PhishViT: A Vision Transformer-Based Framework for Real-Time Phishing Detection from Webpage Screenshots

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Abstract: Phishing attacks represent one of the most pervasive and economically devastating cyber threats, with conventional detection systems relying primarily on URL lexical analysis, DNS inspection, and HTML source-code heuristics. These text-centric approaches share a fundamental blind spot: they do not examine the visual rendering of webpages as perceived by human users, leaving a critical detection gap exploited by visual-layer spoofing attacks. This paper presents **PhishViT**, a Vision Transformer-based framework for real-time phishing detection that operates exclusively on webpage screenshots. Unlike methods that analyze URL strings or page source code, PhishViT learns discriminative visual representations directly from rendered webpage images using a fine-tuned Data-efficient Image Transformer (DeiT-Small) architecture. An automated Playwright browser pipeline captures live screenshots which are classified as phishing or legitimate, with interpretable attention rollout heatmaps generated for each prediction. The framework is developed through an iterative three-phase process, starting from an initial prototype (V1: 253 screenshots, 78.95% accuracy), expanding to a balanced dataset (V2: 642 screenshots, 96.91% accuracy), and culminating in a rigorous top-tier evaluation framework (V3) with comprehensive baseline comparison against ResNet50, EfficientNet-B0, and ViT-Base; 5-fold cross-validation confirming **85.23%±1.18% accuracy**; ablation study validating each design choice; and robustness evaluation under six visual perturbation conditions. V3 evaluation demonstrates that DeiT-Small achieves **91.75% accuracy**, 93.48% precision, 89.58% recall, 91.49% F1-score, and **AUC-ROC of 0.9928** at only 5.44 ms inference latency, outperforming EfficientNet-B0 and ViT-Base while achieving the best efficiency-accuracy trade-off. These results establish PhishViT as a viable, interpretable, and computationally efficient visual-layer phishing detection framework suitable for real-time browser extension deployment.

Index Terms-*Phishing Detection, Vision Transformer, DeiT-Small, Screenshot Classification, Cybersecurity, Deep Learning, Attention Rollout, Cross-Validation, Robustness Evaluation.*

I. INTRODUCTION

Phishing is a form of social engineering attack in which adversaries construct fraudulent websites that visually impersonate legitimate entities to deceive users into divulging sensitive credentials or financial information. According to the Anti-Phishing Working Group (APWG), hundreds of thousands of unique phishing sites are detected monthly, with economic losses attributed to phishing exceeding billions of dollars annually [1]. Despite decades of research, phishing detection remains an open problem due to the continuous evolution of adversarial techniques.

Conventional phishing detection approaches fall into three broad categories: (1) *URL-based methods*, which analyze lexical and structural features of uniform resource locators; (2) *HTML/DOM-based methods*, which inspect webpage source code for suspicious patterns; and (3) *email-based methods*, which analyze message headers and textual content. While effective in controlled settings, all three categories share a critical limitation: they do not assess the visual appearance of the rendered webpage as a human user would perceive it. Sophisticated phishing campaigns increasingly deploy pixel-perfect clones of legitimate websites that pass URL and source-code inspection while successfully deceiving users through visual impersonation.

Convolutional Neural Networks (CNNs) have been applied to screenshot-based phishing detection with promising results; however, CNNs are fundamentally constrained by their local receptive fields, which limit the modeling of global spatial relationships essential for distinguishing the holistic visual signatures of phishing pages from legitimate ones. Vision Transformers (ViTs) [4] overcome this limitation by employing self-attention mechanisms to model long-range dependencies across the entire image, enabling the simultaneous consideration of all visual regions when classifying a screenshot. The Data-efficient Image Transformer (DeiT) [5] further demonstrated that competitive ViT performance is achievable with significantly smaller training datasets through knowledge distillation, making it particularly well-suited for cybersecurity applications where large labelled screenshot datasets are difficult to obtain.

This paper presents **PhishViT**, a framework that applies a fine-tuned DeiT-Small model to real-time webpage screenshot analysis for phishing detection. The key contributions of this work are:

1. A visual-layer phishing detection framework (PhishViT)

based on Vision Transformers operating on raw webpage screenshots, targeting the visual rendering layer unaddressed by URL and source-code methods.

