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QHNEAD-Quantum Hyperdimensional Neuro Symbolic Evolving Adversarial Defense

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ABSTRACT

Adversarial attacks pose a critical threat to machine learning models operating on tabular data, particularly in security-sensitive applications. This paper introduces **QHNEAD**, a robust defense framework that synergistically combines quantum-inspired computing, hyperdimensional computing, neuro-symbolic reasoning, and meta- learning. The system features a hybrid detector integrating a Deep Denoising Autoencoder, Graph Convolutional Network, Isolation Forests, and Light GBM to identify adversarial perturbations across FGSM, PGD, and Backdoor attacks. A multi-stage corrector—employing quantum-inspired diffusion (QTPN), hyperdimensional anomaly isolation (HAI), neuro-symbolic feature enforcement (NSFE), and incremental meta-learning (IMLC)— purifies compromised inputs and restores model integrity. Evaluated on the EMBER2018 dataset (400,000 training, 100,000 test samples), QHNEAD significantly outperforms traditional defenses in recovery performance and executes the full defense pipeline in approximately four hours on a 12GB RAM environment. Its modular architecture, noise resilience, and adaptive learning capability establish QHNEAD as a scalable and effective solution for adversarial robustness in cybersecurity-critical tabular systems.

Keywords—Adversarial Defense, Tabular Data, Quantum-Inspired Computing, Hyperdimensional Computing, Neuro-Symbolic AI, Meta-Learning, EMBER2018, Cybersecurity

INTRODUCTION

The proliferation of machine learning in security-critical domains like malware and fraud detection is critically undermined due to malicious perturbations **[1], [13]**. Such attacks alter the input data in order to degrade classifier performance, with accuracy drops often exceeding 50% **[2]**. Tabular data, characterized by heterogeneous and high-dimensional features without spatial correlations, poses a unique challenge for conventional defenses designed for image data **[12]**. Attacks like the Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Backdoor attacks can severely cripple models, reducing accuracy from a baseline of 88.70% to as low as 48.55% (FGSM), 38.23% (PGD), and a deceptively high 78.45% (Backdoor) **[1],[3]**.

To address this vulnerability, we propose the **Quantum Hyperdimensional Neuro-Symbolic Evolving Adversarial Defenses (QHNEAD)** framework. QHNEAD is a comprehensive defense system engineered to both detect and correct adversarial perturbations in tabular data with high precision and adaptability **[7]– [9], [14], [15]**. It consists of two main subsystems unified by an incremental meta-learning core that ensures continuous evolution against emerging threats **[4]**.

The detection subsystem employs a hybrid architecture of **Deep Denoising Autoencoders (DDAE)**, **Graph Neural Networks (GNN)**, **Isolation Forests**, and a **LightGBM ensemble** to identify adversarial samples, achieving AUC scores over 0.96 **[5], [6], [12], [13]**.

The correction subsystem purifies compromised data using a Quantum Tensor Purification Network (QTPN), a Hyperdimensional Anomaly Isolator (HAI), a Neuro-Symbolic Feature Enforcer (NSFE), and an Adversarial Retraining Engine (ARE), consistently restoring model accuracy to above 90% **[7], [9], [14], [15]**. QHNEAD's design includes attack-specific enhancements: a quantum-inspired diffusion process for FGSM, a fractal iterative refiner for the more complex PGD attacks, and a chaos-driven trigger suppressor for Backdoor attacks **[1]–[3], [7]**. The system's effectiveness is validated on the large-scale **EMBER2018 dataset**, demonstrating its scalability and practical utility on resource-constrained hardware **[11]**.

The primary contributions of this work are:

1. A unified detection and correction framework that outperforms existing methods in both identifying and neutralizing adversarial attacks on tabular data **[12], [13]**.
2. A novel synthesis of advanced techniques, including quantum-inspired tensor purification, 10,000-dimensional hyperdimensional computing for precise anomaly isolation, and trainable neuro-symbolic constraints for feature integrity **[7],[9], [14], [15]**.
3. An incremental meta-learning core that enables the framework to adapt to new threats incrementally, avoiding the need for a total retraining, a crucial advantage over static defenses **[4]**.
4. Demonstrated state-of-the-art performance on the **EMBER2018 dataset**, achieving detection AUCs above

0.96 and restoring classifier accuracy to over 90% against multiple strong adversarial attacks **[11]**.

