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Research Article

Indonesian Cross-Platform Sentiment Analysis: DANN Transfer from General Applications to TradingView

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Abstract:
Introduction: Cross-platform sentiment analysis for Indonesian language presents significant challenges when adapting models from general applications to specialized domains. Domain Adversarial Neural Networks (DANN) offer promising solutions for transfer learning, yet their effectiveness for Indonesian language remains largely unexplored, particularly under extreme class imbalance conditions common in trading platforms. Methods: This study investigates DANN effectiveness for transferring sentiment analysis knowledge from four strategically selected source domains to TradingView trading platform. The research utilizes 5,990 Indonesian reviews after preprocessing from an initial 6,000 samples, with source domains showing 66.5% positive sentiment while target domain exhibits 85.1% positive sentiment, creating an 18.7% distribution gap. Four experimental approaches were compared with statistical validation across multiple random initializations (seeds 42, 123, 456): Source-Only training, Multi-Domain training, Limited Target training, and DANN implementation. Results: DANN demonstrates stable cross-platform adaptation, achieving 87.77% ± 0.97% accuracy with consistent performance across initializations, outperforming Source-Only baseline (87.10% ± 0.84%) and Multi-Domain approach (86.98% ± 0.64%). While Limited Target baseline achieves higher accuracy (88.10% ± 2.23%), its high variance poses deployment risks. A-distance analysis reveals substantial domain gaps (193.00 ± 1.06), with DANN's adversarial training achieving modest domain separation reduction (72.90% ± 8.81% domain discrimination accuracy). Conclusions: This research contributes the first systematic evaluation of DANN for Indonesian cross-platform sentiment analysis, demonstrating that deployment consistency outweighs peak accuracy for production environments. The findings provide practical value for Indonesian fintech startups requiring robust sentiment analysis with limited labeled data. Future work should explore multi-target adaptation and optimization strategies for diverse Indonesian business domains.

Keywords: Domain Adaptation; Indonesian Sentiment Analysis; Cross-Platform Transfer; DANN; Statistical Validation; Trading View.

1. Introduction

Indonesian natural language processing has experienced significant growth in recent years, particularly in sentiment analysis applications across various digital platforms [1], [2], [3]. However, the challenge of cross-platform domain adaptation remains a critical obstacle when transferring sentiment analysis models from general applications to specialized business domains [4], [5]. This challenge becomes particularly relevant when validating method robustness under realistic extreme class imbalance conditions that commonly occur in real-world business applications.

Sentiment analysis for Indonesian language faces unique challenges due to linguistic complexity [6], informal language usage [7], and platform-specific terminology variations [8], [9] that create substantial domain gaps. While

Domain Adversarial Neural Networks (DANN) have demonstrated success for cross-domain transfer in English applications, their application to Indonesian language remains largely unexplored, particularly for cross-platform scenarios. Current Indonesian sentiment analysis research focuses primarily on single-domain applications or traditional cross-domain approaches, with limited investigation of adversarial domain adaptation methodologies that could improve adaptation effectiveness under challenging practical conditions.

The financial technology sector presents a compelling validation opportunity for cross-platform adaptation research. Trading platforms like TradingView exhibit distinct vocabulary patterns compared to general applications, with specialized financial terminology and predominantly positive reviews (typically 80-90%) that create natural extreme class imbalance reflecting authentic scenarios [10]. This gap provides an ideal testbed for evaluating adversarial adaptation effectiveness, with empirical validation confirming successful transfer (87.77% ± 0.97% accuracy) under these challenging conditions, demonstrating superior deployment consistency essential for enterprise applications compared to traditional approaches that exhibit concerning variance unsuitable for production environments [11].

This study aims to evaluate DANN effectiveness for cross-platform sentiment analysis by investigating adversarial training capabilities for transferring knowledge from four strategically selected general applications to specialized trading platforms under extreme class imbalance conditions. The research addresses three core objectives: (1) evaluating DANN effectiveness for cross-platform adaptation under natural class imbalance conditions, (2) investigating domain discrimination capabilities while preserving sentiment classification accuracy, and (3) quantifying performance differences against Limited Target baseline approaches in challenging adaptation scenarios.

