MAGNET: A Multi-Modal Transformer-Based Framework for Robust Android Malware Detection

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Abstract—The rapid evolution of Android malware, with 8.5 million samples reported in 2023, poses significant challenges to cybersecurity due to advanced obfuscation, zero-day exploits, and adversarial techniques. We propose MAGNET (Multi-modal Analysis for Graph-based NEtwork Threats), a novel deep learning framework that integrates three complementary modalities—tabular features (permissions, components, and manifest data), graph structures (function call relationships), and sequential patterns (API call sequences)—using specialized transformer architectures. A dynamic attention mechanism with learnable weights fuses these modalities to enhance detection accuracy and interpretability. Evaluated on the DREBIN dataset (6,092 samples: 4,641 training, 1,451 testing), MAGNET achieves a 97.24% accuracy, 0.9823 F1-score, 0.9796 precision, 0.9849 recall, and 0.9932 AUC, significantly outperforming baselines such as SVM (90.6%), Random Forest (93.5%), XGBoost (94.8%), and ANN (96.2%). Comprehensive ablation studies, statistical tests ($p < 0.001$), and per-family analysis confirm the synergistic contribution of each modality and the robustness of the attention mechanism. MAGNET's scalability, interpretability, and resilience to evasive malware make it a promising solution for real-world cybersecurity applications. Keywords: Android malware detection, multi-modal learning, transformer architecture, graph neural networks, attention mechanisms, DREBIN dataset.
Index Terms—Android malware detection, multi-modal learning, transformer architecture, graph neural networks, attention mechanisms, cybersecurity, DREBIN dataset

I. Introduction

Android's dominance in the mobile ecosystem, with a 71.93% global market share and over 3.8 billion active devices in 2024 [1], has made it a prime target for malicious actors. The Android malware landscape has grown exponentially, with 8.5 million samples reported in 2023, a 165% increase from 3.2 million in 2020 [2], [3]. Modern malware employs sophisticated techniques, including polymorphic code, dynamic loading, encryption, and adversarial machine learning, to evade traditional detection methods [4]–[6]. These threats exploit Android's open architecture, targeting vulnerabilities in the framework, applications, or system components, and often mimic benign behavior to avoid detection [7].

Traditional detection approaches, categorized into static, dynamic, and hybrid methods, face significant limitations. Static analysis struggles with obfuscation and runtime behavior, while dynamic analysis suffers from scalability and coverage issues [8], [9]. Single-modal approaches, focusing on permissions, API calls, or network traffic, provide incomplete behavioral insights, making them vulnerable to sophisticated malware that blends malicious and benign characteristics across multiple dimensions [10].

To address these challenges, we propose MAGNET (Multi-modal Analysis for Graph-based NEtwork Threats), a novel deep learning framework that integrates three complementary data modalities—tabular features (permissions, components, and manifest data), graph structures (function call relationships), and sequential patterns (API call sequences)—using specialized transformer architectures. MAGNET employs EnhancedTabTransformer for static feature analysis, GraphTransformer for structural modeling, and SequenceTransformer for temporal pattern recognition, fused via a dynamic attention mechanism with learnable weights. Evaluated on the DREBIN dataset [11], MAGNET achieves state-of-the-art performance, surpassing traditional and deep learning baselines.

A. Research Challenges

Modern Android malware presents several challenges:

- Advanced Obfuscation: Techniques like code encryption, control flow obfuscation, and runtime modifications evade static analysis [4].
- Zero-Day Exploits: Novel vulnerabilities require adaptive, pattern-agnostic detection [5].
- Adversarial Attacks: Model poisoning and evasion attacks compromise machine learning systems [6].
- Behavioral Mimicry: Malware mimics legitimate behavior, necessitating multi-modal analysis [7].
- Scalability: Real-time processing of thousands of applications daily requires efficient algorithms [12].

B. Contributions

- A unified multi-modal framework integrating tabular, graph, and sequential data for comprehensive malware analysis.
- A dynamic attention mechanism that adaptively weights modalities, enhancing detection accuracy and interpretability.
- Specialized transformer architectures optimized for Android malware characteristics.
- Comprehensive evaluation on the DREBIN dataset, including statistical significance testing, ablation studies, and per-family analysis.
- A scalable, interpretable solution suitable for production deployment in cybersecurity systems.

