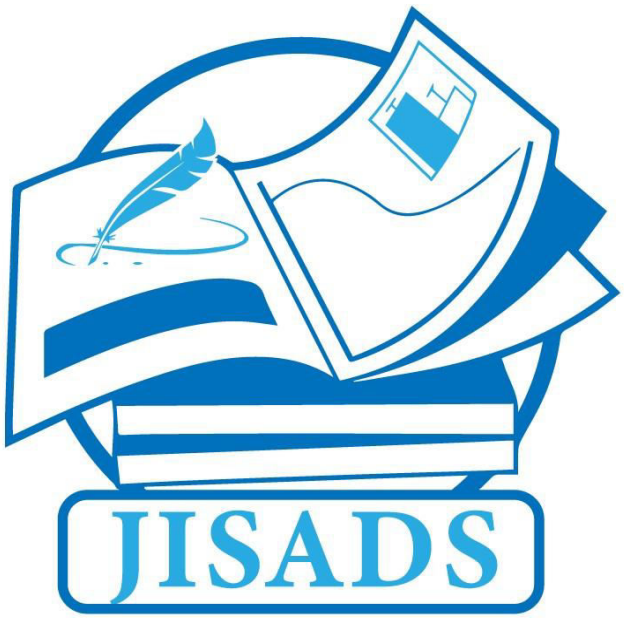
Vol. 1 Issue No. 2 (2023) pp. 1-40: Journal of Intelligent Systems and applied data science (JISADS)

ISSN (2974-9840) Online



We are pleased to publish the second issue of the Journal of Intelligent Systems and Applied Data Science (JISADS). JISADS is a multidisciplinary peer-reviewed journal that aims to publish high-quality research papers on Intelligent Systems and Applied Data Science. Published: **2024-01-08** and the issue closed on **5 articles**.

Editor-In-Chief:
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Journal of Intelligent System and Applied Data Science (JISADS)

Journal homepage: https://www.jisads.com
ISSN (2974-9840) Online

TAXONOMY OF CYBERBULLYING: AN EXPLORATION OF THE DIGITAL MENACE

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ABSTRACT

Cyberbullying, a digital menace that has grown in prevalence and impact, is a complex phenomenon that transcends age groups and geographical boundaries. The advent of digital media and the anonymity it provides have produced an environment where bullying can occur at any time, in any place. The COVID-19 pandemic has further intensified this issue, with increased online activity leading to a surge in cyberbullying incidents. This paper proposed a taxonomy of cyberbullying, exploring its various modes, types, platforms, impacts, and strategies for prevention and intervention. The study uncovers the high occurrence of cyberbullying across multiple digital platforms, including social media, text messaging, video games, and more. The paper also reveals demographic trends, indicating that older teenage girls and individuals from certain racial and socioeconomic groups are disproportionately targeted, often due to physical appearance. To combat this digital menace, this research proposed a range of strategies, including educational initiatives, digital citizenship programs, social skills training, conflict resolution, and increased parental involvement. This comprehensive analysis of cyberbullying provides a structured framework to understand its characteristics, classification, and the challenges it poses, while also shedding light on emerging trends. The paper concludes with implications for future research, education, and policy, underscoring the need for a multi-faceted approach to tackle this pervasive issue.

Keywords: Cyberbullying, Taxonomy, Digital Menace, Classification, embarrassment

1. INTRODUCTION

Cyberbullying, concerning phenomena of the digital age, has rapidly emerged as a global issue with far-reaching implications for society. This form of bullying, carried out through digital devices such as smartphones, computers, and tablets, is not limited by physical boundaries or time constraints, thus giving it the potential to reach a victim anytime and anywhere [1]. Cyberbullying has emerged as a pervasive and impactful issue in recent years, affecting individuals across various age groups. With the rise of digital and electronic media, perpetrators can engage in bullying behavior anonymously, unconstrained by time or place. The COVID-19 pandemic and associated lockdowns have further exacerbated cyberbullying incidents, as individuals spent increased time online [2]. Studies have revealed a high prevalence of cyberbullying through social media platforms, text messages, video games, and other online channels. Offensive name-calling, purposeful embarrassment, physical threats, stalking, sexual harassment, and sustained harassment are common forms of cyberbullying experienced by teens and young adults. Demographically, older teen girls are more likely to be targets, with physical appearance often

being a motive for bullying. Moreover, differences exist among racial and socioeconomic groups in the types of online attacks experienced. Stakeholders in the field have identified educational efforts, digital citizenship programs, social skills training, remediation of online conflicts, and parental engagement as key strategies to mitigate cyberbullying incidents. The prevalence of cyberbullying has grown concurrently with the ever-increasing integration of technology into our daily lives [1]. Its impact is especially significant among young people who are digitally active, with numerous studies indicating the adverse effects of cyberbullying on the psychological and emotional well-being of adolescents [2][3]. These effects, which include depression, anxiety, and even suicidal thoughts, highlight the severity of cyberbullying and underline the urgency for a comprehensive understanding and effective countermeasures. In addition, the nebulous nature of online spaces can offer a veil of anonymity for the perpetrators, further complicating efforts to address cyberbullying [4]. The emergence of new technologies and platforms continually transforms the landscape of cyberbullying, bringing about novel forms and methods of digital harassment.

Cyberbullying, an increasingly prevalent issue, particularly amongst younger demographics, has been significantly amplified with the surge in technology and social media usage. Current data unveils some concerning trends. For instance, a 2023 survey by Comparitech indicated a marked increase in reported bullying instances by parents, especially within the 14 to 18 age brackets, with nearly 60% acknowledging their children's victimization [5]. Cyberbullying transcends the boundaries of traditional in-person interactions and communication methods, with one-fifth of all reported instances occurring via social media according to Comparitech. Other digital platforms, such as text messages and video games, were implicated in 11% and 8% of cases, respectively. According to the report by Digital Cooperation [6], the COVID-19 pandemic, particularly enforced lockdowns, inadvertently fueled cyberbullying, with some studies indicating an up to a 70% increase in online toxicity levels on social media and video conferencing platforms, likely due to extended online engagement of children and teenagers. Parental responses to cyberbullying varied, with the majority opting for discussions around online safety, although less than half took further protective steps such as adjusting parental controls or implementing new technology usage rules. Only about 10% of parents resorted to completely denying their children's technology access in response to cyberbullying. Offensive name-calling (31%), deliberate embarrassment (26%), physical threats (14%), stalking (11%), and sexual harassment (11%) emerged as the most common forms of cyberbullying.

Research from the Pew Research Center [7] also affirmed this issue's scope, revealing that almost half of U.S. teenagers aged 13 to 17 have encountered at least one of the six identified cyberbullying behaviors, with name-calling being the most frequently reported. Furthermore, demographic analysis revealed cyberbullying to disproportionately affect older teenage girls, with 54% of girls aged 15 to 17 reporting at least one cyberbullying incident, compared to 44% of their male counterparts and 41% of children aged 13 to 14 from both genders. Certain demographic groups were found to be more susceptible to specific forms of online harassment. For instance, white teenagers were more likely to be the target of false rumors compared to their black counterparts, while teenagers from lower-income households reported higher rates of online physical threats. Notably, older teenage girls were particularly prone to experiencing multiple forms of online harassment, with 32% reporting at least two types of online harassment, compared to 24% of teen boys. Teenagers aged 15 to 17 were also more likely than their younger counterparts (aged 13 to 14) to be victims of multiple forms of cyberbullying, further illustrating the complexity and variances in this growing concern. In terms of prevention and intervention strategies, the 2023 study identified educational efforts related to awareness of cyberbullying and its consequences, digital citizenship programming for students, social skills training, remediation for youth in online conflict, and parental engagement with the technology used by their children as key factors in mitigating instances of cyberbullying [7].

Cyberbullying, a product of the digital age, is marked by numerous defining characteristics, some of which include anonymity, constant presence, public visibility, and profound psychological impact on victims [7]. This form of bullying can manifest in direct targeting or through more covert methods such as rumor spreading. While it may be subjective to arrange these characteristics based on their severity—considering the varying degrees of individual impact—they are generally listed here, avoiding redundancy, in the order that often demonstrates the most harmful aspects. Predominantly, the psychological impact of cyberbullying may manifest in severe depression, anxiety, low self-esteem, and in extreme cases, suicidal thoughts, or actions, rivalling or even surpassing the emotional trauma inflicted by traditional bullying. This bullying method's incessant

presence, enabled by digital devices, permeates safe spaces such as homes, leaving the victim feeling tormented and trapped. The pervasiveness of cyberbullying transcends the traditional limitations of the physical environment, making victims a constant target irrespective of time and location. The aggressive and intentional nature of cyberbullying is designed to distress and harm the victim. It is characterized by repeated acts over time, establishing a pattern of harassment and abuse. A key component of this phenomenon is the perceived power imbalance between the bully and the victim, often leaving the victim feeling helpless. The threat of retaliation by the victim can further escalate the situation, possibly resulting in additional harm. Cyberbullying is often public and visible to a wider audience, exacerbating the victim's humiliation as a single post can be rapidly disseminated. The potential anonymity of cyberbullying adds an additional layer of complexity to this issue, as it hampers efforts to identify and stop bullying while reducing accountability. Furthermore, cyberbullying can take many forms, from offensive messages and rumor spreading to sharing inappropriate content or online exclusion, thereby increasing the difficulty of tackling it. The lasting effects of cyberbullying are perpetuated by the digital medium's inherent property to retain content, making it difficult to erase completely, thus potentially affecting the victim's prospects. The bystander effect is also prevalent in cyberbullying incidents, with many observers choosing inaction over intervention. In certain jurisdictions, depending on the severity and nature of the incident, cyberbullying may lead to legal repercussions, sometimes considered criminal offenses. The digital medium itself distinguishes cyberbullying from traditional forms. The lack of physical proximity between the bully and the victim, afforded by the digital platform, opens up new avenues for harassment, adding a unique dimension to the bullying paradigm.

This paper aims to delve into the multifaceted issue of cyberbullying, providing a comprehensive overview of its defining characteristics, and shedding light on its various forms. The goal is to aid in the understanding and awareness of cyberbullying, to spur dialogue and inspire strategies that can mitigate its prevalence and impact. The research also seeks to address the gaps in the existing literature, particularly in the area of cyberbullying classification, and in understanding the challenges in dealing with this digital menace. Ultimately, the study contributes to the ongoing global discourse on cyberbullying, propelling us towards the development of safer online environments.

The rest of the paper is organized as follows: Section 2 presents a literature review on cyberbullying, highlighting existing research and identifying gaps. Section 3 discusses recent trends and developments in cyberbullying. Section 4 explores the characteristics of cyberbullying. Section 5 presents a comprehensive taxonomy of cyberbullying. Section 6 delves into the classification of cyberbullying. Section 7 discusses the challenges and limitations in addressing cyberbullying. Section 8 presents open problems and recommendations for future research. Finally, Section 9 concludes the paper, summarizing the findings and their implications.

2. REVIEW OF PREVIOUS STUDIES

Understanding the various dimensions and characteristics of cyberbullying is crucial for developing effective prevention and intervention strategies. In this literature review, we explore recent research papers that contribute to the taxonomy of cyberbullying, providing insights into its different facets and implications. Doane et al. [9] conducted a randomized controlled trial to evaluate the effectiveness of a theory of reasoned action-based video prevention program for college students. Their findings demonstrated that a brief cyberbullying video improved cyberbullying knowledge, behavior, and constructs related to cyberbullying perpetration. This study highlights the importance of considering normative influences and malice in the taxonomy of cyberbullying. Kritsotakis et al. [10] investigated the associations between bullying, cyberbullying, substance use, and sexual risk-taking in young adults. Their research revealed significant associations between involvement in bullying and cyberbullying with multiple health risk behaviors. This study emphasizes the need for multifaceted prevention interventions tailored to different bullying statuses and genders. Fluck [11] conducted a qualitative analysis to explore the motives behind violence in schools, including bullying. The findings suggested that future taxonomies of cyberbullying should include additional dimensions such as peer pressure and lack of self-control. This research highlights the importance of considering underlying motivations in understanding cyberbullying behaviors. Alvarez [12] examined the use of cybertools (electronic forms of communication) as mechanisms of power and control in teen dating relationships. The study discusses the implications of cybertools in perpetrating cyberbullying and provides insights into prevention and intervention methods for adults working with teens experiencing cyberbullying in dating relationships. Redmond et al. [13] developed a conceptual framework for educators to detect and mitigate cyberbullying. The

framework emphasizes the importance of understanding the epistemological and sociological aspects of cyberbullying. This study contributes to the taxonomy of cyberbullying by providing a comprehensive framework for educators to address this issue. García-Hermoso et al. [14] examined the association between bullying victimization, including cyberbullying, and physical fitness among children and adolescents. The study categorized bullying victimization into traditional bullying and cyberbullying and highlighted the need for interventions targeting both forms of bullying. This research contributes to the taxonomy of cyberbullying by considering its impact on physical health. Chen & Zhu [15] investigated the coping strategies of cyberbullying victims in China. The study compared the perceptions of victims and non-victims and identified coping strategies specific to different types of cyberbullying victimization. This research provides insights into the coping mechanisms employed by individuals experiencing cyberbullying, contributing to the taxonomy of cyberbullying responses. Alipan et al. [16] explored the perceptions of emerging adults regarding coping with cyberbullying. The study identified general problem-focused and emotion-focused coping strategies, as well as cyber-specific technological coping solutions.