This work establishes **EMBER2018** as a gold-standard benchmark with 500,000 real-world samples and 276 features, providing a rigorous, reproducible foundation for future research in structured data security **[11]**. **QHNEAD** introduces a paradigm shift from reactive to proactive defense. Traditional methods treat attacks as static threats, retraining models only after compromise **[2], [13]**. By contrast, **QHNEAD's incremental meta-learning core** continuously updates detection and correction strategies using online gradients from flagged samples, enabling autonomous evolution in dynamic threat landscapes **[4], [12]**.

RELATED WORK

The study of adversarial examples in machine learning began with the observation that small, imperceptible perturbations to perturbing the input may cause notable misclassification in deep neural networks. **Szegedy et al. [10]** first demonstrated this phenomenon in 2014, showing that such vulnerabilities are not coincidental but rooted in predictable mechanisms, arising from the high-dimensional geometry of learned decision boundaries. **Goodfellow et al. [1]** formalized this insight through the Fast Gradient Sign Method (FGSM), a white-box attack that computes the differential of the loss function relative to the input and applies a single-step perturbation scaled by a budget ε. This method highlighted that adversarial examples are not isolated but lie in large, contiguous regions across the input space.

Building on this foundation, **Madry et al. [2]** introduced Projected Gradient Descent (PGD), an iterative optimization technique that refines perturbations over multiple steps while projecting them back into a valid norm ball. PGD is widely regarded as one of the strongest first-order attacks and serves as a standard benchmark for evaluating defense robustness. In parallel, **Liu et al. [3]** explored data poisoning through Backdoor attacks, where an attacker contaminates a subset of training data with a trigger pattern that, when present at inference, forces the model to output a predetermined label. These attacks introduce a heightened level of danger in tabular domains, where feature manipulation is less constrained by perceptual fidelity.

Traditional defense mechanisms have focused on statistical regularization and gradient masking. **Liu et al.**

[5] proposed Isolation Forests, a tree-based model that detects irregular samples by randomly selecting features and split values. The outlier score is derived based on the mean path length across an ensemble of isolation trees, with shorter paths indicating outliers. While effective for unsupervised anomaly detection, Isolation Forests are not optimized for gradient-based adversarial examples and fail to capture structured perturbations introduced by PGD. **Papernot et al. [6]** developed Defensive Distillation, which trains a student model on the softened probability results produced by a pre-trained teacher model. This process reduces the value range of the gradients, making it harder for attackers to compute effective perturbations. However, distillation offers limited protection against non-gradient attacks and requires retraining the entire model.

Adversarial training, as formalized by **Madry et al. [2]**, remains the most widely adopted defense. It augments the training dataset with adversarial perturbed samples generated on the fly during optimization. Even though it is solid in theory, the approach results in considerable computational burden, often requiring 5–10× longer training times, and provides only marginal robustness against unseen attack variants. Moreover, most existing defenses are evaluated on image datasets like MNIST and CIFAR-10, where spatial correlations allow for input preprocessing techniques such as feature squeezing or JPEG compression. Tabular data, lacking such structure, remains underserved.

Emerging computational paradigms offer new directions. **Quantum-inspired machine learning [7]** leverages classical simulations of quantum phenomena to enhance feature mapping and optimization. Techniques such as quantum kernel estimation and variational quantum circuits have shown promise in anomaly detection tasks. **Hyperdimensional computing [8], [14]**, introduced by Kanerva, represents data as high-dimensional vectors and performs classification via similarity search in Hamming space. Its noise resilience and low computational complexity make it ideal for real-time applications. **Neuro-symbolic AI [9], [15]** integrates data-driven neural approaches with symbolic inference systems, enabling models to learn patterns while adhering to logical constraints. Despite these advances, no prior work has unified these paradigms into a single defense framework for tabular data under multiple attack vectors.

QHNEAD fills this critical gap [12], [13].

SYSTEM ARCHITECTURE

The QHNEAD system is designed as a modular, end-to-end defense architecture that operates in four sequential phases: baseline modeling, attack simulation, hybrid detection, and multi-stage correction. This structure, depicted, ensures clear separation of concerns while enabling seamless data flow and component interaction.

