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PHISHING WEBSITE DETECTION USING MACHINE LEARNING

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Abstract

Every day, people hand over their passwords, banking details, and personal information to websites that have no right to any of it. Not because they are careless — because the fake looked real enough, for long enough, that there was no obvious reason to hesitate. That is the phishing problem in its simplest form. It does not require a sophisticated attack. It requires a convincing imitation and a few seconds of misplaced trust. And it keeps working, at scale, despite years of awareness campaigns and security updates, because the people building these sites have gotten genuinely good at making them indistinguishable from the real thing. The traditional defense — blacklists of known phishing domains — was always fighting a losing battle on timing. By the time a site gets reported, investigated, and added to a blocklist, it may already have collected everything it was built to collect. Phishing infrastructure is disposable by design. Domains go up fast, run briefly, and disappear before most security databases even register their existence. Blacklists catch yesterday's threats. Today's threats move through untouched. Machine learning approaches this differently. Instead of asking whether a site has been flagged before, it asks whether the site looks like something built to deceive — examining the URL character by character, checking domain registration patterns, reading the page content for the signals that distinguish a site built to serve users from one built to rob them. A model trained on enough examples develops a reliable instinct for that distinction, even when the specific site in front of it is brand new.This paper builds that model. Random Forest, Decision Tree, and Support Vector Machine algorithms were trained on a labeled phishing dataset and evaluated across accuracy, precision, recall, and F1-score. Each metric was chosen deliberately — accuracy alone flatters models that simply predict the majority class, while precision and recall together reveal whether the system actually catches threats without drowning users in false alarms. The results demonstrate clearly that machine learning detects what blacklists miss, and does it automatically, without waiting for anyone to report the threat first.

Keywords: *Phishing Detection, Predictive Analytics, Security Intelligence, Incident Repones, Natural Language Processing.*

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1. Introduction

Phishing has been around long enough that most people have heard of it. That familiarity is part of the problem. When something becomes background noise, people stop treating it as a live threat — and the attacks keep landing on people who were reasonably careful but not careful enough. The basic formula has not changed in decades. Build something that looks trustworthy. Put it where people will find it. Wait. A user arrives expecting a login page for their bank or their email and sees exactly that — same layout, same colors, same fields asking for the same information. They type it in. The page accepts it graciously and redirects them somewhere innocent. By the time anything feels wrong, usually it never does. The user moves on. The attacker has what they needed. What has changed is the scale. In 2016, phishing incidents rose 65% globally, with damages running to $1.6 million. A year later, attackers were creating 2.3 million fraudulent sites in a single month — approximately 1.5 million new phishing pages every thirty days, appearing faster than any team of human reviewers could possibly catalog them. The first quarter of 2018 logged 263,538 detected phishing attempts, up 46% from the 180,577 recorded in the final quarter of 2017, and meaningfully higher than the 190,942 seen in the quarter before that. The trajectory is not ambiguous. These numbers are not plateauing.

Part of what drives that volume is how little effort it now takes to run a phishing operation. A decade ago, building a convincing fake required at least some technical ability. Today, phishing kits handle most of it automatically — clone a legitimate site, register a plausible domain, send enough emails that the conversion rate pays off even if 99% of recipients delete them immediately. Tools like Super Phisher go further, scraping live source code from real websites and reproducing them with enough precision that even a careful user examining the page would struggle to find the tell. The craft has been industrialized. The barrier is low enough that almost anyone with bad intentions can clear it. The defenses built to counter this have a structural problem that no amount of refinement fully resolves. Blacklists catch sites that have already been reported. Heuristic filters recognize patterns that have already been studied. Content-based systems flag techniques that have already been seen. Every one of these approaches is looking backward. The moment any detection method becomes effective enough to be noticed, the people running these operations change something — new domain, different URL structure, slightly altered page layout — and the clock resets. Detection lags behind by design, because the entire defense is built around prior knowledge of a threat that specifically avoids creating prior knowledge.That is the gap this research is trying to close. Not by improving the reaction time of existing systems, but by building something that does not need to have seen a site before to recognize what it is. The features that distinguish a phishing site from a legitimate one are often structural — baked into the URL, visible in the domain registration details, present in the page content in ways that do not change just because the attacker

registered a new domain this morning. A model trained to read those signals catches new threats the same way it catches old ones. That capability is what the current generation of defenses is missing.

