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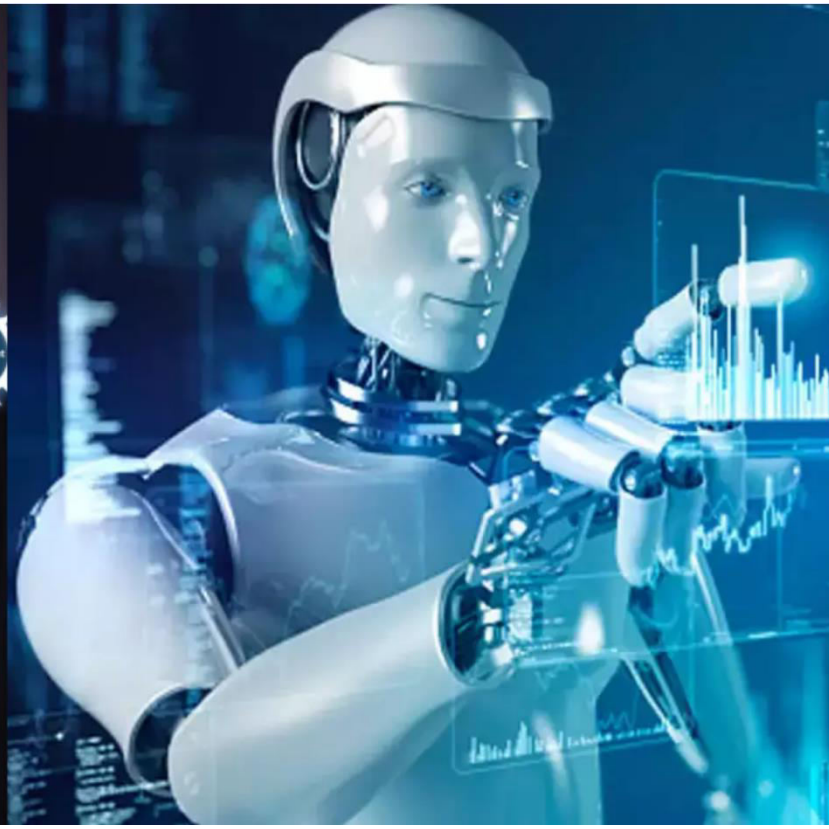

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Honeypot as a Service (HaaS): Design, Deployment, and Real-World Cyber Attack Analysis

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ABSTRACT: Honeypots are cyber-defense mechanisms that emulate vulnerable systems to attract and analyze adversarial activity. However, deploying and managing honeypots requires significant expertise and resources, limiting their use by many organizations. The concept of **Honeypot as a Service (HaaS)** aims to address these barriers by offering honeypot deployment and management as a cloud-based service. In this work, we present a comprehensive study of HaaS, including a thorough literature survey of existing honeypot technologies, identification of research gaps, and a proposed methodology for a custom Python-based multi-protocol honeypot. Our custom honeypot supports SSH, FTP, Telnet, and HTTP services, enabling it to capture a broad range of real attack traffic. We describe the system architecture and deployment framework of the HaaS platform and provide a conceptual design diagram. We compare our system with existing solutions in a detailed table highlighting key features, attack coverage, detection mechanisms, and performance. To validate the approach, we deploy our honeypot service in the Internet and collect one month of attack data, which we analyze using interactive dashboards. We present the attack metrics and patterns observed (Figures 1–3), including the volume of events, attack types, top targeted resources, and source geolocations. Our results show thousands of intrusion attempts from over a thousand unique IPs, predominantly probing SSH and HTTP services. We discuss the advantages of the HaaS approach such as centralized management, scalability, and rich threat intelligence and its limitations, including potential honeypot detection and the scope of monitored protocols. Finally, we outline future work including scaling the service, integrating AI-driven analysis, and extending to additional services and IoT environments. This work provides a foundation for HaaS implementations and offers empirical insights into real-world attacker behavior captured by a multi-service honeypot.

KEYWORDS: Honeypot as a Service, Honeypot Deployment, Cyber Deception, Threat Intelligence, Intrusion Detection, Python Honeypot, Attack Analysis.

