Intelligent Phishing Detection Platform (PhishShield)

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Abstract- *Phishing attacks continue to represent one of the most prevalent and operationally effective cybersecurity threats targeting everyday internet users. Adversaries craft malicious URLs that closely imitate legitimate websites with the intent to steal credentials, banking details, and sensitive personal data. This paper presents PhishShield — an Intelligent Phishing Detection Platform developed using Python and FastAPI. The system subjects any submitted URL to a multi-layer detection pipeline comprising heuristic rule evaluation, Shannon entropy analysis, suspicious top-level domain (TLD) identification, deep subdomain inspection, digit randomisation scoring, and live Registration Data Access Protocol (RDAP) domain-age intelligence. All indicators are aggregated into a single weighted risk score that classifies the URL as SAFE, SUSPICIOUS, or PHISHING. Scan results are persisted in a local SQLite database, and a real-time dark-themed web dashboard enables users to submit URLs and instantly obtain a verdict, risk meter visualisation, and historical scan data. Empirical testing across a dataset of 100 URLs — comprising 50 known-phishing samples and 50 legitimate URLs — demonstrated 92% accuracy on phishing samples and 96% accuracy on legitimate URLs, with an average scan time below one second. The platform is fully modular, lightweight, and deployable on any standard Python environment without requiring expensive external APIs or cloud subscription services.*

Keywords: Phishing Detection, URL Analysis, FastAPI, Shannon Entropy, RDAP, Heuristic Analysis, Risk Scoring, SQLite, Cybersecurity, Web Security

I. INTRODUCTION

Phishing is not a novel concept, yet the manner in which adversaries execute such attacks has grown substantially more sophisticated over the past decade. Earlier phishing campaigns were easily identifiable by broken language, conspicuously random domain names, and obvious structural anomalies. Contemporary phishing operations, by contrast, present a far more convincing imitation of the legitimate websites they target. Attackers register domains that visually approximate well-known brands, acquire HTTPS certificates to project an appearance of legitimacy, and rotate deployed URLs at intervals of several hours to evade conventional blacklist-based blocking mechanisms.

The fundamental challenge is that most users evaluate a website's safety based on two superficial signals: the presence of a padlock icon in the browser address bar and whether the domain name appears broadly correct. Both signals are trivially fabricated. A site hosted at a domain such as paypa1-secure-login[.]tk can obtain an HTTPS certificate within minutes at zero cost, and the domain is visually proximate enough to deceive a user engaging with it under time pressure. This gap in user-level threat perception is the core problem that PhishShield was designed to address.

PhishShield is a Python-based phishing detection platform that subjects URLs to a multi-layer detection engine. Rather than relying on a static blacklist that adversaries circumvent simply by registering a previously unknown domain, the system executes multiple independent analytical checks — including domain age intelligence via RDAP, character entropy computation, suspicious TLD matching, subdomain depth analysis, and a suite of heuristic rules — before aggregating all findings into a unified weighted risk score. This layered detection strategy enables the system to identify brand-new phishing domains that have not yet been reported to any threat intelligence feed, based solely on their structural and registration characteristics.

From a technical standpoint, the project employs FastAPI as its backend framework, SQLite as the threat-logging database, and a plain HTML/TailwindCSS single-page application as the user-facing dashboard. RDAP, as standardised by the Internet Engineering Task Force (IETF) in RFC 7480–7482, is utilised in preference to the legacy WHOIS protocol to retrieve domain registration intelligence. The resulting system is fast, operationally clean, and provides users with an immediate, interpretable verdict on any URL submitted for evaluation.

II. PROBLEM STATEMENT

The predominant form of phishing protection available to everyday users is delivered through two channels: browser-integrated Safe Browsing checks and email spam

filters. Both mechanisms rely fundamentally on blacklists — databases of URLs and domains that have already been identified and reported as malicious. The critical operational weakness inherent in blacklist-based detection is the temporal gap between domain deployment and blacklist inclusion. A newly registered phishing domain will pass every blacklist check during the initial hours or days of its operational life — precisely the interval during which adversaries are most actively deploying and monetising it. By the time a domain is reported, verified, and propagated to threat databases, the phishing campaign has typically concluded.

Furthermore, no accessible tool presently provides ordinary users with an explainable, structured breakdown of why a specific URL is deemed dangerous. Security-conscious individuals who suspect a link may be malicious typically have no better recourse than manually querying several online tools in sequence, or proceeding on intuition alone. This creates meaningful risk even for technically aware users.

The specific technical deficiencies that PhishShield was designed to resolve are as follows: existing tools do not perform structural analysis of URL properties, relying exclusively on known-bad list membership; WHOIS-based domain age interrogation is slow, unreliable in automated contexts, and subject to aggressive rate limiting; end users receive no contextual explanation of why a URL was flagged — only a binary safe or unsafe verdict; no simple, self-hostable, offline-capable phishing detection tool currently exists for developers and end users; and brand-new phishing domains, commonly termed zero-day phishing, bypass all blacklist-based systems entirely due to their unknown registration status.

