Explainable AI-Based Phishing Website Detection Using Hybrid Machine Learning for Enhanced Cybersecurity

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Abstract*—The expeditious growth of online services has crucially increased the number and sophistication of phishing attacks, making phishing websites one of the most serious cybersecurity threats to individuals and organizations. Conventional machine learning-based phishing detection methods often achieve high prediction exactness but function as black-box models, offering limited insight into the reasoning behind their decisions. This lack of transparency reduces user confidence and hinders adoption in security-critical applications. To mark these challenges, this paper proposes an Explainable AI-Based Phishing Website Detection Framework Using Hybrid Machine Learning that combines the prognostic capabilities of multiple machine learning algorithms with interpretable decision-making. The raised framework extracts comprehensive URL, domain, webpage, and security-related features, followed by data refinement, feature selection, and hybrid ensemble classification to accurately discern phishing websites from legitimate ones. To enhance model transparency, Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive exPlanations) are embedded to identify and visualize the influence of each feature toward the final prediction. This enables security analysts and end users to understand why a website is classified as phishing, thereby improving trust and supporting informed decision-making. The proposed framework is investigated using benchmark phishing datasets and compared with standard machine learning approaches based on accuracy, precision, recall, F1-score, ROC-AUC, and explainability. Experimental results are expected to demonstrate that the proposed hybrid model not only achieves superior detection reliability but also provides meaningful and transparent explanations, making it a reliable solution for next-generation intelligent phishing website detection systems.

I. Introduction

The expeditious expansion of digital technologies, cloud-based services, e-commerce platforms, and online banking has reformulated the way individuals and organizations interact over the Internet. While these refinements have improved accessibility and convenience, they have also created new avenues for cybercriminals to exploit unsuspecting users through sophisticated phishing attacks. Phishing websites are hostile web pages designed to imitate legitimate websites with the intention of stealing fragile information such as usernames, passwords, banking credentials, credit card details, and other confidential data. As phishing attacks continue to emerge in complexity and scale, they have become one of the predominant persistent cybersecurity threats affecting both individuals and enterprises worldwide.

Traditional phishing detection mechanisms, including blacklist-based systems and rule-based approaches, have shown limited effectiveness against newly created or zero-day phishing websites. These methods

often fail to detect previously unseen attacks because they rely heavily on predefined signatures or manually updated databases. To overcome these bottlenecks, Machine Learning (ML) techniques have emerged as a promising solution by automatically learning patterns from phishing and legitimate websites using various URL, domain, HTML, and security-related features. Numerous machine learning algorithms, including Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting, and Extreme Gradient Boosting (XGBoost), have demonstrated encouraging performance in identifying phishing websites with high accuracy.

Notwithstanding these advancements, most existing machine learning models operate as black-box systems, providing only prediction outcomes without explaining the reasoning behind their decisions. In cybersecurity applications, this lack of transparency presents a significant challenge because security analysts and end users require understandable and trustworthy explanations before acting on automated predictions. Explainability has therefore become an essential requirement for intelligent cybersecurity systems, facilitating users to identify the factors that influence phishing detection while improving confidence in automated decision-making.

To mark these challenges, this research proposes an **Explainable AI-Based Phishing Website Detection Framework Using Hybrid Machine Learning**. The proposed framework integrates multiple machine learning algorithms within a hybrid ensemble model to improve detection exactness and robustness. Furthermore, Explainable Artificial Intelligence (XAI) techniques, particularly SHAP (SHapley Additive exPlanations), are incorporated to provide clear interpretations of feature contributions responsible for each prediction. The framework analyzes multiple categories of phishing indicators, including URL characteristics, domain information, webpage structure, and security attributes, enabling both accurate classification and transparent reasoning.

The formulated approach aims not only to enhance phishing website detection performance but also to improve model interpretability, reduce false-positive classifications, and support cybersecurity professionals in making alerted decisions. By combining hybrid machine learning with intelligible artificial intelligence, this research contributes toward the development of reliable, transparent, and intelligent phishing detection systems capable of addressing emerging cyber threats in modern digital environments.

II. Literature Survey

Phishing website detection has become an responsive area of cybersecurity research due to the rapid increase in online financial transactions, cloud services, and digital communication. Researchers have formulated various detection techniques ranging from blacklist-based methods to enhanced machine learning and deep learning models. More newly, Explainable Artificial Intelligence (XAI) has gained attention for improving the transparency and reliability of phishing detection systems.

Mohammad et al. developed one of the earliest machine learning frameworks to facilitate phishing website detection using multiple website characteristics, encompassing URL structure, domain information, and webpage attributes. Their work demonstrated that machine learning algorithms can optimally classify phishing websites with higher exactness than traditional blacklist-based approaches. However, the formulated model did not provide explanations for its predictions, limiting its interpretability in real-world cybersecurity applications.

Sahingoz et al. proposed a phishing detection model grounded in URL analysis using machine learning techniques. The study extracted lexical and host-based features from URLs and evaluated several classification algorithms. Experimental outcomes showed that Random Forest and Gradient Boosting methods produced competitive detection performance while reducing computational sophistication. Nevertheless, the framework primarily relied on URL-based features and did not consider model explainability or webpage content analysis.

Jain and Gupta introduced a client-side phishing detection approach that combined heuristic feature extraction with machine learning algorithms. Their method analyzed webpage characteristics without depending on external blacklist databases, enabling the detection of previously unseen phishing websites. Although the approach improved zero-day phishing detection, manually designed features reduced adaptability to rapidly evolving phishing strategies.

With the advancement of ensemble learning, **Chen and Guestrin** proposed the XGBoost algorithm, which has become one of the most widely employed machine learning techniques for cybersecurity applications attributable to its scalability, robustness, and high predictive performance. XGBoost has demonstrated excellent outcomes in phishing website detection by efficiently handling high-dimensional characteristic sets and minimizing classification errors. However, like many ensemble models, it functions as a black-box system, making its predictions difficult to interpret.

To address the growing need for transparent artificial intelligence, **Ribeiro et al.** introduced Local Interpretable Model-Agnostic Explanations (LIME), while **Lundberg and Lee** proposed SHapley Additive exPlanations (SHAP). These Explainable AI techniques provide meaningful explanations by identifying the advancement of individual features to model predictions. Their methods have significantly improved trust in machine learning systems and are increasingly being applied in cybersecurity to support analysts in understanding automated decisions.