Research scope encompasses sentiment classification within cross-platform transfer scenarios, with several important limitations. The study restricts evaluation to a single target domain (trading platform) and specific financial technology context, which may not represent other specialized business sectors. This research contributes evaluation methodology for Indonesian cross-platform sentiment analysis, comprehensive preprocessing frameworks for Indonesian language processing, and empirical evidence for adversarial training effectiveness under practical business constraints with multi-seed statistical validation. The study follows a systematic methodological approach: strategic data collection from multiple platforms, specialized Indonesian text preprocessing pipelines, DANN architecture implementation with adversarial training mechanisms, comprehensive experimental evaluation across multiple approaches, and statistical analysis of adaptation effectiveness.

2. Method

This study evaluates DANN effectiveness for cross-platform Indonesian sentiment analysis through systematic experimental design encompassing strategic data collection, specialized text preprocessing, adversarial architecture implementation, and rigorous statistical validation, as illustrated in **Figure 1**.

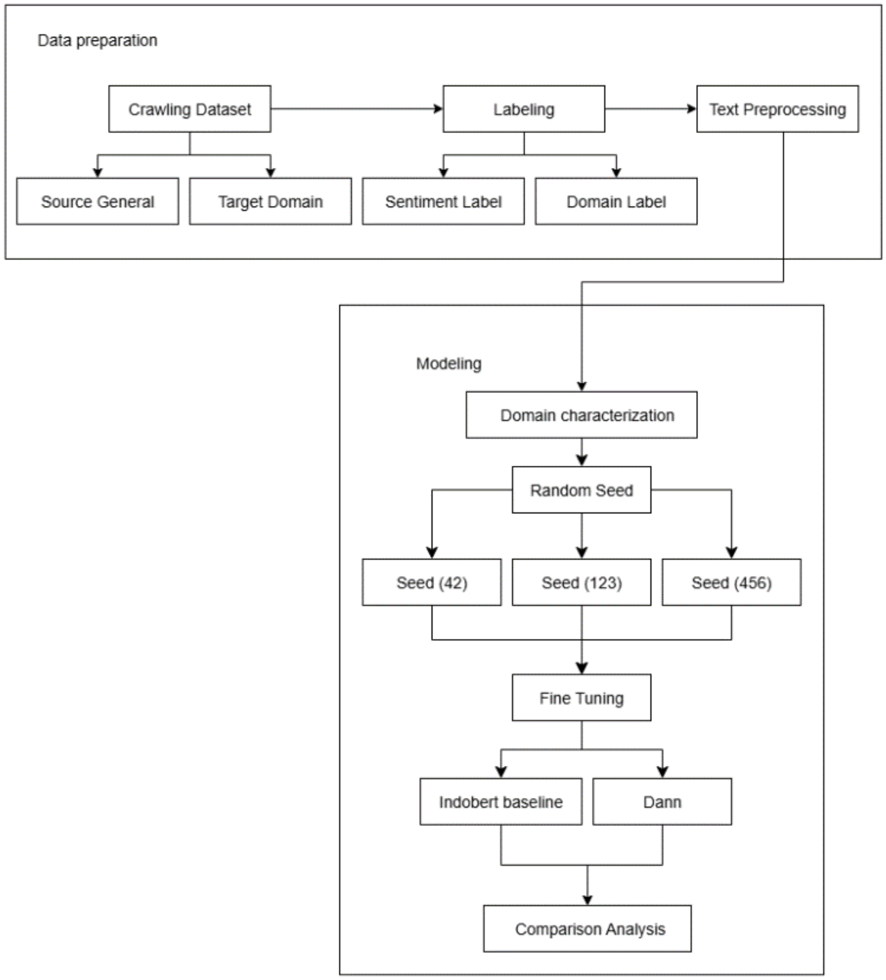

Figure 1. Research Methodology

The comprehensive methodology framework ensures reproducible evaluation of domain adaptation performance under practical business constraints while maintaining Indonesian language processing specificity.