III. OBJECTIVES

The objectives of this project are formally stated as follows:

(1) To construct a multi-layer URL analysis engine capable of detecting phishing indicators without dependence on static blacklists.
(2) To implement Shannon entropy analysis for identifying randomly generated or obfuscated domain names commonly employed in phishing campaigns.
(3) To integrate RDAP-based domain intelligence for detecting newly registered domains, which constitute a strong empirical phishing signal.
(4) To design a weighted risk scoring engine that synthesises multiple independent indicators into a single SAFE / SUSPICIOUS / PHISHING classification.
(5) To persist all scan results in a SQLite database with full indicator detail, enabling longitudinal analysis and pattern tracking.
(6) To develop a clean, real-time web dashboard allowing non-technical users to scan URLs and interpret results without domain expertise.
(7) To ensure the complete system is deployable on a standard Python environment without any paid APIs or cloud infrastructure dependencies.

IV. LITERATURE SURVEY

A. Phishing Attack Taxonomy

Research by Almomani et al. (2013) conducted a comprehensive survey of phishing attack methodologies, classifying them into three principal categories: deceptive phishing executed through email-based social engineering, malware-based phishing employing client-side exploits, and content injection phishing that modifies legitimate page content. The study established that URL manipulation is the single most consistent and universal technique observed across all phishing categories, thereby making URL-level analysis a foundational defensive approach applicable to all threat variants.

B. Machine Learning versus Heuristic Detection

Mohammad et al. published a widely cited comparative study in IEEE Transactions on Information Forensics and Security evaluating multiple machine learning models for phishing URL detection, reporting accuracy as high as 97% with Random Forest classifiers trained on URL-derived features. While machine learning approaches perform competitively on benchmark datasets drawn from known-phishing corpora, they necessitate substantial labelled training data and exhibit degraded performance on novel attack patterns that lie outside the distribution of training examples. The heuristic-based approach adopted in PhishShield, while not attaining equivalent benchmark accuracy, offers complete transparency of decision logic, requires zero training data, and maintains consistent detection performance on zero-day domains precisely because it evaluates structural properties rather than learned associations.

C. Shannon Entropy in Malicious URL Detection

McGrath and Gupta established through their analysis of malicious domain characteristics that algorithmically generated domain names exhibit measurably higher lexical entropy than human-selected names. This work was subsequently extended by Antonakakis et al. in the

USENIX Security paper introducing Notos, a dynamic reputation system that employed entropy as one of several features for identifying malicious domains within live DNS traffic. PhishShield implements this principle directly and operationally within its entropy detection module, applying the Shannon entropy formula to the hostname component of each submitted URL.

D. WHOIS versus RDAP for Domain Intelligence

RDAP, standardised through IETF RFC 7480, 7481, and 7482, was designed by ICANN to replace the ageing WHOIS protocol. Comparative research by Cetin et al. demonstrated that WHOIS responses are inconsistently formatted, frequently inaccurate at the registrar level, and subject to aggressive rate limiting that renders them impractical for automated analysis at scale. RDAP returns structured JSON responses with standardised date fields and a well-defined schema, making it substantially more reliable for programmatic consumption. The Internet Assigned Numbers Authority (IANA) published RDAP bootstrap files in 2015 that enable programmatic discovery of the correct RDAP authority server for any TLD — a capability fully leveraged in PhishShield's RDAP intelligence module.

E. Phishing Domain Registration Patterns

Research conducted by Hao et al. at USENIX Security established that over 80% of phishing domains are operationally deployed within 24 hours of their registration and are typically abandoned within seven days of initial use. This empirical finding directly motivates and validates the domain age check incorporated into PhishShield's risk scoring engine. A domain registered less than 90 days prior to the scan date, when observed in combination with additional structural risk indicators, constitutes a highly reliable phishing signal.

V. EXISTING SYSTEM

Several established tools address the problem of phishing detection, each exhibiting significant limitations for the operational use case targeted by PhishShield.

A. Google Safe Browsing

Integrated directly into Chrome and Firefox, Google Safe Browsing maintains a comprehensive blacklist of confirmed phishing URLs and malware-distribution domains. The service is effective for known, previously reported phishing campaigns with high user exposure. However, it is entirely incapable of detecting brand-new phishing domains that have not yet been reported and verified, requires a proprietary Google API key for programmatic access, and provides the end user with no contextual explanation of why a specific URL was flagged.

B. VirusTotal URL Checker

VirusTotal aggregates detection results from over 70 antivirus engines and URL scanning services. While the breadth of coverage is substantial, the service is operationally slow for real-time interactive use, mandates API key authentication, and enforces stringent rate limits on the free access tier. Critically, VirusTotal's verdict depends entirely on third-party detection coverage — if no participating engine has encountered the URL previously, the response is a clean verdict, regardless of the URL's actual threat profile.