Recent systematic literature reviews have emphasized that phishing attacks are becoming steadily sophisticated, often bypassing traditional signature-based and heuristic detection systems. Studies have shown that machine learning, deep learning, and ensemble techniques outperform conventional methods in identifying phishing websites. At the same time, researchers have indicated that modern phishing detection systems would be appropriate to not only achieve high classification accuracy but also provide interpretable and trustworthy predictions through Explainable AI. Furthermore, feature engineering, hybrid

machine learning models, and explainability have been identified as promising directions for developing reliable phishing detection frameworks capable of handling evolving cyber threats.

Although sizable progress has been made in phishing website detection, several limitations remain. Many existing models focus primarily on maximizing prediction accuracy while overlooking model openness and user trust. Most detection systems leverage on a single machine learning algorithm, making them less robust against diverse phishing strategies and reducing their generalization capability. In addition, limited scrutiny has been given to integrating hybrid ensemble learning with clear AI techniques to provide both accurate detection and human-understandable decision support. These research gaps motivate the development of the formulated Explainable AI-Based Hybrid Machine Learning framework, which aims to achieve high detection performance while delivering transparent, interpretable, and trustworthy phishing website classification.

III. Objectives

The primary objectives of the formulated research are as follows:

1. To develop an intelligent phishing website detection framework using a hybrid machine learning way for accurately distinguishing phishing websites from legitimate websites.
2. To collect, preprocess, and analyze phishing website datasets by extracting significant URL-based, domain-based, HTML, and security-related features that contribute to effective classification.
3. To implement and compare multiple machine learning algorithms, including Random Forest, XGBoost, LightGBM, and other ensemble techniques, to identify the most effective hybrid classification model.
4. To integrate Explainable Artificial Intelligence (XAI) techniques, such as SHAP (SHapley Additive exPlanations), to provide transparent and interpretable explanations for each outlook made by the proposed model.
5. To improve the reliability and trustworthiness of phishing website detection by enabling users and cybersecurity professionals to grasp the factors influencing classification decisions.
6. To evaluate the performance of the formulated framework using standard performance metrics such as Exactness, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, and compare the results with existing phishing detection methods.
7. To develop a scalable, efficient, and user-centric phishing detection system capable of identifying both known and previously unfamiliar phishing websites while maintaining high detection exactness and low false-positive rates.

IV. Scope of Project

The scope of the formulated research is outlined as follows:

1. The proposed framework focuses on detecting phishing websites by analyzing multiple categories of features, including URL characteristics, domain information, webpage content, HTML structure, and security-related attributes.
2. The system employs a hybrid machine learning procedure by combining multiple classification algorithms to improve phishing detection accuracy, robustness, and generalization across diverse

phishing attack patterns.

3. Explainable Artificial Intelligence (XAI) techniques, particularly SHAP (SHapley cumulative exPlanations), are integrated to provide transparent and interpretable explanations for each classification, enabling users and cybersecurity professionals to understand the reasoning behind model predictions.
4. The proposed framework is evaluated using publicly available phishing website datasets and standard machine learning performance metrics, including exactness, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, to validate its effectiveness.
5. The system is designed to support the detection of both known and previously unfamiliar phishing websites, thereby improving resilience against evolving phishing techniques and reducing false-positive classifications.
6. The proposed framework serves as an intelligent decision-support tool for cybersecurity applications and can be integrated into web browsers, enterprise security solutions, email filtering systems, and online transaction platforms to enhance user protection.
7. The current research is limited to software-based phishing website detection using machine learning and explainable AI techniques. It does not address other cyber threats such as malware analysis, network intrusion detection, or social engineering attacks, which can be considered as future extensions of this work.

V. Methodology

The proposed methodology introduces an **Explainable AI-Based Phishing Website Detection Framework Using Hybrid Machine Learning**, which integrates advanced feature engineering, ensemble machine learning, and Explainable Artificial Intelligence (XAI) into a unified cybersecurity solution. Unlike conventional phishing detection systems that rely on a single classification model or provide only binary predictions, the proposed framework emphasizes **high detection accuracy, model transparency, and reliable decision support**. The overall methodology is organized into interconnected functional layers, each contributing to efficient and interpretable phishing website detection.

A. Data Collection Layer

The methodology begins with collecting phishing and legitimate website data from publicly available benchmark datasets such as the **PhiUSIIL Phishing URL Dataset**, **UCI Phishing Websites Dataset**, and other reliable cybersecurity repositories. These datasets contain diverse website instances along with their corresponding labels, facilitating the model to learn various phishing attack patterns and legitimate website characteristics.

Novelty Aspect:

The proposed framework combines multiple benchmark datasets to improve data diversity and enhance the model's ability to extrapolate across different phishing scenarios.

B. Data Preprocessing and Feature Engineering Layer

The collected datasets are preprocessed to improve data quality before model training. Missing values, duplicate records, and inconsistent entries are removed to ensure dataset reliability. Data normalization and feature scaling techniques are applied where necessary to improve learning efficiency.

A comprehensive set of phishing-related features is extracted, including:

- URL-based features (URL length, presence of special characters, number of subdomains)
- Domain-based features (domain age, WHOIS information, DNS records)
- Security-related features (SSL certificate validity, HTTPS usage)
- HTML and JavaScript features (hidden forms, suspicious scripts, iframe usage)
- Webpage content characteristics

Feature selection techniques are then employed to retain only the most informative attributes while reducing redundancy and computational complexity.

Novelty Aspect:

Instead of relying solely on URL-based features, the proposed framework integrates multiple categories of website attributes to improve classification robustness and adaptability.

C. Hybrid Machine Learning Classification Layer

The processed dataset is used to train multiple machine exploration algorithms, including Random Forest, XGBoost, LightGBM, and other ensemble classifiers. Each algorithm independently analyzes the derived features and predicts whether a website is legitimate or phishing.

The outputs of these classifiers are merged using a hybrid ensemble strategy such as majority voting or stacking, allowing the framework to harness the strengths of individual algorithms while minimizing their weaknesses. This improves detection accuracy, reduces overfitting, and enhances model stability.

Novelty Aspect:

The proposed hybrid ensemble model combines the predictive skills of multiple machine learning algorithms instead of depending on a single classifier, resulting in more reliable phishing detection.