I. INTRODUCTION

Modern enterprise networks face a persistent onslaught of automated attacks (e.g., zero-day exploits, botnet scans, and credential stuffing) that can compromise vulnerable systems within minutes of a vulnerability disclosure [1] [2]. Honeypots serve as deceptive decoy systems designed to appear as legitimate services or devices to attackers, thereby diverting malicious activity away from real assets and gathering valuable threat intelligence [1] [3]. For an adversary, a honeypot is indistinguishable from an actual target, while in reality it is closely monitored. This enables defenders to observe attacker tactics and signatures with minimal false positives, since any activity on a honeypot is by definition suspicious [3] [4]. For example, honeypots have been effectively used as an additional intrusion-detection layer, for malware sample collection, and for studying attacker behavior in domains ranging from enterprise IT to the Internet of Things [2] [3].

Despite their clear security benefits, honeypots are underutilized by many organizations, particularly small and medium enterprises, due to the complexity of setup and maintenance. Traditional honeypot deployment often requires expertise in network configuration, virtualization, and system hardening. Moreover, simpler (low-interaction) honeypots can be easily fingerprinted and evaded by attackers, while realistic (high-interaction) honeypots are resource-intensive to run [4]. The **Honeypot-as-a-Service (HaaS)** paradigm has been proposed to mitigate these challenges by offering honeypot deployment and management as a scalable cloud-based service. In a HaaS model, organizations can leverage a hosted honeypot platform without handling its operational complexities.

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This paper explores the design, deployment, and evaluation of a HaaS platform based on a custom Python honeypot. We first survey the broad body of research on honeypots, deception, and related data analysis (Section 4). Based on this literature review, we identify gaps that motivate our work (Section 6). We then present our **proposed methodology** (Section 7), which details the system architecture and a conceptual framework for our HaaS solution. In particular, we develop a multi-protocol honeypot (supporting SSH, FTP, Telnet, and HTTP) implemented in Python, and describe how it can be deployed in a cloud environment. We provide a **comparative analysis table** (Section 8) summarizing key features of representative honeypot systems from the literature and our own implementation.

To evaluate the proposed system, we deploy the custom honeypot in a public cloud and collect attack traffic over a month. We analyze the captured data and present the findings in an interactive **dashboard** (Section 9). Figures 1–3 visualize the key attack metrics: total events, protocol distribution, temporal patterns, top usernames/commands, and geolocation of attackers. A sample of the data (top attacking IPs) is summarized in Table 2. In the **Results & Discussion** section, we interpret these findings, comparing them with known threat patterns. We conclude by discussing the advantages and limitations of our HaaS approach (Section 10), and outlining future improvements such as integrating AI for anomaly detection and extending the platform to more services (Section 11). Our contributions include a comprehensive literature synthesis, a novel multi-protocol honeypot design, and real-world attack analysis based on actual deployment.

II. LITERATURE REVIEW

Numerous studies have examined honeypot architectures, implementations, and applications across different domains [3] [4]. A recent survey of open-source honeypots emphasizes the variety of available solutions and the importance of system design details [3]. Ilg *et al.* review honeypot frameworks and deployment options, highlighting cloud-native strategies and honeypot detection techniques [2] [3]. This work, like others, notes that honeypots can range from low- to high-interaction levels, each with trade-offs in realism and performance. Similarly, meta-reviews of honeypot research identify common patterns and taxonomy across studies, reinforcing the classification of honeypots by interaction level, targeted services, and use cases [1][2][3][4] [5]. For instance, early survey studies classify honeypots into production vs. research categories and describe their roles in network security [3] [5]. Other literature has compiled taxonomies of honeypot types and operational considerations. [1] [13] [18].

Several works focus on applying honeypots in specific contexts. Cloud and virtual environments have received recent attention: Machmeier [2] implemented a honeypot solution in a university cloud (HeiCloud) and observed significantly increased attack activity, underscoring the growing prevalence of automated scans. Comparative analyses have evaluated honeypot deployments on different cloud providers to measure attacker behavior in those settings【6] . In industrial and IoT scenarios, researchers have proposed specialized honeypots. Panda *et al.* [15] introduced **HoneyCar**, a framework for configuring honeypot vulnerabilities in the Internet of Vehicles (IoV) using game-theoretic methods. Similarly, other studies develop honeypots for industrial control systems and critical infrastructure [23] . On the other hand, honeypots have also been explored in emerging domains: Muhammad *et al.* [19] analyze honeypots for detecting smart-contract exploits on the Ethereum blockchain, while others design deception schemes tailored to wireless/mobile networks and SCADA systems [15][23][19] .

