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Research Article

AI and Cyber-Security: Enhancing threat detection and response with machine learning.

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ARTICLE INFO **ABSTRACT**

As cyber threats continue to evolve and become more sophisticated, traditional security measures are no longer sufficient to protect networks and sensitive data. Artificial intelligence (AI) and machine learning (ML) techniques offer powerful tools to enhance cyber security by enabling more effective and efficient threat detection and response. This paper provides an overview of the current state of AI and ML in cyber security, discussing key techniques, applications, challenges, and future directions. We review ML algorithms used for tasks such as anomaly detection, malware classification, and network intrusion detection. Case studies are presented showing the successful implementation of AI/ML in real-world cyber security systems. Limitations and challenges are also discussed, including the need for large labelled datasets, adversarial attacks on ML models, and the difficulty of interpreting black-box ML models. Finally, we highlight promising research directions, such as explainable AI for cyber security, unsupervised learning approaches, and the integration of ML with other security tools and frameworks. AI and ML will play an increasingly crucial role in cyber security going forward, and ongoing research will help unlock their full potential for safeguarding our digital infrastructure.

Keywords: artificial intelligence; machine learning; cyber security; intrusion detection; malware detection; anomaly detection; cyber threats

1. Introduction

In the modern digital age, cyber threats pose a serious and ever-growing risk to individuals, organizations, and society as a whole. Malicious actors are constantly developing new attack vectors and strategies to compromise computer networks, steal sensitive data, and disrupt critical systems and services [1]. Traditional cyber security approaches, based on signature-based detection and manually defined security policies, struggle to keep pace with the rapidly evolving threat landscape [2]. Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools to bolster cyber defenses by enabling more proactive, adaptive, and autonomous security solutions [3].

AI refers to the broad field of creating intelligent machines that can perform tasks that typically require human-level intelligence, such as visual perception, speech recognition, decision-making, and language translation [4]. Machine learning is a subset of AI that focuses on teaching computers to learn and improve from experience without being explicitly programmed [5]. By leveraging AI and ML techniques, cyber security systems can analyze massive amounts of data to uncover hidden patterns, detect subtle anomalies, and make intelligent decisions to prevent, detect, and respond to cyber incidents [6].

This paper aims to provide a comprehensive overview of the current state and future potential of AI and ML in enhancing cyber security. We begin by discussing the key challenges and limitations of traditional cyber security approaches that motivate the need for AI/ML-powered solutions. We then introduce the main categories of ML algorithms and their applications in various cyber security domains, including malware detection, network intrusion detection, fraud detection, and user behavior analytics. Next, we present several case studies showcasing the successful implementation of AI/ML techniques in real-world cyber security systems. We also discuss the limitations and challenges associated with applying AI/ML in cyber security, such as the need for large labeled datasets, the vulnerability of ML models to adversarial attacks, and the difficulty of interpreting and explaining the decisions made by ML models. Finally, we highlight promising research directions and future trends in AI for cyber security, including the development of explainable AI techniques, the use of unsupervised and semi-supervised learning approaches, and the integration of AI/ML with other security tools and frameworks.

2. Background and Motivation

2.1. The Evolving Cyber Threat Landscape

The cyber threat landscape is constantly evolving, with attackers employing increasingly sophisticated techniques to evade detection and maximize their impact [7]. Some of the most significant cyber threats facing organizations today include:

- Malware: Malicious software designed to infiltrate, damage, or gain unauthorized access to computer systems, such as viruses, worms, trojans, and ransomware [8].
- Phishing: Social engineering attacks that trick users into revealing sensitive information or installing malware by masquerading as trustworthy entities in electronic communications [9].
- Advanced Persistent Threats (APTs): Stealthy and continuous cyber attacks, often sponsored by nation-states, that target specific organizations to steal sensitive data or disrupt operations [10].
- Insider Threats: Security risks originating from within the organization, either from malicious insiders or negligent employees who inadvertently expose systems to external threats [11].
- Distributed Denial of Service (DDoS) Attacks: Attempts to disrupt the normal traffic of a targeted server, service, or network by overwhelming it with a flood of Internet traffic from multiple sources [12].

Table 1 summarizes some of the major cyber incidents in recent years, illustrating the severity and diversity of modern cyber threats.

Table 1. Notable cyber incidents in recent years.

Year	Incident	Impact
2017	WannaCry ransomware	Infected over 200,000 computers across 150 countries
2018	Marriott data breach	Exposed personal data of 500 million guests
2019	Capital One data breach	Compromised data of over 100 million customers and applicants
2020	SolarWinds supply chain attack	Affected 18,000 customers, including government agencies
2021	Microsoft Exchange Server vulnerabilities	Impacted 30,000 U.S. organizations and 250,000 globally

2.2. Limitations of Traditional Cyber security Approaches

Traditional cyber security approaches rely heavily on signature-based detection, where known threat patterns are identified and blocked based on predefined rules and blacklists [13]. While effective against known threats, these methods struggle to detect novel or evolving attacks that do not match existing signatures. Moreover, maintaining up-to-date signature databases requires constant effort and can lead to high false positive rates [14].

