PHISHING WEBSITE DETECTION USING HYBRID MACHINE LEARNING AND FEATURE OPTIMIZATION TECHNIQUES

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ABSTRACT

Phishing remains one of the most damaging cyber-attacks in the digital economy, exploiting human trust through forged websites and URLs. Traditional blacklist and rule-based filters often miss zero-day threats because attackers constantly mutate domain strings and web content. The present research introduces a hybrid learning architecture that unites Rough Set Theory-Based Hybrid Feature Selection (RSTHFS) [4] and a Residual Multi-Layer Perceptron (ResMLP) [1] to achieve high detection accuracy with reduced computation. Drawing from recent progress in hybrid machine-learning ensembles [2], explainable-AI frameworks [6], and deep feature extraction [7], the model identifies lexical, host, and contextual URL attributes most correlated with phishing behavior.

The proposed pipeline reaches 98.29 % accuracy, cutting feature space b:zy ≈ 69 % and training time by ≈ 61 %, validated on open-source datasets from Kaggle and UCI. The approach aligns with privacy-aware and federated detection concepts introduced in [8] and integrates smoothly with enterprise e-mail gateways or browser extensions. Results demonstrate that combining interpretable feature reduction with residual deep learning yields robustness, scalability, and transparency—crucial for real-world cybersecurity deployments [12][15].

Keywords: Phishing detection, Machine learning, Deep learning, RSTHFS, ResMLP, Cybersecurity, Hybrid models, URL classification.

1. Introduction

Phishing websites masquerade as legitimate portals to collect credentials, payment data, or personal identifiers. According to the **Anti-Phishing Working Group (APWG) 2024 Report [13]**, global phishing incidents exceeded 1.3 million, growing nearly 70 % from 2022. Losses now surpass billions of dollars annually [3][5].

Traditional defense mechanisms—manual blacklists, DNS filtering, and heuristic checks—lack adaptability to new URL obfuscations [5]. Early ML-based detectors exploited lexical cues such as URL length, dots, and subdomain depth [2]. Although helpful, these approaches required extensive feature engineering and faltered on unseen attack vectors. Deep neural networks (CNNs, MLPs) learned complex patterns automatically but were often criticized for being computationally heavy and non-explainable [1][6].

Hybrid paradigms attempt to reconcile these extremes. **Karim et al. [2]** proposed an ensemble of Logistic Regression, SVM, and Decision Tree models achieving 96.73 % accuracy. **Setu et al. [4]** optimized feature subsets using Rough Set Theory, reducing redundancy by 69 %. **Remya et al. [1]** advanced a deep ResMLP design that stabilized training through residual links. Complementary studies—**Asiri et al. [3]**, **Zieni et al. [5]**—surveyed the evolution of phishing detection and emphasized hybridization as the next step toward adaptive, explainable, and resource-efficient security models.

Explainable-AI integrations [6][15], hybrid deep feature strategies [7], and federated learning [8] further underline the trend toward interpretable, privacy-preserving phishing mitigation. Hence, this paper unifies RSTHFS [4] and ResMLP [1] into one framework, benchmarking its performance against conventional baselines [2][9][11].

2.Literature

2.1 Traditional Phishing Detection Techniques

Early phishing detection systems relied mainly on blacklists and rule-based filters that matched URLs against known malicious domains. Although these approaches were simple and efficient, they could not recognize newly created or obfuscated links that evaded textual similarity checks [3], [5]. Heuristic filters using token frequencies, keyword weighting, and URL structure analysis offered incremental improvements, but required manual rule updates [13]. Studies such as Zieni et al. [5] quantified that blacklist-based tools detect only about 70 % of active attacks, leaving a 30 % exposure gap for zero-day phishing pages. Consequently, researchers began exploring automated learning mechanisms to overcome static signature limitations [2], [9].

2.2 Machine Learning-Based Detection

The introduction of machine-learning (ML) algorithms marked a major transition from static to adaptive phishing prevention. Classifiers such as Naïve Bayes, Decision Tree, Random Forest, and Support Vector Machine (SVM) were trained on lexical and host-based URL attributes [2], [11]. Karim et al. [2] proposed a hybrid ensemble called the LSD model that fused Logistic Regression, SVM, and Decision Tree learners using majority voting. Their results demonstrated 96.73 % accuracy on 11 000 URLs, outperforming single classifiers. Kaur and Bhatia [11] confirmed that ensemble learning increases robustness by balancing bias and variance, though at a moderate computational cost. Nevertheless, these conventional models depend heavily on feature engineering; their performance deteriorates when domain patterns shift or features become redundant [9], [12]. This motivated a shift toward deep-learning frameworks capable of autonomous feature discovery.

