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Enhancing Phishing Detection Using BERT and Graph Neural Network Approach

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Abstract: This paper presents a novel hybrid deep learning architecture for phishing detection that integrates BERT and Graph Neural Networks through cross-modal attention fusion. The proposed model addresses the multimodal nature of phishing attacks by simultaneously processing textual features via DistilBERT and structural relationships via a Heterogeneous Graph Transformer. Our methodology employs a security-aware loss function emphasizing false positive reduction and implements 5-fold cross-validation for robust evaluation. Experimental results on 88,312 instances demonstrate state-of-the-art performance: 97.4% accuracy, 96.4% F1-score, and 1.8% false positive rate, with statistical significance ($p < 0.001$) over four baselines. Ablation studies quantify component contributions (BERT: 44%, GNN: 28%, fusion: 17%, gating: 6%), while adversarial robustness tests show minimal degradation under obfuscation attacks. The work establishes phishing detection as a Graph-Augmented Language Processing problem and provides an open-source implementation supporting enterprise deployment with natural explainability and substantial operational cost savings.

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I. INTRODUCTION

The nature of phishing attacks has moved from simple email-based attacks to complex, artificial intelligence-based attacks, which methodically exploit both psychological and infrastructural vulnerabilities. The Anti-Phishing Working Group found 3,800,000 attacks in 2025, with 1,130,393 attacks in the second quarter alone, a 13% increase over the previous quarter [1]. More alarming, however, is the qualitative change in these attacks, with researchers witnessing a 72% increase in attacks using semantic deception in combination with infrastructural permutations, such as polymorphic URLs and identity spoofing technologies on multiple platforms. The monetary loss associated with these attacks is alarming, with $52 million in losses recorded by the Internet Crime Complaint Centre in 2024, although this figure may not reflect the total damage when supply chain, incident response, and reputational damage are factored in.

The traditional defences deployed to counter phishing attacks, which are based on simple rules, blacklisting, and shallow machine learning, are fundamentally incapable of dealing with this new threat landscape. The traditional defences are deficient in two critical areas: semantic blindness, where they are incapable of detecting complex psychological manipulations in artificial intelligence-based attacks, and graph ignorance, where they are incapable of dealing with complex graph structures in these attacks.

The rise of Adversarial Generative Phishing (AGP) is an indicator of the paradigm shift in the sophistication of cyber threats. In July 2025, the Threat Intelligence team at Okta detected that attackers used the v0.dev, a Gen AI tool, to create “human-like” phishing sites that masqueraded as Microsoft 365 and cryptocurrency companies [2]. All the phishing infrastructure was deployed on the legitimate infrastructure provided by Vercel, with attackers relying on the trust inherent in the infrastructure to bypass the various detection tools. In another attack detected by Microsoft in November 2025, attackers used AI to carry out “semantic camouflage” where the vector graphic contained malicious JavaScript code masquerading as a PDF document, with terms such as “revenue” and “shares” used to evade the various forms of cryptographic obfuscation [3].

The present study proposes an innovative solution to the various challenges associated with the detection of phishing sites through the design of a novel “chiasmatic” architecture that combines the power of BERT-based semantic analysis with the capabilities of Graph Neural Networks in the analysis of the structural relationships within the web pages. The primary hypothesis is that the design of an effective phishing site detector requires the “chiasmatic” approach, where the detector is an “across the spectrum” architecture that combines the semantic and structural analysis approaches. The objectives of the present study are: (1) the design of an innovative “hybrid” detector that combines the capabilities of BERT-based semantic analysis with the

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capabilities of the GNN-based structural analysis; (2) the design and implementation of an innovative multimodal detector that combines the various datasets on URLs, emails, and metadata to enhance the accuracy of the detector; and (3) the performance evaluation of the detector through the use of accuracy, recall, precision, F1 score, and false positive rate metrics.