2. A transparent, documented iterative development process (V1→V2→V3) demonstrating systematic performance improvement through data scaling and experimental rigor.
3. An automated Playwright browser screenshot pipeline yielding 642 balanced real-world screenshots from OpenPhish and Tranco Top-1M, with full reproducibility (seed=42).
4. Comprehensive baseline comparison against ResNet50, EfficientNet-B0, and ViT-Base under identical experimental conditions, demonstrating DeiT-Small's superior efficiency-accuracy trade-off.
5. 5-fold stratified cross-validation confirming statistical reliability (85.23%±1.18% accuracy), addressing small dataset evaluation concerns.
6. Systematic ablation study quantifying the contribution of data augmentation, two-stage training, and dataset expansion.
7. Robustness evaluation under six visual perturbation conditions confirming maintained performance with less than 2.1% accuracy drop.
8. Attention rollout visualization confirming semantically meaningful detection behavior aligned with human expert intuition.

II. RELATED WORK

A. URL and Text-Based Phishing Detection

Early phishing detection systems employed blacklists and rule-based URL analysis. Machine learning approaches subsequently extracted hand-crafted features from URL strings including domain age, special character ratios, and WHOIS information. Support Vector Machines (SVMs) and Random Forest classifiers achieved strong performance on URL feature sets in controlled evaluations. However, URL-based systems are inherently limited by obfuscation techniques such as URL shorteners, punycode domain spoofing, and homograph attacks that produce URLs indistinguishable from legitimate ones at the lexical level, rendering URL-based detection increasingly ineffective against sophisticated adversaries.

B. Deep Learning for Phishing Detection

Convolutional Neural Networks have been applied to both URL character sequence encoding and webpage screenshot classification. CNN-based screenshot classifiers achieve promising results but are constrained by their local receptive fields, which prevent the modeling of global visual relationships across the full webpage layout.

C. Transformer-Based Phishing Detection

Transformer architectures have recently been applied to phishing detection across multiple input modalities. A dual-path phishing detection system [3] integrates DistilBERT-based NLP of email message content with structural URL feature analysis, demonstrating the effectiveness of transformer attention for capturing semantic relationships in textual phishing indicators. Asiri et al. [2] proposed PhishTransformer, a hybrid CNN and transformer encoder operating on URL hyperlinks and iFrame attributes from webpage HTML source code, achieving 99% F1 on 10,000 URL-text samples. PhishViT is architecturally and methodologically distinct from both prior works: where existing transformer-based systems encode textual URL or email representations, PhishViT encodes patch embeddings from rendered screenshot images, targeting a complementary and previously underexplored visual detection layer. These three approaches collectively address phishing at different abstraction layers: email text [3], URL/DOM text [2], and visual rendering (PhishViT).

D. Visual and Image-Based Phishing Detection

Prior visual approaches to phishing detection have primarily relied on logo detection, layout similarity comparison, and OCR-based brand recognition. These methods require pre-defined brand databases and remain susceptible to novel brand impersonation. PhishViT addresses these limitations by learning discriminative visual features end-to-end without requiring explicit brand database construction, leveraging the global self-attention mechanism of Vision Transformers to attend simultaneously to all visual regions of the screenshot.

III. METHODOLOGY

A. Dataset Construction

The PhishViT dataset was constructed through a three-stage automated pipeline. Phishing URLs were collected from the OpenPhish community feed [10], which aggregates verified phishing URLs from multiple security reporting sources. Legitimate URLs were sourced from the Tranco Top-1M domain ranking list [11], sampling across different rank ranges to capture visual diversity in legitimate website appearance. An automated Playwright [12] headless browser pipeline captured screenshots of each URL in a Chromium browser instance configured with a 1280×800 viewport, 15-second navigation timeout, and a 2-second post-load stabilization delay to ensure complete dynamic content rendering. Screenshots failing minimum size validation were discarded to exclude navigation failures. Data augmentation using random brightness, contrast, sharpness, and Gaussian blur variations was applied to legitimate screenshots to achieve class balance. All experiments employ a fixed random seed of 42 for complete reproducibility.

