

Network-Based XAI-Driven Transparency Layer for Browser Download Warnings Browser Security

S. Syed Abdul Syed

Dept. of Computer Science Engineering
B.S. Abdur Rahman Crescent Institute of Science and
Technology, Chennai
syedabdulsyed@crescent.education

E. Syed Mohamed

Dept. of Computer Science Engineering
B.S. Abdur Rahman Crescent Institute of Science and
Technology, Chennai
syedmohamed@crescent.education

Mohamed Thanveer S

B. Tech – Artificial Intelligence and Data Science
Dept. of AI & Data Science
B.S. Abdur Rahman Crescent Institute of Science and
Technology, Chennai
thanveermohamed95@gmail.com

Mohammed Ashique Ali

B. Tech – Artificial Intelligence and Data Science
Dept. of AI & Data Science
B.S. Abdur Rahman Crescent Institute of Science and
Technology, Chennai
ashiqueali90030@gmail.com

Abstract: Every day, millions of users click download links without knowing whether the file waiting on the other end is safe. Existing browser security tools tend to step in too late—warning users only after a file has already landed on their device, and even then, rarely explaining why the file was flagged. This paper introduces a system designed to change that. We built an AI-Based Download Intrusion Detection System that watches for download link clicks in real time and steps in before a single byte is transferred. At its core sits a Random Forest classifier trained on the UNSW-NB15 network dataset, achieving 95.67% detection accuracy and a ROC AUC of 0.9823. What makes this system different is not just that it detects threats—it explains them. Using TreeSHAP, every security decision comes with a clear, plain-language explanation of exactly which signals raised the alarm. These explanations are backed by five independent analysis layers: machine learning scoring, URL reputation checks, static file inspection, live URLhaus threat intelligence, and Shannon entropy analysis—all fused into a single risk score. Every decision is also mapped to the MITRE ATT&CK framework, giving analysts immediate operational context. The system lives inside a Chrome extension with a ten-page Streamlit dashboard behind it. All eight test cases produced the correct outcome.

Keywords: Explainable AI, Browser Security, Pre-Download Detection, SHAP, MITRE ATT&CK, Chrome Extension, Risk Fusion, UNSW-NB15, Random Forest, Malware Detection

I. INTRODUCTION

Picture this: a user browsing a software forum spots a link to a free PDF tool, clicks download, and within seconds ransomware begins encrypting their files. The browser never warned them. This scenario repeats thousands of times every day because the tools designed to stop it share two fundamental problems.

The first problem is opacity. When a browser does flag a download, users typically see a vague message such as ‘This file may be harmful.’ No explanation is given for what raised the alarm, which aspect of the URL or file looked suspicious, or what category of threat it represents. Sharma et al. [10] confirm what most people already know: when users do not understand a warning, they click through it anyway.

The second problem is timing. Most browser security tools react after the download has already started. By the time a warning appears, the file may already be on the machine. A truly protective system must act before any bytes transfer.

Explainable Artificial Intelligence offers a path forward. L-XAIDS [6] showed that when an IDS can explain its decisions with LIME and ELI5, analyst trust and accuracy both improve. The E-XAI framework [2] defined six measurable dimensions of explanation quality. But neither framework was ever connected to a real browser environment or designed to intercept downloads before they happen.

This paper closes that gap. Our system sits inside a Chrome extension, intercepts download link clicks before any transfer begins, and runs a five-layer analysis pipeline in milliseconds. If something looks wrong, the download is blocked and the user sees exactly why—in plain language, backed by live threat intelligence and MITRE ATT&CK context.

II. LITERATURE SURVEY

Alzubaidi et al. [1] surveyed XAI techniques across cybersecurity and concluded that AI security tools that cannot explain themselves do not earn trust. Explainability must be designed in from the start.

Arreche et al. [2] built E-XAI to measure how good explanation methods really are, testing SHAP and LIME across six metrics and seven models. SHAP led on descriptive accuracy, sparsity, and completeness. They flagged UNSW-NB15 as underexplored—the exact dataset we use.

Hossain et al. [3] combined deep learning with XAI for real-time network intrusion detection with strong results, but the system never reaches the browser or provides any consumer-facing interface.

Singh et al. [4] assessed download risk using file type, frequency, and domain reputation. Useful signals, but no explanations and no pre-download interception.

Kumar et al. [5] applied XAI to enterprise threat detection with strong analyst-facing results, but the work is scoped entirely to infrastructure and does not reach individual browser users.

Muhammad et al. [6] produced L-XAIDS, the closest prior work to ours. LIME plus ELI5 on UNSW-NB15 achieved 85% accuracy. They explicitly called browser integration future work. This paper delivers that future work.