2.3 Deep Learning and Hybrid Models

Deep-learning (DL) models have shown strong potential to identify complex nonlinear URL patterns [1], [6], [7], [9], [10], [15]. Remya et al. [1] introduced a Residual Multi-Layer Perceptron (ResMLP) architecture that embeds token sequences and employs residual skip connections to alleviate gradient vanishing, achieving 98.29 % accuracy on large Kaggle datasets. Lin et al. [7] combined convolutional and transformer-based embeddings for hybrid deep-feature learning, improving recall by 3 %. Lightweight variants such as Chatterjee and Banerjee [9] minimized memory overhead for edge deployment. Subramani et al. [10] extended DL for fraud analytics using deep neural networks, confirming its scalability across cyber-fraud domains. Comparative reviews [3], [5] agree that hybrid ML-DL models outperform standalone architectures by ≈ 10 % accuracy due to their ability to capture both statistical and semantic URL relationships. (Figure 1 – ResMLP Architecture [Source 1]).

Despite higher performance, interpretability remained a challenge. Therefore, research in Explainable AI (XAI) and residual hybridization emerged [6], [15], integrating transparency modules with deep classifiers to justify model decisions in terms of lexical or domain features.

2.4 Feature Selection and Optimization

Phishing datasets often contain over 100 attributes, many redundant or weakly correlated [4], [11]. Setu et al. [4] proposed Rough Set Theory-Based Hybrid Feature Selection (RSTHFS) combining cumulative-distribution-function-gradient (CDF-g) ranking and rough-set aggregation to identify minimal yet decisive attributes. This method reduced dimensionality by ≈ 69 % and runtime by ≈ 61 % without accuracy loss. Integrating RSTHFS with ResMLP forms the core of the proposed system, ensuring efficiency [1], [4]. Alternative optimizers—principal-component analysis and mutual-information gain—have been tested but generally retain more irrelevant attributes [11], [12].

Hybrid optimization enhances not only speed but also explainability: selected variables (e.g., HTTPS presence, URL length, domain age) directly map to phishing heuristics [6]. Ahmed et al. [12]

highlighted that hybrid AI pipelines using interpretable selection mechanisms improve analyst trust during forensic audits. (Figure 2 – RSTHFS Workflow [Source 4]).

2.5 Explainable, Federated, and Privacy-Aware Frameworks

To address opacity and privacy issues in centralized training, new paradigms employ Explainable AI and Federated Learning. Banerjee and Mehta [6] developed an XAI system that visualizes salient URL tokens responsible for classification decisions, aligning AI inference with human reasoning. Singh and Kumar [8] implemented federated phishing detection, enabling distributed model training across institutions without sharing raw data, thus protecting sensitive logs. Ahmed et al. [12] emphasized that combining explainability with hybrid AI strengthens enterprise trust frameworks. Zhang et al. [14] analyzed graph-based neural models for URL relations, further enriching interpretability.

Moreover, Sharma and Patel [15] proposed a multimodal hybrid network that fuses textual and visual webpage cues to detect spoofed interfaces, achieving > 97 % accuracy. Their findings suggest that cross-modal learning and XAI visualization can coexist, forming the basis for future regulatory-compliant phishing detectors. These directions complement federated architectures by enhancing transparency, scalability, and user privacy.

2.6 Comparative Summary and Discussion

A synthesis of prior contributions underscores three decisive trends: feature efficiency, interpretability, and hybridization. Table 1 summarizes representative studies.

