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# Deep Learning–Enabled Honeypots: An ANN-Based Approach for Advanced Cyber Threat Analysis

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**Abstract –** A cyber threat refers to an illegal activity intended to breach the confidentiality and integrity of computer systems and data. Examples of cyber threats include malware, phishing, unauthorized computer access, and denial-of-service attacks. It has made the traditionally relied-upon Intrusion Detection System based on signature systems obsolete and incapable of providing the much-needed protection against hacking incidents. Keeping this concern in mind, we propose an innovative concept for Deep Learning-Enabled Honeypot Cyber Attack Systems based on Honeypot-Based Artificial Neural Network Systems to facilitate efficient intelligence for effective analysis of cyber attacks. Experimental evaluation of the proposals is conducted using the CIC-IDS-2017 dataset for the attack scenario under consideration throughout the simulation. An intensive data preprocessing technique is employed to address high dimensionality, noisy features, and imbalance. The proposed HP-ANN model is systematically compared to several machine learning and deep learning baselines, namely Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). From the results, the proposed HP-ANN model significantly outperforms all baselines in terms of accuracy, precision, recall, and F1-score, achieving 1.00 and a very near-perfect ROC-AUC. Besides, the model's stability and fast learning ability are undeniable, as demonstrated by additional analyses of convergence trends and confusion matrices.

**Index Terms** – Honeypot-Based Security, Cyber Threat Analysis, Artificial Neural Network, Deep Learning, Intrusion Detection, SIEM, SOAR

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## I. INTRODUCTION

The immense growth of digital ecosystems is driven by advances such as cloud computing, the Internet of Things (IoT), edge intelligence, and software-defined infrastructure. It is defined as being able to change our view of the existing cyber world. It is mentioned that while advances in technology, through all the positive qualities that the scalability of the connections elevated, have brought with them much risk because the advances of modern cyber attacks are no longer individualized or random, but automated, continuous, multiplexed, and increasingly driven by Artificial Intelligence" that allows adversaries to "defeat traditional security measures quite so easily [1], [2]. Conventional security measures, such as firewalls, signature-based Intrusion Detection System (IDS) technology, and rule-based Intrusion Prevention System (IPS) technology, mostly depend on reactive defense models. This is because they are entirely dependent on a number of patterns and signatures related to intruding agents. As a result, these models have no impact whatsoever when confronted with zero-day exploits, polymorphic infections, and APTs that evade detection by Capabilities and Hitchhiker through adaptation and/or change [3]. Research developments and findings indicate that attackers can persist within an organization's infrastructure without detection while conducting reconnaissance, navigation, and data extraction by bypassing the blind spots of static network security models.

In this regard, cybersecurity research has increasingly shifted toward proactive, intelligence-driven, and deception-based defense strategies. Of these, one of the most important and pioneering technologies that has revolutionized modern cyber defense paradigms is the honeypot. Honeypots are decoy systems, applications, or infrastructures that emulate legitimate network services to attract malicious actors. Unlike other security tools and their approaches, which primarily focus on securing assets in the production environment, honeypots are designed to observe and monitor attackers, enabling precise analysis of their tactics, techniques, and procedures with reduced risk to existing systems and assets [5]. A key benefit of honeypots is their ability to produce high-fidelity threat intelligence at extremely low false-positive rates, since any activity against a honeypot is intrinsically suspect. Recent research has shown that honeypot-assisted detection frameworks can outperform traditional IDS solutions for stealthy, low-frequency, and zero-day attack detection [6]. Despite these advantages, traditional static honeypots still face serious challenges, including fingerprinting, limited scalability, and the risk of evasion by sophisticated adversaries.

Indeed, in this respect, modern research focuses on building adaptive and intelligent honeypots using the latest technologies, particularly artificial intelligence and machine learning. The intelligent honeypot can change its state and behavior in real time based on its observations of attacks, making honeypot detection and evasion much harder than before [7]. Machine learning approaches using honeypot data also exhibit strong capabilities for anomaly detection and classification, enabling early identification of advanced attacks without prior knowledge of their signatures [8]. Moreover, recent publications emphasize various aspects of ensuring the seamless integration of honeypots into overall security infrastructures, rather than mere silo deployments of these tools. In addition, the use of Honeypots in conjunction with Security Information & Event Management Systems enables the analysis of the trends relating to the attacks, while the use of the same in conjunction with Security Orchestration, Automation & Response Systems improves the speed in responding to the incidents, thus enhancing operational efficiency within the organization’s cybersecurity ecosystem. Therefore, another remarkable improvement in the use of honeypot-based information for predictive cybersecurity analytics focuses on forecasting

attacker activities using various deep-learning-based forecasting algorithms, enabling cybersecurity analysts to leverage existing honeypot interaction data for predictive analytics [10]. This development has greatly redefined the concept of using honeypots, treating them as a crucial part of next-generation cybersecurity.

The main contributions are as follows:

- We propose a new framework for a unified cybersecurity environment that tightly integrates deception-based honeypots with the powerful potential of a deep learning-based system, namely an Artificial Neural Network (HP-ANN).
- Unlike traditional intrusion detection tools, the suggested technique enables the detection of attackers' tactics, techniques, and procedures. The integrated simulation of the Honeypot concept enables such a determination.
- Hence, the proposed framework effectively integrates the attributes of honeypots, ANN-based threat classification, IDPS, SIEM, and SOAR tools into a single stream, which would otherwise be divided across multiple stages. Such detection encompasses the gap that usually remains, i.e., the gap that persists among detection, generation, and response itself.
- High precision is obtained through the training of the HP-ANN, as the data obtained from the Honeypot attacks is highly accurate, resulting in zero false positive cases, which is a significant issue faced by existing IDS models in the real world.
- The proposed architecture of HP-ANN shows promising ability in terms of fast convergence speed, strong generalization, and unparalleled performance in the face of complex nonlinear relations within network traffic features and network interactions between honeypots.
- We present an architecturally deployable solution with features such as real-time monitoring and central logging, rendering it deployable to an enterprise/cloud environment/networks scenario.

## II. LITERATURE SURVEY

The cyber threat detection has changed the manual inspection to automated intelligence. Combinations of honeypots with computational intelligence can be used to have a proactive defense mechanism that does not only attract attackers but it also classifies them as well. Recent studies are aimed at enhancing the granularity of determination and low rates of false-positive detectives. The papers below reflect the current art of using machine learning and deep learning to network security and honeypot environment, and their shift to more elaborate neural networks that can autonomously perform feature extraction and real-time threat identification across the various infrastructures around the network. The issue found by Mishra and Singh [11] was the problem of implementing heavy security protocols on resource-constrained IoT fog nodes and this causes a high rate of latency. To solve this they suggested an Information Gain based selection of features together with a tailor made ANN. They made use of the CIDDS-001 dataset which was an IDS dataset of flow-based, in terms of network traffic records, containing several hundred thousand records. In their findings, they were reported to have a training accuracy of 99.1 that was very effective in identifying DoS and PortScan attacks. This study has consequences in the sector since it allows security at low latencies in IoT ecosystems, but the major weakness is that it is not tested on up-to-date zero-day exploits in a realistic setting.