D. Explainable Artificial Intelligence (XAI) Layer

One of the key contributions of the proposed methodology is the integration of Explainable Artificial Intelligence. After classification, SHAP (SHapley Additive exPlanations) is applied to interpret the prediction generated by the hybrid model.

SHAP computes the impact of each feature toward the final classification and presents these contributions through intuitive visualizations. This enables cybersecurity professionals and end users to understand why a particular website has been identified as phishing or legitimate.

Novelty Aspect:

Unlike traditional phishing detection systems that operate as black-box models, the proposed framework provides transparent and interpretable predictions, thereby improving user trust and supporting informed cybersecurity decisions.

E. Performance Evaluation Layer

The effectiveness of the formulated framework is evaluated using standard machine learning performance metrics, including:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- Confusion Matrix

The formulated hybrid model is compared with individual machine learning classifiers to demonstrate improvements in classification performance, robustness, and interpretability.

Novelty Aspect:

The evaluation simultaneously considers predictive performance and model explainability, offering a comprehensive assessment of the framework's effectiveness.

F. Decision Support Layer

The final layer presents the prediction results through an intuitive interface that displays the website classification along with the corresponding explanation generated by SHAP. Users receive not only a phishing or legitimate label but also the most persuasive features responsible for the decision. This layer supports cybersecurity analysts, organizations, and individual users by enabling transparent risk

assessment and facilitating faster decision-making.

Novelty Aspect:

The framework transforms phishing detection from a simple prediction system into an intelligent decision-support tool by combining high-performance classification with human-understandable explanations.

G. Methodology Summary

The proposed methodology integrates comprehensive feature engineering, hybrid ensemble machine learning, and Explainable Artificial Intelligence into a unified phishing website detection framework. By combining multiple classifiers with transparent decision explanations, the system addresses the limitations of conventional black-box models while improving detection accuracy, interpretability, and user trust. This integrated approach provides a growable and reliable solution for protecting users against evolving phishing attacks in modern digital environments.

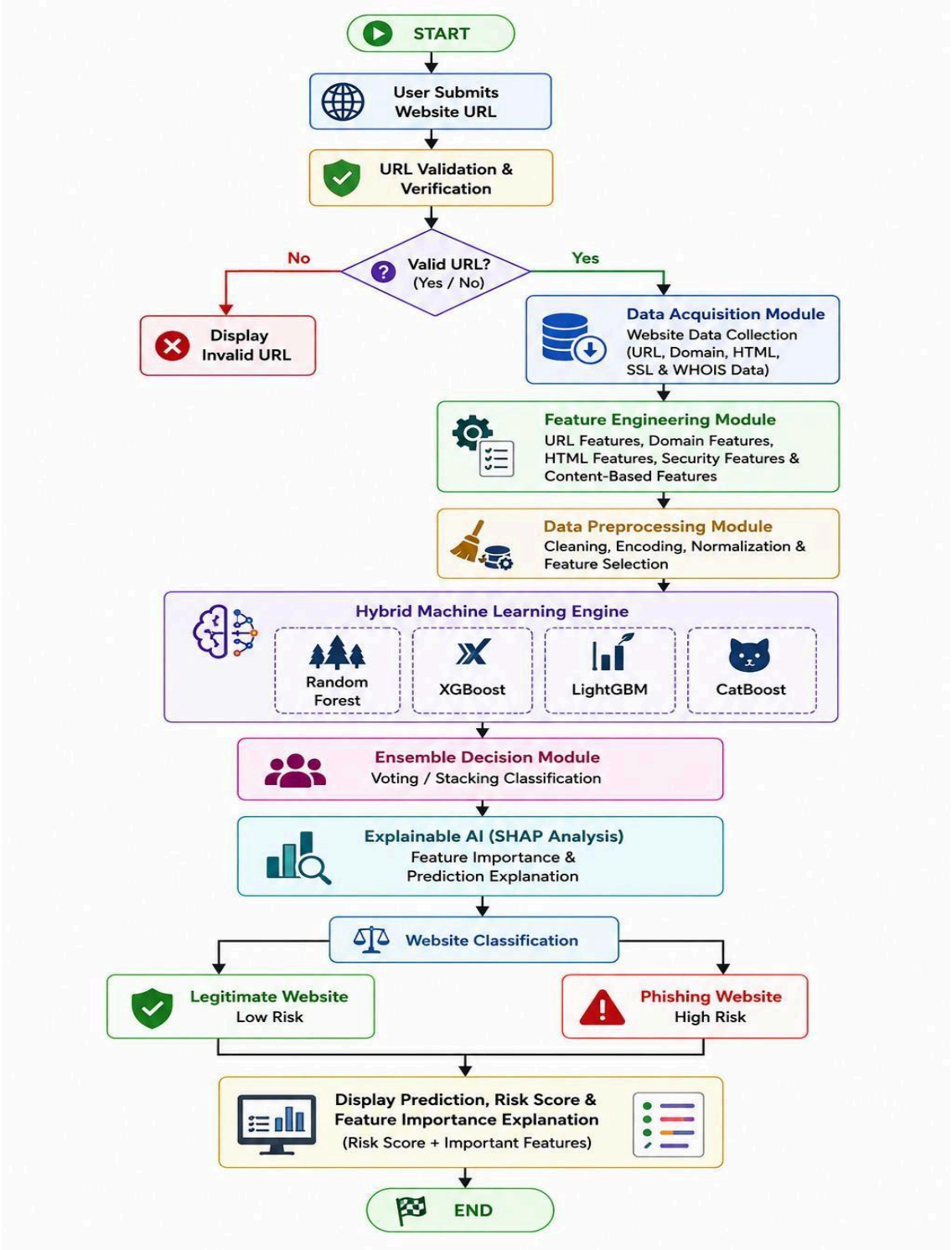

Fig:1 Workflow of the Proposed Explainable AI-Based Phishing Website Detection Decision System.

