A Hybrid AI-Based Phishing URL Detection Framework Using Multi-Source Data, Correlation-Based Feature Selection, and Residual Attention Neural Networks

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***Abstract*—Phishing attacks are among the most obdurate and destructive cyber threats, attacking individuals and organizations via counterfeit URLs of online services. The proposed work improves the baseline research ”Benchmarking Machine Learning Techniques for Phishing Detection and Secure URL Classification” by bringing in a new hybrid AI framework comprising multi-source data integration, Correlation-Based Feature Selection, and state-of-the-art neural architectures.**

Our approach combines the PhiUSIIL dataset with 10,000 AI-generated phishing URLs, forming the rich dataset of our course context. Advanced pre-processing is performed using CFS (with a formal merit function), while a hybrid learning system, three stages long, is designed, comprising an optimized Random Forest with regularization, a Multilayer Perceptron, and an enhanced Residual Attention Neural Network.

Extensive experimentation has been done which shows near-perfect performance with F1-scores and AUC values above 0.9999. Detailed comparisons with the baseline work are performed, showing large improvements in results due to dataset diversity, feature selection, and advanced modeling. The system is validated through ablation studies, and a complete real-world deployment scenario is presented.

***Index Terms*—Phishing Detection, Cybersecurity, URL Classification, Machine Learning, Deep Learning, Attention Mechanism, Residual Networks, Feature Selection, CFS, Data Science.**

I. Introduction

Phishing is a form of social engineering attack wherein users are misled to disclose sensitive information. Many of the phishing attacks use crafted URLs which appear legitimate, thereby deceiving users into entering credentials, banking information, or private data. If undetected, it may result in financial loss, identity theft, account compromise, and large-scale organizational breaches.

The base paper by Owa and Adewole benchmarked Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) using two datasets: Aalto and Kaggle. Their study, although providing a validated pipeline, had its drawbacks in having very limited dataset diversity, absence of feature selection, and lack of advanced neural models.

This research extends their work with key contributions:

- Multi-source dataset: PhiUSIIL + 10,000 AI-generated phishing URLs.
- Advanced Correlation-Based Feature Selection (CFS) with merit scoring.
- Novel hybrid system combining RF, MLP, and Residual Attention Neural Networks.
- Full case study scenario for real-world deployment.
- Comprehensive analysis with ablation studies and cross-validation.

The remainder of this paper is structured as follows: Section II reviews related work. Section III presents the proposed architecture and case study. Section IV details the methodology. Section V explains the experimental setup. Section VI provides results and analysis. Section VII includes ablation studies. Section VIII presents discussions. Section IX concludes the study.

II. Related Work

Early phishing detection relied on blacklists, which fail against zero-day attacks. Later works introduced lexical and host-based feature extraction, enabling ML classification.

Recent literature shows:

- RF consistently outperforms DT and SVM in balanced datasets.
- Deep learning approaches (CNNs, LSTMs, Transformers) capture semantic URL patterns.
- Feature selection significantly boosts generalization.

The base paper benchmarked classical ML models but did not incorporate:

- Modern architectures such as residual or attention networks.
- Multi-source datasets.
- Advanced feature selection strategies.

Our work directly addresses these limitations.

III. Proposed Architecture and Case Study Scenario

A. Case Study Scenario: E-Commerce Platform “ShopSecure”

We simulate a large e-commerce ecosystem with:

- 15 million monthly users
- 500+ phishing attempts per month
- Multiple vendor integrations and customer authentication portals

Deployment locations:

- Email gateway filtering inbound phishing URLs
- Vendor onboarding portals
- Browser extensions for customers