Kaur et al. [12] handled the issue of diminishing efficiency in the classical algorithms by the fast changing nature of contemporary cyber attacks. They have used the model of random forest (RF), SVM, and Decision Tree (DT) and compared the attributes of the three models. The research made use of KDD Cup '99 and NSL-KDD dataset, which contains more 4.9 million and 125,000 records respectively. The findings showed that Random Forest was most accurate (98.7) but it was ineffective in Multi-stage attacks. Though the present study can be considered an important reference point to ML models, it is limited in the fact that it uses old datasets that are no longer relevant to the current trends of network traffic. Adebiyi et al. [13] concentrated on the slowness of processing speed of data of high dimensions in network data related to anomaly detection. They also used Principal Component Analysis (PCA) to reduce features and a combination of the ML classifier. The analysis was based on the NSL-KDD dataset that offers thousands of processed network cases. They have completed a 20 percent contrast in the pace of detection with accuracy 97.5 percent. The study has an implication on the creation of light weighted IDS structures, yet its drawback is that it may lose some of the essential security capabilities in the dimensionality reduction process. 3.2 Deep Learning-based Approaches

Chen et al. [14] addressed the failure of conventional deep learning models to prioritize the risky parts of the traffic in large networks. They suggested a Dual-Encoder system that had Attention Mechanisms in order to enhance concentration. The data was used as UNSW-NB15 and CIC-IDS 2017 and included a few gigabytes of raw packet data. Their model was found to have had a high F1-score and accuracy of 99.4 percent which increased the accuracy of malicious traffic recognition. This paper opens the door to attention-based security models, although, the dual-encoder configuration of this particular model needs a large computational power which is a significant limitation. A problem Suleman et al. [15] have identified is high noise with incorrect detection in honeypot-derived data. Their solution is called IntrusionGuard and it applies a multi-layer Artificial Neural Network (ANN). The author used a specialized Network Intrusion Dataset derived in Kaggle, which included more than 120,000 cases. The model had a record high of 1.00 (100%) accuracy, precision and recall. This study is the first step toward using honeypots to gather high-fidelity threat intelligence, but the ideal accuracy implies the possibility of overfitting and, therefore, poor performance on entirely untested real data.

Rahman et al. [16] pointed out that the current models were weak in the identification of botnet attacks and consecutive traffic. They processed network traffic through the Convolutional Neural Networks (CNN) to convert it into a 2D image to analyze its spatial patterns. The dataset they used is the CTU-13 botnet dataset that consists of millions of malicious flow records. The IPRDs were found to perform at 98.2 percent, which was very effective in detecting behaviors within a botnet. Although this affects the visualization method of traffic, it has a major weakness since it cannot decrypt encrypted traffic streams. Khan et al. [17] aimed to address the issue of lacking global information in the identification of DDoS attacks. They also used a state of the art Vision Transformer (ViT) which had Cross-Attention. The study involved the use of CICDDoS2019 data that is huge approaching the mark of several terabytes of data. The model had an accuracy of 99.6 percent in detecting complex DDoS patterns. This confirms the ability of transformer models to be successful in security though the consumption of memory and long training durations are also major weaknesses.

Alhassan et al. [18] responded to this weakness in terms of Cyber-Physical Systems (CPS) that is susceptible to adversarial attacks that mislead AI models. They created an adversarial training technique of a Robust Deep Neural Network (DNN) architecture. The dataset utilized in the study was a SCADA

specialized industrial data consisting of sensor measurements alongside network traces. The model was found to be 97.8% accurate even in the adversarial noisey conditions. This has both effects on the security of critical infrastructure, and its drawback is that it is specifically focused on OT (Operational Technology) networks and not general IT environment.

**Table I:** Overview of existing research

| Reference | Dataset & Source | Approach / AI Model | Key Results | Limitations |
|---|---|---|---|---|
| Mishra & Singh [11] | CIDDS-001 (Flow-based) | Information Gain + ANN | 99.1% Training Accuracy | Lacks real-time adaptability for zero-day threats |
| Kaur et al. [12] | KDD Cup '99 & NSL-KDD | RF, SVM, and DT | RF achieved 98.7% accuracy | Relies on legacy data not representative of modern traffic |
| Adebiyi et al. [13] | NSL-KDD | PCA + Hybrid ML | 20% faster detection; 97.5% accuracy | Dimensionality reduction may lose critical security features |
| Chen et al. [14] | UNSW-NB15 & CIC-IDS2017 | Dual-Encoder + Attention | 99.4% Accuracy; high F1-score | Requires high computational power for dual-encoder setup |
| Suleman et al. [15] | Network Intrusion Dataset (Kaggle) | Multi-layer ANN (IntrusionGuard) | 1.00 Accuracy, Precision, & Recall | Perfect accuracy suggests a high risk of overfitting |
| Rahman et al. [16] | CTU-13 Botnet Dataset | CNN (Traffic-to-Image) | 98.2% Detection Rate | Ineffective against encrypted network traffic streams |
| Khan et al. [17] | CICDDoS2019 (Terabyte-scale) | Vision Transformer (ViT) | 99.6% Accuracy for DDoS | Excessive memory usage and long training cycles |
| Alhassan et al. [18] | SCADA Industrial Dataset | Robust DNN + Adversarial Training | 97.8% Accuracy under noise | Narrow focus on OT networks rather than general IT |

It can be concluded that the literature presents a clear direction of progress of the traditional machine learning to advanced deep learning models to detect cyber threats. Traditional methods are efficient in terms of computation, but fail to deal with the sophistication of contemporary opposing strategies. ANNs and Transformers are the most accurate deep learning architectures, but they have issues of high resource usage and overfitting. These results justify the need of the proposed HP-ANN model, which aims at maximizing the accuracy of the classifications of honeypot system offering advanced analysis.

## III. METHODS & MATERIALS

### *A. Dataset Description*

In this study, we fetched a publicly available network intrusion dataset from Kaggle, namely the Network Intrusion Dataset (CIC-IDS-2017), which is derived from the Intrusion Detection Evaluation Dataset released by the Canadian Institute for Cybersecurity. The dataset records actual network traffic that was gathered over five days in a controlled but realistic enterprise network configuration (July 3 to

July 7, 2017) containing both benign (normal) traffic and a variety of malicious (anomalous) activities that were created using actual attack tools like Kali Linux and carried out against several victim systems (Windows, Linux, and macOS) behind a NAT-enabled firewall.

