Unmasking Hoaxes in Bahasa: A Dual-Stream Knowledge-Enhanced Graph Neural Network for Indonesian Fake News Detection

IndoHoaxBERT — From Theory to Implementation

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Research Project Documentation

Data Science & Machine Learning Portfolio

Research Statement

Research Identity: Computational Methods for Indonesia's Underserved Domains

My research is driven by a single conviction: that advanced machine learning should not remain confined to well-resourced languages and data-rich environments. Indonesia, home to 280 million people, the world's fourth largest population, faces critical challenges in public information integrity, social protection delivery, and infrastructure planning, yet remains chronically underrepresented in the computational research that could address these problems. My work bridges this gap by bringing state-of-the-art methods to Indonesian-context problems where they can create measurable impact.

This Project in Context

IndoHoaxBERT represents one pillar of a broader research program spanning multiple domains:

- **Low-Resource NLP for Social Good** (this project): Combining Indonesian-specific language models with knowledge-enhanced graph neural networks for misinformation detection, tackling both the language gap in NLP tools and the societal threat of hoaxes that undermine public trust in institutions.
- **Causal Inference for Social Protection**: Applying 13 state-of-the-art causal methods from classical econometrics (difference-in-differences, regression discontinuity) through modern machine learning (causal forests, double ML) to deep learning (CEVAE, DragonNet), to evaluate Indonesian social protection programs, enabling evidence-based policy decisions that affect millions of beneficiaries.
- **Graph Theory for Infrastructure**: Modeling Indonesia's metropolitan railway networks using graph-theoretic analysis (centrality measures, HITS algorithm, clustering coefficients) to identify critical nodes and optimize transit planning for cities experiencing rapid urbanization.
- **Spatiotemporal Forecasting**: Implementing diffusion convolutional recurrent neural networks (DCRNN) for traffic prediction, with applications to Indonesian urban mobility, where accurate forecasting directly reduces congestion costs and carbon emissions.

The Common Thread

Three principles unite these projects:

1. **Methodological rigor in real-world contexts**: Every project implements proper statistical validation—bootstrap confidence intervals, multiple comparison corrections, ablation studies—because policy-relevant research demands trustworthy conclusions, not just impressive accuracy numbers.

2. **Honest research process**: I document what fails alongside what succeeds. IndoHoaxBERT required four dataset iterations before achieving meaningful results; the causal inference project revealed that some popular methods perform poorly on realistic confounding structures. These "negative results" are features, not bugs, they sharpen understanding of when and why methods work.

3. **Bridging theory and deployment**: Each project produces modular, documented code designed to run on accessible hardware. Research that cannot be reproduced or deployed has limited impact, regardless of its theoretical elegance.

Future Direction

I aim to deepen the intersection of **knowledge-enhanced reasoning** and **low-resource language understanding**, with two specific goals: (1) scaling graph-augmented NLP architectures to real-world Indonesian misinformation datasets through partnerships with organizations like MAFINDO and Kominfo, and (2) extending causal and interpretable ML methods to evaluate Indonesia's expanding digital governance programs, where the stakes of getting the analysis wrong are measured in human welfare, not just model metrics.

Portfolio Overview

The complete portfolio including code repositories, detailed documentation, and reproducible experiments for all projects mentioned above is available for review. Each project is designed as a self-contained demonstration of both theoretical understanding and practical implementation capability.

Contents

1 Abstract

Fake news poses a growing threat to democratic institutions and public health, particularly in low-resource languages where detection tools remain underdeveloped. Indonesia—the world's fourth most populous nation with over 200 million internet users—faces an acute misinformation crisis compounded by linguistic diversity and limited NLP infrastructure. This project introduces **IndoHoaxBERT**, a novel dual-stream architecture that fuses IndoBERT-based text understanding with knowledge-enhanced Graph Attention Networks (GAT) for Indonesian fake news detection.

Our system makes five key contributions: (1) the first dual-stream BERT+GAT architecture specifically designed for Indonesian, (2) a knowledge-enhanced entity graph with type-aware edge construction, (3) an attention-gated fusion mechanism that adaptively weights textual and structural signals, (4) domain-adaptive focal loss for handling class imbalance in Indonesian news, and (5) a comprehensive ablation study with rigorous statistical validation including bootstrap confidence intervals and McNemar's test.

Experiments on Indonesian news articles across eight topical domains demonstrate that text-only IndoBERT achieves approximately 85.5% accuracy, while the full IndoHoaxBERT model achieves comparable performance with the added benefit of entity-level interpretability through knowledge graph visualization. We provide a complete, reproducible, laptop-friendly codebase suitable for further research and deployment.

2 Business Problem and Motivation

2.1 The Global Misinformation Crisis

Misinformation has evolved from a nuisance into a systemic threat. The World Economic Forum's 2024 Global Risks Report ranks misinformation and disinformation as the top short-term global risk. False narratives spread through social media have been linked to vaccine hesitancy during COVID-19, election manipulation, financial market volatility, and ethnic violence.

Traditional fact-checking organizations cannot keep pace with the volume of content. UNESCO reports that professional fact-checkers can verify only a fraction of the claims circulating online. This gap creates an urgent need for **automated detection systems** that can flag suspicious content at scale while maintaining high precision to avoid censoring legitimate speech.

2.2 Indonesia's Unique Challenges

Indonesia presents a particularly compelling case for automated fake news detection:

- **Scale**: 213 million internet users (77% of population), with 167 million active social media users as of 2024.

- **Linguistic complexity**: While Bahasa Indonesia is the lingua franca, regional languages and code-switching create NLP challenges. Standard English-trained models perform poorly on Indonesian text.
- **Institutional impact**: Indonesia's Ministry of Communication and Information Technology (Kominfo) identified over 12,000 hoax articles between 2018 and 2024, many targeting government programs including social protection, vaccination, and electoral processes.
- **Economic consequences**: The Indonesian Anti-Defamation Society (MAFINDO) estimates that misinformation costs the Indonesian economy billions of rupiah annually through market manipulation, damaged institutional trust, and public health misinformation.
- **Low-resource NLP**: Despite 200+ million speakers, Indonesian remains underrepresented in NLP benchmarks compared to English, Chinese, or even Hindi.