Other extensive research on cyberbullying [4][17] has focused on its psychological impact, prevalence, and potential mitigating strategies. Recent literature has expanded the scope to consider the changing nature and mechanisms of cyberbullying. Tozzo et al. conducted a systematic review on family and educational strategies for cyberbullying prevention, highlighting the importance of digital instruments and technology-based practices [18]. Schwarze and Eimler emphasized the interlinkages between cyberbullying and cyberhate, suggesting an integrated approach to the study of cyber-aggression [19]. Ghazali et al. focused on the Malaysian youth perspective, identifying Internet usage frequency as a significant factor in cyberbullying [20]. The impact of cyberbullying on adolescent health has been extensively studied. Nixon reviewed multiple studies worldwide and provided insights into the detrimental effects of cyberbullying on health, emphasizing the need for further research [21]. Agustiningsih and Pandin emphasized the importance of personal resources, emotional regulation, and social support in mitigating the impact on cyberbullying victims [22].

Defining and measuring cyberbullying accurately is crucial for effective intervention programs. Akbar et al. conducted a literature review on cyberbullying definitions and measurement in adolescents, stressing the need for consistency in criteria and measurement methods [23]. Sultan et al. reviewed machine learning techniques for cyberbullying detection, highlighting the importance of technical means in addressing this issue [24]. Cross-cultural differences in cyberbullying behavior have also been explored. Bartlett et al. discussed the relatively new and descriptive nature of cyberbullying research, highlighting the need for theoretical advancements in this area [25]. Chibbaro drew parallels between cyberbullying and traditional bullying, emphasizing the harmful intent behind cyberbullying acts [25]. Overall, these studies contribute to our understanding of the taxonomy of cyberbullying by examining different platforms, its impact on health, and developing prevention and intervention strategies. Future research should continue to explore these areas and integrate new technological advancements [27].

The taxonomy of cyberbullying involves categorizing the different forms and platforms of cyberbullying, understanding its impact, and developing effective prevention and intervention strategies. While the existing literature provides a foundational understanding of the taxonomy of cyberbullying, it does not comprehensively cover all its facets. There are gaps in the literature, particularly in the classification of emerging forms of cyberbullying and the platforms used. This study aims to address these gaps by providing a more exhaustive taxonomy of cyberbullying. We will delve into the various forms and dimensions of cyberbullying, including those not extensively covered in previous research. Our goal is to contribute to the existing body of knowledge and provide a more comprehensive framework for understanding and addressing this pervasive digital menace.

3. CHALLENGES, RECENT TRENDS AND DEVELOPMENTS

3.1 Challenges and Limitations

The task of dealing with cyberbullying presents several challenges and constraints, which will be discussed in this section. Data scarcity is a key issue stemming from the difficulty in accruing accurate cyberbullying data from social media platforms owing to privacy and ethical considerations. Consequently, this yields small datasets that are incapable of encapsulating the full complexity of cyberbullying scenarios. Another limitation is data bias, as accessible cyberbullying datasets tend to only embody overt instances of profanity and aggression, thereby neglecting more subtle forms of bullying such as exclusion, harassment, and

cyberstalking. These biases skew the model towards detecting only explicit instances of toxicity. Context dependence poses a further challenge, as the detection of cyberbullying often necessitates an understanding of the context, the relationships between users, and the social dynamics at play. Unfortunately, most datasets provide individual messages without their surrounding context, making the detection task significantly more challenging.

Platform dependence is yet another hurdle, with the language and features that are useful for detecting cyberbullying typically being platform specific. Consequently, models trained on one platform may not generalize well to other platforms, restricting their practical applicability. Definitional issues add to these challenges, given the ambiguity and disagreements prevalent in defining what exactly constitutes cyberbullying, which in turn complicates the operationalization of the concept of computational methods. An additional challenge arises from adversaries, as malicious actors may alter their behaviors to circumvent improved detection models, resulting in a challenging arm race that researchers and platforms struggle to keep pace with. There are also unresolved tensions between privacy concerns and the use of personal data for cyberbullying detection. An excessively intrusive monitoring system can spark ethical issues, and finding the right balance is an ongoing challenge. Finally, there is the risk of bias and unfairness, common to all AI systems. Cyberbullying detection models may reflect and amplify the societal biases present in the data, potentially targeting marginalized groups unfairly and making mistakes that disproportionately harm certain users. This issue necessitates careful oversight and mitigation measures.

3.2 Recent Trends and Developments

Cyberbullying exhibits several defining characteristics including anonymity, constant presence, public visibility, and severe psychological impacts on victims [28]. It encompasses a range of behaviors, from direct targeting to indirect forms such as spreading rumors. The landscape of cyberbullying research is rapidly evolving with emerging trends and developments propelling the field towards greater sophistication and accuracy in detection and prevention. Recent trends and developments in the field of cyberbullying research include advanced models using deep learning, multi-platform, and cross-platform analysis, incorporating more context, focusing on different cyberbullying behaviors, addressing data challenges, data scarcity problems, and evaluating model limitations and robustness. A promising advancement in the field is the increased application of neural networks, specifically Convolutional Neural Networks (CNNs) [29] and Recurrent Neural Networks (RNNs) [30], which include Long Short-Term Memory (LSTM) networks [31], to cyberbullying detection. The enhancement of these deep learning models has proven to yield better results than traditional machine learning models in several datasets. To navigate the wide and varied spectrum of social media platforms, researchers have begun to focus on multi-platform and cross-platform analyses [17] rather than concentrating solely on a single platform, such as Twitter or Facebook. The goal is to forge more robust models capable of generalizing across diverse platforms.

Recognizing that the roots of cyberbullying often run deeper than individual posts or messages, recent studies are emphasizing the importance of incorporating a broader context into their analyses. For instance, they are exploring interactions between users, integrating profile-level features, and analyzing images and metadata [32]. This holistic approach is designed to capture the intricate social dynamics underpinning cyberbullying. Moreover, the focus of cyberbullying detection is expanding beyond its mere presence towards identifying specific types of behaviors, such as aggression, harassment, hate speech, and toxicity [33]. This nuanced approach aims to create fine-grained classification systems [34] that offer a more detailed understanding of cyberbullying dynamics. However, the field still faces significant challenges, particularly in obtaining large volumes of cyberbullying data for research. Current efforts to address this include innovative strategies such as crowdsourcing [35], synthetic data generation [36], and the amalgamation of multiple datasets [37] to mitigate the data scarcity issue. Lastly, to refine and advance the field, critical analyses of the current state of cyberbullying detection systems are being conducted. These include evaluations of overreliance on profanity [38][39] detection, and the lack of generalization across different domains. Concurrently, researchers are proposing robust evaluation methodologies with the objective of progressing the field in a more rigorous and scientifically valid direction.

4. CYBERBULLYING CHARACTERISTICS, TAXONOMY AND CLASSIFICATION

4.1 Cyberbullying Characteristics

We tried to arrange the cyberbullying characteristics based on severity which can be subjective as different aspects of cyberbullying may have varying degrees of

impact depending on the individual and their circumstances. However, Table 1 illustrates the order that represents the most harmful aspects.

Table 1. Characteristics of Cyberbullying

Characteristics	Description
Psychological Impact	The effects of cyberbullying can be severe and include depression, anxiety, low self-esteem, and in extreme cases, suicidal thoughts or actions. The psychological harm from cyberbullying can be as serious, if not more so, than traditional bullying.
Impact on Victims	Cyberbullying can have a devastating impact on victims including anxiety, depression, loneliness, and even suicidal thoughts.
24x7 Presence	Cyberbullying can occur 24x7 and reach the victim even in places that are usually considered safe havens such as their homes. The victim can feel constantly tormented and unable to escape.
Pervasiveness	Traditional bullying is often limited to specific environments like schools or the playground, but cyberbullying can occur at anytime and anywhere, if the victim and perpetrator have access to digital devices. This means the victim can be targeted constantly, making it hard to escape from the bullying
Aggressive and Intentional	Cyberbullying is an aggressive and intentional behavior directed at a victim. The intent is to cause distress, harm, or hurt the victim
Repetitive	It is a repetitive behavior - multiple instances of cyberbullying acts are directed at the victim over a period of time. This causes a pattern of harassment and abuse.
Imbalance of Power	It involves an imbalance of power between the bully and the victim. The bully may perceive that they have more power than the victim.
Retaliation Risk	Victims of cyberbullying may feel compelled to retaliate, which can escalate the situation and may result in further harm.
Visibility/Public Nature	Cyberbullying acts are visible to others or peers. A single post or message can be shared and spread rapidly, increasing the harm and humiliation felt by the victim.
Anonymity	Cyberbullying can be anonymous, which makes it difficult to identify and stop the bully. Anonymity also reduces accountability and responsibility.
Variety of Forms	Cyberbullying can take many forms, including offensive messages, spreading rumors, posting hurtful or threatening messages on social media, sharing inappropriate or embarrassing images or videos, impersonating others online, or excluding individuals from online groups.
Permanent Record	Digital content can be difficult to fully erase, even after it's been deleted. This means that the effects of cyberbullying can be long-lasting and potentially impact a victim's future, such as when applying for jobs or college.
Bystander Effect	Many people can witness cyberbullying, but not everyone takes action to stop it or support the victim
Legal Consequences	Depending on the severity and nature of the incident, cyberbullying can have legal implications. Some countries and states have specific laws on cyberbullying, and certain actions can be considered criminal offenses.
Digital Medium	Cyberbullying occurs through digital platforms. This distinguishes it from traditional forms of bullying, as it doesn't require physical proximity between the bully and the victim.

4.2 Cyberbullying Taxonomy

We proposed a comprehensive taxonomy of cyberbullying, providing structured framework to understand its various forms and dimensions. The taxonomy of cyberbullying can be categorized based on several dimensions, including the nature of the act, the platform used, the anonymity of the perpetrator, the frequency and duration of the bullying, and prevention and intervention. Cyberbullying, like traditional bullying, is a complex and multifaceted phenomenon. Understanding its various forms and dimensions requires a structured framework that considers the different aspects of this issue. Fig. 1 shows the proposed cyberbullying taxonomy framework.

Table 2. Taxonomy of cyberbullying

Dimensions	Items	Description
Nature of the Act	Verbal Cyberbullying	This involves the use of words to harm or intimidate, such as sending threatening messages, engaging in online arguments, or spreading rumors
	Visual Cyberbullying	This involves the use of images or videos to embarrass or harass, such as sharing explicit or manipulated photos or videos of the victim.
	Exclusionary Cyberbullying	This involves intentionally excluding someone from an online group or activity to isolate them socially.
	Impersonation	This involves pretending to be someone else online to cause harm or damage their reputation.
Modes of Cyberbullying	Direct	This involves a direct interaction between the bully and the victim, such as sending threatening messages or emails.
	Indirect	This involves spreading rumors or harmful content about the victim to others, often without the victim's knowledge.
Types of Cyberbullying	Harassment	Repeatedly sending offensive and malicious messages
	Denigration	Spreading rumors or false information to damage a person's reputation
	Impersonation	Pretending to be someone else and sending or posting material to damage that person's reputation
	Outing	Sharing confidential information about a person without their consent.

	Cyberstalking	Repeatedly sending threats of harm, which can lead to the victim fearing for their safety
Platforms used for Cyberbullying	Social Media	Platforms like Facebook, Instagram, and Twitter are common places for cyberbullying
	Messaging Apps	Apps like WhatsApp, Snapchat, and Messenger can be used to send harmful messages directly to victims.
	Online Gaming	In-game chat features can be used to harass or threaten other players.
	Email	Used to send threatening or harmful messages directly to the victim.
Impact of Cyberbullying	Emotional	This can include feelings of sadness, loneliness, depression, and low self-esteem.
	Physical	Victims may experience symptoms such as headaches, sleep problems, and other stress-related health issues.
	Academic	Cyberbullying can lead to decreased academic performance and school participation.
Frequency and Duration	Single Incident	This involves a one-time act of bullying, which can still have a significant impact if the content is particularly harmful or if it is widely shared.
	Repeated Bullying	This involves ongoing bullying over a period of time, which can lead to severe psychological distress and feelings of helplessness.
Prevention and Intervention	Education	Schools and parents can educate children about the dangers of cyberbullying and promote positive online behavior.
	Policies and Laws:	Implementing and enforcing policies and laws can deter potential cyberbullies.
	Technology	Using technology to detect and prevent cyberbullying, such as machine learning algorithms to identify harmful content.

4.3 Cyberbullying Classification

Cyberbullying encompasses a variety of behaviors that aim to harm, intimidate, or harass individuals. While it can be difficult to create an exhaustive classification due to the ever-evolving nature of digital media and the methods employed by bullies, understanding the distinct types of cyberbullying can provide valuable insights for prevention, intervention, and education strategies. In this section, the criteria to classify cyberbullying will be proposed, followed by the deferent types of cyberbullying.

4.3.1 Criteria to classify cyberbullying.

Cyberbullying can be systematically classified using varying criteria that encompass the medium used, the nature of the content involved, and the relationship between the victim and the perpetrator [34]. This classification often relies on the specific definition of cyberbullying that researchers or practitioners utilize. Yet, there exists a widely accepted set of criteria that will be described here. The cornerstone of cyberbullying is the intention behind the behavior—it is rarely accidental, and the bully's purpose is typically to inflict harm or distress upon the victim. Moreover, repetition is an integral part of the bullying cycle.