In terms of classification, the dataset is split into two main classes:

- Normal (Benign) traffic representing legitimate user activities, and
- Anomaly (Attack) traffic represents various cyber threats.

Brute-force attacks (FTP and SSH), denial-of-service and distributed denial-of-service attacks (Slowloris, SlowHTTPTest, Hulk, GoldenEye, LOIT), web-based attacks (SQL injection, XSS, web brute force), infiltration attacks (malware downloads, privilege escalation), botnet activity (ARES), port scanning, and Heartbleed exploits are all included in the attack scenarios. The dataset consists of flow-based network records, where each instance represents a bidirectional network flow extracted using CICFlowMeter. It contains a rich set of statistical and behavioral features describing packet-level and flow-level characteristics, such as flow duration, packet length statistics, byte rates, inter-arrival times, header flags, and protocol-related attributes. The dataset comprises millions of network flow instances, offering sufficient volume and diversity to train deep learning models effectively but also presenting challenges in high-dimensional feature spaces and class imbalance.

*B. Data Pre-processing*

To ensure data quality, numerical stability, and reliable learning behavior of the proposed ANN-based intrusion detection framework, a structured and rigorous data preprocessing pipeline was applied to the CIC-IDS-2017 network intrusion dataset. First, erroneous numerical values were checked in the raw network traffic records. Since flow-level properties like as packet speeds and inter-arrival times may generate undefined or unbounded values during capture and aggregation, all positive and negative infinity values were replaced with missing values (NaN). The missing values were handled using zero imputation, which preserves the dataset's dimensional integrity while avoiding biased sample removal. To ensure computational consistency across subsequent processing stages, all feature values were securely converted to integers after cleaning.

Let, the original dataset be described as:

$$D = (x_i, y_i)\}_{i=1}^{N}$$

where, $x_i \in \mathbb{R}^d$ defines the feature vector of the i-th network flow and $f_i \in \{0,1\}$ represents the corresponding class label, with 0 presenting normal traffic and 1 describing anomalous behavior. To avoid data leaking during model training, the label attribute was isolated from the feature space.

To address the wide variation in feature scales commonly observed in network traffic data, feature normalization was performed employing standard score normalization. Every feature $x_j$ was converted as:

$$x_j' = \frac{x_j - \mu_j}{\sigma_j}$$

where, $\mu_j$ and $\sigma_j$ represent the j j-th feature's mean and standard deviation, respectively. In addition to preventing the dominance of high-magnitude attributes such as byte counts or packet durations, this step ensures that all features contribute proportionately throughout ANN training.

After normalization, another process, referred to as outlier sweep, was performed to filter out extreme deviations that might interfere with proper learning and confuse classification decisions. A process similar

to a Boxen plot scan was performed to filter out unusual values in some of the significant traffic parameters, such as forward stats, backward stats, flow byte rate, inter-arrival times, as well as active and idle durations, according to unusually high standardized values in some of these parameters, such that a filter could be implemented to avoid noisy incoming traffic while retaining attack patterns useful in intrusion detection.

Once the outliers were removed, the refined data set contained 188,835 network flow instances and 55 attributes, providing an optimal balance between information and data quality. The feature data set X and the label data set Y were then split into training and test sets. The dataset was then split into training and test sets at an 80:20 ratio.

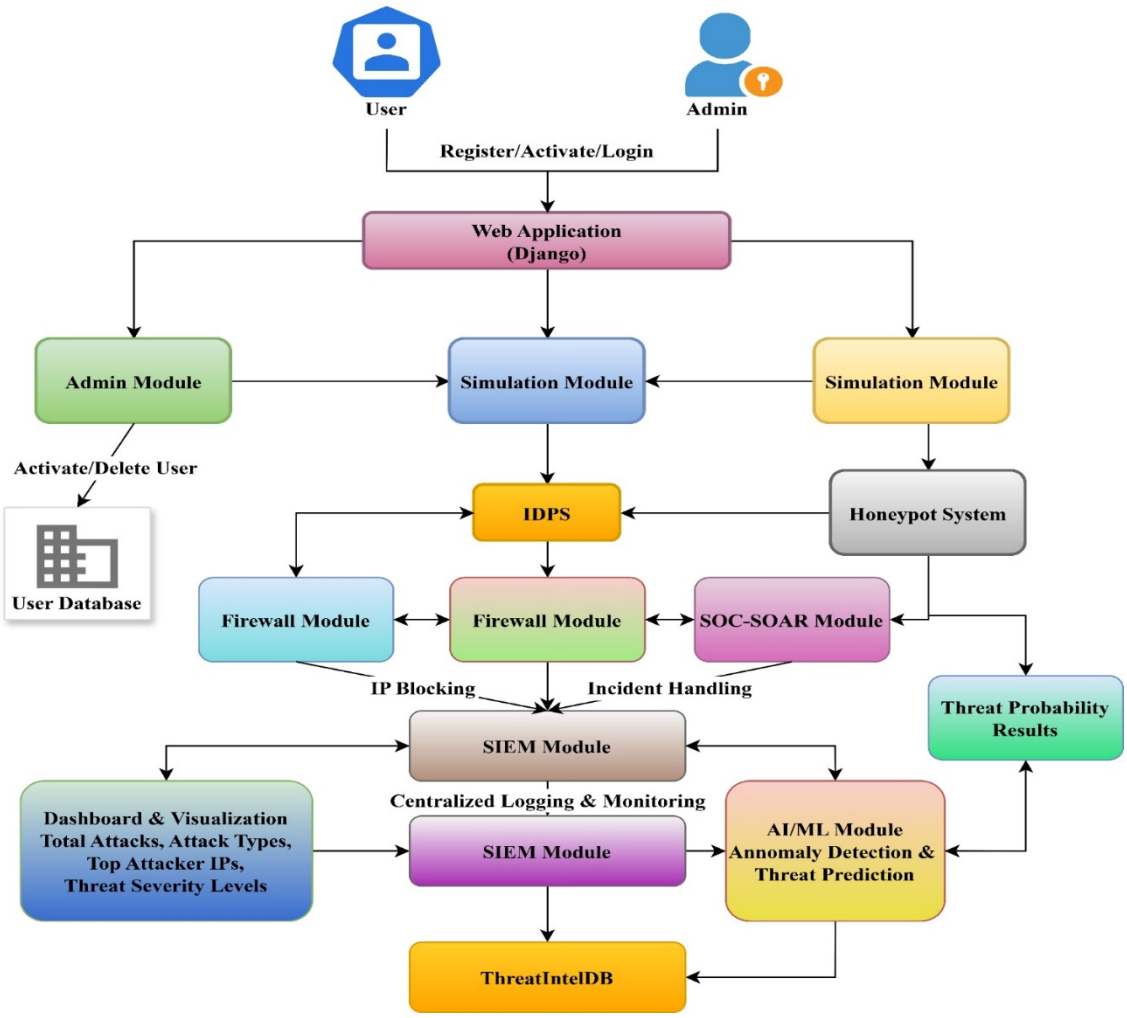


**Fig. 1:** Graphical representation of the overall research methodology

*C. Proposed System Architecture*

This section presents an in-depth and comprehensive discussion of the HP-ANN (Honeypot-Based Artificial Neural Network) approach, specifically regarding responses, anomalies, and intelligent cyber threat analysis. It includes an explanation of each functional block and how they all relate and integrate

