

**PENGEMBANGAN MODEL INDOBERT DALAM *CHATBOT*
PENGELOLAAN KOMUNIKASI BEASISWA IKATAN ALUMNI UPI**

SKRIPSI

Diajukan Untuk Memenuhi Sebagian dari Syarat Memperoleh gelar Sarjana
Program Studi Ilmu Komputer



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FAKULTAS PENDIDIKAN MATEMATIKA DAN ILMU PENGETAHUAN ALAM
UNIVERSITAS PENDIDIKAN INDONESIA**

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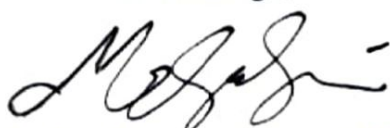
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ABSTRAK

Komunikasi efektif antara alumni dan organisasi penting untuk penyampaian informasi salah satunya terkait beasiswa. Di IKA UPI, Sumber Daya Manusia (SDM) terbatas membuat respons lambat dan inefisiensi komunikasi. Penelitian ini membuat *chatbot* menggunakan model IndoBERT yang merupakan model berbasis BERT (*Bidirectional Encoder Representations from Transformers*) untuk menjawab terkait beasiswa secara otomatis. Model diadaptasi melalui lima *fine-tuning*, yaitu *Masked Language Modeling* (MLM), *Next Sentence Prediction* (NSP), *Intent Classification*, *Extractive QA* (SQuAD), dan *Semantic Retrieval*. Evaluasi memakai metrik *accuracy*, *recall*, *f1-score*, *exact match* (EM), *top-k accuracy*, *mean reciprocal rank* (MRR), dan *latency*. Hasil uji menunjukkan kinerja kuat di tugas dasar seperti *f1-score* 93,33% untuk NSP dan 86,74% untuk *intent*. Tantangan tampak pada pemahaman konteks lebih dalam seperti pada *extractive QA* meraih *f1-score* 43,57% dan *retrieval* MRR 0,34. Temuan ini menegaskan kelayakan penerapan *chatbot* menggunakan model IndoBERT untuk pengelolaan komunikasi beasiswa IKA UPI, sekaligus memetakan tantangan dalam tugas-tugas pemahaman konteks yang lebih dalam.

Kata kunci: Beasiswa, BERT, *Chatbot*, *Fine-Tuning*, *Natural Language Processing* (NLP)

*DEVELOPMENT OF THE INDOBERT MODEL IN THE UPI ALUMNI ASSOCIATION
SCHOLARSHIP COMMUNICATION MANAGEMENT CHATBOT*

Aranged by

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ABSTRACT

Effective communication between alumni and organizations is crucial for conveying information, including scholarships. At IKA UPI, limited human resources (HR) make communication responses slow and inefficient. This study created a chatbot using the IndoBERT model, a BERT-based model (Bidirectional Encoder Representations from Transformers) to automatically answer questions about scholarships. The model was modified through five fine-tunings: Masked Language Modeling (MLM), Next Sentence Prediction (NSP), Intent Classification, Extractive QA (SQuAD), and Semantic Retrieval. The evaluation used metrics of accuracy, recall, f1-score, exact match (EM), top-k accuracy, mean reciprocal rank (MRR), and latency. Test results showed strong performance in basic tasks, such as an f1-score of 93.33% for NSP and 86.74% for intent. Challenges arose in deeper understanding, such as in extractive QA, which achieved an f1-score of 43.57% and a retrieval MRR of 0.34. This finding of the feasibility of implementing a chatbot using the IndoBERT model for managing IKA UPI scholarship communications, reflects both the challenges in the tasks of understanding the context more deeply.

Keywords: BERT, Chatbot, Fine-Tuning, Natural Language Processing (NLP), Scholarship

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