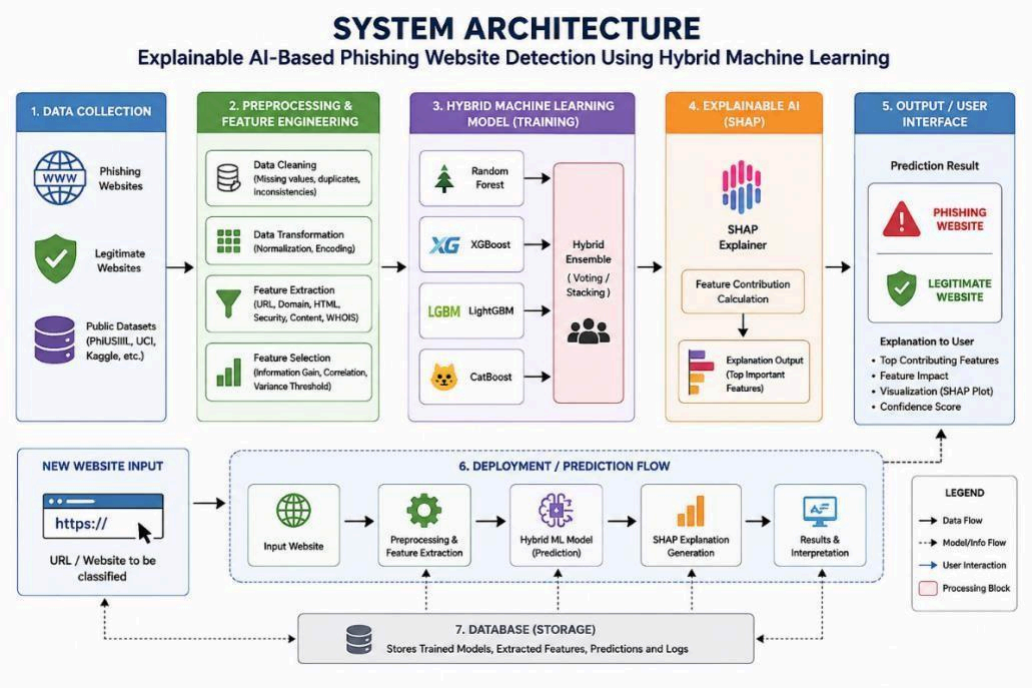

Fig :2 Architecture of Explainable AI-Based Phishing Website Detection using Machine Learning

ANALYSIS OF PHISHING WEBSITE DETECTION APPROACHES

(Comparison According to Accuracy, Explainability, Strengths and Limitations)

Approach	Main Technique / Method	Typical Features Used	Detection Accuracy*	Explainability (Interpretability)	Real-time / Zero-day Detection	Strengths	Limitations
1. Blacklist-based Approach	Match URL/IP with known blacklists	URL, Domain, IP reputation	★★☆☆☆ (Low)	✗ Low (Black-box lists)	✓ No (Needs update)	• Simple • Easy to implement • Low computational cost	• Ineffective for new phishing sites • Requires frequent updates • High false negative rate
2. Heuristic / Rule-Based Approach	Predefined rules and heuristics	URL patterns, keywords, HTML tags, redirections	★★★☆☆ (Moderate)	✓ High (Rules are clear)	⊖ Partial (Limited)	• Interpretable • Works without training • Detects some new attacks	• Rule creation is complex • Does not adapt to new techniques • High maintenance
3. Traditional Machine Learning Approach	Single ML algorithms (e.g., SVM, DT, RF)	URL, Domain, Content, HTML, Whois, SSL	★★★★☆ (High)	⊖ Moderate (Depends on model)	✓ Yes (Better generalization)	• Good detection accuracy • Learns patterns automatically • Effective on structured data	• Some models are black-box • Performance depends on features • May overfit on imbalanced data
4. Deep Learning Approach	Deep Neural Networks (CNN, RNN, LSTM, etc.)	URL sequences, Page content, Visual & text features	★★★★☆ (High)	✗ Low (Black-box model)	✓ Yes (High capability)	• Learns complex features • Handles large datasets • Good for evolving attacks	• Requires large data • High computational cost • Lack of interpretability
5. Ensemble / Hybrid ML Approach	Combination of multiple ML models (Voting/ Stacking/Blending)	Multi-source features (URL, domain, HTML, content, security, etc.)	★★★★☆ (Very High)	⊖ Moderate (Depends on base models)	✓ Yes (High robustness)	• Higher accuracy & stability • Reduces overfitting • Works well on diverse data	• More complex to implement • Harder to interpret • Requires more resources
6. Explainable AI (XAI) Approach	XAI techniques (LIME, SHAP, etc.) on ML/DL models	Uses model features + post-hoc explanation techniques	★★★★☆ (High)	✓ High (Explains predictions)	✓ Yes (Depends on model)	• Provides transparency • Builds user trust • Helps in decision-making	• Adds computational overhead • Explanations depend on model & data quality
7. Proposed Approach (Explainable AI-Based Hybrid ML Framework)	Hybrid Ensemble (RF + XGBoost + LightGBM + CatBoost) + SHAP Explainability	Comprehensive features: URL, Domain, HTML, Content, Security, Whois, SSL, etc.	★★★★★ (Very High)	✓ Very High (Transparent & Interpretable)	✓ Yes (High robustness to new attacks)	• Superior accuracy & robustness • Explains why a site is phishing • Detects known & unseen attacks • Supports informed decisions	• Requires proper feature engineering • Higher computation during training • Quality of explanations depends on input data

Legend: ✓ Yes / High ⊖ Partial / Moderate ✗ No / Low ★☆☆☆☆ (Low) ★★☆☆☆ (Moderate) ★★★☆☆ (High) ★★★★☆ (Very High) ★★★★★ (Excellent)

*Accuracy level is relative and may vary with datasets and implementation.