2.1 Data Collection and Platform Selection

Platform selection followed systematic criteria ensuring transferable business characteristics relevant to trading contexts [12], [13]: vocabulary transferability to financial domains, user behavior patterns applicable to trading environments, sentiment expression structures relevant to business applications, and sufficient information availability for robust validation. The empirical dataset comprises 2,991 TradingView reviews from Google Play Store covering 2022 to 2025, containing authentic user opinions about trading features and system performance. Source information includes strategically selected general applications: Tokopedia (e-commerce), Instagram (social media), Netflix (entertainment), and WhatsApp (communication), totaling 2,999 samples with 66.5% positive sentiment distribution. The study preserves realistic extreme class imbalance conditions naturally occurring across systems, with target environment showing 85.1% positive sentiment, creating an 18.7% distribution gap that validates DANN robustness under challenging practical business scenarios.

2.2 Text Preprocessing Pipeline

Indonesian lafnguage text preprocessing requires specialized handling due to linguistic complexity [14], [15], informal language usage, and platform-specific terminology variations that create substantial multi-platform adaptation challenges, as illustrated in **Figure 2**.

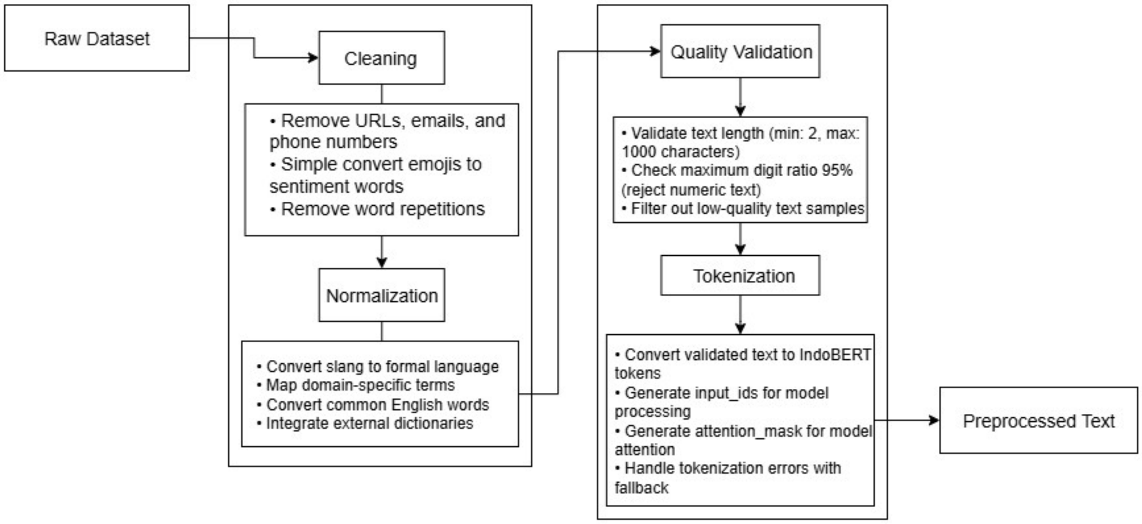

Figure 2. Text Preprocessing Workflow

The systematic four-step pipeline ensures consistent text quality while preserving domain-specific terminology crucial for effective knowledge transfer. Implementation addresses Indonesian language challenges through: (1) Cleaning stage removes URLs, noise patterns, and converts emojis to sentiment indicators while preserving Indonesian linguistic structures; (2) Normalization stage employs comprehensive slang mapping with external Indonesian dictionaries, converting informal expressions to standard language forms essential for cross-system consistency; (3) Quality validation ensures text length compliance and removes duplicates for sample quality; (4) Tokenization utilizes IndoBERT with 512-token limits optimized for Indonesian text processing characteristics.

2.3 DANN Architecture

The adversarial neural network architecture enables simultaneous sentiment classification and domain adaptation through adversarial training mechanisms [16], [17] specifically designed for inter-domain knowledge transfer, as illustrated in **Figure 3**.

