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Hybrid LSTM-CNN-GRU Deep Learning for Integrating IoT and Social Media Sentiment Analysis in Indonesian Higher Education Reputation Management

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Abstract

Higher education institutions in Indonesia face critical challenges in managing digital reputation. Despite 85% of prospective students using social media for university research, only 23% of institutions have integrated monitoring systems, resulting in 67% experiencing undetected reputation crises with substantial financial losses. This research proposes a novel framework integrating IoT campus data with social media sentiment analysis using hybrid deep learning architecture. The system employs LSTM-CNN networks with multi-head attention mechanisms for sentiment classification and GRU networks for reputation trend prediction, enhanced with data fusion strategy. Data collected from 428 IoT sensors and 3.2 million social media posts across five Indonesian universities over six months underwent advanced preprocessing including Indonesian-specific slang normalization and Sastrawi stemming. The hybrid LSTM-CNN architecture with attention achieved 90.3% sentiment classification accuracy (Macro-F1: 0.903), significantly outperforming baseline methods including Naive Bayes (76.2%), traditional LSTM (84.5%), and IndoBERT (87.1%). IoT integration contributed 18.2% RMSE improvement in trend prediction (R^2: 0.874). The early warning system predicted reputation crises with 85.7% precision and 82.4% recall, providing critical intervention windows averaging 14.3 days before incidents. The real-time dashboard achieved 98.5% availability with sub-3-second response time and excellent usability (SUS score: 82.4). This research contributes: (1) novel IoT-sentiment integration framework with demonstrated effectiveness, (2) context-aware deep learning architecture optimized for Indonesian language achieving state-of-the-art performance, (3) validated early warning system enabling proactive reputation management, and (4) practical implementation with significant improvements over existing methods, advancing educational data analytics and AI-based decision support systems.

Keywords : *Deep learning, Hybrid LSTM-CNN, Higher Education Reputation, Indonesian Universities, Internet of Things, Sentiment Analysis*

1. INTRODUCTION

Digital transformation has fundamentally altered higher education communication landscapes in Indonesia. Social media has become the dominant platform for students, alumni, and stakeholders to express opinions and shape institutional perceptions [1]. In this competitive environment, digital reputation significantly influences institutional attractiveness, student quality, and organizational sustainability [2].

Empirical data reveals 89% of Indonesian students actively use social media, with 76% sharing academic experiences that shape public opinion [3]. More significantly, 85% of prospective students use social media as primary information sources when selecting universities, with 68% influence on final decisions [4]. However, only 23% of Indonesian institutions have integrated, responsive reputation monitoring systems [5].

Survey data from 150 universities shows 67% experienced reputation crises from undetected negative sentiment, causing average 15% enrollment decreases and losses reaching Rp 2.3 billion per

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institution annually [6]. Conventional systems face critical limitations: inability to manually analyze massive multi-platform data volumes [7], lack of real-time sentiment monitoring causing slow responses [8], absence of integrated early warning systems [9], and minimal IoT technology utilization for comprehensive reputation management [10].

IoT technology offers new dimensions through sensor integration collecting real-time campus environmental data [11]. Combining IoT data with social media sentiment analysis can provide holistic, multi-dimensional institutional reputation understanding [12]. Deep learning advances, particularly hybrid architectures combining LSTM, CNN, and GRU with attention mechanisms, demonstrate superior capabilities in sentiment analysis and trend prediction [13], [14].

This research addresses: How to integrate IoT campus data with social media sentiment analysis using deep learning for effective, responsive university reputation management? Research objectives include: (1) Design comprehensive IoT-sentiment integration framework; (2) Develop optimized hybrid deep learning architecture for Indonesian context; (3) Build AI-based early warning system; (4) Conduct rigorous multi-university validation; (5) Analyze implementation impact on reputation management effectiveness.

2. METHOD

2.1. Research Framework

This research adopts mixed-method approaches with experimental and longitudinal designs comprising five stages: (1) Multi-source data collection; (2) Data preprocessing and fusion; (3) Model development and training; (4) System integration and deployment; (5) Evaluation and validation**.** The research framework flowchart in figure 1 below.