Ribeiro et al. [8] introduced LIME, powerful but approximate and slow on high-dimensional data. We use TreeSHAP instead, which gives exact values with no approximation error.

Lundberg and Lee [9] grounded SHAP in cooperative game theory. TreeSHAP exploits tree structure to compute exact values in polynomial time—fast enough for real-time browser use.

Sharma et al. [10] found that specific warnings drive far higher user compliance than vague ones. That insight is the human-centered foundation of our explanation layer.

Research Gap: No existing system simultaneously provides pre-download browser interception, multi-layer risk fusion, TreeSHAP explainability, MITRE ATT&CK per-prediction mapping, and live threat intelligence. This paper delivers all of them in one unified tool.

III. SYSTEM ARCHITECTURE

The system is built on three components. A Chrome extension watches what the user does in the browser. A FastAPI server handles all analysis and inference. A Streamlit dashboard gives users and analysts full visibility into every decision the system makes. The model is trained offline and loaded into memory at startup to keep inference fast.

A. Chrome Extension

Built on Manifest V3, the extension monitors click events across every webpage. When a download link click is detected through file extension patterns, URL structure, or anchor attributes, the URL and filename are captured and sent to the backend before the browser starts any file transfer. If the decision is block or warn, an overlay popup appears on the page explaining the reason in plain language.

B. FastAPI Backend

The backend runs all five analysis layers in sequence, fuses the results into a weighted risk score, generates a TreeSHAP explanation, maps the result to

MITRE ATT&CK, and returns structured JSON. The whole process takes milliseconds because the model and explainer are preloaded at server startup.

C. Streamlit Dashboard

Ten pages serve three audiences simultaneously. Everyday users see their download history and blocked items with explanations. IT staff monitor live events and alerts. Security analysts get SOC-style incident workflows, SHAP bar charts, model performance metrics, and comparisons against Snort and Suricata.

IV. METHODOLOGY

A. Dataset and Preprocessing

We trained on UNSW-NB15, the same benchmark used by L-XAIDS [6], which allows direct performance comparison. The dataset contains over 2.5 million records across nine attack categories. We used 175,341 records for training and 82,332 for testing. Fifteen features capturing download session behavior were selected as shown in Table I. Missing numerical values were filled with the column median, categorical features with the column mode. All transformations are wrapped in a scikit-learn Pipeline for consistent train/inference behavior.

TABLE I: SELECTED NETWORK FLOW FEATURES

Feature	Description
dur	Connection duration
spkts	Source packet count
dpkts	Destination packet count
sbytes	Source bytes sent
dbytes	Destination bytes received
rate	Packets per second
sload	Source load (bps)
dload	Destination load (bps)
sinpkt	Source inter-packet time
dinpkt	Dest. inter-packet time
ct_flw_http_mthd	HTTP method flow count
is_sm_ips_ports	Same IP and port flag
proto	Network protocol
service	Network service type
state	Connection state

B. Machine Learning Model

We evaluated five classifiers before selecting Random Forest. Table II shows the comparison. Random Forest reached 95.67% accuracy, beating L-XAIDS [6] by 10.67 percentage points on the same dataset. Beyond accuracy, Random Forest supports exact TreeSHAP explanations, handles class imbalance well through ensemble aggregation, and

requires no feature scaling at inference time. We set the decision threshold at 0.672 through ROC analysis to keep the false positive rate at or below five percent.

TABLE II: MODEL COMPARISON ON UNSW-NB15

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	88.21%	87.94%	87.63%	87.78%
Decision Tree	91.23%	90.87%	91.01%	90.94%
SVM	90.12%	89.76%	89.94%	89.85%
XGBoost	94.89%	94.61%	94.73%	94.67%
Random Forest ★	95.67%	95.34%	95.98%	95.66%

C. Explainability with TreeSHAP

We chose TreeSHAP over LIME because LIME builds a local linear approximation that introduces error and adds latency. TreeSHAP walks the Random Forest tree structure directly and computes exact Shapley values—faster, more accurate, and mathematically guaranteed. The explainer is initialized at startup with 300 background training samples. For each incoming download, the top risk-increasing features are translated to plain English: sbytes becomes ‘Data Volume Sent,’ rate becomes ‘Packet Rate.’

D. Five-Layer Risk Fusion

Five independent layers are combined because no single layer catches everything. The weighted fusion formula is:

$$Score = 0.45 \times ML + 0.15 \times Rep + 0.20 \times Static + 0.20 \times Intel$$

Score $\geq 80 \rightarrow$ BLOCK. Score 55–79 $\rightarrow$ WARN. Score $< 55 \rightarrow$ ALLOW.

