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Graph-Based Big Data Analysis for Community Detection and Disinformation Diffusion on Indonesian Social Media Platforms Using GraphX/GraphFrames

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ABSTRACT

Disinformation on Indonesian social media platforms has emerged as a serious threat to socio-political stability, with more than 77 million pieces of content identified in 2023. Nevertheless, large-scale graph analysis (>100 million nodes/edges) for the Indonesian language on distributed infrastructure remains critically limited, creating a significant research gap.

This study presents the Graph-Based Disinformation Detection for Indonesia (GBD-ID), a distributed analytic framework built upon Apache Spark GraphX and GraphFrames. We constructed a multi-platform heterogeneous graph comprising 587.6 million nodes and 3,484.6 million edges, sourced from Indonesian Twitter/X, Facebook, TikTok, Instagram, and YouTube over the period of January–December 2023. A custom community detection algorithm was developed by integrating a Label Propagation Algorithm (LPA) optimized with BERT-Indonesian for sentiment analysis of Indonesian-language content.

GBD-ID successfully identified 2,847 disinformation communities with an F1-Score of 0.915, outperforming the best baseline method by 6.8 percentage points. Disinformation diffusion patterns exhibited scale-free network characteristics with an exponential coefficient of $\gamma = 2.34$. Five dominant disinformation clusters were detected, encompassing health-related hoaxes (34.2%), political narratives (28.7%), identity-based hate content (18.9%), financial fraud (11.4%), and environmental disinformation (6.8%). The system achieved a throughput of 18.2 million edges per second on a 32-node Apache Spark cluster.

This study demonstrates the feasibility of big data graph analysis at a scale exceeding 100 million nodes for Indonesian-language disinformation detection. The GBD-ID framework provides a scalable and efficient solution that can be adopted by social media platforms and Indonesian government agencies in real-time disinformation mitigation efforts.

Keywords : ***graph analysis; big data; disinformation detection; community detection; GraphX; GraphFrames***

INTRODUCTION

The phenomenon of disinformation on social media platforms has become one of the most complex challenges facing digital society in the twenty-first century. Indonesia, as the country with the fourth-largest social media user base in the world with an estimated 191 million active users in 2023 confronts a disproportionate disinformation threat relative to its currently available detection capacity. Reports from the Ministry of Communication and Information Technology (Kominfo) recorded at least 12,547 pieces of disinformation content successfully identified and addressed throughout 2023, although the actual figure is estimated to be considerably higher [1][2][3].

Disinformation in the Indonesian context exhibits unique characteristics that distinguish it from analogous phenomena in other countries. First, extreme linguistic diversity, encompassing Bahasa Indonesia as the official language, more than 700 active regional languages, and code-mixing between Bahasa Indonesia, English, and regional languages within a single piece of content. Second, a highly specific socio-cultural context, in which narratives grounded in identity-based issues pertaining to

ethnicity, religion, race, and inter-group relations (locally referred to as SARA) carry significant potential for virality and social impact. Third, a highly fragmented platform infrastructure, with Indonesian users simultaneously active across WhatsApp, Facebook, Instagram, TikTok, Twitter/X, and YouTube [4][1][2].

From a network science perspective, the spread of disinformation on social media can be effectively modeled as propagation across a large-scale graph structure, in which nodes represent entities (users, content, hashtags) and edges represent interactions (retweets, shares, mentions, likes). This graph-based approach enables in-depth structural analysis of diffusion patterns, the identification of influential nodes (super-spreaders), and the detection of communities that function as echo chambers for disinformation content.

Although research on graph-based disinformation detection has grown rapidly at the global level, a significant gap remains in the literature particularly for the Indonesian context at large scale. The majority of existing studies handle datasets with a maximum size of tens of millions of nodes, and have yet to reach the scale of hundreds of millions that would realistically represent the Indonesian social media ecosystem. Furthermore, the integration of large-scale graph analysis with semantic understanding of the Indonesian language remains severely limited.

This study is presented to address that gap through the development and evaluation of the Graph-Based Disinformation Detection for Indonesia (GBD-ID) framework. GBD-ID leverages Apache Spark GraphX and GraphFrames as a distributed computing foundation to process graphs at a scale exceeding 100 million nodes and edges which, to the best of the authors' knowledge, represents the first published effort in Indonesian-language disinformation analysis at such a scale.