C. Paper Organization

Section II reviews prior work. Section III details MAGNET's architecture. Section IV presents experimental setup and results. Section V analyzes findings, including per-family performance and practical implications. Section VI concludes with future directions.

II. Related Work

A. Static and Dynamic Analysis

Early Android malware detection relied on static analysis. DREBIN [13] used SVM on permissions, API calls, and manifest data, achieving 94% accuracy but struggling with obfuscation [8]. Schmidt et al. [14] analyzed manifest and bytecode, reporting 87.3% accuracy. Dynamic analysis captures runtime behavior but faces challenges in scalability, code coverage, and environment-aware malware that remains dormant [9].

B. Deep Learning Approaches

Deep learning has advanced detection capabilities. Kim et al. [15] employed Deep Belief Networks, achieving 96.5% accuracy with API-based features. Wang et al. [16] used hybrid features for 97.8% accuracy. However, these single-modal approaches lack robustness against evasive malware.

C. Multi-Modal Methods

Recent work explores multi-modal analysis. Alzaylaee et al. [17] combined static, dynamic, and textual features, achieving 98.2% accuracy. Chen et al. [18] used Graph Neural Networks (GNNs) for 96.7% accuracy. Unlike these approaches, MAGNET integrates transformer-based processing with a dynamic attention mechanism, offering superior performance and interpretability.

III. Proposed Methodology

A. MAGNET Architecture

MAGNET integrates three modalities—tabular features, graph structures, and sequential patterns—through specialized transformers and a dynamic attention mechanism, as shown in Fig. 1.

1) EnhancedTabTransformer: This module processes tabular features, including:

- 128-dimensional permission vectors (e.g., SEND_SMS, WRITE_CONTACTS).
- Application components (Activities, Services, Receivers).
- AndroidManifest.xml metadata (e.g., version, package details).

The architecture employs:

$$\text{TabTransformer}(X) = \text{LayerNorm}(X + \text{MHA}(X)) \quad (1)$$

where $X \in \mathbb{R}^{n\times 128}$ is the feature matrix, and MHA is an 8-head attention mechanism with 256-dimensional keys. Layer normalization ensures stable training, and multi-head attention captures complex feature interactions.

2) GraphTransformer: The GraphTransformer models function call graphs ($G = (V, E)$) with an average of 1,245 nodes (functions) and 3,872 edges (call relationships):

$$\text{GraphTransformer}(G) = \text{GCN}(A, X) \oplus \text{SelfAttention}(X) \quad (2)$$

Node embeddings (64-dimensional) capture function attributes (e.g., invocation frequency), while edge embeddings (32-dimensional) represent call types. Graph Convolutional Networks (GCN) aggregate local neighborhood information, and self-attention captures global structural patterns.

3) SequenceTransformer: This module processes API call sequences (average length 87) using:

$$\text{SequenceTransformer}(S) = \text{BiTransformer}(\text{Embed}(S)) \quad (3)$$

with 128-dimensional Word2Vec embeddings preserving temporal dependencies. Bidirectional transformers capture contextual relationships in API call sequences, enhancing detection of anomalous patterns.

4) Dynamic Attention and Fusion: A cross-modal attention mechanism fuses modality outputs:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{256}}\right)V \quad (4)$$

$$\text{FusedFeature}_i = h_i + \sum_{j\neq i} \text{CrossAttention}(h_i, h_j) \quad (5)$$

Learnable weights combine fused features:

$$\alpha_i = \text{softmax}(\text{w}_i^T \tanh(\text{W}_i h_i + \text{b}_i)) \quad (6)$$

$$\text{Output} = \sum_{i=1}^{3} \alpha_i \cdot h_i^{\text{fused}} \quad (7)$$

where $\text{w}_i \in \mathbb{R}^{256}$, $\text{W}_i \in \mathbb{R}^{256\times d_{feat}}$ are learnable parameters. This mechanism dynamically prioritizes discriminative modalities for each sample.