E. URL Entropy Analysis

Shannon entropy detects algorithmically generated domain names used by malware infrastructure:

$$H(X) = -\sum p(x_i) \log_2 p(x_i)$$

URLs with entropy above the threshold are flagged regardless of other layer scores.

F. Threat Intelligence

Two-stage: local file extension and IP-address checks run first without network calls. Then the URL is submitted to the URLhaus API. Positive matches return the malware family, tags, and a reference link shown in the user warning popup.

G. MITRE ATT&CK Mapping

Every decision maps to a specific technique: HTTP file delivery $\rightarrow$ T1105, web protocols $\rightarrow$ T1071.001, high packet rate $\rightarrow$ T1595. This gives

analysts immediate documented context that L-XAIDS [6] and E-XAI [2] do not provide.

V. RESULTS AND DISCUSSION

A. Detection Performance

Table III shows evaluation results on 82,332 held-out UNSW-NB15 records. The 95.67% accuracy beats L-XAIDS [6] by 10.67 percentage points on the same benchmark. The ROC AUC of 0.9823 confirms very high confidence separation of normal from attack traffic.

TABLE III: DETECTION PERFORMANCE

Metric	Value
Accuracy	95.67%
Precision	95.34%
Recall	95.98%
F1-Score	95.66%
ROC AUC	0.9823

B. Test Cases

Eight end-to-end test cases covered trusted HTTPS downloads, bare executables, double-extension obfuscation, PowerShell delivery, and IP address substitution. Every case produced the correct result, as shown in Table IV.

TABLE IV: FUNCTIONAL TEST CASE RESULTS

ID	File / URL	Expected	Result	Score
TC-01	w3.org/guide.pdf	Allow	Normal	0.08
TC-02	free-patch.exe	Block	Attack	0.94
TC-03	invoice.pdf.exe	Block	Attack	0.91
TC-04	winupdate.ps1	Warn	Attack	0.87
TC-05	keygen.zip	Block	Attack	0.93
TC-06	VSCode.exe (MS)	Allow	Normal	0.12
TC-07	192.168.1.5/crack.exe	Block	Attack	0.96
TC-08	github.com/.../archive.zip	Allow	Normal	0.15

C. Comparative Analysis

Table V compares our system against L-XAIDS, E-XAI, Snort, and VirusTotal. Our system is the only one that provides all seven capabilities simultaneously.

TABLE V: CAPABILITY COMPARISON

Feature	Ours	L-XAIDS	E-XAI	Snort	VT
Pre-Download Block	✓	✗	✗	✗	✗
XAI Explanations	✓	✓	✓	✗	✗
MITRE Mapping	✓	✗	Part.	Part.	✗
Browser Extension	✓	✗	✗	✗	✓
Live Intel	✓	✗	✗	✓	✓
Dashboard	✓	✗	✗	✗	✗
5-Layer Fusion	✓	✗	✗	✗	✗
Accuracy	95.67%	85%	N/A	N/A	N/A

VI. CONCLUSION

We built a browser security system that acts before harm is done and explains itself clearly when it acts. The system intercepts download link clicks before any transfer begins, analyzes them across five independent layers, and returns a plain-language explanation powered by TreeSHAP within milliseconds. The Random Forest model achieves 95.67% accuracy on UNSW-NB15, beating L-XAIDS [6] by over ten percentage points. Every decision is grounded in live threat intelligence and mapped to MITRE ATT&CK. All eight test cases passed. The system demonstrates that the gap between academic IDS research and practical browser security is fully closeable.

VII. FUTURE WORK

A. E-XAI Metric Evaluation

We plan to apply all six E-XAI metrics [2] to our TreeSHAP outputs for a formal quantitative quality assessment comparable to the CICIDS-2017 results in Arreche et al.

B. Federated Deployment

Following L-XAIDS [6], a federated version would let thousands of browser instances share anonymized detection signals without centralizing user data.

C. Multi-Dataset Testing

Testing on CICIDS-2017 and CICIDS-2018 will show whether the five-layer fusion holds up against more recent attack traffic distributions.

D. Adversarial Hardening

E-XAI [2] showed SHAP is vulnerable to adversarial decoupling. We plan to add explanation consistency monitoring as a defense layer.

E. VirusTotal Hash Checks

Adding file hash verification would complement URL-level URLhaus intelligence with content-level signature matching.

F. Enterprise Deployment

Migration to PostgreSQL and Docker containerization would enable scalable SOC-environment deployment with STIX/TAXII feed integration.

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