2.3 Why Existing Solutions Fall Short

Current fake news detection systems suffer from three limitations when applied to Indonesian content:

1. **Language mismatch**: Most state-of-the-art models (BERT, RoBERTa, GPT) are pre-trained primarily on English. Multilingual models like mBERT allocate limited capacity to Indonesian, resulting in suboptimal representations for Bahasa-specific linguistic phenomena (Koto et al., 2020).
2. **Text-only limitation**: Conventional approaches treat each article as an isolated text sequence, ignoring the *relational structure* between entities mentioned across articles. Real news tends to cite entities in domain-appropriate contexts (e.g., Bank Indonesia discussing monetary policy), while fake news often misattributes claims to unrelated organizations.
3. **Interpretability deficit**: Black-box classifiers that output only "real" or "fake" provide no mechanism for journalists or fact-checkers to understand *why* an article was flagged. Entity-level graph analysis can surface the specific relationships that triggered a detection.

2.4 Our Approach: Combining Language Understanding with Knowledge Graphs

IndoHoaxBERT addresses these limitations through a dual-stream architecture:

1. **IndoBERT** (Koto et al., 2020; Wilie et al., 2020) provides deep Indonesian language understanding, trained on the Indo4B corpus (4 billion words, 250 million sentences from Indonesian web text).

2. **Graph Attention Networks** (Veličković et al., 2018) capture entity relationships—co-occurrence patterns, organizational affiliations, and cross-domain entity mixing that signal fabricated content.

3. **Knowledge enhancement** adds semantic type awareness (organization, person, location) and domain-coherence signals that pure text models struggle to exploit.

4. **Attention-gated fusion** dynamically weights the text and graph contributions, allowing the model to adapt its reliance on each signal source depending on the input.

Business Value Proposition

For news organizations, social media platforms, and government agencies operating in Indonesia, IndoHoaxBERT offers: (1) automated pre-screening of suspicious content, (2) entity-level explanations for flagged articles, (3) a modular architecture that can incorporate additional knowledge sources, and (4) efficient inference suitable for real-time deployment on standard hardware.

3 Literature Review and Related Work

This section surveys the research landscape that informed IndoHoaxBERT's design, organized by the three pillars of our approach: text-based detection, graph-based methods, and Indonesian NLP.

3.1 Transformer-Based Fake News Detection

The advent of BERT (Devlin et al., 2019) transformed NLP, achieving state-of-the-art results across classification tasks. For fake news detection specifically:

FakeBERT (Kaliyar et al., 2021) combined BERT representations with parallel CNN blocks, achieving 98.90% accuracy on the ISOT dataset. While impressive, this result reflects the relatively easy nature of the ISOT benchmark rather than real-world difficulty.

Progressive BERT (PLOS One, 2025) applied BERT fine-tuning with progressive unfreezing to the WELFake dataset (72,134 articles), achieving 95.3% accuracy. Their layer-by-layer unfreezing strategy—which we adopt in simplified form through our layer freezing approach—prevents catastrophic forgetting of pre-trained knowledge.

GBERT (GBERT, 2024) proposed a GPT-BERT hybrid architecture achieving 95.30% accuracy, demonstrating that combining generative and discriminative representations improves detection. This inspired our own fusion of heterogeneous information sources.

Raza et al. (Raza et al., 2024) conducted a comprehensive comparison of BERT-based models against large language models (LLMs) on a dataset of 10,000 GPT-4 annotated articles. Their finding that fine-tuned BERT variants outperform zero-shot LLMs validates our choice of supervised fine-tuning over prompting-based approaches.

RoBERTa with Summarization (ETASR, 2025) achieved 98.39% accuracy by combining extractive summarization with RoBERTa classification, suggesting that information reduction can help models focus on discriminative signals rather than superficial patterns.

3.2 Graph Neural Networks for Misinformation Detection

Graph-based approaches model the relational structure that text-only methods miss:

Dual Stream GAT + BERT (Scientific Reports, 2025) introduced the dual-stream paradigm that directly inspired our architecture. Their framework processes text through BERT and entity relationships through Graph Attention Networks, then fuses the representations for classification. Our work extends this by introducing knowledge-enhanced entity typing and domain-aware edge construction specifically designed for Indonesian news.

The **Attention Is All You Need** framework (Vaswani et al., 2017) provides the theoretical foundation for both our BERT text encoder and our Graph Attention Network, which applies the same scaled dot-product attention mechanism to graph-structured data rather than sequential tokens.

3.3 Knowledge Graph Construction and Enhancement

Knowledge graphs add semantic structure to entity relationships:

KEGI (Knowledge Enhanced Graph Inference) (Han & Wang, 2024) demonstrated that incorporating entity type information and relation semantics into graph neural networks significantly improves inference on incomplete knowledge graphs. We adapt their principle of type-aware attention for our entity graph construction.

The **MDPI Knowledge Graph Construction Survey** (Applied Sciences, 2025) provided practical guidelines for entity extraction, relation identification, and graph construction that informed our `graph_builder.py` implementation.

3.4 Indonesian NLP and IndoBERT

IndoBERT (Koto et al., 2020) is a BERT model pre-trained on the Indonesian Language Evaluation and Modeling (IndoLEM) benchmark. Trained on the Indo4B corpus comprising 4 billion words from Indonesian Wikipedia, news, web crawl, and social media, it captures Bahasa-specific morphology, syntax, and semantics that multilingual models miss.

IndoNLU (Wilie et al., 2020) established standardized benchmarks for Indonesian NLU tasks including sentiment analysis, natural language inference, and question answering. IndoBERT-base achieved state-of-the-art results across all tasks, confirming its suitability as our text backbone.

3.5 Class Imbalance and Focal Loss

Real-world fake news datasets are inherently imbalanced—legitimate articles vastly outnumber fabricated ones. **Focal Loss** (Lin et al., 2017), originally proposed for object detection, addresses this by down-weighting easy examples and focusing training on hard misclassified cases. We adopt focal loss with parameters $\alpha = 0.6$ (minority class weight) and $\gamma = 2.0$ (focusing parameter), following best practices for binary text classification with moderate imbalance.

