

**ANALISIS SENTIMEN DAN PEMODELAN TOPIK PADA
POST TENTANG MEREK TEKNOLOGI DI MEDIA SOSIAL X
MENGUNAKAN *FINE-TUNING* INDOBERT DAN
BERTOPIC**

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



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FAKULTAS PENDIDIKAN MATEMATIKA DAN
ILMU PENGETAHUAN ALAM
UNIVERSITAS PENDIDIKAN INDONESIA
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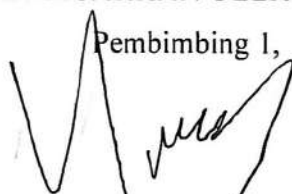
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ABSTRAK

Media sosial telah menjadi wadah bagi konsumen untuk menyampaikan persepsi dan opini. Opini yang beredar tersebut berpotensi menjadi sumber data yang berharga bagi *brand*, termasuk Xiaomi, dalam memahami persepsi publik terhadap produk mereka. Penelitian ini bertujuan untuk menganalisis sentimen dan mengidentifikasi topik diskusi pada unggahan (*post*) mengenai merek teknologi Xiaomi di platform X (sebelumnya Twitter) dengan pendekatan berbasis Transformer. Dua metode utama yang digunakan adalah *fine-tuning* IndoBERT untuk model klasifikasi sentimen dan BERTopic untuk pemodelan topik. Data yang berhasil dikumpulkan sebanyak 10.130 *post* dari bulan Mei 2023 hingga Mei 2025 yang dilanjutkan menuju tahapan praproses serta pelabelan. Model klasifikasi dilatih dengan berbagai kombinasi konfigurasi *hyperparameter*, dengan hasil pengujian terbaik menghasilkan nilai *accuracy* 79,8%, *precision* 73,0%, *recall* 67,7%, dan *f1-score (macro)* sebesar 0,699. Distribusi sentimen dalam data menunjukkan dominasi sentimen netral, sedangkan BERTopic berhasil menghasilkan 16 *cluster* topik dengan rata-rata nilai *coherence (C_v)* sebesar 0,5437. Topik paling dominan dengan jumlah anggota *cluster* terbanyak membahas mengenai produk Xiaomi *Series* dan Poco. Topik dengan persentase sentimen negatif tertinggi berkaitan dengan layanan *service center*, dan sentimen positif tertinggi mengenai produk komputer tablet (*tab*) Xiaomi. Penggabungan hasil analisis sentimen dan pemodelan topik memberikan pemahaman yang lebih mendalam terhadap isu yang dibicarakan serta persepsi konsumen sekaligus memberikan wawasan yang relevan bagi perusahaan untuk mengidentifikasi kekuatan dan potensi peningkatan yang dapat dilakukan.

Kata Kunci: Media Sosial X, Analisis Sentimen, Pemodelan Topik, IndoBERT, BERTopic

**SENTIMENT ANALYSIS AND TOPIC MODELING ON POSTS ABOUT
TECHNOLOGY BRAND ON SOCIAL MEDIA X USING FINE-TUNED
INDOBERT AND BERTOPIC**

Compiled By

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ABSTRACT

Social media has become a platform for consumers to express their perceptions and opinions. These circulating opinions have the potential to be a valuable source of data for brands, including Xiaomi, in understanding public perception of their products. This study aims to analyze sentiment and identify discussion topics in posts about the Xiaomi technology brand on platform X (formerly Twitter) using a Transformer-based approach. Two main methods used are fine-tuning IndoBERT for sentiment classification models and BERTopic for topic modeling. Data collected amounted to 10,130 posts from May 2023 to May 2025, which proceeded to the preprocessing and labeling stages. The classification model was trained with various combinations of hyperparameter configurations, with the best test results producing an accuracy of 79.8%, a precision of 73.0%, a recall of 67.7%, and an f1-score (macro) of 0.699. The distribution of sentiment in the data shows a dominance of neutral sentiment, while BERTopic successfully generated 16 topic clusters with an average coherence value (C_v) of 0.5437. The most dominant topic, with the largest number of cluster members, discussed Xiaomi Series and Poco products. The topic with the highest percentage of negative sentiment related to service center services, and the highest positive sentiment concerned Xiaomi tablet computers (tabs). Combining sentiment analysis and topic modeling results provides a deeper understanding of the issues discussed and consumer perceptions, while providing relevant insights for the company to identify strengths and potential improvements.

Keywords: *Social Media X, Sentiment Analysis, Topic Modeling, IndoBERT, BERTopic*

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