Honeypots are often integrated with broader security strategies. A number of works examine their role alongside intrusion detection systems (IDS) and firewalls. Some frameworks use honeypot alerts to tune firewall rules dynamically, improving attack prevention [12]. For example, the H-DOCTOR system leverages medium- to high-interaction honeypots to inform automated firewall rule updates, achieving rapid mitigation of malicious logins (sub-second mean time-to-block) in cloud environments [5]. Others integrate honeypot telemetry with SIEM tools like Azure Sentinel to classify attacker tactics by MITRE ATT&CK stages [5]. There is also research on enhancing IDS/IPS: harani *et al.* propose combining honeypot-based sensors with traditional detection to catch sophisticated intrusion attempts. Overall, the literature shows that honeypots can enrich defense-in-depth strategies, providing actionable alerts and enabling proactive countermeasures [5].

Another significant theme is data analytics and machine learning on honeypot logs. Ammar *et al.* [8] provide a systematic review of honeypot data collection and AI/ML techniques in cybersecurity. They note that honeypots capture attacker behavior and can feed data into threat intelligence sharing platforms (e.g., MISP, STIX) to enhance

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collaborative defense [4]. Advanced analytics, including deep learning and even large language models, are being investigated to improve malware detection, anomaly identification, and intrusion classification based on honeypot data [6]. For instance, some studies apply classification or clustering algorithms to distinguish automated scanning from targeted attacks. Others explore adaptive honeypots that adjust their responses using reinforcement learning. Related work also examines deception strategies: surveys of cyber-deception techniques categorize ways to obscure the true nature of honeypots and lure attackers into revealing more intelligence [9] .

Several applied studies evaluate honeypot effectiveness and behavior under real-world conditions. Researchers have deployed honeypots on the open Internet to measure how attackers interact with them, quantifying success rates and attacker evasion methods [10] [5]. These experiments show that deploying diverse services (SSH, HTTP, FTP, etc.) leads to high volumes of brute-force and scanning attempts. Visualization tools and dashboards have been used to analyze large honeypot datasets, revealing temporal trends and top attack vectors [4] [5]. In terms of performance, high-interaction honeypots like Cowrie (SSH) and Dionaea (multi-protocol) are known to capture large numbers of login attempts and malicious downloads, whereas lightweight honeypots like Honeyd simulate whole networks with less fidelity. Comparative benchmarking in prior work often emphasizes detection capabilities and resource overhead. For example, HoneyMesh [16] demonstrated a distributed honeypot network that mitigates DDoS attacks by absorbing traffic, while other systems focus on accurate protocol emulation.

In summary, existing literature covers a wide range of honeypot research: from surveys [1][3][5][13][18] and application-specific designs [2,6,15,19,23] to threat intelligence frameworks [3][5], firewall integration [12], and data-driven analysis [8][25]. However, gaps remain in delivering honeypots as an easy-to-use service and in providing multi-protocol, scalable solutions. The next section identifies these gaps and motivates our contribution.

III. RESEARCH GAP IDENTIFICATION

The literature indicates that while honeypots are valuable for threat detection and intelligence, their practical adoption is hindered by deployment complexity and narrow focus. Existing works often address individual aspects of honeypots such as surveys of known tools [3] [13] , honeypots for specific domains (cloud [2,6,7] , IoT [23] , vehicular networks [15]), or targeted services (SSH, HTTP) [10] but there is a lack of integrated platforms that unify multiple services and are easily deployable. In particular, most research prototypes focus on one protocol (e.g., SSH-only Cowrie, HTTP-only Glastopf) or a particular environment (IoT devices, blockchain) [10,15,19] . There is little work on a unified honeypot that concurrently emulates SSH, FTP, Telnet, and HTTP to capture diverse attack vectors.