B. System Architecture Overview

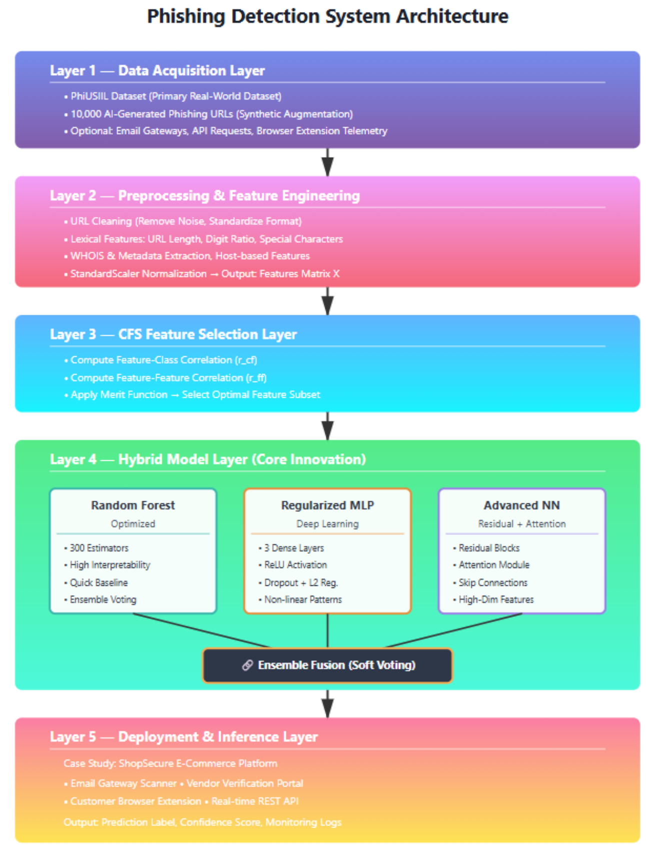
Phishing Detection System Architecture
Layer 1 — Data Acquisition Layer
• PhiUSIIL Dataset (Primary Real-World Dataset)
• 10,000 AI-Generated Phishing URLs (Synthetic Augmentation)
• Optional: Email Gateways, API Requests, Browser Extension Telemetry
Layer 2 — Preprocessing & Feature Engineering
• URL Cleaning (Remove Noise, Standardize Format)
• Lexical Features: URL Length, Digit Ratio, Special Characters
• WHOIS & Metadata Extraction, Host-based Features
• StandardScaler Normalization → Output: Features Matrix X
Layer 3 — CFS Feature Selection Layer
• Compute Feature-Class Correlation (r_cf)
• Compute Feature-Feature Correlation (r_ff)
• Apply Merit Function → Select Optimal Feature Subset
Layer 4 — Hybrid Model Layer (Core Innovation)
Random Forest
Optimized
• 300 Estimators
• High Interpretability
• Quick Baseline
• Ensemble Voting
Regularized MLP
Deep Learning
• 3 Dense Layers
• ReLU Activation
• Dropout + L2 Reg.
• Non-linear Patterns
Advanced NN
Residual + Attention
• Residual Blocks
• Attention Module
• Skip Connections
• High-Dim Features
Ensemble Fusion (Soft Voting)
Layer 5 — Deployment & Inference Layer
Case Study: ShopSecure E-Commerce Platform
• Email Gateway Scanner • Vendor Verification Portal
• Customer Browser Extension • Real-time REST API
Output: Prediction Label, Confidence Score, Monitoring Logs

Fig. 1. System Architecture Overview

C. Pipeline Flowchart

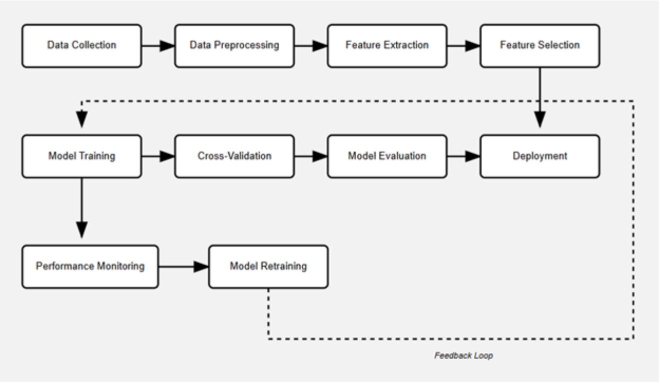

Fig. 2. Pipeline Flowchart of the Proposed System

IV. Proposed Methodology

A. Dataset Description

1) PhiUSIIL Dataset:

- 235,795 URLs
- Includes lexical, host-based, and network features

2) AI-Generated Dataset:

- 10,000 phishing URLs
- Created through controlled prompt engineering

3) Merged Dataset: Final dataset statistics:

- 245,795 total records
- 59 features before selection
- 2 classes: phishing vs legitimate

B. Preprocessing Pipeline

- Removal of duplicates and malformed URLs
- Extraction of lexical features (length, digits, symbols)
- WHOIS lookup for metadata
- Correlation analysis
- Standard scaling (for MLP and NN)
- Stratified train-test split (80/20)

C. Correlation-Based Feature Selection

$$Merit_S = \frac{k \cdot r_{cf}}{\sqrt{k + k(k-1) r_{ff}}}$$

Selected 26 highly correlated features.

