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Machine Learning for Cyber Defense: A Comparative Analysis of Supervised and Unsupervised Learning Approaches

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Abstract

Machine Learning presents itself as a game changer within the domain of cyber defense, but a systematic review of literature denotes that research effort is largely skewed towards a supervised learning approach. This paper will extend and add value to the literature by filling this gap and investigating the supervised and unsupervised learning approaches within this disciplinary context. By using a clustering algorithm to group research articles, and association rule mining to further understand those groupings, a comparative analysis of both approaches is provided. The results indicate that, despite supervised learning's dominance, the use of unsupervised algorithms has seen a rapid ascent over recent years. Moreover, it also shows that unsupervised learning is more focused on data or information gathering and identification, stemming from event logs, alerts or white and dark data. In this study, several implications and recommendations have been evaluated in order to more effectively combat cyber security threats.

Machine Learning (ML) and its subsets have gained rapid momentum in cyber security research and play crucial roles in maturing data. To understand emerging threat vectors and security domains, ML algorithms are employed to codify the threat behavior exploitation. Despite the various applications, research initiatives into cyber security and the different machine learning algorithms used to revolutionize the understanding of data and the approach of intelligent decisions associated with the data are discussed. This mode of research exposes a noteworthy observation of a slight comparative evolution of the body of knowledge when it comes to supervised or unsupervised methods in this critical domain. Therefore, a comprehensive evaluation is presented of previous studies and methodologies. To consolidate these results, a meta-analytical process is scaled. This analysis breaks down the existing research by defining the applied learning algorithms. In addition, the most extensively used algorithm is elucidated to indicate trends and analysis that are revealing about the innovative application and KDD processes in the context of cyber security.

Keywords: Machine Learning, Cyber Defense, Supervised Learning, Unsupervised Learning,Cyber Defense,Supervised Learning, Unsupervised Learning,Intrusion Detection,Anomaly Detection,Threat Prediction,Clustering Algorithms, Intrusion Prevention Systems (IPS),Machine Learning Security,Data Labeling.

1. Introduction

In light of the escalation in the volume and complexity of cyber threats, the comparative analysis of the application of machine learning (ML) techniques in cybersecurity represented as a game approach is put forth to provide organizations and researchers with improved insights to develop better cyber defense mechanisms. The rapid expansion of cybercrime motives points to the complexity of cyber threats that organizations face. Ordinary protective mechanisms, isolated from a broader perspective, can no longer be fully effective in preventing data breaches and other security incidents. For this reason, both organizations and researchers need to think about advanced technological solutions that can anticipate malicious activities in the digital environment.

The following research questions are explored by means of comparing supervised and unsupervised ML techniques: What is the overall perception of machine learning in the field of cyber defense? Has the sophistication of machine learning applications in the cyber defense field grown exponentially in recent years? Are there solid hypotheses about the direct impact of the anova factors to accept or reject the research questions and how this will influence the conclusions made at the end of the paper? To increase the understanding of these research questions, discussion is conducted on the application of differences in supervised and unsupervised ML in the case of detecting malware in the network using a dataset obtained from the most widely used data repository in the cybersecurity subsection of IEEE. By comparing and explaining the results obtained in applying these two types of learning, the overall results are discussed on the perception of the

application of ML techniques more generally in the cyber defense field, whether the sophistication has grown significantly in the last two years and how the effect of these two learning techniques would be if applied to various situations. This research aims to comparatively study the use of supervised and unsupervised learning techniques in cyberdefense, e.g., for email spam, malware analysis, intrusion detection, etc. It is synonymous in the NS community that machine learning approaches can assist in improving cyber security and situational awareness; the majority of the existing literature focuses on black box anomaly detection models, albeit not statistically validated.