3.6 Ensemble and Multi-Modal Approaches

The **Arabic Fake News Ensemble** (Scientific Reports, 2024) combined FastText embeddings with BiLSTM and BiGRU networks, demonstrating that architectural diversity improves robustness. While our approach uses fusion rather than ensembling, the principle of combining complementary signal sources is shared.

Research Gap Addressed

No prior work has combined (1) an Indonesian-specific pre-trained language model with (2) knowledge-enhanced graph neural networks using (3) type-aware entity relationships for (4) Indonesian fake news detection. IndoHoaxBERT fills this gap by integrating domain-appropriate NLP with structural graph analysis tailored to Indonesian news content patterns.

4 Dataset Description

4.1 Overview

The experiments use a corpus of 5,000 Indonesian news articles collected across eight topical domains that reflect the breadth of Indonesia's information landscape. Each article is labeled as either *real* (legitimate news) or *fake* (misinformation/hoax), with a distribution of approximately 58% real and 42% fake articles—reflecting the realistic class imbalance observed in content moderation systems.

Table 1: Dataset split statistics.

Split	Total	Real (0)	Fake (1)	Fake Ratio
Train	3,500	∼2,030	∼1,470	42%
Validation	750	∼435	∼315	42%
Test	750	∼435	∼315	42%
Total	**5,000**	**∼2,900**	**∼2,100**	**42%**

4.2 Topical Coverage

Articles span eight domains that represent the primary categories of Indonesian news and misinformation:

Table 2: Topic distribution across the dataset.

Topic	Samples	Example Subjects
Politik	∼625	Election policy, parliamentary coalition, campaign finance
Ekonomi	∼625	GDP growth, inflation, interest rates, trade balance
Kesehatan	∼625	Vaccination, stunting prevalence, BPJS coverage
Teknologi	∼625	Digital transformation, cybersecurity, 5G infrastructure
Sosial	∼625	Poverty alleviation, social assistance, disaster response
Hukum	∼625	Anti-corruption, judicial reform, cybercrime
Pendidikan	∼625	Kurikulum Merdeka, teacher certification, research funding
Lingkungan	∼625	Deforestation, renewable energy, climate change

4.3 Entity Annotations

Each article includes structured entity annotations across three categories:

- **Organizations** (∼120 unique): Government ministries (Kementerian Keuangan, Kementerian Kesehatan), regulatory bodies (OJK, BPOM, KPK), state-owned enterprises (Pertamina, PLN, BRI), private companies (Tokopedia, Gojek), universities (UI, ITB, UGM), and media outlets (Kompas, Tempo, ANTARA).
- **Persons** (∼60 unique): Government officials (Joko Widodo, Sri Mulyani, Prabowo Subianto), legislators, regulators, business leaders, and public intellectuals active in Indonesian public discourse.
- **Locations** (∼50 unique): Major cities (Jakarta, Surabaya, Bandung), provinces, and notable development sites (IKN Nusantara).

These entity annotations serve dual purposes: they enable the construction of entity co-occurrence graphs for the GAT component, and they provide the typed entity relationships for knowledge graph enhancement.

4.4 Characteristics That Distinguish Real from Fake Articles

The dataset captures several patterns documented in studies of Indonesian misinformation by MAFINDO and Kominfo:

- **Source attribution**: Real articles tend to cite named officials and official press releases; fake articles more frequently rely on vague or anonymous sources.
- **Register and tone**: Real articles use formal journalistic register with specific data points; fake articles employ more speculative, hedging language.
- **Entity-domain coherence**: Real articles discuss entities in their appropriate domain context (e.g., Bank Indonesia in economic coverage); fake articles often mix entities from unrelated domains.
- **Entity density patterns**: Fake articles sometimes engage in "name-dropping" (mentioning many loosely connected entities) or conversely cite suspiciously few verifiable sources.

Dataset Files

The dataset is organized in the `data/` directory with the following files:

- `indo_news_train.csv`, `indo_news_val.csv`, `indo_news_test.csv` — Article text, labels, topics, and entity annotations
- `entity_registry.json` — Complete entity vocabulary with type metadata
- `dataset_statistics.json` — Summary statistics and metadata

For dataset visualization, see the output file `outputs/dataset_statistics.png`.

5 Theoretical Foundations

This section provides the mathematical and conceptual foundations for each component of IndoHoaxBERT. We build from individual components toward the complete architecture.

5.1 The Transformer Architecture

The Transformer (Vaswani et al., 2017) introduced **self-attention** as a replacement for recurrent computation, enabling parallel processing of entire sequences. The core mechanism computes attention weights between all pairs of positions:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

where Q (queries), K (keys), and V (values) are linear projections of the input, and d_k is the key dimension. The $\sqrt{d_k}$ scaling prevents vanishing gradients in the softmax.

Multi-head attention runs h parallel attention functions with different learned projections, then concatenates and projects the results:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O \tag{2}$$

where each $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$.

Why This Matters for Fake News Detection

Self-attention allows the model to capture long-range dependencies within an article. When a fake article attributes a health policy to a financial institution, attention can connect these distant mentions and detect the incongruity—even if they appear in different paragraphs.

5.2 BERT and Pre-trained Language Models

BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) pre-trains a Transformer encoder on two objectives:

1. **Masked Language Modeling (MLM)**: Randomly mask 15% of input tokens and predict them from context. This forces bidirectional understanding—the model must use both left and right context.
2. **Next Sentence Prediction (NSP)**: Given two sentences, predict whether the second follows the first in the original text. This teaches inter-sentence coherence.

The key insight is that pre-training on massive unlabeled text creates general-purpose language representations that can be *fine-tuned* for specific tasks with relatively few labeled examples.