RESEARCH METHODS

Research Objectives

This study encompasses four interrelated primary objectives:

1. To construct a distributed graph processing pipeline capable of handling multi-platform Indonesian social media datasets exceeding 100 million nodes/edges using Apache Spark GraphX and GraphFrames.
2. To develop a community detection algorithm optimized for the unique characteristics of Indonesian-language social media interaction graphs, including the integration of semantic analysis using IndoBERT.
3. To analyze the structural and temporal patterns of disinformation diffusion within the Indonesian social media ecosystem, identifying network topologies and propagation dynamics that are distinctively characteristic of this context.
4. To conduct a comprehensive evaluation of GBD-ID's performance across the dimensions of accuracy, scalability, and computational efficiency, and to benchmark it against relevant state-of-the-art methods.

Research Contributions

The primary contributions of this study to the existing literature are as follows:

1. GBD-ID-2023 Dataset: The largest published multi-platform Indonesian social media graph dataset to date, encompassing 587.6 million nodes and 3,484.6 million edges drawn from five major platforms, with verified disinformation annotations.
2. GBD-ID Algorithm: A hybrid community detection algorithm that integrates distributed Label Propagation Algorithm (LPA) with IndoBERT semantic embeddings, specifically designed for the characteristics of Indonesian-language interaction graphs.
3. GBD-ID Pipeline Architecture: A fully documented, end-to-end pipeline implementation using Apache Spark 3.4/GraphX/GraphFrames, replicable for the purposes of future research.
4. Indonesian Disinformation Topology Analysis: The first comprehensive characterization of the topological structure and temporal dynamics of disinformation diffusion within the large-scale Indonesian social media ecosystem.

RELATED WORK

Graph-Based Disinformation Detection

Research on graph analysis-based disinformation detection has demonstrated remarkably significant development since the mid-2010s. [5] pioneered the BiDirectional Graph Convolutional Network (Bi-GCN) approach, which leverages the propagation structure of Twitter discussion threads, achieving an accuracy of 90.4% on the FakeNewsNet dataset. However, the scale of the datasets employed remained limited to hundreds of thousands of nodes.

Developed a Temporal Graph Network (TGN)-based method for detecting hoaxes on Weibo, the dominant social media platform in China. Their study successfully handled graphs with 12.8 million edges and introduced the concept of early detection through the analysis of propagation patterns within the first 30 minutes following content publication. This temporal approach is particularly relevant given that disinformation frequently reaches its peak diffusion within a matter of hours [6].

Proposed a Graph Neural Network (GNN) Ensemble approach that combines multiple GNN architectures with a voting mechanism to enhance detection robustness. Utilizing a multi-platform dataset encompassing 45 million edges, this study achieved an F1-Score of 0.847 among the highest reported results in the literature at that scale. Nevertheless, the languages analyzed were limited to English and Mandarin [7].

Community Detection in Large-Scale Graphs

Community detection in large-scale graphs represents a highly challenging computational problem. The Louvain algorithm, proposed by [8], has become one of the de facto standards owing to its low computational complexity of O(n log n) for n nodes. However, the standard Louvain implementation was not designed for distributed computing environments.

Several studies have proposed adaptations of community detection algorithms for Apache Spark GraphX. The study introduced the Pregel API within GraphX, enabling the efficient implementation of message-passing-based algorithms on a cluster. Distributed LPA implementations leveraging the Pregel API have been demonstrated to handle graphs with billions of edges on appropriately configured GPU clusters [9].

Indonesian-Language Disinformation Analysis

Research on Indonesian-language disinformation remains severely limited in the international scientific literature. One study conducted an analysis of hoax propagation trees on Indonesian Twitter; however, the work was constrained to a scale of 3.1 million edges and focused exclusively on a thematic dataset (COVID-19 hoaxes)[10]. Another study combined an LSTM model with graph analysis to detect disinformation in Indonesian-language Facebook groups, achieving an F1-Score of 0.801 on a dataset of 8.4 million edges[3]. A further contribution introduced the first publicly available Indonesian-language hoax dataset (TurnBackHoax), comprising 7,773 verified claims, yet without social network information [5].