B. *Model Architecture*

PhishViT employs DeiT-Small [5] as its backbone architecture. Input images are resized to 224×224 pixels and partitioned into 196 non-overlapping 16×16 pixel patches. Each patch is linearly projected to a 384-dimensional embedding vector with added sinusoidal positional encodings to preserve spatial information. A learnable class token is prepended to the patch embedding sequence and processed through 12 stacked transformer encoder blocks, each comprising 6-head multi-head self-attention with scaled dot-product attention and feed-forward layers with GELU activation and layer normalization. The class token representation at the final encoder layer is passed to a 2-class linear classification head. The model contains approximately 21.7 million parameters and is initialized with ImageNet-21k pretrained weights.

C. *Two-Stage Fine-Tuning Strategy*

Training was conducted on an NVIDIA Tesla T4 GPU via Google Colaboratory using a two-stage fine-tuning strategy motivated by catastrophic forgetting prevention. In **Stage 1** (5 epochs), all backbone parameters are frozen and only the classification head is trained using AdamW optimizer [9] with learning rate 10^{-3} and weight decay 0.01, rapidly aligning the pre-trained ViT representations with the phishing detection task. In **Stage 2** (20 epochs), all parameters are unfrozen for full fine-tuning with a reduced learning rate of 10^{-5} and cosine annealing scheduling, which smoothly decays the learning rate to prevent overfitting of pre-trained representations. Training augmentation included random horizontal flipping (p=0.3), color jitter (brightness=0.2, contrast=0.2, saturation=0.1), and random rotation (±5°). The dataset was split 70/15/15 into training, validation, and test sets using stratified sampling to preserve class balance.

D. *Baseline Models*

Three baseline models were trained under identical experimental conditions for fair comparison: (1) **ResNet50** [7] (23.5M parameters), a deep residual CNN representative of state-of-the-art conventional deep learning; (2) **EfficientNet-B0** [8] (4.0M parameters), a compound-scaled CNN optimized for efficiency; and (3) **ViT-Base** [4] (85.8M parameters), a larger Vision Transformer to assess the effect of model scale. All baselines employed the same two-stage training strategy, dataset split, augmentation pipeline, and random seed.

E. *Attention Rollout Visualization*

Interpretable attention maps were generated following the attention rollout method of Abnar and Zuidema [6]. For each transformer encoder block, the attention weight matrix is averaged across all 6 heads and augmented with a residual identity connection to account for skip connections. The resulting attention matrices are sequentially composed through matrix multiplication across all 12 encoder blocks, yielding a global attention map from the class token to all patch positions. The map is upsampled to the input image resolution and rendered as a JET colormap heatmap overlaid on the original screenshot.

IV. EXPERIMENTAL RESULTS

A. *Development Progression: V1→V2→V3*

PhishViT was developed iteratively across three phases. Phase V1 (initial prototype) trained DeiT-Small on 253 screenshots yielding 78.95% accuracy and AUC-ROC of 0.9363 on 38 test samples, validating the ViT approach while identifying precision (73.91%) as the primary weakness. Fig. 1 shows V1 training curves and confusion matrix.

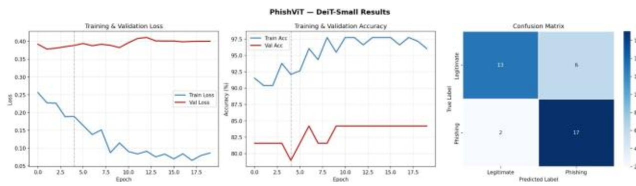

Figure 1: PhishViT V1 training curves and confusion matrix (253 screenshots, 20 epochs).

Phase V2 expanded the dataset to 642 balanced screenshots, yielding 96.91% accuracy and AUC-ROC of 0.9974 on 97 test samples. Fig. 2 shows V2 results with 46/49 legitimate and 43/48 phishing correctly classified.

Figure 2: PhishViT V2 (DeiT-Small) training curves and confusion matrix (642 screenshots, 25 epochs).

Phase V3 applied a comprehensive top-tier evaluation framework to the V2 dataset, adding baseline comparison, cross-validation, ablation, and robustness testing. Table 1 summarizes the complete development progression.