Another common approach is anomaly-based detection, which aims to identify deviations from normal system or user behavior [15]. However, defining what constitutes "normal" behavior is challenging, especially in complex and dynamic environments. Anomaly-based systems are prone to high false positive rates and can be difficult to tune and maintain over time [16].

Furthermore, traditional cyber security tools often operate in silos, focusing on specific aspects of the network or system (e.g., endpoints, servers, or applications) without a holistic view of the entire security posture [17]. This fragmented approach can lead to blind spots and inefficiencies in detecting and responding to threats that span multiple domains.

2.3. The Need for AI and Machine Learning in Cyber security

The limitations of traditional cyber security approaches, coupled with the increasing volume, velocity, and variety of cyber threats, have driven the need for more advanced and adaptive security solutions powered by AI and ML [18]. By leveraging the ability of ML algorithms to learn from vast amounts of data and improve over time, AI-powered cyber security systems can offer several key benefits:

- Improved Threat Detection: ML algorithms can analyze massive datasets to identify patterns and anomalies that may indicate malicious activity, enabling the detection of previously unknown or "zero-day" threats [19].

- Faster Incident Response: AI-powered systems can automatically triage and prioritize security alerts, reducing the time and effort required for manual investigation and response [20].
- Adaptive and Scalable Protection: ML models can continuously learn and adapt to new threat scenarios, providing a more flexible and scalable approach to cyber security compared to rule-based systems [21].
- Predictive Analytics: By analyzing historical data and trends, AI techniques can help predict potential future threats and vulnerabilities, enabling proactive risk mitigation [22].

3. Machine Learning Techniques for Cyber security

3.1. Overview of Machine Learning

Machine learning is a subset of AI that focuses on the development of algorithms and models that can learn and improve from experience without being explicitly programmed [23]. At a high level, ML techniques can be categorized into three main types:

- Supervised Learning: The algorithm learns from labeled training data, where the desired output is known in advance. The goal is to learn a function that maps input features to output labels, enabling the prediction of labels for new, unseen data [24].
- Unsupervised Learning: The algorithm learns from unlabeled data, aiming to discover hidden patterns or structures within the data without any predefined output [25].
- Reinforcement Learning: The algorithm learns through interaction with an environment, receiving rewards or penalties for its actions. The goal is to learn a policy that maximizes the cumulative reward over time [26].

Table 2 summarizes the main characteristics and applications of these three types of ML in cyber security.

Table 2. Characteristics and applications of ML types in cyber security.

ML Type	Characteristics	Cyber security Applications
Supervised	Learns from labeled data to predict output	Malware classification, spam detection
Unsupervised	Discovers patterns in unlabeled data	Anomaly detection, clustering
Reinforcement	Learns through interaction with an environment	Adaptive network security policies, agent-based systems

3.2. Popular Machine Learning Algorithms

Within the broader categories of supervised, unsupervised, and reinforcement learning, there are numerous specific ML algorithms that have been applied to various cyber security tasks. Some of the most widely used algorithms include:

- Decision Trees and Random Forests: Tree-based models that learn hierarchical decision rules from training data, used for both classification and regression tasks [27].
- Support Vector Machines (SVMs): Algorithms that find the optimal hyperplane to separate different classes in a high-dimensional feature space, often used for binary classification problems [28].
- Naive Bayes: A probabilistic classifier based on Bayes' theorem, which assumes that the features are conditionally independent given the class label [29].
- k-Nearest Neighbors (k-NN): A non-parametric method that classifies new instances based on the majority class of the k nearest training instances in the feature space [30].
- Artificial Neural Networks (ANNs): A family of models loosely inspired by biological neural networks, consisting of interconnected nodes (neurons) that learn to map input features to output labels through a process of training and backpropagation [31].

3.3. Feature Engineering and Selection

The performance of ML models heavily depends on the quality and relevance of the input features used for training [32]. Feature engineering involves the process of transforming raw data into informative features that can be used as inputs to ML algorithms. In the context of cyber security, this may include extracting statistical properties, header information, or byte sequences from network traffic data, or computing various metrics and indicators from system logs and events [33].

Feature selection is the process of identifying the most relevant and discriminative features from a larger set of candidates, aiming to improve model performance, reduce over fitting, and enhance interpretability [34]. Common feature selection techniques include filter methods (e.g., correlation-based selection), wrapper methods (e.g., recursive feature elimination), and embedded methods (e.g., L1 regularization) [35].

3.4. Model Training and Evaluation

Once the features have been engineered and selected, the next step is to train the ML model using a suitable algorithm and hyper parameter settings. The training process involves optimizing the model parameters to minimize a predefined loss function, which measures the discrepancy between the predicted and actual outputs [36].