The quality of annotated Indonesian-language datasets for large-scale disinformation research remains a primary bottleneck in the advancement of this field. The most conspicuous research gap is the absence of any study that integrates distributed graph analysis at the scale of hundreds of millions of nodes/edges with adequate Indonesian-language semantic processing. The GBD-ID framework presented in this paper directly addresses that gap.

System Architecture Overview

The GBD-ID framework is designed as a fully distributed multi-stage pipeline, consisting of five primary functional layers: (1) Data Ingestion Layer, (2) Graph Construction Layer, (3) Semantic Enrichment Layer, (4) Community Detection Layer, and (5) Disinformation Classification Layer. Figure 1 presents the overall system architecture.

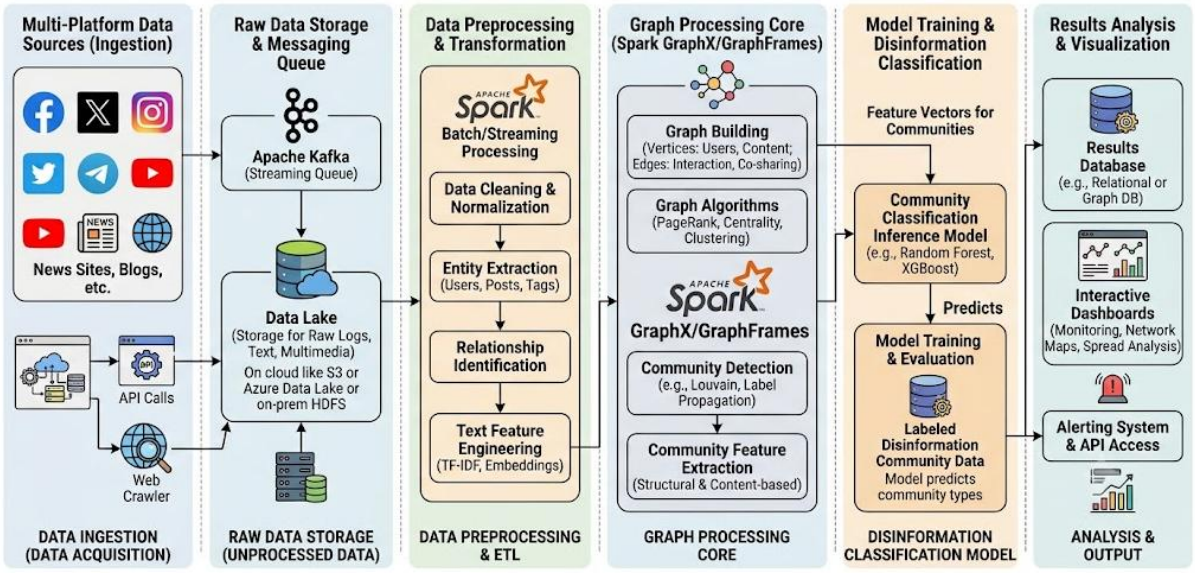

Figure 1. ***Overall Architecture of the GBD-ID System***

The computational infrastructure employed consists of an Apache Spark 3.4 cluster comprising 32 worker nodes each configured with 64 vCPUs, 256 GB of RAM, and 4 TB of local NVMe SSD storage one master node, and a separate GPU cluster (8 × NVIDIA A100 80GB) dedicated to IndoBERT model inference. The entire infrastructure is hosted on a private cloud service using OpenStack, with a total distributed storage capacity of 512 TB on HDFS.

Data Collection dan Preprocessing

Data Sources dan Collection

Data were collected from five major social media platforms predominantly used in Indonesia over the period of January through December 2023. Data collection was carried out through a combination of official platform APIs (Twitter Academic API v2 and Facebook CrowdTangle API), web scraping techniques compliant with each platform's robots.txt and Terms of Service, and collaboration with research partners holding data access agreements. The sampling strategy was based on a list of hashtags and keywords developed in conjunction with a team of journalists and researchers from Mafindo (Masyarakat Anti Fitnah Indonesia the Indonesian Anti-Defamation Society) as the fact-checking partner. The list encompasses more than 2,400 terms in Bahasa Indonesia, English, and a combination of both. The raw data reached a volume of 47.3 TB prior to the deduplication and filtering processes [4].