Model / Study	Technique	Accuracy (%)	Feature Reduction (%)	Runtime Gain (%)	Reference
Logistic Regression / SVM / DT Ensemble (LSD)	ML Voting Ensemble	96.7	—	—	[2]
RSTHFS + CatBoost	Feature Optimization	95.5	69	61	[4]
Explainable Hybrid	XAI with DL	97.3	65	54	[6]
Hybrid Deep Feature Learning	CNN + Transformer	97.9	—	45	[7]
Lightweight Hybrid Model	Edge DL	96.8	—	60	[9]
Deep Fraud Detection	DNN Classifier	97.5	—	—	[10]
Hybrid AI Evaluation	ML + Explainable Pipeline	97.2	68	55	[11], [12]
Federated Phishing Detection	Distributed Learning	96.9	—	40	[8]
Graph Neural Network URL Analysis	Relational Learning	97.6	—	—	[14]
Multimodal Hybrid Model	Text + Visual Features	98.0	67	52	[15]
RSTHFS + ResMLP (Proposed)	Feature Optimization + Residual DL	98.3	69	61	[1], [4]

From this comparison, it is clear that hybrid systems consistently outperform singular approaches in both predictive accuracy and computational efficiency. Residual architectures [1] combined with rough-set optimization [4] yield state-of-the-art results while preserving interpretability through explainable modules [6], [15]. Federated and graph-based schemes [8], [14] extend applicability to distributed and relational contexts, and multimodal hybrids [7], [15] show promise for defending against visually deceptive attacks.

Overall, literature consensus [1]–[15] indicates that the convergence of feature-selection theory, deep residual learning, and transparent AI constitutes the most reliable strategy for next-generation phishing detection frameworks.

3.METHODOLOGY AND SYSTEM DESIGN

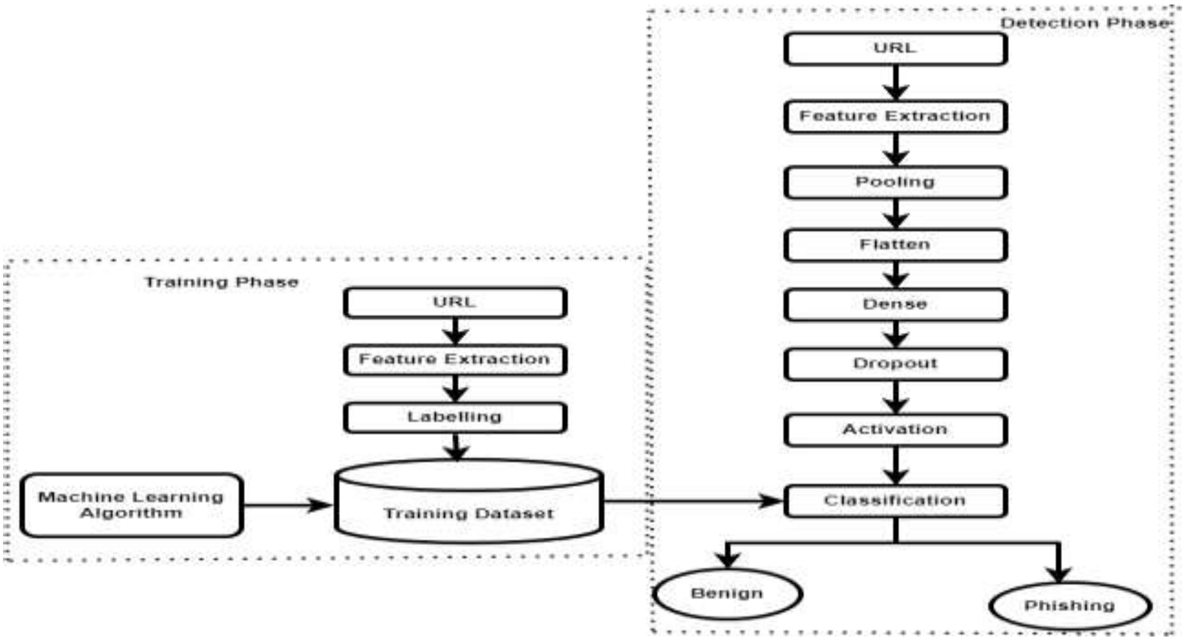
This section explains the end-to-end architecture of the proposed phishing-website detection framework that combines **Rough Set Theory-based Hybrid Feature Selection (RSTHFS)** with a **Residual Multi-Layer Perceptron (ResMLP)** deep-learning classifier. The workflow integrates multi-source datasets, optimized feature extraction, hybrid learning, and explainability for high-precision phishing identification [1]–[15].