To assess the performance of the trained model, it is essential to use appropriate evaluation metrics and validation techniques. Common evaluation metrics for classification tasks include accuracy, precision, recall, F1 score, and area under the receiver operating characteristic (ROC) curve [37]. For unsupervised learning tasks like anomaly detection, metrics such as precision at k, average precision, and area under the precision-recall curve are often used [38].

To ensure the generalization ability of the model and avoid over fitting, it is crucial to use proper validation techniques such as k-fold cross-validation or stratified sampling [39]. These methods help assess how well the model performs on unseen data and provide a more reliable estimate of its real-world performance.

4. Applications of AI and Machine Learning in Cyber security

4.1. Malware Detection and Classification

Malware, short for malicious software, poses a significant threat to computer systems and networks. Traditional malware detection methods rely on signature-based approaches, which struggle to keep up with the rapidly evolving nature of malware [40]. AI and ML techniques have shown promising results in detecting and classifying malware based on its behavioral and structural characteristics.

One common approach is to use supervised learning algorithms, such as decision trees, random forests, or SVMs, to classify software samples as benign or malicious based on a set of extracted features [41]. These features may include static properties (e.g., file size, header information, or byte sequences) or dynamic behavior (e.g., API calls, network traffic, or system resource usage) [42].

Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also been applied to malware detection, leveraging their ability to learn hierarchical feature representations from raw data [43]. For example, CNNs can be used to classify malware based on visual representations of their binary code, while RNNs can model the sequential nature of API call sequences or network traffic patterns [44].

Table 3 presents a comparison of various ML-based malware detection approaches, highlighting their key features, advantages, and limitations.

Table 3. Comparison of ML-based malware detection approaches.

Approach	Features	Advantages	Limitations
Static analysis	File properties, byte sequences, header information	Fast, low resource requirements	Can be evaded by obfuscation and packing techniques
Dynamic analysis	API calls, network traffic, system resource usage	Captures runtime behavior, resilient to obfuscation	Higher resource requirements, potential sandbox evasion
Hybrid analysis	Combination of static and dynamic features	Improved accuracy, robustness to evasion techniques	Increased complexity, may require manual feature engineering
Deep learning	Automatically learned hierarchical features	Ability to learn complex patterns, minimal feature engineering	Requires large labeled datasets, computationally expensive

4.2. Network Intrusion Detection

Network intrusion detection systems (NIDS) aim to identify unauthorized access, misuse, or modification of computer networks and resources [45]. Traditional NIDS rely on signature-based or rule-based approaches, which are effective against known attacks but struggle to detect novel or zero-day threats [46].

AI and ML techniques can enhance NIDS by enabling the detection of previously unseen attack patterns and adaptively learning from network traffic data. Supervised learning algorithms, such as decision trees, SVMs, or neural networks, can be trained on labeled datasets containing normal and malicious network traffic to classify new instances based on their features [47].

Unsupervised learning approaches, such as clustering or anomaly detection, can be used to identify unusual patterns or deviations from normal network behavior without relying on labeled data [48]. These methods are particularly useful for detecting novel attacks or insider threats that may not match known signatures.

Deep learning models, such as auto encoders or recurrent neural networks, have also shown promise in network intrusion detection, thanks to their ability to learn complex representations of network traffic patterns [49]. For example, auto encoders can be trained to reconstruct normal network traffic, and deviations from the learned reconstruction can be used to detect anomalies [50].

Table 4 summarizes some of the key ML techniques used for network intrusion detection, along with their typical input features and target attack types.

Table 4. ML techniques for network intrusion detection.

Technique	Input Features	Target Attack Types
Decision trees	Connection-level features (e.g., duration, protocol, bytes transferred)	DoS, probe, R2L, U2R
Support vector machines	Flow-level features (e.g., packet size, inter-arrival time)	DoS, probe, R2L, U2R
Neural networks	Packet-level features (e.g., header fields, payload)	DoS, probe, R2L, U2R
Clustering	Flow-level or connection-level features	Novel attacks, insider threats
Anomaly detection	Flow-level or connection-level features	Zero-day attacks, insider threats
Deep learning	Raw network traffic data (e.g., packet captures)	Complex attack patterns, novel threats

4.3. Fraud Detection

Fraudulent activities, such as credit card fraud, insurance fraud, or identity theft, cause significant financial losses and pose a major challenge for businesses and individuals [51]. AI and ML techniques can help detect and prevent fraud by identifying patterns and anomalies in vast amounts of transactional data.

Supervised learning algorithms, such as logistic regression, decision trees, or neural networks, can be trained on labeled datasets containing fraudulent and legitimate transactions to classify new instances based on their features [52]. These features may include user behavior patterns, transaction amounts, location data, or device fingerprints.

Unsupervised learning approaches, such as clustering or anomaly detection, can be used to identify unusual patterns or outliers in transactional data without relying on labeled examples [53]. These methods are particularly useful for detecting novel or evolving fraud schemes that may not match known patterns.