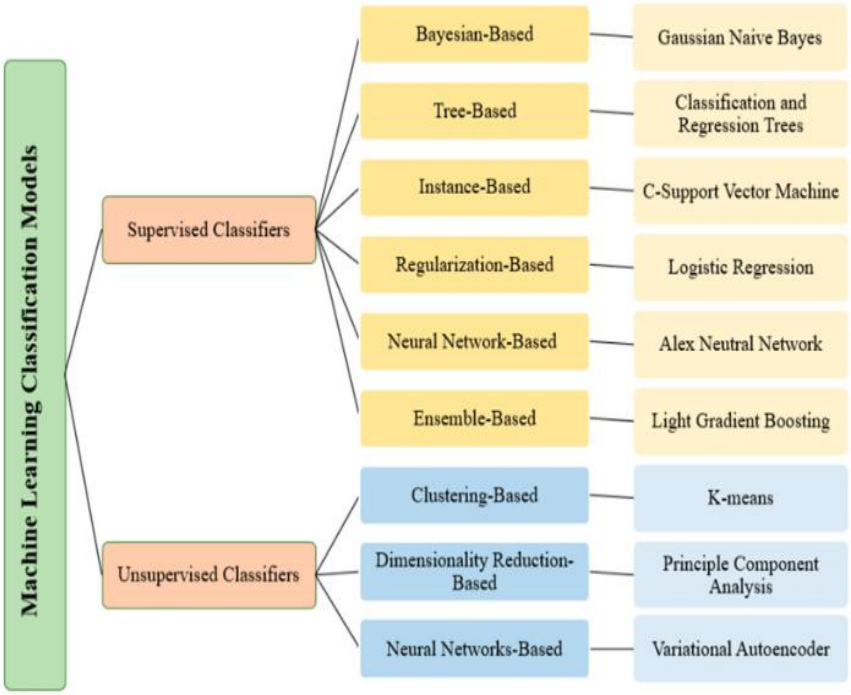

Fig 1: Supervised and Unsupervised Models

1.1. Background and Significance

Cyber threats have evolved over the years, from benign incidents like virus outbreaks in the 1980s to financially motivated activities in the form of phishing emails and hacking in the late 20th century. The malware infection method, origin, method of propagation, scalability of attacks, and the international perspective of cyber intrusion attempts have changed since the first computer virus. Throughout the eras, an increase in integrating machine learning into cyber defense systems can be observed . Lately, the security trends and possible technical solutions were regulated with a focus on machine learning. With increasing complexity of computing infrastructure, the attack surface mass of the threats, where machine learning, especially to comply with or to provide big data methodologies, can be utilized more efficiently as an IR system for attacks, or it can be employed as a proactive approach to the vulnerability analysis to prevent threats before they occur. Computer security experts generally focus on the prevention and treatment of insider threats or the compromise of critical computing assets by deploying vulnerability detecting IDS, which is an entirely different approach. Historically, set-based security policy complaints about routers, firewalls, and subject-based security solutions that rely on low-security requirements simulations effectively computerized operations through password guessing and common security policy. The study demonstrates that approaches to traditional IDS blades to prevent purpose-designed security attacks can at least provide better resistance even if they return a false positive for non-particular inquiries. Most commercial systems will inevitably have gaps that a knowledgeable attacker can exploit. Automated target systems provide operational feedback on the viability of the attacks and discuss the potential of automated software agents executed internally to the network-mediated elicitation of insider threats.

With the exponential growth of the internet and networking in general, and the proliferation of so-called cloud computing, the overall complexity of computer systems has shown even a much increased geometric rise. This has led to operation of complex systems that are very hard to understand or debug; in some cases, machine failure occurs due to transient, unexplained effects. Historically, machine learning researchers have exploited modeling software as a research platform; however, the effect of software bugs on computational results is understudied in the context of machine learning research. Rising preprocessing, feature extraction, and modeling code complexity encourages utilization of modeling platforms developed in-house; they can be unaware of the dangers of racing conditions, deadlock, and non-deterministic bugs in general.

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Equ 1: Supervised Learning Approach

$$L = -\sum_{i=1}^{N} [y_i \log(f(x_i)) + (1 - y_i) \log(1 - f(x_i))]$$

Where:

- N is the number of data points.
- y_i is the true label (0 or 1).
- $f(x_i)$ is the predicted probability.

1.2. Research Objectives

This work aims to investigate and comparatively analyze the effectiveness of applying supervised and unsupervised machine learning methods in cyber defense with respect to the development of useful evaluation metrics. The reasons for machine learning employment in cyber defense is discussed. The objectives of this work are to illustrate a framework that can be utilized as a reference for cyber defense and to develop a set of evaluation metrics for assessing the results. The experiment settings for implementing the comparative analysis are described and the work is concluded.

The research objectives and approach can be generalized under four key themes: The effectiveness of employing supervised and unsupervised machine learning methods in cyber defense is explored. A framework to inform specialists in cyber defense of the strengths and weaknesses inherent in various machine learning methods is presented. A set of evaluation metrics that can assist specialists in cyber defense to make practical use of the experimental results is proposed. The research approach is illustrated and work on better understanding of comparative analysis methods is hopefully fostered. It is noted that there are many ways to apply machine learning methods in cybersecurity. For that matter, a comparative analysis of supervised and unsupervised methods is investigated. To the best knowledge of the authors, studies on the comparative analysis of supervised and unsupervised machine learning methods for cyber defense have seldom been conducted.

2. Machine Learning in Cyber Defense

Modern day cyber defense infrastructure necessitates the increased application of machine learning technologies. This. By automating decisions, machine learning enables computing devices to either advance the efficiency of existing predefined tasks, or achieves automation for tasks that before seemed infeasible. The applicability of machine learning in the cyber defense domain is evident by the extensive amount of related academic research, detailing the development and testing of a variety of different processes and workflows. Broadly constraining the cyber defense domain and the nature of attacks that could occur, the machine learning models are applied using incoming data. Furthermore, with case studies included, highlighting instances of use for either newly implemented cyber defense products or sophisticated pre-existing solutions in the face of curated cyber attacks, the possibility exists for groundbreaking deepening of the cyber defense strategies currently in place within restrictively model-definable environments. This functions as an intermediary between academic theory and practical solution execution, detailing fundamental facets whilst still allowing for implementation of operational response options to incoming cyber threat intelligence (CTI). The primary aim is to understand the assimilation of machine learning approaches within the cyber defense landscape. This overall goal is delaminated into the following bunch of objectives, specifically addressing the landscape as a whole and its role in current research—(A) application of machine learning models to cyber defense; (B) development of machine learning models in defense against cyber infiltrations; (C) comparison of the effectiveness prior to and post cyber attack engagement; and (D) the application of ML and accompanying results following the assault for emerging strategies in defense, along with the development and testing of the cyber infiltration model implementation. Machine learning is a field with multiple subdomains, necessitating the understanding of fundamental concepts and paradigms such as deep learning, natural language processing, or support vector machines. Moreover, this provides insight into the diverse applications of machine learning within cyber defense, detailing attack prevention and detection, intelligence analysis, as well as the decision making to engage and drop the enemy or direct resources to certain sections of a cyber system. Finally, the practical application of machine learning due to the decision-making enhancement gained as compared to traditional cyber defense practices is also discussed. Data-driven decision-making in regards to fortifying cyber defenses is a transforming trend that enhances the need for machine learning capabilities as part of the cyber defense infrastructure, and is explicitly delineated. By demonstrating both the theoretical understanding of why machine learning strategies are suitable for potential widespread current and future implementation within a defensive landscape, the benefit of these systems is underscored.