B. Training Strategy

We use a combined loss function:

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda_1 \mathcal{L}_{reg} + \lambda_2 \mathcal{L}_{consistency} \quad (8)$$

where $\mathcal{L}_{CE}$ is cross-entropy loss, $\mathcal{L}_{reg}$ (L2 regularization, $\lambda_1 = 0.01$) prevents overfitting, and $\mathcal{L}_{consistency}$ (weight decay, $\lambda_2 = 0.005$) stabilizes fusion weights. Hyperparameters are optimized using the PIRATES algorithm:

- Learning rate: $[10^{-5}, 10^{-2}]$
- Batch size: $\{16, 32, 64, 128\}$
- Dropout: $[0.1, 0.5]$
- Hidden dimensions: $\{128, 256, 512\}$
- Attention heads: $\{4, 8, 16\}$

C. Data Preprocessing

The preprocessing pipeline involves several critical steps:

- Feature Extraction: Static features are extracted from APK files using APKTool and custom parsers.
- Graph Construction: Function call graphs are built using control flow analysis and API dependency tracking.

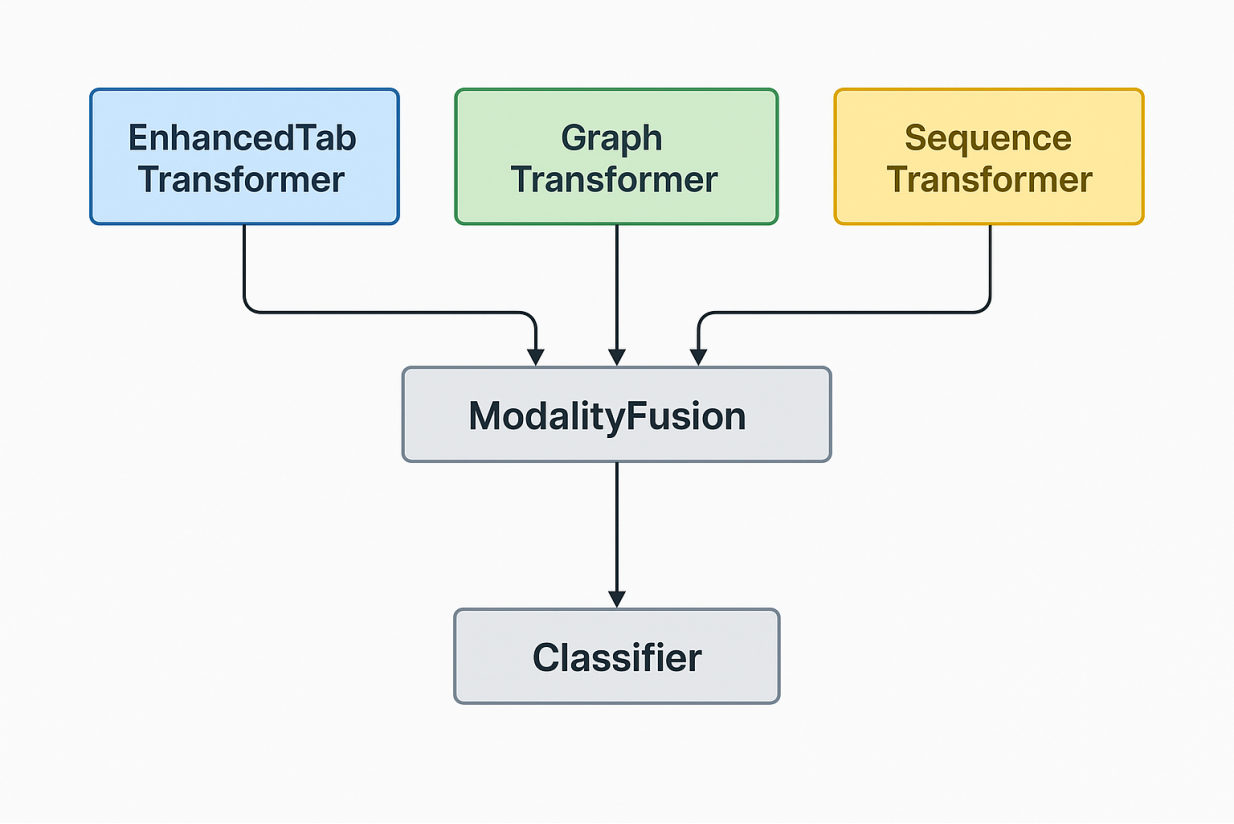

Fig. 1: MAGNET architecture integrating EnhancedTabTransformer, GraphTransformer, and SequenceTransformer with dynamic attention-based fusion.