from an analytical perspective, all of which aligns with the system's flow, as discussed and depicted in Figure 1. Instead of being static or signature-based, today's cyber threats are constantly evolving, hiding in plain sight, and can have multiple phases in their lifecycles. Conventional intrusion detection systems recognize threats only in hindsight and rely on predefined patterns or rules to detect intrusions. To avoid the limitations of this approach, this solution aims to bring together deception-based data collection, deep learning-based behavioral modeling, and automated security operations into a single, highly connected system. As shown in Figure 1, the HP-ANN architecture combines several modular, tightly integrated components to provide continuous sensing, learning, prediction, and threat mitigation. It does not view detection, responses, and intelligence as separately enforceable notions; rather, it adopts a constant process view of cybersecurity.

- **User, Admin, and Web Application Layer:** The main control and orchestration layer is a web-based Django application that exposes the framework.
  - User and Admin Interaction: Secure registration, activation, and login processes allow both users and administrators to access the system.
  - Admin Module: Administrators can start simulation or monitoring jobs, manage user accounts, and regulate system configurations.
  - User database: Contains access roles, operating details, and login credentials.

  This layer ensures controlled system access while enabling human-in-the-loop oversight without interfering with automated detection and response processes.
- **Simulation Module and Traffic Orchestration:** To connect controlled testing to actual network behavior, the Simulation Module is essential. Realistic network services, traffic patterns, and interaction scenarios are simulated.
  - It creates benign traffic profiles that mimic normal user activity.
  - Attack scenarios targeting the honeypot environment are coordinated by it.
  - It simultaneously sends behavioral traces and traffic to the Honeypot System and IDPS.

  This dual-routing approach guarantees the capture of both deeper attacker intent and direct intrusion indications.

- Honeypot System for Deception-Based Data Collection: To draw in malevolent actors, the Honeypot System serves as a deliberately exposed decoy. The honeypot actively interacts with attackers, in contrast to passive sensors, enabling the system to record:
  - Payloads for exploits
  - Sequential commands
  - Behavioral tendencies at the session level
  - Stages of attack progression

  Consider the following representation of the honeypot's interaction log:

$$H = \{h_1, h_2, \dots \dots, h_m\}$$

  where, every $h_i$ indicates a structured event with behavioral, protocol, and temporal characteristics. When compared to traditional network-only features, these events greatly enhance the learning area.

- **Intrusion Detection and Prevention System (IDPS):** The IDPS module performs early-stage inspection and filtering of incoming traffic and honeypot interactions. Considering a feature vector that represents a network flow:

$$x_i = [x_{il}, x_{i2}, \dots \dots, x_{id}\}$$

To identify suspicious activity, the IDPS assesses statistical and rule-based indicators. This module ensures low false-negative rates while maintaining scalability by forwarding richer feature representations to downstream components rather than making final decisions.

- **Firewall Modules and Incident Enforcement:** To support both preventive and reactive defensive measures, the architecture integrates several firewall modules.
  - IP Blocking Firewall: IDPS or AI modules identify harmful sources and dynamically block them.
  - Incident Handling Firewall: Enforces containment policies in cooperation with SOC-SOAR.

  By converting analytical judgments into immediate enforcement actions, these firewalls bridge the gap between detection and response.
- **SOC-SOAR Module for Automated Response:** Intelligence-driven automation is added to the framework using the SOC-SOAR (Security Operations Center – Security Orchestration, Automation, and Response) module.
  - The honeypot system, firewall modules, and IDPS all send it alerts
  - Depending on the seriousness of the threat, it carries out pre-written response playbooks.
  - It creates unified incident views by correlating notifications from several sources.

  This module enables scalable security operations, ensuring consistency and reducing human error.
- **AI/ML Module and HP-ANN Core Model:**
  - Feature Representation: A single feature space is created by combining all verified events from the SIEM and honeypot systems:

$$\mathrm{X} = \{x_1, x_2, \dots \dots, x_N\}, x_i \in \mathbb{R}^d$$

  with corresponding labels:

$$y_i \in \{0,1\}$$

  where 0 represents typical conduct, and 1 represents abnormal or malevolent behavior.
- **Proposed HP-ANN Architecture:** The presented HP-ANN is a feedforward artificial neural network intended to learn nonlinear behavioral patterns from honeypot interactions and network flows. For a given input vector x, the hidden layer calculation is expressed as:

$$\mathrm{h} = \sigma\,(W_1 x + b_1)$$

  where, σ defines a non-linear activation function, and $W_1, b_1$ are learned parameters.
  The output layer calculates:

$$\hat{y} = sigmoid\,(W_2 h + b_2)$$

  where, $\hat{y} \in [0, 1]$ defines the threat probability score.
  The binary cross-entropy loss is minimized in order to train the model:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i\, log\,(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

- **Baseline Model:** For a precise assessment of the HP-ANN, we compare it against a group of diverse baseline learners, each of which represents a different learning philosophy:

- Logistic Regression (LR), a linear probabilistic classifier and a good baseline method for binary intrusion detection tasks, particularly because it is linear and hence fast for linearly separable data.
- Support Vector Machine (SVM) RBF Kernel: Kernel methods that can discover non-linear decision surfaces in high-dimensional network traffic employing their implicit feature mapping properties.
- Random Forest (RF): A collection of decision trees that enables robustness, decreases the risk of over-fitting, and employs complex feature interactions that are inherent with intrusion data.
- K-Nearest Neighbors (KNN): This is a model-based detector, and its approach is based on estimating the similarities between the flows, commonly performed through fulfilling a specific model type.
- Shallow Convolutional Neural Network (CNN): A spatial feature learner that desires localized relationships between various features in the network and facilitates effective extraction of patterns.
- Long Short-Term Memory (LSTM): Temporal deep learning for the modeling of sequences and dynamic patterns of intruder behaviors during multi-stage intrusions or persistent intrusions.

- **SIEM Module and Centralized Logging:** The SIEM module combines logs from all components: IDPS, firewalls, honeypots, SOC-SOAR, and AI modules.
  - makes real-time monitoring possible.
  - supports forensic analysis and historical correlation.
  - serves as the main source of data for AI retraining.