Graph analysis and network-based approaches have also shown promise in fraud detection, leveraging the relational structure of transactional data [54]. By representing transactions As a graph or network, where nodes represent entities (e.g., users or accounts) and edges represent interactions or relationships, fraud detection can be framed as a problem of identifying suspicious subgraphs or anomalous connectivity patterns [55].

Table 5 presents a comparison of various ML-based fraud detection techniques, highlighting their strengths and weaknesses in different fraud scenarios.

Table 5. Comparison of ML-based fraud detection techniques.

Technique	Strengths	Weaknesses
Supervised learning	High accuracy for known fraud patterns	Requires labeled data, may miss novel fraud schemes
Unsupervised learning	Detects novel fraud schemes, requires no labeled data	May have higher false positive rates
Graph analysis	Captures relational structure of transactional data	Computationally expensive, requires graph modeling
Hybrid approaches	Combines strengths of multiple techniques	Increased complexity, may require manual integration

4.4. User Behavior Analytics

User Behavior Analytics (UBA) is an approach to cyber security that focuses on understanding and modeling the normal behavior of users within an organization, aiming to detect anomalous or suspicious activities that may indicate insider threats or compromised accounts [56].

ML techniques play a crucial role in UBA by enabling the automated learning of user behavior patterns and the identification of deviations from these patterns. Unsupervised learning methods, such as clustering or anomaly detection, are commonly used to group users based on their behavioral similarities and detect outliers or anomalies [57].

Supervised learning algorithms, such as decision trees, SVMs, or neural networks, can be trained on labeled datasets containing normal and anomalous user behavior to classify new instances based on their features [58]. These features may include login patterns, resource access, email and web browsing habits, or file transfer activities.

Sequential pattern mining and Markov models have also been applied to model the temporal dynamics of user behavior, capturing the sequences and transitions of user actions over time [59]. Deviations from the learned behavioral models can be used to detect anomalous or suspicious activities.

Table 6 summarizes some of the key ML techniques used for UBA, along with their typical input features and target anomaly types.

Table 6. ML techniques for User Behavior Analytics.

Technique	Input Features	Target Anomaly Types
Clustering	User activity logs, resource access patterns	Insider threats, compromised accounts
Anomaly detection	Login patterns, email and web browsing habits	Insider threats, compromised accounts
Decision trees	File access patterns, network traffic features	Data exfiltration, unauthorized access
Markov models	Sequences of user actions, state transitions	Deviations from normal behavior patterns

5. Case Studies

5.1. Darktrace: AI-Powered Network Intrusion

Detection Darktrace is a leading provider of AI-based cyber security solutions, offering an Enterprise Immune System that leverages unsupervised machine learning to detect and respond to cyber threats in real-time [60]. The system works by creating a dynamic, evolving understanding of normal network behavior, enabling it to identify and neutralize anomalous activities that may indicate an ongoing attack or breach.

The core of Darktrace's solution is based on unsupervised learning techniques, such as clustering and anomaly detection, which do not require pre-defined rules or signature databases. Instead, the system continuously learns and adapts to the unique patterns of activity within the network, creating a bespoke understanding of normal behavior for each organization [61].

One of the key advantages of Darktrace's approach is its ability to detect novel and previously unseen threats, including insider threats and zero-day exploits. By modeling the complex relationships and interactions between users, devices, and applications, the system can spot subtle deviations from normal behavior that may be invisible to traditional security tools [62].

Real-world case studies have demonstrated the effectiveness of Darktrace's AI-powered intrusion detection. For example, the system was able to detect and neutralize a sophisticated cyber attack on a major US retailer, which had gone unnoticed by traditional security measures [63]. In another case, Darktrace identified a previously unknown strain of malware that was exfiltrating sensitive data from a European banking institution [64].

5.2. Spark Cognition

Machine Learning for Malware Detection Spark Cognition is an AI company that provides a range of ML-based cyber security solutions, including Deep Armor, a next-generation antivirus platform that uses deep learning to detect and prevent malware infections [65]. The platform leverages convolutional neural networks (CNNs) to analyze the binary code of software files, learning to distinguish between benign and malicious code based on their inherent patterns and structures.

One of the key advantages of Deep Armor's approach is its ability to detect novel and evolving malware threats, even if they have never been seen before. By learning the intrinsic characteristics of malicious code, rather than relying on signature-based detection, the system can identify new malware variants and zero-day exploits with high accuracy [66].

Deep Armor's CNN architecture is trained on a vast dataset of millions of software files, including both benign and malicious samples. The training process involves learning hierarchical feature representations directly from the raw binary code, without the need for manual feature engineering [67]. This allows the system to capture complex patterns and relationships that may be difficult to express through hand-crafted rules or heuristics.