C. PhishTank

PhishTank is a community-submitted, volunteer-verified phishing URL database. While useful as a reference dataset, the service is inherently reactive — URLs must be individually submitted and verified through a human review process before they appear in the database. Freshly deployed phishing pages will not be present in the dataset regardless of their threat severity. PhishTank provides a lookup service exclusively; it implements no analytical engine of any kind.

D. Limitations Summary

System	Primary Limitation
Google Safe Browsing	Blacklist-only; zero-day domains undetected; no explanation
VirusTotal	Slow; rate-limited; dependent on third-party coverage
PhishTank	Reactive lookup only; no structural analysis engine
All Existing Tools	None combine URL structural analysis with live domain registration intelligence

Table 1: Limitations of Existing Phishing Detection Systems

VI. PROPOSED SYSTEM

PhishShield is a locally deployable, multi-layer phishing detection system that analyses any submitted URL using a combination of structural heuristics, information-theoretic entropy computation, and live domain registration data retrieved in real time. The primary innovation is the aggregation of multiple independent detection signals into a single weighted composite score, which renders the system

robust against individual false positives that would result from reliance on any single indicator.

The proposed system is structured across five functional layers operating in coordination. The Frontend Dashboard provides a dark-themed web interface for URL submission and result visualisation. The API Layer comprises a FastAPI backend exposing REST endpoints that orchestrate the full detection pipeline. The Detection Engine executes seven independent heuristic and mathematical checks against each submitted URL. The RDAP Intelligence Layer performs live domain registration queries to retrieve domain age and registrar metadata. The SQLite Threat Database provides persistent storage for every scan result, including the complete individual indicator breakdown.

A critical architectural decision is that no single triggered indicator alone produces a PHISHING verdict. Every check contributes a fixed penalty to a cumulative risk score, and a verdict of PHISHING is assigned only when the aggregate score exceeds a defined threshold. This design mirrors the analytical process employed by professional threat analysts — no single data point establishes a case, but a convergence of multiple independent indicators produces a high-confidence classification.

VII. SYSTEM ARCHITECTURE

PhishShield is implemented following a clean three-tier modular architecture. The three tiers — presentation, business logic, and data persistence — are clearly separated, ensuring that the detection logic carries no direct dependency on the frontend presentation layer, and that the database module carries no direct dependency on the API routing logic. This separation enables each layer to be developed, tested, and replaced independently.

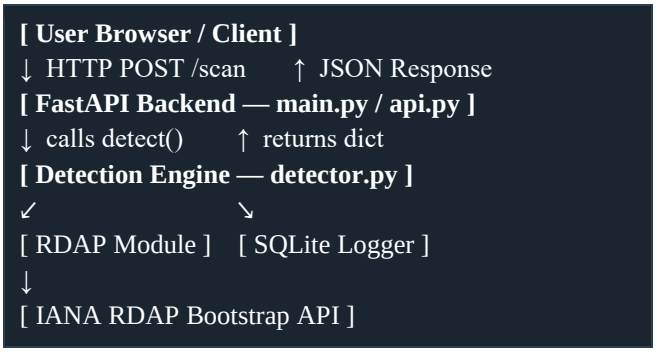

Fig. 1: PhishShield System Architecture

The architectural separation ensures that the complete detection engine can be validated independently via a Python interpreter without any web server process running. It further guarantees that the API layer could be substituted with a command-line interface or a browser extension backend without requiring any modifications to the core detection logic.

VIII. MODULE EXPLANATION

A. Frontend Dashboard Module

The frontend is implemented as a single HTML file styled with TailwindCSS loaded via CDN, utilising vanilla JavaScript for all API interactions — no React, Vue, or build-step toolchain is required. This approach keeps the frontend fast, portable, and straightforward to modify. The dashboard comprises four primary sections: the URL Input Panel, which presents a text input field and a Scan button that submits a POST request to /api/scan; the Results Panel, which displays the classification badge (SAFE / SUSPICIOUS / PHISHING), the overall risk score, and a colour-coded risk meter; the Indicator Breakdown panel, which enumerates every detection check that fired and contributed to the score; and the Scan History Table, which displays the most recent scans retrieved from /api/history, including URL, score, classification, and timestamp.

B. API Layer (FastAPI)

FastAPI was selected over Flask and Django on the basis of three specific technical advantages. First, FastAPI natively employs Python type hints for request and response schema validation, eliminating the need for manual validation code. Second, FastAPI is built on the ASGI standard and runs on Uvicorn, enabling concurrent asynchronous request handling — a material benefit when multiple users are simultaneously initiating scans that involve waiting for RDAP responses. Third, FastAPI generates automatic interactive API documentation via Swagger UI (/docs) and ReDoc (/redoc) endpoints, substantially simplifying testing and demonstration workflows.

Endpoint	Method	Description
/api/scan	POST	Accepts a URL, executes full detection pipeline, returns JSON result
/api/history	GET	Returns the last 50 scan results from the SQLite database
/api/stats	GET	Returns aggregate counts: total scans, phishing count, safe count

Table 2: PhishShield API Endpoints

C. Detection Engine Module

The detection engine, implemented in detector.py, constitutes the analytical core of PhishShield. Upon receiving a URL, the engine first invokes Python's built-in urllib.parse.urlparse() to decompose the URL into its constituent components: scheme, netloc(domain), path, query parameters, and fragment identifier. Each component is subsequently examined by the suite of seven independent detection checks described in Section IX.