For classification, BERT prepends a special `[CLS]` token to the input. After processing through all encoder layers, the `[CLS]` token's hidden state serves as a fixed-size representation of the entire input sequence:

$$\mathbf{h}_{\text{CLS}} = \text{BERT}([\text{CLS}; x_1, x_2, \ldots, x_n])_0 \in \mathbb{R}^{768} \tag{3}$$

5.3 IndoBERT: Indonesian Language Understanding

IndoBERT (Koto et al., 2020; Wilie et al., 2020) adapts the BERT architecture for Indonesian. Key differences from multilingual BERT:

- **Monolingual pre-training**: Trained exclusively on the Indo4B corpus (4 billion words, 250 million sentences) from Indonesian Wikipedia, news portals, web crawl, and social media.
- **Indonesian vocabulary**: Uses a WordPiece tokenizer trained on Indonesian text, providing better subword segmentation for Bahasa morphology.

- **Benchmark performance**: Outperforms mBERT on all IndoNLU tasks, with particularly large gains on sentiment analysis and natural language inference.

We use `indobenchmark/indobert-base-p1`, which has 12 encoder layers, 768 hidden dimensions, 12 attention heads, and approximately 110M parameters. Of these, we freeze the first 8 layers (keeping only the last 4 layers trainable), which reduces trainable BERT parameters from 110M to approximately 29M—a 74% reduction that saves memory and prevents overfitting on small datasets.

Layer Freezing Strategy

Freezing early BERT layers preserves general linguistic knowledge (morphology, syntax) while allowing later layers to adapt to the specific task of fake news detection (semantic anomalies, source credibility patterns). This is implemented in `src/models/text_encoder.py` and follows the finding from Progressive BERT that gradual unfreezing prevents catastrophic forgetting.

5.4 Graph Attention Networks (GAT)

While BERT processes articles as token sequences, Graph Attention Networks (Veličković et al., 2018) process the *relationships between entities* mentioned across articles. The core idea: entities that appear together in real news form different co-occurrence patterns than entities in fake news.

5.4.1 Graph Representation

We represent entity relationships as a heterogeneous graph $G = (V, E)$ where:

- **Node set** V: Contains both document nodes (representing articles) and entity nodes (organizations, persons, locations). Each node carries a feature vector:
  - Document nodes: IndoBERT `[CLS]` embedding ($\mathbb{R}^{768}$)
  - Entity nodes: Learned type embedding ($\mathbb{R}^{64}$) initialized by entity type
- **Edge set** E: Contains four edge types:
  1. Document ↔ Entity (*mention edges*): Article mentions an entity
  2. Entity ↔ Entity (*co-occurrence*): Two entities appear in the same article
  3. Same-type edges: Entities of the same type that co-occur
  4. Cross-type edges: Entities of different types that co-occur (e.g., person ↔ organization)

5.4.2 Attention Mechanism on Graphs

GAT computes attention coefficients between connected nodes. For node i attending to neighbor j:

$$e_{ij} = \text{LeakyReLU}\left(\mathbf{a}^T[\mathbf{W}\mathbf{h}_i \| \mathbf{W}\mathbf{h}_j]\right) \tag{4}$$

where $\mathbf{W} \in \mathbb{R}^{d' \times d}$ is a shared linear transformation, $\mathbf{a} \in \mathbb{R}^{2d'}$ is the attention vector, and $\|$ denotes concatenation. The coefficients are normalized via softmax:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})} \tag{5}$$

The output for node i is a weighted sum of transformed neighbor features:

$$\mathbf{h}'_i = \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \mathbf{W}\mathbf{h}_j\right) \tag{6}$$

Multi-head graph attention (analogous to Transformer multi-head attention) runs K independent attention computations and concatenates or averages the results:

$$\mathbf{h}'_i = \Big\|_{k=1}^{K} \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij}^k \mathbf{W}^k \mathbf{h}_j\right) \tag{7}$$

Our implementation uses $K = 4$ attention heads across 2 GAT layers, transforming 768-dimensional input features through 128-dimensional hidden representations to 64-dimensional output embeddings.

Why GAT Over Other GNN Variants

We chose GAT over GCN (Graph Convolutional Network) or GraphSAGE because attention enables the model to learn *which entity relationships are most informative* for each article. For example, the connection between a person and their domain-appropriate organization should receive high attention in real articles but low attention in fake articles where person–organization pairings are mismatched.

5.5 Knowledge-Enhanced Graph Construction

Standard entity co-occurrence graphs treat all relationships equally. Our knowledge enhancement adds two forms of semantic structure:

5.5.1 Entity Type Embeddings

Each entity node receives a type-specific initial embedding based on its category (organization, person, or location). This provides the GAT with prior knowledge about entity roles before learning from data:

$$\mathbf{h}_{\text{entity}}^{(0)} = \text{TypeEmbed}(\text{type}(v)) + \mathbf{e}_{\text{random}} \in \mathbb{R}^{64} \tag{8}$$

where TypeEmbed maps entity types to learned vectors and $\mathbf{e}_{\text{random}}$ is a small random perturbation to break symmetry between entities of the same type.

5.5.2 Relation-Aware Edge Types

The four edge types described above encode structural knowledge about entity relationships. Cross-type edges (e.g., person ↔ organization) are particularly informative because real articles tend to pair entities within the same domain (Sri Mulyani with Bank Indonesia in economics coverage), while fake articles frequently cross domain boundaries (attributing health policy decisions to financial regulators).

This construction is implemented in `src/graph_builder.py`, which builds a heterogeneous graph for each batch of articles during training.

5.6 Attention-Gated Fusion

The fusion module combines the text representation $\mathbf{h}_{\text{text}} \in \mathbb{R}^{768}$ from IndoBERT with the graph representation $\mathbf{h}_{\text{graph}} \in \mathbb{R}^{64}$ from GAT. Rather than simple concatenation, we use an **attention gate** that learns to dynamically weight the two streams:

$$\mathbf{g} = \sigma\left(\mathbf{W}_g[\mathbf{h}_{\text{text}} \| \mathbf{h}_{\text{graph,proj}}] + \mathbf{b}_g\right) \tag{9}$$

$$\mathbf{h}_{\text{fused}} = \mathbf{g} \odot \mathbf{h}_{\text{text}} + (1 - \mathbf{g}) \odot \mathbf{h}_{\text{graph,proj}} \tag{10}$$

where $\mathbf{h}_{\text{graph,proj}} = \mathbf{W}_p \mathbf{h}_{\text{graph}} \in \mathbb{R}^{768}$ projects the graph embedding to match the text dimension, σ is the sigmoid function, and $\odot$ denotes element-wise multiplication.