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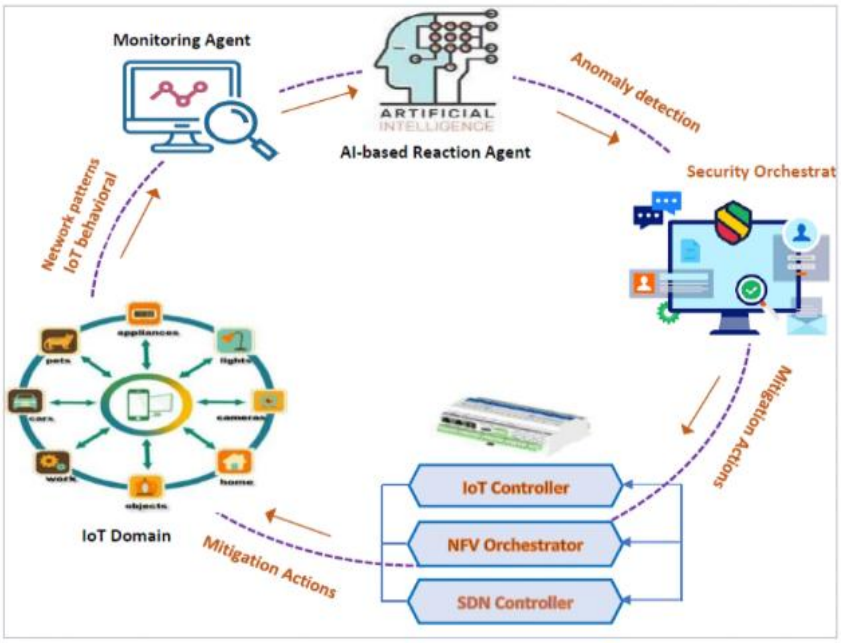

Fig 2: Machine Learning in Cyber Defense

2.1. Overview of Machine Learning

Since its inception as a scientific field in the 1960s, machine learning has rapidly grown and carved itself a niche in various industries and applications. Ubiquitous in everyday life, from filtering spam email to recognising the speech in the latest smartphone, machine learning is also used in critical applications, such as handling the national power grid, controlling computer networks of fortune 100 companies, and routinely assists physicians in making a more accurate diagnosis of complex diseases. In a real-world context, machine learning can diagnose disease faster and more accurately when compared to a human specialist, classify documents more efficiently and accurately than a team of hundreds of human experts, and optimize industrial processes vastly more successfully than a panel of human engineers. Moreover, machine learning has the ability to train computers to make decisions by analyzing large amounts of data, conveyed via training data, for which each input in the data is accompanied by a relevant output. Here, data refers to information extracted from object phenomena, be it abstract, physical, or conceptual; in theory, data stands for the training instances. Several types of machine learning tasks are prevalent in real applications, such as predicting the long-term behaviours behind the time series data, identifying hidden patterns in previous unlabelled data, and learning NP-hard functions under big data conditions. With the advent of the deep learning concept, neural network models now sometimes exceed the human-level of accuracy, with several application domains demonstrating remarkable improvements, making it now an indispensable tool for various industries in recent years. Over the past decades, machine learning has been pushed to evolve and expand beyond its original scope. Mainstream machine learning branches at a macro level include supervised, unsupervised, and reinforcement learning; along with a plethora of subfields. Further additional classifications could be based on the learning fact of working with noisy data, the number of outputs, multiple aims and properties, and the time of decision prediction. There is an array of prominent and notable machine learning algorithms and systems, each upholding a set of core rules and principles, abstractly defining the problem they try to solve. These rules and principles are formulated by mathematical models described by statistics, probability theory, and information theory, along with concrete training methods to optimize their model parameters using training data. On this basis, there are an abundance of machine learning platforms, libraries and APIs with a broad spectrum of Big Data, Internet of Things (IoT) resources and data manipulation and handling tools. Combining these ingredients, an industrially-focused company, institution, researcher, or specialist can potentially build an effective and efficient machine learning pipeline to address real-world, large-scale problems by mining valuable information out of provided data, increasing the productivity and competitiveness of the application domains.