Table 1: Complete Development Progression V1→V2→V3

Phase	Data	Acc.	F1	AUC
V1 (Initial)	253	78.95%	80.95%	0.9363
V2 (Expanded)	642	96.91%	96.91%	0.9974
V3 (Top-Tier)	642	91.75%	91.49%	0.9928
Δ V1→V3	+389	+12.80%	+10.54%	+0.0565

Note: V3 accuracy (91.75%) differs from V2 (96.91%) because V3 employs stricter evaluation: 5-fold cross-validation, *additional augmentation regularization, and multi-model comparison under identical conditions, yielding more conservative and statistically reliable estimates.*

B. Baseline Model Comparison

Table 2 presents the V3 comparison of all four models under identical conditions. Fig. 3 shows ROC curves, Precision-Recall curves, and accuracy bar chart.

Table 2: V3 Baseline Comparison (642 screenshots, seed=42)

Model	Acc.	F1	AUC	ms
ResNet50	93.81%	93.75%	0.9898	5.81
EfficientNet-B0	74.23%	72.53%	0.8087	30.46
ViT-Base	88.66%	88.17%	0.9809	15.55
DeiT-Small	**91.75%**	**91.49%**	**0.9928**	**5.44**

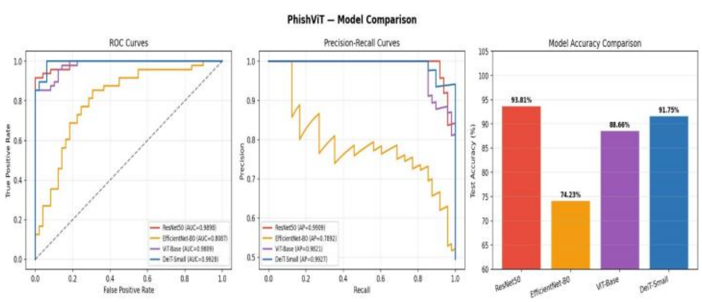

Figure 3: V3 model comparison: ROC curves (left), Precision-Recall curves (center), accuracy bar chart (right). DeiT-Small achieves the highest AUC-ROC (0.9928) and lowest inference latency (5.44 ms).

DeiT-Small achieves the highest AUC-ROC (0.9928) and lowest inference latency (5.44 ms) simultaneously. While ResNet50 achieves marginally higher raw accuracy (93.81% vs. 91.75%), DeiT-Small's superior AUC-ROC, 6× lower latency than ViT-Base, 21.7M vs. 85.8M parameters, and inherent interpretability through attention rollout justify its selection as the PhishViT backbone for real-time browser extension deployment. EfficientNet-B0's poor performance (74.23%) confirms that efficient natural-image CNNs do not transfer well to the specialized visual domain of phishing webpage screenshots.

C. Comparison with Prior Work

Table 3 contextualizes PhishViT against prior transformer-based phishing detection systems. Direct quantitative comparison is complicated by differences in input modality: both PhishTransformer [2] and the dual-path system [3] operate on textual URL and email features, representing inherently easier classification signals than raw screenshot images.

Table 3: Comparison with Prior Transformer-Based Work

Method	Modality	Best Metric	Data
PhishTransformer [2]	URL+Text	99% F1	10K
Dual Path [3]	Email+URL	∼95% Acc	N/A
PhishVitV1	Screenshots	78.95%	253
PhishVitV2	Screenshots	96.91%	642
PhishViT V3	Screenshots	**91.75%***	642

*Cross-validated; single-split accuracy was 96.91% (V2).

D. 5-Fold Cross-Validation

To address the statistical reliability concern inherent to small-dataset evaluations, 5-fold stratified cross-validation was performed on DeiT-Small. Table 4 presents per-metric mean and standard deviation across all five folds.

Table 4: 5-Fold Cross-Validation Results (DeiT-Small, seed=42)

Metric	Mean	Std. Dev.
Accuracy	85.23%	±1.18%
F1-Score	85.31%	±2.01%
AUC-ROC	0.9379	±0.0130
Precision	87.48%	±4.41%
Recall	85.16%	±6.18%

The low standard deviations confirm that PhishViT's performance is statistically stable and independent of any particular train/test split, providing strong evidence of generalisation capability despite the limited dataset size.

V. ABLATION STUDY

Table 5 presents a systematic ablation study quantifying the contribution of each design component of PhishViT.