Real-world deployments of Deep Armor have shown impressive results in detecting and preventing malware infections. In one case study, the platform was able to identify and block a previously unknown ransomware attack on a healthcare organization, which had evaded traditional antivirus solutions [68]. Another case study demonstrated Deep Armor's ability to detect a sophisticated nation-state attack that used a novel malware variant to target a critical infrastructure provider [69].

6. Challenges and Future Directions

6.1. Challenges in Applying AI and Machine Learning to Cyber security

While AI and ML techniques offer significant promise for enhancing cyber security, there are also several challenges and limitations that need to be addressed. Some of the key challenges include:

- Data Quality and Availability: ML models require large amounts of high-quality, labeled data for training and evaluation. In the cyber security domain, obtaining such data can be difficult due to privacy concerns, data scarcity, or the rapidly evolving nature of cyber threats [70].
- Adversarial Attacks: ML models can be vulnerable to adversarial examples, which are carefully crafted inputs designed to deceive the model into making incorrect predictions [71]. In the context of cyber security, attackers may try to evade detection by manipulating malware code or network traffic to fool ML-based defenses.
- Interpretability and Explainability: Many ML models, particularly deep learning architectures, are often seen as "black boxes," making it difficult to understand and interpret their decision-making process [72]. In cyber security, where the stakes are high, it is crucial to have transparent and explainable models that can justify their predictions and actions.
- Concept Drift: Cyber threats are constantly evolving, and the statistical properties of the data used to train ML models may change over time, leading to a phenomenon known as concept drift [73]. This requires ML models to be continuously updated and adapted to maintain their effectiveness in the face of changing threat landscapes.
- Integration and Scalability: Integrating ML-based cyber security solutions into existing security architectures and workflows can be challenging, requiring careful consideration of factors such as performance, scalability, and interoperability [74]. As the volume and velocity of cyber security data continue to grow, ensuring the scalability of ML models and infrastructure becomes increasingly important.

6.2. Research Directions and Opportunities

Despite the challenges, there are also significant research opportunities and promising directions for advancing the application of AI and ML in cyber security. Some of these include:

- Explainable AI for Cyber security: Developing techniques for interpretable and explainable ML models that can provide clear justifications for their predictions and decisions, enhancing trust and accountability in AI-based cyber security solutions [75].
- Adversarial Machine Learning: Investigating methods for detecting and mitigating adversarial attacks on ML models, such as adversarial training, defensive distillation, or input preprocessing techniques [76].
- Transfer Learning and Few-Shot Learning: Leveraging transfer learning techniques to adapt pre-trained ML models to new cyber security tasks or domains with limited labeled data, and exploring few-shot learning approaches to enable rapid learning from small amounts of data [77].
- Autonomous and Adaptive Security: Developing AI-powered cyber security systems that can autonomously learn, adapt, and respond to evolving cyber threats in real-time, minimizing the need for human intervention and reducing response times [78].
- Collaborative and Federated Learning: Exploring collaborative and federated learning approaches that enable multiple organizations to jointly train ML models on decentralized data, while preserving privacy and security [79].
- Integration with Security Orchestration and Automation: Integrating AI and ML techniques with security orchestration, automation, and response (SOAR) platforms to enable intelligent and automated incident response and remediation [80].

7. Conclusion

The rapid evolution of cyber threats and the increasing complexity of modern networks and systems have made traditional cyber security approaches insufficient for effective protection. AI and ML techniques offer powerful tools to enhance cyber security by enabling more proactive, adaptive, and autonomous threat detection and response.

This paper has provided a comprehensive overview of the current state and future potential of AI and ML in cyber security. We have discussed the key challenges and limitations of traditional security approaches, and introduced the main categories of ML techniques and their applications in various cyber security domains, including malware detection, network intrusion detection, fraud detection, and user behavior analytics.

Real-world case studies have demonstrated the successful implementation of AI and ML in cyber security, highlighting their ability to detect novel and evolving threats that may evade traditional security measures. However, we have also discussed the challenges and limitations of applying AI and ML in cyber security, such as data quality issues, adversarial attacks, interpretability concerns, and scalability challenges.

Looking forward, we have identified several promising research directions and opportunities for advancing the field of AI-powered cyber security. These include the development of explainable AI techniques, adversarial machine learning, transfer learning, autonomous and adaptive security, collaborative and federated learning, and integration with security orchestration and automation platforms.

As cyber threats continue to evolve and become more sophisticated, the integration of AI and ML into cyber security solutions will become increasingly crucial. By leveraging the power of these technologies, organizations can develop more robust, adaptive, and intelligent defenses against the ever-changing landscape of cyber threats. However, realizing the full potential of AI and ML in cyber security will require ongoing research, collaboration, and innovation across academia, industry, and government.

In conclusion, AI and ML have the potential to revolutionize the field of cyber security, enabling organizations to stay one step ahead of cyber adversaries. By embracing these technologies and investing in their development and deployment, we can build a more secure and resilient digital future.

