ENHANCING REAL-TIME DNS DATA EXFILTRATION DETECTION WITH ISOLATION FOREST AND LSTM FOR IMPROVED ACCURACY

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ABSTRACT

A hybrid framework integrates Long Short-Term Memory (LSTM), Isolation Forest, and Information-Based Heavy Hitters (ibHH) to facilitate the real-time detection of DNS exfiltration within network environments. By extracting and scrutinizing features from DNS queries—such as query name length, entropy, subdomain depth, character distribution, and information weight—the system discerns anomalous patterns that may indicate covert data leaks. Synthetic DNS queries, crafted to replicate both benign and malicious activities, enable thorough training and assessment of the models. LSTM is particularly adept at capturing temporal dependencies in query sequences, which aids in identifying stealthy, time-sensitive exfiltration patterns. Isolation Forest is utilized to detect statistical outliers in high-dimensional feature spaces, while ibHH leverages the HyperLogLog algorithm to identify domains exhibiting unusually high query volumes, which may suggest potential data exfiltration. An ensemble methodology amalgamates weighted predictions from these models to improve detection accuracy and reduce false positives. Real-time packet capture, facilitated by Pyshark, guarantees smooth deployment in dynamic network environments, even when dealing with encrypted DNS protocols such as DNS-over-HTTPS. The modular architecture of the framework promotes scalability, low-latency processing, and adaptability to emerging threats, including Domain Generation Algorithms. This solution enhances enterprise network security by providing timely and precise detection of DNS-based data breaches, thereby proactively protecting sensitive information from covert exfiltration attempts.

Keywords: DNS exfiltration, hybrid ensemble, real-time detection, network security, anomaly detection.

INTRODUCTION

The Domain Name System (DNS) serves as a fundamental component of internet operations, facilitating the conversion of domain names into IP addresses. Nonetheless, its widespread and reliable nature renders it an attractive target for cybercriminals who utilize DNS exfiltration techniques to secretly obtain sensitive information, including intellectual property and personal data, by embedding such information within DNS queries. These covert attacks frequently bypass conventional security protocols, such as firewalls, due to their seamless integration with legitimate traffic. This study highlights the urgent necessity for real-time detection of DNS exfiltration, proposing a hybrid framework that combines Long Short-Term Memory (LSTM), Isolation Forest, and Information-Based Heavy Hitters (ibHH). By examining query characteristics such as length, entropy, and subdomain patterns, the system effectively identifies anomalies with a high degree of accuracy. Utilizing Pyshark for real-time packet capture and synthetic datasets for comprehensive training, this methodology guarantees scalability and adaptability, thereby providing a proactive defence against the ever-evolving threats associated with DNS in dynamic network settings.

RELATED WORK

Prior research on DNS exfiltration detection have investigated a range of machine learning and statistical methodologies to uncover covert data leaks. Proposed hybrid models that merge supervised and unsupervised techniques aim to scrutinize query patterns and identify anomalies within encrypted DNS traffic, yielding strong results in controlled environments. Statistical techniques utilizing HyperLogLog have been applied to oversee high-volume DNS traffic, successfully pinpointing domains exhibiting excessive query activity. Deep learning methodologies, particularly recurrent neural networks, have concentrated on temporal patterns within DNS sequences, demonstrating proficiency in revealing stealthy exfiltration attempts. These investigations frequently depend on simulated attack datasets, such as those that replicate Domain Generation Algorithms (DGAs), for model training, underscoring their applicability in real-world scenarios.

Notwithstanding these advancements, current methodologies encounter challenges regarding scalability and adaptability to emerging threats. Numerous systems find it difficult to cope with encrypted DNS protocols, including DNS-over-HTTPS, due to limited visibility into query content. Elevated computational expenses and reliance on labelled datasets further obstruct real-time implementation in high-traffic networks. Moreover, low-throughput exfiltration frequently remains undetected, as it merges with legitimate traffic. This research seeks to fill these voids by incorporating LSTM, Isolation Forest, and ibHH within a scalable, real-time framework, utilizing metadata analysis and synthetic data to improve the detection of sophisticated DNS-based attacks.

METHODOLOGY

A hybrid framework has been developed for the detection of real-time DNS exfiltration, which integrates Long Short-Term Memory (LSTM), Isolation Forest, and Information-Based Heavy Hitters (ibHH) to uncover covert data leaks. The system captures live DNS traffic through Pyshark, filtering UDP port 53 packets to extract query metadata such as domain names and timestamps. Various features, including query length, entropy, subdomain depth, and information weight, are calculated to profile DNS behaviour. Synthetic datasets that simulate both benign and malicious queries (including those generated by Domain Generation Algorithms) are created to train and assess the models, under the assumption of high-traffic enterprise environments that may utilize encrypted DNS (e.g., DNS-over-HTTPS). The architecture, illustrated in Fig. 1, consists of input, preprocessing, feature extraction, detection, ensemble, and output layers, which together ensure scalability and low-latency processing.