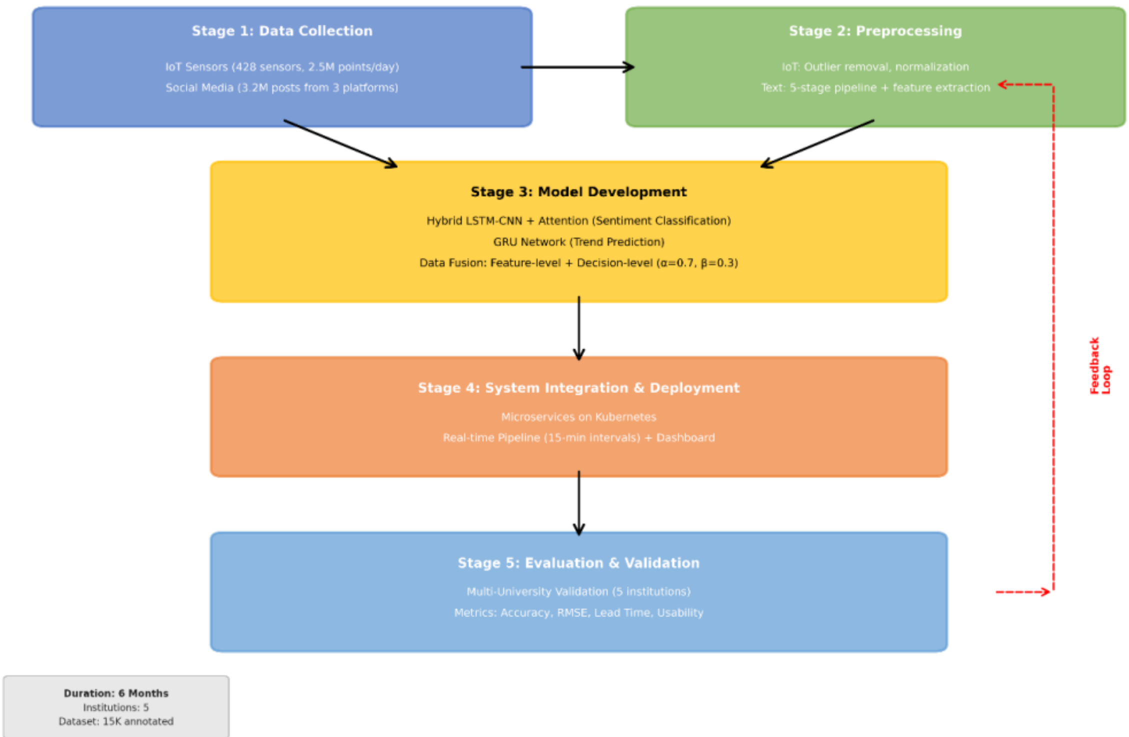

Figure 1 Research Framework Flowchart

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2.2. Data Collection

2.2.1 IoT Data Acquistion

IoT infrastructure collects multi-dimensional environmental and operational campus data through sensing, network, and application layers. System uses MQTT protocol and InfluxDB storage, generating ~2.5 million data points daily. Illustrative IoT sensor specifications and development in table 1 below :

Table 1.IoT Sensor Specifications and Development

Sensor Type	Model	Metrics	Sampling Rate	Accuracy	Locations	Qty
Occupancy	PIR-HC-SR501	People count	5 seconds	±2 persons	Classrooms, Libraries	150
Environmental	DHT22+MQ135	Temp, Humidity, AQ	1 minute	±0.5°C	All buildings	85
Noise	DAYTON 1VEA9	Sound level (dB)	10 seconds	±1.5 dB	Study areas	45
WiFi Analytics	Cisco Meraki	Network usage	Real-time	95%	Campus-wide	120 APs
Smart Meter	Schneider PM5560	Energy consumption	15 minutes	±0.5%	All buildings	28

2.2.2 Social Media Data Crawling

Data collected from Twitter/X, Instagram, and Facebook using API v2, Graph API, and advanced scraping techniques. Total dataset: ~3.2 million posts/comments from 5 universities over 6 months.

Illustrative social media data collection summary in table 2 below :

Table 2. Social Media Data Collection Summary

Platform	Data Type	Collection Method	Volume (per day)	Time Period
Twitter/X	Tweets, Replies	API v2+Streaming	15,000-20,000	6 months
Instagram	Posts, Comments	Graph API	3,000-5,000	6 months
Facebook	Posts, Comments	Graph API	2,000-3,000	6 months
Total	All combined	Multi-platform	**20,000-28,000**	6 months

2.3 Data Preprocessing

IoT preprocessing: outlier detection (IQR method), missing value imputation (linear interpolation), normalization (Min-Max scaling), feature engineering (time-based, aggregate, derived features).