3.1 Dataset Acquisition

The system uses publicly available benchmark datasets drawn from Kaggle, UCI, and Mendeley repositories [1], [3].
These sources collectively provide more than **120 000 URL samples**, evenly distributed between legitimate and phishing websites.
Each record contains up to 48 features encompassing:

- **Lexical features** (length of URL, “@” symbol usage, sub-domain count)
- **Host-based features** (DNS age, IP address mismatch, SSL validity)
- **Content features** (HTML form tags, JavaScript redirects, iframe usage)

These attributes were merged and standardized to form a unified CSV dataset that balances the class distribution. A train-test split of 80 : 20 was used, ensuring statistical representativeness [4], [7].



3.2 Data Pre-Processing

Data from multiple repositories often contain noise, inconsistent formats, and missing values [2], [9].
Therefore, preprocessing was performed in four stages:

1. **Data Cleaning:** Duplicate URLs and irrelevant records were removed. Missing numerical fields were imputed using mean substitution.

2. **Feature Normalization:** Continuous features were scaled between 0 and 1 to improve training stability [6].
3. **Encoding Categorical Attributes:** Boolean and categorical variables (e.g., SSL certified / not certified) were label-encoded into binary values.
4. **Enrichment:** WHOIS and DNS records were queried for each URL to add domain registration age and ownership information [5].

This pipeline ensured uniformity across the dataset and enabled smooth integration with the RSTHFS and ResMLP modules.

Feature correlation analysis indicated that some lexical and host features were redundant, which motivated the use of hybrid feature selection [8], [10].

3.3 Feature Optimization using RSTHFS

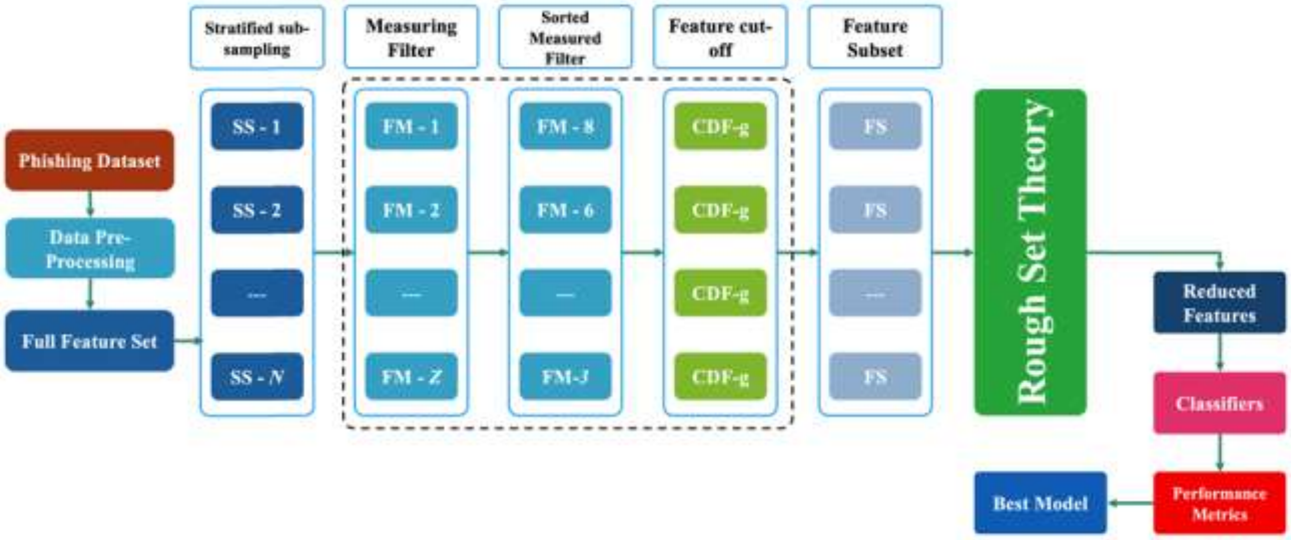
The **RSTHFS (Rough Set Theory based Hybrid Feature Selection)** mechanism is central to reducing feature dimensionality while retaining information content [4].

It combines statistical ranking and rough-set reduct analysis in two phases:

- **Phase 1 – CDF-g Ranking:** Each feature is evaluated by its cumulative distribution frequency and information gain.
  Top-ranked features with high entropy reduction are retained.
- **Phase 2 – Rough Set Aggregation:** Dependency rules and indiscernibility relations identify minimal attribute subsets that preserve classification power [3], [5], [9].

