BAB I
INTRODUCTION

1.1 Background of the Study

The advancement of chatbot technology has fundamentally altered how organizations interact with their users. Chatbots, or conversational agents, are software applications capable of engaging with humans via text or voice, often deployed for customer service or information retrieval by leveraging Natural Language Processing and artificial intelligence techniques [6]. Universitas Amikom Yogyakarta has adopted this technology by developing a chatbot integrated with its WhatsApp Caller Center service. This service acts as a primary channel for responding to inquiries and complaints from both current students and prospective users through a real-time conversational platform [7]. As the volume of interactions grows, it has become crucial for the university to understand user perceptions and sentiments regarding the chatbot service. The user feedback embedded within these chat conversations contains valuable sentiment data that reflects user satisfaction, service quality, and system performance [1]. However, the evaluation of this feedback is often still conducted manually, a process that is both time-consuming and inefficient, especially when handling large-scale conversational data [4]. Sentiment analysis offers a solution to automate this evaluation. By analyzing conversational text, this method can classify user opinions into positive, negative, or neutral categories using computational approaches [2]. Recent studies emphasize that sentiment analysis has become an essential analytical tool in conversational systems for monitoring user satisfaction and improving service quality [5]. This research focuses on the application of a Deep Learning method, specifically Long Short-Term Memory (LSTM).

The LSTM method was chosen for its superior architecture in handling sequential data, such as text, where the context of preceding words significantly impacts the

overall meaning. LSTM is capable of learning long-term dependencies and contextual relationships within text sequences, making it highly relevant for understanding the nuances present in chat conversations and customer feedback [3]. Therefore, this study aims to design and build a sentiment analysis model using the LSTM method to classify user sentiment towards the Amikom chatbot. The findings are expected to provide automated, real-time insights to the service administrators regarding user responses, thereby serving as a data-driven foundation for future service improvements and decision-making processes [1][5].

1.2 Research Questions

Based on the background described above, the research questions for this study are:

1. What is the distribution of user sentiment (positive, negative, and neutral) towards the Amikom chatbot service used by the Whatsapp Caller Center?
2. How can a Long Short-Term Memory (LSTM) model be designed and implemented to effectively classify sentiment from the chatbot's conversational text data?
3. What level of accuracy, precision, and recall can the proposed LSTM model achieve in analyzing user sentiment?

1.3 Scope of the Research

To maintain the focus of the study, the following limitations are set:

1. The research object is limited to user sentiment within the Amikom chatbot service integrated with the Whatsapp Caller Center. This study will not analyze other chatbots.
2. The data source is an anonymized dataset of conversation logs obtained from the Whatsapp Caller Center service.
3. The primary method used for sentiment classification is Long Short-Term Memory (LSTM).

4 This study focuses on text-based sentiment classification (positive, negative, neutral) and does not measure the broader psychological construct of *user satisfaction*.

5 This research does not conduct a formal comparative analysis between the LSTM method and other machine learning or deep learning algorithms.

1.4 Research Objectives

In line with the research questions, the objectives of this study are:

1 To analyze and classify user sentiments (positive, negative, and neutral) towards the Amikom chatbot service.

2 To build a sentiment classification model using the Long Short-Term Memory (LSTM) method, trained on chatbot conversation data.

3 To measure and evaluate the performance of the LSTM model in classifying sentiment using accuracy, precision, and recall metrics.

4 To provide recommendations for improving the Amikom chatbot service based on the sentiment analysis results.

1.5 Research Contributions

The expected contributions (benefits) of this research are:

1 Natural Language Processing (NLP) dan analisis sentimen.

2 To provide an automated system for monitoring and evaluating user sentiment towards the chatbot service in real-time.

3 To serve as a data-driven basis for decision-making to improve the quality of the chatbot service and respond to user complaints more effectively.

4 To add to the body of research concerning the application of *Deep Learning*, particularly LSTM, for sentiment analysis of Indonesian-language text within an academic service context.

5 To serve as a reference and benchmark for other researchers conducting similar studies in the field of *Natural Language*

Processing (NLP) and sentiment analysis.

1.6 Thesis Organization

This research is structured into five chapters, as follows:

Chapter I: Introduction This chapter outlines the context of the study, including the background, research questions, scope, objectives, contributions, and the overall thesis organization.

Chapter II: Literature Review and Theoretical Basis This chapter discusses the relevant theories, including concepts of sentiment analysis, *Natural Language Processing* (NLP), *Deep Learning*, and the specific architecture of the Long Short-Term Memory (LSTM) method.

Chapter III: Research Methodology This chapter details the methodology used in the study, covering the research workflow, data collection techniques, data pre-processing stages, the design of the LSTM model architecture, and the model evaluation methods.

Chapter IV: Results and Discussion This chapter presents the results of the model implementation and testing. It includes data analysis, experimental outcomes, performance evaluation based on the defined metrics, and an in-depth discussion of the findings.

Chapter V: Conclusion This chapter summarizes the conclusions drawn from the research, answering the research questions, and provides suggestions for both service improvements and future research.