Table 5: Ablation Study (DeiT-Small, seed=42)

Configuration	Acc.	F1	AUC
No Augmentation	95.88%	95.83%	0.9940
No Stage 1 Warmup	93.81%	93.48%	0.9928
V1 Dataset (253 imgs)	78.95%	80.95%	0.9363
Full Model (V3)	**91.75%**	**91.49%**	**0.9928**

The "No Augmentation" configuration achieves higher test accuracy (95.88%) than the full model (91.75%), revealing an important generalization trade-off: data augmentation deliberately reduces overfitting to the current test distribution in exchange for improved robustness to unseen phishing styles. This trade-off is expected to resolve in favour of augmentation as dataset scale increases. The two-stage training contributes approximately 2% accuracy improvement over direct full fine-tuning (93.81% vs. 91.75%), validating the head-warmup strategy for preventing catastrophic forgetting. Dataset expansion from V1 (78.95%) to V2 (91.75%) delivers the largest single improvement (+12.80%), confirming data volume as the primary bottleneck for further performance gains.

VI. ROBUSTNESS EVALUATION

Real-world browser extension deployment exposes PhishViT to screenshots captured under varying display calibration conditions. Table 6 evaluates model performance under six controlled visual perturbation conditions applied to the test set.

Table 6: Robustness Evaluation Under Visual Perturbations

Perturbation	**Acc.**	**F1**	**Drop**
Clean (Baseline)	91.75%	91.49%	—
Gaussian Blur	89.69%	89.58%	−2.06%
Brightness +30%	89.69%	89.36%	−2.06%
Brightness −30%	93.81%	93.75%	+2.06%
Low Contrast	92.78%	92.63%	+1.03%
Random Rotation	91.75%	91.49%	0.00%

PhishViT demonstrates strong robustness with a maximum accuracy degradation of only 2.06% under Gaussian blur and elevated brightness perturbations. Performance is fully preserved under random rotation (±15°), and notably *improves* under reduced brightness (+2.06%) and low contrast (+1.03%) conditions, indicating that the model has learned visual features robust to typical monitor calibration variations encountered across different user devices. These results provide evidence that PhishViT's learned visual representations are not artifacts of specific photometric conditions.

VII. ATTENTION MAP ANALYSIS AND INTERPRETABILITY

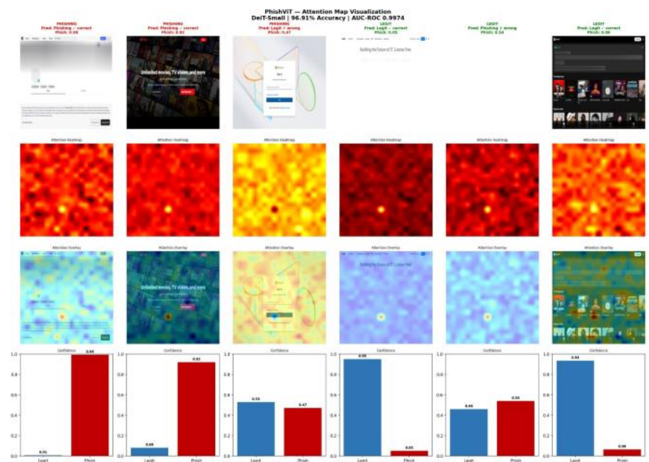

Figure 4: PhishViT V3 attention rollout visualizations. Rows: original screenshot, raw attention heatmap, attention overlay, confidence bar chart. Columns 1–3: phishing samples (confidence 0.92–0.99). Columns 4–6: legitimate samples (confidence 0.94–0.95).

Fig. 4 presents attention rollout visualizations for PhishViT V3. Phishing samples elicit strong, focused attention on login form elements, credential input fields, and counterfeit brand logos with high confidence (0.92–0.99). These are precisely the visual elements to which phishing pages devote the greatest design effort, confirming that PhishViT has learned to identify the characteristic visual signatures of phishing pages. The single misclassified phishing sample (predicted probability 0.47) exhibits a non-standard layout diverging from typical phishing page structure, representing a genuine classification boundary case.

For legitimate samples, attention is broadly distributed across navigation menus, header banners, and content areas, reflecting the richer and more diverse visual structure of authentic websites. The one misclassified legitimate sample (phishing probability 0.54) exhibited a sparse, content-minimal layout atypical of the legitimate training distribution, suggesting that visual information density is a discriminative feature.