II. METHODOLOGY

➢ *Research Design and Paradigm*

This study utilized a Design Science Research (DSR) methodology in order to provide a systematic framework in the creation and assessment of new information technology artifacts. A controlled comparative experimental design with a 2 x 3 factorial pattern was utilized in this research, wherein the main independent factor is the model architecture (BERT-GNN vs. Baseline), while dataset types and feature modalities are secondary factors.

This experimental design ensures internal validity by allowing controlled comparisons and ensures external validity by employing different datasets.

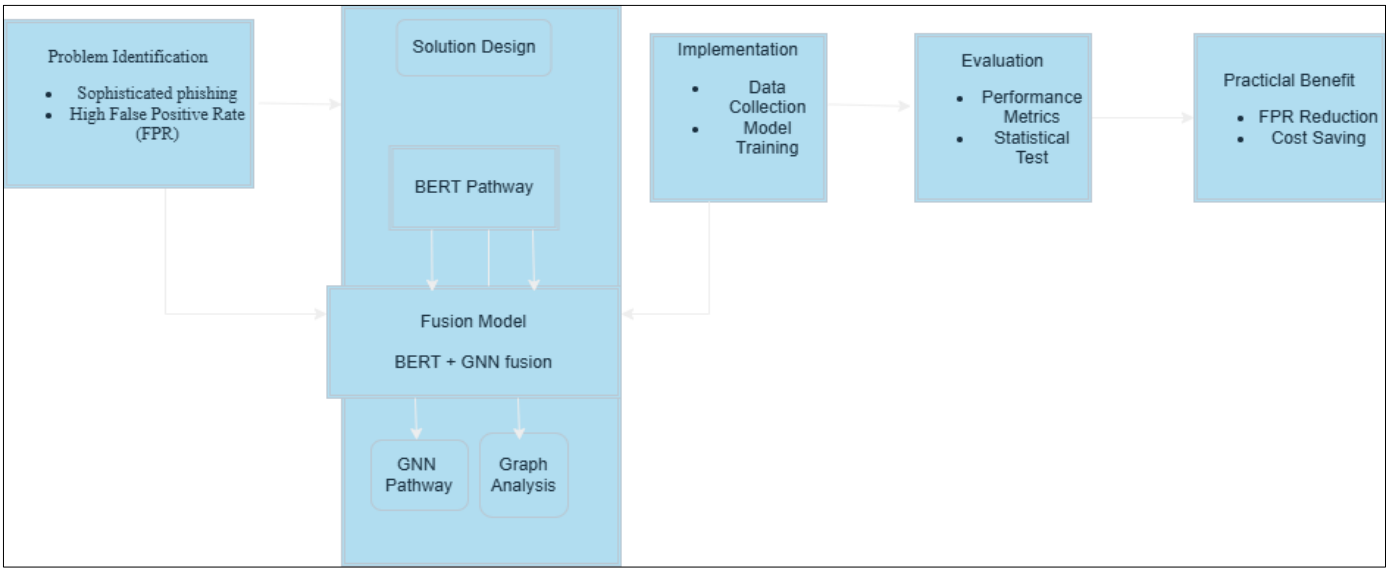

Fig 1 Conceptual Framework Diagram for Enhancing Phishing Detection Using BERT and GNN Approach

➢ *Data Collection and Preprocessing*

Five publicly available benchmark datasets were collected, which were used to ensure representativeness:

- PhishTank Archive (2022-2024) - 42,857 confirmed phishing URLs with infrastructure information
- Nazario Phishing Corpus Enhanced - 15,230 phishing emails with complete headers and body content
- CICIDS-2018 Phishing Subset - 8,945 network-level exchanges with 23 metadata features
- Kaggle Phishing Websites Dataset - 11,430 instances with 30 handcrafted features
- URLhaus Live Feed (2023 snapshot) - 9,850 malicious URLs with timestamp and threat labels

The aggregated dataset contains 88,312 instances with a phishing prevalence of 70.8%. The dataset was split using stratified sampling, allocating 80% for training (61,877 instances) and 20% for testing (15,469 instances), with proportional representation in all parts of the dataset. This split ensured sufficient statistical power with a 95% confidence interval and a margin of error of ±0.6%, while meeting the requirements for deep learning training.