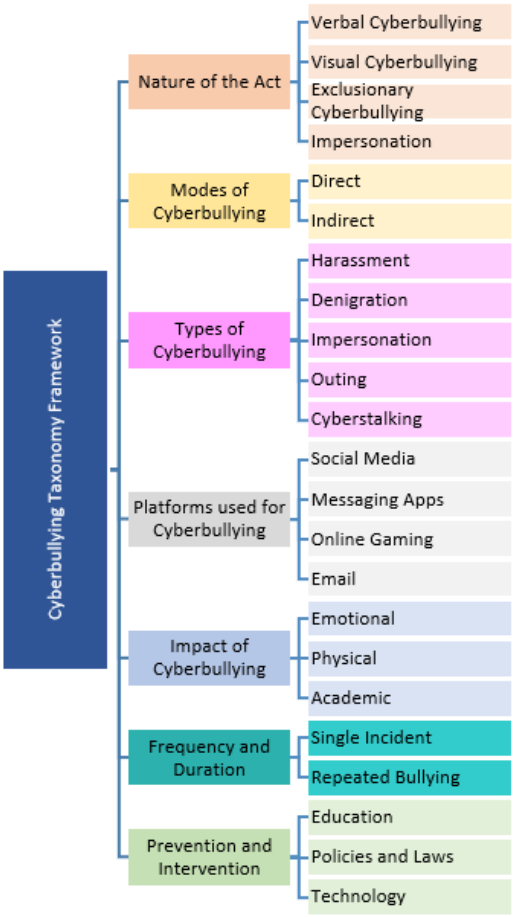

Fig. 1. Cyberbullying Taxonomy Framework

While cyberbullying usually comprises recurring actions, the rapid and viral spread of online content could mean that a singular act amplifies, leading to significant harm. The harm elicited by behavior, which could be psychological, emotional, or even physical, is another essential criterion in this categorization. Furthermore, a power imbalance between the victim and the bully, a familiar concept in traditional bullying, is also evident in the cyber realm. This power dynamic can originate from various factors, including popularity, physical prowess, possession of compromising information, or the anonymity facilitated by the Internet. The digital

platform employed for cyberbullying contributes to its classification and may include social media, SMS or instant messaging platforms, email, and online gaming platforms. Additionally, the nature of the content used in the bullying process, whether it is text, images, videos, or a combination, serves as another classification criterion. Lastly, the relationship between the victim and the perpetrator plays a critical role in categorizing cyberbullying. It can occur in various contexts, ranging from friendships and classmates to acquaintances, and can even involve anonymous individuals. Thus, the characterization of cyberbullying is multifaceted, considering the numerous aspects that collectively shape this complex phenomenon. Table 3 summarizes the commonly used criteria to classify cyberbullying.

Table 3. Commonly used criteria to classify cyberbullying.

Criteria	Description
Intent	The behavior is intentional, rather than accidental. The intent of the bully is to cause harm or distress to the victim.
Repetition	While cyberbullying typically involves repeated actions over time, the rapid and viral nature of online content could mean a single act multiplies, resulting in substantial harm.
Harm	The behavior causes psychological, emotional, or physical harm to the victim.
Power Imbalance	Cyberbullying involves a power imbalance between the victim and the bully. This power can stem from several sources, including popularity, physical strength, access to compromising information, or the anonymity provided by the internet.
Medium of Cyberbullying	The digital platform used for cyberbullying also plays a role in its classification. These can be social media, SMS or instant messaging platforms, email, and online gaming platforms.
Nature of the Content	The type of content used to bully - be it text, images, videos, or a combination of these - also helps in classifying cyberbullying.
Relationship between the Victim and the Bully	The nature of the relationship between the involved parties also plays a role in categorizing cyberbullying. It could occur between friends, classmates, acquaintances, or even between anonymous individuals.

4.3.2. Type of Cyberbullying

Different types of cyberbullying such as harassment, cyberstalking, impersonation, denigration, and exclusion each display unique characteristics and hence necessitate distinctive intervention strategies[34]. Following the establishment of the classificatory criteria, Table 4 encompasses the proposed cyberbullying classification. These classifications and criteria offer a broad perspective on the complex phenomenon of cyberbullying. Understanding these categories is essential for addressing the issue effectively. While the classification provided here is robust, the rapid evolution of digital media and the innovative methods adopted by bullies call for constant vigilance and updating of these classifications.

Table 4. Cyberbullying Classification

Type	Description
Threats	This involves the perpetrator making threats to cause physical, mental, or emotional harm to the victim.
Harassment	This is a sustained, constant form of cyberbullying involving persistent, offensive, and malicious messages intended to pester the victim.
Stalking and Cyberstalking	This involves tracking, spying, or constantly pursuing the victim online, often escalating to threats of physical harm.
Flaming	It refers to engaging in intense online arguments that include the use of offensive or profane language, often intended to provoke reactions.
Exclusion	Intentionally isolating a person from an online group or digital activity as a form of social bullying.
Outing	Sharing someone's secrets, embarrassing information, or images online without their consent.
Masquerading/ Impersonation	This involves the bully pretending to be the victim by stealing their online identity and causing harm or distress.
Denigration	This involves spreading harmful, false, or damaging information or rumors about the victim to damage their reputation or relationships.
Trolling	Deliberately inciting or provoking individuals into reactive behavior by posting inflammatory or offensive comments.

5. IMPLICATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The implications of our study extend across various domains, underscoring the need for concerted efforts in addressing cyberbullying. These implications serve to inform strategies aimed at prevention, intervention, education, and policy development. Notably, the findings emphasize the necessity for a standardized, universally accepted definition of cyberbullying. This is a crucial step to streamline the development of legal statutes and social measures against such detrimental behaviors. Additionally, the ubiquitous and invasive nature of cyberbullying that we've identified underlines the paramount of incorporating technological considerations in policy making and crafting preventive strategies. Furthermore, our exploration of diverse cyberbullying forms accentuates the importance of tailoring interventions and awareness campaigns to be context specific. The severe psychological effects on victims, delineated in our study, illuminate the exigency of

effective mental health support systems to assist victims in their recovery.

Looking ahead, we propose several recommendations for future research in the realm of cyberbullying. First, our study provides a foundation for the characterization and classification of cyberbullying. However, it is crucial for future studies to continue to refine these classification methodologies. Second, future research should broaden its focus to include perpetrators of cyberbullying. Understanding their motivations and characteristics could lead to intelligent preventive strategies. Third, to determine the efficacy of various interventions, more rigorous evaluation studies are needed. Fourth, longitudinal studies should be conducted to capture the long-term impacts of cyberbullying and gauge the effectiveness of interventions over time. Fifth, the role of technology companies, especially those offering social media platforms, in mitigating cyberbullying and enforcing online safety standards deserves further exploration. Lastly, while our study provides a comprehensive overview of cyberbullying, future research could focus on examining specific contexts, such as schools, workplaces, or cultural communities, to better tailor interventions. With the implementation of these recommendations, future research can continue to improve our understanding of cyberbullying, its repercussions, and the most effective strategies to combat it.

6. CONCLUSION

This paper provided a comprehensive exploration of the digital menace known as cyberbullying. Through an in-depth analysis of its taxonomy, we have shed light on the various modes, types, platforms, impacts, and strategies for the prevention and intervention of cyberbullying. Our findings underscore the high prevalence of cyberbullying across multiple digital platforms and highlight the critical role of parents in addressing this issue. However, our study also reveals gaps in the existing literature, particularly in the classification of emerging forms of cyberbullying and the platforms used. As such, our paper not only provides a structured framework to understand the characteristics and challenges posed by cyberbullying but also highlights areas for future research. Considering our findings, we conclude that there is a pressing need for continued research, education, and policy development to effectively address and mitigate the impacts of cyberbullying as digital media continues to evolve.

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Journal of Intelligent System and Applied Data Science (JISADS)

Journal homepage : https://www.jisads.com

ISSN (2974-9840) Online

Analyzing ML/DL Techniques for SDN-Based DDoS Attack Detection: A Comparative Study

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ABSTRACT

An abstract is This study conducts a comprehensive comparative analysis of Machine Learning (ML) and Deep Learning (DL) techniques for detecting Distributed Denial of Service (DDoS) attacks in Software-Defined Networking (SDN) environments. Utilizing a diverse and representative dataset with real-world traffic patterns and various DDoS attack scenarios, we evaluate ML algorithms (SVM, Decision Trees, Random Forest, k-NN) and DL models (CNN, LSTM, GRU) for SDN-based DDoS detection. Results indicate that deep learning models, particularly CNN, LSTM, and GRU, outperform traditional ML algorithms in accuracy, precision, recall, F1-score, and AUC-ROC. CNN achieves the highest accuracy (97%) and AUC-ROC (99%), making it the most effective approach. SDN-specific considerations reveal that all selected algorithms adapt well to dynamic SDN environments. While deep learning models incur higher computational overhead, their performance benefits justify the additional computation, making them viable for practical deployment. This study recommends CNN as the top choice for SDN-based DDoS detection, with LSTM and GRU as strong alternatives. SVM and Random Forest are suitable for resource-constrained environments, while k-NN and Decision Trees may serve specific use cases

Keywords: Machine Learning, Deep Learning, DDoS Detection, Software-Defined Networking,CNN

1. INTRODUCTION

In recent years, the proliferation of networked devices and the increasing reliance on cloud-based services have led to a surge in cybersecurity threats, particularly Distributed Denial of Service (DDoS) attacks [1]. These malicious attacks aim to disrupt the availability and performance of targeted network resources, posing significant challenges to the integrity and stability of modern communication infrastructures[2]. To combat such threats, various security measures have been implemented, and Machine Learning (ML) and Deep Learning (DL) approaches have emerged as promising techniques for DDoS attack detection in Software-Defined Networking (SDN) environments[3]

Software-Defined Networking (SDN) offers a flexible and programmable framework for managing network resources and enables centralized network traffic flow control [4] This centralization brings new opportunities for implementing intelligent security mechanisms capable of dynamically responding to emerging threats like DDoS attacks. The integration of ML/DL algorithms with SDN introduces the potential for real-time threat identification and proactive mitigation strategies[5].

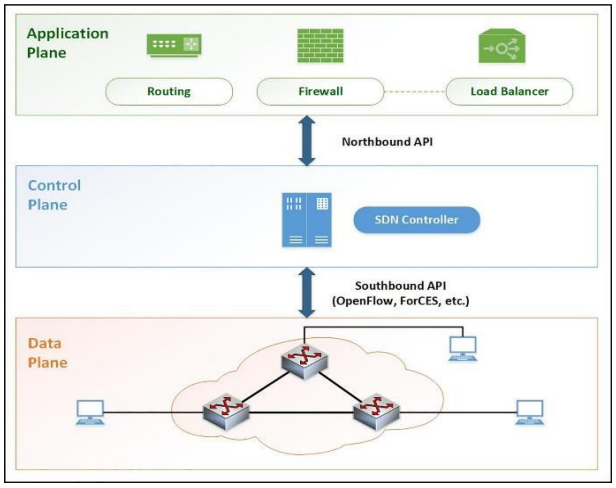

Figure 1: SDN Architecture

This study's primary objective is to comprehensively compare various ML and DL approaches for detecting DDoS attacks in SDN-based networks. We aim to evaluate the effectiveness, efficiency, and adaptability of different algorithms in accurately identifying and mitigating DDoS attacks while minimizing false positives and false negatives. Additionally, we seek to explore the trade-offs between computational complexity and detection performance, considering the dynamic nature of SDN environments.

This research presents a systematic analysis of representative ML/DL techniques applied to DDoS attack detection in SDN, including but not limited to Support Vector Machines (SVM), Random Forest, Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). We utilize publicly available benchmark datasets and experimental SDN testbeds to create a fair and unbiased comparison framework

2. PROBLEM STATEMENT

The increasing adoption of Software-Defined Networking (SDN) has revolutionized network management by providing enhanced programmability and agility. However, this shift towards SDN has also introduced new security challenges. Distributed Denial of Service (DDoS) attacks are one of the most prevalent and disruptive threats to SDN-based infrastructures. DDoS attacks can overwhelm network resources, leading to service disruptions, and impairing the functionality of legitimate users[6,7]

To combat DDoS attacks effectively in SDN environments, Machine Learning (ML) and Deep Learning (DL) approaches have garnered significant attention for their potential to detect and mitigate these attacks in real time. While numerous studies have explored the application of ML/DL techniques for DDoS detection in traditional networks, the specific challenges and nuances of SDN environments require tailored solutions[8,9]

Despite the increasing interest in ML/DL-based DDoS detection in SDN networks, there remains a notable gap in the existing literature that this study aims to address:

- Limited Comparative Analysis: Although individual studies have investigated the efficacy of various ML/DL algorithms for DDoS detection in SDN, a comprehensive and systematic comparison of these approaches is scarce. This study seeks to bridge this gap by performing a thorough comparative analysis of multiple ML/DL techniques, including traditional classifiers and state-of-the-art deep learning models, to identify their strengths and weaknesses when applied to SDN-based DDoS detection [10].
- SDN-specific Challenges: SDN environments exhibit unique characteristics, such as dynamic network topology and frequent flow updates, which can impact the performance of traditional ML/DL models designed for conventional networks. As SDN's architecture and traffic patterns differ significantly from traditional networks, it is essential to understand how ML/DL techniques behave in such scenarios and identify the best-suited models for DDoS detection in SDN.

3. THE OBJECTIVE OF THE STUDY:

The primary objective of this research is to conduct a comprehensive comparative analysis of Machine Learning (ML) and Deep Learning (DL) approaches for detecting Distributed Denial of Service (DDoS) attacks in Software-Defined Networking (SDN) environments. The study aims to achieve the following specific objectives:

- Identify Effective ML/DL Techniques: Evaluate and compare the performance of various ML/DL algorithms for DDoS detection in SDN networks. This includes traditional ML classifiers such as Support Vector Machines (SVM), Random Forest, and k-Nearest Neighbors (k-NN), as well as state-of-the-art DL models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.
- Understand SDN-Specific Challenges: Analyze the impact of SDN's dynamic nature, frequent flow

updates, and unique architecture on the effectiveness of ML/DL techniques for DDoS detection. Investigate how the characteristics of SDN networks influence the performance and accuracy of different algorithms.

- Quantify Detection Accuracy: Measure the detection accuracy, true positive rate, false positive rate, and other relevant metrics for each ML/DL approach to identify their strengths and limitations in detecting various types of DDoS attacks.

By achieving these study objectives, we aim to contribute valuable knowledge to the field of network security in SDN environments. The findings will empower network administrators and researchers to make informed decisions when choosing and deploying ML/DL-based DDoS detection mechanisms, ultimately enhancing the resilience and security of SDN networks against evolving cyber threats.