References

[1] R. Von Solms and J. Van Niekerk, "From information security to cyber security," Computers & security, vol. 38, pp. 97-102, 2013.

[2] A. Kott, C. Wang, and R. F. Erbacher, Cyber defense and situational awareness. Springer, 2014.

[3] D. Berman, A. L. Buczak, J. S. Chavis, and C. L. Corbett, "A survey of deep learning methods for cyber security," Information, vol. 10, no. 4, p. 122, 2019.

[4] S. Russell and P. Norvig, Artificial intelligence: a modern approach. Pearson, 2002.

[5] T. M. Mitchell, Machine learning. McGraw-hill New York, 1997.

[6] R. Sommer and V. Paxson, "Outside the closed world: On using machine learning for network intrusion detection," in 2010 IEEE symposium on security and privacy, 2010, pp. 305-316: IEEE.

[7] M. Kjaerland, "A taxonomy and comparison of computer security incidents from the commercial and government sectors," Computers & Security, vol. 25, no. 7, pp. 522-538, 2006.

[8] M. Egele, T. Scholte, E. Kirda, and C. Kruegel, "A survey on automated dynamic malware-analysis techniques and tools," ACM computing surveys (CSUR), vol. 44, no. 2, pp. 1-42, 2008.

[9] J. Hong, "The state of phishing attacks," Communications of the ACM, vol. 55, no. 1, pp. 74-81, 2012.

[10] P. Chen, L. Desmet, and C. Huygens, "A study on advanced persistent threats," in IFIP International Conference on Communications and Multimedia Security, 2014, pp. 63-72: Springer.

[11] C. Colwill, "Human factors in information security: The insider threat–Who can you trust these days?," Information security technical report, vol. 14, no. 4, pp. 186-196, 2009.

[12] S. T. Zargar, J. Joshi, and D. Tipper, "A survey of defense mechanisms against distributed denial of service (DDoS) flooding attacks," IEEE communications surveys & tutorials, vol. 15, no. 4, pp. 2046-2069, 2013.

[13] D. E. Denning, "An intrusion-detection model," IEEE Transactions on software engineering, no. 2, pp. 222-232, 1987.

[14] P. Garcia-Teodoro, J. Diaz-Verdejo, G. Maciá-Fernández, and E. Vázquez, "Anomaly-based network intrusion detection: Techniques, systems and challenges," computers & security, vol. 28, no. 1-2, pp. 18-28, 2009.

[15] M. H. Bhuyan, D. K. Bhattacharyya, and J. K. Kalita, "Network anomaly detection: methods, systems and tools," Ieee communications surveys & tutorials, vol. 16, no. 1, pp. 303-336, 2013.

[16] C. Modi, D. Patel, B. Borisaniya, H. Patel, A. Patel, and M. Rajarajan, "A survey of intrusion detection techniques in cloud," Journal of network and computer applications, vol. 36, no. 1, pp. 42-57, 2013.

[17] N. Miloslavskaya and A. Tolstoy, "Application of big data, fast data, and data lake concepts to information security issues," in 2016 4th International Conference on Future Internet of Things and Cloud Workshops (FiCloudW), 2016, pp. 148-153: IEEE.

[18] Y. Xin et al., "Machine learning and deep learning methods for cyber security," Ieee access, vol. 6, pp. 35365-35381, 2018.

[19] M. Alazab, S. Venkatraman, P. Watters, M. Alazab, and A. Alazab, "Cybercrime: The case of obfuscated malware," in Global Security, Safety and Sustainability & e-Democracy: Springer, 2012, pp. 204-211.

[20] E. Vasilomanolakis, S. Karuppayah, M. Mühlhäuser, and M. Fischer, "Taxonomy and survey of collaborative intrusion detection," ACM Computing Surveys (CSUR), vol. 47, no. 4, pp. 1-33, 2015.

[21] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," IEEE Communications surveys & tutorials, vol. 18, no. 2, pp. 1153-1176, 2015.

[22] I. Amit, J. Matherly, W. Hewlett, Z. Xu, Y. Meshi, and Y. Weinberger, "Machine learning in cyber-security-problems, challenges and data sets," arXiv preprint arXiv:1812.07858, 2018.

[23] E. Alpaydin, Introduction to machine learning. MIT press, 2020.

[24] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, "Supervised machine learning: A review of classification techniques," Emerging artificial intelligence applications in computer engineering, vol. 160, no. 1, pp. 3-24, 2007.

[25] X. J. Zhu, "Semi-supervised learning literature survey," University of Wisconsin-Madison Department of Computer Sciences, 2005.

[26] R. S. Sutton and A. G. Barto, Reinforcement learning: An introduction. MIT press, 2018.

[27] L. Breiman, "Random forests," Machine learning, vol. 45, no. 1, pp. 5-32, 2001.

[28] C. Cortes and V. Vapnik, "Support-vector networks," Machine learning, vol. 20, no. 3, pp. 273-297, 1995.

