare AI as a practical entry point for digital emotional first aid.

However, challenges remain in effectively translating nuanced language and evaluating the system with native Indonesian input. Future work should focus on building native datasets, enhancing cultural contextualization, and integrating pathways for professional referrals.

MyCare AI demonstrates that a Dual-AI framework is technically feasible and socially impactful in bridging mental health support gaps in under-resourced communities.

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APPENDIX

This appendix provides supplementary links to the system implementation, datasets, model training notebook, and deployed chatbot application developed in this study.

Appendix A — Source Code and Model Notebook

- GitHub Repository (Frontend & Backend): https://github.com/zaenalSamsul/MyCareAi.git
- "Vertex AI was accessed using Google Cloud's Vertex AI API. The deployed model is llama-4-maverick-17b-128e-instruct-maas via the Model Garden. Detailed API calls and prompt formatting can be found in the backend source code repository."

Appendix B — Source Code and Model Notebook

- Emotions Dataset: https://www.kaggle.com/datasets/nelgiriyewithana/emotions
- Mental Health Sentiment Dataset: https://www.kaggle.com/datasets/suchintikasarkar/sentiment-analysis-for-mental-health

Appendix C — Deployed Web Application

- MyCare AI (Live Demo): https://mycare-ai.netlify.app/