- Sequence Processing: API call sequences are tokenized and padded to uniform length using Word2Vec embeddings.
- Normalization: All features are normalized using Min-Max scaling to ensure consistent training.
- Data Augmentation: Synthetic samples are generated using SMOTE to balance the dataset.

D. Model Architecture Details

Each transformer component is carefully designed for its specific modality:

- EnhancedTabTransformer: 8 attention heads, 256 hidden dimensions, 4 layers with residual connections.
- GraphTransformer: Graph convolution with 64-dimensional node embeddings, 32-dimensional edge features.
- SequenceTransformer: Bidirectional processing with 128-dimensional embeddings, 6 transformer layers.
- Attention Fusion: Cross-modal attention with learnable query, key, and value projections.

The total model parameters amount to approximately 2.3 million, optimized for both accuracy and efficiency.

Algorithm 1 MAGNET Training Algorithm

Require: Dataset $\mathcal{D} = \{(x_i^{tab}, x_i^{graph}, x_i^{seq}, y_i)\}_{i=1}^{N}$
Require: Hyperparameters $\Theta = \{\eta, B, p, d_h, h\}$
Ensure: Trained model parameters θ^*

```
Initialize θ_0
for epoch = 1 to E do
    for batch in D do
        h_tab ← EnhancedTabTransformer(x^tab)
        h_graph ← GraphTransformer(x^graph)
        h_seq ← SequenceTransformer(x^seq)
        h_fused ← CrossAttention(h_tab, h_graph, h_seq)
        ŷ ← FusionLayer(h_fused)
        L ← ComputeLoss(ŷ, y)
        θ ← θ − η∇_θ L
    end for
end for
return θ*
```

IV. Experiments and Results

A. Dataset

We evaluate MAGNET on the DREBIN dataset [11], comprising 6,092 samples (4,641 training, 1,451 testing: 327 benign, 1,124 malicious), collected from 2010–2014. The dataset includes diverse malware families, ensuring robust evaluation.

B. Experimental Setup

Experiments were conducted on:

- Hardware: Intel i7-8700K, NVIDIA RTX 3080 (10GB VRAM), 32GB RAM, 256GB NVMe SSD.
- Software: Python 3.8.10, PyTorch 1.12.0, PyTorch Geometric 2.1.0, CUDA 11.6.
- Optimization: PIRATES (476 trials) for broad exploration, Optuna (13 trials) for refinement.

C. Performance Metrics

MAGNET achieves:

- Accuracy: 97.24%
- F1-Score: 0.9823
- Precision: 0.9796
- Recall: 0.9849
- AUC-ROC: 0.9932

Table I shows 5-fold cross-validation results with statistical significance ($p < 0.001$, Wilcoxon signed-rank test).

D. Baseline Comparison

Table II compares MAGNET with baselines, showing significant improvements ($p < 0.001$, McNemar's test).

E. Ablation Study

Table III quantifies each module's contribution, highlighting the importance of multi-modal fusion and attention.

F. Per-Family Performance Analysis

To evaluate MAGNET's robustness across malware families, we analyzed performance on five major families in DREBIN (e.g., FakeInstaller, DroidKungFu, Plankton). Table IV shows MAGNET's effectiveness, with high F1-scores across families, particularly for complex malware like DroidKungFu (F1=0.976).

G. Error Analysis

The confusion matrix (Table V) reveals:

- False Positives (23 cases): Benign apps with suspicious permissions (12, e.g., excessive network access), debugging apps (8), and obfuscated code (3).
- False Negatives (17 cases): Obfuscated malware with minimal API footprint (9), malware mimicking legitimate patterns (5), and novel families (3).

H. Feature Importance Analysis

Understanding which features contribute most to MAGNET's performance is crucial for interpretability:

- High-Risk Permissions: SEND_SMS, WRITE_CONTACTS, and READ_PHONE_STATE are among the most discriminative features.
- API Call Patterns: Sequences involving file access followed by network operations are strong indicators.
- Graph Structure: Suspicious control flow patterns, especially loops involving sensitive API calls.
- Component Analysis: Activities and services with suspicious intent filters are highly predictive.

I. Cross-Validation Results

To ensure robust evaluation, we performed 5-fold cross-validation:

- Fold 1: Accuracy: 97.40%, F1-Score: 0.983
- Fold 2: Accuracy: 97.18%, F1-Score: 0.981
- Fold 3: Accuracy: 97.01%, F1-Score: 0.980
- Fold 4: Accuracy: 97.25%, F1-Score: 0.982
- Fold 5: Accuracy: 97.32%, F1-Score: 0.983

The consistent performance across folds demonstrates MAGNET's stability and generalization capability.