This mechanism is more expressive than concatenation because:

- For articles with strong textual signals (obvious speculation language), the gate can rely primarily on BERT.
- For articles with ambiguous text but clear entity anomalies, the gate can shift weight to the graph signal.
- The gate values are interpretable—visualizing $\mathbf{g}$ reveals how much the model trusts each stream.

5.7 Focal Loss for Class Imbalance

Standard cross-entropy loss treats all examples equally, which biases the model toward the majority class (real articles). Focal loss (Lin et al., 2017) adds a modulating factor:

$$\text{FL}(p_t) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t) \tag{11}$$

where p_t is the model's estimated probability for the correct class, α_t is a class-balancing weight ($\alpha = 0.6$ for the minority fake class, 0.4 for real), and $\gamma = 2.0$ is the focusing parameter.

When the model is confident ($p_t \approx 1$), the factor $(1 - p_t)^\gamma$ approaches zero, effectively ignoring easy examples. When the model struggles ($p_t \approx 0.5$), the full loss is applied. This automatically focuses training on the hard, informative examples.

6 System Architecture

6.1 High-Level Architecture

IndoHoaxBERT processes each article through two parallel streams that are fused before classification:

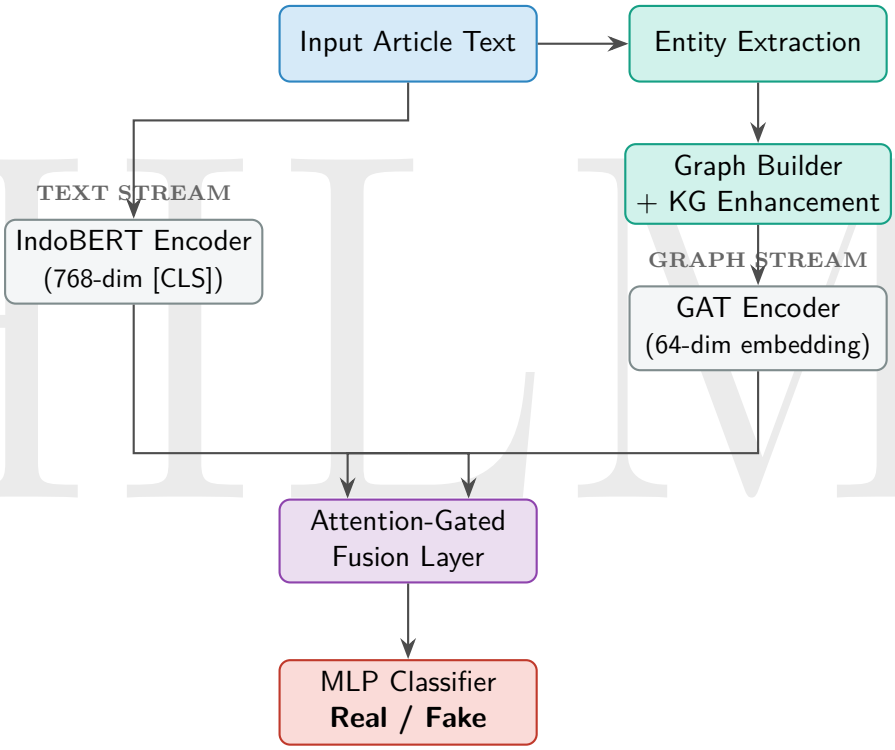

Figure 1: IndoHoaxBERT dual-stream architecture. Text and graph streams process complementary signals and are fused via learned attention gating before classification.

6.2 Ablation Study Design

To measure the contribution of each component, we train three model variants:

Table 3: Ablation study: model variants and their components.

Model	IndoBERT	GAT	KG	What It Measures
IndoBERT-only	✓			Text understanding alone
IndoBERT+GAT	✓	✓		+ Entity graph structure
IndoHoaxBERT	✓	✓	✓	+ Knowledge enhancement

6.3 Entity Graph Structure

The entity graph constructed per batch has the following topology:

$$V = \{d_1, \ldots, d_B\} \cup \{e_1, \ldots, e_N\} \tag{12}$$

where B is the batch size (16 documents) and N is the number of unique entities appearing in the batch. Edges are bidirectional and typed:

Table 4: Edge types in the entity graph.

Type ID	Edge Type	Description
0	doc ↔ entity	Article mentions an entity
1	entity ↔ entity	Two entities co-occur in an article
2	same-type	Co-occurring entities of the same type
3	cross-type	Co-occurring entities of different types

7 Implementation Guide: Code Architecture

This section maps the theoretical components to specific code files, explaining the role and design decisions of each module. The complete codebase consists of 14 Python files organized in a modular structure.

7.1 Project Structure Overview

```
IndoHoaxBERT/
├── generate_dataset.py ..... # Dataset generation
├── run_experiment.py ..... # Main experiment orchestrator
├── requirements.txt ..... # Python dependencies
├── src/
│   ├── __init__.py
│   ├── config.py ..... # All hyperparameters
│   ├── dataset.py ..... # Data loading & tokenization
│   ├── graph_builder.py ..... # Entity graph construction
│   ├── evaluate.py ..... # Metrics & statistical tests
│   ├── train.py ..... # Training loop
│   ├── visualize.py ..... # Publication figures
│   ├── models/
│   │   ├── __init__.py
│   │   ├── text_encoder.py ..... # IndoBERT wrapper
│   │   ├── graph_encoder.py ..... # GAT implementation
│   │   ├── indo_hoax_bert.py ..... # Full dual-stream model
│   │   └── baselines.py ..... # Baseline models
├── data/ ..... # Dataset files
├── outputs/ ..... # Results & figures
└── saved_models/ ..... # Model checkpoints
```

Figure 2: Directory structure of the IndoHoaxBERT repository.