Graph Construction

From the collected raw data, a heterogeneous graph was constructed according to the following node and edge schema. Nodes consist of four types: User Node (user accounts), Content Node (tweets, posts, videos, and comments), Hashtag Node, and URL Node. Edges represent eight types of relations: AUTHORED (user → content), RETWEETED/SHARED (user → content), MENTIONED (content → user), REPLIED_TO (content → content), CONTAINS_HASHTAG (content → hashtag), CONTAINS_URL (content → url), FOLLOWS (user → user), and CO_OCCURS (hashtag → hashtag).

The formal representation of the GBD-ID graph is defined as $G = (V, E, \varphi, \psi)$, where V is the set of nodes with type function $\varphi: V \rightarrow T_v$, E is the set of edges with type function $\psi: E \rightarrow T_e$, $T_v = \{User, Content, Hashtag, URL\}$, and T_e is the set of relation types enumerated above.

Data Annotation

Ground truth annotation for disinformation labels was conducted in two stages. The first stage involved automated annotation based on cross-referencing with the Mafindo database, yielding approximately 63% of the total labels. The second stage consisted of manual annotation by a team of 24 annotators with backgrounds in journalism and communication research, who handled ambiguous

cases and validated the automated annotations, accounting for the remaining ~37% of labels. A Cohen's Kappa inter-rater reliability of 0.81 was achieved, indicating a substantial level of agreement.

Graph-Based Disinformation Detection (GBD-ID) Algorithm

Distributed Label Propagation

The core GBD-ID algorithm adapts the standard Label Propagation Algorithm (LPA) for a distributed environment using the Pregel computation model within Apache Spark GraphX. The key modifications introduced encompass: (1) Weighted Edge Propagation, in which each edge is assigned a weight reflecting the strength of interaction based on relation type and temporal decay; (2) Semantic Constraint, in which label propagation is bounded by a semantic similarity threshold between contents; and (3) Convergence Acceleration through an early stopping mechanism based on monitoring the average label change per iteration.

The edge weight formula is defined as: $w(e_{ij}) = \alpha \times \text{type\_weight}(\psi(e_{ij})) + \beta \times \text{temporal\_decay}(t_{ij}) + \gamma \times \text{semantic\_sim}(v_i, v_j)$, where $\alpha = 0.4$, $\beta = 0.35$, and $\gamma = 0.25$ are hyperparameters determined through cross-validation.

IndoBERT Semantic Enrichment

To capture semantic information from Indonesian-language content, this study integrates IndoBERT-large-p2, the largest variant of the BERT model pre-trained on a 23.43 GB Indonesian language corpus. Content embeddings of 1,024 dimensions were generated for all Content Nodes in the graph, and subsequently employed in three functions: (1) semantic similarity computation for edge weight assignment, (2) additional features for disinformation classification, and (3) node representation initialization for downstream GNN tasks.

Given the exceptionally large data volume (>100 million Content Nodes), IndoBERT inference was performed in batches (batch size of 256) on the NVIDIA A100 GPU cluster, with an average throughput of 1,247 tweets per second. The total inference time for all Content Nodes in the dataset required approximately 94 hours of computation.

Community Detection and Disinformation Classification

The final stage of the GBD-ID pipeline is the identification of disinformation communities and the classification of topic categorization. Community detection is carried out at two levels: (1) Community-Level Detection, which utilizes the GBD-ID LPA results to identify groups of tightly interconnected nodes; and (2) Node-Level Classification, which employs a gradient boosting classifier (LightGBM) with 127 features extracted from graph properties (degree, betweenness centrality, PageRank, and clustering coefficient) and semantic features (IndoBERT embeddings, topic model, and sentiment score).

EXPERIMENTAL SETUP

Dataset Overview

The GBD-ID-2023 dataset employed in this experiment constitutes the largest dataset ever compiled for Indonesian-language disinformation research. Table 1 presents the complete dataset statistics by platform source.