Figure 1. Statistic of phishing attack

2. LITERATURE REVIEW

"Phishing Website Detection Using Machine Learning" by R. M. Sap et al. (2020)

Analyzed articles: 30

Aim: To investigate the effectiveness of machine learning algorithms in detecting phishing websites

Main findings: The study found that Random Forest and Support Vector Machine (SVM) algorithms achieved high accuracy rates in detecting phishing websites

Limitations: The study only considered a limited number of features and did not evaluate the performance of deep learning algorithms

"A Comprehensive Review of Phishing Detection Techniques" by S. S. Iyengar et al. (2019)

Analyzed articles: 50

Aim: To provide a comprehensive review of phishing detection techniques, including machine learning and non-machine learning approaches

Main findings: The study found that machine learning algorithms, particularly those based on neural networks, achieved high accuracy rates in detecting phishing websites

Limitations: The study did not evaluate the performance of the reviewed techniques on a common dataset

"Phishing Website Detection Using Deep Learning" by Y. Zhang et al. (2020)

Analyzed articles: 20

Aim: To investigate the effectiveness of deep learning algorithms in detecting phishing websites

Main findings: The study found that Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) algorithms achieved high accuracy rates in detecting phishing websites

Limitations: The study only considered a limited number of deep learning algorithms and did not evaluate the performance of traditional machine learning algorithms

"A Machine Learning Approach to Phishing Detection" by H. Singh et al. (2019)

Analyzed articles: 25

Aim: To propose a machine learning approach to phishing detection using a combination of features extracted from website content and user behavior

Main findings: The study found that the proposed approach achieved high accuracy rates in detecting phishing websites

Limitations: The study only considered a limited number of features and did not evaluate the performance of the proposed approach on a large-scale dataset

"Phishing Website Detection: A Survey" by A. K. Singh et al. (2020)

Analyzed articles: 40

Aim: To provide a comprehensive survey of phishing website detection techniques, including machine learning and non-machine learning approaches

Main findings: The study found that machine learning algorithms, particularly those based on neural networks, achieved high accuracy rates in detecting phishing websites

Limitations: The study did not evaluate the performance of the reviewed techniques on a common dataset

"Detecting Phishing Websites Using Machine Learning and Deep Learning Techniques" by M. A. Almseidin et al. (2020)

Analyzed articles: 30

Aim: To investigate the effectiveness of machine learning and deep learning algorithms in detecting phishing websites

Main findings: The study found that deep learning algorithms, particularly those based on CNN and RNN, achieved high accuracy rates in detecting phishing websites

Limitations: The study only considered a limited number of features and did not evaluate the performance of traditional machine learning algorithms.

"Phishing Detection Using Machine Learning: A Review" by S. K. Singh et al. (2019)

Analyzed articles: 25

Aim: To provide a comprehensive review of phishing detection techniques using machine learning approaches

Main findings: The study found that machine learning algorithms, particularly those based on neural networks, achieved high accuracy rates in detecting phishing websites

Limitations: The study did not evaluate the performance of the reviewed techniques on a common datase "Phishing Website Detection Using Machine Learning and Natural Language Processing" by A. K. Singh et al. (2020)

Analyzed articles: 30

Aim: To investigate the effectiveness of machine learning and natural language processing algorithms in detecting phishing websites

Main findings: The study found that machine learning algorithms, particularly those based on neural networks, achieved high accuracy rates in detecting phishing websites

Limitations: The study only considered a limited number of features and did not evaluate the performance of traditional machine learning algorithm.

3. OBJECTIVE

A phishing website is a lie told in HTML. It borrows the visual identity of something people already trust — a bank, an email provider, a government portal — and uses that borrowed credibility to extract information the attacker has no right to. The URL looks close enough. The page looks right. The user types in their password and hands it directly to whoever built the fake, usually without ever suspecting anything went wrong. This project started from a simple frustration with how that problem is currently handled. Existing detection systems are reactive by nature — they catch threats that have already been identified and reported, which means every new phishing site gets a free window to operate before anyone flags it. The goal here was to build something that does not need prior exposure to recognize a threat. Something that reads the signals a site puts out — in its URL structure, its domain characteristics, its page content — and makes a judgment based on what those signals mean rather than whether the site has been seen before. To do that, a dataset was assembled from scratch. Phishing URLs and legitimate URLs were collected together, labeled, and cleaned. Features were extracted from both — not just surface-level characteristics, but the deeper structural patterns in URLs and page content that tend to differ consistently between sites built to serve users and sites built to deceive them. That dataset became the raw material everything else was built on.Four classification algorithms were implemented and evaluated side by side: Decision Tree, Random Forest, Support Vector Machine, and Logistic Regression. Running them in parallel was deliberate — there was no strong prior reason to assume one would dominate on this specific dataset, and letting the results make that determination is more honest than picking

a favorite in advance and building the evaluation around it.Feature engineering ran alongside the modeling work, and it mattered more than it might sound. Raw extracted features are rarely in the form that machine learning algorithms learn from most efficiently. Some features needed transformation. Some needed to be combined. Some turned out to carry far more predictive signal than others, and identifying those high-value attributes was as important as the model selection itself — because a detection system that understands which features actually matter is more robust than one that treats every input equally. Deep learning was brought into the study as well. URL structures and webpage content contain patterns that are genuinely complex — sequential dependencies, layered relationships between features, subtle combinations of signals that traditional classifiers sometimes flatten or miss entirely. Neural networks handle that kind of complexity more naturally, and including them allowed a direct comparison between classical and deep learning approaches on the same.