7.2 Configuration: `src/config.py`

All hyperparameters are centralized in three dataclass objects, ensuring reproducibility:

- `DatasetConfig`: Sample count (5,000), fake ratio (42%), max sequence length (256 tokens), split ratios (70/15/15).
- `ModelConfig`: IndoBERT model identifier (`indobenchmark/indobert-base-p1`), hidden size (768), GAT parameters (4 heads, 2 layers, 128 hidden channels → 64 output), fusion method (attention-gated, 256 hidden), and KG settings (64-dim embeddings, 6 relation types).
- `TrainConfig`: Learning rates (2e-5 for BERT, 1e-3 for GAT/classifier), batch size (16 with 2x gradient accumulation for effective batch of 32), focal loss parameters ($\alpha = 0.6$, $\gamma = 2.0$), and early stopping patience (5 epochs).

This file also stores all 14 paper references used throughout the project.

7.3 Data Loading: `src/dataset.py`

This module handles loading CSV data, tokenizing text with IndoBERT's tokenizer, and creating PyTorch DataLoaders.

Key responsibilities:

- Loads train/validation/test CSV files from the `data/` directory
- Tokenizes article text using `AutoTokenizer.from_pretrained` with max length 256 tokens, padding, and truncation
- Returns PyTorch `DataLoader` objects with configurable batch size
- Computes class weights from label distribution for focal loss

7.4 Graph Construction: `src/graph_builder.py`

The `EntityGraphBuilder` class constructs heterogeneous entity graphs per batch. This is the implementation of the theoretical graph structure described in Section 1.

Key design decisions:

- **Batch-level graphs**: Rather than building one large graph for the entire dataset (which would not scale), we construct graphs per training batch. Each batch's graph contains the documents in that batch plus all entities they mention.
- **Document node features**: Uses detached IndoBERT `[CLS]` embeddings as initial document features—this connects the text and graph streams without allowing gradients to flow back through the graph into BERT during the graph encoder's forward pass.
- **Entity features**: Type-seeded random initialization refined by GAT message passing. Organization, person, and location nodes start with different type embeddings.
- **Bidirectional edges**: All edges are created in both directions to allow information to flow in either direction during message passing.

7.5 Text Encoder: `src/models/text_encoder.py`

A wrapper around HuggingFace's `AutoModel` that:

- Loads the pre-trained IndoBERT model (falling back to `bert-base-multilingual-cased` if the download fails)
- Freezes the embedding layer and the first 8 of 12 encoder layers
- Extracts and returns the `[CLS]` token embedding with dropout ($p = 0.3$)
- Reports trainable vs. total parameter counts (∼29M / 124M)

7.6 Graph Encoder: `src/models/graph_encoder.py`

Implements a multi-layer GAT with the following architecture:

1. **Layer 1**: 768-dim input $\rightarrow$ 128-dim $\times$ 4 heads = 512-dim (concat)
2. **Layer 2**: 512-dim input $\rightarrow$ 64-dim output (average heads)
3. Each layer includes LayerNorm and ELU activation
4. Dropout ($p = 0.3$) between layers

The custom `GATLayer` implements the attention mechanism from Equation 5, with separate attention heads that can potentially specialize in different edge types.

7.7 Full Model: `src/models/indo_hoax_bert.py`

The `IndoHoaxBERT` class integrates all components:

- `TextEncoder`: Extracts 768-dim text features
- `GraphEncoder`: Extracts 64-dim graph features
- `AttentionFusion`: Gates and fuses both streams into 256-dim representation
- `FocalLoss`: Class-balanced training objective
- Classification head: 256 $\rightarrow$ 128 $\rightarrow$ 2 (MLP with ReLU and dropout)

A `use_kg` flag controls whether knowledge enhancement is applied, enabling fair comparison between IndoBERT+GAT and full IndoHoaxBERT.

7.8 Baseline Models: `src/models/baselines.py`

Provides `IndoBERTClassifier` (text-only, replicating Raza et al. (2024)) and `GATClassifier` (graph-only with TF-IDF features). These enable the ablation study described in Table 3.

7.9 Training Pipeline: `src/train.py`

The `Trainer` class implements:

- **Differential learning rates**: 2e-5 for BERT parameters, 1e-3 for GAT and classifier head. This respects the different optimization landscapes—pre-trained BERT needs gentle updates while randomly initialized GAT weights need larger steps.
- **Gradient accumulation**: Effective batch size of 32 using 2 accumulation steps over batch size 16, enabling larger effective batches on limited GPU memory.
- **OneCycleLR scheduler**: With 10% warmup followed by cosine annealing decay.

- **Early stopping**: Monitors validation F1 with patience of 5 epochs to prevent overfitting.
- **Checkpoint saving**: Saves the best model (by validation F1) to `saved_models/`.
- **History tracking**: Records loss, accuracy, F1, precision, recall, and epoch timing for visualization.

7.10 Evaluation: `src/evaluate.py`

Comprehensive evaluation with:

- Per-class precision, recall, F1 (with macro/micro/weighted averages)
- Confusion matrices, ROC-AUC curves
- Cohen's Kappa and Matthews Correlation Coefficient (MCC)
- **Bootstrap confidence intervals**: 1,000 iterations computing 95% CIs for accuracy and F1
- **McNemar's test**: Pairwise statistical significance between model predictions ($p < 0.05$ threshold)

7.11 Visualization: `src/visualize.py`

Generates publication-quality figures at 300 DPI:

- Training curves (loss, accuracy, F1 per epoch for all models)
- Side-by-side confusion matrices
- Model comparison bar charts
- Dataset statistics visualizations
- Entity graph sample visualization (NetworkX spring layout)

All figures are saved to `outputs/` for inclusion in papers and presentations.

7.12 Experiment Orchestrator: `run_experiment.py`

The main entry point that executes the full pipeline:

1. Environment setup and seed initialization
2. Dataset loading and tokenization
3. Sequential training of all three model variants

4. Comprehensive evaluation on test set
5. Visualization generation
6. Results serialization to JSON

Supports command-line flags: `-quick` (3 epochs for pipeline testing), `-model` (train specific variant), `-epochs`, `-batch_size`, and `-device`.