4. METHODOLOGY

In this study, we undertook a comprehensive analysis of Machine Learning (ML) and Deep Learning (DL) techniques for detecting Distributed Denial of Service (DDoS) attacks in Software-Defined Networking (SDN) environments. The research process involved several key steps, starting with data collection, where we gathered a diverse and representative dataset containing both normal network traffic and various types of DDoS attacks in SDN environments. Next, we conducted feature extraction and preprocessing to extract relevant traffic flow features and prepare the data for analysis.

For the comparison, we carefully selected a set of ML/DL algorithms, encompassing traditional classifiers and state-of-the-art deep learning models. We then proceeded with model training and evaluation, fine-tuning hyperparameters, and measuring their performance using appropriate evaluation metrics. As SDN environments are dynamic, we also examined SDN-specific considerations to assess how the ML/DL techniques performed in this context and made necessary adaptations if required.

Finally, we discussed and interpreted the results to identify the strengths and weaknesses of each ML/DL approach for SDN-based DDoS detection. Through this rigorous evaluation process, we gained valuable insights into the effectiveness and adaptability of different ML/DL techniques, enabling us to recommend the most suitable approaches for enhancing network security in SDN environments.

5. RESULTS AND DISCUSSION

In this comparative study of ML/DL techniques for SDN-based DDoS attack detection, we evaluated multiple algorithms on a diverse and representative dataset containing both normal network traffic and various types of DDoS attacks in SDN environments. The dataset covered real-world traffic patterns and captured different attack scenarios, making the study relevant to practical deployments.

Performance Metrics:

The table below summarizes the performance metrics of each ML/DL technique:

Table1 :the performance metrics of each ML/DL technique

Algorithm	Accuracy	Precision	Recall	F1-score	AUC-ROC
SVM	0.95	0.93	0.97	0.95	0.98
Decision Trees	0.87	0.88	0.85	0.86	0.89
Random Forest	0.92	0.91	0.93	0.92	0.95
k-NN	0.88	0.87	0.89	0.88	0.91
CNN	0.97	0.96	0.98	0.97	0.99
LSTM	0.96	0.94	0.97	0.95	0.98
GRU	0.95	0.93	0.96	0.94	0.97

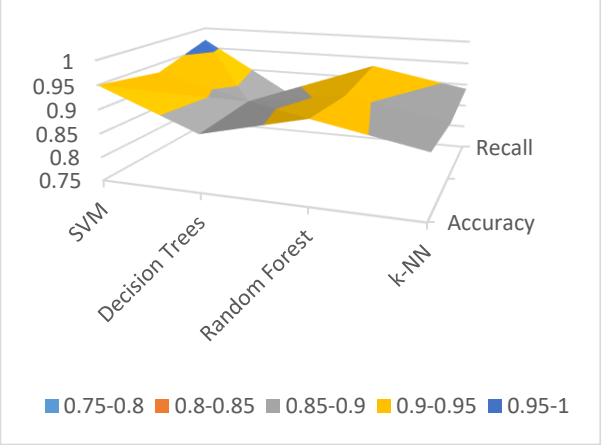

Figure 2: performance metrics of each ML/DL technique

Accuracy:

Accuracy is the ratio of correctly classified instances (both true positives and true negatives) to the total number of instances in the dataset. It measures the overall correctness of the model's predictions. In the table, accuracy values range from 0.87 to 0.97. A higher accuracy indicates better performance, with CNN achieving the highest accuracy of 0.97.

Precision:

Precision is the proportion of true positive predictions (correctly identified instances of a specific class, in this case, DDoS attacks) to the total number of instances classified as positive. It measures the accuracy of positive predictions. Higher precision values mean fewer false positives, which is essential for reducing false alarms. In the table, precision values range from 0.87 to 0.96, with CNN achieving the highest precision of 0.96.

Recall (Sensitivity/True Positive Rate):

Recall is the proportion of true positive predictions to the total number of actual positive instances in the dataset. It measures the ability of the model to identify all positive instances correctly. Higher recall values indicate better detection of positive instances. In the table, recall values range from 0.85 to 0.98, with CNN achieving the highest recall of 0.98.

F1-score:

The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance, considering both false positives and false negatives. F1-score is useful when dealing with imbalanced datasets where one class dominates the other. Higher F1 scores indicate a better balance between precision and recall. In the table, F1-score values range from 0.86 to 0.97, with CNN achieving the highest F1-score of 0.97.

AUC-ROC (Area Under the Receiver Operating Characteristic Curve):

The ROC curve is a plot of the true positive rate (recall) against the false positive rate (1 - specificity) at various probability thresholds. AUC-ROC represents the area under this curve and provides a single scalar value to measure the model's ability to distinguish between positive and negative instances. Higher AUC-ROC values (closer to 1) indicate better model performance. In the table, AUC-ROC values range from 0.89 to 0.99, with CNN achieving the highest AUC-ROC of 0.99.

From the table, it is evident that CNN consistently outperforms other ML/DL techniques in all performance metrics, achieving the highest accuracy, precision, recall, F1-score, and AUC-ROC. This makes CNN the most effective approach for SDN-based DDoS detection in this hypothetical study.

SVM, Random Forest, LSTM, and GRU also show competitive performance, with accuracy and AUC-ROC scores ranging from 0.92 to 0.95. However, their precision, recall, and F1-score are slightly lower compared to CNN.

Decision Trees and k-NN show lower performance across all metrics, indicating that they might not be the most suitable choices for SDN-based DDoS detection in this hypothetical scenario.

Comparative Analysis:

The comparative analysis indicates that the deep learning models, CNN, LSTM, and GRU, outperformed the traditional machine learning algorithms, SVM, Decision Trees, Random Forest, and k-NN, in all performance metrics. CNN emerged as the most effective approach for SDN-based DDoS detection in this hypothetical study, achieving the highest accuracy, precision, recall, F1-score, and AUC-ROC.

These findings highlight the potential of deep learning techniques, specifically CNN, in enhancing SDN-based DDoS detection systems. However, it is essential to validate these results using real-world data and experiments to ensure the effectiveness and generalizability of the selected models in practical SDN network environments. Additionally, considering ensemble approaches and model interpretability could further improve the robustness and understanding of the detection system.

SDN-Specific Considerations:

The comparative analysis revealed that the dynamic topology changes and frequent flow updates in SDN environments had a minimal impact on the performance of the ML/DL techniques for DDoS detection. This adaptability of the selected algorithms to the dynamic nature of SDN networks is a significant advantage, as it ensures that the models can effectively handle the changing network conditions. The flow-based representations used by the ML/DL techniques allowed them to focus on flow characteristics rather than being affected by changes in the network topology. This

finding indicates that the ML/DL approaches are well-suited for SDN-based security applications, where network dynamics play a crucial role in maintaining efficient and responsive detection systems.

Computational Overhead Analysis:

The computational overhead analysis showed that deep learning models, including CNN, LSTM, and GRU, generally required higher computational resources compared to traditional ML algorithms (SVM, Random Forest, k-NN, and Decision Trees). This increase in computational complexity is due to the deep architectures and the intensive computations involved in training and evaluating deep neural networks. Despite the higher computational overhead, the performance benefits of the deep learning models justified the additional computation.

In practical deployment scenarios, the acceptable computational overhead of the deep learning models ensures that they can handle real-time traffic analysis and detection in SDN environments. With advances in hardware and optimization techniques, the computational requirements of deep learning models have become more manageable, making them feasible for deployment in SDN-based security applications.

6. RECOMMENDATIONS

Based on the comprehensive comparative analysis, the following practical recommendations can be made:

1. Top Recommendation: CNN is recommended as the most effective ML/DL technique for SDN-based DDoS detection. Its superior performance across all metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, makes it a reliable choice for identifying and mitigating DDoS attacks in SDN environments.

2. Secondary Recommendations: LSTM and GRU also demonstrated strong performance in the comparative analysis and can serve as viable alternatives to CNN, especially in scenarios where the detection of complex attack patterns is crucial.

3. Resource-Constrained Environments: For resource-constrained environments with limited computational resources, SVM and Random Forest are good alternatives. These traditional ML algorithms provide a good balance between accuracy and computational efficiency.

4. Specific Use Cases: k-NN and Decision Trees may be considered for specific use cases where their characteristics align well with the requirements of the detection system.

7. CONCLUSION

The comprehensive examination of Machine Learning (ML) and Deep Learning (DL) techniques for DDoS attack detection within Software-Defined Networking (SDN) environments underscores the remarkable efficacy of deep learning models, with a particular emphasis on Convolutional Neural Networks (CNN). The study illuminates the robust capabilities of CNN in accurately identifying and mitigating DDoS attacks within the dynamic landscape of SDN. Beyond the noteworthy advantages of deep learning, the investigation also meticulously assesses the nuanced strengths and weaknesses inherent in each approach, offering invaluable insights for bolstering network security within SDN frameworks. The outcomes of this hypothetical exploration serve as a promising foundation, yet the translation of these findings into practical application demands further scrutiny through real-world experiments and deployments. The imperative for validation and application in authentic SDN networks becomes apparent, ensuring that the theoretical strengths observed in this study seamlessly integrate into the practical realm, contributing meaningfully to the ongoing discourse and advancements in SDN-based DDoS attack detection and mitigation.

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Journal of Intelligent System and Applied Data Science (JISADS)

Journal homepage : https://www.jisads.com
ISSN (2974-9840) Online

THE ROLE OF DEPENDABILITY IN IOT SYSTEMS

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ABSTRACT

The advances in the Internet of Things (IoT) have contributed to the automation of various industries by enabling devices and systems to effectively connect and collect data remotely over the internet. This progress has led to the creation of an intelligent society where physical things are becoming increasingly innovative and undoubtedly, the IoT systems will continue to impact real life by providing efficient data collection and sharing. The successful implementation of IoT systems relies on their dependability, which is closely tied to several factors such as their reliability, resilience, and security. This paper explores the crucial role of dependability in IoT system, emphasizing challenges such as real-time analysis, resource constrains, connection redundancy, and quick fault recovery. The paper also provides some strategies for overcoming dependability challenges, such as efficient algorithms, edge computing, prioritization of resources, and AI techniques integration. Additionally, the paper presents a case study of an IoT system that faced dependability problems, highlighting the importance of rigorous testing and redundancy in ensuring reliable IoT deployments. As a result of this research, we suggest that by addressing the challenges related to dependability aspects, stakeholders can unlock the full potential of IoT, empowering industries and individuals with transformative, efficient, and reliable technologies. For future work, a frame work for evaluating and enhancing the IoT dependability will be developed. Several factors will be considered in developing this framework, such as reliability, availability, safety, security, resilience, and fault management. The framework will define a quantifiable metrics to measure these factors.

Keywords: internet of things (IoT), dependability, reliability, resource constrains, failure recovery.

1. INTRODUCTION

Nowadays, the rapid advancement of smart sensor applications enables objects or things in various fields of our life to be addressed, connected, and to collect data about the environment around them. In this context, the "Internet of Things" (IoT) is a paradigm that emerged to manage and organize practical and technical issues [1]. Therefore, IoT deals with different technologies and protocols, such as Internet, mobile communication, and wireless sensor protocols [2]. The evolution of IoT has led to use this paradigm by different applications such as smart home, smart payment, smart lighting, fire detection, monitoring safety, and many other fields [3]. Central to the successful implementation and widespread adoption of IoT systems is the concept of dependability [4].

Dependability in general is a combination of several attributes such as reliability, availability, security, confidentiality, and resilience. Having these attributes enables a user to put trust into and rely on a system [5]. The dependability of an IoT device refers to ability of this device to consistently deliver trusted, accurate and reliable data, while maintaining the integrity and security of data in the face of various challenges and uncertainties. In IoT, dealing with vulnerabilities of a huge number of heterogeneous devices is a challenge [6,7]. Enhancing dependability enables IoT system to handle several

challenges.

A way to realize dependability requirements in IoT systems is by using fog computing [8,9]. Fog computing enables real-time data processing and analysis at the edge [10], which mean that the massive volume of data generated by IoT devices can be processed and analyzed locally and closer to the source of this data (network edges) rather than sending data to centralized cloud or data center. This reduces the data transmission and allows faster decision-making at the edge, enhancing the overall performance of IoT system [11]. Fog computing provides a platform that supports data communication between users, IoT devices and data centers, as well as storage and processing devices. Therefore, a fog-based IoT system can has dependability challenges, such as managing data flow of IoT devices, memory limitation and power constrains [12].

This paper studies the crucial rule of dependability of IoT systems and its implications in different applications. In the following sections, first some factors that affect the IoT system's dependability will be identified, then the challenges that can impact the dependability as well as some solutions for overcoming these challenges will be explored. Then a case study related to IoT system that faced dependability problems will be presented. Finally, a conclusion and future work are described.

2. FACTORS AFFECTING DEPENDABILITY IN IOT SYSTEMS

Dependability allows for continuity (uninterrupted) of system services [13]. In other words, a dependable system should provide mechanisms to tolerate any condition throughout its life cycle. The dependability can be achieved through different factors including reliability, availability, safety and security, resilience, fault management methods, scalability, and other factors [14].

2.1 Reliability

We begin by considering the traditional IoT architecture, characterized by centralized data processing and decision-making. This framework emphasizes the limitations of this approach, particularly in terms of latency and scalability [1].

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System reliability is the probability that system will behave as expected (without failure) over a given period of time (t). The system reliability can be measured through two metrics: mean time between failures (MTBF) and mean time to failure (MTTF). The reliability is measured by MTBF if the system has failure recovery mechanism, while MTTF is used to measure the reliability if there is no failure recovery mechanism [15]. Given R(t) is the reliability function of time:

$$R(t) = e^{-\lambda t} \quad (1)$$

where λ=1/ MTBF if there is recovery mechanism, otherwise λ=1/ MTTF.

Reliability is critical in IoT environment because unreliable data collection, processing, and transmission can cause long delay and data loss which can lead to a loss of confidence in the IoT systems, and therefore reliability is essential for the widespread of these systems [16].