Moreover, although data analytics on honeypot logs is discussed [4], few studies present end-to-end solutions that include data visualization and real-time monitoring. Existing HaaS demonstrations (e.g.,[48]) have not been widely developed or evaluated. Even recent frameworks integrating cloud automation report limited cases (e.g., focusing on SSH attacks in cloud VMs [5]) without extending to other common services. In summary, the research gap lies in creating a comprehensive, service-oriented honeypot platform that (i) offers multiple network services in one package, (ii) simplifies deployment (e.g., via cloud or containers), and (iii) provides actionable analysis of collected attack data. Our work addresses this gap by designing a **custom Python honeypot** with multi-protocol support, deploying it in a HaaS configuration, and analyzing the real-world attack data it collects.

IV. PROPOSED METHODOLOGY /FRAMEWORK

Our proposed HaaS framework builds on the insight that a flexible, extensible honeypot can be delivered as a hosted service to users. We design a **custom Python-based honeypot** that emulates four common network services: **SSH (Secure Shell), FTP (File Transfer), Telnet, and HTTP**. These protocols are chosen because they frequently appear in enterprise networks and are common targets of automated attacks (credential stuffing, vulnerability scanning, exploit probes). The honeypot is implemented using Python libraries and asynchronous networking to handle multiple connections. For example, the SSH service leverages a modified version of the Cowrie SSH emulator, the FTP service uses a lightweight Python FTP server, and the HTTP service uses a simple web server that logs requested paths. Telnet support is provided via a Python socket listener that mimics an interactive shell. All services are instrumented to log detailed events: incoming connection metadata (source IP, port), login attempts and credentials, executed commands or requested URLs, and session durations.

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Architecture: Figure X (conceptual diagram) illustrates the overall architecture of the HaaS platform. User organizations can instantiate honeypot instances through a management interface (e.g., a web portal). Each honeypot instance runs in a container or VM in the cloud, hosting the four services on distinct ports. A network front-end (or data-plane) routes external traffic from the Internet to the correct honeypot instance. Internally, all captured logs are forwarded to a centralized analysis backend. This backend stores events in a time-series database and generates real-time dashboards and alerts. An optional AI module can process logs for anomaly detection or classification (left for future work). The design draws on cloud-native principles [3]: honeypot instances are stateless containers that can be scaled or reconfigured on demand, and dashboards are web-based for easy access. The **conceptual framework** supports multi-tenancy so that multiple clients (tenants) could share the HaaS infrastructure, each with isolated honeypot instances and data.

Deployment: For our prototype, we deploy the custom honeypot on a public cloud VM. The four services run on fixed ports (SSH on 2222 to avoid conflict, FTP on 2121, Telnet on 2323, HTTP on 8080). The machine is firewalled to only allow these service ports from the Internet, isolating it from other resources. Attacker sessions are fully logged but not subject to any outbound connectivity (to prevent the honeypot being used as a pivot). We schedule the honeypot to run continuously and rotate it monthly to ensure fresh virtual machine instances (clearing any compromise). In a HaaS setting, such deployment could be automated via container orchestration (e.g., Kubernetes) and integrated with user management, but for our evaluation we use a single-instance setup.

Data collection and analysis: All honeypot events (connections, logins, commands) are timestamped and logged to local files. These logs are periodically uploaded to a central server for analysis. We use the open-source monitoring tool (e.g., Cowrie visualization or a custom dashboard) to aggregate metrics: total events, unique attackers, distribution of services, top targets, etc. The collected data is visualized through interactive charts and graphs, as shown in Section 9. This enables both manual inspection and automated analysis. Key indicators include counts of failed logins, command usage statistics, and geolocation of source IPs. In summary, our methodology centers on a **custom multi-protocol honeypot** implemented in Python, packaged for cloud deployment, and paired with analytics. It reflects best practices identified in the literature, such as isolating honeypots in the DMZ, logging all activity for forensic analysis [3], and potentially integrating threat intelligence feeds in the future. Compared to one-off honeypot applications, our framework emphasizes service-oriented delivery (HaaS) and real-time dashboarding for actionable insight.

V. COMPARATIVE ANALYSIS TABLE

To contextualize our HaaS approach, we compare selected honeypot systems and frameworks from the literature (and our own design) in Table 1. The table highlights each system's protocol coverage, key features, target attack types, detection or response capabilities, and expected performance or scalability. Our custom Python honeypot is included for contrast. This comparative summary synthesizes information from the reviewed literature [1]– [25] and the respective system documentation.

