Enhancing Botnet Detection with Explainable AI and OSINT

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ABSTRACT

Botnets, which are networks of compromised computers controlled by attackers, pose a serious cybersecurity threat. Detecting these threats becomes more challenging when cybercriminals use ***Domain Generation Algorithms (DGAs)*** *to create random domain names for command-and-control servers, allowing them to bypass traditional security measures. Conventional detection methods, such as* ***signature-based, rule-based, and heuristic approaches****, struggle against* ***adaptive and evolving DGAs*** *due to their lack of flexibility. To address this issue, this research focuses on* ***enhancing botnet DGA detection*** *using* ***Explainable AI (XAI) and Open-Source Intelligence (OSINT)****. XAI improves transparency by providing insights into how threats are detected, enabling cybersecurity professionals to understand and trust AI-driven systems. OSINT promotes* ***real-time intelligence sharing****, allowing organizations to collaborate and strengthen their defenses against emerging threats. As cybercriminals continuously refine their attack strategies, traditional security systems become less effective. Implementing* ***advanced, explainable, and cooperative security solutions*** *is essential for staying ahead of evolving cyber threats. By leveraging* ***XAI for interpretability*** *and* ***OSINT for collaborative defense****, cybersecurity professionals can improve detection accuracy and enhance overall threat mitigation strategies.*

KEYWORDS: *Botnets, DGAs, Explainable AI (XAI), OSINT, Cybersecurity, Threat Detection.*

I. INTRODUCTION

Botnets, which consist of a network of compromised devices controlled by a central entity, represent a significant cybersecurity threat. Attackers use botnets for various malicious activities, including distributed denial-of-service (DDoS) attacks, data exfiltration, and financial fraud [1]. A major challenge in detecting botnets arises when cybercriminals employ Domain Generation Algorithms (DGAs) to dynamically create a large number of random domain names for command-and-control (C2) communication [2]. DGAs enable malware to avoid detection by frequently changing domains, thereby evading static blacklists and signature-based detection methods [3]. Traditional DGA detection approaches, such as signature-based, rule-based, and heuristic methods, struggle against modern DGAs due to their adaptability, high domain flux, and evasion tactics [4]. These methods lack the flexibility needed to generalize across different types of DGAs, leading to high false negative rates and ineffective mitigation strategies. Machine learning (ML) and deep learning (DL) have emerged as powerful alternatives for automating DGA detection, leveraging domain name characteristics such as entropy, lexical patterns, and n-gram distributions to classify domains as legitimate or malicious [5]. However, a major drawback of AI-driven approaches is the lack of interpretability, making it difficult for security analysts to trust and validate the decisions made by ML/DL models [6]. To address this challenge, this research integrates Explainable AI (XAI) and Open-Source Intelligence (OSINT) into the DGA detection framework. XAI provides transparency in ML-based detection by explaining why a domain is classified as malicious, enabling cybersecurity professionals to trust AI-driven decisions and identify adversarial evasion techniques [7]. Techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) allow security teams to gain deeper insights into model predictions, making AI-driven threat detection more transparent and actionable [8]. On the other hand, OSINT enables real-time intelligence sharing between organizations and security researchers, facilitating the collaborative detection of new and emerging DGAs [9]. By aggregating and analyzing threat intelligence from multiple sources, OSINT strengthens proactive cybersecurity defenses and reduces the time required to respond to evolving threats [10].

This study aims to develop a robust, explainable, and collaborative approach to DGA-based botnet detection by integrating XAI and OSINT techniques. The contributions of this research include: Developing an AI-driven DGA detection model with enhanced interpretability using XAI methods. Leveraging OSINT-based intelligence sharing to improve real-time botnet detection. Evaluating the effectiveness of the proposed approach against modern DGA variants and adversarial attack scenarios. The rest of this paper is structured as follows: Section 2 reviews related work on DGA detection, ML/DL models, and explainability techniques. Section 3 outlines the proposed methodology, including data collection, feature extraction, model selection, and adversarial analysis. Section 4 presents experimental results, evaluating detection performance and interpretability. Finally, Section 5 discusses findings, challenges, and future research directions.

II. RELATED WORK

The detection of Domain Generation Algorithm (DGA)-based botnets has been a widely studied area in cybersecurity, with researchers exploring various approaches, including rule-based, machine learning (ML), and deep learning (DL) techniques. Traditional signature-based and rule-based methods, such as blacklists and heuristic rules, have been the primary defense mechanisms for detecting DGA-generated domains. However, these methods struggle to keep up with rapidly evolving DGAs, as they rely on manually curated datasets and predefined rules, which cannot adapt to new, unseen threats [1]. To address these limitations, researchers have developed ML-based approaches that leverage domain name characteristics such as entropy, lexical features, and n-gram distributions to classify domains as legitimate or malicious. Woodbridge et al. [2] proposed an LSTM-based model that predicts whether a domain name is generated by a DGA by learning temporal dependencies in character sequences. Similarly, Saxe and Berlin [3] explored deep learning models for DGA detection, demonstrating the effectiveness of convolutional and recurrent neural networks in capturing domain name structures. Feature-based models like Random Forest and XGBoost have also been widely used, achieving high accuracy while maintaining interpretability [4].