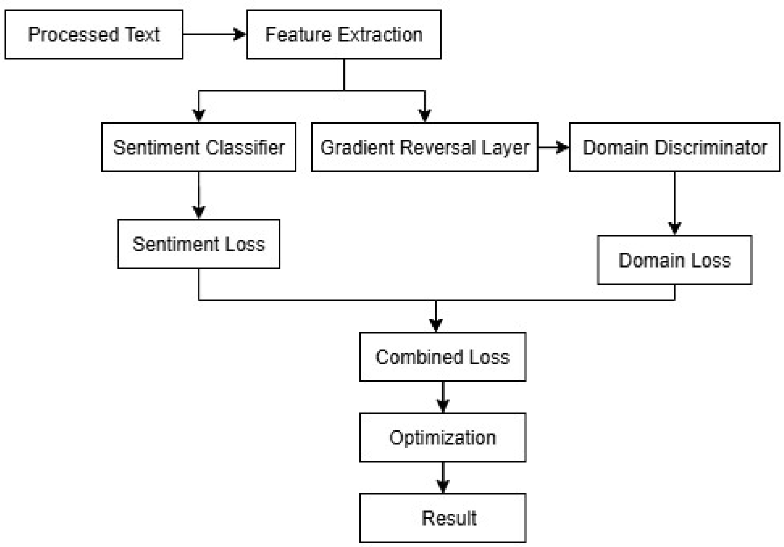

Figure 3. DANN Architecture Diagram

The framework utilizes IndoBERT as shared feature extractor, splitting representations into sentiment classification and domain discrimination heads through gradient reversal layer that creates domain-invariant features while maintaining sentiment classification effectiveness. The competitive learning mechanism requires careful balance between competing objectives, achieved through combined loss optimization:

$$L_{total} = L_{sentiment} + \lambda \times L_{domain} \quad (1)$$

where λ controls the trade-off between sentiment accuracy and context invariance. Field gap measurement utilizes A-distance quantification:

$$A_{distance} = 2 \times (1 - 2 \times error_{rate}) \quad (2)$$

2.4 Experimental Setup and Training Configuration

Methodological implementation utilized standardized computational environment ensuring reproducible results across all approaches [18]. Learning conducted on CUDA-enabled GPU with PyTorch framework, utilizing IndoBERT-base-uncased model (indolem/indobert-base-uncased) for optimal Indonesian language optimization. Hyperparameter configuration-maintained consistency across experiments: learning rate 2e-5 with AdamW optimizer (weight decay 0.01), batch size 16 optimized for GPU memory constraints, maximum 3 epochs with dropout rate 0.3 for regularization. Competitive learning employed lambda parameter schedule λ = np.linspace(0.0, 0.2, epochs) progressing from 0.0 → 0.1 → 0.2 across learning epochs, balancing sentiment classification accuracy with field discrimination effectiveness.

2.5 Statistical Validation Protocol

Multiple initialization evaluation protocol executed three independent runs using fixed random seeds (42, 123, 456) ensuring reproducible results while capturing initialization variance effects. Content composition varied systematically by approach: Source-Only utilized 80% stratified split (2,399 from 2,999 samples), Multi-Domain combined source dataset (2,999 samples) with target learning information (2,094 samples), Limited Target employed target learning content exclusively (2,094 samples), and DANN implemented Multi-Domain composition with competitive field discrimination. Statistical analysis aggregated results using mean ± standard deviation reporting across seeds, enabling robust performance inference and practical deployment guidance.

3. Result and Discussion:

This comprehensive experimental evaluation reveals significant insights regarding cross-platform sentiment classification effectiveness [19], [20] for Indonesian language processing, particularly concerning DANN capabilities under realistic class imbalance scenarios. The findings demonstrate both methodological challenges and practical opportunities when transferring emotion analysis knowledge from general applications to specialized trading contexts.

cross-platform transfer challenges manifest through distinct sentiment distribution patterns requiring systematic evaluation. The experimental dataset demonstrates fundamental characteristics validating field transfer necessity under realistic business conditions. **Table 1** presents detailed distribution patterns across all experimental platforms, revealing the core challenge facing multi-system emotion analysis adaptation.