2.2. Applications in Cyber Defense

Perhaps the most practical application of machine learning in cyber defense is in the enhancement of the efficiency of fundamental cyber defense mechanisms. There are various use cases of machine learning for cyber defense, spanning from enhancing basic security measures to transforming sophisticated cyber threats. Machine learning can improve well-established security methods such as next-generation firewalls by enabling them to perform deep analysis of network

traffic. Machine learning techniques have been used to significantly improve log correlation-based approaches for intrusion detection system (IDS) demand, supporting the automatic generation of rule-based addresses.
In addition to the general highlights presented above, the effectiveness and potential risks of machine learning in cyber defense are also discussed in-depth in the appended conference paper. The paper provides analysis and case studies outlining the use of machine learning techniques within organizations to improve their cyber resilience posture. There are also notes on the deployment and management of machine learning solutions, such as the integration with existing security infrastructures, which are essential to ensuring the success of these solutions.

3. Supervised Learning in Cyber Defense

Machine learning enables systems to automatically learn and improve performance from historical data without being explicitly programmed. Machine learning, with its unique set of algorithms, has been leveraged in cybersecurity research for more robust attack detection. Machine learning operates in two major spaces, supervised and unsupervised. Supervised learning requires a supervisor who knows the correct answer to train the model on which features to gather, then the model is trained on the historical instances to classify the new instance correctly. The common supervised learning algorithms include linear Support Vector Machine (SVM), Decision Trees (DT), random forests, and Multilayer Perceptron. Unsupervised learning does not require a labeled dataset for training purposes, the model is trained on the only historical normal instances, and it flags the instances as an anomaly which does not follow the distribution of the historical normal instances.
Machine learning for cybersecurity has had a remarkable impact. One work highlights leading-edge efforts to motivate further research in the domain by presenting the domain taxonomy, applications, benchmark datasets, challenges, and recommendations. Data-driven industrial control systems (ICSs) in critical infrastructure use complex industrial processes and communication protocols. That complexity, along with the interconnectivity of IT with OT (Operational Technology), makes ICSs a desirable target for persistent adversaries. Traditional rule-based intrusion detection mechanisms often fail to detect evasive attacks like man-in-the middle, stealth, masquerade, and denial-of-service, which could be disastrous for industrial environments. Researchers have investigated Machine Learning (ML) and Deep Learning (DL) techniques to detect such attacks. Depending on the training data, ML and DL techniques can be classified into four major categories: Supervised Learning, Unsupervised Learning, Semi-Supervised Learning, and Reinforcement Learning. The performance comparison investigates supervised and unsupervised approaches, including both DL and ML methods. It was observed that supervised learning algorithms are generally more efficient in attack detection and parameter configurations compared to unsupervised learning.

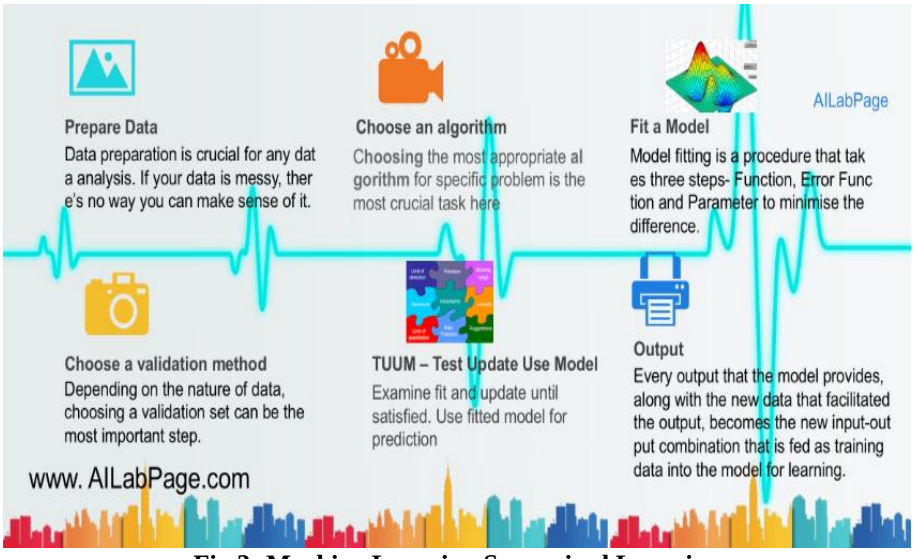

Fig 3: Machine Learning Supervised Learning

3.1. Definition and Principles

Machine learning (ML) has emerged as a paradigm for the detection of cyberthreats. Significant resources have been committed to the development and implementation of custom algorithms to perform the ML tasks. A substantial amount of empirical work has been expended as well, investigating which algorithms are best suited to perform a particular task. Despite all the successes, the usability of ML for Cyber Threat detection (CTD) is still constrained by the difficulty in gaining broad access to high-quality labelled data. A possible solution to this is to apply learning with small amounts of

labelled data (semi-supervised learning, SsL). Employing this approach allows the combination of scarce labeled data with larger unlabelled data. It is expected that similar points present in the input space of new statistically "similar" data points and share the same output labels. This assumption enables an increase in precision in the generalization of the problem beyond the available labeled data.
There are two general types of learning algorithms: supervised and unsupervised learning. In supervised learning, the training dataset consists of pairs of input vectors and output labels. In unsupervised learning, the training data consists of a set of input vectors. Cyber defense applications observe a high number of very specific cyber-attacks, generating a highly imbalanced dataset. This paper investigates how these assumptions manifest in cyber defense applications and why semi-supervised algorithms would be useful for networks. Achieving this requires understanding: a) the cost of labelling data in various CTD tasks, b) the utility of unlabelled data, and c) a focused investigation on SSL in CTD, including a description of useful methods available in the current state-of-the-art.