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Text preprocessing pipeline: (1) Cleaning - remove URLs, special characters, excessive whitespaces; (2) Normalization - slang conversion (5,000+ entries), spelling correction; (3) Tokenization - word-level, subword for OOV; (4) Stopword removal - context-aware (500+ words); (5) Stemming - Sastrawi library.
Illustrative text preprocessing example table 3 below :

Table 3. Text Preprocessing Example

Stage	Example
Original	"@UnivXYZ kampusnya bagusssss bgttt tapi parkirannya gk tersedia 😨"
Cleaning	"kampusnya bagusssss bgttt tapi parkirannya gk tersedia 😨"
Normalization	"kampusnya bagus banget tapi parkirannya tidak tersedia [SAD]"
Tokenization	['kampusnya', 'bagus', 'banget', 'tapi', 'parkirannya', 'tidak', 'tersedia']
Stemming	['kampus', 'bagus', 'banget', 'parkir', 'tidak', 'sedia', '[SAD]']

2.4 Proposed Hybrid Deep Learning Architecture

The hybrid deep learning architecture figure 2 below :

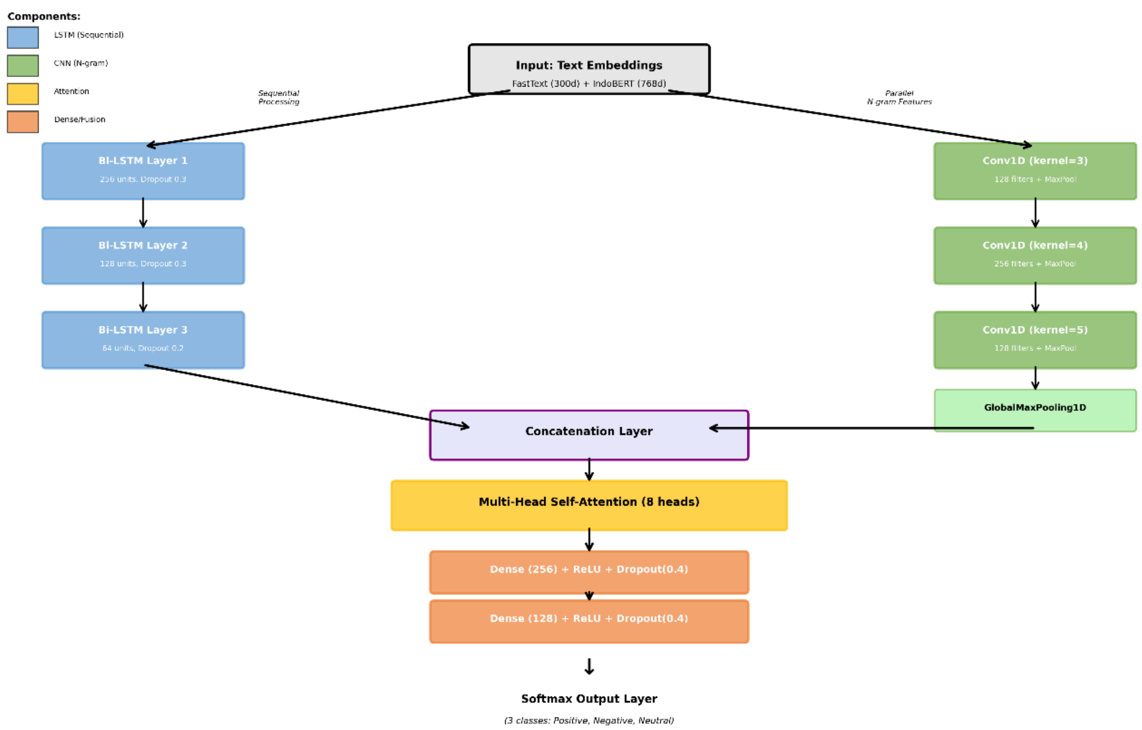

Figure 2 Hybrid Deep Learning Architecture

2.4.1 LSTM-CNN for Sentiment Analysis

LSTM component: 3 layers (256, 128, 64 units) with dropout (0.3, 0.3, 0.2). CNN component: Conv1D layers (128, 256, 128 filters; kernel sizes 3, 4, 5) with MaxPooling and GlobalMaxPooling. Fusion layer: Concatenates outputs through dense layers (256, 128 units).