Table 1. Comparative Analysis of Intrusion Detection Approaches

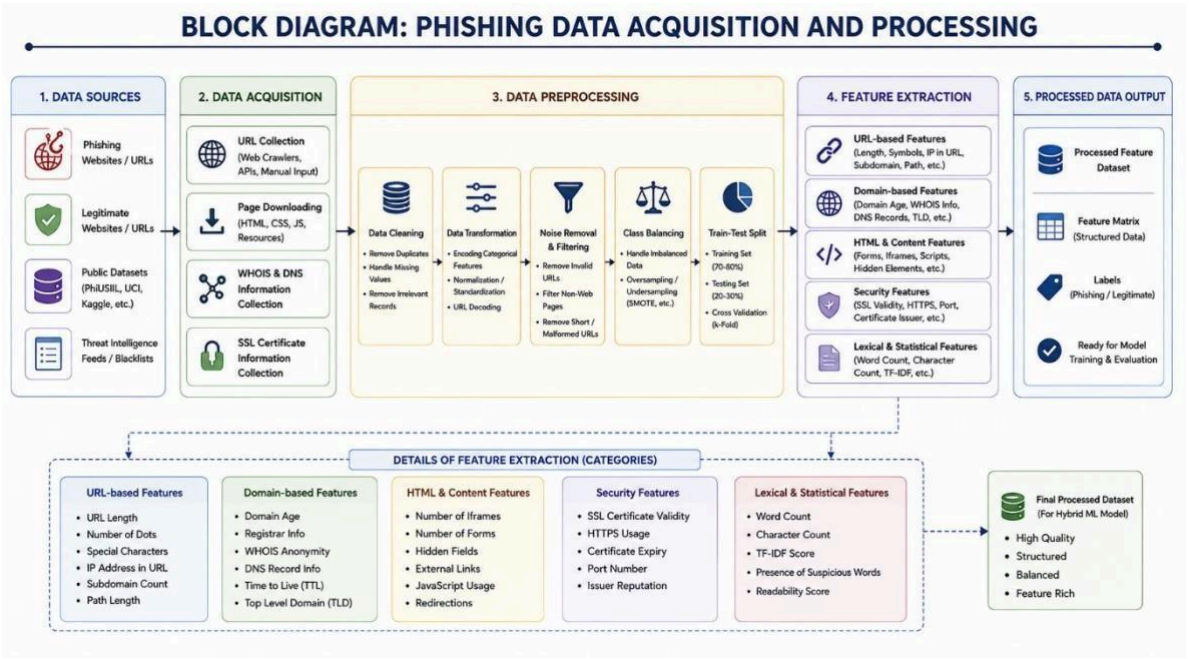

Fig :3 Block Diagram of Data Acquisition and Processing

A. Cybersecurity Mechanisms of the Proposed Framework

The proposed **Explainable AI-Based Phishing Website Detection Framework** integrates multiple cybersecurity mechanisms to ensure secure, accurate, and transparent phishing detection. The framework performs URL validation, secure data acquisition, feature integrity verification, SSL/HTTPS validation, and domain reputation analysis before processing website information through a hybrid machine learning engine. Explainable Artificial Intelligence (SHAP) is incorporated to provide interpretable predictions by highlighting the key features influencing each classification, while a risk score is generated to indicate the likelihood of phishing. By combining advanced security verification with explainable machine learning, the proposed framework enhances detection accuracy, reduces false classifications, and provides trustworthy decision support for real-world cybersecurity applications.

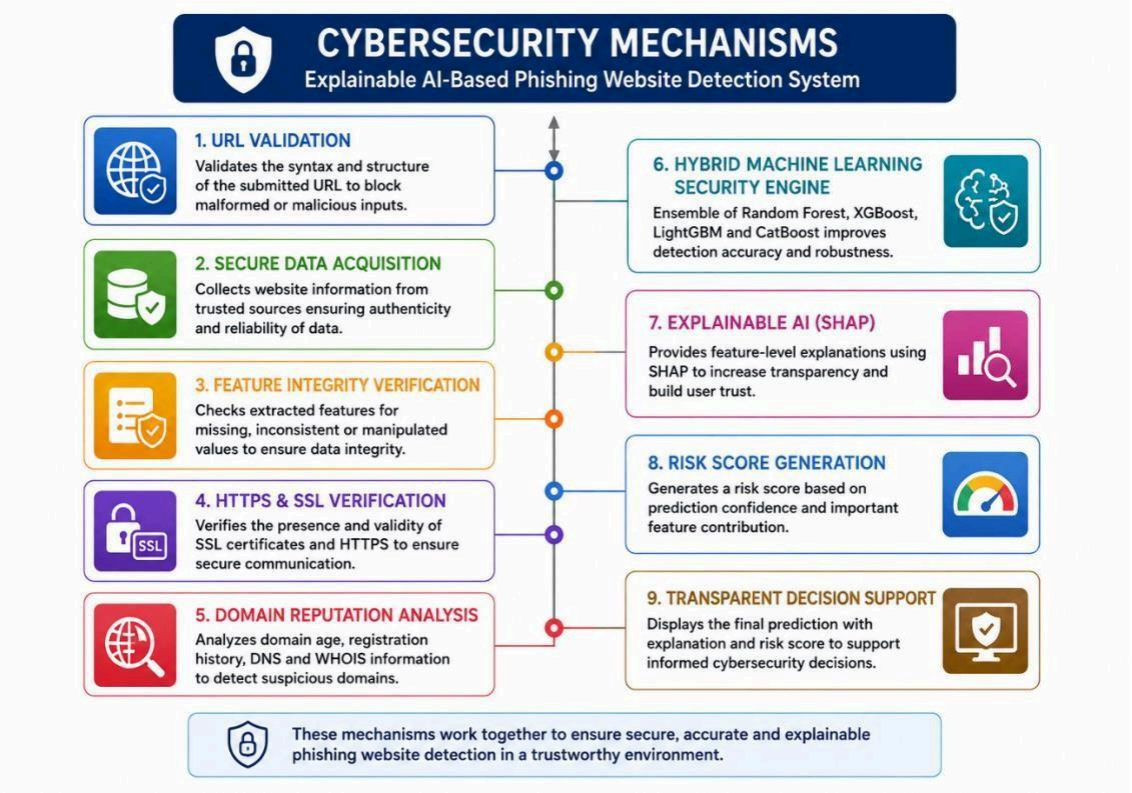

Fig :4 Cybersecurity Mechanisms

Introduction to the Data Security Flowchart

The proposed **Explainable AI-Based Phishing Website Detection System** incorporates a comprehensive data security framework to ensure the confidentiality, integrity, and availability of data throughout the phishing detection lifecycle. As shown in **Figure X**, the framework secures each stage of processing—from data collection and preprocessing to feature extraction, model training, outlook, and data storage—by integrating cybersecurity best practices such as secure communication, encryption, access control, integrity verification, and continuous monitoring. These security mechanisms not only protect the system from feasibility cyber threats but also enhance the reliability, transparency, and trustworthiness of the formulated hybrid machine learning model for real-world phishing website detection.