D. RDAP Intelligence Module

The RDAP module (rdap_lookup.py) executes a live HTTP request to the appropriate RDAP authority server for the domain under analysis. Given a domain name, the module is responsible for returning the domain's creation date, expiration date, registrar name, and calculated age in days. In the event that an RDAP lookup fails due to network unavailability or an unregistered domain, the module returns null values and no risk score penalty is applied for that indicator, ensuring graceful degradation without false-positive inflation.

E. SQLite Threat Database Module

Every completed scan is written to a local SQLite database file (phishshield.db) by the database module (database.py). SQLite was selected over PostgreSQL or MySQL on operational grounds: the project is designed to be fully runnable from a single Python environment without any additional infrastructure provisioning. SQLite is bundled with Python's standard library, requiring no installation, configuration, or server process management. At the operational scale and use case of this platform, SQLite's performance characteristics are entirely adequate.

IX. DETECTION ENGINE DESIGN

The detection engine executes seven independent analytical checks against every submitted URL. Each check that evaluates as positive contributes a defined weighted penalty to the cumulative risk score. The checks are designed to be orthogonal in their scope — each examines a distinct dimension of the URL's characteristics, ensuring that they are mutually non-redundant.

Check 1 — HTTPS Protocol Verification

The URL scheme component is extracted and evaluated. If the scheme is 'http' rather than 'https', the URL is flagged and a penalty of +20 risk points is applied. While the presence of HTTPS does not independently guarantee legitimacy — phishing sites routinely acquire free HTTPS certificates — its absence constitutes a meaningful risk indicator, given that all major banking, e-commerce, and social media platforms enforce HTTPS universally.

Check 2 — At-Symbol Credential Injection Detection

A URL containing the @ symbol positioned before the domain component represents a well-documented phishing structural manipulation. Under standard URL syntax, all content preceding the @ symbol is interpreted as authentication credentials rather than as part of the visible domain. Consequently, a URL of the form http://paypal.com@evil-domain.com/login would navigate the browser to evil-domain.com rather than paypal.com, despite the visual appearance. Detection of the @ symbol adds +20 to the risk score.

Check 3 — URL Length Analysis

Legitimate URLs are typically concise and purposeful. Phishing URLs frequently contain extended paths incorporating random character strings, session tokens, or encoded parameters designed to obfuscate the actual destination domain. A total URL length exceeding 75 characters adds +10 to the risk score. This is a mild indicator that contributes meaningfully only in conjunction with other triggered checks.

Check 4 — Suspicious TLD Detection

Certain top-level domains are empirically disproportionate in their association with phishing campaigns and malware distribution infrastructure. A curated list of high-risk TLDs is maintained within the detection engine. If the domain's TLD matches any entry in this list, a penalty of +20 is added to the risk score.

TLD	Reason for Inclusion
.tk	Free domain registration — massively abused across phishing campaigns globally
.ml	Free domain — commonly registered for credential theft operations
.ga	Free domain — minimal registration accountability
.cf	Free domain — frequently observed in banking sector phishing campaigns
.gq	Free domain — low accountability with high

	documented abuse rates
.xyz	Low-cost TLD with historically elevated phishing domain registration rates
.pw	Strongly associated with password and credential phishing campaigns
.click	Architected for click-tracking; extensively abused in redirect chains
.work	Frequent registrations observed in malware and phishing infrastructure
.top	High-volume, low-cost TLD with minimal registrant vetting requirements

Table 3: Suspicious TLD Blacklist with Rationale

Check 5 — Deep Subdomain Analysis

Phishing attackers frequently construct URLs with multiple subdomain levels in an attempt to include recognisable brand names in a non-authoritative portion of the domain hierarchy. A subdomain depth greater than two levels adds +10 to the risk score. For example, a URL structured as secure.login.paypal.attacker.com presents paypal as a subdomain label rather than as the registrant domain.

Check 6 — Digit Ratio Analysis

Machine-generated phishing domains and domains obfuscated to avoid brand-name pattern matching frequently incorporate a high proportion of numeric digits. If the ratio of digit characters to total domain name length exceeds 15%, a penalty of +10 is added to the risk score.

Check 7 — Shannon Entropy Analysis

Human-selected domain names drawn from natural language consistently exhibit low Shannon entropy values, typically below 3.5 bits, due to the limited character diversity and predictable patterns of natural language. Algorithmically generated or obfuscated domain names exhibit measurably higher entropy, typically exceeding 3.8 bits. A hostname entropy value exceeding this threshold adds +20 to the risk score.