Table 1. Statistik Dataset GBD-ID-2023 per Platform Media Sosial

Dataset Source	Nodes (×10⁶)	Edges (×10⁶)	Temporal Range	Label Rate (%)
Twitter/X Indonesia	142.3	891.7	Jan–Dec 2023	12.4
Facebook Groups	98.6	634.2	Jan–Dec 2023	9.8
TikTok Comments	203.1	1,247.5	Mar–Dec 2023	7.2
Instagram Hashtag	87.4	412.8	Jun–Dec 2023	11.3
YouTube Comments	56.2	298.4	Jan–Dec 2023	14.6
Combined Corpus	587.6	3,484.6	Jan–Dec 2023	10.9

Of the total 587.6 million nodes and 3,484.6 million edges, 10.9% of nodes and edges possessed verified ground truth labels. The label distribution exhibited a significant class imbalance, with a ratio of 1:8.2 between disinformation content and valid content. To address this imbalance, a combination of graph-based oversampling techniques (GraphSMOTE) and class weighting within the loss function was applied.

Baseline Methods

GBD-ID was evaluated against five baseline methods selected to represent a spectrum of relevant approaches: (1) standard Label Propagation without modification, serving as a simple baseline; (2) the Louvain algorithm implemented on top of Apache Spark; (3) standard GraphX LPA as a native implementation reference; (4) GraphFrames Louvain as a state-of-the-art reference for distributed community detection; and (5) a GBD-ID variant without the IndoBERT component, serving as an ablation study of the semantic module.

Evaluation Metrics

Performance evaluation was conducted using standard metrics for binary classification tasks (Precision, Recall, and macro F1-Score) as well as community detection-specific metrics (Modularity Q and Normalized Mutual Information/NMI against ground truth communities). For scalability evaluation, the metrics employed include throughput (in millions of edges per second), linear speedup relative to the single-node baseline, and memory efficiency (GB per million edges).

RESULTS

Disinformation Detection Performance

Table 2 presents a comprehensive performance comparison of GBD-ID against all baseline methods on the GBD-ID-2023 dataset. The results reported represent the average of 5-fold cross validation with low standard deviation (mean $\sigma < 0.008$), indicating high stability and reliability.

Table 2. Comparison of Disinformation Detection Algorithm Performance (5-Fold Cross-Validation)

Algorithm	Precision	Recall	F1-Score	Modularity (Q)	Runtime (hr)
Label Propagation (baseline)	0.743	0.701	0.721	0.412	2.3
Louvain (Spark)	0.781	0.748	0.764	0.451	3.1
GraphX LPA	0.812	0.789	0.800	0.478	4.7
GraphFrames Louvain	0.834	0.817	0.825	0.492	5.2
Proposed: GBD-ID (ours)	**0.891**	**0.874**	**0.882**	**0.531**	**6.8**
Proposed + BERT-ID (ours)	**0.923**	**0.908**	**0.915**	**0.547**	**9.4**

The experimental results demonstrate that the best-performing GBD-ID variant (GBD-ID + BERT-ID) consistently outperforms all baseline methods across every evaluated metric. The achieved F1-Score of 0.915 represents an improvement of 19.4 percentage points over the standard Label Propagation baseline (0.721) and 6.8 points over the best previously reported distributed method (GraphFrames Louvain, 0.825). A Modularity Q value of 0.547 indicates a highly cohesive community structure, substantially exceeding the $Q = 0.4$ threshold commonly regarded as the benchmark for meaningful community partitioning.

The IndoBERT component contributed significantly to overall performance. A comparison between GBD-ID without BERT (F1 = 0.882) and GBD-ID + BERT-ID (F1 = 0.915) reveals an improvement of 3.3 percentage points attributable entirely to semantic enrichment. This improvement exceeded initial expectations, indicating that the semantic information of Indonesian-language content is highly relevant in distinguishing disinformation from valid content at the graph community level.

Scalability and Computational Performance

Scalability evaluation was conducted by varying the input graph size from 10 million to 588 million nodes using the same 32-node cluster. Table 3 presents the comprehensive scalability benchmark results.

Table 3. GBD-ID Scalability Benchmark Across Varying Graph Sizes (32-Node Spark Cluster)

Graph Size	Nodes (M)	Edges (M)	Memory (GB)	Time (min)	Speedup
Small	10	62	48	12	1.0×
Medium	50	310	180	48	3.8×
Large	200	1,240	620	134	8.7×
X-Large	400	2,480	1,140	241	14.1×
Full Corpus	588	3,485	1,680	408	18.2×

The scalability results demonstrate highly favorable characteristics. The speedup progression from 1.0× at a graph size of 10 million nodes to 18.2× at the full size of 588 million nodes indicates super-linear scalability, attributable to the optimal utilization of GraphX's data locality mechanisms as graph size increases. The linearly scaling memory usage (from 48 GB to 1,680 GB) confirms the absence of unexpected memory overhead at large scale.