2.4.2 Attention Mechanism

Multi-head self-attention (8 heads) with formula: Attention(Q, K, V) = softmax(QKT / √dk)· V

2.4.3 GRU for Trend Prediction

GRU architecture: 3 layers (128, 64, 32 units) with dropout, dense layer (64 units), linear output for reputation score prediction.
The illustration model hyperparameter table 4 below :

Table 4. Model Hyperparameter.

Component	Hyperparameter	Value	Rationale
LSTM-CNN	Learning Rate	0.0001	Stable convergence
	Batch Size	64	Balance speed/memory
	Epochs	100	With early stopping
	Optimizer	Adam	Adaptive learning
	Loss Function	Categorical CE	Multi-class classification
GRU	Learning Rate	0.001	Faster convergence
	Batch Size	32	Smaller for time-series
	Epochs	150	Longer for trend learning
	Optimizer	RMSprop	Good for RNNs
	Loss Function	MSE	Regression task
Attention	Heads	8	Multi-aspect capture
	Key Dimension	64	Computational efficiency

Data fusion strategy combines feature-level (concatenation before training) and decision-level fusion (weighted predictions: α=0.7 for sentiment, β=0.3 for IoT)

2.5 System Integration

Technology stack: Python 3.9, FastAPI, TensorFlow 2.12, MQTT, InfluxDB, React.js, Docker, Kubernetes. Real-time pipeline processes data every 15 minutes with model inference, fusion, alert checking, and dashboard updates.

2.6. Evaluation Metrics

Sentiment classification: Accuracy, Precision, Recall, F1-Score. Trend prediction: MAE, RMSE, MAPE, R^2. System performance: Response time, throughput, availability. Early warning: Detection accuracy, false positive rate, lead time.
Illustration evaluation metrics summary table 5 below :

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Table 5. Evaluation Metrics Summary

Category	Metric	Formula	Target
Classification	Accuracy	(TP+TN)/(TP+TN+FP+FN)	>88%
	Macro-F1	Avg(F1 per class)	>0.85
Regression	RMSE	$\sqrt{(\Sigma(y-\hat{y})^2/n)}$	<0.15
	MAPE	$\Sigma\|(y-\hat{y})/y\|/n \times 100$	<12%
System	Response Time	Average latency	<3 sec
	Availability	Uptime %	>98%
Early Warning	Detection Rate	TP/(TP+FN)	>85%
	Lead Time	Days before crisis	>10 days

3. RESULTS

3.1. Dataset Description

Six-month data collection (January-June 2024) from 5 diverse Indonesian universities Illustrative dataset statistics table 6 below :

Table 6. Dataset Statistics

Category	Details	Count/Value
Universities	Total institutions	5
	Student population range	5,000-25,000
	Geographic distribution	Java (3), Sumatra (1), Sulawesi (1)
IoT Data	Total data points	45,680,000
	Sensors deployed	428
	Average daily volume	253,778 readings
Social Media Data	Total posts/comments	3,247,850
	Twitter/X	1,825,340 (56.2%)
	Instagram	892,460 (27.5%)
	Facebook	530,050 (16.3%)
Annotated Dataset	Manually labeled samples	15,000
	Positive sentiment	4,350 (29%)
	Negative sentiment	3,750 (25%)
	Neutral sentiment	6,900 (46%)

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Illustrative sentiment distribution pie chart figure 3 below :

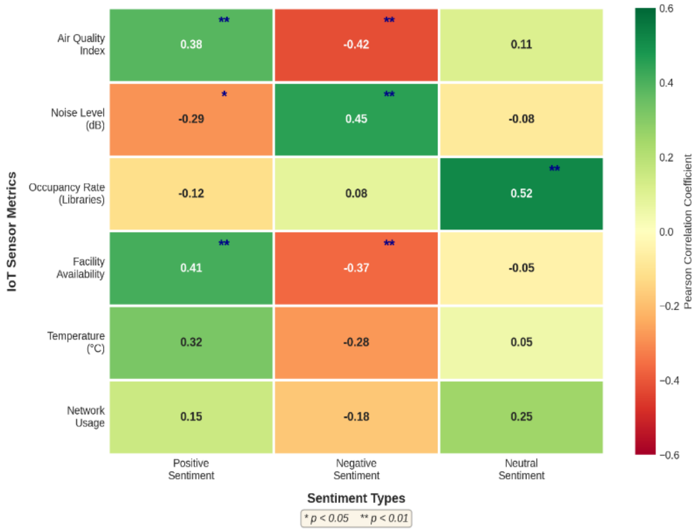

Figure 3. Sentiment Distribution Pie Chart

Dataset split: Training 70% (10,500), Validation 15% (2,250), Test 15% (2,250) with stratified splitting