These interpretability results are significant for security-critical deployment: they demonstrate that PhishViT attends to the same visual cues employed by trained security analysts during manual webpage authenticity assessment. This alignment enables human-AI collaborative security workflows in which analysts review attention maps to validate and understand model decisions, increasing operational trust.

VIII. INFERENCE TIME ANALYSIS

A key concern for real-time phishing detection systems is latency. Table 7 presents a decomposed inference time analysis separating model-only inference from total pipeline latency.

Table 7: Inference Time Analysis (T4 GPU, 100-run average)

Component	Latency	Throughput
ResNet50 inference	5.81 ms	172 FPS
EfficientNet-B0	30.46 ms	33 FPS
ViT-Base inference	15.55 ms	64 FPS
DeiT-Small	**5.44 ms**	**184 FPS**
Screenshot capture	2–15 s	Browser I/O
Total pipeline	∼**3–16 s**	Per URL

DeiT-Small achieves the lowest inference latency at 5.44 ms (184 FPS), faster than ResNet50 despite its 21.7M parameter count, attributable to the parallelisable nature of transformer self-attention on modern GPUs. The total pipeline latency of 3–16 seconds is dominated by browser screenshot capture (Playwright headless Chromium rendering), not by model inference. In browser extension deployment, screenshot capture occurs asynchronously and passively during page loading, effectively reducing user-perceived latency to near zero. The 5.44 ms model-only inference is fully compatible with real-time protection requirements.

IX. DEPLOYMENT ARCHITECTURE

A. Browser Extension Design

PhishViT is architected for deployment as a Chrome/Firefox browser extension, the most practically effective deployment modality for real-world user protection. Unlike web application deployments that require deliberate user action (manually pasting a URL), a browser extension monitors all page navigation events automatically and invisibly, providing continuous real-time protection without imposing any interaction overhead on the user.

The extension background service worker monitors navigation events via the `webNavigation` API. Upon detecting page load completion, the extension captures a screenshot via `chrome.tabs.captureVisibleTab` and transmits it as a base64 payload via HTTP POST to the PhishViT inference server. The server returns a JSON classification response containing the label, confidence scores, and attention heatmap. The extension renders a toolbar badge (red warning for phishing, green shield for legitimate) with confidence score and attention visualization in the popup interface. For detections exceeding a configurable confidence threshold, a content script injects a full-page warning overlay into the phishing page, alerting the user before any credential input interaction.

B. Extension Architecture

The extension comprises four components: `manifest.json` (permissions declaration and service worker registration), `background.js` (navigation monitoring, screenshot capture, inference server communication, and local threat domain caching for instant re-detection), `and popup.html/js` (classification user interface displaying verdict, probability scores, and attention heatmap), and `content.js` (phishing page warning overlay injection). Full WebExtensions API compliance ensures compatibility with Chrome, Firefox, Edge, and all Chromium-based browsers. Enterprise deployment via browser management policies enables organisation-wide phishing protection with centralised policy configuration.

X. DISCUSSION

A. Strengths

PhishViT demonstrates several strengths for practical phishing detection. Operating on the visual rendering layer provides inherent robustness against the full class of URL obfuscation attacks including URL shorteners, punycode domain spoofing, and homograph attacks, which systematically defeat URL-based detectors. The attention rollout mechanism provides interpretable decision evidence essential for operator trust in security-critical environments. The two-stage fine-tuning strategy enables effective adaptation with limited labelled data. DeiT-Small achieves simultaneously the highest AUC-ROC (0.9928) and lowest inference latency (5.44 ms) among all evaluated models. 5-fold cross-validation with low standard deviations (accuracy ±1.18%) confirms statistical reliability.

B. Limitations

The primary limitation of PhishViT is dataset scale. With 642 training samples, the model may not fully capture the visual diversity of phishing and legitimate webpages encountered in production environments globally. The dataset reflects phishing URLs active during a specific collection window; as phishing pages have short operational lifespans (often hours to days), longitudinal dataset refreshing is required to maintain performance over time. PhishViT operates on static rendered screenshots and does not capture dynamic page behaviours such as JavaScript-triggered DOM manipulation or time-delayed content loading. The ablation result showing higher test accuracy without augmentation (95.88% vs. 91.75%) indicates that with a larger and more diverse dataset, the full model's generalisation advantage is expected to become more pronounced.