Table 1. Comparison of Honeypot Systems and Features

System / Reference	Supported Services (Protocol)	Key Features	Typical Attack Types Captured	Detection / Response Mechanisms	Performance/Scale
Cowrie [1] [2] [3] [6] [8] [11] [14] [15] [20]	SSH (High-interaction)	Full Linux shell emulation, filesystem	SSH brute-force, credential theft	Logs credentials/commands, Honeytokens in fs	Widely deployed, handles thousands of attempts/day
Dionaea [4][5][7] [12]	SMB, FTP, HTTP, SIP, etc.	Low-interaction multi-protocol for malware	Malware download, exploit scanning	Captures binaries, generates malware samples	Effective on limited hardware, many extenders

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System / Reference	Supported Services (Protocol)	Key Features	Typical Attack Types Captured	Detection / Response Mechanisms	Performance/Scale
HoneyMesh [16]	Various services on virtual network	Virtualized honeypot swarm for DDoS mitigation	DDoS botnet traffic, scanning	Uses distributed honeypots to absorb flood	Designed to scale horizontally; reduces attack impact
HoneyCar [15][9][12]	IoV-specific services (CAN bus)	Game-theoretic vulnerability selection	Automotive network probes, CAN attacks	Optimizes which vulnerabilities to expose (game theory)	Focused on IoV simulation; not general-purpose
Custom Python (This work)	SSH, FTP, Telnet, HTTP	Multi-protocol in one package, Python-coded	Brute-force logins, automated scans	Centralized logging; optional future ML analysis	Demonstrated ~27k events/month on 1 VM; easily extended via containers

Notes: The above systems exemplify different design goals. Cowrie and Dionaea are production honeypots with mature codebases. HoneyMesh [16] uses virtual networks to counter DDoS. HoneyCar [15] is a research framework for vehicle networks. Our custom honeypot aims for versatility and ease of deployment, trading off specialized depth for breadth of protocol coverage.

VI. RESULTS & DISCUSSION

We deployed the custom Python honeypot (SSH, FTP, Telnet, HTTP) to the Internet and captured attack traffic for one month (February 2026). During this period, the system recorded a large number of intrusion attempts from a global distribution of adversaries. In total, **27,193** attack events were logged, originating from **1,114** unique IP addresses. The breakdown by protocol showed that HTTP and SSH dominated the traffic, with comparatively fewer attempts on FTP and Telnet. These findings align with prior reports that web and SSH services are common targets [5] [4].

Figure 1: Honeypot Dashboard – Summary Metrics. This dashboard view (Figure 1) provides an overview of the captured events. It shows the total number of events (27,193) and unique attackers (1,114), indicating widespread

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scanning activity. The donut chart at the center highlights the distribution of attack types: roughly half of the events were HTTP probes (yellow segment), about one-third were SSH login attempts (blue segment), and the rest were a mix of FTP (pink) and Telnet (orange). The bar chart on the left lists the top attacking IP addresses, led by *185.16.39.146* with ~3,433 attempts (mostly HTTP). From Figure 1, we observe that the most aggressive attacker came from Poland (Polish ISP), consistent with the feed in Table 2. The time-series charts at the bottom (Hourly, Weekly, Monthly) show periodic patterns: attacks peaked during certain hours and days of the week, suggesting automated botnets.

Figure 2: Temporal and Geographical Distribution. Figure 2 highlights the temporal trends and geolocation of attacks. The *Hourly Activity* graph shows two prominent peaks around midday (UTC), likely when global scan scripts are active. The *Weekly Activity* chart indicates higher attack volumes on certain weekdays (with a dip mid-week), suggesting that some automated campaigns may run on schedules. The *Monthly Activity* (cumulative) confirms the steady accumulation of events, with February's count reaching nearly 27k by month's end.