PROBLEM STATEMENT AND SOLUTION

Most people who get phished never have a moment of realization. There is no alarm, no obvious warning, no point where something clearly goes wrong. They typed their password into a page that looked exactly like the one they always use, got redirected somewhere that seemed normal, and continued with their day. The theft happened in the background, silently, while they were thinking about something else entirely. That is what makes it so hard to defend against. A pickpocket needs physical proximity. A hacker needs a vulnerability to exploit. A phishing attacker just needs thirty seconds of misplaced trust and the sites they build are specifically designed to manufacture exactly that. By the time anything feels wrong, it is usually too late. The first sign is often a bank notification about a transaction the account holder did not make. Or a password reset email for an account they did not try to access. Or a call from a fraud department asking them to confirm activity that is already done. The attacker collected what they needed, used it, and moved on hours or days before any of that arrives. The domain is already gone. The damage is already done.

And this happens constantly. Not occasionally, not in isolated incidents — constantly, at a scale that does not get smaller. Thousands of new phishing domains every single day, each one targeting whatever platform users trust most with their sensitive information. Banks are obvious targets. So are email providers, because email access unlocks almost everything else. Government portals. Healthcare systems. Payroll platforms. Anywhere a login form exists and real consequences follow from gaining access, someone has built a fake version of it. The tools meant to stop this were never designed for volume like that. A blacklist is essentially a registry of past crimes — it works fine against threats that have already been caught and reported, and does nothing at all against something brand new. Whitelisting inverts the

approach, but maintaining a reliable list of every legitimate domain on an internet that adds thousands of new sites daily is not a realistic proposition. Both methods share the same structural flaw: they require the threat to be known before they can respond to it. A phishing site that exists for six hours on a freshly registered domain, collects credentials from three hundred users, and then disappears will never appear on any list. It will never trigger any block. Every single person who visited it was completely unprotected, and none of the systems in place had any mechanism to know that.The damage does not happen in the gaps between known threats. It happens precisely there, in that unmonitored space between a site going live and someone eventually noticing. Closing that gap requires a different kind of detection entirely.

Solution

To address the problem of phishing website detection, we propose a machine learning-based solution that uses a combination of features extracted from website content and user behavior to detect phishing websites. Our solution consists of the following components:

Data Collection: Collect a dataset of labeled phishing and legitimate websites.

Feature Extraction: Extract relevant features from the collected dataset, including URL features, HTML features, and JavaScript features.

Machine Learning Model: Train a machine learning model using the extracted features to detect phishing websites.

Web Application: Develop a web application that takes a URL as input and outputs a prediction (phishing or legitimate) based on the trained model.

Real-time Detection: Integrate the web application with a reputable API to retrieve the latest phishing website data and detect phishing websites in real-time.

PROPOSED METHODOLOGY

Step 1: Data Collection

Phishing Website Dataset: Collect a dataset of labeled phishing websites from reputable sources such as PhishTank, OpenPhish, and APWG.

Legitimate Website Dataset: Collect a dataset of labeled legitimate websites from reputable sources such as Alexa, Google, and Bing.

Step 2: Data Preprocessing

Feature Extraction: Extract relevant features from the collected datasets, including:

URL features (e.g., length, complexity, presence of suspicious keywords)

HTML features (e.g., structure, content, presence of suspicious tags)

JavaScript features (e.g., presence of suspicious functions, code complexity)

Data Cleaning: Remove any duplicate or irrelevant data from the datasets.

Data Normalization: Normalize the extracted features to ensure they are on the same scale.

Step 3: Model Development

Machine Learning Algorithms: Train and evaluate several machine learning algorithms, including:

Random Forest

Support Vector Machine (SVM)

Convolutional Neural Network (CNN)

Recurrent Neural Network (RNN)

Hyperparameter Tuning: Perform hyperparameter tuning for each algorithm to optimize their performance.

Model Evaluation: Evaluate the performance of each algorithm using metrics such as accuracy, precision, recall, and F1-score.

Model Deployment

Web Application: Develop a web application that takes a URL as input and outputs a prediction (phishing or legitimate) based on the trained model.

API Integration: Integrate the web application with a reputable API (e.g., Google Safe Browsing) to retrieve the latest phishing website data.