3.2. Common Algorithms

Supervised learning: it refers to the process of an algorithm to learn from the input-output pairs it is trained on. Thereafter, the algorithm makes inferences and predictions about new data that is fed to it. The most common classes of algorithms used practically in this field are: Decision Trees; Support Vector Machines; Multilayer Perceptrons; Deep Belief Networks; and Recurrent Neural Networks. The distinguishing characteristics and advantages of decision trees, random forests, support vector machines, multilayer perceptrons, and deep belief networks with respect to cyber defense applications are as follows: (1) Decision trees are often used because of their ease of interpretability and efficiency. When random forests aggregate multiple 'weak' decision trees, randomness contributes to the algorithm's ability of mitigating overfitting and increasing diversity in models. Being the prominent algorithm used to train cyber security datasets; (2) SVMs are used for tasks where numerical datasets are prevalent and are arguably the most effective linear classifier available. The kernel function in SVMs helps transform data into higher dimensions, which is useful when the inherently nonlinear nature of the data suggests the necessity of employing such a method. (3) MPLs are classic and simple feedforward neural networks and often come to mind first for many data practitioners. It is chosen for image, video, or voice applications. But in practice, the MLP tends to overfit easily and may require extensive hyperparameter tuning to optimize; (4) There is a rise in the usage of DBNs in recent years. This is because such models can learn and then sample joint hidden feature vector spaces. DBN models are capable of modeling complex distributions once trained, and are quite suitable for modeling semi-structured domain data; and (5) Due to the sequential nature of log data and the dependence on what prior sequences have occurred, it makes RNNs a possible choice for training cyber security datasets to detect intrusion attempts. The four types are the Gated Recurrent Unit, Elman Jordan, Long Short-Term Memory, and Simple Recurrent. Each variant has its own characteristics depending on the number of connections, hidden layers, and use of peers that can feedback output. Data representation is an important step in this work, as deep learning algorithms require a simple and clear dataset structure, and common data tools do not cover all possible data types and are not ready to use.

Equ 2: The Mean Squared Error (MSE)

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i))^2$$

Where:

- y_i is the true value.
- $f(x_i)$ is the predicted value.

4. Unsupervised Learning in Cyber Defense

One impactful way in which the society is increasingly reliant on networked information technology for dependable operation is security of these systems. As enterprises reach an agreement to make intelligent anonymizing solutions to these obstacles, it is an essential procedure for creating the most out of advanced technology. This paper presents a comparative analysis of the impact of machine learning in supervised and unsupervised style on concurrent cyber defensive solutions. The focus is on the present capacity of these modes of machine learning in the context of cyber defense by scrutinizing up-to-date research. The purpose is to provide a thorough account of the strengths and weaknesses for each, and to characterize data conditions that are favorable to one approach or the other. The hope is that the overview will bring some benefit to beginners modeling cyber defense and more experienced practitioners wrestling with new data targets and platforms in the creation of cyber defense strategies. A unique contribution of this article is a practitioner's perspective on the ability of machine learning to be applied to the most common categories of cyber defense data available and of an analysis of the suitability of advanced models in practical implementations.

A significant advantage a cyber defense strategy can afford is to make a potential attacker look elsewhere, to switch effort to another possible target. The principal aim here is to fascinate actors specifically in cybersecurity situations in which a business or an institution operates; nonetheless, cybersecurity technology is at the end of the day just a piece of a company's entirety, and capacity in cybersecurity is not usually equivalent with a general scope. That is, whereas a specific technology might be very strong against many attacks, its usefulness might be ruled out by operating .