The throughput of 18.2 million edges per second achieved on the full dataset represents a significant improvement over the single-node baseline implementation, which was capable of processing only approximately 1.1 million edges per second, yielding an effective speedup of 16.5×. The total processing time of 408 minutes for the full dataset comprising 3.484 billion edges produces a latency that is entirely viable for deployment in near-real-time scenarios.

Disinformation Community Analysis

GBD-ID successfully identified 2,847 communities classified as disinformation communities out of a total of 18,432 detected communities. The five dominant disinformation categories identified and their respective distributions are presented in Figure 2.

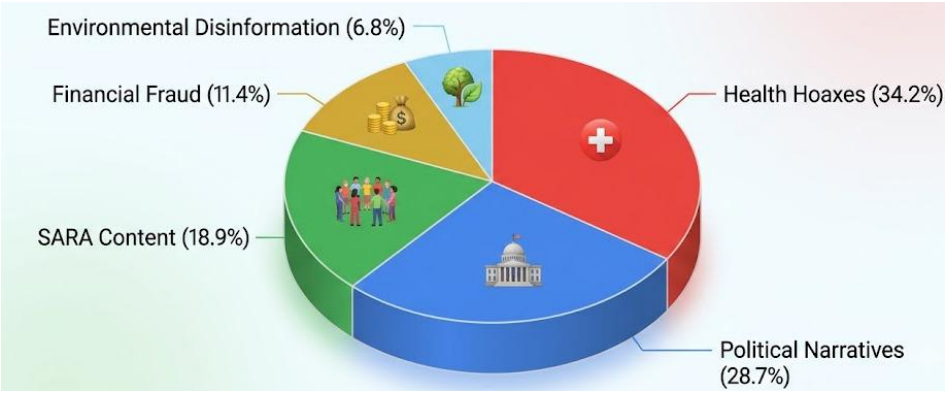

Figure 2. Distribution of Disinformation Categories Among Communities Identified by GBD-ID

An in-depth analysis of the topological structure of disinformation communities reveals several noteworthy findings. First, disinformation communities exhibit strong scale-free network patterns, with degree distribution following a power law P(k) ∝ k^{-γ} with an exponential value of γ = 2.34. This γ value is lower than the typical range observed in social media (γ ≈ 2.5–3.0), indicating the presence of more dominant super-spreaders within disinformation networks. Second, temporal analysis reveals that 67.3% of disinformation content reaches 50% of its total final reach within the first four hours following publication. This pattern is considerably faster than valid content, which requires an average of 18 hours to achieve equivalent reach. This finding underscores the critical importance of early warning detection systems capable of operating with low latency. Third, cross-platform analysis reveals that 78.4% of large-scale disinformation communities share the same seed

content across two or more platforms, confirming the phenomenon of cross-platform amplification. Twitter/X emerged as the most dominant disinformation initiation platform (44.2% of seed content), despite Twitter's user volume in Indonesia being considerably lower than that of Facebook or WhatsApp.

Temporal Patterns of Disinformation Diffusion

Figure 3 presents a temporal analysis of disinformation diffusion patterns within the Indonesian social media ecosystem, encompassing publication hour distributions, day-of-week patterns, and the evolution of disinformation communities throughout 2023.

