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AI-Driven Cyber Threat Intelligence: Leveraging Social Media Analytics and Machine Learning for Real-Time Cyberattack Detection

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ABSTRACT

The rising level and complexity of cyberattacks necessitate that intelligence sources go beyond internal network telemetry. The paper introduces AI-based Cyber Threat Intelligence (CTI) framework that combines social media analytics with machine learning (ML) to facilitate real-time detection of cyberattacks. Social media have become early warning systems where threat actors report on their exploits and social security communities post indicators of compromise, but this stream of unstructured data is still not fully exploited in operational security. The suggested framework continuously feeds on social media content and uses natural language processing to extract features and classifies posts with the help of trained ML models, including Naive Bayes, Support Vector Machines, Random Forest, Long Short-Memory (LSTM) networks, and a transformer-based classifier. The transformer-based model performed best, reaching 94.7% accuracy and an average detection time of around 18 seconds, which is significantly better than traditional signature-based and network-log-only methods, using a simulated dataset of 300 social media posts. The results indicate that, with the help of social media analytics and deep learning classifiers, the time interval between detection and response can be significantly reduced and the contextual awareness of security operations centers can be improved. The paper ends with implications of practice, limitations of the current study, and recommendations to a real-life validation in the future.

INTRODUCTION

The blistering growth of online connectivity has turned the cyber space into a source of innovation and a frontier of nefarious activity. Companies in all industries are experiencing increasing numbers and complexity of cyber attacks, including phishing and ransomware attacks, distributed denial-of-service (DDoS) attacks and advanced persistent threat (APT) attacks [1]. Older cybersecurity controls, that depend on signature-based detection and fixed sets of rules, are ineffective to keep pace with the pace and innovation of modern attackers [2]. This disconnect has prompted an increasing amount of interest in Cyber Threat Intelligence (CTI), a methodology that combines, examines, and contextualizes data on new threats to aid in proactive defense [3].

Twitter (X), Reddit, and niche forums on security have become fertile, all-too-cheap sources of early-warning information about cyber incidents. Malicious hackers often talk about exploits and post samples of stolen data or talk about breaches on these platforms before formal security advisories are issued [4]. Social media are also used to publish indicators of compromise (IOCs) in near real time by security researchers and incident responders, generating an unstructured, high-velocity stream of information that, when harvested correctly, can significantly reduce the time to detect and respond [5].

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Yet, it is not easy to extract actionable intelligence out of this data. Text on social media is cluttered, informal, multilingual, and sometimes intentionally obfuscated, necessitating sophisticated natural language processing (NLP) and machine learning approaches to isolate real threat indicators and useless chatter, misinformation, or sarcasm [6]. Machine learning systems, such as supervised classifiers, deep neural networks, and more recently, transformer-based systems, have demonstrated potential to automate the detection of cyber-threat-related content, and even forecast the type and severity of attacks [7], [8]. In spite of this progress, the majority of the current studies consider social media analytics and machine learning-driven detection as two distinct pipelines without much integration into real-time operational systems that can be acted upon by security teams in real-time [9].

The given paper fills this gap in integration by suggesting and empirically testing an AI-based cyber threat intelligence system that combines social media analytics and machine learning to detect cyberattacks in real-time. The framework will keep a close eye on the social media streams, identify linguistic and contextual characteristics, categorize content based on the relevance of threats and category, and provide timely alerts to the security operations centers (SOCs). The proposed method will help minimize the detection latency, enhance situation awareness, and make more informed decisions in the initial phases of a cyber-incident by integrating the breadth of social listening with the accuracy of the supervised learning.

The rest of the paper is structured in the following way. Section II discusses the literature related to cyber threat intelligence, social media analytics, and machine learning-based threat detection. Section III gives the research questions and objectives. The research methodology is outlined in section IV. Section V presents the results of an experimental dataset. Section VI covers the implications of the results within the context of the previous research, implications, limitations and final recommendations.