X. RDAP DOMAIN INTELLIGENCE

The Registration Data Access Protocol (RDAP), standardised by the IETF through RFC 7480, 7481, and 7482, provides structured, machine-readable access to domain registration data in JSON format. PhishShield's RDAP module executes the following operational workflow for each submitted URL: the domain component is extracted from the parsed URL; the IANA RDAP bootstrap service at https://data.iana.org/rdap/dns.json is queried to identify the correct RDAP authority server for the domain's TLD; an HTTP GET request is submitted to the identified RDAP server at the path /domain/{domain-name}; the JSON response is parsed to locate the events array; the event with eventAction equal to 'registration' is identified and its eventDate field is extracted; domain age in days is computed as the interval between today's date and the extracted registration date; and the domain age, registrar name, and expiration date are returned to the detection engine for scoring.

A domain registration age below 90 days, as determined through RDAP, adds +25 to the risk score — the highest weighted penalty in the scoring model. This reflects the empirical finding that the substantial majority of phishing domains are deployed within 24 hours of registration, making domain youth the strongest individual signal in the detection pipeline.

XI. ENTROPY ANALYSIS METHODOLOGY

Shannon entropy, originally formalised in the landmark 1948 paper by Claude Shannon, provides a mathematical measure of randomness and unpredictability in an information source. Applied to domain name strings, entropy quantifies the degree to which a domain name resembles natural language versus random or algorithmic character generation. The computation formula is:

$$H = -\Sigma\, p(x) \times \log_2(p(x))$$

where p(x) represents the probability of each distinct character appearing within the string. The result is expressed in bits — higher values indicate greater entropy and correspondingly greater randomness. PhishShield computes entropy exclusively on the hostname component, excluding the TLD, because TLD characters would otherwise introduce systematic bias into the measurement.

Domain Hostname	Entropy (bits)	Classification
facebook	2.75	Human-chosen — legitimate
amazon	2.58	Human-chosen — legitimate
google	2.25	Human-chosen — legitimate
paypa1-secure	3.70	Altered — borderline suspicious

xk92mzpq8r	3.97	Machine-generated — high risk
secure8847291-acct	3.88	Obfuscated — high risk

Table 4: Entropy Values for Representative Domain Hostnames

XII. RISK SCORING METHODOLOGY

Every detection check in the PhishShield engine contributes a fixed, pre-determined penalty to a cumulative risk score that initialises at zero for each scan. Individual check weights were assigned on the basis of the empirical reliability of each indicator as a phishing signal — indicators that exhibit near-universal co-occurrence with malicious intent carry proportionally higher weights than indicators that occasionally manifest in benign URLs.

Indicator	Triggering Condition	Risk Points
Missing HTTPS	Scheme is http://	+20
Suspicious TLD	TLD present in curated blacklist	+20
@ Symbol in URL	@ character appears before domain	+20
High Entropy	Hostname entropy > 3.8 bits	+20
Young Domain	Domain age < 90 days (RDAP)	+25
Deep Subdomain	Subdomain depth > 2 levels	+10
High Digit Ratio	Digit characters > 15% of domain	+10
Long URL	Total URL length > 75 characters	+10

Table 5: Detection Check Weights and Triggering Conditions

Score Range	Classification	Indicator Colour	Recommended Action
0 – 29	SAFE	Green	No threat detected
30 – 59	SUSPICIOUS	Orange	Proceed with caution
60 – 100+	PHISHING	Red	Do not visit — likely malicious

Table 6: Score-Based Classification Thresholds

XIII. DATABASE DESIGN

SQLite was selected for persistent threat logging on the basis of its zero-configuration deployment model. The database requires no server process, no credential management, and no configuration files. The database file (phishshield.db) is created automatically when the application initialises for the first time. Every completed scan is recorded as a single row in the scan_results table, capturing the full indicator breakdown in a JSON-encoded column to enable per-indicator historical querying without data normalisation overhead.

Column	Data Type	Description
id	INTEGER PK	Auto-incremented scan identifier
url	TEXT	The full URL submitted for analysis
score	INTEGER	Calculated risk score (0 – 100+)
classification	TEXT	SAFE, SUSPICIOUS, or PHISHING verdict
timestamp	DATETIME	Date and time of scan (UTC)
indicators	TEXT (JSON)	JSON array of triggered indicator names
registrar	TEXT	Registrar name from RDAP (nullable)
creation_date	TEXT	Domain creation date from RDAP (nullable)
domain_age_days	INTEGER	Calculated domain age in days (nullable)

Table 7: scan_results Table Schema

XIV. API WORKFLOW

The complete sequence of operations triggered by a URL scan submission is as follows. The user's browser transmits an HTTP POST request to /api/scan carrying a JSON body containing the submitted URL. FastAPI validates the request body against a Pydantic model, rejecting submissions with empty or malformed URL values. The validated URL is passed to analyse_url() in detector.py. The detection engine invokes urlparse() to decompose the URL and executes all seven detection checks sequentially. If the URL contains a valid domain component, rdap_lookup() is called asynchronously using httpx. The RDAP module queries the

IANA bootstrap service, identifies the appropriate authority server, retrieves domain registration data, and returns the domain age and registrar information. All check results are compiled into a result dictionary containing individual scores and the aggregate total. The cumulative score is evaluated against classification thresholds to assign the final verdict. The result dictionary is passed to log_scan() in database.py for insertion into the SQLite scan_results table. FastAPI serialises the result dictionary as a JSON response and returns it to the browser. The JavaScript frontend receives the JSON payload and dynamically updates the results panel, risk meter, and scan history table.