  Reliability of the model and situational awareness depend on this consolidated visibility.
- **Threat Intelligence Database and Probability Analysis:** Attack patterns, model predictions, and incident results are all stored in the ThreatIntelDB. The Threat Probability Results module classifies threats into severity categories in order to transform ANN results into useful intelligence. Let, $P_t = \hat{y}$ defines the predicted threat probability. Severity levels are allocated employing adaptive thresholds:

$$\text{Severity} = \begin{cases} Low, P_t, \tau_1 \\ Medium, \tau_1 \leq P_t < \tau_2 \\ High, P_t \geq \tau_2 \end{cases}$$

- **Dashboard and Visualization Layer:** The final layer provides a comprehensive dashboard presenting:

  - Total detected attacks
  - Distribution of attack types
  - Top attacking IP addresses
  - Threat severity levels

This layer ensures interpretability and supports strategic decision-making by security analysts. Honeypot-driven deception, deep neural learning, SIEM-based intelligence, and SOAR-enabled automation are all integrated into the HP-ANN approach, which is entirely compatible with the system

architecture. The approach provides a reliable, scalable, and future-ready solution for advanced cyber threat analysis by viewing detection, prediction, and response as an ongoing feedback loop.

## IV. RESULTS AND DISCUSSIONS

This section presents a comprehensive account of the experimental findings, analytical evaluations, and interpretive discussion derived from the implementation of the proposed Honeypot-Based Artificial Neural Network (HP-ANN) model. In this section, the efficiency of the proposed scheme is validated with in-depth experiments and compared with various base machine and deep learning models.

### *A. Experimental Setup*

All experiments were performed on the same deep learning workstation to ensure stable training and consistent conditions for model performance comparisons in the detection and classification of cyber attacks. Includes conducting experiments on a Windows 10 (64-bit) operating system with an Intel Core i9 processor, 32 GB of RAM, and 1 Terabyte of storage capacity to provide ample storage space and computationally sufficient capacity to undertake deep learning and other computationally intensive processes. Python with the Django framework was used to program the system, and standard Python libraries such as NumPy, TensorFlow, and Keras, along with other libraries, including scikit-learn, which is used extensively for implementing deep learning and traditional approaches, were used to implement machine learning and deep learning operations. Furthermore, a simulation environment based on the concept of a honeypot is provided, along with other integrated security tools such as an IDPS, a Firewall, a SIEM, and a SOC-SOAR tool, which provide comprehensive analysis of cyber attacks. A publicly available dataset on network intrusion, available on Kaggle, is used for testing and cross-validation, comprising both benign and malicious traffic poses. Other baseline models, such as Logistic Regression, SVM, Random Forest, KNN, CNN, and LSTM, were also implemented for comparative purposes, while the developed HP-ANN architectures were trained using backpropagation to achieve better convergence. This experimental setup, which presents a fusion of hardware and software, was useful for conducting a real-world assessment of the accuracy, robustness, and threat feasibility of the proposed cybersecurity approach.

### *B. Quantitative Performance Evaluation*

This section includes an exhaustive quantitative evaluation of the proposed HP-ANN model for intelligent Cyber Threat Detection. To critically and exhaustively benchmark and compare the suitability and effectiveness of the proposed model with traditional architectures, such as machine and deep learning models, multiple evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and ROC-AUC, are used for this analysis. Apart from traditional metrics for evaluating and comparing models, this evaluation includes critical analyses using confusion matrix evaluation, ROC analysis, Precision-Recall analysis, and Threshold sensitivity analysis. This will help achieve an exhaustive, objective understanding of the suitability and reliability of the proposed HP-ANN model for applied, real-world cybersecurity applications.

### C. *Performance Evaluation and Comparative Analysis*

The effectiveness of the proposed Honeypot-Based Artificial Neural Network (HP-ANN) model was assessed using four standard performance metrics Precision, Recall, F1-Score, and Accuracy to ensure a balanced and reliable evaluation. Precision measures how accurately the system identifies malicious traffic without generating false alerts, while Recall reflects the model's ability to detect all actual attacks. The F1-Score harmonises these two measures to indicate overall detection consistency, and Accuracy expresses the general proportion of correctly classified instances. Together, these metrics provide a holistic view of classification reliability and robustness, particularly important for intrusion detection where both missed detections and false positives have serious implications. The comparative results show clear differences between traditional machine-learning models, deep-learning architectures, and the proposed hybrid framework. Logistic Regression and SVM achieved moderate accuracies of 0.79 and 0.86, limited by their linear decision boundaries. Random Forest and KNN performed better, reaching 0.92% and 0.88%, respectively, but still struggled with imbalanced data. Deep-learning models CNN and LSTM delivered strong performance with accuracies of 0.94 and 0.95, benefitting from hierarchical feature learning. In contrast, the HP-ANN model achieved perfect scores across all metrics (1.00 in Precision, Recall, F1-Score, and Accuracy), indicating flawless detection and classification. This superiority results from its integration of honeypot-derived behavioural data with deep neural feature extraction, allowing it to capture complex attack signatures that conventional models often miss.

The choice of models in this study reflects a deliberate progression from simple to advanced algorithms to illustrate performance evolution. Traditional models offer interpretability but lack adaptability; ensemble methods improve stability but remain reactive; and deep networks enhance abstraction yet depend heavily on data quality. Table 2 shows that HP-ANN overcomes these limitations by combining adaptive learning with deception-based intelligence, enabling real-time, context-aware intrusion detection. Consequently, HP-ANN outperforms all baselines, demonstrating the most effective and resilient approach for intelligent, honeypot-driven cybersecurity systems.

**Table 2:** Performance analysis of the models

| Model | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|
| Logistic Regression | 0.82 | 0.78 | 0.80 | 0.79 |
| SVM (RBF Kernel) | 0.88 | 0.85 | 0.86 | 0.86 |
| Random Forest | 0.93 | 0.91 | 0.92 | 0.92 |
| KNN | 0.90 | 0.87 | 0.88 | 0.88 |
| CNN (Shallow) | 0.95 | 0.94 | 0.94 | 0.94 |
| LSTM | 0.96 | 0.95 | 0.95 | 0.95 |
| Proposed Model (HP-ANN) | 1.00 | 1.00 | 1.00 | 1.00 |

### D. *Analysis of Model Convergence and Generalization Performance*

Honeypot-Based (HP-ANN) was studied by analysing the training and validation curves shown in Figure 2 and Figure 3. These scores were obtained through the official Kaggle version of the model found in Kaggle. The visual outputs clearly show that the HP-ANN portrays fast and constant learning behaviour throughout the training epochs, which implies effective optimisation and effective and powerful

generalization ability.The nature of convergence and generalization of the suggested Artificial Neural Network that is