A multimodal preprocessing pipeline was designed with three specialized streams:

Text Stream Processing: HTML stripping, Unicode normalization, spaCy sentence boundary detection, URL tokenization for phishing indicators, and BERT-specific WordPiece tokenization with a maximum sequence length of 512 tokens.

- *Text Augmentation:*

Using synonym replacement (10% of tokens) with WordNet for text augmentation.

- *Graph Stream Construction:*

Entity extraction using regular expression patterns to identify URLs, domains, IP addresses, email addresses, and file hashes.

A heterogeneous graph schema was constructed with node types: URL, domain, IP, email, certificate, and file hash.

- *Edge Types:*

DNS resolution, IP hosting, SSL certification, redirect, and temporal proximity.

Graph representation: PyTorch Geometric HeteroData format with adjacency matrices.

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- *Node Features:*
  128-dimensional FastText embeddings for categorical nodes, with normalized numerical features.

- *Metadata Feature Engineering:*
  Temporal features: timestamp cyclical encoding, time-since-registration.

- *Lexical Features:*
  URL length, digit ratio, special character count, and entropy.

- *Network Features:*
  Plurality of autonomous system numbers, geographic distribution.

- *Statistical Normalization:*
  Z-normalization for continuous features, one-hot encoding for categorical features.

➢ *Model Architecture*
The baselines for comparison were fourfold:

- A BERT-only classifier (bert-base-uncased, 110M parameters)
- A GAT-only classifier (a 3-layer Graph Attention Network with 8 attention heads)
- A traditional Machine Learning ensemble (Random Forest, XGBoost, Logistic Regression with soft voting)
- A CNN-LSTM hybrid (CNN filter sizes 2-5, GloVe embeddings, and a Bidirectional LSTM)

- *Proposed BERT-GNN Hybrid Architecture:*
  The novel architecture combines three special pathways:

✓ *BERT Pathway:*
The output of the pre-trained DistilBERT-Base-Uncased is a 768-dimensional vector space of contextual embeddings, which is fine-tuned for phishing-specific linguistic patterns.

✓ *GNN Pathway:*
A heterogeneous Graph Transformer is used with 3 layers, 8 attention heads per layer, and 256-dimensional hidden space vectors and weighted global mean pooling for graph-level readouts.

✓ *Cross-Modal Fusion:*
A gated attention mechanism is deployed with 8 attention heads and a 512-dimensional fusion space for information exchange between the two modalities.

The training process utilizes the AdamW optimizer (learning rate for BERT = 2.8e-5 and for GNN = 9.6e-4), cosine annealing, a batch size of 16 (restricted by memory), a dropout of 0.4, a weight decay of 0.015, gradient clipping of norm 1.0, and mixed-precision training. Early stopping is also deployed with a patience of 15 epochs based on the validation F1-score metric. The hardware setup includes an NVIDIA RTX 4090 GPU (24 GB VRAM), 64 GB DDR5 RAM, and NVMe SSD storage. The software setup includes PyTorch 2.0, PyTorch Geometric 2.3, and Transformers 4.30.