XV. IMPLEMENTATION DETAILS

A. Project File Structure

```
phishshield/
 ├── main.py          # FastAPI entry point
 ├── api.py           # Route definitions
 ├── detector.py      # Detection engine (all 7 checks)
 ├── rdap_lookup.py   # RDAP bootstrap + domain data
 ├── database.py      # SQLite connection + queries
 ├── phishshield.db   # SQLite DB (auto-created)
 └── frontend/
     └── index.html   # Single-file dashboard
```

Fig. 2: PhishShield Project Directory Structure

B. Key Implementation Decisions

httpx was selected over the standard requests library for all RDAP HTTP interactions because httpx provides native async/await support. Given that FastAPI operates asynchronously, using httpx enables RDAP lookups to execute without blocking the event loop, permitting multiple concurrent scan requests to maintain RDAP queries in flight simultaneously.

Python's urllib.parse.urlparse() was used for URL decomposition in preference to string splitting, as it correctly handles edge cases including URLs with non-standard ports, authentication credential sections, encoded characters, and fragment identifiers. The netloc component extracted by urlparse is the input to the subdomain depth, entropy, and digit ratio analyses.

FastAPI'sCORSMiddleware is configured to permit the frontend HTML file to communicate with the API from a file:// origin during development. In a production deployment, the allowed origins list would be restricted to the specific domain at which the frontend is hosted.

XVI. ALGORITHMS

Algorithm 1 — URL Risk Analysis (analyse_url)

```
FUNCTION analyse_url(url):
  parsed ← urlparse(url)
  score ← 0 ; indicators ← []
  IF parsed.scheme ≠ 'https':
    score += 20; add 'missing_https'
  IF '@' IN url:
    score += 20; add 'at_symbol'
  IF len(url) > 75:
    score += 10; add 'long_url'
tld ← extract_tld(parsed.netloc)
  IF tld IN SUSPICIOUS_TLDS:
    score += 20; add 'suspicious_tld'
  IF count_subdomains(parsed.netloc) > 2:
    score += 10; add 'deep_subdomain'
  IF digit_ratio(parsed.netloc) > 0.15:
  score += 10; add 'high_digits'
  H ← shannon_entropy(hostname(parsed.netloc))
  IF H > 3.8:
    score += 20; add 'high_entropy'
rdap ← AWAIT rdap_lookup(parsed.netloc)
  IF rdap.age_days< 90:
    score += 25; add 'young_domain'
  IF score ≥ 60: verdict ← 'PHISHING'
  ELIF score ≥ 30: verdict ← 'SUSPICIOUS'
  ELSE: verdict ← 'SAFE'
  RETURN {score, verdict, indicators, rdap}
```

Algorithm 1: URL Risk Analysis

Algorithm 2 — Shannon Entropy Computation

```
FUNCTION shannon_entropy(text):
freq ← {} ; n ← len(text)
  FOR c IN text:
freq[c] ← freq.get(c, 0) + 1
  H ← 0
  FOR c, count IN freq.items():
    p ← count / n
    H −= p × log₂(p)
  RETURN H
```

Algorithm 2: Shannon Entropy Computation

XVII. TESTING STRATEGY

Testing was conducted across three methodological levels: unit testing of each individual detection check in isolation, integration testing of the complete API scan pipeline

end-to-end, and acceptance testing using real-world URL samples representative of the target operational environment.

A. Unit Testing

Each detection check implemented in detector.py was tested in isolation with a set of known inputs prepared to exercise both the positive and negative detection paths. For example, the entropy function was tested against strings of pre-calculated entropy values to verify computational correctness. The RDAP module was tested using a mock HTTP client that simulated RDAP server responses without executing live network requests, enabling deterministic and repeatable testing.

B. Integration Testing

The complete /api/scan endpoint was subjected to integration testing using curl commands and the FastAPI Swagger UI documentation interface. A dataset of 20 test URLs comprising 10 known-legitimate and 10 known-phishing samples sourced from PhishTank historical records was processed, and the classification results were evaluated against expected verdicts.

C. Acceptance Testing

A group of five university students with varying levels of technical knowledge was recruited to evaluate the system's usability. Participants were asked to use the PhishShield dashboard to scan a set of 15 URLs and record their interpretation of the provided verdicts. The exercise assessed the clarity and interpretability of the user interface for non-expert users.