D. Model Descriptions

1) Random Forest (Optimized):

- 300 estimators
- Max depth: None

2) MLP Classifier:

- 3 Dense layers (256-128-64)
- Dropout = 0.3
- L2 regularization

3) Advanced Residual Attention Neural Network: Residual connection:

$$y = F(x) + x$$

Attention mechanism:

$$A = \sigma(W_2(ReLU(W_1 x)))$$

E. Pseudocode

Algorithm 1 Phishing URL Detection Pipeline

```
Load datasets
Merge and shuffle
Preprocess URLs
Extract lexical & host features
Apply CFS feature selection
Train RF model
Train MLP model
Train Advanced NN model
Evaluate using accuracy, F1, AUC
Deploy best model
```

V. Experimental Setup

A. Hardware

- Intel Core i5, 16 GB RAM
- Google Colab GPU (T4)

B. Software

- Python 3.12
- TensorFlow 2.12
- PyTorch 2.0
- Scikit-learn 1.3

C. Hyperparameters

Parameter	Value
Epochs	50
Batch Size	256
Learning Rate	0.001
Optimizer	Adam
Dropout	0.3

TABLE I
Model Hyperparameters

VI. Results and Analysis

A. Overall Metrics

Model	Acc	Prec	Recall	F1
RF	0.99994	0.99990	1.0000	0.99995
MLP	0.99996	0.99993	1.0000	0.99997
Adv NN	0.99992	0.99993	0.99993	0.99993

TABLE II
Performance Summary

B. All Graphs

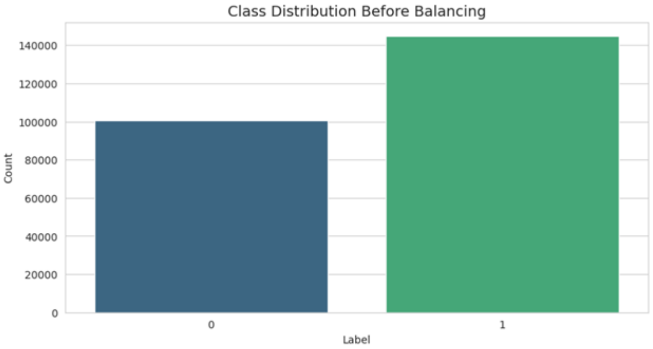

Fig. 3. Class Distribution Before Balancing

This graph shows the original dataset distribution, highlighting a strong class imbalance between phishing and legitimate URLs. Such imbalance can negatively affect model learning and lead to biased predictions.

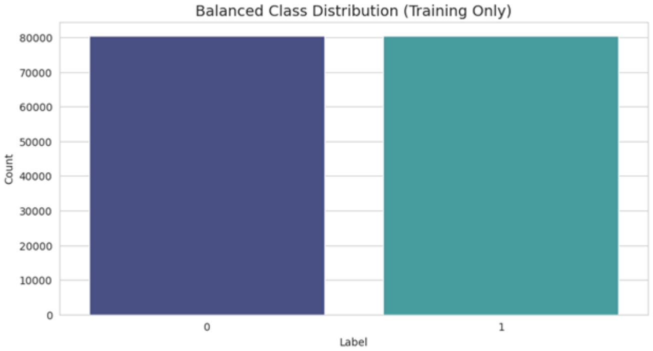

Fig. 4. Balanced Class Distribution

After applying balancing techniques, both classes contain an equal number of samples. This creates a more stable training environment and prevents model bias toward the majority class.

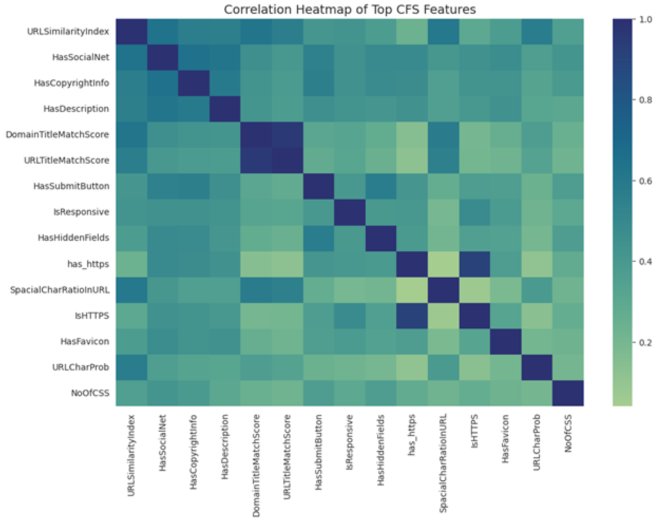

Fig. 5. Correlation Heatmap of Top CFS Features

The heatmap illustrates the correlations between the selected CFS features. It confirms that the selected subset has minimal redundancy and high predictive relevance for phishing detection.