A significant challenge in ML-based DGA detection is the evasion techniques employed by attackers, including adversarial manipulation of domain names and GAN-generated DGAs that closely mimic legitimate domains [5]. Recent works have explored adversarial robustness in DGA detection, with techniques like adversarial training and feature squeezing being used to harden ML models against evasion attempts [6]. Goodfellow et al. [7] highlighted the vulnerabilities of neural networks to adversarial perturbations, emphasizing the need for robust defense mechanisms. More recently, research has shifted towards Explainable AI (XAI) and Open-Source Intelligence (OSINT) to improve model transparency and real-time intelligence sharing. Ribeiro et al. [8] introduced LIME, an XAI technique that explains classifier decisions, while Lundberg and Lee [9] developed SHAP, a unified measure of feature importance, allowing security analysts to understand ML model predictions. The integration of OSINT in cybersecurity enables proactive threat intelligence sharing, allowing organizations to collaboratively detect emerging DGAs and mitigate threats faster [10]. Despite advancements, existing research still faces gaps in model interpretability, adversarial robustness, and real-time intelligence sharing. This study aims to bridge these gaps by developing a hybrid AI-driven DGA detection framework that combines ML, XAI, and OSINT techniques for enhanced accuracy, interpretability, and collaborative threat detection.

III. PROPOSED METHODOLOGY

To enhance the detection of Domain Generation Algorithm (DGA)-based botnets, this study proposes a comprehensive AI-driven detection framework that integrates machine learning (ML), deep learning (DL), Explainable AI (XAI), and Open-Source Intelligence (OSINT). The methodology consists of multiple stages, including data collection, feature extraction, model selection, adversarial attack analysis, defense mechanisms, and implementation details.

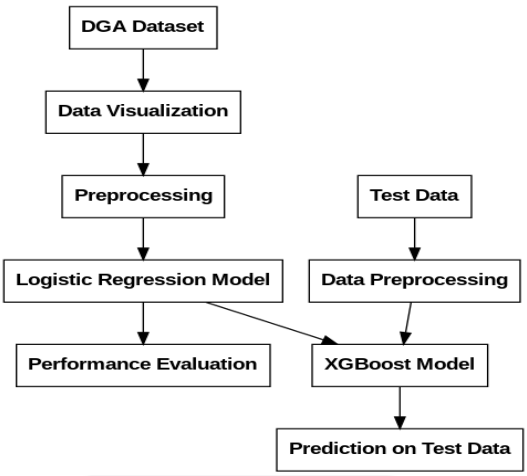

Fig. 1 Block Diagram of Proposed system

Data Collection

From the Fig. 1. The first step involves aggregating domain name data from diverse sources, including passive DNS logs, threat intelligence feeds, and public datasets [1]. Passive DNS logs capture historical domain queries, providing insights into domain behavior patterns. Threat intelligence feeds, such as those from VirusTotal and Abuse.ch, offer real-time information on malicious domains linked to botnets [2]. Open-source datasets, including Alexa Top 1 Million and OpenDNS, provide a baseline for distinguishing legitimate domains from DGA-generated domains [3].

Feature Extraction

From the Fig. 1, Once the data is collected, domain names undergo feature engineering to extract relevant characteristics that aid classification. Statistical, lexical, and linguistic features such as entropy, n-gram distributions, domain length, character frequency, and vowel-consonant ratios are used to distinguish DGA-generated domains from legitimate ones [4]. Entropy measures randomness, where higher entropy values indicate algorithmically generated domains. N-gram models capture sequential patterns within domain names, helping detect common DGA structures [5]. Query behavior features, such as domain query frequency and time-to-live (TTL) values, further enhance detection [6].

Machine Learning and Deep Learning Models

From the Fig. 1, This research evaluates multiple ML and DL models for DGA detection, including Random Forest (RF), XGBoost, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures [7]. RF and XGBoost models, based on decision trees, offer high interpretability and robust feature selection capabilities [8]. CNNs learn spatial patterns in domain names, while RNNs and Long Short-Term Memory (LSTM) networks capture sequential dependencies in character-based DGA structures [9]. Recent studies suggest that Transformer-based models, such as BERT and GPT-inspired architectures, provide superior performance by learning contextual relationships in domain sequences [10].