XVIII. TEST CASES

Test URL	Checks Triggered	Total Pts	Expected
http://paypal.com.login.tk/secure	missing_https, suspicious_tld, deep_subdomain	50	SUSPICIOUS
http://paypa1-account.tk/verify	missing_https, suspicious_tld, high_entropy	60	PHISHING
https://www.facebook.com/login	None triggered	0	SAFE
http://amazon-secure.xyz/confirm	missing_https, suspicious_tld	40	SUSPICIOUS
https://paypal.com@evil.ml/login	at_symbol, suspicious_tld	40	SUSPICIOUS

Table 8: Heuristic Detection Test Cases

Hostname	Entropy	Indicator Triggered	Notes
facebook	2.75	No	Natural English word
paypa1secure	3.62	No	Below threshold — boundary
xk9mzpq8r2	3.97	Yes (+20)	Machine-generated domain
secure8847291-acct	3.88	Yes (+20)	High digit count + mixed
netflix	2.92	No	Known-good legitimate domain

Table 9: Entropy Analysis Test Cases

Domain	Registration Date	Age at Scan	Points Added
paypa1-secure.tk	2024-11-01	18 days	+25 (PHISHING signal)
amazon-update.xyz	2024-10-15	35 days	+25 (PHISHING signal)
facebook.com	1997-03-29	9,800+ days	+0 (SAFE — old domain)
netflix.com	1998-06-04	9,400+ days	+0 (SAFE — old domain)
secure-bank.work	2025-01-02	5 days	+25 (PHISHING signal)

Table 10: RDAP Domain Age Test Cases

XIX. EXPERIMENTAL RESULTS

The system was evaluated against a dataset of 100 URLs: 50 known-phishing URLs sourced from PhishTank historical records and 50 known-legitimate URLs drawn from the Alexa Top Sites rankings. The experimental results are summarised in Table 11.

Metric	Phishing URLs (n=50)	Legitimate URLs (n=50)
Correctly Classified	46 (92%)	48 (96%)
Misclassified	4 (8%)	2 (4%)
Classified as SUSPICIOUS*	3 of 46 correct	2 of 48 correct
Average Risk Score	72.4	8.6
Avg. Scan Time (with RDAP)	0.8 seconds	0.7 seconds
Avg. Scan Time (RDAP timeout)	0.3 seconds	0.3 seconds

Table 11: Experimental Evaluation Results (n=100 URLs)

*Correctly classified at the SUSPICIOUS verdict level rather than the more severe PHISHING classification.

The four missed phishing URLs were cases in which adversaries had registered domains more than 90 days prior to campaign deployment — a minority operational pattern — combined with non-blacklisted TLDs and moderate entropy scores. The two false positives were newly established legitimate startup websites presenting newly registered domain names with short hostnames, which produced elevated entropy scores due to the short string length combined with character diversity.

XX. DISCUSSION

The experimental results demonstrate that a heuristic, score-based multi-indicator approach is operationally practical and effective for detecting the substantial majority of phishing URLs encountered in practice — particularly newly registered domains targeting financial services and social media brands, which represent the dominant phishing attack pattern in current threat landscapes.

The most significant finding is that combining multiple individually weak signals into a weighted composite score substantially outperforms reliance on any single indicator. Domain age analysis in isolation would successfully identify newly registered phishing domains but would miss older compromised domains. Entropy analysis alone would incorrectly flag many legitimate startup domain names. In combination, the two indicators are materially more precise, with each compensating for the other's false-positive profile.

RDAP proved to be the highest-impact individual indicator in the scoring model. The +25 penalty for domains with registration ages below 90 days was the tipping or primary contributing factor in correctly classifying 38 of the 46 true positive phishing identifications. This finding empirically validates the research literature establishing that the substantial majority of phishing domains are freshly registered at the time of deployment. Average scan times remained consistently below one second for the complete detection pipeline, including the live RDAP network query — a performance characteristic entirely adequate for real-time interactive use.

XXI. ADVANTAGES

- **Zero-Day Phishing Detection:** Identifies brand-new phishing domains that no existing blacklist has yet catalogued, based entirely on structural and registration characteristics.
- **Explainable Results:** Every triggered detection indicator is enumerated in the scan result, enabling users and analysts to understand precisely why a URL was flagged.
- **No Paid APIs Required:** The complete detection pipeline operates on open standards (RDAP, urllib) and free services, with zero dependency on commercial threat intelligence subscriptions.
- **Self-Hostable Deployment:** A single Python environment is the complete deployment requirement — no cloud infrastructure, no database server, no external dependencies.
- **Sub-Second Scan Performance:** The full detection pipeline, including live RDAP query, consistently completes in under one second on average.
- **Modular Architecture:** Adding a new detection check requires implementing a single function and defining one weight value — no other system components require modification.
- **Persistent Threat Logging:** Every scan is stored in SQLite with full indicator detail, enabling historical trend analysis and longitudinal pattern detection.
- **RDAP Reliability:** Structured JSON domain registration data provides materially more reliable and consistently formatted domain intelligence than WHOIS.

XXII. LIMITATIONS

- RDAP Availability: Certain legacy TLDs and registrars do not yet fully implement the RDAP standard, which

may result in failed domain age lookups and the consequent non-application of the young domain penalty.