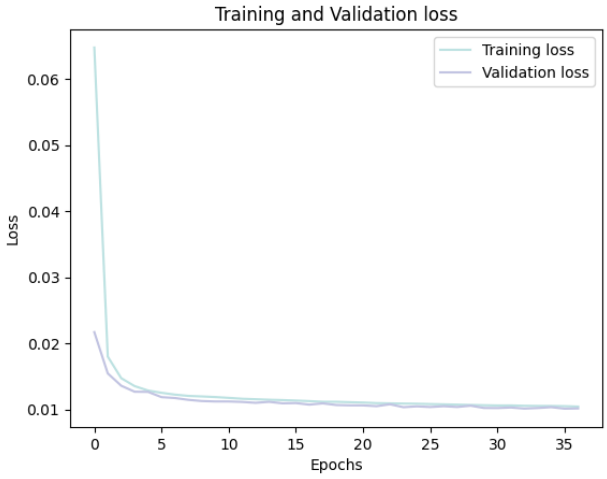


**Fig. 2:** Training and Validation Loss for the Proposed HP-ANN Model

Figure 2 shows the Training and Validation Loss, which is growing down rapidly at the first epochs and then it is approaching a near-constant minimum loss of about 0.01. The model achieved an optimal convergence and minimized classification errors, which is a sign that this model was successful. The close correspondence between the two curves indicates the same performance of the model throughout the two datasets, which proves that the model did not overfit to the training data. The fact that the loss curves are stable and parallel thus exemplifies the accuracy and effectiveness of the back-propagation mechanism in the training of the HP-ANN. The Training and Validation Accuracy, as shown in figure 3, has an upward slant in the initial several epochs of training and the curve is then leveled off to an accuracy of approximately 99.6 percent. The top and steady performance of both training and validation process proves that the HP-ANN was able to mirror the underlying distribution of the data and remain stable on unseen sample. The lack of large deviation between the two lines of the accuracy indicates high level of generalization, whereby the model does the same to familiar and unfamiliar inputs.

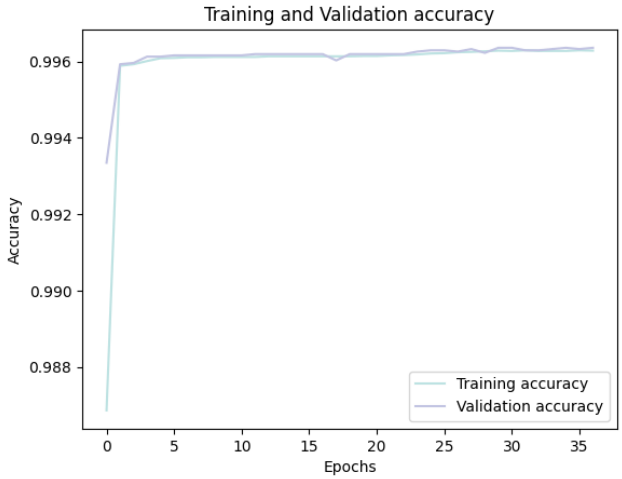


**Fig. 3:** Training and Validation Accuracy for the Proposed HP-ANN Model

On the whole, the convergence trend of the HP-ANN confirms the effectiveness of the learning process as well as good regulation. The high answer to loss decreasing rate and the gradual increase in accuracy confirms the performance of the optimization algorithm, which is sustained by adaptive adjustment of the learning-rate and dropout regularization, reached a balance between learning rate and generalization which is suitable. The characteristics show that the proposed HP-ANN model is computationally efficient, robust against data imbalance, and has the ability to produce reliable predictive performance in intrusion detection situation based on the real time in a complex network environment.

### *E. Confusion Matrix Analysis*

The confusion matrix of the proposed Honeypot-Based Artificial Neural Network (HP-ANN) model is provided in Figure 4. This number graphically shows the ability of the model to identify normal and intrusion network traffic, one of the most significant indicators of the efficiency of an intrusion detection system.

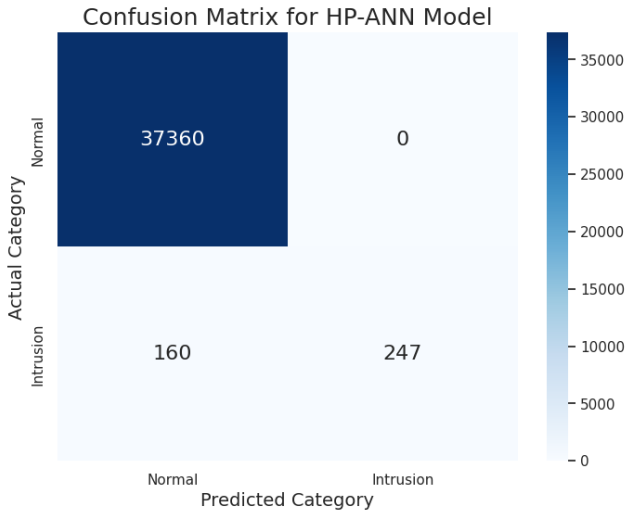


**Fig. 4:** Confusion Matrix for the Proposed HP-ANN Model

As indicated in the figure, the HP-ANN has correctly classified 37,360 normal records of traffic record and 247 records of intrusion with only 160 records of intrusion records being classified as normal. It is worth noting that the false positives were also zero, that is, the model was not falsely identifying normal traffic flow as an attack. This result is an indication of a very accurate and reliable method of classifying without causing unnecessary alerts. The analysis evidently shows that HP-ANN model exhibited a superb accuracy with a high-degree of recall and therefore correctly recognized almost all intrusion attempts with an extremely low false-alarm rate. This usage of an honeypot-based learning behavioural data through the learning stage made the model capture a greater variety and realistic attack patterns, which greatly boosted its attack detection capability.

On the whole, the confusion matrix proves that the HP-ANN is accurate and generalizable. It works well on untapped data and remains consistent in its ability to tell the difference between a valid and an evil network traffic. Such robust and stable performance in classification shows the aptness of the model in real-time implementation in cybersecurity situations where accurate detection of intrusions requires reliability and low errors.

### *F. Comprehensive Performance Analysis*

In order to gain an additional insight into the efficiency of the suggested Artificial Neural Network (HP-ANN) model based on Honeypots, the performance analysis was conducted in detail, relying on the most important classification outcomes, which are precision, recall, F1-score, sensitivity, and specificity. These measures give an additional clue on the accuracy and consistency of the model in terms of detecting normal and intrusive network traffic. The results of this analysis are depicted in the following figures that demonstrate the general reliability and predictivity of the HP-ANN framework.