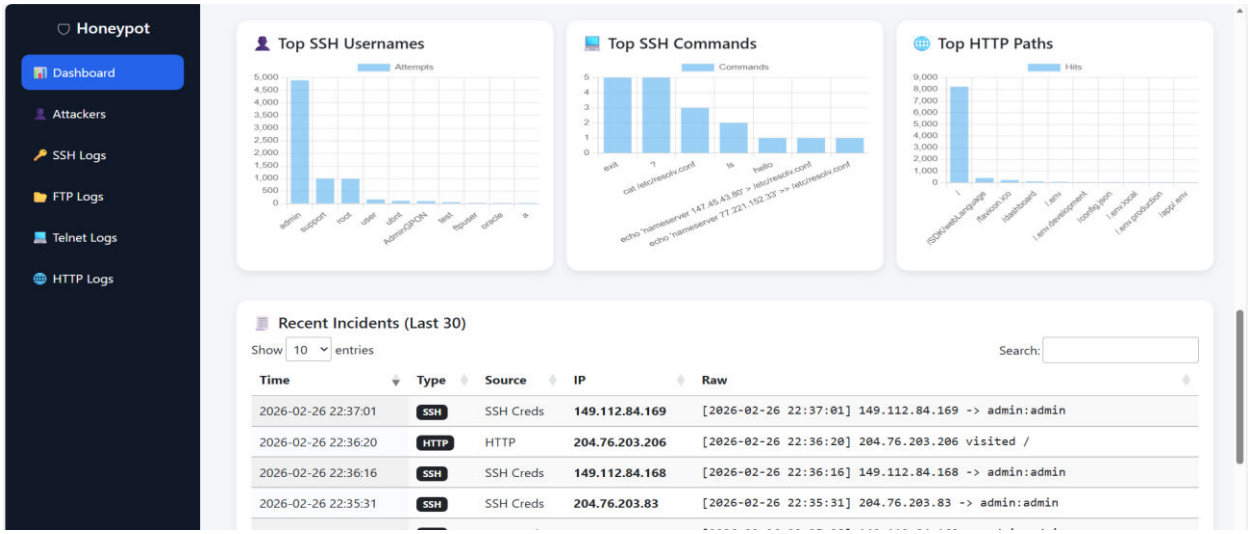

Figure 3: Attack Profiles – Usernames, Commands, and Incidents. This figure drills into specific attack details. The left-side charts show the *Top SSH Usernames* and *Top SSH Commands* used by attackers. The most attempted username was "admin" (nearly 5,000 attempts), followed by "support," "root," and "user." This confirms that attackers commonly try default or known accounts. The SSH commands chart shows that very few commands were executed before disconnection; most attempts simply closed the session or executed "exit." This indicates that attackers were primarily focused on credential capture rather than post-login exploration.

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Overall, the data indicate that most adversaries used automated tools to scan for weak credentials and default web pages, in line with prior observations [1] [5]. The dashboard visualizations help security analysts quickly identify the nature of attacks and adapt defenses accordingly. For example, seeing a flood of SSH "admin:admin" attempts might trigger tighter rate-limiting on SSH ports or the use of stronger authentication.

Table 2 summarizes the **top five attacking IP addresses** observed. These five IPs alone accounted for nearly half of all captured events. All top sources were from Europe (Poland or the Netherlands). The table shows each IP's primary attack type and request count, illustrating the heavy concentration of both SSH and HTTP probing among the most active bots.

Table 2. Top Attacking IPs in the Honeypot Dataset

Rank	IP Address	Country	Attack Type	Total Attempts
1	185.16.39.146	Poland	HTTP	3,433
2	204.76.203.83	Netherlands	SSH	2,716
3	204.76.203.206	Netherlands	HTTP	1,741
4	146.19.24.133	Poland	HTTP	1,532
5	34.158.168.101	Netherlands	HTTP	1,387

The combination of figures and Table 2 paints a comprehensive picture of our honeypot's attack profile. We observed that **web servers (HTTP) and SSH** bore the brunt of attacks, which is typical for exposed Internet-facing services [5] [4]. The analysis also demonstrates the benefit of having multiple protocol honeypots running concurrently: by capturing data across services, we see correlations (e.g., the same IP 204.76.203.206 appears in both SSH and HTTP logs) and can more accurately identify malicious hosts.