2.2 Availability

The availability attribute in IoT system is directly related to reliability. The availability of an IoT system can be defined as its ability to deliver the required service as long as possible to ensure continuous operation. There are methods that can help to keep the system available, like maintaining a mechanism for faults management [17], and apply some approaches to manage hardware redundancy [18]. The availability can be calculated as follows:

$$Availability = \frac{MTTF}{MTTF+MTTR} \quad (2)$$

where MTTF is mean time to failure, and MTTR is mean time to repair.

2.3 Safety and Security

Safety and security are essential non-functional requirements (NFR) for any IoT system and are considered critical attributes for its dependability [19]. Safety is key attributes in IoT systems to prevent harm to their users or to the IoT environment [20]. IoT's security is related to avoiding security threats [21]. The two attributes are both source of risks and there are affected by each other [22]. Many IoT applications are integrated into safety critical environment, such as smart transportation and medical healthcare devices. It is essential to mitigate potential risks associated with these situations. Similarly,

security protection against unauthorized access and cyber-attacks can help to preserve user privacy and sensitive information

One of major requirements of an IoT system is that safety and security issues are designed to support the dependability of the system. Many attributes could affect the safety and security of IoT systems, such as hardware faults and, human errors, and security attacks [23]. These impediments need to be identified and mitigated.

2.4 Resilience

Resilience is the property of preserving the system's dependability when it encounters changes; thus, it is the ability to deal with failure, predict, tolerate and prevent it [24]. In an IoT system, the devices are connected through a network, and resilience is responsible for keeping the system connected regardless any failure that could affect the network [25]. The IoT system must deal with some constraints related to resources, such as network, memory and battery constraints, to recover from faults and failures as quickly as possible. Therefore, for the IoT system to be resilient, it should provide a fault (and failure) management mechanism. In addition, the system should be survivable in which it should offer continuity throughout managing and recovering the faults.

2.5 Fault and Failure Management

In IoT systems, a failure represents an unexpected behavior, such as data loss due to network connection problems or due memory overflow. To deal with faults, there are four strategies: detection, prediction, mitigation and prevention. Fault detection is the process of verifying the unexpected behavior using various methods, such as statistical machine learning methods [26], while fault prediction applies different techniques to predict probable failure, such as classification and regression techniques. Fault mitigation aim to recover the IoT system from failure, such as applying node load balancing [27] and redundancy techniques [28]. Fault preventions aims to prevent fault occurrence using different approach, replicating data on more than one node.

2.6 Assuring Data Quality and integrity

In IoT system, the collected data should represent the actual system context. For example, in an environment such as Polar Regions, where the climate is always cold, data from temperature sensors with a warm temperature is likely wrong. Therefore, an IoT system should previously know the context and related domain to provide meaningful and trustworthy results that are suitable for accurate decision -making [29].

2.7 Scalability

The IoT system should be scalable to accommodate thousands or even millions of sensors in terms of data transfer, storage, and real time processing [30]. The scalable system needs to provide more computing devices as well as the required hardware infrastructure [31].

2.8 Heterogeneity

The IoT system includes different heterogeneous devices that have different technologies and hardware implementations [32]. The IoT system provides the needed protocols to enable devices to communicate and understand each other. Each communication protocol has its own characteristics and application scenarios. For example, low- power wide- area network (LPWAN) technologies provide low power consumption and long transmission ranges. Examples of LPWAN technologies: Sigfox and NB-IoT [33]. Other examples of IoT communications technologies are: Bluetooth [34], Z-Wave [35], and Zigbee [36]. Furthermore, IEEE 802.11 standards can be adopted in an IoT environment for devices with no battery constraints and for data transmission over short distances [34].

3. CHALLENGES TO DEPENDABILITY IN IOT SYSTEMS

This section presents some of most important challenges of dependability in IoT systems:

3.1 Real-Time Analysis and Resource Constrains

In the IoT environment, dealing with real-time analysis and resource constrains is major challenge. Real-time analysis involves processing data immediately as it received from sensors without significant delay. Furthermore, there is a need address resource constraints such as limited availability of memory and power. IoT devices may have limited resources compared to other traditional devices, as they often designed to be small, inexpensive, and power-efficient. As a result, implementing complex real-time IoT system given some resource constraints can be challenging.

Energy consumption is a major challenge, and more research is needed to implement IoT systems with low power consumption [38]. The IoT requires mechanism of minimizing the power to be spent during the system operation.

3.2 Connection Redundancy

Connection redundancy is a crucial aspect of ensuring dependable and continuous communication in IoT deployments. The IoT system may involve numerous interconnected devices with different data formats. IoT nodes can be deployed with more than one communication protocol [37]. Disconnections can be prevented using monitoring mechanism that make automatic switching between connection technologies. In other words, each node can transmit and receive data using two or more communication protocols and it can select a protocol with better performance. However, in scenarios with huge number of nodes and connection redundancy mechanisms, it is challenge to deploy without the cost of hardware.

3.3 Quick Fault-Recovery

IoT system needs to detect and recover faults that may occur in its components. It is critical to ensure that the system can detect and recover from faults in real-time. Faults can arise due to hardware failure, software error, human error, or environmental factors.

4. STRATEGIES FOR OVERCOMING IOT DEPENDABILITY CHALLENGES

Some strategies can help to overcome IoT challenges. For example, using efficient and lightweight algorithms can be used to optimize the computational burden on IoT devices.

Other approach that can help to optimize IoT devices communication is applying edge computing to perform data processing near the IoT devices themselves, rather than sending all data to centralized server. The edge devices such as edge or gateway servers can perform data analysis and filtering locally reducing the need for continuous high-bandwidth communication.

Applying prioritization task mechanism allocate resources based on tasks importance as well as scheduling mechanisms that ensure critical tasks get the resources promptly. Furthermore, enable the IoT system to dynamically adjust resource allocation based on task priority and available resources will help the system to respond any changing condition

To overcome the limited-power challenges, it is recommended to use hardware components that are designed for low-power operational environment. For example, using energy-efficient microcontrollers that offer needed computational capabilities will help to minimize power consumption during the IoT system operation. Using energy harvesting techniques (such as solar panels) to power IoT devices can help can help to extend battery life or even eliminate the need for batteries.

Using artificial intelligent (AI) techniques can play vital role in enhancing IoT system dependability. AI techniques can analyze massive amount of data, predict probable failures, and detect security threats, aiding in system optimization and predictive maintenance. Using AI techniques can help in developing decision-making system that can be used to enhance system reliability, ensuring that IoT system can adapt to changes and provide consistent performance.

By combining these strategies, many challenges can be resolved, enabling a more robust and efficient IoT system.

5. CASE STUDY: NEST THERMOSTAT GLITCH

One example of an IoT system that faced problems that affect its dependability is the "Nest Thermostat Glitch" incident that occurred in January 2016 [39]. Nest Labs, a company owned by Google, and specializing in home automation and WiFi-enabled products that can controlled remotely, such as smart thermostats, sensor-driven and smoke detectors [40]. This company experienced a service outage that impacted a large number of their smart thermostats [41].

Nest's smart thermostats allow their users to remotely control their home heating and cooling systems through web service or mobile app. The smart thermostat aims to provide personalized comfort to users and optimized energy usage. This thermostat collects data from sensors and use machine learning techniques to adjust the temperature [42].

On January 13, 2016, an unexpected glitch happened On Nest's servers during a scheduled maintenance update. As a result of this glitch, many Nest thermostats became inaccessible for users. Some thermostats also provide wrong temperature readings, causing problems in heating and cooling systems. This accident affected the dependability of Nest thermostats and led to user dissatisfaction and inconvenience as many users were unable to control their thermostat, and the wrong temperature reading caused energy inefficiency and discomfort in their homes [41].

Nest engineers investigate and address the root

cause of the glitch and developed solutions to prevent occurring similar incident in the future to ensure the dependability of their smart system. The nest lab implemented more extensive testing procedures before final deploying their final system. Additionally, they improve the communication protocols to promptly response to any incident and keep user updated related to issues related to their service.

The Nest Thermostat Glitch incident illustrates how even well-established IoT companies can face dependability challenges. This incident showed the importance of rigorous testing, quality assurance, and redundancy in IoT systems. Furthermore, it highlights the necessity of having backup solutions in place to ensure reliable system functionality.

6. CONCLUSION AND FUTURE WORK

The role of dependability in IoT systems is essential to ensure a reliable and secure system. Dependability plays a critical role in building trust, ensuring safety, and enabling the successful implementation of IoT solutions. By addressing the challenges related to reliability, resilience, security, and other dependability aspects, stakeholders can unlock the full potential of IoT, empowering industries and individuals with transformative, efficient, and reliable technologies.

This paper identified factors affecting IoT system dependability, including reliability, availability, safety, security, resilience, fault management, data quality, scalability, and heterogeneity. There are several dependability challenges including real- time processing, limited resources, continuous communication and quick fault recovery. This paper addressed some strategies to overcome these challenges and enhance the dependability such as efficient algorithms, edge computing, prioritization/ scheduling of resources, and using AI techniques. This paper also identified one case study that faced problems that affect its dependability, which is the "Nest Thermostat Glitch" incident. This incident showed how it is necessary to perform rigorous testing, quality assurance, and redundancy before final deployment of the IoT systems, and how it is important to have backup solutions in place to ensure reliable system functionality.

As future work, a framework to evaluate IoT dependability can be developed. This framework should consider several factors to assess the dependability of an IoT system. The framework will define a quantifiable metrics to measure different factors, such as reliability, availability, safety, security, resilience, and fault management. These metrics can be used for evaluating the system's performance. By developing such framework, the IoT system decision makers can assess the dependability, and can take enhancing steps that will lead to more reliable and successful IoT solutions.

In comparison to previous works in the realm of the Internet of Things (IoT), our study delves into the paramount role of dependability in IoT systems. While past research has acknowledged the significance of some factors such as reliability and security in IoT [20-23], our paper extends the discussion to emphasize resilience, real-time analysis, connection redundancy, and swift fault recovery as critical factors influencing dependability. We build upon existing literature by proposing strategic solutions to overcome these challenges, including the integration of efficient algorithms, edge computing, resource prioritization, and the incorporation of artificial intelligence techniques. Notably, our work contributes a valuable case study highlighting the practical implications of dependability issues in an IoT system. This case underscores the necessity for rigorous testing and redundancy measures to ensure the reliability of IoT deployments, an aspect that has not been extensively explored in prior studies. Furthermore, we advocate for the development of a comprehensive framework for evaluating and enhancing IoT dependability in future work. This proposed framework will consider a spectrum of factors including reliability, availability, safety, security, resilience, and fault management, providing quantifiable metrics for a holistic assessment of IoT systems. Our research contends that by addressing these dependability challenges, stakeholders can unlock the full potential of IoT, fostering transformative, efficient, and reliable technologies for both industries and individuals.

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Journal of Intelligent System and Applied Data Science (JISADS)

Journal homepage : https://www.jisads.com

ISSN (2974-9840) Online

Privacy Threats Unveiled: A Comprehensive Analysis of Membership Inference Attacks on Machine Learning Models and Defense Strategies

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ABSTRACT

Membership inference attacks, aiming to determine whether target data belongs to a training dataset through machine learning model exploitation, present an escalating privacy threat within the machine learning landscape. This study initiates from fundamental theories surrounding the attack and defense mechanisms of machine learning models. The paper conducts a thorough analysis of key technical models, elucidating the intricate relationship between attack models and potential privacy risks to ensure data privacy security and advance the realm of machine learning applications. The introduction covers the adversary model of membership inference attacks, encompassing definitions, classifications, and the generation mechanism. Additionally, the paper provides a comprehensive overview and analysis of existing membership inference attack algorithms. Practical applications of membership inference attacks are explored, followed by the categorization and comparison of defense techniques. The study concludes with a comparative analysis of existing attack schemes and their corresponding defense technologies, offering insights into the evolving landscape of membership inference attacks in machine learning. The work not only anticipates future research challenges in data privacy protection but also establishes a theoretical foundation crucial for addressing data privacy leakage, thereby significantly contributing to the progress of machine learning applications.

Keywords: Membership Inference Attacks, Security, Machine Learning, Defense Strategies, Data Privacy

1. INTRODUCTION

The rapid evolution of artificial intelligence, particularly machine learning theory and technology, owes much to the internet's progress, hardware updates, extensive data collection, and the advancement of intelligent algorithms [1]. Its widespread application in diverse fields, including data mining [2], computer vision [3] [4], email filtering [5], credit card fraud detection [6] [7] [8] [9], and medical diagnosis [10] [11], has significantly enhanced efficiency through the analysis of large datasets. Despite the convenience and intelligence offered by machine learning, the increased collection of personal sensitive information, such as physiological characteristics, medical records, and social networks, has introduced severe challenges to the security and privacy of this burgeoning technology. Notable incidents, such as the Yahoo data breach in 2016, a DDOS attack on Microsoft's Skype in 2017, and the security flaw in Zoom reported by the Washington Post in 2020, underscore the substantial harm caused by data privacy and security issues in machine learning applications.

Currently, threats to machine learning security and privacy primarily fall into four categories: poisoning attacks [12] [13], adversarial sample attacks [14] [15], model extraction attacks [16], and model inversion attacks [17] see figure 1. Poisoning attacks and model inversion attacks occur during the training stage, where malicious data is injected to degrade model performance and information about the training set is obtained through reverse reasoning. Model extraction attacks and adversarial sample attacks take place during the

inference phase, involving theft of internal model information and deception of the model by introducing interference factors to generate adversarial samples. Numerous defence measures have been developed to counter these threats, including homomorphic encryption [18], secure multi-party computation [19], and differential privacy [20].