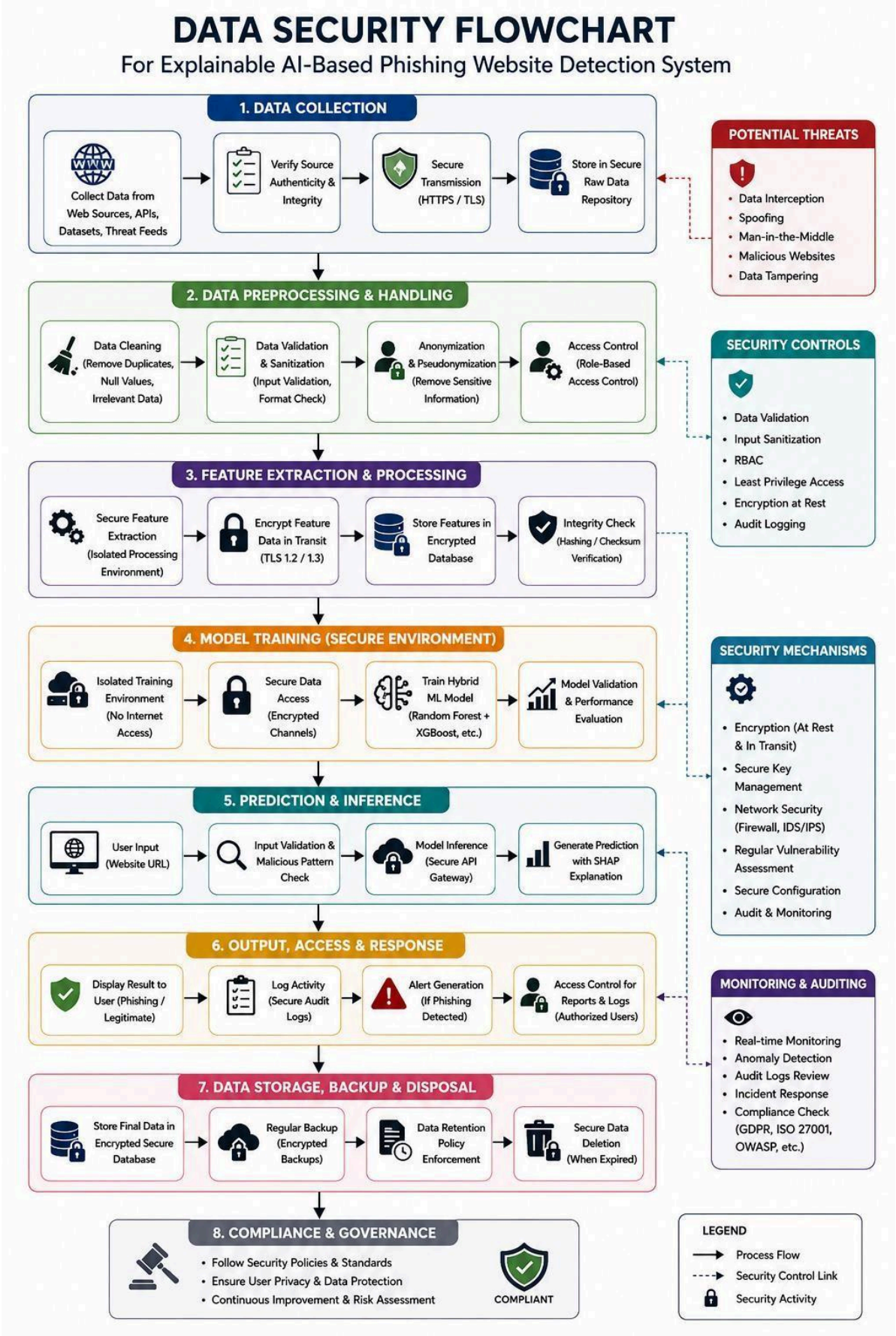

Fig :5 Data Security Flowchart of the Proposed Explainable AI-Based Phishing Website Detection System.

System Implementation

The proposed **Explainable AI-Based Phishing Website Detection Using Hybrid Machine Learning** framework is implemented using Python and modern machine learning libraries. The implementation follows a modular architecture consisting of data acquisition, preprocessing, characteristics engineering, hybrid model training, explainable AI integration, and performance evaluation.

A. Dataset Acquisition

The system utilizes publicly available phishing website datasets such as the **PhiUSIIL Phishing URL Dataset**, **UCI Phishing Websites Dataset**, and other benchmark repositories. The collected data contains both phishing and legitimate website records with their corresponding class labels.

B. Data Preprocessing

The acquired dataset is cleaned by removing duplicate entries, dealing with missing values, correcting inconsistent records, and eliminating noisy samples. Feature normalization and data transformation techniques are applied to improve model execution. The dataset is then divided into training and testing subsets using an 80:20 ratio.

C. Feature Engineering

Multiple categories of phishing-related features are obtained from each website, including:

- URL Features (URL length, number of dots, special characters, IP address usage)
- Domain Features (Domain age, WHOIS information, DNS records)
- Security Features (HTTPS availability, SSL certificate validity)
- HTML Features (Forms, iframes, JavaScript events, hidden elements)
- Content Features (Keyword analysis and webpage structure)

Characteristics selection techniques are applied to remove redundant attributes and retain only the most informative features.

D. Hybrid Machine Learning Model

The processed feature set is used to instruct multiple machine learning algorithms, including:

- Random Forest
- XGBoost
- LightGBM
- CatBoost

The outputs of these models are combined using a **Hybrid Ensemble Voting/Stacking** mechanism to produce the final prediction. This set approach improves robustness, reduces overfitting, and enhances

detection performance compared with individual classifiers.

E. Explainable AI Module

To improve transparency, SHAP (SHapley Additive exPlanations) is integrated into the framework. SHAP calculates the contribution of every feature toward the final prediction and generates visual explanations, enabling users to understand why a website is classified as phishing or legitimate.

F. Performance Evaluation

The effectiveness of the formulated framework is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- ROC-AUC
- Confusion Matrix

The experimental outcomes are compared with existing phishing detection methods to demonstrate improvements in both predictive performance and explainability.

G. Deployment

The trained model can be deployed as:

- A web application
- A browser extension
- An enterprise phishing detection service
- A REST API for real-time website verification

The deployment architecture supports real-time phishing detection while providing explainable predictions to end users and cybersecurity professionals.