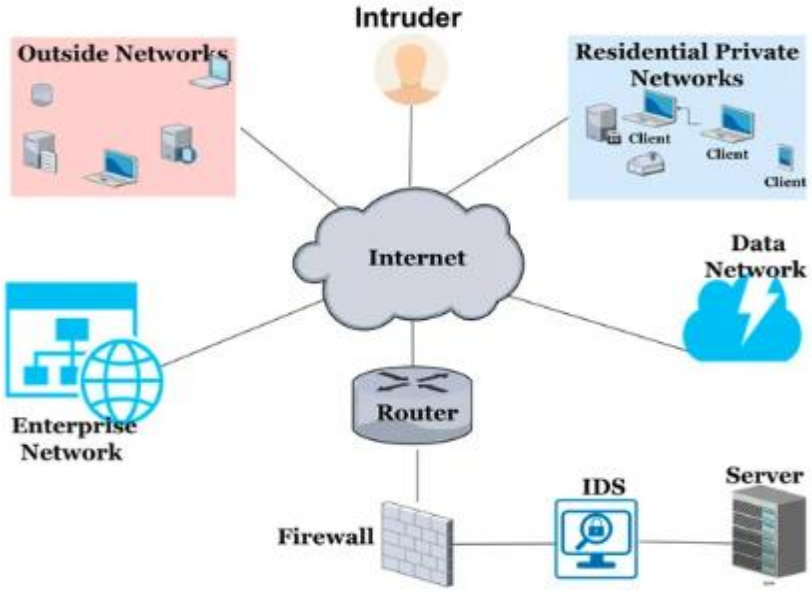

Fig 4: Unsupervised Learning Approach for Enhanced Cybersecurity

4.1. Definition and Principles

Broadly speaking, machine learning techniques can be classified as supervised or unsupervised learning, among several other techniques and sub-techniques, such as supervised learning, unsupervised learning (UML), semi-supervised learning (SSL), reinforcement learning, and deep learning. However, most of the research studies are related to supervised and unsupervised machine learning (ML) for cyber defense. Unsupervised learning methods have gained significant attention in recent years to cope with the flexibility of handling different security challenges. It is a type of learning where the function to predict an output variable is not explicitly learned. Furthermore, different attack scenarios identify the potential inputs that indicate the occurrence of unwanted events based on malicious network traffic.

Unsupervised learning is the procedure of learning that undertakes a program to find out how to accomplish tasks by example largely untagged observations that signify the information to be retained. And this is distinct from supervised learning to deduce from observations and a teaching signal that specifies the preferred states. This term refers to what is done with the observed data through unsupervised learning programs to explain its prospects that express the concept of the method, as well as the empirical behavior of the method. Such procedures are distinguishable from actual learning methods that aim to make such a program to perform given an explanation of the task. Besides, unsupervised learning principles are divided into association and clustering principles. Broadly, these two principles give a paradigm for representing the desired likelihoods conditioned on a small set of facts, and algorithms are reviewed that aim to learn millions of such facts as parameters for a wide energy function by compensating for its graph structure. Furthermore, unsupervised learning is also differentiated from the point of view of supervised learning, and difficulties with learning such models are discussed.

4.2. Common Algorithms

As stated in the earlier part of this article, Feature Analysis via Supervised Learning is a technique to turn raw data into knowledge. It cannot turn raw data into understanding or wisdom. It is therefore beneficial to benchmark the solution from any supervised learning algorithm used in Feature Analysis to those from unsupervised learning. By also applying Feature Analysis techniques to the same data, a separate realization can be found for the aim of turning raw data into wisdom. One of the main differences between algorithms of supervised and unsupervised learning is the relation of different instances or features. That is, when doing Markov Blanket Discovery, Symmetrical Uncertainty, ReliefF, and other supervised learning algorithms can easily handle how well each feature can explain others all conditioned on class label(s), but information of how to separate instances via features back is missing. For the symmetry of this relation, unsupervised learning solutions must be sought. Symmetric properties must be found between the class(es) and features.

Thus, it is meaningful to compare Feature Analysis with Clustering in terms of cyber intrusion detection. Just like in bioinformatics where Feature Analysis focused on feature selection (ReliefF) or weighting (Symmetrical Uncertainty) prescreening before other techniques like Neural Networks or Bayesian Networks were applied, the same should be done in cyber security and cyber defense so that results generated from supervised learning are not considered unfair due to its modeling of asymmetric relation. The belief is that by illustrating many common algorithms in both realms unbiased judgements will be facilitated. Moreover, debates can be focused on scalability, complexity, feature-enrichment, and other issues than comparison fairness. Next, a few common algorithms in unsupervised learning that are frequently applied in cyber defense are mentioned. At the end is an illustration of a typical solution to how those unsupervised learning algorithms are operated. It includes the DARPA 2000 dataset, which is commonly called the KDD99 dataset. The data preparation and setup are explained separately for readers who are not familiar with this dataset and focused on the algorithm examples.

5. Comparative Analysis

Passive cyber defense mechanisms have the inherent limitation of not being able to prevent a zero-day attack. Moreover, the adversary may perform actions on the IT infrastructure to learn the vulnerabilities of the system. This calls for a change of strategy from the traditional cyber defense, and machine learning may provide a sophisticated alternative to defend the critical systems of an organization. On a high level, supervised learning and unsupervised learning can be applied for cyber defense. This Section offers a comparative analysis and implications of deploying supervised learning and unsupervised learning for cyber defense.

Evaluation metrics to evaluate the effectiveness of the supervised and unsupervised methods are defined. The evaluation metrics include true positive (i.e., the number of actionable alerts that are correctly generated), false positive (i.e., the number of unactionable alerts that are incorrectly generated), true negative (i.e., the number of unactionable alerts that are correctly not generated), false negative (i.e., the number of actionable alerts that are incorrectly not generated), and time (i.e., the time needed to generate an alert set). These metrics jointly measure the fundamental capabilities of a detection system, i.e., accuracy, and how quickly and efficiently it identifies the malicious actions, i.e., speed and resource efficiency. Unlike in the spam email filtering context, the detection system receives input from the adversary proactively, thus there is no concept of a time threshold to judge whether a detected alert is false positive or irrelevant. Instead, the detection system will remove the actions of the adversary at an effort-proportional rate to the number of defenses, and the remainder will be discovered and verified. The detection model is assumed to be model-agnostic. Because of the continuous threat of actions, model parameters need to be changed regularly by the organization, hence a negligible effort-proportional rate to the number of actions is imposed. The detection model, irrespective of being supervised or unsupervised, then applies algorithms to learn a model that observes data and generates features, conditions on an alert and the time delta to the action to generate the response.