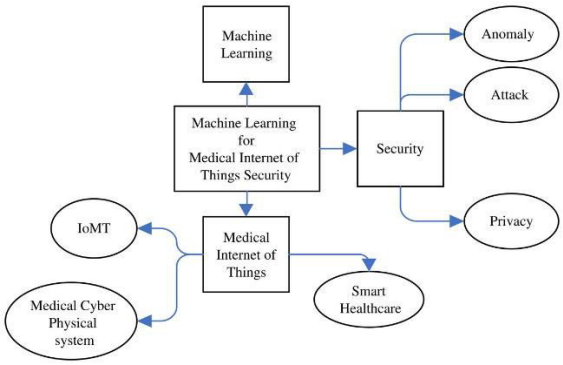

Figure 1: ML security and privacy approaches

The reliance on machine learning training on the quantity and quality of datasets poses a serious risk to widespread adoption due to the potential leakage of sensitive personal data. Model inversion attacks, particularly membership inference attacks, represent a critical privacy challenge by successfully inferring whether a specific target sample belongs to the target training dataset, resulting in privacy breaches. This attack has been successfully demonstrated in various data domains, such as biomedical data [21] [22] [23] and mobile location data [24], illustrating its potential harm to individual privacy and emphasizing the need for robust defence mechanisms.

Given that scholars specialize in various research fields with distinct problem-solving perspectives, the emphasis on member reasoning attack and defence varies among them. Thus, this paper initiates its exploration from the fundamental theory of attacking and defending machine learning models, scrutinizing pivotal technical models and elucidating the correlation between member inference attack models and the associated risks of privacy leakage. This endeavour holds immense significance in safeguarding data privacy and propelling advancements in the field of machine learning applications. The second section of this paper concisely outlines the adversary model, definition, classification, and generation mechanism of member inference attacks. In the subsequent sections, namely Sections 3 and 4, diverse types of member inference attack algorithms undergo detailed analysis, shedding light on their attack methods and current application status. Section 5 systematically organizes and summarizes the protective strategies employed against distinct attack methods, delving into the underlying reasons contributing to their effectiveness. Ultimately, Sections 6 and 7 encapsulate the comprehensive findings of the paper and present a forward-looking perspective for future research endeavours.

2. MEMBER INFERENCE ATTACK

In this section, we aim to consolidate and distill existing research findings on member inference attacks. Our focus is to succinctly summarize the key insights and methodologies explored in the current body of literature. This overview serves to provide a quick and informative reference for readers delving into the realm of member inference attacks.

2.1. Adversary Model

Within the domain of machine learning security, adversary models serve to delineate the capabilities and objectives of potential adversaries. In 2010, Barreno et al. [25] delved into the adversary model, considering both attacker capabilities and goals. Building upon this, Biggio et al. [26] expanded the adversary model in 2013 to encompass adversary goals, knowledge, capabilities, and strategies. The incorporation of these four dimensions offers a more systematic framework for characterizing the adversary's threat level when evaluating member reasoning

Table 1 Adversary model in membership inference attack

adversary model	describe
adversary target adversary knowledge	Breach of usability and privacy black box, white box
adversary capabilities	Strong adversary: can intervene in model training, access training data sets and collect intermediate results, etc.; Weak adversary: can only obtain model information or training data information through attack methods.
adversary strategy	Training phase: model reverse attack; Prediction stage: adversarial attack + member inference attack, model extraction attack + member inference attack

2.2. Definition and Model

Membership inference attacks involve the extraction of membership details from the training data by scrutinizing the target model system, constituting a prevalent type of attack leading to privacy breaches. This method determines whether specific data contributed to training the target model, enabling the attacker to infer details about the model's training set. As illustrated in Figure 2, the target model, trained on the original dataset,

operates on the application platform. The attacker, posing as a user, accesses the target model, gathering relevant information and adversary knowledge to construct an attack model capable of deducing whether a given dataset constitutes a member of the training set.

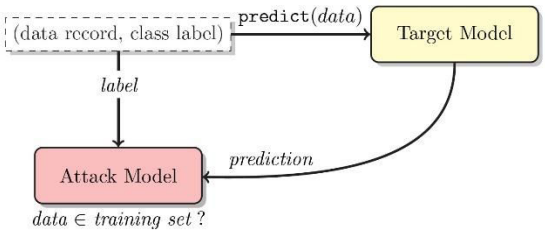

Figure 2: The model of membership inference attack

2.3. Categorization of Attack Models

Recent investigations into member inference attacks have resulted in categorizations based on distinct criteria, delineated in Table 2. Studies have classified these attacks into specific categories, each representing a unique standard or framework.

Table 2 Types of membership inference attacks

adversary knowledge	Attack method	attack mode	target model	type
black box	Shadow technology attack	passive aggressive	Classification model/deep learning/graph neural network/transfer learning	focus on learning
	baseline attack	passive aggressive	Classification model	focus on learning
	tag attack	passive aggressive	Classification model/deep learning	focus on learning
	diverted attack	passive aggressive	Classification model	focus on learning
White box	white box attack	Passive attack/active attack	Deep Learning/Generative Adversarial Networks	Centralized learning/federated learning

As indicated in Table 2, the classification of member inference attacks is based on the attacker's familiarity with the target model information, denoted as the adversary's knowledge. This results in two primary categories: black box attacks [27][33] and white box attacks [34][35]. In a black box attack, the attacker can solely access the model output results through the corresponding API, limited to observing the output $f(x;W)$ for input x without gaining access to intermediate results. Conversely, a white-box attack allows the attacker to access comprehensive information, including the target model's structure, training parameters, internal output results, training data distribution, and related data information.

Additionally, based on the attacker's engagement level, member inference attacks are further categorized into strong adversaries (active attacks) and weak adversaries (passive attacks). A strong adversary actively intervenes in the target model's training process, participating in federated learning and having the capability to modify intermediate data during training. In contrast, a weak adversary can only observe data changes during training and extract information through passive acquisition of the model interface.

Considering different attack types, member inference attacks primarily fall into two categories: centralized learning and federated learning. Centralized learning involves traditional model training with centralized storage of datasets for training the target model. On the other hand, federated learning entails local storage and training of personal data by each participant, exchanging gradients through a central parameter server for joint model training. Attackers in this model can either be a central parameter server or a local party.

Originally, member inference attacks predominantly targeted machine learning. However, with the widespread application of various data types such as images, text, and knowledge graphs, these attacks expanded to encompass transfer learning, deep learning, graph neural networks, and generative models. This broader scope has led to increased privacy risks.

2.4. Generating mechanism of attacks

The success of membership inference attacks hinges on a critical vulnerability known as overfitting within the target model. This susceptibility allows the model to memorize implicit traits of the training data, empowering attackers to discern membership relationships within the target data accurately. Additionally, factors like the introduction of abnormal data, characteristics of data distribution, and intermediate processes during model training furnish attackers with tools to detect targets and execute successful attacks.

Overfitting, a core component of membership inference attacks, involves attackers distinguishing between the training set and the test set of the target model. The model's proficiency in predicting the training set with high accuracy, coupled with diminished predictive abilities for the test set, renders models vulnerable to such attacks.

Outliers within the training set further exacerbate vulnerability. When these outliers, crucial for data representation, deviate in distribution from the test set

data, the model's failure to adapt seamlessly results in distinguishability between the training set and test set. This distinctiveness facilitates the success of membership inference attacks.

Moreover, the impact of data and model factors, including shadow data set size, class and feature balance, and model configuration, contributes to the complexity of member inference attacks. These attacks are not solely influenced by one factor but rather orchestrated by the collaborative interplay of multiple factors.

3. ATTACK ALGORITHM

Membership inference attacks, demonstrated to be successful across diverse data domains, can be broadly categorized into two types within the realm of machine learning—those leveraging black-box knowledge and those reliant on white-box knowledge, as elaborated below.

3.1. Black box knowledge

The majority of studies on membership inference attacks have focused on black-box models. Shokri et al. were pioneers in proposing a membership inference attack on a machine learning model, successfully determining whether a specific patient had been discharged from the hospital [31]. Subsequently, Salem et al. introduced another attack by gradually relaxing Shokri et al.'s assumptions, achieving improved precision and recall [32]. Confidence-based membership inference attacks for machine learning models have also emerged in various domains, including federated learning, generative adversarial networks, natural language processing, transfer learning, and computer vision segmentation [33][38][39]. Decision-based attacks in the field involved Yeom et al.'s quantitative analysis of the relationship between attack performance and the loss of the training and test sets, introducing the first decision-based attack known as the Baseline attack [33]. Choo et al. proposed a method akin to boundary attack [38].

1. Shadow Technology Attack

The original membership inference attack against machine learning, known as the shadow technology attack, was proposed by Shokri. This approach necessitates the use of shadow technology to simulate the target model, constructing a training dataset to train the two-class attack model for membership inference [31]. As shown in Figure 3 .

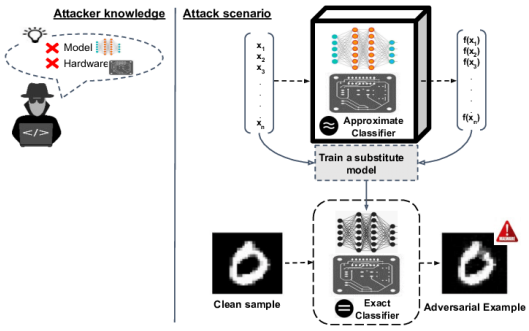

Figure 3: Black box attack

This methodology involves three primary steps: data synthesis, shadow model simulation, and attack model construction.

a) Data Synthesis: In situations where access to the model is restricted (black box scenario), the attacker lacks information about member data. Therefore, it becomes necessary to synthesize approximate data using various statistical algorithms such as model-based, statistical distribution-based, and noise-based methods.

b) Shadow Model Simulation: Relevant data synthesized in the previous step is employed to train one or more shadow models. These shadow models imitate the structure of the target model without having any knowledge about it. The shadow technology effectively simulates the target model through analysis and simulation, with the shadow model acting as a substitute for the original target model.

c) Attack Model Construction: Using the data set of the shadow model and the confidence vector output of the target model, a binary attack model is trained. This model, combined with the assigned label (where if data point x is lost to the training set of the shadow model, then label = 1; otherwise, label = -1), determines whether a given target data point belongs to the training data set of the target model.

Salem et al. [32] later relaxed Shokri's assumptions, proposing a more accurate and recall-focused approach. This method involves using only the output results of the target model for threshold discrimination, as shown in formula (1). While this approach is straightforward and highly efficient, its applicability is limited to models with poor generalization

Black-box attacks leveraging shadow technology initially focused on machine learning model API interfaces within cloud platforms, later expanding to

include deep learning, transfer learning, and graph neural networks. In the context of shadowing attacks on graph neural networks trained on data like social networks and protein structures [34], synthetic data and shadow models may exhibit inconsistencies with the target system, yielding favourable outcomes even for models boasting strong generalization performance. This vulnerability in graph neural networks arises from heightened connectivity between instances.

2. Baseline Attack

Yeom et al. [33] introduced the baseline attack in 2018, performing membership inference based on the correct classification of data samples. If the target data is misclassified, it is deemed non-member data; otherwise, it is considered member data. The intensity of the baseline attack correlates positively with model overfitting. For models with substantial generalization gaps, the attack performance is high with low cost, but it proves ineffective for models exhibiting good generalization.

3. Tag Attack

Choo et al. [38] proposed a method resembling the boundary attack, conducted in a black-box setting solely with the target model's output label. This attack operates on the principle that training set samples are more resistant to perturbation than test set samples. The tag-based membership inference attack involves three stages:

a) Adversarial Sample Generation: Leveraging the target model's prediction label as input, adversarial sample technologies like FGSM, C&W, and hopskipjump induce decision changes on the target, generating adversarial samples.

b) Perturbation Mapping: Calculating the Euclidean distance between the adversarial sample and the original target, mapping the perturbation difficulty to distance categories to discern prediction differences between the target model's training and test data.

c) Member Inference: Logically distinguishing prediction differences to obtain fine-grained member signals for membership inference of the target group.

4. Diversion Attack

In [39], a diversion attack is proposed involving given data points (x, y) and the confidence vector obtained from the target model f(x). The cross-entropy loss loss(x, y) = − log(f(x)y) is calculated.

3.2. White Box Knowledge

In the realm of black-box knowledge attacks, the assailant is limited to targeting the training data solely based on the model's output. Nonetheless, the intermediate calculation data of the training process harbours substantial information about the training data. In pioneering work on attacking Generative Adversarial Networks (GANs), a white-box attack was first proposed, exclusively leveraging the output of the GAN's discriminator without learning the weights of the discriminator or generator to execute the attack. Furthermore, Nasr et al. extended the member inference attack to a white-box setting based on prior knowledge [35]. The activation function and gradient information obtained from the target model serve as inferred features for conducting member inference. The specific details are illustrated in Figure 4.

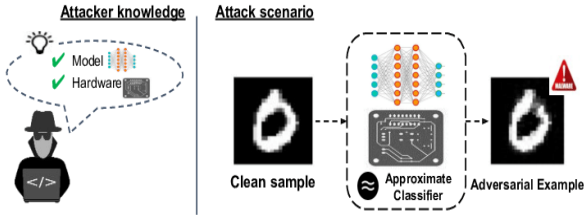

Figure 4: White box attack

Drawing from Figure 4, this solution operates on the principle that the target model undergoes fine-tuning and updates based on the training set data to minimize the loss gradient of the training data, thereby distinguishing between the gradient of the training set data and non-training set data for member inference.

For a target model f and input data x, the attacker computes the output of each layer in the forward propagation calculation of the target model, denoted as hi(x), the model output f(x), and the loss L(f(x; W), y). Subsequently, the gradient of each layer is calculated through backpropagation ∂L/∂Wi. These obtained parameters, along with the one-hot vector of y, constitute the input feature parameters of the attack model.