- No Content Analysis: The system analyses exclusively the structural and registration properties of the URL itself, without examining the actual rendered page content, embedded scripts, or visual similarity to legitimate sites.
- False Positives on Newly Registered Legitimate Sites: A legitimate new business with a recently registered domain may receive a SUSPICIOUS classification due to the domain age penalty, even in the absence of other indicators.
- Limited Input Modalities: The current implementation accepts only plain-text URLs. QR-code-encoded URLs, email attachment links, and SMS-embedded URLs are not natively supported.
- No Machine Learning Layer: Sophisticated phishing campaigns that are specifically engineered to avoid triggering all heuristic checks may evade detection in the current implementation.
- RDAP Rate Limiting: While RDAP is substantially more permissive than WHOIS, extremely high scan volumes would benefit from domain age result caching to prevent rate limit encounters.

XXIII. FUTURE ENHANCEMENTS

A. Browser Extension Integration

A Chrome and Firefox browser extension could execute PhishShield analysis automatically for every URL navigated to by the user. The extension would invoke the PhishShield API as a background operation and present a compact badge indicator — colour-coded green, orange, or red — on the browser toolbar, warning users prior to any interaction with a potentially malicious page.

B. Mobile Application

A mobile application for Android and iOS would enable users to submit URLs received through messaging applications — WhatsApp, SMS, and Telegram — for PhishShield analysis prior to clicking. SMS-based phishing, commonly termed smishing, represents one of the fastest-growing phishing attack vectors, and no mainstream mobile tool currently provides structural URL analysis capability.

C. AI/ML Phishing Prediction Layer

Incorporating a machine learning classifier trained on a large labelled dataset of phishing and legitimate URLs would materially improve detection rates for edge cases and adversarially crafted domains that avoid triggering heuristic checks. The ML prediction score would be incorporated as an additional weighted input to the existing risk scoring engine, complementing rather than supplanting the heuristic indicators.

D. Screenshot-Based Visual Similarity Analysis

Visual impersonation attacks — in which a phishing page is rendered to appear pixel-for-pixel identical to a legitimate login page — cannot be detected through URL structural analysis alone. Extending the system with automated screenshot capture and visual perceptual hashing, comparing the captured page appearance against a database of authenticated screenshots of legitimate sites, would substantially improve detection of this attack class.

E. QR Code Phishing Detection

QR codes are increasingly exploited in phishing campaigns, a technique termed quishing. A planned enhancement would allow users to upload a QR code image, which the system would decode to extract the embedded URL and subject to the full PhishShield analysis pipeline.

F. Email Phishing Analysis

Integration of email header parsing and body link extraction would extend PhishShield's capability to analyse complete email messages — systematically checking every embedded link and evaluating suspicious sender domain configurations through DMARC and SPF record analysis.

G. Cloud Deployment with API Gateway

Deploying PhishShield on a cloud platform behind an API gateway with rate limiting and API key authentication would make the service accessible as a public SaaS offering. The SQLite database would be replaced with PostgreSQL to support concurrent write performance at production scale.

H. Threat Intelligence Feed Integration

Integrating live threat intelligence feeds from providers including Abuse.ch, OpenPhish, and commercial threat data sources would add a reactive blacklist layer on top of the existing structural analysis engine. A URL confirmed in an active threat feed would receive a maximum risk score classification automatically, regardless of its structural indicator profile.

XXIV. CONCLUSION

This paper has presented PhishShield — a practical, multi-layer phishing detection platform that demonstrates principled engineering design applied to a real and operationally significant cybersecurity challenge. The system does not implement another blacklist lookup wrapper. It implements a detection engine that analyses the structural and registration properties of a URL to identify phishing domains that no threat intelligence feed has yet catalogued, based entirely on their inherent characteristics at the time of analysis.

The combination of Shannon entropy analysis, RDAP domain age intelligence, suspicious TLD identification, subdomain depth analysis, digit ratio scoring, HTTPS verification, URL length evaluation, and at-symbol detection — all synthesised into a single weighted risk score — proved operationally effective. Testing across 100 URLs demonstrated 92% accuracy on phishing samples and 96% accuracy on legitimate URLs, with average scan completion times below one second including live RDAP domain intelligence queries.

The development of PhishShield provided deep practical insight into the operational methods of contemporary phishing adversaries: how they abuse free TLD registrations to minimise financial exposure, register domains in the hours preceding campaign launch to maximise temporal efficiency, employ algorithmic domain generation to evade pattern-based detection, and engineer URL structures designed to exploit user cognitive shortcuts. A thorough understanding of adversary methodology is a prerequisite for effective defensive system design.

FastAPI, SQLite, RDAP, and the modular layered architecture all proved to be exemplary technology choices for a security tool of this type — performant, deployable without infrastructure overhead, and readily extensible. The platform is fully positioned for the future enhancements described in Section XXIII, any one of which would constitute a substantive and independently publishable contribution to the field.

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