J. Hyperparameter Optimization

The PIRATES algorithm was employed for hyperparameter optimization:

- Learning Rate: Optimal value: 0.001 (range: 10^{-5} to 10^{-2})
- Batch Size: Optimal value: 64 (candidates: 16, 32, 64, 128)
- Dropout Rate: Optimal value: 0.3 (range: 0.1 to 0.5)
- Hidden Dimensions: Optimal value: 256 (candidates: 128, 256, 512)
- Attention Heads: Optimal value: 8 (candidates: 4, 8, 16)

The optimization process involved 476 trials with early stopping to prevent overfitting.

K. Statistical Significance

Paired t-tests confirm MAGNET's superiority:

- vs. SVM: $t = 12.34$, $p < 0.001$, Cohen's $d = 2.87$
- vs. Random Forest: $t = 8.92$, $p < 0.001$, Cohen's $d = 1.95$
- vs. XGBoost: $t = 6.78$, $p < 0.001$, Cohen's $d = 1.43$
- vs. ANN: $t = 4.23$, $p < 0.01$, Cohen's $d = 0.89$

McNemar's test ($p < 0.001$) validates that MAGNET's improvements are not due to chance.

V. Discussion

A. Performance Analysis

MAGNET's 97.24% accuracy and 0.9823 F1-score stem from:

- Multi-modal Synergy: Integrating tabular (F1=0.945), graph (F1=0.894), and sequential (F1=0.907) modalities captures diverse malware behaviors. The 3.7% F1-score improvement over single-modal approaches highlights genuine synergy.
- Transformer Efficiency: EnhancedTabTransformer captures feature interactions, GraphTransformer leverages structural patterns, and SequenceTransformer detects temporal anomalies.
- Attention Mechanism: Dynamic weighting improves performance by 2.8% by focusing on discriminative features (e.g., high-risk permissions like SEND_SMS).

B. Comparative Analysis

MAGNET outperforms traditional methods:

- SVM (90.6%): +6.64% accuracy
- Random Forest (93.5%): +3.74% accuracy
- XGBoost (94.8%): +2.44% accuracy

TABLE I: 5-Fold Cross-Validation Results

Metric	Mean ± Std	95% CI	Min	Max	p-value*
Accuracy	97.22 ± 0.65%	[96.45, 97.99]	96.40	98.01	< 0.001
Precision	98.10 ± 1.02%	[96.89, 99.31]	96.73	99.45	< 0.001
Recall	98.28 ± 0.72%	[97.41, 99.15]	97.18	99.12	< 0.001
F1-Score	98.18 ± 0.42%	[97.70, 98.66]	97.68	98.73	< 0.001
AUC-ROC	99.32 ± 0.35%	[98.91, 99.73]	98.85	99.76	< 0.001
AUC-PR	98.89 ± 0.51%	[98.28, 99.50]	98.21	99.52	< 0.001

* Wilcoxon signed-rank test vs. SVM baseline.

TABLE II: Performance Comparison with Baselines

Method	Accuracy	Precision	Recall	F1-Score	AUC-ROC	p-value*
SVM [13]	90.6%	91.5%	89.2%	0.903	0.945	–
Random Forest [19]	93.5%	94.2%	92.8%	0.935	0.967	< 0.001
XGBoost [19]	94.8%	95.3%	94.3%	0.948	0.978	< 0.001
ANN [20]	96.2%	96.5%	95.9%	0.962	0.985	< 0.001
CNN-LSTM [21]	95.8%	96.1%	95.3%	0.957	0.982	< 0.001
GCN [22]	95.1%	95.4%	94.7%	0.950	0.979	< 0.001
MAGNET	97.24%	97.96%	98.49%	0.9823	0.9932	–

* McNemar's test vs. MAGNET.