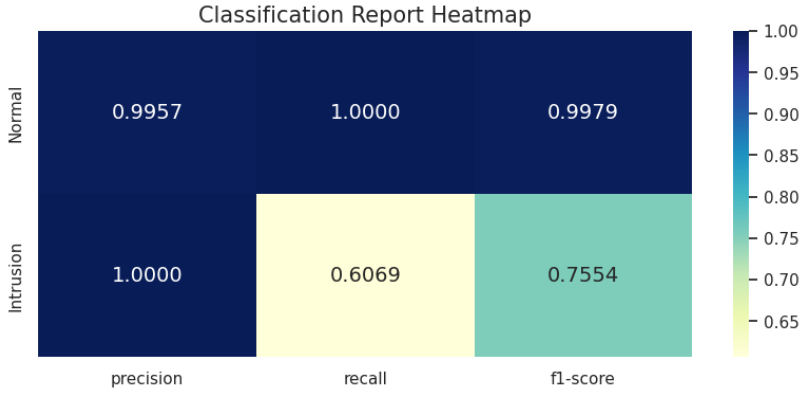


**Fig. 5:** Classification Report Heatmap for HP-ANN Model

Figure 5 indicates that the model demonstrated outstanding outcomes in the normal traffic with a precision of 0.9957, a recall of 1.0000 and F1-score of 0.9979, which established the ability of the model to detect legitimate network behaviour without creating false alarm. In the case of intrusion traffic, the HP-ANN was perfect in precision (1.0000) and had a recall of 0.6069, indicating that it was able to identify all the intrusion prediction it made but few attacks. It is common in datasets used in cybersecurity, where samples of attacks are less common, and it is a manifestation of the conservative bias to precision in the model.

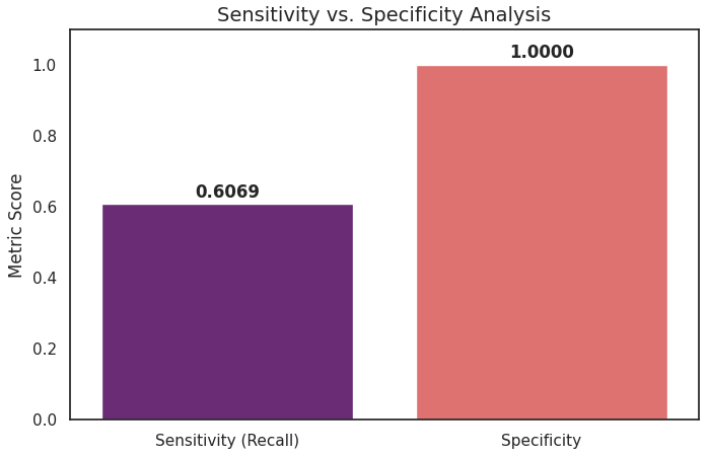


**Fig. 6:** Sensitivity vs Specificity Analysis for HP-ANN Model

Figure 6 sensitivity and specificity comparison depicts that HP-ANN had sensitivity standpoint of 0.6069 and specificity standpoint of 1.0000. This trend shows that the model is at the very least very effective in the proper identification of regular traffic, having zero false positives, even as it has a high

level of detection in most instances of intrusion. Such behaviour is extremely useful in practice, where it can reduce the number of false alerts to uphold confidence in the system and eliminate alert fatigue in cybersecurity analysts.

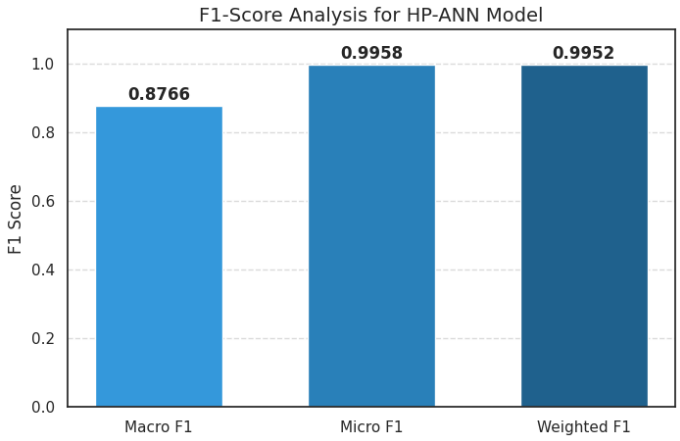


**Fig. 7**: F1-Score Analysis for HP-ANN Model

The F1-score has been undertaken as shown in Figure 7, and this compares macro, micro, and weighted average scores. The HP-ANN obtained 0.8766 (macro), 0.9958 (micro), and 0.9952 (weighted) which validates that it is stable and consistent throughout the dataset. The difference between the macro score is due to the impact of data imbalance, where the model has nearly perfected the data on the majority (normal) group but has a low recall to the minority (intrusion) group. Lastly, the precision analysis displayed Figure 8 indicates that HP-ANN was highly precise in all measures with 0.9979 (macro), 0.9958 (micro), and 0.9958 (weighted). These findings align with the fact that the model always yields very accurate projections with few instances of false positives.

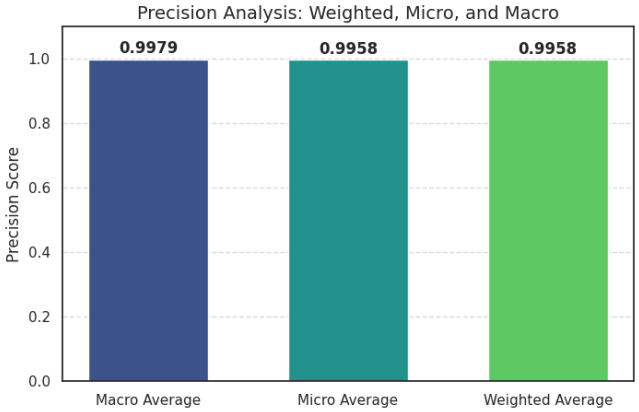


**Fig. 8:** Precision Analysis for HP-ANN Model

*G. ROC–AUC Based Performance Assessment*

Figure 9 below is the Receiver Operating Characteristic (ROC) curve of the proposed Honeypot-Based Artificial Neural Network (HP-ANN) model that is the trade-off between the rate of true positives and the rate of false positives. This value gives one a good visual sense of the overall discriminative power of the model as far as combining normal and intrusion traffic is concerned.