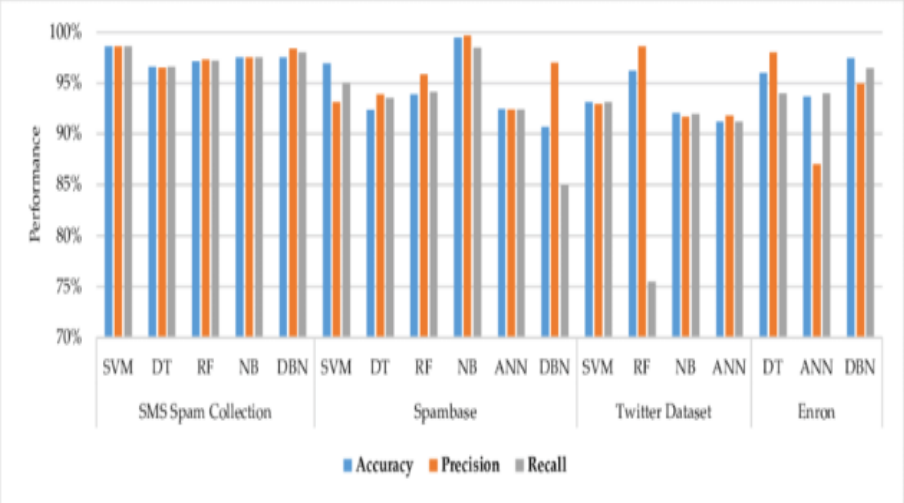

Fig 5: A comparative Analysis of Spam Detection using Machine Learning Techniques

5.1. Evaluation Metrics

Due to variations in the evaluation of metrics, it is important to utilize understanding in different scenarios. There are several important metrics and fundamental concepts to be considered in adopting these metrics. A confusion matrix is the

most important metric for the assessment of supervised learning, It allows the assessment of the performance of the learned model in classifying alarming and normal instances. It provides the basis of accuracy, precision, recall and F1-score metrics. There are trap reactions and a low value of one metric can lead to a high-value change in another metric. The metrics selected for evaluation significantly influence the interpreted results of the proposed system which are not unique and definitive. In many cases, a decision of the utilization metrics is shaped by the improvement of the proposed system or other related works. There are various related works where all options are evaluated in terms of available metrics. In unsupervised learning, predefined alarm based on unknown instances, and usual anomaly detection unsupervised learning model can cluster all instances in the same population, yielding very large precision values, but not alarm all instances. The proposed assessment metric is a silhouette score that assesses that the mean distance between instances in the same cluster is smaller than the distance to instances in another cluster.

As a result, good clustering k-means provide a high silhouette score. If the instances' cluster decreases, a low number of false alarms can lead to a low precision value but an impossible-to-reduce recall value or true alarm. The majority of unsupervised learning algorithms involve different systems. Therefore, the use of cluster validity indexes is proposed to select the number of clusters. Unfortunately, very low cardinality mini-batch algorithms always return only a cluster even with the use of higher cardinality populations. A cluster validity index would be used in an attempt to prevent the utilization of mini-batch algorithms or even to avoid the development of a mini-batch algorithm given satisfactory evaluation results. On the other hand, open research problems, considering the cyber threat response of modern IT systems, we need to conduct research into scale evaluation, detection and impact assessment of distributed alarms on the entire IT platform and validation of simulated scenarios by cleaning datasets.

5.2. Advantages and Limitations

There are some advantages and limitations with supervised and unsupervised learning, which have impact on the efficiency and the final decision. A statement that more malicious and attack traffic are included in the UNS dataset, more normal traffic is included in the N dataset, and the percentage of NA traffic in the UNS dataset is greater than the N dataset, which is proved to be 0.52. Supervised learning is a type of machine learning in which the model is trained on a labelled dataset, which assigns less probability to the class in the minority based on the class distribution. Supervised learning algorithm is an algorithm that learns patterns from labelled data, this method categorizes the new data by training on a labelled dataset. Therefore, it is very effective on the behaviour-based dataset for known malicious and they have well-defined output capabilities, which is preferable for binary classification datasets. With the increase in the size of the training set, supervised learning grows well in performance. Additionally, supervised learning provides the possible classification of the reason as a feature.

One of the significant disadvantages of supervised learning is that learning depends on the dependencies between the input-output relationships decided during training. The model overfits the data, which includes the noise that can misguide the model. It happens when a model captures the noise along with the underlying data distribution. The overfitted model works well on the training data but poorly on new data. One concern for companies in working on supervised learning for cyber defense is the originality of the attack pattern, which remains unknown to the algorithm. Another issue is that the use of only supervised methods will make it difficult to develop new architectures that are not generally considered in the field given their average results. Detection for these new architectures will most likely rely on unsupervised and semi-supervised approaches. Regarding the time problem, new instances of the attack pattern will come in at the last minute. Cloning the model for new architectures will take some time to train more models. On the other hand, UNS provides a more abstract perspective and is generally characterized by the adaptability of the model to new patterns that have not been observed before. It has a big similarity to IDS, because the model will also adapt to the changing landscape of technology, network behaviour, type of configuration, etc. Uncoulter in a broader aspect also detects vulnerabilities.