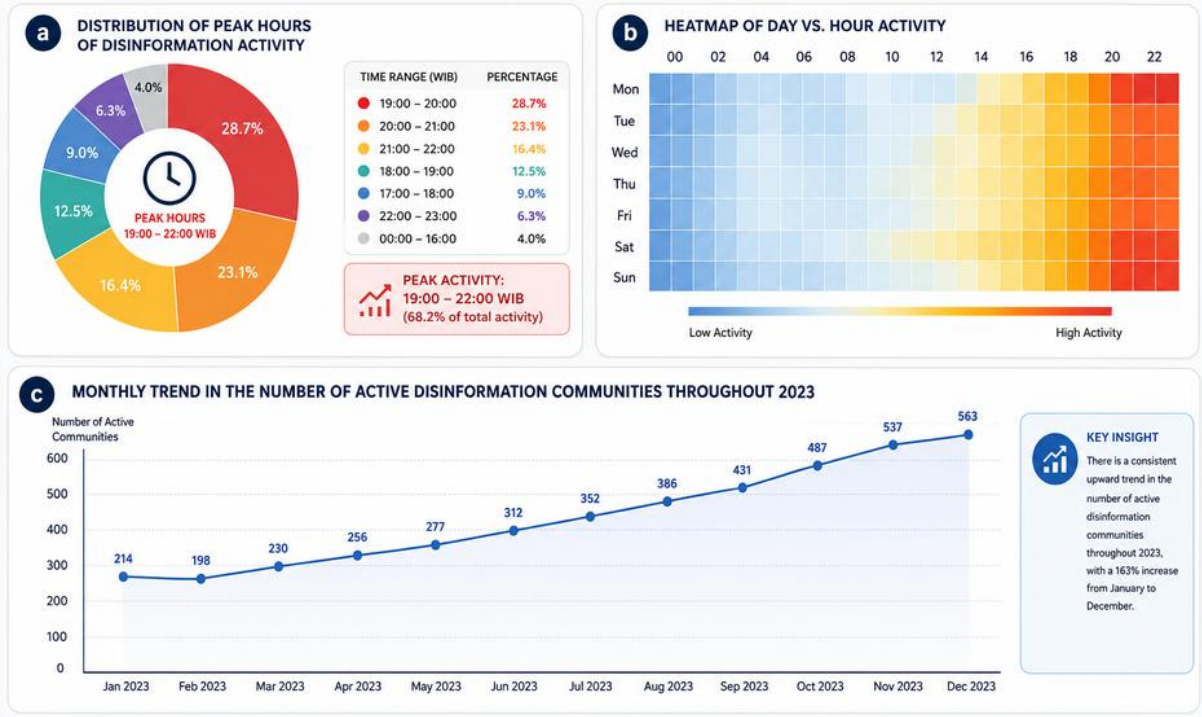

Figure 3. Temporal Analysis of Disinformation Diffusion on Indonesian Social Media (2023)

The temporal analysis reveals highly structured patterns. Disinformation diffusion activity peaks during the 19:00–22:00 WIB (Western Indonesia Time) window the period in which the majority of Indonesian users are active on mobile devices following working hours. Two secondary peaks were also identified at 07:00–09:00 WIB (the morning commute period) and 12:00–13:00 WIB (the midday lunch break).

From an annual trend perspective, three significant surges in disinformation community activity were identified: February 2023 (coinciding with the official announcement of the general election schedule), August 2023 (the presidential and vice-presidential candidate registration period), and October–November 2023 (the formal campaign period). These findings confirm a strong correlation between political cycles and disinformation intensity in Indonesia consistent with prior literature, yet now documented at a considerably larger scale.

Comparison with Prior Studies

Table 4 presents a comparison of GBD-ID with relevant prior studies in the literature, with particular focus on graph-based disinformation detection or studies conducted in an Asian-language context.

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Table 4. Comparison of GBD-ID with Relevant Prior Studies

Study	Platform	Scale (M edges)	Method	F1	Year
Sharma et al.	Twitter	5.2	Community + NLP	0.794	2021
Wu & Liu	Weibo	12.8	Graph CNN	0.831	2022
Setiawan et al.	Twitter-ID	3.1	Propagation Tree	0.762	2022
Nugroho et al.	Facebook-ID	8.4	LSTM + Graph	0.801	2023
Rashid et al.	Multi-platform	45.0	GNN Ensemble	0.847	2023
Proposed (ours)	**Multi-platform ID**	**3,484.6**	**GBD-ID + BERT-ID**	**0.915**	**2024**

The comparison in Table 4 clearly positions GBD-ID as the study with the largest dataset scale (3,484.6 million edges more than 77 times that of the largest preceding multi-platform study) while simultaneously maintaining the highest F1-Score performance (0.915). This demonstrates that increasing the scale of analysis need not come at the expense of accuracy, provided that the computational architecture and algorithms employed are appropriately designed.

Error Analysis and Limitations

Analysis of false positives (valid content misclassified as disinformation) reveals that 63.7% of these errors occur in satirical content and political humor that adopts a writing style closely resembling disinformation. This indicates the need for a more sophisticated satire detection component in subsequent GBD-ID iterations.