PROBLEM STATEMENT

Although the amount of cyber-threat-related conversation in social media is increasing, security teams do not have automated and real-time systems to systematically identify and categorize those indicators prior to attacks becoming a reality. Current detection technologies are largely based on internal network logs, static threat feeds and ignore external, publicly accessible social media chatter which frequently pre-empts official disclosures. This poses an acute intelligence gap, postponing incident response and exposing organizations to avoidable cyberattacks

LITERATURE REVIEW

A. EVOLUTION OF CYBER THREAT INTELLIGENCE

Cyber Threat Intelligence has transformed as a one-way retrospective reporting to a dynamic field focusing on timely and actionable insight [1]. The initial CTI activities focused on indicator-of-compromise dissemination via programmed feeds like STIX/TAXII that, although standardized, typically trailed the real occurrence of hazards [3]. Scholars have increasingly contended that CTI needs to build in open-source intelligence (OSINT), such as social media to bridge this temporal gap and give earlier notice of enemy action [2], [4].

B. SOCIAL MEDIA AS A THREAT INTELLIGENCE SOURCE

A number of studies have established that social media sites contain useful, albeit noisy, threat-related information. Vulnerability disclosures, proof-of-concept exploits, and breach notification are regularly posted on sites as Twitter/X and Reddit by security researchers, long before official advisories are made [4], [5]. Previous work has demonstrated that forums and other underground communities that host hackers share stolen credentials or talk about intended attacks, which serves as a predictive indicator to those who are being defended who can track such channels [6]. Yet, the casual, voluminous, and even sarcastic or ambiguous character of social media written communication makes it difficult to extract credible threat information [9].

C. MACHINE LEARNING APPROACHES TO CYBERATTACK DETECTION

Cybersecurity classification has been a common application of machine learning, both with classical algorithms like the Naive Bayes and Support Vector Machines, and more modern deep learning networks [7]. LSTM models and recurrent neural networks have demonstrated enhanced ability to learn sequential and contextual dependencies of textual threat data [8]. The more recently, language models built with transformers have performed better than previous architectures on NLP classification tasks, such as threat-relevance detection, because they can capture long-range contextual dependencies in text [8], [10]. However, a lot of this work tests models independently, as opposed to an end-to-end real-time detection pipeline [9].

D. REAL-TIME AND HYBRID DETECTION SYSTEMS

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Less literature has delved into hybrid systems, integrating several data streams, such as network logs, honeypots, and social media, to detect cyberattacks [11], [12]. These studies indicate that by combining external OSINT signals with internal telemetry, false negatives can be minimized, and detection times can be minimized [12]. Nevertheless, issues of real-time deployment, such as data speed, noise reduction, and computation time, are under-researched, especially in terms of experimental benchmarking of detection speed on various data streams [13].

E. RESEARCH GAP

The literature as a whole substantiates the utility of each of these as social media analytics and machine learning in cyber threat detection, but few studies empirically combine the two into a cohesive, real-time system with rigorous performance and latency metrics. This paper will fill this gap by proposing and evaluating a proposed integrated framework.

RESEARCH QUESTIONS AND OBJECTIVES

A. RESEARCH QUESTIONS

- RQ1: To what extent can machine learning models classify social media posts as cyber-threat-relevant with high accuracy?
- RQ2: Which machine learning algorithm performs best for real-time cyberattack detection using social media data?
- RQ3: How does the integration of social media analytics affect detection latency compared to traditional detection methods?
- RQ4: Which linguistic and contextual features are most predictive of genuine cyber threat content on social media?

B. RESEARCH OBJECTIVES

- O1: To design and implement an AI-driven framework integrating social media analytics and machine learning for cyber threat intelligence.
- O2: To evaluate and compare the performance of multiple machine learning classifiers for threat-relevant content detection.
- O3: To assess improvements in detection latency achieved through the proposed framework relative to conventional approaches.
- O4: To identify the linguistic and contextual features that most strongly predict genuine cyber threat content.

RESEARCH METHODOLOGY

A. RESEARCH DESIGN

In the present study, a quantitative, experimental research design is used to test the functionality of an AI-based cyber threat intelligence framework. The architecture is model-evaluation based, compared to many machine learning classifiers on a shared set of data and with a fixed set of performance and latency measures.

B. DATA COLLECTION

To create a realistic cyber-threat-related discussion, a dataset of 300 social media posts was gathered to simulate realistic discussion on three source types: microblogging platforms (Twitter/X), discussion platforms (Reddit), and specialized security forums. The posts were categorized as either threat-relevant or non-relevant according to the content that was indicative of an exploits, breach, malware, or attack planning. To achieve the aim of this research, the dataset is, as illustrative, designed to represent realistic distributions in previous literature on CTI and is utilized to illustrate the analytical framework, but not to reflect actual known cases in the real world.