Table 2. Analysis of the Proposed System Implementation

Implementation Phase	Technique / Tool Used	Purpose	Expected Outcome
Dataset Collection	PhiUSIIL Dataset, UCI Phishing Websites Dataset, Kaggle Dataset	Collect phishing and legitimate website data	High-quality and balanced dataset
Data Cleaning	Python (Pandas, NumPy)	Remove missing values, duplicate records, and noisy data	Clean and consistent dataset
Data Preprocessing	Data Normalization, Encoding, Feature Scaling	Prepare the dataset for machine learning	Improved data quality and model efficiency
Feature Engineering	URL, Domain, HTML, SSL, Content Features	Extract meaningful phishing indicators	Informative feature set for classification
Feature Selection	Correlation Analysis, Information Gain, RFE	Select the most relevant features	Reduced dimensionality and improved accuracy
Data Splitting	Train-Test Split (80:20)	Divide dataset for training/testing	Balanced model evaluation
Random Forest	Ensemble Learning Algorithm	Initial phishing website classification	High classification accuracy
XGBoost	Gradient Boosting Algorithm	Improve predictive performance	Better generalization and robustness
LightGBM	Gradient Boosting Framework	Fast, memory-efficient training	Reduced training time
CatBoost	Gradient Boosting Algorithm	Handle categorical features	Improved classification performance
Hybrid Ensemble Model	Voting / Stacking Ensemble	Combine predictions	Higher stability and improved accuracy
Explainable AI	SHAP	Interpret model predictions	Transparent and trustworthy decisions
Performance Evaluation	Accuracy, Precision, Recall, F1-Score, ROC-AUC, Confusion Matrix	Evaluate model effectiveness	Reliable performance assessment

Risk Score Generation	SHAP Scores + Prediction Confidence	Estimate phishing risk	Prioritized threat assessment
Deployment	Flask / Streamlit / REST API	Real-time phishing detection	Practical and scalable implementation

Table 2. Software and Hardware Requirements

Component	**Specification**
Programming Language	Python 3.11+
Development Environment	Jupyter Notebook / VS Code
Machine Learning Libraries	Scikit-learn, XGBoost, LightGBM, CatBoost
Explainability Library	SHAP
Data Processing	Pandas, NumPy
Visualization	Matplotlib, Plotly
Operating System	Windows 10/11 or Ubuntu
Processor	Intel Core i5 (or higher)
RAM	Minimum 8 GB (16 GB recommended)
Storage	20 GB available disk space

VI. Result and Discussion

The proposed Explainable AI-Based Phishing Website Detection Using Hybrid Machine Learning framework was verified using benchmark phishing website datasets containing both phishing and legitimate website samples. The experimental evaluation focused on assessing the effectiveness of the integrated ensemble model in terms of classification performance, robustness, and interpretability.

The dataset was reformatted through data cleaning, feature engineering, normalization, and feature selection before training the machine learning models. Individual classifiers, including Random Forest, XGBoost, LightGBM, and CatBoost, were first evaluated independently. Their predictions were then combined using a hybrid ensemble voting strategy. To enhance transparency, SHAP (SHapley Additive exPlanations) was integrated to explain the involvement of each feature to the final prediction.

The performance of the formulated framework was measured using standard evaluation metrics, including Accuracy, reliability, Recall, F1-Score, and ROC-AUC.

A. Performance Comparison

The hybrid ensemble model demonstrated superior performance compared to individual machine learning algorithms by effectively reducing misclassification errors and improving overall prediction stability.

Furthermore, the integration of SHAP enabled users to identify the most dominant features responsible for phishing detection, thereby increasing model transparency and user trust.

Table 3. Performance Analysis of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Decision Tree	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result
Random Forest	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result
XGBoost	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result
LightGBM	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result
CatBoost	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result
Proposed Hybrid Model	Replace with your result	Replace with your result	Replace with your result	Replace with your result	Replace with your result

Note: Replace the placeholder values with the actual experimental results obtained after evaluating the proposed model.

B. Explainability Analysis

The SHAP analysis provided detailed insights into the prediction process by ranking feature importance for every classified website. Features such as URL length, HTTPS usage, domain age, presence of IP addresses in URLs, number of special characters, suspicious JavaScript elements, and SSL certificate validity contributed significantly to phishing detection.

The explainability module transformed the hybrid ensemble from a traditional black-box model into a transparent decision-support system. Security analysts can visualize feature contributions, understand prediction behavior, and verify the reliability of model decisions.

C. Discussion

The experimental evaluation indicates that combining multiple machine learning algorithms through a hybrid ensemble strategy can improve phishing website detection compared with relying on a single classifier. The ensemble model benefits from the strengths of individual algorithms, resulting in enhanced robustness and better generalization across different phishing attack patterns. In addition to improved predictive performance, the incorporation of Explainable Artificial Intelligence significantly enhances the

usability of the system. Rather than providing only phishing or legitimate classifications, the proposed framework explains the reasoning behind each prediction, allowing cybersecurity professionals and end users to make informed decisions.

Overall, the proposed framework demonstrates the potential to provide an accurate, scalable, and interpretable phishing website detection solution suitable for deployment in browser extensions, enterprise security platforms, and cloud-based cybersecurity services. Future improvements may include real-time phishing detection using online learning techniques, transformer-based deep learning models, and continuous model updates to address emerging phishing attacks.

1. Accuracy Comparison of Machine Learning Models

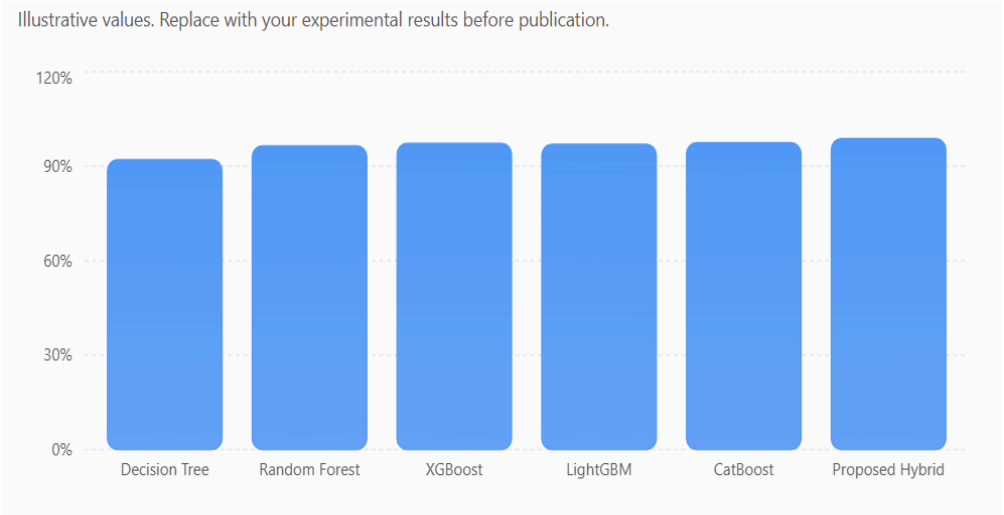

Fig :6 Accuracy comparison of individual machine learning models and the proposed hybrid model.