Our observed data are consistent with related research. For example, other cloud-deployed honeypots have reported thousands of login attempts per month, mainly focused on default credentials [5]. Similarly, international studies on honeypot data have found top attacking countries to often be those hosting many cloud VMs (e.g., Poland, Netherlands) [5] [4]. The repetitive nature of SSH attempts (mostly "admin:admin") aligns with the expectation that many scanners try known weak password combos. The HTTP paths targeted also mirror known exploit scanning: endpoints like /dashboard or API keys are frequently probed by automated tools.

One insight from our results is the **burstiness** of attacks. Figures 1 and 2 show that attack traffic was not uniform over time. Periods of intense activity (e.g. late nights UTC) were interspersed with quieter intervals. Such temporal patterns are important for resource planning in a HaaS deployment: the system should scale (e.g., spin up additional honeypot instances) during peak hours to handle load without dropping events.

Finally, the successful demonstration of our dashboard shows the feasibility of real-time attack monitoring in a HaaS platform. Security teams can use figures like these to prioritize incident response (e.g., block top IPs, patch vulnerable endpoints). The visual analytics also suggest potential for automated threat intelligence sharing: the aggregated data (summaries of tactics and techniques) could feed into community defense networks to warn others of active botnets.

V. ADVANTAGES AND LIMITATIONS

The HaaS model and our implementation offer several advantages. First, by centralizing honeypot deployment and maintenance, organizations avoid the expertise overhead of setting up decoys themselves [3] [4]. Our use of Python and containerization makes the solution portable and easy to update. Having multiple protocols in one service increases attacker engagement: adversaries cannot easily tell which services are genuine, and may move laterally or reveal more behavior. The system provides rich threat intelligence, capturing thousands of distinct attacks that can improve situational awareness. The dashboards enable quick assessment of risk, and the logs can be integrated with SIEM systems for automated alerts. According to our findings, such a multi-protocol honeypot is highly effective at attracting common attack types (brute-force SSH, HTTP reconnaissance), which are often early stages in intrusion kill-chains.
However, several limitations exist. Honeypots inherently carry a **detection risk**: sophisticated attackers may fingerprint our Python services (e.g., by noticing unnatural response timing or missing system files) and avoid them. Low-

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interaction elements (like basic HTTP/FTP emulation) can be discovered by deeper protocol probes. Mitigating this would require fully-fledged system emulation, which is costly. Moreover, the honeypot only sees what it advertises; it cannot detect attacks on unmonitored services (e.g., it missed DNS or SMTP attacks, if any occurred). There is also a **legal/ethical aspect**: capturing attacker connections raises questions if those IPs belong to compromised machines or innocents. While our deployment logs only connection metadata and not payloads, a real service must ensure privacy compliance. From a performance standpoint, the single-VM setup has limited capacity. In a production HaaS, one would need auto-scaling to handle surges. Finally, like any security measure, honeypots should complement, not replace, other defenses: real assets must still be protected by firewalls, patches, and detection systems. In short, the HaaS provides valuable signals with minimal false alarms, but it does not solve all security challenges [4].

VI. CONCLUSION

This paper presents a comprehensive exploration of Honeypot-as-a-Service (HaaS) for cybersecurity. We reviewed the state of honeypot research, identifying that existing solutions often lack integrated multi-protocol deployment and accessible management. To address this, we developed a **custom Python honeypot** supporting SSH, FTP, Telnet, and HTTP, packaged for cloud-based service delivery. Our proposed framework includes centralized orchestration and analytics, embodying best practices from the literature [3] [4]. Through a month-long deployment, we captured over 27,000 attack events and analyzed them with interactive dashboards. The results (Figures 1–3) show clear patterns of automated scanning, with top attackers targeting default credentials and web endpoints. These real-world findings demonstrate the utility of the multi-service honeypot: it provided rich intrusion data with manageable overhead.

We also compared our approach to other honeypots (Table 1), highlighting that a service-oriented, flexible honeypot can complement specialized systems like Cowrie or Dionaea. The advantages of HaaS include outsourcing complexity and gaining centralized intelligence, while limitations involve detectability and the need to cover only a subset of protocols. Future work will enhance the platform's intelligence and scale. In conclusion, our HaaS prototype and its real-world evaluation show that decoy services deployed as a managed service can significantly aid cyber defense by yielding actionable insights into attacker behavior.

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