[29] I. Rish, "An empirical study of the naive Bayes classifier," in IJCAI 2001 workshop on empirical methods in artificial intelligence, 2001, vol. 3, no. 22, pp. 41-46.

[30] N. S. Altman, "An introduction to kernel and nearest-neighbor nonparametric regression," The American Statistician, vol. 46, no. 3, pp. 175-185, 1992.

[31] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," nature, vol. 521, no. 7553, pp. 436-444, 2015.
[32] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," Journal of machine learning research, vol. 3, no. Mar, pp. 1157-1182, 2003.
[33] A. L. Buczak and E. Guven, "A survey of data mining and machine learning methods for cyber security intrusion detection," IEEE Communications surveys & tutorials, vol. 18, no. 2, pp. 1153-1176, 2015.
[34] G. Chandrashekar and F. Sahin, "A survey on feature selection methods," Computers & Electrical Engineering, vol. 40, no. 1, pp. 16-28, 2014.
[35] J. Li et al., "Feature selection: A data perspective," ACM Computing Surveys (CSUR), vol. 50, no. 6, pp. 1-45, 2017.
[36] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning. MIT press, 2016.
[37] T. Fawcett, "An introduction to ROC analysis," Pattern recognition letters, vol. 27, no. 8, pp. 861-874, 2006.
[38] J. Davis and M. Goadrich, "The relationship between Precision-Recall and ROC curves," in Proceedings of the 23rd international conference on Machine learning, 2006, pp. 233-240.
[39] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in Ijcai, 1995, vol. 14, no. 2, pp. 1137-1145: Montreal, Canada.
[40] M. Siddiqui, M. C. Wang, and J. Lee, "A survey of data mining techniques for malware detection using file features," in Proceedings of the 46th annual southeast regional conference on xx, 2008, pp. 509-510.
[41] J. Z. Kolter and M. A. Maloof, "Learning to detect and classify malicious executables in the wild," Journal of Machine Learning Research, vol. 7, no. Dec, pp. 2721-2744, 2006.
[42] M. Egele, T. Scholte, E. Kirda, and C. Kruegel, "A survey on automated dynamic malware-analysis techniques and tools," ACM computing surveys (CSUR), vol. 44, no. 2, pp. 1-42, 2008.
[43] R. Pascanu, J. W. Stokes, H. Sanossian, M. Marinescu, and A. Thomas, "Malware classification with recurrent networks," in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2015, pp. 1916-1920: IEEE.
[44] B. Kolosnjaji, A. Zarras, G. Webster, and C. Eckert, "Deep learning for classification of malware system call sequences," in Australasian Joint Conference on Artificial Intelligence, 2016, pp. 137-149: Springer.
[45] P. Garcia-Teodoro, J. Diaz-Verdejo, G. Maciá-Fernández, and E. Vázquez, "Anomaly-based network intrusion detection: Techniques, systems and challenges," computers & security, vol. 28, no. 1-2, pp. 18-28, 2009.
[46] A. Patcha and J.-M. Park, "An overview of anomaly detection techniques: Existing solutions and latest technological trends," Computer networks, vol. 51, no. 12, pp. 3448-3470, 2007.
[47] W. Lee, S. J. Stolfo, and K. W. Mok, "A data mining framework for building intrusion detection models," in Proceedings of the 1999 IEEE Symposium on Security and Privacy (Cat. No. 99CB36344), 1999, pp. 120-132: IEEE.
[48] P. Casas, J. Mazel, and P. Owezarski, "Unsupervised network intrusion detection systems: Detecting the unknown without knowledge," Computer Communications, vol. 35, no. 7, pp. 772-783, 2012.
[49] C. Yin, Y. Zhu, J. Fei, and X. He, "A deep learning approach for intrusion detection using recurrent neural networks," Ieee Access, vol. 5, pp. 21954-21961, 2017.
[50] N. Shone, T. N. Ngoc, V. D. Phai, and Q. Shi, "A deep learning approach to network intrusion detection," IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 2, no. 1, pp. 41-50, 2018.
[51] C. Phua, V. Lee, K. Smith, and R. Gayler, "A comprehensive survey of data mining-based fraud detection research," arXiv preprint arXiv:1009.6119, 2010.
[52] S. Bhattacharyya, S. Jha, K. Tharakunnel, and J. C. Westland, "Data mining for credit card fraud: A comparative study," Decision support systems, vol. 50, no. 3, pp. 602-613, 2011.
[53] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM computing surveys (CSUR), vol. 41, no. 3, pp. 1-58, 2009.
[54] C. C. Noble and D. J. Cook, "Graph-based anomaly detection," in Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining, 2003, pp. 631-636.
[55] J. Gao, F. Liang, W. Fan, C. Wang, Y. Sun, and J. Han, "On community outliers and their efficient detection in information networks," in Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining, 2010, pp. 813-822.
[56] Y. Hu, B. C. Fung, Y. Dong, A. Basu, Y. Xia, and R. W. Ware, "User behavior analytics: Modeling and anomaly detection," in 2018 IEEE International Conference on Intelligence and Security Informatics (ISI), 2018, pp. 173-175: IEEE.
[57] A. A. Rashid, A. Mohamad, M. Alobaedy, J. Abdullah, and M. Mahmod, "User behavioral analytics using unsupervised anomaly detection for user authentication," in 2019 International Conference on Cyber security (ICoCSec), 2019, pp. 162-167: IEEE.
[58] E. Aleskerov, B. Freisleben, and B. Rao, "Cardwatch: A neural network based database mining system for credit card fraud detection," in Proceedings of the IEEE/IAFE 1997 computational intelligence for financial engineering (CIFEr), 1997, pp. 220-226: IEEE.
[59] M. Ye, J. Liu, S. Ji, and J. Li, "User behavior analysis based on Markov chains and its application in identifying malicious users," in 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD), 2015, pp. 533-538: IEEE.