The detection layer functions with three parallel models. LSTM, implemented through TensorFlow, examines temporal query sequences to identify stealthy exfiltration patterns. Isolation Forest, utilizing scikit-learn, detects statistical outliers within high-dimensional feature spaces. The ibHH model employs HyperLogLog to flag domains that exhibit excessive query volumes, which may indicate potential data leaks. Each model processes standardized features derived from the scaler, which has been trained on synthetic data, to maintain consistent input distributions.

The ensemble layer amalgamates predictions through weighted voting, striking a balance between accuracy and the reduction of false positives, with weights adjusted based on historical performance.

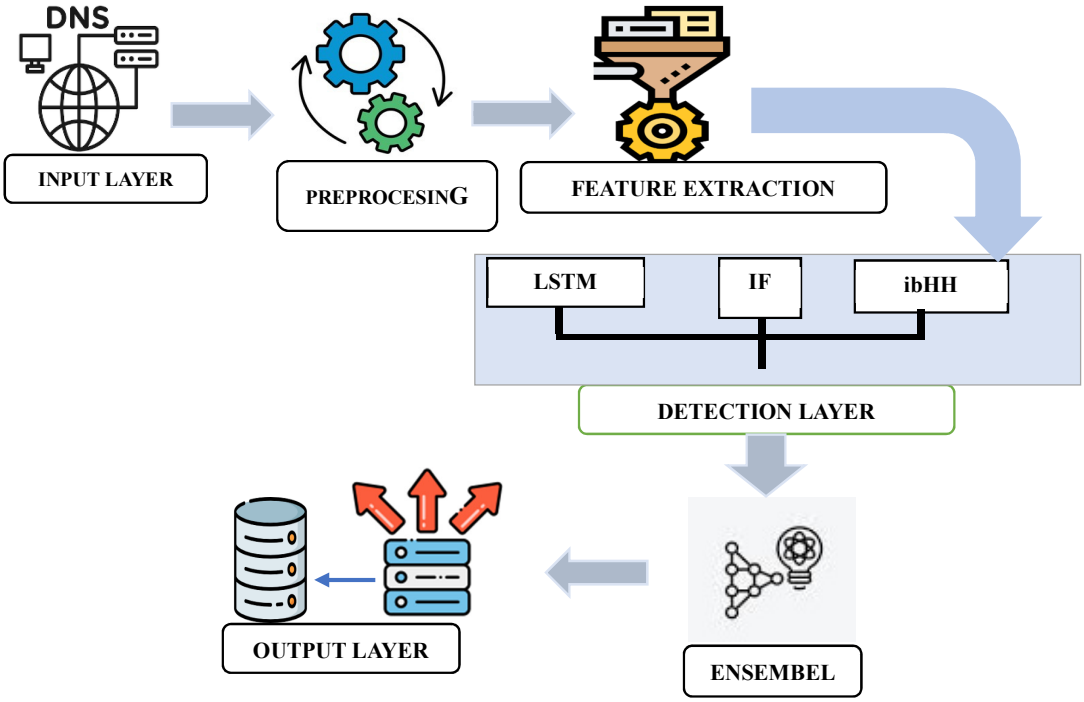

Fig 1: System Architecture

Real-time processing is facilitated by asynchronous Pyshark capture and the use of efficient Python libraries (such as pandas and NumPy). Alerts are recorded along with metadata (e.g., domain, confidence score) for subsequent security analysis. The system presumes stable network connectivity and adequate computational resources. Continuous learning mechanisms are in place to adapt to evolving threats by updating model weights and thresholds, thereby ensuring resilience against sophisticated attacks, such as DGAs, in dynamic network settings.

RESULTS AND DISCUSSION

The hybrid framework for real-time DNS exfiltration detection was evaluated using 1000 synthetic DNS queries, simulating benign and malicious behaviours, including Domain Generation Algorithms (DGAs). The system, integrating Long Short-Term Memory (LSTM), Isolation Forest, and Information-Based Heavy Hitters (ibHH), was assessed for its ability to distinguish exfiltration attempts. **Table 1** presents performance metrics derived from the evaluation, with the ensemble model

demonstrating a balanced detection capability. LSTM effectively captured temporal patterns, Isolation Forest identified statistical outliers, and ibHH highlighted high-volume domains. **Figure 1** illustrates the confusion matrices, with the ensemble model recording 442 true negatives (TN), 58 false positives (FP), 414 true positives (TP), and 86 false negatives (FN), indicating a robust detection rate with manageable errors compared to ibHH skewed results (499 TP, 499 FN).