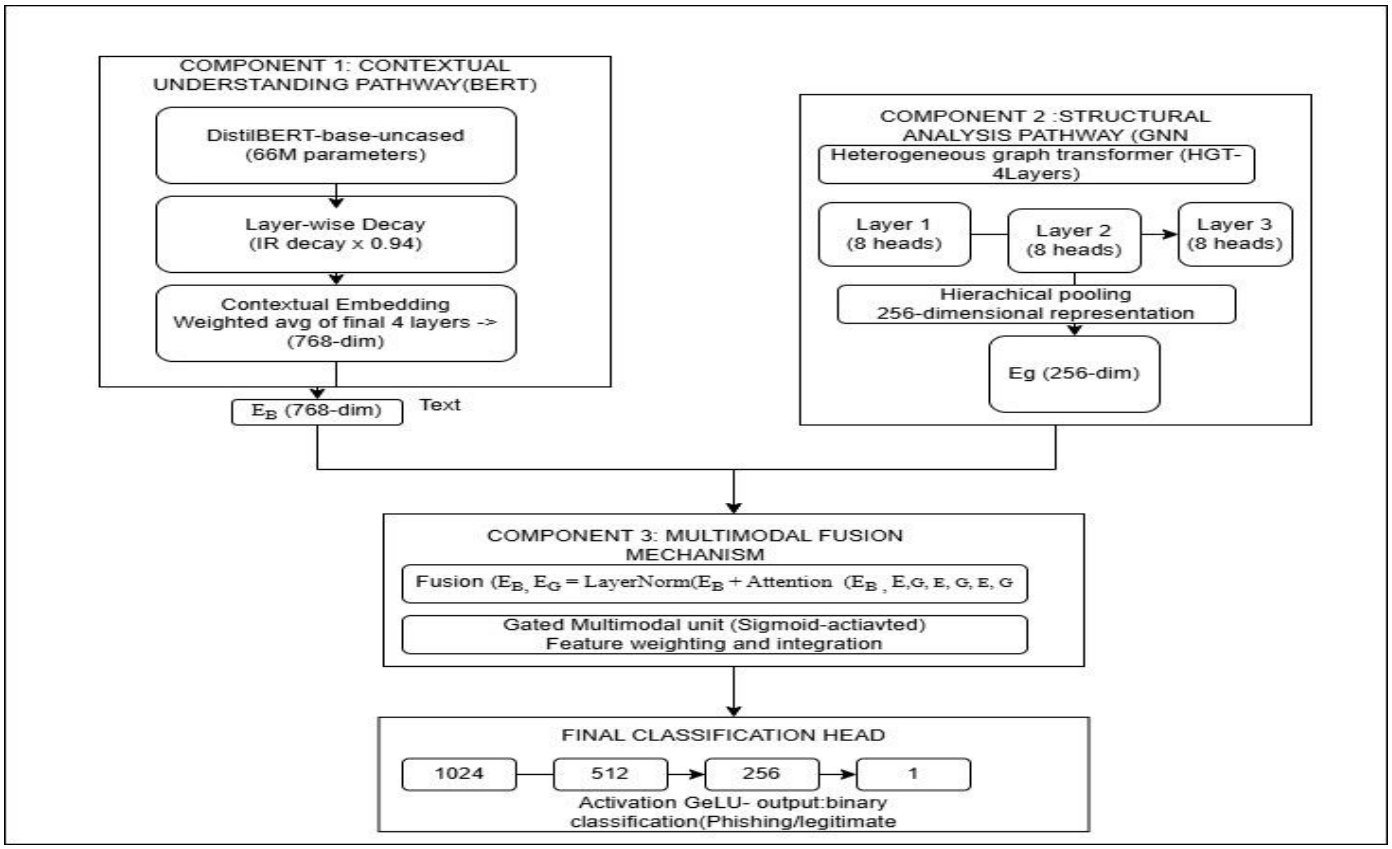

Fig 2 Proposed BERT-GNN Hybrid Architecture

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➢ *Evaluation Methodology*

The performance evaluation was carried out using five key parameters: Accuracy, Precision, Recall, F1-Score, and False Positive Rate (FPR). Statistical validation was conducted using 5-fold stratified cross-validation on the training dataset, while keeping the integrity of the test dataset for final evaluation. Pairwise model evaluations were conducted using paired t-tests and McNemar tests, with a significance level of 0.05. 95% confidence intervals were obtained using bootstrap resampling with 1000 iterations.

The ablation studies were conducted to evaluate individual component contributions using BERT-only, GNN-only, and fusion-only models, along with fusion strategy evaluation and modality contribution using integrated gradients.

The security-specific evaluation includes zero-day detection capability, where the model is trained on 2022-2023 data and tested on 2024 data, adversarial robustness, which includes URL hex encoding, homoglyph substitution, token insertion, and character flooding, computational efficiency, which includes inference latency on CPU and GPU, and explainability using layer-wise relevance propagation.