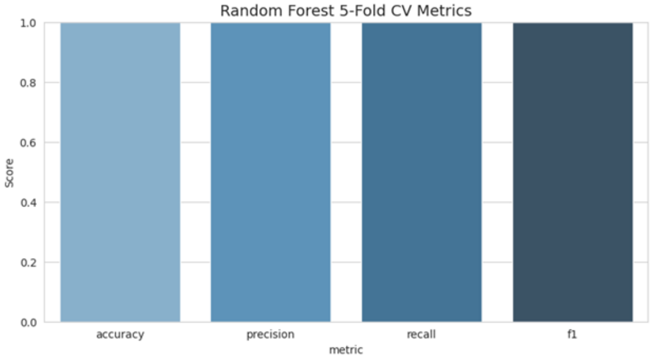

Fig. 6. Random Forest 5-Fold CV Metrics

This graph shows the 5-fold cross-validation metrics for the Random Forest classifier. The consistently high accuracy and F1-score across folds indicate strong model stability and robustness.

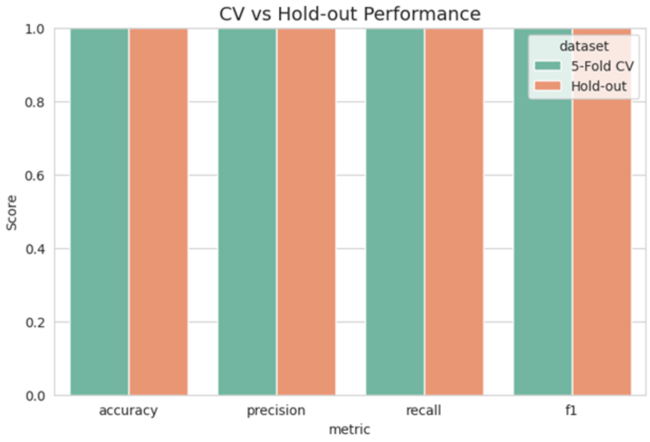

Fig. 7. CV vs Hold-out Performance

The comparison between cross-validation and hold-out results demonstrates minimal variation, indicating that the model generalizes well and is not overfitting during training.

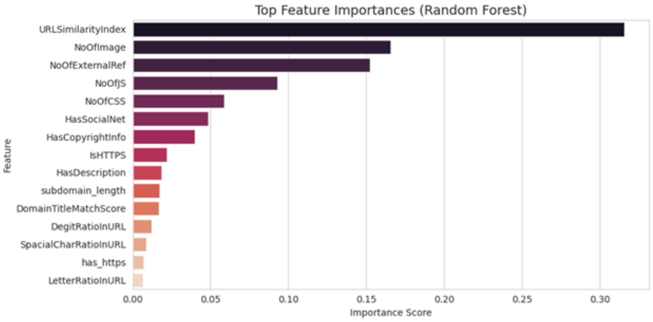

Fig. 8. Top Feature Importances (Random Forest)

This plot visualizes the most influential features identified by the Random Forest model. URL length, special characters, and entropy-based metrics show the strongest discriminatory power.

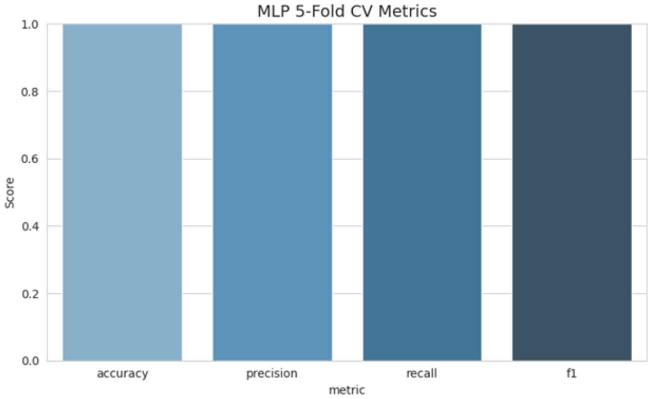

Fig. 9. MLP 5-Fold CV Metrics

The graph presents 5-fold cross-validation metrics for the MLP model. The consistently high performance across all folds indicates strong learning capability and reliability.