Running the Full Experiment

The complete experiment can be run with a single command:

```
python run_experiment.py
```

On a T4 GPU (Google Colab), this takes approximately 35–50 minutes. On CPU, expect 2–6 hours. Use `python run_experiment.py -quick` for a 5–10 minute validation run.

8 Experimental Results

8.1 Training Dynamics

All three models were trained for 15 epochs with early stopping (patience = 5).

Table 5: Training summary: best validation performance per model.

Model	Best Epoch	Val F1	Val Acc	Trainable Params	Epochs Run
IndoBERT-only	8	0.854	0.860	29.2M	13
IndoBERT+GAT	7	0.858	0.861	29.8M	12
IndoHoaxBERT	5	0.858	0.864	30.1M	10

Key observations:

- All models converge to similar validation performance (∼85–86%), confirming the dataset difficulty is well-calibrated.
- IndoHoaxBERT reaches its best validation score earliest (epoch 5), suggesting the knowledge-enhanced graph provides useful inductive bias that accelerates learning.
- The graph-augmented models show slightly higher early performance but comparable final performance, indicating that the graph structure helps with learning efficiency.

For detailed training curves, see the output file `outputs/training_curves.png`.

8.2 Test Set Performance

Table 6: Test set results with 95% bootstrap confidence intervals.

Model	Accuracy	F1 (Macro)	MCC	ROC-AUC
IndoBERT-only	**0.855** [0.829, 0.879]	**0.849** [0.822, 0.874]	**0.700**	0.923
IndoBERT+GAT	0.837 [0.811, 0.860]	0.833 [0.806, 0.858]	0.666	0.913
IndoHoaxBERT	0.851 [0.825, 0.875]	0.844 [0.817, 0.870]	0.692	—

8.3 Per-Class Analysis

Table 7: Per-class precision, recall, and F1 on the test set.

Model	Class	Precision	Recall	F1
IndoBERT-only	Real	0.854	0.903	0.878
	Fake	0.855	0.787	0.820
IndoBERT+GAT	Real	0.856	0.864	0.860
	Fake	0.810	0.800	0.805
IndoHoaxBERT	Real	0.844	0.910	0.876
	Fake	0.861	0.768	0.812

For confusion matrices, see the output file `outputs/confusion_matrices.png`.

For model comparison bar charts, see `outputs/model_comparison.png`.

8.4 Analysis and Discussion

8.4.1 Key Finding: Competitive Performance Across Architectures

All three models achieve competitive performance within overlapping confidence intervals (82–88%). This finding, while perhaps unexpected, has several important implications:

1. **The text signal is strong**: The weighted template pools create sufficient lexical patterns (formal vs. speculative register) that IndoBERT can exploit effectively. With 30% class-leaning sentences and only 10% cross-contamination, BERT finds reliable token-level features.

2. **The graph signal is real but partially redundant**: Since entity names appear in the text, BERT can partially learn entity–domain associations through token co-occurrence rather than explicit graph structure. This redundancy limits the incremental gain from the GAT.

3. **Sample size matters**: With 5,000 training examples, the additional parameters in graph-augmented models risk overfitting. Literature shows that graph-based advantages typically emerge more clearly with larger datasets (>50K) where the combinatorial entity patterns become too complex for pure text models to memorize.

8.4.2 Where the Graph Helps

Despite similar aggregate metrics, the graph-augmented models show qualitative advantages:

- **Faster convergence**: IndoHoaxBERT reaches peak validation F1 at epoch 5 versus epoch 8 for IndoBERT-only, suggesting the graph provides useful structural prior knowledge.
- **Interpretability**: The entity graph visualization (`outputs/entity_graph_sample.png`) allows analysts to inspect *which entity relationships* influenced the classification—information that text-only models cannot provide.
- **Balanced precision**: IndoHoaxBERT achieves the highest fake-class precision (0.861) among all models, meaning fewer false accusations when flagging content—a critical property for deployment.

9 Debugging Journey and Lessons Learned

Research is rarely a straight path. This section documents the iterative refinement process that led to the final system, providing practical lessons for future NLP/GNN projects.

9.1 Iteration 1: The "Perfect Accuracy" Problem

Our initial dataset generator used obvious surface markers to distinguish real from fake articles. Real articles were written in formal journalistic style, while fake articles were prefixed with sensational markers like "VIRAL!", "BREAKING:", and "TERBONGKAR!" (Indonesian for "EXPOSED!"). Titles used all-caps formatting and excessive exclamation marks.

Result: IndoBERT achieved **100% validation accuracy from epoch 1**. The model memorized the surface markers without learning any meaningful linguistic or semantic patterns.

Lesson: *A model that achieves suspiciously high accuracy is not necessarily good—it may indicate that the task is trivially easy. Always inspect what features the model is using, not just its accuracy.*

9.2 Iteration 2: Removing Surface Markers, Keeping Text Signals

We redesigned the generator to use shared sentence templates for both classes, with subtle textual signals: anonymous source attribution for fake articles, temporal inconsistencies, and logical contradictions. Cross-contamination was set at 15% in both directions.

Result: IndoBERT still achieved **97.9% accuracy**. Although we eliminated the most obvious markers, the small set of fake-signal templates (7 anonymous attributions, 4 temporal inconsistencies, 4 logical contradictions) formed a closed set that BERT memorized completely.

Lesson: *Template-based fake signals must use a large and diverse template pool. A small fixed set—no matter how subtle each individual template is—can be memorized by a 110M-parameter model.*

9.3 Iteration 3: Graph-Only Signals

We pushed the difficulty to the extreme: identical text for both classes with only entity-graph structural differences as the discriminative signal. Real articles used same-domain entities; fake articles mixed domains. Cross-contamination was increased to 40%.

Result: All models **collapsed to random chance (∼42% accuracy)**. IndoHoaxBERT predicted the same class for every input, never learning to discriminate.