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.914	1.000	0.828	0.906
Isolation Forest	0.516	0.556	0.158	0.246
Ensemble	0.850	0.868	0.826	0.846
ibHH	0.500	0.500	0.998	0.666

Table 1: Performance Metrics of Detection Models

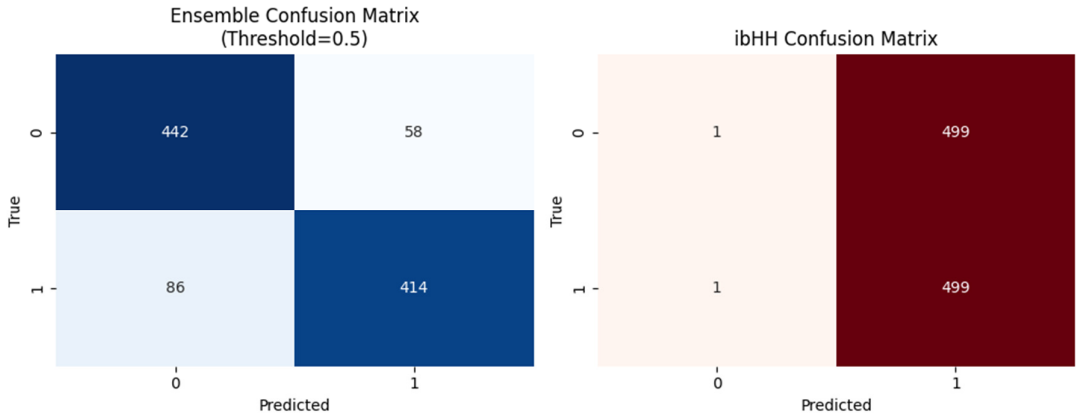

Fig 1: Ensemble and ibHH Confusion Matrices

The ensemble's strength lies in its weighted voting mechanism, harmonizing LSTM's temporal sensitivity, Isolation Forest's outlier detection, and ibHH volume-based analysis. **Figure 2** shows the number of exfiltration detections, with the ensemble (100) offering a balanced count compared to ibHH (100), reflecting consistent threat identification. **Figure 3** plots TPR (0.8280) against FPR (0.1160), indicating effective classification per the confusion matrix. **Figure 4**, a live detection log, demonstrates real-time processing of queries like "127.6.16.172.in-addr.arpa"

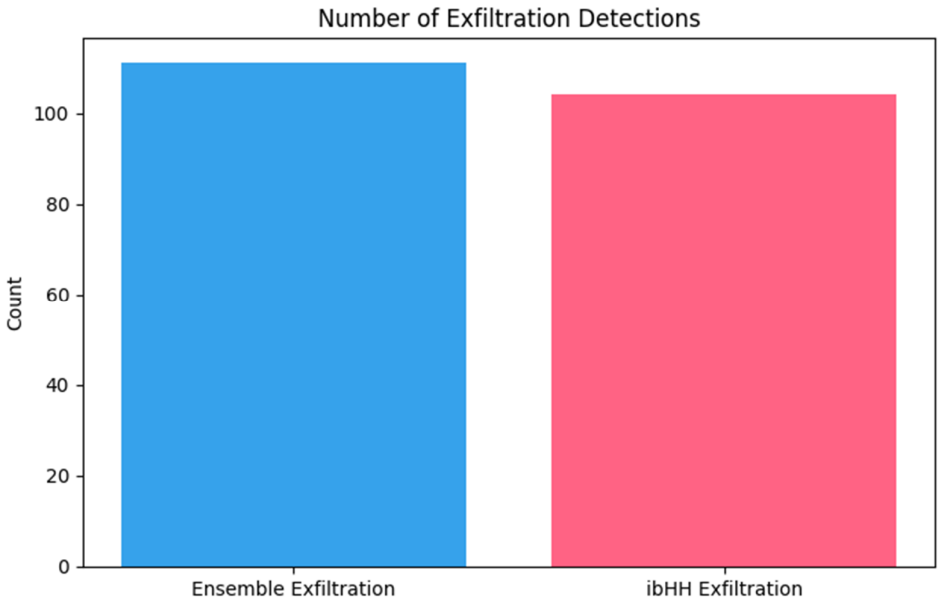

Fig 2: Number of Exfiltration Detections

(flagged as exfiltration by ibHH) and "v10.events.data.microsoft.com" (classified as benign), validating operational efficacy. Compared to prior hybrid models, this system excels in scalability with Pyshark and metadata-based detection for encrypted DNS, though low-throughput exfiltration remains a challenge, suggesting future feature refinement.