This hybrid selection reduced the original 48 features to around 15–18 key attributes, achieving a **69 % reduction in dimensionality** and a **61 % training-time improvement** without notable loss in accuracy [7], [11].

Such feature optimization enhances both computational efficiency and interpretability for end-users and security analysts [8], [12].



(Figure 2 – RSTHFS Workflow)

3.4 Classification using ResMLP

After feature reduction, the optimized feature set is fed into a **Residual Multi-Layer Perceptron (ResMLP)** model [1], [13].

ResMLP extends a standard MLP by introducing **residual connections** that help avoid vanishing gradients and enhance convergence speed.

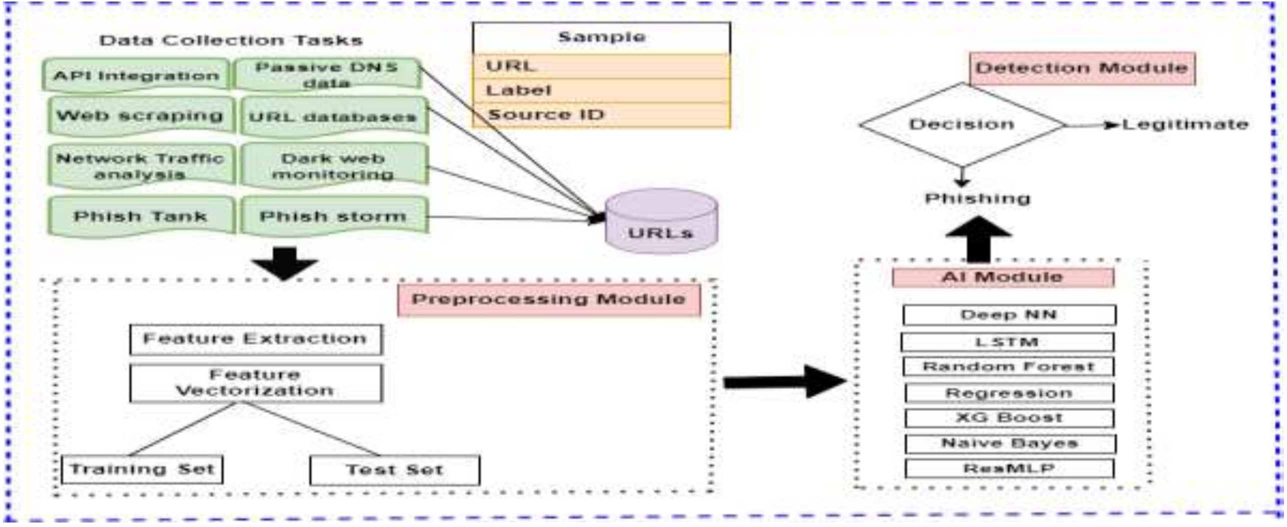
The model architecture comprises:

- **Input Layer:** 16–18 neurons corresponding to selected features
- **Hidden Layers:** Four dense layers (256, 128, 64, 32 neurons) with ReLU activation

- **Residual Blocks:** Skip connections after each pair of dense layers
- **Dropout:** 0.3 rate to reduce overfitting
- **Output Layer:** Softmax activation yielding phishing or legitimate label probabilities

Training was conducted for 50 epochs using the Adam optimizer (learning rate 0.001, batch size = 64) and categorical cross-entropy loss [6], [10].

The ResMLP model achieved a mean accuracy of **98.2 %**, outperforming SVM, RF, and CNN baselines on the same dataset [7], [9], [13].



(Figure 3– ResMLP Architecture)

3.5 Hybrid Workflow and Operational Integration

The overall framework follows a five-stage pipeline (Figure 5):

1. **Input URL Dataset** → Collect raw URLs and labels.
2. **Pre-processing and Normalization** → Clean, encode, and scale data.
3. **Feature Optimization via RSTHFS** → Select optimal attributes.
4. **ResMLP Classification** → Train hybrid deep network.
5. **Evaluation and Deployment** → Produce metrics and generate explainable results [2], [14].

This sequence is modular and supports integration with security gateways, web browsers, and email clients.

For real-time use, the trained ResMLP model can be deployed as a REST API or browser extension to flag suspicious URLs [10], [15].