[60] Darktrace, "Darktrace Cyber AI Platform," 2021, https://darktrace.com/en/platform/.
[61] J. Tan, "AI-Based Cyber Defense: The Future of Cyber security?," 2019, https://www.darktrace.com/en/blog/ai-based-cyber-defense-the-future-of-cyber security/.
[62] Darktrace, "Use Case: Insider Threat," 2021, https://darktrace.com/en/resources/wp-insider-threat.pdf.
[63] Darktrace, "Case Study: Major US Retailer," 2021, https://darktrace.com/en/resources/cs-major-us-retailer.pdf.
[64] Darktrace, "Case Study: European Bank," 2021, https://darktrace.com/en/resources/cs-european-bank.pdf.
[65] SparkCognition, "DeepArmor: AI-Powered Endpoint Protection," 2021, https://www.sparkcognition.com/product/deeparmor/.
[66] S. Das et al., "Deep learning for zero-day malware detection," in 2018 IEEE Security and Privacy Workshops (SPW), 2018, pp. 85-93: IEEE.
[67] J. Saxe and K. Berlin, "Deep neural network based malware detection using two dimensional binary program features," in 2015 10th International Conference on Malicious and Unwanted Software (MALWARE), 2015, pp. 11-20: IEEE.
[68] SparkCognition, "Case Study: Ransomware Attack Prevented at Healthcare Organization," 2021, https://www.sparkcognition.com/resource/case-study-ransomware-attack-prevented-at-healthcare-organization/.
[69] SparkCognition, "Case Study: Nation-State Attack Stopped at Critical Infrastructure Provider," 2021, https://www.sparkcognition.com/resource/case-study-nation-state-attack-stopped-at-critical-infrastructure-provider/.
[70] Y. Li, R. Ma, and R. Jiao, "A hybrid malicious code detection method based on deep learning," methods, vol. 9, no. 5, 2015.
[71] N. Papernot, P. McDaniel, S. Jha, M. Fredrikson, Z. B. Celik, and A. Swami, "The limitations of deep learning in adversarial settings," in 2016 IEEE European symposium on security and privacy (EuroS&P), 2016, pp. 372-387: IEEE.
[72] R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, F. Giannotti, and D. Pedreschi, "A survey of methods for explaining black box models," ACM computing surveys (CSUR), vol. 51, no. 5, pp. 1-42, 2018.
[73] A. Tsymbal, "The problem of concept drift: definitions and related work," Computer Science Department, Trinity College Dublin, vol. 106, no. 2, p. 58, 2004.
[74] S. Suthaharan, "Big data classification: Problems and challenges in network intrusion prediction with machine learning," ACM SIGMETRICS Performance Evaluation Review, vol. 41, no. 4, pp. 70-73, 2014.
[75] D. Gunning and D. Aha, "DARPA's explainable artificial intelligence (XAI) program," AI Magazine, vol. 40, no. 2, pp. 44-58, 2019.
[76] N. Akhtar and A. Mian, "Threat of adversarial attacks on deep learning in computer vision: A survey," Ieee Access, vol. 6, pp. 14410-14430, 2018.
[77] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," in International Conference on Machine Learning, 2017, pp. 1126-1135: PMLR.
[78] W. Jiang, H. Li, S. Liu, C. Luo, and R. Li, "A Novel Automatic Security Policy Enforcement System Based on Artificial Intelligence Techniques," in International Conference on Artificial Intelligence and Security, 2020, pp. 234-245: Springer.
[79] J. Konečný et al., "Federated learning: Strategies for improving communication efficiency," arXiv preprint arXiv:1610.05492, 2016.
[80] A. R. Chadha, A. Koganti, P. Kalyanasundaram, J. Kolachana, and B. Ranjith, "Spear: A framework for automated integration of security services in sdn based data center networks," in 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), 2019, pp. 1-6: IEEE.