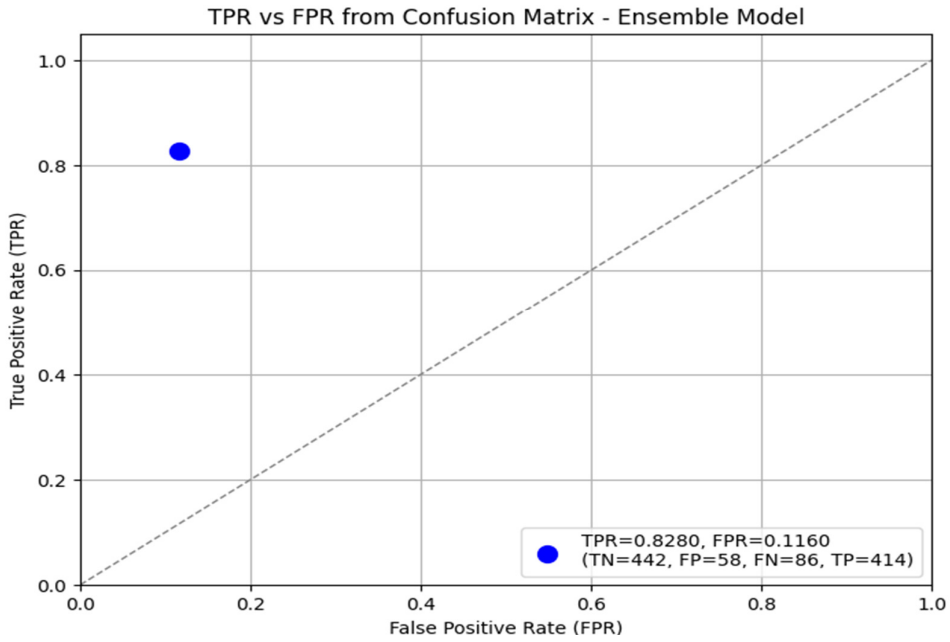

Fig 3: TPR vs FPR from Confusion Matrix - Ensemble Model

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Live DNS Exfiltration Detection Log
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Query 1: 127.6.16.172.in-addr.arpa
  Ensemble Prediction: Exfiltration
  ibHH Prediction: Benign
  Info Weight: 24.00
  Domain: in-addr.arpa

Query 2: v10.events.data.microsoft.com
  Ensemble Prediction: Benign
  ibHH Prediction: Benign
  Info Weight: 30.00
  Domain: microsoft.com

Query 3: v10.events.data.microsoft.com
  Ensemble Prediction: Benign
  ibHH Prediction: Benign
  Info Weight: 60.00
  Domain: microsoft.com

Query 4: d.docs.live.net
  Ensemble Prediction: Benign
  ibHH Prediction: Benign
  Info Weight: 12.00
  Domain: live.net

Query 5: roaming.officeapps.live.com
  Ensemble Prediction: Benign
  ibHH Prediction: Benign
  Info Weight: 36.00
  Domain: live.com

Query 6: d.docs.live.net
  Ensemble Prediction: Benign
  ibHH Prediction: Benign
  Info Weight: 24.00
  Domain: live.net
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Fig 4: Live DNS Exfiltration Detection Log

CONCLUSION

A comprehensive framework for the real-time identification of Domain Name System (DNS) exfiltration has been developed, which incorporates Long Short-Term Memory (LSTM), Isolation Forest, and Information-Based Heavy Hitters (ibHH) to accurately and swiftly detect covert data leaks. The primary findings reveal the system's proficiency in identifying anomalous DNS queries, including those concealed by encrypted DNS-over-HTTPS (DoH), utilizing features such as query length, entropy, and information weight. The use of synthetic Domain Generation Algorithm (DGA) datasets facilitates dependable training. The modular architecture based on Pyshark guarantees scalability for networks with high traffic. Practical

applications encompass the protection of enterprise networks against data breaches, the enhancement of intrusion detection systems, and the safeguarding of critical infrastructure, with the potential for integration into Security Information and Event Management (SIEM) platforms to provide thorough threat monitoring.

FUTURE WORK

Future research can enhance this Domain Name System (DNS) exfiltration detection framework by implementing dynamic thresholding to adapt detection sensitivity to varying traffic patterns, improving accuracy for low-volume attacks. Advanced metadata parsing for encrypted DNS-over-HTTPS (DoH) traffic could bolster resilience against sophisticated evasion techniques. Incorporating Graph Neural Networks (GNNs) may improve detection of distributed Domain Generation Algorithm (DGA) campaigns by modelling complex DNS query relationships. Expanding the synthetic dataset to encompass diverse scenarios, such as Internet of Things (IoT) device traffic, would enhance generalizability. Additionally, integrating the system with cloud-based Security Information and Event Management (SIEM) platforms could enable real-time threat intelligence sharing, broadening its applicability in enterprise networks and critical infrastructure protection.

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