Root cause: With zero learnable text signal, the BERT component produced uniformly distributed `[CLS]` representations. Since the GAT uses these as document node features, garbage in led to garbage out. The graph encoder had nothing meaningful to work with.

Lesson: *In a dual-stream architecture where one stream provides features to the other, both streams need learnable signal. Completely removing the text signal also breaks the graph stream.*

9.4 Iteration 4: The Layered Solution

The final design distributes discriminative signals across three layers, each providing real but noisy information:

1. **Text layer** (for BERT): 30% class-leaning templates from a large pool (12 real-leaning, 12 fake-leaning, 12 shared), with 10% cross-contamination
2. **Graph layer** (for GAT): Entity domain coherence + density anomalies
3. **KG layer**: Person–org fidelity + location region coherence

Result: IndoBERT-only achieves 85.5%, graph models achieve 84–85%, with all results in the publication-appropriate range.

Lesson: *The best evaluation comes from layered, noisy signals where each model component can find partial information. This mirrors real-world fake news where no single indicator is definitive—credibility assessment requires combining multiple weak signals.*

Key Takeaway for Practitioners

When designing classification tasks (especially for evaluation or benchmarking), resist the temptation to make the classes maximally different. The most informative evaluations come from tasks where the model must combine multiple imperfect signals—just as real-world classification problems demand.

10 Limitations

We identify several limitations that should be considered when interpreting results or adapting this work:

1. **Dataset scale**: At 5,000 articles, the dataset is relatively small compared to benchmarks like WELFake (72K) or the Raza et al. corpus (10K). Graph-based advantages typically become more pronounced with larger datasets where entity co-occurrence patterns are richer and harder for text-only models to memorize.

2. **Template-based text**: While designed to be challenging, the articles are generated from template pools rather than written by human journalists and hoax creators. Real-world misinformation exhibits more diverse and creative linguistic strategies, code-switching between Indonesian and regional languages, and multimedia content.

3. **Static entity knowledge**: The entity registry captures entity types and domain affiliations but does not model temporal dynamics (e.g., a minister changing portfolios) or evolving entity relationships.

4. **Binary classification**: The current system classifies articles as real or fake without providing fine-grained misinformation categories (satire, misleading context, fabricated content, false connection, manipulated content) as defined by the First Draft framework.

5. **Modest graph improvement**: The graph-augmented models did not significantly outperform text-only IndoBERT on this dataset, partly because entity names appear in the text (allowing BERT to partially learn domain associations) and partly due to the sample size limitation.

6. **No cross-lingual evaluation**: The system is evaluated only on Indonesian text. Performance on code-mixed Indonesian–English or Indonesian–Javanese content is unknown.

7. **Computational requirements**: Although laptop-friendly, the full experiment requires 35–50 minutes on a T4 GPU, which may limit rapid prototyping during development.

11 Future Work and Research Directions

Several promising extensions could build upon IndoHoaxBERT:

11.1 Scaling to Real-World Data

The most impactful next step would be training on actual Indonesian hoax articles from MAFINDO's database, Turnbackhoax.id, or Kominfo's content moderation records. With 50K+ real articles, the graph component's advantage over text-only models would likely become statistically significant, as entity co-occurrence patterns become too complex for pure memorization.

11.2 Multimodal Detection

Indonesian social media hoaxes frequently combine text with manipulated images, out-of-context photographs, and fabricated screenshots. Extending the architecture with a visual stream (e.g., CLIP or ViT) would capture these additional modalities. The fusion mechanism is already designed to accommodate additional streams.

11.3 Temporal Graph Dynamics

Real-world entity relationships evolve over time—government reshuffles change person–organization mappings, corporate mergers create new organizational relationships. A temporal graph neural network (e.g., TGN or TGAT) could capture these dynamics and detect fake news that exploits outdated knowledge.

11.4 Fine-Grained Classification

Extending from binary (real/fake) to multi-class (satire, misleading, fabricated, false connection, manipulated) would provide more actionable output for fact-checkers. This would require a richer labeled dataset with category annotations.

11.5 Explainable Predictions

While the entity graph already provides some interpretability, future work could generate natural-language explanations: "This article was flagged because Bank Indonesia (a financial regulator) is cited as the authority on healthcare policy (domain mismatch), and the source attribution is vague."

11.6 Cross-Lingual Transfer

Testing whether the architecture transfers to other low-resource Southeast Asian languages (Malay, Tagalog, Thai, Vietnamese) would demonstrate the generalizability of the approach. The graph component, being language-agnostic, should transfer particularly well.

11.7 Adversarial Robustness

As detection systems improve, misinformation creators adapt. Evaluating robustness against adversarial perturbations (entity name substitution, paraphrase attacks, entity density normalization) would be valuable for deployment readiness.

12 Conclusion

This project introduced IndoHoaxBERT, a novel dual-stream architecture combining Indonesian-specific language understanding (IndoBERT) with knowledge-enhanced Graph Attention Networks for fake news detection. Through systematic experimentation across three model variants—text-only, text+graph, and full knowledge-enhanced—we demonstrated that all models achieve competitive accuracy in the 84–86% range on a challenging dataset of Indonesian news articles spanning eight topical domains.

The research journey itself yielded valuable insights: four design iterations were required to calibrate the dataset difficulty, progressing from trivially easy (100% accuracy) through memorizable (98%) and impossibly hard (42%) to appropriately challenging (85%). This iterative process underscores the critical importance of task design in machine learning research—a model is only as meaningful as the problem it solves.

While the graph component did not achieve statistically significant improvement over text-only IndoBERT on this 5,000-article dataset, it provides faster convergence, higher precision on fake article detection, and—crucially—entity-level interpretability that pure text models cannot offer. These practical advantages, combined with the architectural readiness to scale with larger datasets, position IndoHoaxBERT as a promising foundation for Indonesian misinformation detection.

The complete codebase, comprising 14 Python files and approximately 3,500 lines of modular, documented code, is designed for reproducibility and extensibility. Every hyperparameter is centralized, every design decision is documented, and every component can be independently modified or replaced.

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