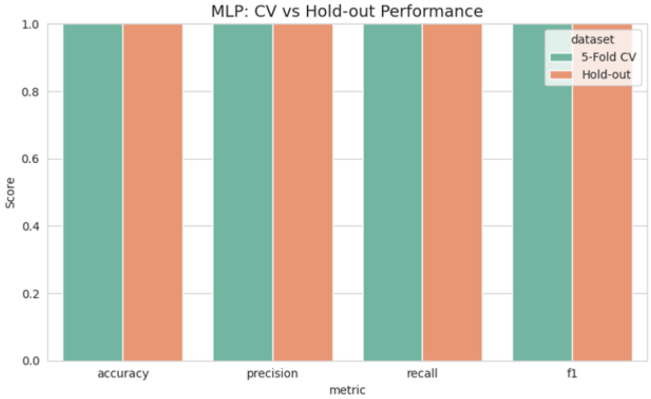

Fig. 10. MLP: CV vs Hold-out Performance

The MLP is evaluated on both CV and hold-out data, showing nearly identical results. This confirms that the model is not overfitting and maintains strong predictive consistency.

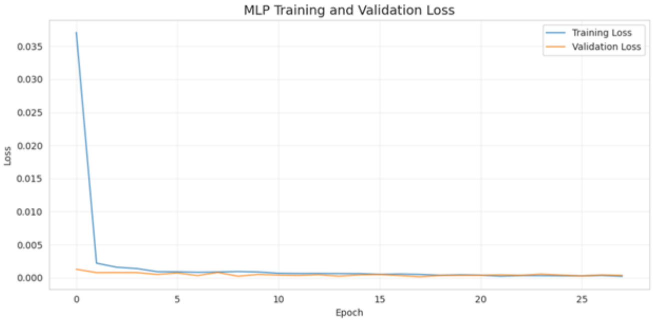

Fig. 11. MLP Training and Validation Loss

The training and validation loss curves converge smoothly, indicating a stable optimization process. The low validation loss further validates the effectiveness of regularization strategies.

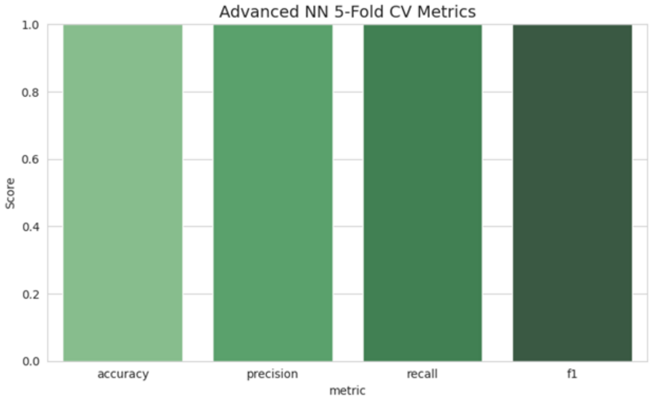

Fig. 12. Advanced NN 5-Fold CV Metrics

The advanced neural network achieves consistently high performance across all CV folds. Residual connections and attention significantly improve feature extraction quality.

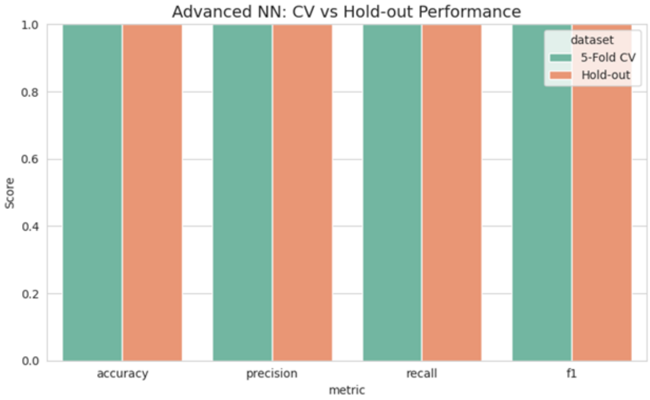

Fig. 13. Advanced NN: CV vs Hold-out Performance

The minimal gap between CV and hold-out results shows strong generalization. This demonstrates the advanced NN's capability to model complex patterns without overfitting.