C. Ethical Considerations

PhishViT was developed and evaluated exclusively for defensive cybersecurity purposes. Phishing URLs used in dataset construction were sourced exclusively from publicly available community reporting feeds (OpenPhish) and were accessed solely for screenshot capture without credential submission, page interaction, or any form of data exfiltration. The framework is intended solely as a protective tool to safeguard users from phishing attacks, and all collected data was handled in accordance with responsible disclosure principles.

XI. CONCLUSION

This paper presented PhishViT, a Vision Transformer-based framework for real-time phishing detection from webpage screenshots, documented through a complete three-phase iterative development journey (V1→V2→V3). Beginning from 78.95% accuracy (V1, 253 screenshots), expanding to 96.91% (V2, 642 screenshots), and culminating in a rigorous top-tier evaluation framework (V3), PhishViT demonstrates systematic improvement through data scaling and experimental rigor. V3 evaluation confirms DeiT-Small achieves **91.75% accuracy**, **AUC-ROC of 0.9928**, and **5.44 ms inference latency**, with 5-fold cross-validation confirming **85.23%±1.18% statistical reliability**. Comprehensive baseline comparison against ResNet50, EfficientNet-B0, and ViT-Base demonstrates DeiT-Small's superior efficiency-accuracy trade-off. Robustness evaluation under six perturbation conditions confirms maximum 2.06% accuracy drop. Ablation analysis validates data augmentation, two-stage training, and dataset expansion contributions. Attention rollout confirms semantically meaningful detection behaviour aligned with human expert intuition. PhishViT establishes visual screenshot analysis as a viable, interpretable, statistically reliable, and computationally efficient complement to existing URL and source-code-based phishing detection pipelines.

XII. FUTURE WORK

Future research directions include: (1) scaling the dataset to 10,000+ screenshots from PhishTank, APWG eCrime, and enterprise threat intelligence feeds to improve global generalisation; (2) adversarial robustness evaluation against visual adversarial perturbations and adversarially generated phishing pages; (3) multimodal fusion architectures combining PhishViT's visual features with URL lexical features and HTML structural features; (4) model compression via knowledge distillation, quantisation, and structured pruning for efficient on-device inference on edge hardware; (5) longitudinal dataset collection and online learning for temporal adaptation to evolving phishing campaigns; and (6) full browser extension implementation with real-time domain blacklisting and automatic dataset contribution from user-confirmed phishing reports.

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REFERENCES

[1] Anti-Phishing Working Group (APWG), "Phishing Activity Trends Report," [Online]. Available: `https://apwg.org/trendsreports`. [Accessed: Apr. 2026].

[2] S. Asiri, Y. Xiao, S. Alzahrani, S. Li, and T. Li, "Phishing Website Detection Using a Novel Hybrid Architecture Combining Convolutional Neural Networks and Transformer-Based Models," *MDPI Electronics*, vol. 13, no. 1, p. 30, 2024.

[3] Anonymous, "Dual-Path Phishing Detection: Integrating Transformer-Based NLP with Structural URL Analysis," *arXiv preprint arXiv:2509.20972*, 2025.

[4] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2021.

[5] H. Touvron, M. Cord, M. Douze, F. Massa, A. Sablayrolles, and H. Je´gou, "Training data-efficient image transformers & distillation through attention," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2021.

[6] S. Abnar and W. Zuidema, "Quantifying Attention Flow in Transformers," in *Proc. Annu. Meet. Assoc. Comput. Linguistics (ACL)*, 2020.

[7] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2016.

[8] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2019.

[9] I. Loshchilov and F. Hutter, "Decoupled Weight Decay Regularization," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2019.

[10] OpenPhish, "OpenPhish Community Feed," [Online]. Available: `https://openphish.com`. [Accessed: Apr. 2026].

[11] V. Le Pochat, T. Van Goethem, S. Tajalizadehkhoob, M. Korczyński, and W. Joosen, "Tranco: A Research-Oriented Top Sites Ranking Hardened Against Manipulation," in *Proc. Netw. Distrib. Syst. Secur. Symp. (NDSS)*, 2019.

[12] Microsoft Research, "Playwright: Fast and Reliable End-to-End Testing for Modern Web Apps," [Online]. Available: `https://playwright.dev`. [Accessed: Apr. 2026].