Equ 3: Unsupervised Learning Approach

$$f(x) = \text{sign}\left(\langle w, x \rangle + b\right)$$

Where:

- w is the weight vector.
- b is the bias term.
- $\langle w, x \rangle$ is the dot product of the weight vector

6. Conclusion

Cyber-attacks have been an increasing threat in recent years and, with the growing reliance on interconnected cyber–physical systems, this trend is set to continue. This paper has contributed a detailed analysis of employing machine

learning technologies to better safeguard critical infrastructure. The research focused on analyzing the current open challenges in the literature regarding the implementation of machine learning in cybersecurity and presented a comparative analysis of employing both supervised and unsupervised learning approaches in the realm of cyber defense. In developing the comparison, 58 research papers published between 2013 and 2019 were examined. The results of the surveyed research are intended to aid both practitioners and researchers in the cyber defense sector to better understand the benefits of employing supervising or unsupervised learning to enhance the overall cybersecurity posture of critical infrastructures. Awareness of the analyzed research is expected to provide practitioners with actionable insights into preventive, detection and post-incident activities, such as designing computer network traffic monitoring systems and their security configurations, creating better network models, DNS engine design and security configurations, the design of collaborative embedded monitoring systems, design of more mature cyber capabilities, real-time DNS stream analysis and interpretation, network optimization, the design of integrated validation environments, the design of a threat information platform, the consideration of behavioral information, the design of preventive controls against APT attacks, the design of IPS effectiveness, and data normalization.

Finally, this paper is expected to help researchers better understand the current limitations and requirements of the open technological challenges in the domain of critical infrastructure cybersecurity. Research implications are summarized at the end of this essay to help both practitioners and academics unlock potential benefits. Furthermore, the limitations of this review are also given, providing a more detailed understanding of the constraints faced in conducting the research, and identifying potential future research topics, addressing the challenges identified and providing a broader perspective.

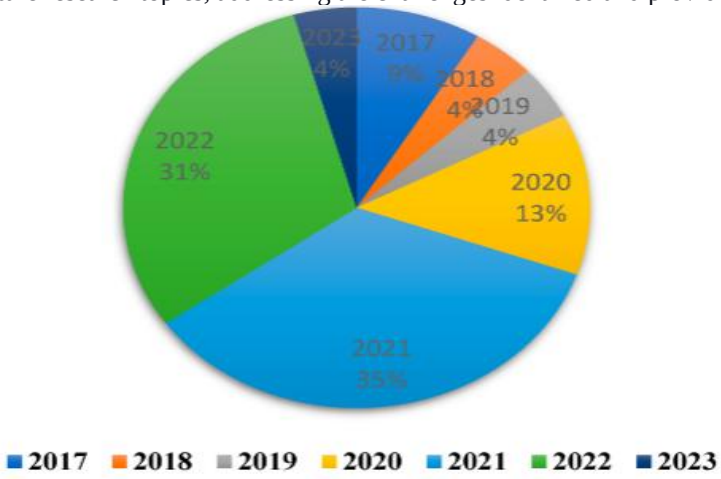

Fig : Cybersecurity Analysis in Smart Distribution Systems

6.1. Summary of Findings

Cybersecurity is an emerging field to provide adaptive services for security in cyberspace. The resources in computer networks are mapped to graphs and analyzed the directed attack graph from the attacker's perspective and analyzed the attack paths and provided the solutions to secure the network. This research work provides a comparative analysis of supervised and unsupervised learning approaches of machine learning in cyber defense which is helpful to select the appropriate approach for the designing of smart cyber defense systems. The research work consolidated the findings in the following subsections. The research work can provide the future directions and challenges in cyber defense to the researchers and practitioners. Cyber defense is the practical application of cyber security and machine learning for providing the protection to the network and systems from various attacks. Cybersecurity is the most significant challenge for the defense of secret information and the internet of things. Recently, machine learning has gained the attention of researchers on protecting the cyber systems due to the increasing need of the dynamic and evolving cyber defense. The present study provides a comparative analysis between the supervised, semi-supervised, and unsupervised learning approaches of machine learning for smart cyber defense. The study is useful for practitioners to secure the secret information and the systems from various types of cyber-attacks and malicious activities. As a result, when designing similar cyber defense mechanisms, it may help to identify suitable methodologies. Furthermore, the potential future of discussions and the challenges in the field of cyber defense relating to the findings could provide future direction to the reader.

6.2. Future Research Directions

Cyber threats have become more sophisticated nowadays, damaging organisations in different sizes and types greatly every year. In recent years, smart infrastructures and digital industries have been more targeted with fourth industrial revolution technologies, such as cyber-physical systems and the Internet of Things (IoT). Hence, effective cyber defenses

must also incorporate advanced technology that are capable of countering these threats and assuring secure functionality and high availability. Machine learning, which was initially aiming at detecting non-random biases or generalizing from data, has been recently selected as a novel tool for enhancing cyber defense strategies. As a response to the rapid emergence of black-box classification algorithms, there is sceptical evidence that DL (Deep Learning) may be a more interpretable model compared to other black-box classifiers.

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