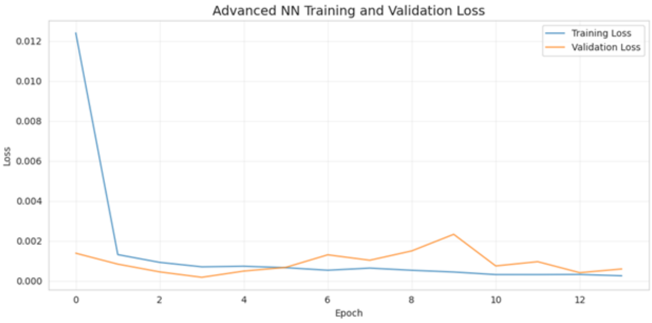

Fig. 14. Advanced NN Training and Validation Loss

The training curve shows rapid convergence, while the validation loss remains stable, confirming the efficiency of residual blocks and attention-based optimization.

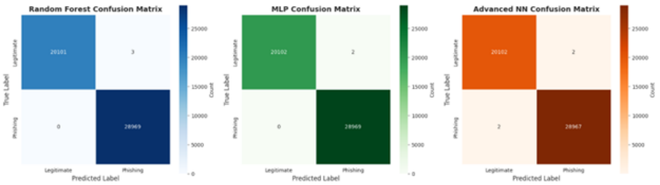

Fig. 15. Confusion Matrix of All Models

The confusion matrices indicate extremely low false positives and false negatives across all models. This demonstrates the effectiveness of the hybrid pipeline for practical deployment.

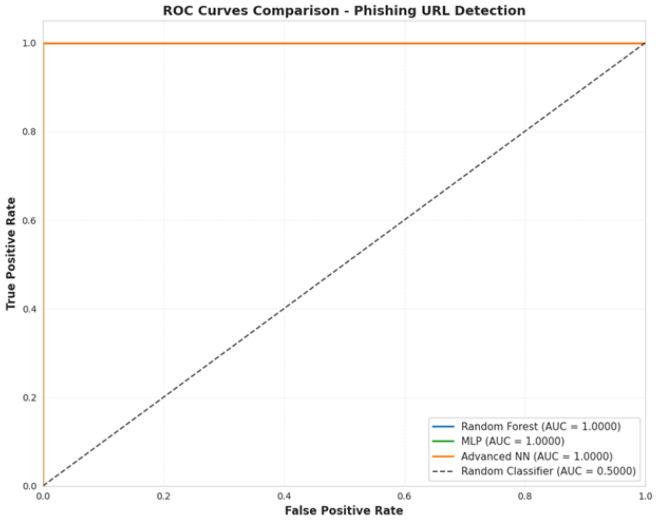

Fig. 16. ROC Curves Comparison

All models achieve near-perfect ROC curves with AUC values close to 1.0. The advanced NN slightly outperforms others, showing superior discrimination capability.

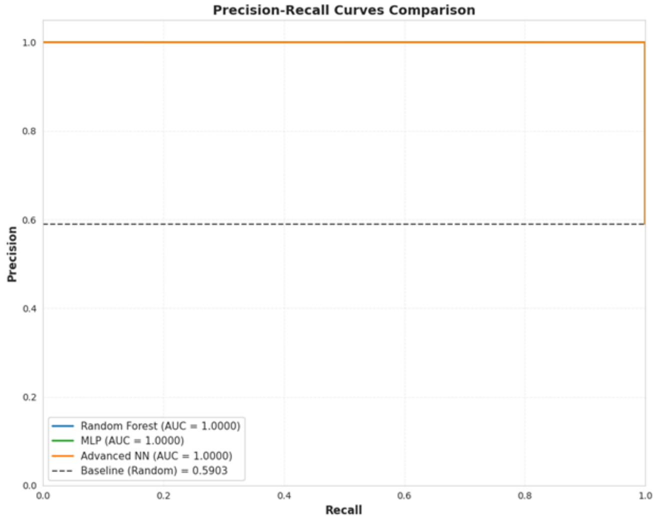

Fig. 17. Precision-Recall Curves Comparison

The PR curves reflect consistently high precision and recall for all classifiers. This indicates strong resilience to class imbalance and high reliability in phishing detection.