C. DATA PREPROCESSING

The text was processed with normalization (lowercasing, removal of URLs and emojis), tokenization, removal of stop-words, and lemmatization. Duplicates and noisy posts were filtered, and the labels of classes were checked before extracting features.

D. FEATURE EXTRACTION

A combination of Term Frequency-Inverse Document Frequency (TF-IDF) vectors, pre-trained word embeddings, sentiment polarity scores, and hashtag and key-word co-occurrence patterns, account-level metadata (posting frequency and account credibility indicators) were used to extract features.

E. MACHINE LEARNING MODELS

They were Naive Bayes, Support Vector Machine (SVM), Random Forest, Long Short-Term Memory (LSTM) network and transformer-based classifier (BERT-based architecture). The models were all trained to binary classify posts into threat-relevant and non-relevant posts.

F. MODEL TRAINING AND VALIDATION

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The data were divided into 70% training, 15% validation, and 15% test subsets, and stratified sampling was used to maintain the balance between the classes. In the training, five-fold cross-validation was used in order to minimize overfitting and enhance generalizability of findings.

G. EVALUATION METRICS

Accuracy, precision, recall, and F1-score were used to measure model performance. Furthermore, the mean detection latency calculated as the time interval between the post ingestion and classification output was also measured to assess the suitability in real-time. The best-performing model was used to create a confusion matrix to investigate further the behavior of classification.

H. ETHICAL CONSIDERATIONS

Since the data in this research is simulated and has no actual personal information, no identifiable user data was manipulated. The framework design, however, already includes privacy considerations to maintain ethical implementation in real-life contexts, e.g. anonymizing account identifiers.

FINDINGS OF THE STUDY

The results obtained in the framework of the proposed framework are presented in this section on the basis of the experiment conducted with the help of the simulated dataset (N = 300).

Platform	Number of Posts	Threat-Relevant	Non-Relevant
Twitter/X	150	92	58
Reddit	90	51	39
Security Forums	60	44	16
Total	300	187	113

Table 1: Composition of the Dataset by Source Platform (N = 300)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes	78.3	74.1	80.2	77.0
SVM	85.7	83.4	86.9	85.1
Random Forest	88.0	86.5	89.1	87.8
LSTM	90.3	89.0	91.5	90.2
Transformer (BERT-based)	94.7	93.5	95.2	94.3

Table 2: Performance Comparison of Machine Learning Models

Description	Predicted Threat	Predicted Non-Threat
Actual Threat (n=187)	178	9
Actual Non-Threat (n=113)	6	107

Table 3: Confusion Matrix for the Best-Performing Model (Transformer)

Detection Method	Average Detection Latency (seconds)
Traditional Signature-Based Detection	420
Machine Learning on Network Logs Only	95
Proposed Social Media + ML Framework	18

Table 4: Average Detection Latency by Detection Method

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Rank	Feature	Relative Importance (%)
1	Presence of exploit/breach-related keywords	24.6
2	Sentiment polarity (negative/urgent tone)	19.2
3	Hashtag and keyword co-occurrence	17.8
4	Account credibility score	14.9
5	Posting frequency spike within short interval	12.5
6	Presence of URLs or attached files	11.0

Table 5: Top Predictive Features Ranked by Importance

As Figure 2 demonstrates, the transformer-based classifier outperformed all other models in all metrics, with a 94.7% accuracy and a 94.3% F1-score. Table 3 shows that the false-negative rate is low (9 out of 187 posts that are threat-relevant and misclassified), which is especially critical when it comes to reducing false detections in security-critical systems. As shown in Table 4, the detection latency has significantly been reduced, where the average detection latency of the conventional signature-based detection is 420 seconds, whereas the detection latency of the proposed integrated framework is about 18 seconds. As noted in Table 5, the strongest predictors of threat-relevant content were keywords presence, sentiment polarity, and the co-occurrence of hashtags.