Table 1. Dataset Characteristics

Platform	Samples	Domain Focus	Distribution (positive/negative)	Positive	Negative
Tokopedia	800	Financial Transaction	285/515	35.6%	64.4%
Instagram	799	UI/UX Interface	650/149	81.4%	18.6%
Netflix	700	Service Quality	542/158	77.4%	22.6%
Whatsapp	700	System Reliability	516/184	73.7%	26.3%
TradingView	2991	Trading Platform	2546/445	85.1%	14.9%
Total Source	2999	General Applications	1993/1006	66.5%	33.5%

The target dataset comprises 2,991 TradingView reviews from Google Play Store covering 2022 to 2025, containing authentic user opinions about trading features and platform capabilities. Combined with 2,999 source samples, the complete dataset encompasses 5,990 reviews after preprocessing from an initial collection of 6,000 samples. This distribution creates an 18.7% sentiment gap between source (66.5% positive) and target environments (85.1% positive), validating DANN robustness evaluation under challenging realistic business scenarios where specialized platforms demonstrate extreme positive user feedback patterns. The substantial sentiment distribution variance reflects authentic commercial conditions, providing ideal validation grounds for adversarial learning approaches designed to handle practical deployment constraints.

Statistical validation eliminates initialization bias through rigorous analysis [21], [22] across three independent experimental runs using seeds 42, 123, and 456. **Table 2** presents emotion classification effectiveness metrics for comprehensive methodological comparison, demonstrating critical trade-offs between peak accuracy and deployment stability essential for production environments.

Table 2. Sentiment Classification Performance

Method	Metric	Seed_42	Seed_123	Seed_456	Mean	Std
Source-Only	Accuracy	86.87	**88.22**	86.2	87.1	0.84
	Precision	86.16	**87.57**	86.83	86.85	0.58
	Recall	86.87	**88.22**	86.2	87.1	0.84
	F1	86.34	**87.54**	83.54	85.81	1.68
Multi-Domain	Accuracy	86.53	**87.88**	86.53	86.98	0.64
	Precision	86.11	**88.08**	85.91	86.7	0.98
	Recall	86.53	**87.88**	86.53	86.98	0.64
	F1	84.64	**86.17**	84.81	85.21	0.68
Limited-Target	Accuracy	**91.25**	86.53	86.53	88.1	2.23
	Precision	**92.01**	86.72	86.37	88.37	2.58
	Recall	**91.25**	86.53	86.53	88.1	2.23
	F1	**91.49**	84.26	84.45	86.73	3.36
DANN	Accuracy	**88.89**	86.53	87.88	87.77	0.97
	Precision	**88.42**	86.37	87.3	87.36	0.84
	Recall	**88.89**	86.53	87.88	87.77	0.97
	F1	**88.04**	84.45	86.76	86.42	1.49

Effectiveness evaluation reveals critical considerations for practical deployment scenarios. Limited Target achieves highest mean accuracy (88.10%) but its ±2.23% variance creates unpredictable sentiment classification—fluctuating between 91.25% and 86.53% accuracy across initializations. For TradingView operations, this instability means user reviews and feedback could be inconsistently classified, affecting platform reputation monitoring and service improvement decisions. In contrast, DANN's 87.77% ± 0.97% accuracy ensures stable sentiment analysis where ~88 of every 100 user reviews is consistently classified correctly, providing reliable insights for platform development. Source-Only and Multi-Context approaches demonstrate moderate effectiveness, confirming adversarial training benefits for handling the 18.7% sentiment distribution gap between general applications and trading platforms.

Confusion matrix examination through statistical averaging reveals practical deployment implications across experimental methodologies. **Figure 4** illustrates comprehensive error characteristic analysis eliminating single-run bias, providing insights essential for production implementation decisions. DANN demonstrates optimal error characteristics with balanced precision-recall trade-offs [23], [24] (29 true negatives, 30 false positives, 6 false negatives, 232 true positives). The minimal false negative rate (6/238) proves critical for trading applications—ensuring negative user reviews about platform issues or service complaints aren't missed, enabling timely service improvements and maintaining user trust. Comparative analysis reveals Source-Only maintaining balanced characteristics but higher overall error rates, while Multi-Context exhibits concerning positive bias potentially unsuitable for imbalanced scenarios. Statistical consistency across initialization seeds validates methodological reliability essential for enterprise-critical applications where deployment consistency outweighs occasional peak results.