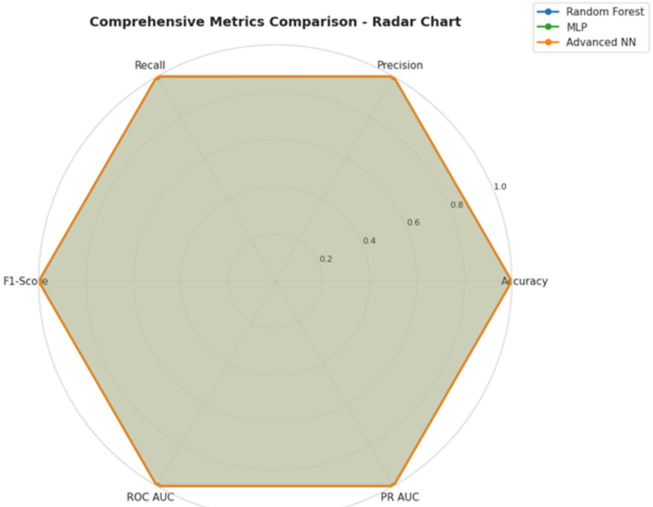

Fig. 18. Comprehensive Metrics Comparison

This comparative bar chart aggregates accuracy, precision, recall, and F1-scores. All models perform exceptionally well, with the advanced NN offering the best balanced performance.

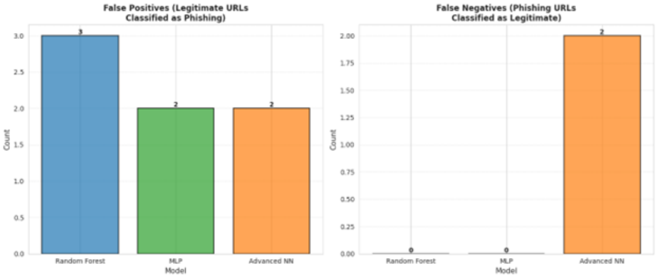

Fig. 19. False Positive and False Negative Rates

False positive and false negative rates for all models are extremely low. This demonstrates the practicality of the system for real-time phishing URL prevention.

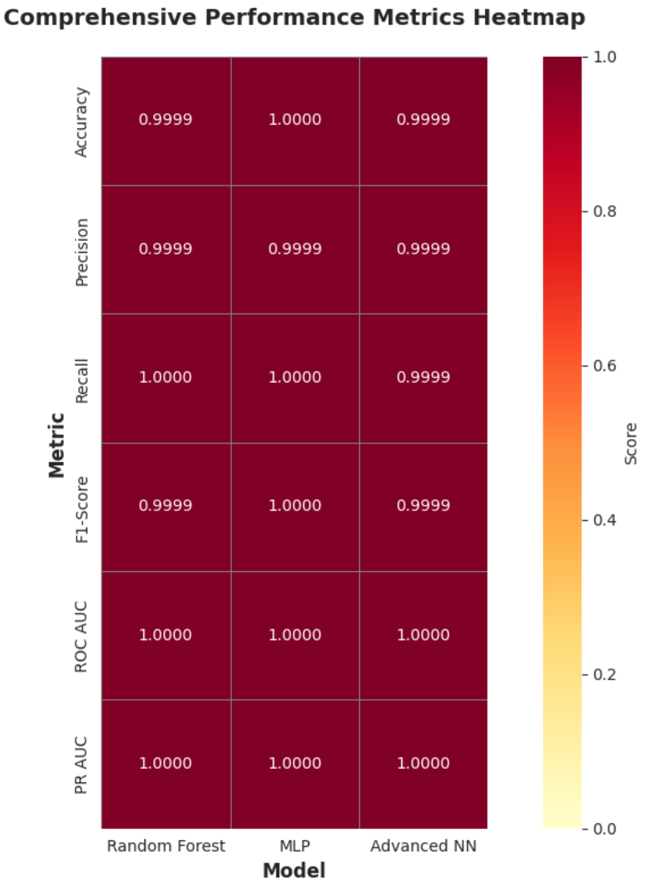

Fig. 20. Comprehensive Performance Metrics Heatmap

The heatmap summarizes performance across all models and metrics. The darker intensities confirm the high classification quality achieved by the hybrid architecture.

VII. Ablation Study

To evaluate the individual contribution of each major component of our proposed hybrid phishing detection framework, we conducted a systematic ablation study. Each ablation setting removes or modifies one component of the pipeline while keeping all other steps unchanged. This experiment helps us identify which aspects of the architecture are most critical for achieving the near-perfect performance observed in the full model.