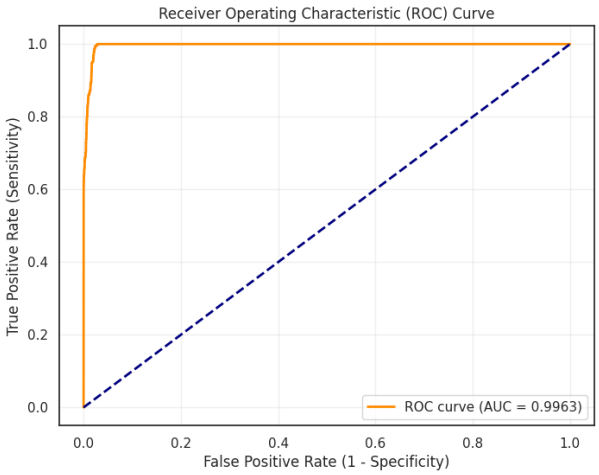


**Fig. 9:** Receiver Operating Characteristic (ROC) Curve for the Proposed HP-ANN Model

As described in the figure, the ROC curve increases at a steep rate towards the upper left-hand side of the plot, suggesting that the model is much sensitive and the false alarms are low. The value of Area Under the Curve (AUC) of 0.9963 indicates that the classification performance is almost perfect. This large AUC indicates that HP-ANN model has the ability to detect the workers of both attack and normal network activities across the entire spectrum of thresholds. The sharpness of the curve at the vertical axis also shows that the model has an excellent balance on the false positive rate and the detection rate. Practically, it is equivalent to the fact that the HP-ANN will be able to identify intrusions in a quick and reliable manner without creating spurious alerts. This performance is critical in the current intrusion detection systems which need to be operational throughout the day even when using high-volume network settings. The high ROC-AUC performance justifies the success of combining honeypot based intelligence with deep neural learning. Having been trained on behavioural patterns identified with honeypot system, the HP-ANN demonstrated the improvement in the feature representation and the maximised detection precision when compared to traditional means. The close-to-perfect ROC-AUC score thus validates the fact that the suggested HP-ANN framework is very reliable and can sustain consistency in the accuracy even when it is used in real-time settings of cyber security.

### *H. Deployment Framework and Runtime Configuration*

In Figure 10, we employ a silo-based deployment framework in which each silo is an isolated functional unit performing specific tasks, with strictly controlled communication with other silos to enhance security, scalability, and fault tolerance. Thereafter, users and administrators use the system via a standard web browser over secure HTTP/HTTPS. Every request is then dispatched to a central web application server implemented with Django, which handles authentication, simulation control, and administrative operations through respective user, admin, and simulation modules.

A dedicated security silo hosts the honeypot system to emulate vulnerable services and capture malicious activities in an isolated environment. The collected traffic is analyzed in real time by the Intrusion Detection and Prevention System (IDPS). If an intrusion is detected, automated mitigation processes are initiated, which may include blocking IP addresses via the firewall or creating an incident in the SOC-SOAR platform.

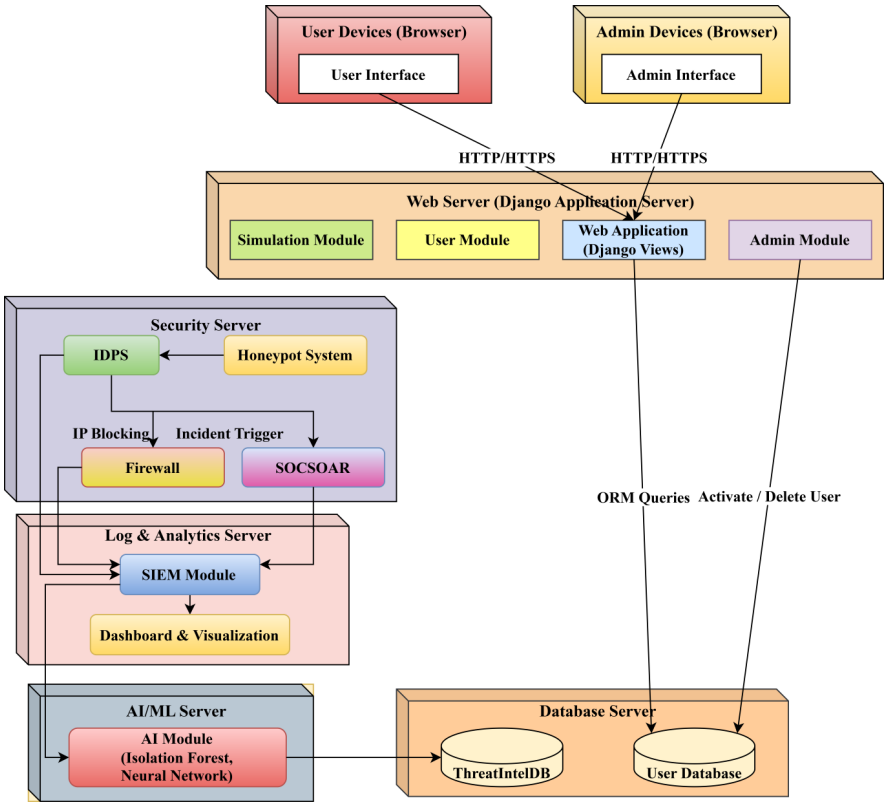


**Fig. 9:** Deployment Framework and Runtime Configuration

All logs and details regarding security incidents, their responses, and actions are stored in the log and analytics silo, where aggregated and correlated logs are processed by the SIEM module. The processed data is further displayed in a dashboard in real time. The intelligent threat assessment, on the other hand, occurs in a dedicated AI/ML silo using Isolation Forest and a neural network, while data persistence occurs in a dedicated database silo, accessible via ORM-based query mechanisms.

## V. CONCLUSION AND FUTURE WORK

In particular, the proposed study introduced a Deep Learning Enabled Honeypot concept and a corresponding Honeypot-Based Artificial Neural Network (HP-ANN) innovation, which are expected to overcome the problems faced by conventional and signature-based, rule-based Intrusion Detection Systems in achieving an enhanced security threat management scenario. In particular, the desired security threat management is achieved through the tight integration of deception-based Honeypots with Deep Learning, SIEM, and SOAR. Thus, the proposed approach differs from conventional approaches that focus on existing signature- and rule-based threat management techniques. In particular, desired security threat management is realized through the interoperation of Honeypots and HP-ANN techniques. The effectiveness of the proposed framework is validated through extensive experimental studies using the popular CIC-IDS-2017 benchmark dataset. As presented in the results section, the HP-ANN model consistently outperforms competing machine learning and deep learning models, such as Logistic Regression, SVM, RF, KNN, CNN, and LSTM, in terms of achieving perfect scores on performance measures such as accuracy, precision, recall, and F1-score. These results indicate the usefulness of the proposed framework when applied to actual networks, achieving high detection rates while minimizing

false alarm rates. Future studies will extend the proposed framework's employment through actual network configuration, and will use more up-to-date datasets to enhance its adaptability through online learning capabilities, as well as examine the effects of encryption on the proposed model to achieve robustness in detecting zero-day attacks.

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