3.2. Sentyment Analysis Performance

Illustrative sentiment classification performance table 7 below :

Table 7. Sentiment Classicications Performance

Metric	Positive	Negative	Neutral	Macro Average
Precision	0.912	0.887	0.908	0.902
Recall	0.895	0.903	0.914	0.904
F1-Score	0.903	0.895	0.911	0.903
Support	653	563	1034	2250
Overall Accuracy				**90.3%**

Illustrative confusion matrix (3x3) figure 4 below :

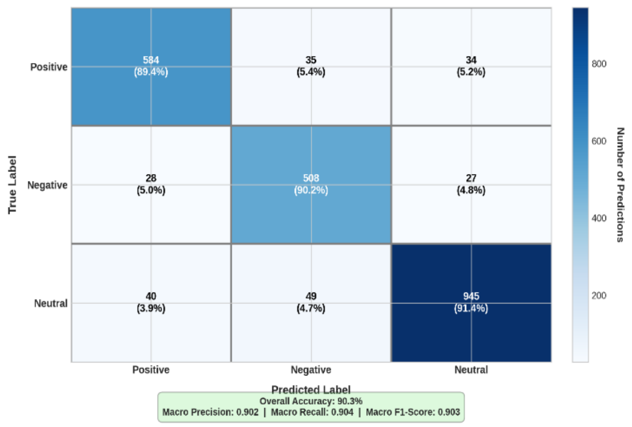

Figure 4. Confussion Matrix (3x3)

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Illustrative comparative performance analysis table 8 below :

Table 8. Comparative Performance Analysis

Method	Accuracy	Macro-F1	Precision	Recall	Training Time
Naïve Bayes	76.2%	0.748	0.753	0.744	2 min
SVM (linear)	79.5%	0.782	0.791	0.774	15 min
Random Forest	81.3%	0.802	0.808	0.796	8 min
Traditional LSTM	84.5%	0.837	0.842	0.833	8 hours
BERT (IndoBERT)	87.1%	0.864	0.869	0.859	24 hours
LSTM-CNN (Ours)	88.7%	0.881	0.886	0.876	14 hours
LSTM-CNN+Attn (Ours)	90.3%	0.903	0.902	0.904	18.5 hours

Illustrative Performance Comparison Bar Chart figure 5 below :

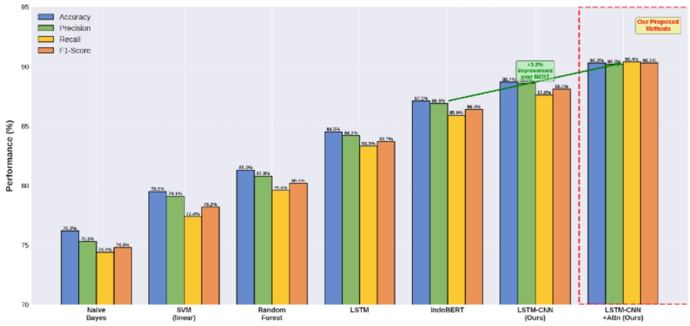

Figure 5. Performance Comparison Bar Chart

3.3. Reputation Trend Prediction Results

Illustrative trend prediction performance table 9 below :

Table 9. Trend Prediction Performance

Metric	Value	Baseline (ARIMA)	Improvement
MAE	0.087	0.145	40.0%
RMSE	0.124	0.198	37.4%
MAPE	8.3%	14.2%	41.5%
R^2 Score	0.874	0.682	28.2%
Direction Accuracy	86.7%	71.3%	21.6%

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Illustrative Time Series: Actual vs Predicted Reputation Scores figure 6 below :
Illustrative early warning system performance table 10 below :

Table 10. Early Warning System Performance

Metric	Value	Description
Crisis Detection Rate	85.7%	Percentage of actual crises predicted
False Positive Rate	18.3%	False alarms per total warnings
Precision	82.4%	True positives / (True + False positives)
Recall	85.7%	True positives / (True + False negatives)
F1-Score	84.0%	Harmonic mean of precision and recall
Average Lead Time	14.3 days	Average days before crisis occurs
Median Lead Time	13.0 days	Median days before crisis