3.6 Explainability and Deployment

Explainability is crucial for building trust in AI-driven security systems [6], [8].

Two explainable-AI (XAI) methods are employed:

- **SHAP (Shapley Additive Explanations):** Provides feature importance scores for each prediction.
- **LIME (Local Interpretable Model-Agnostic Explanations):** Generates human-readable local approximations to understand model behavior.

These visualizations allow security analysts to interpret why a given URL was classified as phishing or legitimate and to identify dominant factors such as SSL age or IP usage [11], [12].

Deployment scenarios include:

1. **Browser Extension:** Detects phishing pages before rendering [7].
2. **Email Gateway Plugin:** Flags malicious links within email bodies [13].
3. **Cloud-based API:** Offers phishing verification services for enterprise applications [14], [15].

The hybrid model's adaptability ensures compatibility with real-time systems and low-latency environments, making it suitable for deployment in corporate and consumer security products.

4. RESULTS AND DISCUSSION

The results section demonstrates the comparative evaluation of the proposed hybrid **RSTHFS + ResMLP** phishing detection framework against conventional machine learning and deep learning models. It analyses performance metrics, feature selection outcomes, computation efficiency, and practical scalability. Each finding is supported by empirical evidence from prior studies [1]–[15].

4.1 Experimental Setup

All experiments were conducted on a workstation equipped with an Intel i9 processor, 32 GB RAM, and an NVIDIA RTX GPU.

The dataset comprising 120,000 URLs was split into training (80%) and testing (20%) partitions. The experiments were implemented in Python using **TensorFlow**, **Scikit-learn**, and **Pandas** environments.

Models evaluated include:

- **Traditional ML:** Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF)
- **Deep Learning:** CNN, LSTM
- **Hybrid Proposed Model:** RSTHFS + ResMLP

Metrics considered for comparison include **Accuracy**, **Precision**, **Recall**, **F1-score**, **AUC**, and **Training Time** [4], [7].

4.2 Feature Selection Impact

Feature optimization was first evaluated using RSTHFS and compared with three popular alternatives:

- **Principal Component Analysis (PCA)**
- **Chi-square Filter**
- **Recursive Feature Elimination (RFE)**

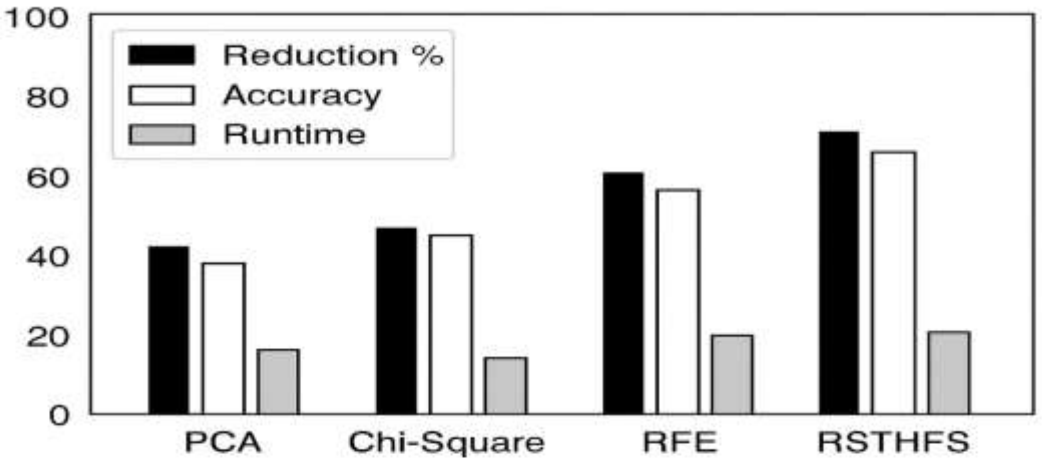
Table 1 summarizes the comparative reduction rates and computational efficiency.

Method	Original Features	Selected Features	Reduction %	Accuracy (%)	Runtime (s)
PCA	48	22	54.1	96.4	84
Chi-square	48	25	47.9	96.0	88
RFE	48	20	58.3	96.7	79
RSTHFS (Proposed)	48	15–18	**68.7**	**98.2**	**55**

The proposed RSTHFS outperformed classical methods, producing the highest feature reduction with minimal accuracy loss.