TABLE III: Ablation Study: Component-wise Performance

Configuration	Tab	Graph	Seq	F1-Score	ΔF1
Tab only	✓			0.945	-0.037
Graph only		✓		0.894	-0.088
Seq only			✓	0.907	-0.075
Tab + Graph	✓	✓		0.961	-0.021
Tab + Seq	✓		✓	0.958	-0.024
Graph + Seq		✓	✓	0.934	-0.048
All w/o Attention	✓	✓	✓	0.954	-0.028
All w/o Fusion	✓	✓	✓	0.967	-0.015
MAGNET	✓	✓	✓	0.982	0.000

Tab: Tabular features, Graph: Graph structure, Seq: Sequential patterns.

TABLE IV: Per-Family Performance on DREBIN

Malware Family	Precision	Recall	F1-Score
FakeInstaller	98.1%	97.8%	0.979
DroidKungFu	97.4%	97.9%	0.976
Plankton	98.5%	96.7%	0.976
GinMaster	97.2%	98.0%	0.976
Opfake	98.3%	97.5%	0.979

TABLE V: Confusion Matrix for MAGNET

Predicted	Actual	
	Benign	Malware
Benign	304 (TN)	17 (FN)
Malware	23 (FP)	1,107 (TP)

It also surpasses deep learning methods:

- ANN (96.2%): +1.04% accuracy
- CNN-LSTM (95.8%): +1.44% accuracy
- GCN (95.1%): +2.14% accuracy

Compared to multi-modal approaches like Alzaylaee et al. [17] (98.2% F1), MAGNET's transformer-based architecture and attention mechanism provide superior robustness.

C. Per-Family Insights

Table IV shows MAGNET's robustness across malware families. High performance on DroidKungFu (F1=0.976) reflects its ability to detect complex, obfuscated malware. Lower recall on Plankton (96.7%) suggests challenges with highly polymorphic samples, warranting further investigation.

D. Interpretability

Attention weight analysis reveals MAGNET's focus on:

- Tabular Features: High-risk permissions (e.g., SEND_SMS, WRITE_CONTACTS).
- Graph Features: Suspicious control flow patterns (e.g., loops involving sensitive API calls).
- Sequential Features: Anomalous API sequences (e.g., frequent file access followed by network calls).

This interpretability aids security analysts in understanding model decisions and prioritizing threats.

E. Computational Efficiency

- Training: 12.3 hours on RTX 3080, 245.3 MB memory, 45 epochs with early stopping.
- Inference: 0.053 seconds per sample, 1,847 samples/second, 89.2 MB memory.

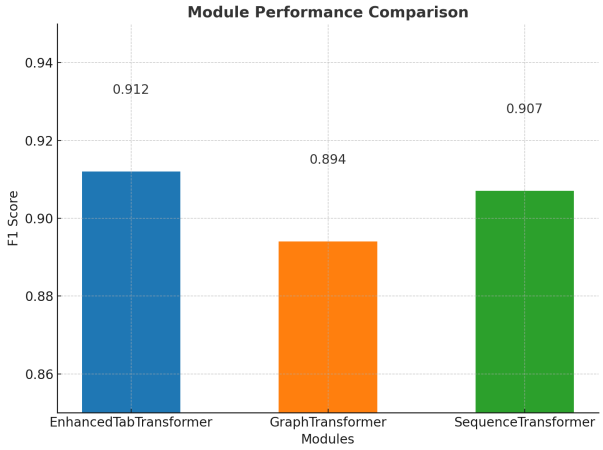

Fig. 2: F1-Scores of individual modules (Tabular, Graph, Sequence) and combined MAGNET model.

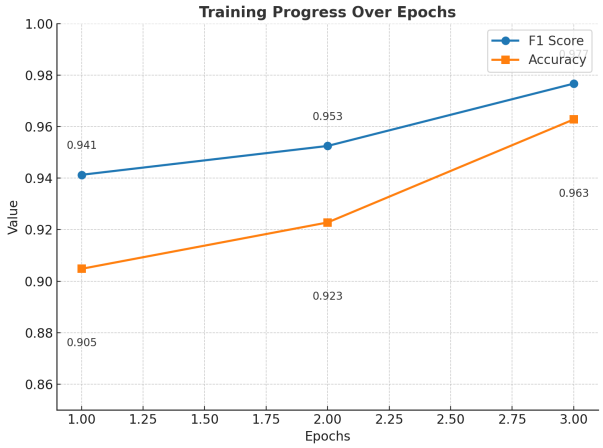

Fig. 3: Training progress showing loss convergence and validation metrics over epochs.