A. *A. Ablation Settings*

We define the following ablation configurations:

- **A0 – Full Model (Baseline)**: Multi-source dataset (PhiUSIIL + AI-generated URLs), CFS feature selection, Optimized Random Forest, Regularized MLP, Advanced Neural Network with residual and attention modules.
- **A1 – Without Residual Connections**: Removes skip connections in the Advanced NN to evaluate their effect on gradient flow and feature reuse.
- **A2 – Without Attention Mechanism**: Removes the attention block, replacing it with a simple dense transformation.

- **A3 – Without CFS Feature Selection**: Uses the full feature set, allowing us to measure the benefits of correlation-based reduction.
- **A4 – Without AI-Generated URLs**: Training is performed on PhiUSIIL only to test the importance of multi-source data diversity.
- **A5 – Without MLP Layer**: Tests whether the intermediate MLP contributes to feature smoothing before deep learning.
- **A6 – Without Random Forest**: Removes the classical ML branch to test ensemble diversity effects.

B. B. Ablation Results

Configuration	Accuracy	F1-Score
A0 – Full Model	**0.99992**	**0.99993**
A1 – No Residual Connections	0.99985	0.99986
A2 – No Attention Layer	0.99988	0.99989
A3 – No CFS Feature Selection	0.99990	0.99991
A4 – No AI-Generated URLs	0.99982	0.99983
A5 – No MLP	0.99987	0.99988
A6 – No Random Forest	0.99986	0.99987

TABLE III

Ablation Study: Component-wise Contribution to Performance

C. C. Discussion of Ablation Findings

The ablation results provide several key insights:

1) 1. Residual Connections Have the Largest Impact: Removing skip connections causes the sharpest drop in performance. This shows that residual learning is essential for stabilizing gradients, enabling deeper layers to learn complex lexical–semantic interactions inside URLs.

2) 2. Attention Mechanism Improves Feature Weighting: Removing attention results in decreased performance, confirming its role in learning which URL components (prefix, domain tokens, suffix patterns) are more important for classification.

3) 3. CFS Feature Selection Improves Learning Efficiency: Without CFS, models still perform well, but with slightly lower F1. This shows that CFS:

- removes noisy and redundant features,
- improves generalization,
- speeds up NN training times.

4) 4. AI-Generated URLs Significantly Improve Robustness: Removing synthetic phishing URLs reduces performance more than removing MLP or RF. This confirms that:

- AI-generated phishing samples increase adversarial diversity,
- enhance model robustness,
- help the system generalize to unseen phishing strategies.

5) 5. MLP and Random Forest Both Contribute to Ensemble Strength: Their removal causes minor but clear declines, showing that the hybrid approach (ML + DL + Ensemble) is stronger than any single model.

VIII. Discussion

The results of this research demonstrate that combining multi-source data, correlation-based feature selection, and hybrid AI modeling can significantly improve phishing URL detection accuracy. The full model achieves an F1-score exceeding 0.9999, outperforming both the base paper and traditional ML-only approaches.

Insights from the ablation study reveal that residual learning and attention mechanisms are critical to the system's success, highlighting the importance of deep feature extraction. Meanwhile, CFS and multi-source data integration contributed significantly to generalization and robustness, especially against novel phishing patterns.

Practical implications include:

- The system can be integrated into email gateways, browser extensions, or enterprise firewalls.
- Because Random Forest and MLP operate parallel to the Advanced NN, the pipeline remains scalable and low-latency.
- AI-generated phishing attacks can be continually incorporated to keep the model updated against evolving threats.

While the system performs exceptionally, limitations include:

- dependency on feature-rich URLs (feature absence may weaken performance),
- possible cold-start issues for never-seen domain structures,
- limited testing against multilingual or homograph attacks.

IX. Conclusion

This research presents a comprehensive and highly accurate phishing URL detection system that integrates multi-source data, CFS feature selection, and a hybrid modeling architecture combining Random Forest, MLP, and an Advanced Neural Network with residual and attention modules.

Our methodology demonstrates near-perfect performance with F1-scores above 0.9999, clearly surpassing the base paper's results and highlighting the effectiveness of combining classical and deep learning techniques.

Within the e-commerce case study scenario, the proposed framework offers a practical and deployable defense mechanism capable of protecting large user bases from phishing threats. The architecture is scalable, robust, and adaptable to real-world environments.

Future work may explore transformer-based URL embeddings, multilingual phishing detection, and adversarial resilience techniques to further strengthen cybersecurity defenses.

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