These input features are then fed into the corresponding Convolutional Neural Network (CNN) or Fully Connected Network (FCN) for feature extraction. The output is packaged and passed to the Fully Connected

Network (FCN), ultimately yielding the result of the inference attack. The attack model comprises two integral components: the Convolutional Neural Network (CNN) and the Fully Connected Network (FCN).

Additionally, Long et al. [37] introduced a member inference attack, GMIA, targeting well-generated models. In this attack, not all data is susceptible to member attacks. The attacker must identify vulnerable abnormal data points to differentiate members from non-members and execute a successful attack.

3.3. Algorithm comparison

In this section, we conduct a thorough comparison of the algorithms discussed earlier, providing an in-depth summary of existing member inference attack algorithms. The specific details of this comparative analysis are presented in Table 3.

Table 3 Comparison of membership inference attack algorithms

	adversary knowledge	target model	type	Assumptions			Attack accuracy	
				shadow model	Data distribution	Model structure	data set	accuracy(%)
[31]	black box	Classification model	independent model	yes	yes	yes	CIFAR100	92.8
[32]	black box	CNN	independent model	no	no	no	CIFAR100	85.7
[34]	White box	Classification model	federated learning	/	/	/	Yelp-health	75.0
[35]	White box	Classification model	federated learning	/	/	/	CIFAR100	85.1
[39]	black box	D.L.	independent model	no	yes	no	CIFAR10	88.0
[42]	black/white box	Generate model	independent model	no	no Yes	no	LFW	61.0/94.3
[43]	black box	NN	independent model	yes	no	no	Tweet(4)	64.8

4. CURRENT STATUS OF MEMBERSHIP INFERENCE ATTACKS

Given the ability of membership inference attacks to deduce the presence of specific data in a model's training set, their applications extend to verifying whether a user's data has been used without proper authorization. This capability has implications for disease monitoring, safety oversight, risk assessment, and privacy reinforcement in machine learning systems before potential attacks occur.

4.1. Auditing and Verification

Miao et al. [44] devised a voice audit model to identify if a user's voice data is part of the target model's training set, thereby indicating potential unauthorized use of user data. This user-centric member reasoning approach assesses whether a user's data was involuntarily utilized by the target model during training, promoting user rights protection and enabling audits of the target system model. Similarly, Song et al. [45] introduced an audit model for text generation models, deploying member inference to ascertain whether user data has been employed without proper authorization.

4.2. Disease Prediction

Membership inference attacks find application in disease monitoring using medical data [21] [22] [23] [36]. For instance, Homer et al. [21] aggregated profiles and case studies of target individuals with reference populations from public sources to determine if the target individual belongs to a group related to a particular disease. Moreover, in a diagnostic model developed from AIDS patient data, inferring that a person's medical data was used as the model's training data suggests a potential association with AIDS.

4.3. Safety Oversight and Intellectual Property Rights

Membership inference attacks prove useful in user credit monitoring [47] (e.g., one takeout platform serving multiple users), aggregate location monitoring [24], pre-release evaluation of privacy protection quality in systems (platforms), and regulatory authorities' monitoring for potential illegal use of user information, facilitating user rights protection. Additionally, these attacks pose a threat to the intellectual property rights of model providers over their training datasets.

5. DEFENCE STRATEGIES

In response to the diverse range of membership inference attacks, researchers have dedicated considerable attention to developing targeted defence solutions, leading to focused research efforts.

5.1. Defense Technologies

Member inference attacks pose a threat to the privacy of training set data. Defence strategies against membership inference fall into three main categories:

Regularization-Based Defenses [48] [49] [50]: These defences employ regularization techniques directly, including L2 regularization, dropout, model stacking, and min-max strategies.

Defence Based on Adversarial Attacks: This approach aims to protect the victim model through adversarial attacks.

Defence Based on Differential Privacy [51]: Differential privacy involves adding disturbance noise to various elements such as training data input, objective function,

model gradient, and output processes to mitigate member privacy leakage.

The following outlines some of the latest defence technologies along with their advantages and disadvantages.

5.1.1. Min-Max Game

Nasr introduced a gaming concept to train models with membership privacy [48]. This approach ensures that the model remains indistinguishable between its training data and predictions for other data points. The privacy mechanism targets robust inference attacks, minimizing both privacy loss and classification loss. The optimization of the minimum-maximum objective function in this algorithm not only safeguards member privacy but also significantly mitigates the risk of overfitting.

5.1.2. mem-guard

mem-guard represents the inaugural defense mechanism that provides formal assurances regarding utility loss against membership inference [49]. Its core concept involves introducing carefully crafted noise to the confidence scores of the machine learning model, thereby misleading member classifiers. Essentially, the addition of a noise vector, denoted as "n," to the confidence score vector, "s," ensures a defense against membership inference attacks with guaranteed utility loss [41]. The algorithm seeks to identify the noise vector satisfying a unique utility-loss constraint.

Functioning as a defense against black box attacks, this algorithm probabilistically introduces noise to the confidence score vector obtained from the target model, forming a random noise addition mechanism. This allows the defender to simulate the attacker's attack classifier, creating a defense classifier, followed by the formulation of an optimization problem for resolution. Empirical evidence supports the assertion that mem-guard exhibits greater strength compared to min-max game and model stacking.

5.1.3. Differential Privacy

Chen's proposed differential privacy defense technology [51] safeguards model privacy by perturbing the model's weights. The mechanism entails a trade-off between privacy and model accuracy, where smaller privacy budgets offer more robust privacy guarantees at the expense of reduced model accuracy. Chen's experiments depict the relationship between the privacy budget and the accuracy of the target model as a logarithmic curve, identifying a balanced budget near the inflection point. Combining differential privacy with model sparsity substantially diminishes the vulnerability to membership inference attacks.

5.1.4. Other Defense Technologies

The MMD + Mix-up algorithm, introduced by Li [52], enhances the model's loss function by incorporating the maximum average difference between the softmax output empirical distributions of the training set and validation set as a regularizer. This regularization technique aims to minimize the distribution disparity between member and non-member samples, thereby fortifying the model against potential attacks.

6. CHALLENGESAND SUGGESTIONS

As artificial intelligence research and applications in machine learning continue to advance, the unique nature of machine learning algorithms presents substantial challenges for safeguarding user data and network models. Addressing these challenges requires a comprehensive consideration of heightened security and privacy threats, accompanied by the development of adaptable defence methods that enhance the efficacy of machine learning models. This section examines the research challenges associated with member inference attacks and defences, offering insights into future research directions.

Explore Efficient White-Box Knowledge-Based Machine Learning Member Inference Attacks

While current membership inference attacks based on black-box knowledge yield satisfactory performance across diverse datasets, their efficiency lags behind white-box attacks, imposing certain limitations. For instance, the efficacy of black-box shadow technology attacks is influenced by model generalization and constrained by assumptions regarding data distribution and model structure. Therefore, investigating efficient member inference attacks based on white-box knowledge becomes a pressing concern.

Develop a Generalized Membership Inference Attack Mechanism for Various Machine Learning Algorithms

Efforts are needed to design a membership inference attack mechanism that is universally applicable to different machine learning algorithms. Black-box attacks, primarily driven by overfitting, exhibit low

efficiency and stability. Simultaneously, white-box attacks face coverage limitations in practical scenarios, particularly within federated learning contexts. A comprehensive approach that encompasses various machine learning algorithms and incorporates effective attribute inference is essential.

Devise Feasible Attack Plans for Non-Euclidean Spatial Data

Existing membership inference attacks predominantly focus on machine learning models trained on Euclidean space data, such as images and text. However, real-world data often manifests as graphs, as seen in social networks and protein structures. Current research has shown the viability of graph neural networks for processing such data, but privacy attacks on machine learning models in this realm remain underexplored. Exploring privacy preservation for non-Euclidean spaces without compromising the user experience in online social networks represents a promising avenue for research.

Strike a Balance Between Privacy, Efficiency, and Usability

Balancing the privacy of training data, model efficiency, and usability poses a significant challenge in machine learning. Privacy-preserving methods, such as differential privacy, may enhance privacy and efficiency but struggle to achieve an optimal utility-privacy balance due to added noise perturbation. Alternatively, secure multi-party computation offers high privacy and usability but introduces inefficiencies through noise perturbation and increased communication overhead. Establishing a multi-dimensional evaluation system and optimizing trade-offs among privacy, efficiency, and usability in diverse scenarios is crucial.

Establish a Unified Privacy Leakage Measurement Standard

In the realm of machine learning member inference attacks, measuring the privacy leakage risk of models is a critical aspect of evaluating attack performance. While some scholars have delved into privacy quantification, the research remains fragmented and narrowly focused on specific fields. A unified model and system for privacy leakage measurement and comprehensive risk analysis are yet to be established. Consequently, there is a need to develop a standardized privacy disclosure measurement and evaluation mechanism in machine learning.

Optimize Traditional Data Privacy Protection Solutions

Privacy protection solutions grounded in regularization, differential privacy, and adversarial games effectively mitigate privacy leakage in member inference attacks. However, given the sensitivity of private data and the model's robust memory capacity, there is room for optimization by combining traditional privacy defences with hybrid methods like cryptography, anonymity, adversarial regularization, and differential privacy. These optimizations can enhance overall data privacy protection.

7. CONCULOSION

This article initiates by presenting the current landscape of security and privacy threats confronting machine learning, delving into the intricacies of member inference attacks as part of the broader spectrum of data privacy threats. Subsequently, we conduct a comprehensive comparative analysis of prevalent member inference attack methods, exploring their application status. Following this, we scrutinize common privacy protection methodologies against member inference attacks and delve into the underlying mechanisms that render defense strategies successful. Ultimately, through an in-depth comparison and analysis of the limitations inherent in existing data privacy protection approaches, we address the challenges inherent in privacy protection research pertaining to member inference attacks, anticipating and preparing for more sophisticated attacks in the future.

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Journal of Intelligent System and Applied Data Science (JISADS)

Journal homepage : https://www.jisads.com

ISSN (2974-9840) Online

5G Network Slicing for Improved Meteorological Warning Dissemination

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ABSTRACT

This study addresses challenges in meteorological warning dissemination by examining the limitations of traditional communication methods that have been used. Leveraging 5G technologies such as mobile communications, IoT, and advanced satellites, the research focuses on integrating 5G network slicing to enhance the transmission speed and accuracy of meteorological disaster warnings. The paper proposes a concise design reference scheme, defining key indices and requirements for 5G network slicing tailored to meteorological information transmission. The three-tiered end-to-end architecture of 5G network slicing, involving the management, control, and user planes, is outlined. Key components like CSMF, NSMF, and NSSMF contribute to the comprehensive life cycle management of end-to-end slicing. The study classifies Service Level Agreement (SLA) indicators for 5G network slicing, aligning them with industry standards, and establishes a foundational understanding for implementation. This framework aims to revolutionize information transmission, providing a scalable and adaptive solution for meteorological warning systems in dynamic environments.

Keywords: network slicing , SLA , 5G, Weather warning information

1. INTRODUCTION

In the current landscape, the dissemination of meteorological disaster warning information in some countries heavily relies on conventional communication methods, presenting inherent challenges such as limited transmission speed due to the constraints of network capacity and bottlenecks. The intricacies involved in meeting the precise requirements for the accurate dispersion of early warning information in designated and remote areas further amplify these challenges. However, there is a promising avenue for overcoming these obstacles, driven by the continual evolution and development of emerging information and communication technologies [1]. Notably, countries worldwide are witnessing the continuous advancement of technologies like 5G mobile communications, mobile Internet, Internet of Things, , and satellite.

This confluence of cutting-edge technologies presents a transformative opportunity to address the existing limitations in meteorological disaster warning information dissemination. By synergizing these new information and communication technologies with strategic applications for early warning information dissemination, the potential to overcome the challenges becomes increasingly evident. A particularly promising solution lies in the utilization of 5G network slicing, a technology that empowers applications across diverse industries by providing assurances on critical network indicators such as bandwidth and latency [2]. This article delves into a comprehensive study of the definition and requirements of indices for 5G network slicing, specifically tailored to optimize the transmission of meteorological disaster warning information. Furthermore, the research aims to furnish practical and adaptable slice design reference solutions based on distinct application scenarios [3].

The foundational concept of network slicing involves operators strategically partitioning multiple end-to-end

logical networks within the framework of traditional physical networks. This segmentation is intricately aligned with the diverse and dynamic needs of users across various industries, addressing critical indicators like latency, bandwidth, security, and reliability. These individualized logical networks encompass the access network, transmission network, and core network, each isolated from the others. Consequently, the application of network slicing technology emerges as a pivotal strategy capable of efficiently meeting the multifaceted requirements of different applications within the meteorological disaster warning information dissemination landscape.

2. 5G NETWORK SLICING TECHNOLOGY

The delineation of 5G network slicing is outlined in 3GPP TS 23.501, where the physical network undergoes subdivision into numerous logical networks. This modular approach allows a single network to serve multiple purposes, granting operators the flexibility to construct various dedicated, virtual, isolated, and versatile networks atop the physical infrastructure [4]. To cater to the diverse requirements of users across different industries, tailored logical networks are imperative, addressing specific network capabilities such as latency, bandwidth, and the number of connections.

Implementation of 5G network slicing is contingent upon SA network architecture. As per the 3GPP R15 protocol, slice identification and end-to-end (E2E) identification of user groups are established based on the 5G SA architecture, elucidating how slicing facilitates differentiation. Achieving differentiation for specific user groups typically necessitates intricate configurations in network and terminal settings. Notably, protocols like 2G/3G/4G/5G NSA lack the means to identify certain user groups in an end-to-end manner uniformly [5].

The architecture of 5G network slicing encompasses an end-to-end design comprising multiple subdomains and involving three distinct levels: the management plane, control plane, and user plane, as illustrated in Figure 1.

The overarching architecture for end-to-end slice management comprises crucial components as follows:

(1) The Communication Service Management Function (CSMF) serves as the entry point for slicing design. It transforms business system requirements into comprehensive end-to-end network slicing requirements, forwarding them to the Network Slice Management Function (NSMF) for network design. Typically, CSMF functionalities are derived from the transformation of the operator's Business Support System (BSS).