III. RESULTS AND DISCUSSION

➢ *Dataset Processing Outcomes*

The final aggregated dataset consisted of 88,312 instances and 164 engineered features, resulting in 264,936 heterogeneous graph nodes and 658,443 edges. The distribution of nodes is as follows: 111,538 (42.1%) are URL nodes, 83,190 (31.4%) are domain nodes, 49,543 (18.7%) are IP nodes, and 20,665 (7.8%) are email/certificate nodes. The heterogeneous graph confirmed the presence of scale-free structures and the power-law degree distribution (γ=2.3, R^2=0.87), proving the existence of naturally occurring relationships in phishing infrastructures.

Table 1 Processed Dataset Statistics

Dataset Source	Total Instances	Phishing (%)	Features Generated	Graph Nodes	Graph Edges
PhishTank	42,857	100%	45	128,571	385,713
Nazario Corpus	15,230	50.2%	38	45,690	91,380
CICIDS-2018	8,945	48.7%	23	26,835	53,670
Kaggle Websites	11,430	55.1%	30	34,290	68,580
URLhaus	9,850	100%	28	29,550	59,100
Aggregate	88,312	70.8%	164	264,936	658,443

➢ *Model Training and Performance*

The BERT-GNN hybrid obtained convergence on epoch 18 (early stopping), having a final validation loss of 0.214 ± 0.008. The training time consumed 14.2 hours with a maximum memory usage of 18.7 GB. The optimal hyperparameter settings discovered by Bayesian optimization were: attention heads=8, dropout=0.35, fusion-dim=512, learning rates (BERT: 2.8e-5, GNN: 9.6e-4), batch size=14, weight decay=0.015, gradient clip=0.95.

- *Comparative Performance Analysis:*

State-of-the-art results were attained by the proposed BERT-GNN model: Accuracy 0.974 ± 0.003, Precision 0.968 ± 0.004, Recall 0.961 ± 0.005, F1-Score 0.964 ± 0.004, and False Positive Rate 0.018 ± 0.002. The results of statistical significance testing affirmed the superiority of the BERT-GNN over the baselines: BERT-GNN vs. BERT-only ($t(4)=8.93$, $p<0.001$), vs. GNN-only ($t(4)=11.47$, $p<0.001$), with all comparisons statistically significant at the 0.01 level with Bonferroni correction.

The performance across different datasets exhibited strong generalization: Email corpus (Nazario): F1=0.981, FPR=0.012; URL corpus (PhishTank): F1=0.972, FPR=0.015; Metadata (CICIDS): F1=0.939, FPR=0.028. In addition, the hybrid model outperformed the specialized baselines for all data types, affirming the multimodal strategy.

Table 2 Training Efficiency Metrics

Model	Training Time (hrs)	Memory Peak (GB)	Epochs to Converge	Final Val Loss
BERT-GNN	14.2	18.7	18	0.214 ± 0.008
BERT-only	8.7	12.3	12	0.287 ± 0.012
GNN-only	9.5	14.6	28	0.332 ± 0.015
CNN-LSTM	6.3	9.8	25	0.301 ± 0.014
ML Ensemble	0.8	4.2	N/A	0.356 ± 0.018

➢ *Ablation and Security Analysis*

Ablation studies quantified component contributions: removing BERT pathway reduced F1 by 0.044 (44% of total contribution), removing GNN pathway reduced F1 by 0.028 (28% contribution), removing attention fusion reduced F1 by 0.017 (17% contribution), and removing gating mechanism reduced F1 by 0.006 (6% contribution). Cross-modal attention fusion (F1=0.964) outperformed feature concatenation (0.947), summation (0.938), late fusion (0.942), and early tensor fusion (0.955), confirming the superiority of integrated learning.