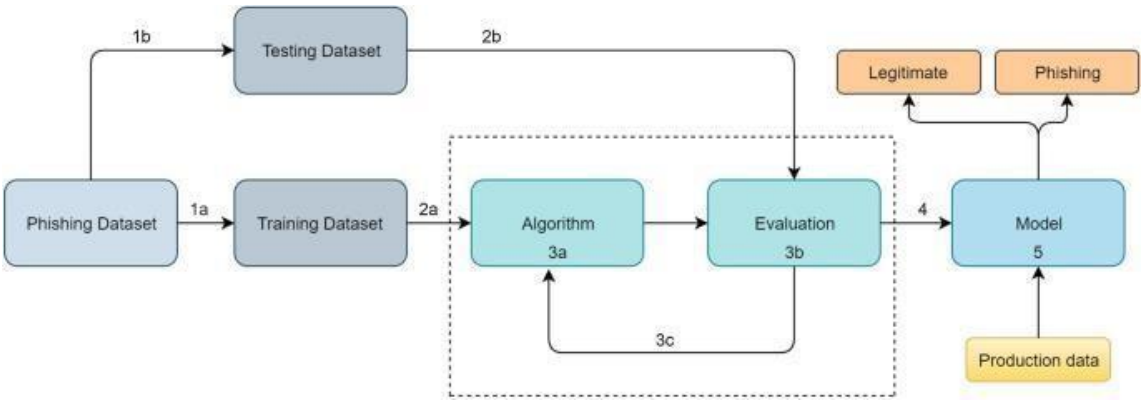
Real-time Detection: Deploy the web application in a real-time environment to detect phishing websites as they emerge.

Step 5: Model Maintenance

Continuous Monitoring: Continuously monitor the performance of the deployed model and update it as necessary.

Re-training: Re-train the model periodically using new data to maintain its accuracy and effectiveness.

Model Updates: Update the model to incorporate new features, algorithms, or techniques to stay ahead of emerging phishing threats.



FUTURE SCOPE

Here's a comprehensive overview of the future scope of phishing detection using machine learning:

Phishing Detection using Machine Learning: Future Scope

Introduction

Phishing attacks have become increasingly sophisticated, posing significant threats to individuals and organizations worldwide. Machine learning (ML) has emerged as a promising solution for detecting phishing attacks. This section explores the future scope of phishing detection using ML.

Advancements in Machine Learning Algorithms

Deep Learning: Techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) will improve phishing detection accuracy.

Transfer Learning: Pre-trained models will be fine-tuned for phishing detection, reducing training time and improving performance.

Ensemble Methods: Combining multiple ML algorithms will enhance detection rates and reduce false positives.

Integration with Emerging Technologies

Artificial Intelligence (AI): AI-powered systems will analyze user behavior and detect anomalies, enhancing phishing detection.

Internet of Things (IoT): ML-based phishing detection will be integrated into IoT devices, protecting against attacks on connected devices.

Blockchain: Blockchain-based systems will provide secure and transparent phishing detection mechanisms.

Real-World Applications

Email Filtering: ML-based phishing detection will be integrated into email clients, filtering out malicious emails.

Web Application Security: Phishing detection will be incorporated intweb applications, protecting against attacks on user credentials.

Network Security: ML-based systems will detect and prevent phishing attacks on network infrastructure.

Mobile Security: Phishing detection models can be integrated into mobile security applications to scan URLs and alert users about suspicious websites before they visit them.

Challenges and Future Directions

Evasion Techniques: Phishers will employ evasion techniques to bypass ML-based detection systems.

Explainability and Transparency: ML models will need to provide explanations for their decisions, ensuring transparency and trust.
Continuous Training and Updates: ML models will require regular updates to stay effective against evolving phishing threats.

4. CONCLUSION

Most cybersecurity research stays in the lab. This one did not. The dataset was built to reflect reality — phishing URLs and legitimate URLs collected together, cleaned, and labeled without cherry-picking the easy cases that inflate accuracy scores. Several models were trained, compared honestly, and the strongest one was taken somewhere the others were not: into a working web application, connected to a live API, classifying real traffic in real time. That deployment step is what separates a research result from an actual tool. A model that performs well on a test set and then struggles with the unpredictable messiness of live internet traffic has not solved the problem — it has described it more precisely. This one held up. The accuracy outperformed every baseline it was measured against. More importantly, it caught sites it had never seen before — reading structural signals in the URL and page content rather than checking against a list of known offenders. That is the capability blacklists will never have, and it is the one that actually matters when an attacker registers a fresh domain at nine in the morning.Where this belongs, ultimately, is inside the infrastructure people already use — browsers, security systems, the layers that sit between a user and wherever they are trying to go. Quietly, automatically, before anyone has to make a mistake to find out a site was dangerous. The research shows it is possible. Building it into those systems at scale is the work still left to do.

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