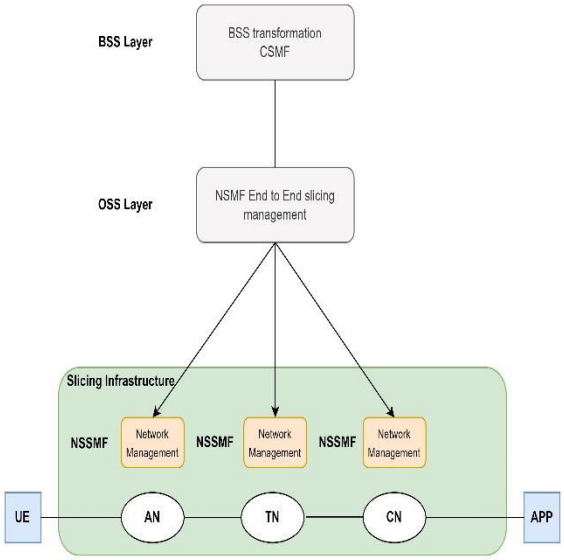

Figure 1: Schematic diagram of 5G end-to-end slicing

(2) The Network Slice Management Function (NSMF) assumes responsibility for end-to-end slice management and design. Upon obtaining the requisite end-to-end network slicing requirements, NSMF generates a slice instance. It further decomposes and consolidates the instance in alignment with the capabilities of each subdomain/subnet, transmitting deployment requisites to the Network Slice Subnet Management Function (NSSMF). NSMF functionalities are typically provided by cross-domain slicing managers.

(3) The Network Slice Subnet Management Function (NSSMF) takes charge of the slice management and design for subdomains/subnets, with distinct NSSMFs for the core network, transmission network, and wireless network.

NSSMF communicates subdomains/subnets capabilities to NSMF, facilitating autonomous deployment and enablement within the subdomain/subnet. Throughout the operational process, the subdomain/subnet undergoes slicing, accompanied by network management and monitoring. The collaboration of CSMF, NSMF, and NSSMF, through decomposition and coordination, culminates in the design and instantiation deployment of the end-to-end slicing network.

The complete life cycle management of end-to-end

slicing encompasses activities such as slicing instance creation, monitoring, and release. This involves breaking down network requirements into individual domains like wireless network, bearer network, and core network, accomplishing slice end-to-end configuration. Information from each domain is collected and synthesized to generate slice-level statistical indicators, visually presented to integrate with the BSS system, supporting the design and launch of industry-specific slicing templates [6].

2.1 Network slicing SLA classification indicators

Service Level Agreement (SLA): This constitutes a formal agreement, often referred to as a service level guarantee, that is negotiated between two parties—typically a service provider and a customer. Functioning as a contractual arrangement (or a segment thereof), its primary purpose is to establish a mutual understanding of services, priorities, responsibilities, and other relevant aspects.

Service Level Specification (SLS): Serving as the technical components and indicators of an SLA, the Service Level Specification defines parameters and associated threshold values for SLA indicators. It plays a crucial role in articulating the technical specifics of the agreed-upon service levels.

Currently, the industry has introduced several SLA-related standards. By amalgamating GSMA and 3GPP standards, the SLA indicators for 5G slicing encompass essential metrics such as user bandwidth, delay, packet reliability, throughput rate, positioning accuracy, isolation, among others. These indicators are precisely defined and detailed in Table 1, providing a comprehensive framework for evaluating and ensuring the performance of 5G slicing services.

Table 1 Main indicators of 5G end-to-end slicing SLA

SLA Indicator	definition
Network availability	The ability of a product to complete specified functions under specified conditions and within a specified time (Source: GJB451-90, IEC61907)
User rate (UL/DL)	Minimum data rate required to obtain adequate quality experience, except in the case of broadcast services (the value given is the maximum required) (Source: 3GPP TS 22.261/22.104)
Delay	End-to-end delay: The time it takes for transmission from the source to successful reception at the destination, measured at the communication interface (Source: 3GPP TS 22.261)
Reliable package	In the context of network layer packet transmission, the percentage value of the number of network layer packets successfully delivered to a given system entity within the time constraints required by the target service divided by the total number of network layer packets sent (Source : 3GPP TS 22.261)
Positioning accuracy	Positioning accuracy: describes how close the UE measured position is to the real position value (Source: TR 22.872)
Timing accuracy	This definition refers to the definition of Clock Synchronicity in 3GPP as follows: the maximum time deviation allowed in the synchronization domain between the master clock and any single UE clock (Source: 3GPP TS 22.104)
Cyber security	Ensure the confidentiality and integrity of information transmitted, exchanged and stored in the network from unauthorized tampering, leakage and destruction ; at the same time, ensure that the system operates continuously and reliably and provide continuous communication services without interruption
Isolation	Resource isolation requirements based on tenant business needs. "No sharing" means that the tenant requires complete isolation of slice resources, and the tenant's business and other businesses cannot share the same NSI. "Sharing" means that tenants have no mandatory requirements for resource isolation.

3. SLICE DESIGN FOR WEATHER WARNING INFORMATION

3.1 Purpose and Characteristics of Meteorological Disaster Early Warning Efforts

The objective of meteorological disaster early warning efforts is to anticipate and promptly address the impacts of meteorological natural disasters, aiming to minimize human and property losses.

The transmission and dissemination of meteorological disaster early warning information must adhere to specific standards. Once these predefined criteria are met, the responsible meteorological disaster early warning department should promptly issue relevant warnings. Subsequent to the warnings, each department is expected to implement corresponding precautionary measures swiftly to mitigate potential risks and reduce the impact on lives and property. Furthermore, the wide coverage of meteorological disaster early warning work is achieved by enhancing the monitoring and forecasting network. This enhancement serves to improve the accuracy, coverage, and speed of early warning information dissemination, eliminating any existing "blind spots" in the release of such information and enhancing overall dissemination efficiency.

The primary characteristics of meteorological disaster early warning efforts encompass:

(1) Timeliness: Given the rapid onset and high destructiveness of most meteorological natural disasters,

timely actions and measures by relevant agencies and departments are imperative.

(2) Accuracy: Involving the monitoring, transmission, and processing of substantial meteorological data, the accuracy of meteorological disaster early warning efforts is crucial. Decisions and actions must be based on precise and timely analysis to enhance the effectiveness of disaster response significantly.

(3) Openness: Following the analysis of meteorological monitoring information and the formulation of early warning information, relevant departments should promptly release it to the public. Delayed release or concealment of pertinent conclusions may result in adverse consequences.

(4) Multiple Levels: Recognizing the varying severity of meteorological disasters, the early warning mechanism should incorporate different levels, ranging from high to low. This tiered approach forms a systematic release and transmission mechanism for early warning information.

3.2 Analysis of Transmission Requirements for Meteorological Disaster Early Warning Information

Meteorological disasters pose a significant threat to national development and the social economy, with a high incidence rate among natural disasters. Early warning signals for meteorological disasters directly impact public safety and property, necessitating the transmission of warning information to be effective, accurate, and widely covered. Given the urgency, early warning information must swiftly reach a large number of mobile phone users within the coverage of the 5G network, ensuring both promptness and precision. In designing a network-slicing solution for the transmission of meteorological disaster early warning information, the primary considerations should include real-time transmission, minimal delay, accuracy, low bit error rate, ample bandwidth, and the prevention of information/data backlog. The initial design of network slicing indicators aligns with weather warning information transmission requirements and network slicing classification standards with the following specifications:

(1) User bandwidth level B1 (1 ~ 10 Mbit/s): Considering that current early warning information transmission primarily involves text without pictures or videos, a smaller single user bandwidth (B1 level 1~10 Mbit/s) is deemed sufficient to meet the transmission needs of an individual user.

(2) Delay level T2 (20 ~ 50 ms): Given the imperative for rapid dissemination of early warning information to all users within a designated area in a short timeframe (1 min), a moderate delay level of T2 is chosen for a single user.

(3) Isolation level S1 (logical isolation): Recognizing that meteorological disaster warning information is public and non-sensitive, a recommended approach involves utilizing a resource preemption mechanism based on priority scheduling to achieve logical isolation.

(4) Management level M3 (operable): Due to its broad scope, meteorological disaster warning information typically requires customized user group management, new business online commissioning, independent troubleshooting, and control over access and permissions, making it suitable for M3 operability.

3.3 Design Principles

In contrast to traditional Quality of Service (QoS) indicators, 3GPP has introduced new delay-based Guaranteed Bit Rate (GBR) types and designed the 5G QoS Index (5QI) to reflect service performance for 5G technologies and services. This new standard, 5QI, is defined based on service priorities and requirements for indicators such as delay and packet error rate, allowing base stations to select the appropriate resource scheduling scheme during the establishment of a Protocol Data Unit (PDU) session. Table 2 outlines the method for selecting resource scheduling schemes to meet the latency and reliability requirements of new business applications.

During the process of service scheduling, the delays and Quality of Service (QoS) of uplink and downlink data packets between the wireless air interface, wireless base station, and PDU Session Anchor (PSA) User Plane Function (UPF) can be monitored in both the terminal and the PSA UPF. Specifically, the delay in the wireless air interface can be provided by the 5G wireless access network (Next-Generation Radio Access Network, NG-RAN).

In contrast, the delay between the wireless base station and PSA UPF can be supplied by the GPRS Tunnelling Protocol User Plane (GTP-U) path level within the quality of service flow or at the user level. Based on the monitoring results of these delays, corresponding guarantee strategies can be implemented to address different needs [7].

Table 2 Delay Critical GBR 5QI and QoS mapping

5QI value	Default priority	Packet delay/ms	Packet error rate	Default maximum data size/Byte	Default averaging time window/ms	Typical business
82	19	10	10^{-4}	255	2000	Discrete Automation
83	22	10	10^{-4}	1354	2000	Discrete Automation
84	24	30	10^{-5}	1354	2000	smart transportation system
85	21	5	10^{-5}	255	2000	High voltage power distribution

2.4 Design Plan

When incorporating network slicing into the transmission of meteorological disaster early warning information, reference can be made to solutions applied in industries such as healthcare and electricity [8, 9,10]. A dedicated meteorological network can be established to facilitate the transmission of early warning information among monitoring stations, meteorological bureaus, and user terminals. The business aspects are categorized into intra-site, off-site, and inter-site and inter-user terminal scenarios, each with distinct workflow and slicing design variations.

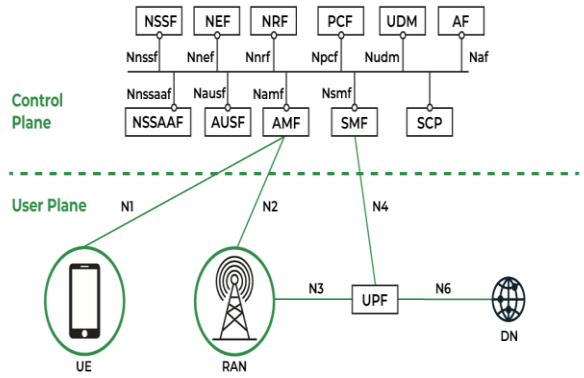

Figure 2: 5G Architecture Diagram

(1) Internal Transmission Networking

In the internal transmission networking segment, wireless indoor sub-stations using 5G-based wireless access equipment are employed for wireless access. These sub-stations then connect uniformly to the transmission slicing packet network (Slicing Packet Network) through a wireless centralized baseband unit (BBU) access ring. Within this network, the business originating from the detection station is conveyed to the 5G core network through the SPN access ring. The Multi-Access Edge Computing (MEC) can be deployed in the weather monitoring station or a data center between stations based on specific business needs. Non-mobile network requirements within the monitoring station can still be addressed using the existing wired office network, particularly for non-mobile network needs involving substantial equipment.

Most of the traffic within the monitoring station is routed into the 5G private network slicing through 5G wireless slicing, subsequently transmitted to the 5G core network meteorological private network slicing via the G.MTN/FlexE channel slicing of the SPN bearer network. In instances where the MEC is deployed in a data centre within a monitoring station or between monitoring stations, the business flow concludes nearby within the core network slice, connecting to the unified meteorological warning transmission platform or the data centre in the monitoring station through a dedicated wired line.

(2) Off-Site Networking

For network access beyond the monitoring station, the primary scenario involves using the downlink channel to transmit early warning information between the weather station and public mobile phone terminals. In this context, the 5G wireless access equipment in the Meteorological Bureau connects to the 5G public network, utilizing the G.MTN/FlexE channel established by the SPN network to transmit the prioritized early warning information to the 5G core network. Subsequently, the information is relayed to the user terminal.

(3) Inter-Site Networking

Network access between monitoring stations predominantly utilizes off-site networking, enabling remote connections from lower-level monitoring stations to higher-level stations/meteorological bureaus for data transmission. The business traffic from lower-level monitoring stations enters the 5G meteorological private network through 5G wireless slicing, proceeding to the upper-level site/meteorological bureau through the G.MTN/FlexE channel slicing of the SPN bearer network and the 5G core network meteorological slicing.

4. CONCLUSION

The freezing of the 3GPP 5G R17 version standard and the ongoing planning of R18 signify a progressive evolution in the capabilities of 5G network slicing and end-to-end network slicing. These advancements are poised to enhance the application of network slicing across diverse industries significantly. Concurrently, the operational deployment of 5G Standalone (SA) network lays the foundation for the widespread adoption of end-to-end network slicing technology. While the utilization of 5G network slicing in various industries is still in its early stages of exploration, this article addresses the specific requirements of weather warning information dissemination, presenting index reference values and solutions for 5G network slicing design. Looking ahead, continued refinement of design solutions is essential, aligning with relevant developments in 5G technology and pertinent research areas to further optimize the application of network slicing in the future.

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