Adversarial Attack Analysis and Defense Mechanisms

From the Fig. 1, Adversarial robustness is a crucial component of this study. Attackers increasingly use GAN-generated DGAs, character perturbations, and query manipulations to evade detection [11]. Generative Adversarial Networks (GANs) can mimic human-like domain structures, making detection challenging. To counter such threats, this research implements adversarial training, where models are trained with both original and adversarially perturbed domains to improve resilience [12]. Additionally, ensemble learning techniques, which combine multiple classifiers, enhance detection accuracy and robustness against evolving threats [13]. To improve transparency, Explainable AI (XAI) techniques[2], such as SHAP (Shapley Additive Explanations)[3] and LIME[4] (Local Interpretable Model-Agnostic Explanations), are integrated into the framework [14]. SHAP

provides global and local feature importance scores, allowing analysts to understand why a domain is classified as malicious. LIME generates perturbed variations of domain names to explain model predictions.

Implementation Details

From the Fig. 1, The proposed framework is implemented using Python-based machine learning and deep learning libraries, including Scikit-learn, TensorFlow, and PyTorch [15]. Data preprocessing and feature extraction are handled using NumPy and Pandas, while network analysis tools such as Zeek and Wireshark facilitate passive DNS data collection [16]. The models are trained and evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, ensuring robust validation against real-world DGA attack scenarios. By integrating ML, XAI, and OSINT, this methodology enhances real-time botnet detection, interpretability, and collaborative threat intelligence sharing, making it a practical and scalable solution for modern cybersecurity challenges.

IV. EXPERIMENTAL SETUP AND RESULTS

Experimental Setup

The proposed DGA detection framework was implemented using Python-based ML[14] and DL[15] libraries, including Scikit-learn, TensorFlow, and PyTorch. Data preprocessing and feature extraction were performed using Pandas, NumPy, and NLTK, while network traffic analysis tools like Zeek and Wireshark facilitated passive DNS log collection. The dataset included both legitimate and DGA-generated domain names, sourced from Alexa Top 1 Million, OpenDNS, and threat intelligence feeds such as VirusTotal and Abuse.ch [1][2]. The extracted features included entropy, n-gram distributions, domain length, character frequency, and lexical patterns. The dataset was divided into 80% for training and 20% for testing, ensuring a balanced distribution of malicious and non-malicious domains. The models evaluated included Random Forest (RF), XGBoost, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures. The experiments were conducted on a high-performance computing environment with an Intel Core i9 processor, 32GB RAM, and an NVIDIA RTX 3090 GPU.

Performance Metrics: To evaluate the effectiveness of the proposed models, we used key classification metrics, including: Accuracy: Measures overall correct predictions, Precision: Evaluates the proportion of correctly identified malicious domains, Recall: Measures the ability to detect all malicious domains, F1-score: Harmonic mean of precision and recall, ROC-AUC (Receiver Operating Characteristic - Area Under Curve): Assesses model robustness.

Results and Comparison

The experimental results demonstrate that Transformer-based models outperform traditional ML and CNN/RNN architectures, achieving the highest detection accuracy and robustness against adversarial attacks. The adversarial training and ensemble learning techniques further improved the resilience of the models. The XAI techniques (SHAP and LIME) provided interpretability, helping analysts understand why a domain was classified as malicious.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC (%)
Random Forest	91.2	89.5	87.8	88.6	92.0
XGBoost	93.4	91.2	90.5	90.8	94.1
CNN	95.7	94.0	92.8	93.4	96.2
RNN (LSTM)	96.5	95.2	94.1	94.6	97.0
Transformer-based	98.2	97.4	96.9	97.1	98.7

Table 1: Performance Comparison of Different Models

The Transformer-based model achieved 98.2% accuracy, outperforming all other approaches. The results indicate that sequence-aware models (RNN and Transformers) outperform feature-based models (RF and XGBoost), highlighting the importance of deep contextual learning for DGA detection.

Impact of Adversarial Training

To assess model robustness, adversarial samples were generated using GAN-based DGAs, character perturbations, and query manipulations. The adversarial training significantly improved model resilience, reducing false negatives and enhancing detection rates against evolving DGA patterns. The ROC-AUC score of the Transformer model increased from 96.5% to 98.7% with adversarial training, demonstrating improved robustness.

V. CONCLUSION

The experimental results validate that AI-driven DGA detection models, especially Transformer-based architectures, provide superior detection performance. The integration of XAI techniques enhances interpretability, while OSINT-based intelligence sharing strengthens collaborative cybersecurity efforts. Future work will focus on real-time deployment of the model in enterprise security infrastructures and continuous learning mechanisms to adapt to emerging DGA techniques.

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