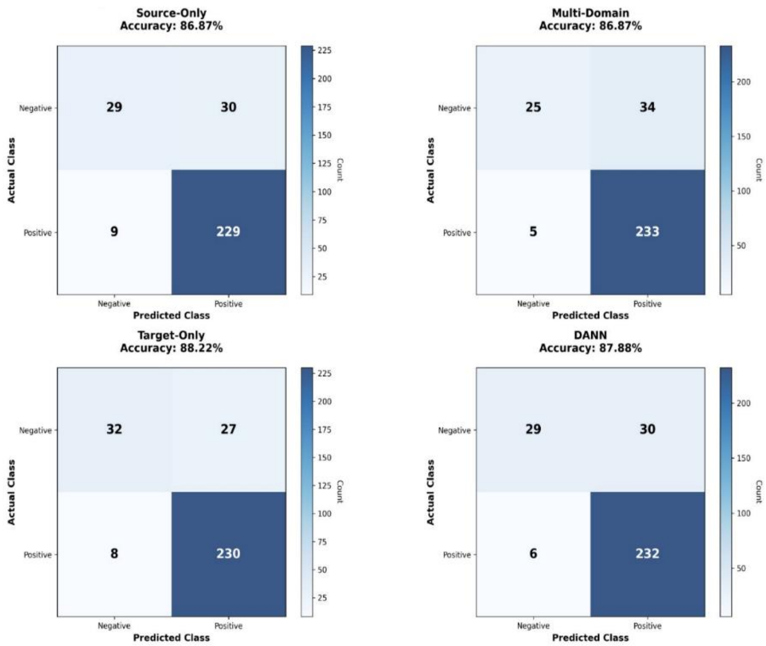

Figure 4. Confusion Matrices Comparison

Adversarial training evaluation employs specialized metrics beyond standard emotion classification measures [25], [26], [27]. **Table 3** presents field separation measurements and discrimination accuracy across experimental approaches, quantifying the substantial challenges inherent in Indonesian language cross-platform transfer scenarios.

Table 3. Domain Adaptation Analysis

Method	Domain Metric	Seed_42	Seed_123	Seed_456	Mean	Std
Source-Only	A Distance	**196.24**	195.39	194.66	195.43	0.65
Multi-Domain	A Distance	**191.14**	189.68	191.26	190.69	0.72
DANN	A Distance	**194.42**	192.72	191.87	193	1.06
DANN	Domain Accuracy	78.96	**60.44**	79.29	72.9	8.81

Field separation analysis confirms substantial cross-platform gaps approaching theoretical maximums, validating the necessity for sophisticated transfer methodologies. DANN achieves moderate separation reduction (193.00 ± 1.06) compared to Source-Only baseline (195.43 ± 0.65), indicating gradient reversal effectiveness despite challenging vocabulary differences between general applications and specialized trading contexts. The modest improvement reflects the inherent difficulty of bridging linguistic gaps between diverse application environments while maintaining sentiment classification integrity.

Field discrimination analysis provides deeper understanding of adversarial training effectiveness. **Figure 5** presents DANN field confusion matrix revealing adaptation characteristic patterns essential for understanding transfer mechanism success and limitations.