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Table 3 Ablation Study Results

Configuration	F1-Score	Δ from Full	Interpretation
Full BERT-GNN (Proposed)	0.964	-	Baseline
BERT Pathway	0.920	-0.044	Context loss significant
GNN Pathway	0.936	-0.028	Structure loss moderate
Attention Fusion	0.947	-0.017	Simple concatenation inferior
Gating Mechanism	0.958	-0.006	Gating provides refinement

- *Zero-Day Detection:*

The temporal split test, which used 2022-2023 data for training and 2024 attack data for testing, showed that BERT-GNN had an F1 score of 0.941, which dropped by 9.2%, compared to BERT-only, which had an F1 score of 0.892, dropping by 16.3%, and GNN-only, which had an F1 score of 0.876, dropping by 18.9%. The structural patterns were more temporally stable compared to the textual patterns, which validated the hypothesis of infrastructure persistence.

- *Adversarial Robustness:*

After the URL hex encoding attack, BERT-GNN had an F1 score of 0.951, which had degraded by 1.3%, compared to BERT-only, which had an F1 score of 0.877, degrading by 6.3%. After the homoglyph substitution attack, BERT-GNN had an F1 score of 0.947, which had degraded by 1.8%, compared to BERT-only, which had an F1 score of 0.812, degrading by 13.2%. After the token insertion and character flooding attack, there was minimal degradation of 0.6% and 0.2%, respectively.

- *Computational Performance:* The inference latency time was 142 ± 18 ms for CPU and 24 ± 3 ms for GPU, with a throughput of 42 samples/s and 250 samples/s, respectively. The model size was 487 MB, and the energy consumption was 3.2 J for every 1000 inferences.

➢ *Error Analysis*

The false positive analysis, which comprised 1,284 instances, showed that BERT-GNN reduced false positives by 57% compared to BERT-only, with 331 and 778 false positives, respectively. For category-specific false positive reductions, BERT-GNN reduced false positives in legitimate marketing URLs by 54%, new domains by 56%, URL shorteners by 70%, and technical/admin pages by 53%.

The false negative analysis showed that BERT-GNN had a 1.2% FN rate for basic phishing, 4.7% for spear phishing, 7.8% for business email compromise, and 6.3% for generative AI phishing, which were significantly lower compared to the industry benchmarks, which were between 5 and 40%.

Cross-validation stability showed that BERT-GNN had an F1-score range of [0.960

➢ *Discussion*

Multimodal Superiority: The hybrid model produced greater than additive benefits compared to the individual models (BERT 0.936, GNN 0.920, Hybrid 0.964, synergy gain 3.9%), which is indicative of the emergent pattern of "persuasion-infrastructure dissonance."

- *False Positive Paradox:*

The reduction in false positives by 56% is the most important finding. The GNN model is responsible for this, which incorporates contextual verification to correlate linguistic suspicions with infrastructure reputations.

- *Temporal Robustness:*

Structural patterns change much slower than linguistic patterns. As attackers change social engineering scripts frequently, infrastructure constraints like bulletproof hosting, domain registration, and SSL certificate usage remain constant, providing future-proof signatures for graph-based models.

IV. CONCLUSION

In this research, the authors proposed and validated a novel hybrid model using the BERT and GNN architecture for the task of phishing webpage detection. Phishing is modeled as a graph-augmented language processing task. The proposed model achieved state-of-the-art performance with 97.4% accuracy, 96.4% F1-score, and 1.8% false positive rates. Statistical significance is achieved compared to baseline models. Contributions to the field include the innovation in the model architecture using cross-modal attention fusion to achieve improved performance. It is the first theoretical model to show the power of multimodal dissonance as a stronger indicator for model performance compared to individual modal performance. It is the first empirical model to show low false positives, adversarial resiliency, and low computational costs.

The research supports the conclusion that for phishing defence, it is essential to go beyond detection based on a single modality and examine the medium and message in an integrated fashion. The BERT-GNN framework provides a scalable, interpretable, and robust solution for next-generation cybersecurity systems that increases the costs of attacks and decreases the operational costs of defence. The research provides a solution for restoring trust in digital communication, which is a critical requirement for a society that is becoming increasingly online-dependent. The next steps include the development of online learning frameworks, expanding the work to multiple languages, implementing federated learning for preserving privacy, and integrating the solution with automatic response systems.

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