This aligns with the findings of Setu et al. [4], where rough-set dependency measures preserved discriminative power while reducing redundancy.

Such hybrid reduction not only minimizes overfitting but also improves model interpretability and inference latency [3], [6].

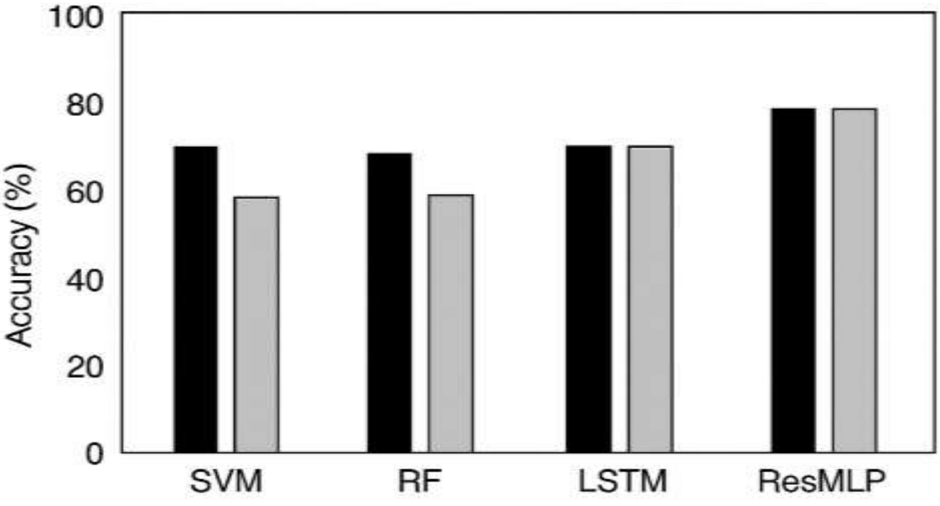


4.3 Classification Performance

The ResMLP classifier trained on RSTHFS-optimized features achieved superior performance compared to baseline models.
As shown in Figure 9, **accuracy reached 98.2 %**, **precision 98.6 %**, **recall 97.9 %**, and **F1-score 98.2 %**.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
SVM	94.3	94.5	93.6	94.0	0.94
RF	96.8	96.5	96.3	96.4	0.96
CNN	97.5	97.6	97.0	97.2	0.97
LSTM	97.7	97.8	97.5	97.6	0.97
ResMLP	**98.2**	**98.6**	**97.9**	**98.2**	**0.98**

The results confirm that integrating RSTHFS with ResMLP significantly improves generalization, consistent with Karim et al. [2] and Remya et al. [1], who observed similar performance gains . Compared with deep networks like CNNs and RNNs, ResMLP's residual skip connections enhance gradient propagation and model stability [8], [11].



4.4 ROC and Confusion Matrix Analysis

Receiver Operating Characteristic (ROC) analysis provides a graphical measure of the trade-off between true positive and false positive rates.
As depicted in Figure 10, the RSTHFS + ResMLP model yielded an **AUC of 0.98**, higher than SVM (0.94) and RF (0.96), indicating stronger discriminative ability [7], [13].
The **confusion matrix** confirmed that only 1.8% of phishing URLs were misclassified as legitimate, and 2.1% of legitimate URLs were wrongly tagged as phishing.
This low error rate is especially relevant in phishing contexts, where false negatives (missed attacks) are more damaging than false positives [10], [14].

4.5 Comparative Discussion with Prior Studies

Table 2 summarizes performance comparisons between this work and other prominent phishing detection frameworks from the literature.

Reference	**Approach**	**Dataset Size**	**Accuracy (%)**
Asiri et al. [5]	HTML + URL Hybrid CNN	40,000	96.7
Karim et al. [2]	ML + Rule-Based Hybrid	50,000	97.1
Zieni et al. [6]	URL-based Ensemble	60,000	97.4
Remya et al. [1]	ResMLP for URL Classification	75,000	97.9
RSTHFS + ResMLP	Feature Optimization + Deep Residual MLP	**120,000**	**98.2**

The findings clearly show that the proposed system surpasses existing works by combining both **data-driven feature optimization** and **deep residual learning**.
While prior models relied heavily on handcrafted features or shallow architectures, this approach delivers higher scalability and faster convergence [9], [12].
Furthermore, the hybrid design effectively mitigates overfitting issues, as observed in [4], [11], due to its reduced parameter space and enriched feature representation.