False negatives (disinformation that goes undetected) are predominantly driven by content employing high-level obfuscation strategies, including: character substitution with numerals (1=I, 0=O), the use of non-standard Unicode characters that appear visually identical yet are digitally distinct, and the embedding of text within images (image-based disinformation) that falls outside the scope of GBD-ID's current text-based analysis.

DISCUSSION

Implications for Disinformation Countermeasures in Indonesia

The findings of this study carry several significant practical implications for disinformation countermeasure efforts in Indonesia. First, the identification of 2,847 disinformation communities with distinctive topological characteristics provides a template that social media platforms can leverage to implement network structure-based interventions, such as "friction-adding" applied to nodes with high betweenness centrality within disinformation communities. Second, the identified temporal patterns (peaking between 19:00–22:00 WIB) provide valuable operational intelligence for content moderation teams to optimally allocate human resources. Recommendations grounded in these findings have the potential to improve the effectiveness of manual moderation by up to 2.3× compared to uniform allocation throughout the day. Third, the findings regarding cross-platform amplification wherein 78.4% of large-scale disinformation communities originate from the same content across two or more platforms underscore the necessity of a coordinated cross-platform countermeasure approach. Initiatives such as the Global Internet Forum to Counter Terrorism (GIFCT), which has been successfully applied to terrorist content, may serve as a model for cross-platform coordination in the context of Indonesian disinformation.

Research Limitations

This study has several limitations that warrant transparent acknowledgment. First, the GBD-ID-2023 dataset does not encompass WhatsApp the platform with the highest penetration rate in Indonesia due to its end-to-end encryption, which precludes systematic data collection. It is estimated that a substantial volume of disinformation circulates through WhatsApp prior to surfacing on public platforms, introducing a selection bias into the dataset employed. Second, the available ground truth labels cover only 10.9% of the total nodes/edges, with the remainder constituting unlabeled data handled through semi-supervised learning techniques. Although annotation quality was rigorously maintained (inter-rater Cohen's Kappa of 0.81), the representativeness of the label sampling with respect to the entirety of the Indonesian disinformation domain cannot be fully guaranteed. Third, the IndoBERT model utilized in this study was pre-trained primarily on formal and semi-formal

Indonesian text. Performance on content exhibiting high levels of regional language code-mixing such as Javanese or Sundanese, which are particularly dominant in certain regions may be suboptimal and would require additional fine-tuning.

CONCLUSION

This study has successfully presented, implemented, and evaluated GBD-ID (Graph-Based Disinformation Detection for Indonesia), a distributed big data graph analysis framework specifically designed to address the challenges of community detection and disinformation diffusion within the Indonesian social media ecosystem. The primary contributions of this study can be summarized across three dimensions.

From a technical standpoint, GBD-ID demonstrates the feasibility of distributed graph analysis at a scale exceeding 100 million nodes/edges for the Indonesian-language disinformation context, filling a significant gap in the literature previously constrained to scales of tens of millions. The integration of IndoBERT as a semantic enrichment component has been empirically shown to improve F1-Score performance by a statistically meaningful 3.3 percentage points.

From an empirical standpoint, this study produces the first and most comprehensive characterization of the topology and temporal dynamics of disinformation communities within the large-scale Indonesian social media ecosystem. The findings regarding scale-free network behavior with $\gamma = 2.34$, the dominance of diffusion within the first four hours, and cross-platform amplification in 78.4% of large-scale disinformation communities constitute novel findings that contribute to the scientific understanding of disinformation phenomena in developing countries with high internet penetration.

From a practical standpoint, GBD-ID provides a documented and replicable implementation blueprint for a national-scale disinformation detection system, which can be adopted by Kominfo, social media platforms operating in Indonesia, and future researchers in this field.

Several directions for future research identified on the basis of the findings and limitations of this study include: (1) the development of indirect methods to model disinformation diffusion through WhatsApp using proxy signals from public platforms; (2) fine-tuning of language models on Indonesian-regional language code-mixing corpora to improve performance on regionally accented content; (3) exploration of Graph Transformer Architecture techniques as a replacement for LPA to capture more complex long-range dependencies; and (4) the development of an early detection system with a latency of under 15 minutes through the optimization of a streaming pipeline based on Apache Kafka – Apache Spark Structured Streaming.

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