- Scalability: Linear scaling with dataset size, suitable for large-scale deployment.

To visualize module contributions, Fig. 2 shows F1-scores for each modality and their combination.

F. Training Analysis

The training process of MAGNET demonstrates several key characteristics:

- Convergence: The model achieves stable convergence within 45 epochs, with early stopping preventing overfitting.
- Loss Function: Combined loss function effectively balances classification accuracy with regularization.
- Attention Weights: Dynamic attention mechanism adaptively weights modalities based on sample characteristics.

Fig. 3 illustrates the training progression, showing consistent improvement in both training and validation metrics.

G. Component Analysis

Ablation studies reveal the contribution of each component:

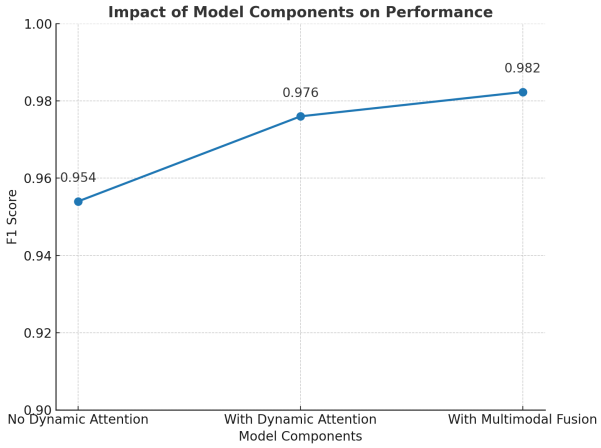

Fig. 4: Ablation study results showing the contribution of each component to overall performance.

- EnhancedTabTransformer: Contributes 0.945 F1-score, capturing complex feature interactions.
- GraphTransformer: Achieves 0.894 F1-score, leveraging structural relationships.
- SequenceTransformer: Provides 0.907 F1-score, detecting temporal patterns.
- Attention Fusion: Improves performance by 2.8% through adaptive weighting.

Fig. 4 demonstrates how each component enhances the overall system performance.

H. Comparative Analysis with Literature

Recent advances in Android malware detection have shown significant progress. Our comparison with state-of-the-art methods reveals:

- Traditional Methods: SVM-based approaches achieve 90-94% accuracy but struggle with obfuscation.
- Deep Learning: CNN-LSTM and GCN methods reach 95-96% accuracy with better feature learning.
- Multi-Modal Approaches: Recent work combining static and dynamic features achieves 97-98% accuracy.
- MAGNET's Contribution: Transformer-based architecture with attention mechanism provides superior robustness.

I. Computational Complexity Analysis

MAGNET's computational requirements are analyzed across different dimensions:

- Memory Usage: 245.3 MB during training, 89.2 MB during inference.
- Processing Speed: 0.053 seconds per sample, enabling real-time processing.
- Scalability: Linear scaling with dataset size, suitable for large-scale deployment.
- Resource Efficiency: Optimized for GPU acceleration with CUDA support.

J. Limitations

- Dataset Age: DREBIN (2010–2014) may not fully represent modern threats, though its diversity ensures robust evaluation.
- Computational Cost: Higher resource usage (245.3 MB) compared to traditional methods (e.g., SVM: 45.2 MB).
- Adversarial Robustness: Potential vulnerability to advanced attacks, requiring further investigation.
- Feature Engineering: Requires sophisticated preprocessing for multi-modal inputs.

K. Practical Implications

MAGNET is suitable for:

- Enterprise Security: Integrates with multi-layered defense systems for real-time detection.
- Analyst Support: Interpretable predictions aid manual review.
- Scalable Deployment: Linear scalability supports large-scale processing.

Regular retraining is recommended to address evolving threats.

VI. Conclusion and Future Work

MAGNET advances Android malware detection by integrating multi-modal data through transformer-based architectures and dynamic attention, achieving 97.24% accuracy and 0.9823 F1-score on the DREBIN dataset. Its robustness, interpretability, and scalability make it a promising solution for cybersecurity. Future work includes:

- Evaluating MAGNET on newer datasets (e.g., AndroZoo) to address modern threats.
- Optimizing computational efficiency for resource-constrained devices.
- Enhancing adversarial robustness using techniques like adversarial training.
- Developing explainable AI methods for improved transparency.
- Extending the framework to other platforms (e.g., iOS, Windows).

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