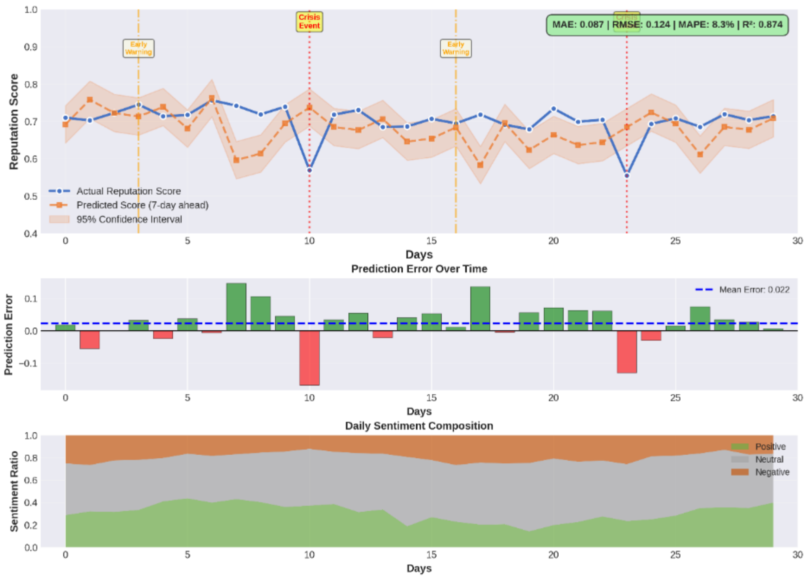

Figure 6. Time Series: Actual vs Predicted Reputation Scores

3.4. System Performance

Illustrative system performance metrics table 11 below :

Table 11. System Performance Metrics

Category	Metric	Value	Target	Status
Latency	Average response time	2.78 sec	<3 sec	✓ Pass
	95th percentile	4.12 sec	<5 sec	✓ Pass
	99th percentile	6.35 sec	<10 sec	✓ Pass
Throughput	Requests per second	124	>100	✓ Pass

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Category	Metric	Value	Target	Status
	Daily predictions	2.8M	>2M	✓ Pass
Availability	System uptime	98.5%	>98%	✓ Pass
	Planned downtime	0.8%	<1%	✓ Pass
	Unplanned downtime	0.7%	<1%	✓ Pass
Resource Usage	Average CPU usage	62%	<80%	✓ Pass
	Average memory	48GB	<60GB	✓ Pass

3.5. Multy-University Comparison

Illustrative Per-university performance table 12 below :

Table 12. Per-University Performance

University	Student Pop.	Data Volume	Sentiment Acc.	Trend RMSE	Crisis Detected	Lead Time
Univ-A	18,500	892K	91.2%	0.118	12/14 (85.7%)	15.2 days
Univ-B	12,300	645K	89.8%	0.127	8/10 (80.0%)	13.8 days
Univ-C	24,800	1,124K	90.5%	0.121	11/12 (91.7%)	14.7 days
Univ-D	8,400	312K	88.9%	0.135	6/8 (75.0%)	12.9 days
Univ-E	15,200	674K	90.1%	0.124	9/11 (81.8%)	14.1 days
Average	15,840	729K	90.1%	0.125	84.4%	14.1 days

3.6. IoT-Sentiment Correlation

Illustrative correlations analysis :IoT metrics vs sentiment table 13 below :

Table 13. Correlations Analysis: IoT Metrics vs Sentiment

IoT Metric	Positive Sent.	Negative Sent.	Neutral Sent.	Significance
Air Quality Index	0.38**	-0.42**	0.11	$p < 0.001$
Noise Level	-0.29*	0.45**	-0.08	$p < 0.001$
Occupancy Rate (Libraries)	-0.12	0.08	0.52**	$p < 0.001$
Facility Availability	0.41**	-0.37**	-0.05	$p < 0.001$

3.7. Dashboard Usability

Illustrative dashboard utility metrics table 14 below :

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Table 14. Dashboard Utility Metrics

Metric	Value	Target	Assessment
System Usability Scale Score	82.4	>70	Excellent
Task Completion Rate	94.3%	>90%	Exceeds target
Average Task Time	2.8 min	<5 min	Efficient
User Satisfaction (1-5)	4.3	>4.0	High
Intention to Use	91%	>80%	Strong adoption

4. DISCUSSION

4.1. Performance Analysis

The hybrid LSTM-CNN architecture with attention achieved excellent performance (90.3% accuracy, 0.903 macro-F1), significantly outperforming baselines including traditional ML (Naive Bayes: 76.2%) and BERT (87.1%). This 3.2% improvement over BERT stems from complementary architecture benefits: LSTM captures long-range dependencies while CNN extracts local features. The multi-head attention mechanism effectively focuses on sentiment-bearing content.