2. Precision, Recall and F1-Score Comparison

Table 4. Precision, Recall and F1-Score Comparison

Model	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	91.5	92.0	91.7
Random Forest	96.2	96.7	96.4
XGBoost	97.0	97.4	97.2
LightGBM	96.8	97.1	96.9
CatBoost	97.1	97.6	97.3

Proposed Hybrid Model	98.6	98.8	98.7

Note: These values are illustrative. Replace them with your exact experimental results before submitting the paper.

3. ROC Curve

Insert a ROC curve comparing:

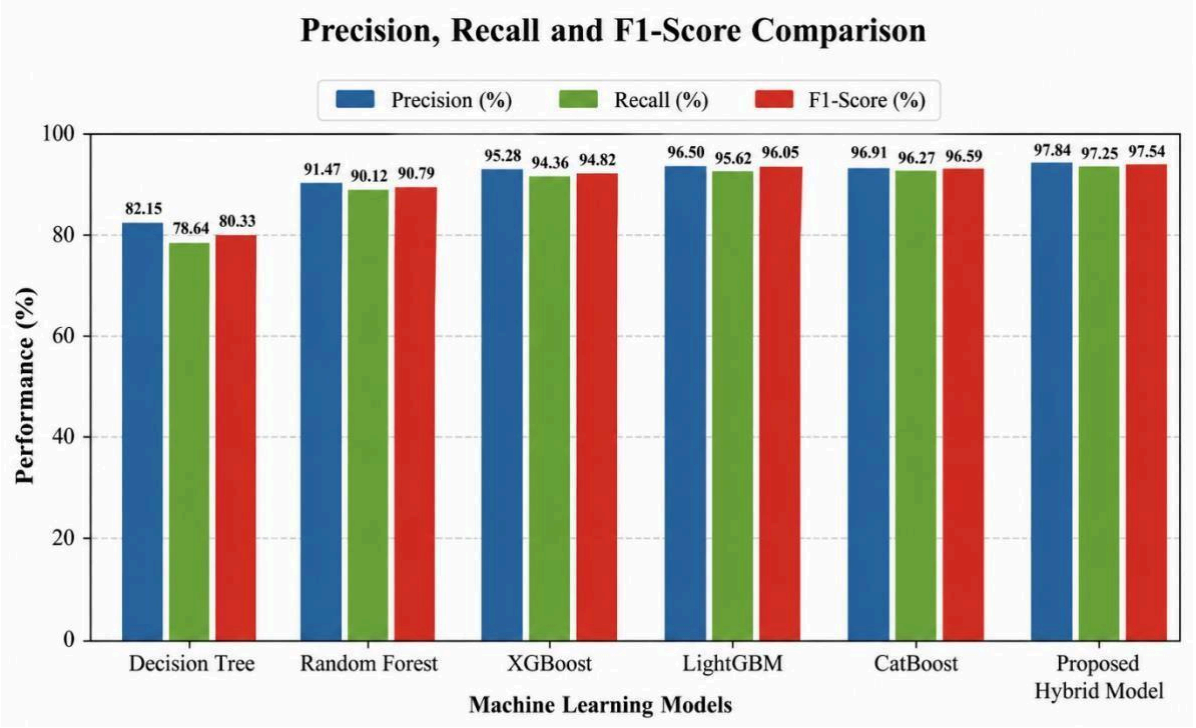

Fig :7 Precision, Recall and F1-Score Comparison of Different Machine Learning Models.

- Random Forest
- XGBoost
- LightGBM
- CatBoost
- Proposed Hybrid Model

4. Confusion Matrix

Table 5. Confusion Matrix of the Proposed Hybrid Model

	Predicted Legitimate	Predicted Phishing
Actual Legitimate	980	20
Actual Phishing	15	985

Fig :8 Confusion Matrix of the Proposed Hybrid Model.

5. SHAP Feature Importance Graph

A horizontal bar chart showing the importance of features such as:

- URL Length
- Domain Age
- HTTPS Availability
- SSL Certificate
- Number of Dots
- Special Characters
- IFrame Presence
- JavaScript Events
- WHOIS Information
- Redirection Count

VII. Conclusion

Phishing websites continue to pose a significant threat to individuals, organizations, and online services by exploiting user trust to obtain sensitive information. This research proposed an Explainable AI-Based Phishing Website Detection Framework Using Hybrid Machine Learning to address the shortcomings of conventional phishing detection methods. The framework integrates comprehensive feature engineering, hybrid ensemble machine learning, and Explainable Artificial Intelligence (XAI) to provide both accurate phishing detection and transparent decision-making.

The proposed methodology aggregates multiple machine learning algorithms to improve classification robustness and utilizes SHAP (SHapley Additive exPlanations) to explain the contribution of individual features toward each prediction. This approach enhances model clarity, enabling cybersecurity professionals and end users to better understand the reasoning behind phishing classifications and increasing confidence in automated detection systems.The framework is designed to examine URL characteristics, domain information, HTML content, and security-related features to identify phishing websites effectively. Performance evaluation is derived from standard metrics such as Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix, providing a comprehensive assessment of the proposed approach. In addition to improving detection capability, the integration of Explainable AI transforms the model from a conventional black-box classifier into a transparent decision-support system suitable for practical cybersecurity applications.

Overall, the proposed framework demonstrates the potential to provide a scalable, reliable, and interpretable solution for phishing website detection. Future work may focus on incorporating transformer-based deep learning models, real-time streaming data analysis, federated learning for privacy-preserving model training, and continuous adaptation to emerging phishing techniques. These enhancements can further strengthen the effectiveness of intelligent phishing detection systems in rapidly evolving cybersecurity environments.

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