DISCUSSION

The results of this paper support and expand on previous studies on the importance of integrating social media analytics with machine learning to detect cyber threats. In line with previous studies indicating the predictive power of social media conversations on early threat prediction [19], [20], the findings indicate that threat-relevant posts have recognizable linguistic and contextual indicators that can be trained by ML models to predict with a high level of accuracy. The enhanced performance of the transformer based model is consistent with earlier results that contextual language models are better than traditional classifiers on fine-grained text classification tasks [16], [10], probably since they can model semantic relationships that are not well represented by simpler models, such as Naive Bayes [17].

The significant decrease in detection latency in this paper lends credence to the thesis that hybrid, OSINT-enhanced detection pipelines are capable of reducing the gap between the appearance of a threat and its detection in a significant way [12], [13]. This has immediate consequences on security operations centers whereby a slight decrease in detection time can narrow down the extent of harm caused by an active attack. The fact that sentiment polarity and keyword co-occurrence are the most effective predictors, also supports previously reported findings that urgency and technical vocabulary are typical signs of authentic threat speech, in contrast with general commentary or misinformation [14], [15].

However, the outcomes are to be viewed with a grain of salt. According to the previous researchers, social media data is vulnerable to noise, sarcasm, and adversarial manipulation, which may impair the performance of a model in uncontrolled and real-life settings [6], [9]. Although the simulated dataset in the study made it possible to benchmark simulated data under control, the dataset did not reflect the volume, velocity, and adversarial dynamics of live social media streams in full, which is also noted in previous hybrid-detection studies [18].

RESEARCH IMPLICATIONS

In theory, the paper adds a comprehensive model of connecting social media analytics and machine learning to CTI. In practice, it implies that security operations centers might minimize the detection latency and enhance the early-warning through the addition of transformer-based classifiers to existing threat monitoring pipelines, which would facilitate prompt and better-informed incident response decisions.

LIMITATIONS OF THE STUDY

- The dataset used (N = 300) is simulated rather than drawn from live, real-world social media streams, limiting external validity.
- The study is restricted to English-language content and does not account for multilingual or code-switched threat discourse.
- Only three source platforms were considered, excluding other channels such as encrypted messaging apps and dark web forums.
- The framework was not tested against adversarial evasion tactics, such as deliberate obfuscation by threat actors.
- Detection latency figures were measured in a controlled experimental setting and may differ under real-world network and data-volume conditions.

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- The study did not evaluate long-term model drift or the need for periodic retraining as threat language evolves.

CONCLUSION AND RECOMMENDATIONS

The purpose of this study was to investigate whether a social media analytics-based framework enhanced by machine learning and run by an AI will enhance the detection of a cyberattack in real-time. The results of the simulated dataset of 300 social media posts demonstrate that machine learning classifiers, especially transformer-based models, are capable of detecting content of cyber-threat relevance with low detection latency, high accuracy, precision, and recall, and with significantly lower detection latency than traditional signature-based and network-log-only methods. These findings reinforce the main assumption that regardless of its noise and informality, social media bears valuable early-warning signals that can be systematically gathered and operationalized in a manner that suits relevant NLP and machine learning methods. The presence of key-words, sentiment polarity and co-occurring hashtags being identified as the most outstanding predictive features further explain what in social media discourse has the most significant intelligence value, which can be used as a good guide in future feature engineering systems. Combined, the results indicate that open-source social media intelligence paired with machine learning classification is more than capable of being transformative in minimizing the detection-to-response gap that has traditionally vexed traditional cybersecurity activities.

Following these findings, a number of recommendations are made. One, the performance of transformer-based classifiers on live, anonymized social media streams should be piloted with security operations centers, to test their operation in real-world conditions of noise and volumes. Second, the systems of the future must introduce the ability to operate in multiple languages to intercept the discourse of threats not only in English language materials but also due to the international and sometimes non-English origin of the actors of cyber threats. Third, companies need to invest in adversarial robustness testing to make sure that detection models are not resistant to intentional obfuscation, coded language, or coordinated misinformation campaigns aimed at avoiding being detected. Fourth, regular model retraining procedures must be introduced that would keep up with the vocabulary and methods of threat actors as time passes. Lastly, future studies must apply this framework to other data sources, such as dark web forums and encrypted channels, and need to perform longitudinal, real-world validation studies on how AI-driven, social-media-augmented cyber threat intelligence can benefit and limit production security settings.

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