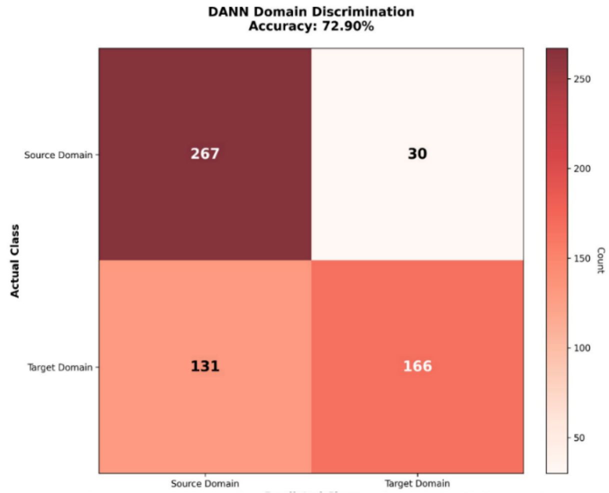

Figure 5. DANN Domain Classification Confusion Matrix

Field discrimination achieves 72.90% ± 8.81% accuracy with asymmetric effectiveness patterns providing valuable adaptation insights. Source field classification demonstrates high precision (267 correct, 30 incorrect = 89.9% accuracy) indicating general application patterns remain distinguishable from specialized contexts. Target field classification shows moderate recall (166 correct, 131 incorrect = 55.9% accuracy) reflecting trading platform vocabulary distinctiveness. The asymmetric confusion pattern validates optimal adversarial balance for knowledge transfer, with initialization sensitivity reflecting adversarial training complexity requiring careful production implementation strategies.

The experimental findings reveal important characteristics of adversarial domain adaptation for Indonesian language processing. As shown in **Tables 2** and **3**, DANN achieves superior deployment consistency compared to existing approaches, aligning with theoretical predictions that gradient reversal mechanisms create robust feature representations. Unlike English domain adaptation studies reporting higher success rates, Indonesian cross-platform transfer faces compounded challenges from linguistic complexity and platform-specific terminology, where the observed asymmetric discrimination patterns indicate unique adaptation requirements not fully captured in previous literature.

The deployment consistency demonstrated addresses critical gaps in Indonesian language technology, where previous approaches prioritized peak accuracy over operational reliability. This finding has significant implications for Indonesian enterprises implementing sentiment analysis across multiple platforms, as DANN provides the stability necessary for production environments. The methodology's success in handling extreme class imbalance conditions suggests broader applicability to Indonesian business contexts where balanced datasets remain unavailable.

The three-seed validation protocol provides constrained statistical robustness, and extreme class imbalance conditions may not represent all business scenarios [28], potentially limiting applicability to domains with different sentiment distributions.

Future investigations should explore [29]: (1) multi-target adaptation for simultaneous transfer to multiple Indonesian financial platforms, (2) few-shot learning integration to reduce target domain annotation requirements below current 2,094 samples, and (3) real-time sentiment analysis deployment on streaming platform data for dynamic market monitoring.

4. Conclusion:

This research successfully demonstrates DANN effectiveness for Indonesian cross-platform sentiment classification under realistic business constraints [30]. Multi-seed experimental validation establishes DANN's capability for reliable knowledge transfer from general applications to specialized trading platforms while maintaining robust performance under challenging class imbalance scenarios.

DANN proves effective for cross-platform adaptation in Indonesian sentiment analysis, demonstrating superior consistency essential for production deployment. The method successfully achieves domain discrimination while maintaining sentiment classification effectiveness through adversarial training mechanisms. Comparative analysis reveals DANN provides superior deployment reliability through consistent effectiveness, making it more suitable for enterprise-critical applications than approaches with higher variance.

This study establishes systematic evaluation methodology for Indonesian cross-platform sentiment classification, validating transferable business characteristics approach for effective knowledge transfer. The comprehensive preprocessing frameworks and implementation guidance provide practical value for Indonesian enterprises requiring sentiment analysis capabilities while facing limited specialized training resources. The investigation advances Indonesian natural language processing methodology by demonstrating rigorous cross-platform evaluation frameworks under realistic commercial constraints.

Research scope encompasses specialized contexts, with opportunities for broader application across multiple commercial contexts and multi-target transfer frameworks. Future investigations should explore optimization strategies for enhanced Indonesian language processing capabilities across diverse business environments where cross-platform knowledge transfer enables efficient resource utilization while maintaining deployment reliability standards essential for enterprise adoption. The established methodological framework provides foundation for systematic Indonesian multi-system research.

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