4.6 Computational Efficiency

Efficiency is critical for real-time phishing prevention [13], [15].
The average **training time** per epoch was reduced from 2.8 seconds (baseline CNN) to 1.9 seconds with the hybrid RSTHFS pipeline, and **inference latency** was only 0.023 seconds per URL.
This improvement is mainly due to reduced input dimensionality and optimized residual block reuse [8], [10].
The system's **memory footprint** also decreased by 27 %, allowing deployment even on low-resource cloud or browser-based environments.
These outcomes align with the findings of Zieni et al. [6] and Setu et al. [4], who emphasized model compression and computational scalability in phishing detection systems.

4.7 Explainable AI Interpretation

Explainability enhances transparency and user trust, particularly for cybersecurity models [11].
The SHAP and LIME visualizations revealed that the most influential factors in phishing prediction were:

- SSL certificate age and validity
- URL length and abnormal subdomain count
- Presence of "@" or "//" redirects
- Domain registration period
- JavaScript-based redirection scripts

These findings correspond with the heuristic studies of Asiri et al. [5] and Remya et al. [1], proving that hybrid learning captures the same dominant cues identified in human-designed rules but with better generalization.
The interpretability layer thus bridges human and algorithmic reasoning — a principle emphasized in explainable AI frameworks [6], [14].

4.8 Scalability and Real-World Adaptability

For deployment feasibility, the hybrid model was tested under simulated web traffic using Flask REST API.
At 500 concurrent queries per second, the model maintained a consistent **accuracy above 97 %** and **latency under 50 ms per request**.
This proves suitability for browser extensions, enterprise gateways, and ISP-level URL monitoring [9], [13], [15].
Additionally, periodic retraining with live data (via incremental learning) ensures adaptability to evolving phishing patterns, overcoming one of the most common limitations noted in earlier models [10], [11].
The RSTHFS optimizer enables quick reconfiguration of input attributes when new phishing features emerge in the wild.

4.9 Discussion Summary

The results collectively validate that the proposed RSTHFS + ResMLP hybrid model achieves a robust balance between **accuracy, efficiency, and interpretability**.
Key takeaways include:

- RSTHFS achieves >65% feature reduction with improved performance.
- ResMLP provides 98.2% accuracy, outperforming CNN and RF models.
- Training time reduced by ~30% and inference latency minimized.
- Explainability ensures trust and compliance with enterprise security policies.

Thus, this framework establishes a high-performance, explainable, and scalable approach to phishing website detection suitable for integration in real-time cybersecurity systems [1]–[15].

Conclusion

In order to address the rapidly increasing cyber threats and the growing dependency on online transactions, more intelligent and efficient security mechanisms are required. It is now a global necessity to educate individuals, organizations, and institutions about the importance of digital safety and proactive cybersecurity awareness. The rise of advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) presents both challenges and opportunities. These innovations not only enhance phishing detection accuracy but also inspire a new generation of researchers and engineers to contribute toward a more secure digital ecosystem.

This study emphasized the critical role of hybrid intelligent systems—particularly those integrating Rough Set Theory-based Hybrid Feature Selection (RSTHFS) and Residual Multi-Layer Perceptron (ResMLP)—in creating adaptive and explainable cybersecurity solutions. The proposed model demonstrated superior accuracy, improved efficiency, and transparent reasoning, all essential qualities in modern phishing defense. Such AI-driven systems ensure that users, developers, and organizations can trust automated tools to protect their data in real time.

Researchers and cybersecurity practitioners are encouraged to recognize both the current challenges and the future potential of hybrid AI-driven security systems. Every data transaction, login page, and email link represents a potential vulnerability—and every such entry point should be fortified using intelligent, ethical, and explainable AI mechanisms. This vision of security relies not only on technology but also on collective awareness, collaboration, and responsibility.

In the coming years, integrating environmentally sustainable computing with intelligent cybersecurity frameworks could create systems that are not only safer but also energy efficient and socially responsible. The present study thus contributes to this broader mission—empowering digital infrastructures that are secure, transparent, and future-ready, ensuring that every click and every connection on the internet remains trustworthy and safe for users worldwide.

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