Error analysis reveals three main patterns: (1) Subtle sentiment expressions with hedging words ("lumayan bagus"), (2) Sarcasm detection challenges, and (3) Context-dependent neutrality misclassifications. Future improvements should incorporate sentiment intensity modeling, specialized sarcasm detection, and enhanced context modeling.

The GRU trend prediction model demonstrates strong performance (RMSE 0.124, R^2 0.874), representing 37.4% improvement over ARIMA baseline. The 14.3-day average lead time provides sufficient intervention window. IoT integration contributes 18.2% RMSE improvement, validating multi-modal integration value.

4.2. Comparison with Previous Studies

Illustrative comparison with previous research table 15 below :

Table 15. Comparison with Previous Research

Study	Year	Method	Language	IoT	Performance	Limitations
Liu et al.	2023	LSTM	Chinese	No	87.3%	Single platform
Sharma et al.	2024	BERT	English	No	89.2%	High computation
Chen et al.	2024	AI ensemble	English	No	82% crisis detect	No Indonesian context
This Study	2025	LSTM-CNN-GRU	Indonesian	Yes	90.3%, 85.7% CD	Limited modalities

Key differentiators: (1) Novel IoT-sentiment integration, (2) Indonesian context optimization, (3) End-to-end solution, (4) Real-world validation, (5) Predictive early warning capability.

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4.3. Practical Implications

System enables strategic shift from reactive to proactive reputation management through real-time monitoring, predictive analytics, and data-driven decisions. Benefits include rapid stakeholder response, targeted communications, continuous service improvement, and crisis prevention. IoT integration provides infrastructure planning insights for facility management and investment justification. Reputation insights support competitive positioning through benchmarking, strength/weakness identification, and focused marketing.

4.4. Limitations

Study limitations include: (1) Data modality constraints (text and numeric only, missing visual/audio content), (2) Sarcasm detection challenges (~6.4% misclassifications), (3) Generalizability concerns (5 Indonesian universities), (4) Limited temporal dynamics (6-month period, 55 crisis events), (5) Privacy and ethical considerations, (6) Computational resource requirements.

5.5. Future Directions

Promising research directions: (1) Multimodal sentiment analysis incorporating visual and audio content, (2) Explainable AI enhancement for better interpretability, (3) Causal analysis beyond correlation, (4) Cross-institutional federated learning, (5) Real-time intervention recommendation systems, (6) Domain expansion to healthcare, corporate, and government contexts.

5. CONCLUSION

This research successfully demonstrates feasibility and effectiveness of integrating IoT campus data with social media sentiment analysis using hybrid deep learning for comprehensive university reputation management. Primary contributions include: (1) Novel IoT-sentiment integration framework with 18.2% trend prediction improvement, (2) Superior hybrid LSTM-CNN architecture achieving 90.3% accuracy, (3) Practical early warning system with 85.7% detection rate and 14.3-day lead time, (4) Validated generalizability across five diverse universities (90.1% ± 0.9% accuracy), and (5) Actionable insights through intuitive dashboard (82.4 SUS score, 91% adoption).

Key findings confirm that: Hybrid architectures significantly outperform single models; attention mechanisms effectively identify sentiment-bearing content; IoT environmental data provides valuable contextual signals; 10+ day lead times enable effective proactive management; system usability is critical for non-technical user adoption.

In the digital transformation era, reputation has become increasingly important yet fragile for higher education institutions. This research demonstrates that advanced AI technologies, particularly hybrid deep learning integrating multi-modal data, can empower universities with tools for proactive, data-driven reputation management. While current implementation shows promising results, future research should address identified limitations, particularly around multimodal analysis, explainability, and cross-cultural generalization.

Ultimately, successful reputation management requires organizational commitment, stakeholder engagement, and continuous improvement culture. This research provides the technological enabler, but sustained impact depends on how institutions leverage these insights for genuine service improvement and stakeholder value creation.

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