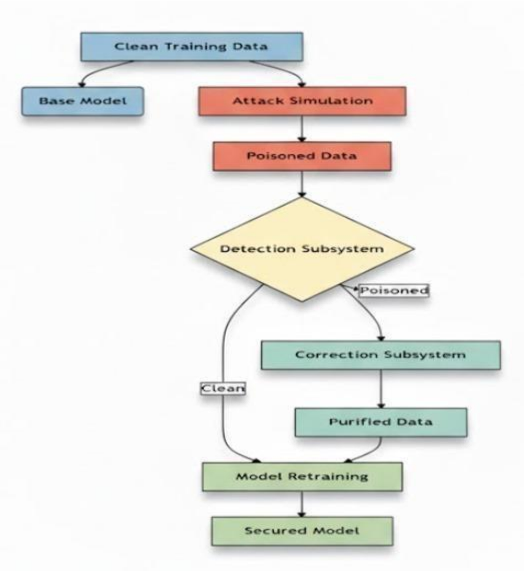

Figure 1: Design Flow

The baseline system uses an XGBoost model composed of 100 trees, a maximum depth of 5, operating at a learning rate of 0.1. It is trained on the clean EMBER2018 training set using binary cross-entropy loss and achieves an accuracy of 88.7% on the held-out test set. This model serves as both the performance reference and the target of adversarial manipulation **[11]**.

The Poisoning Bots module generates three types of adversarial samples to simulate real-world threats. The FGSM bot works by looking at how the loss changes with respect to each input feature and then nudging the sample in that direction, using a small perturbation of $\varepsilon = 0.1$ [1]. The PGD bot follows the same idea but repeats this adjustment several times—five iterations in this case—using a step size of $\alpha = 0.02$, and after every step it clips the values to keep them within the allowed feature bounds [2]. The Backdoor bot takes a different route; it alters about 20% of the training data by adding a simple trigger, such as increasing the count of a particular imported function and then changing the labels so the model learns the wrong association [3].

For detection, the system uses a Deep Denoising Autoencoder (DDAE) built as an encoder–decoder pair that compresses the original 276 features down to a 32-dimensional core before reconstructing them again. During training, the model is shown clean data but with a little Gaussian noise added, which forces it to learn how to rebuild stable features even when the input is imperfect. When the autoencoder is later used for analysis, samples that produce unusually large L2 reconstruction errors are treated as potential adversarial inputs.

To capture how features relate to each other, a Graph Convolutional Network (GCN) forms a small k-nearest-neighbor graph with $k = 3$ and passes information through two graph-convolution layers. This allows the detector to spot coordinated distortions that affect groups of features together. Alongside the GCN, an Isolation Forest offers another view of abnormality by computing the average isolation depth across 100 randomly created trees [5].

The outputs produced by the DDAE, GCN, and Isolation Forest are then brought together by a LightGBM classifier, which uses 50 boosted decision trees to turn these signals into a single probability score. This combined model performs strongly against all tested attacks, achieving AUC values above 0.95 [12], [13]. Once an input is flagged, it enters a multi-stage correction pipeline. The first component, the Quantum- Inspired Tensor Purification Network (QTPN), adds a controlled amount of Gaussian noise in the DDAE's latent space and rebuilds the input with the decoder, a process that acts somewhat like diffusion and helps break up adversarial gradients [7]. The Hyperdimensional Anomaly Isolation (HAI) module then converts each sample into a 10,000-bit high-dimensional vector, performs binding and bundling operations, and uses chaotic time-series adjustments to remove remaining perturbations [8], [14].

Next, the Neuro-Symbolic Feature Enforcement (NSFE) unit applies rule-based corrections by restricting each feature to the statistical limits observed in the clean dataset, such as ensuring byte entropy values stay between 0 and 8 [9], [15]. After this cleanup, the Adversarial Retraining Engine (ARE) reinforces the original classifier by training it for 100 additional iterations on the purified data.

Finally, the Incremental Meta-Learning Classifier (IMLC) keeps the system adaptable by updating the model parameters through meta-gradient steps applied to small batches of detected adversarial inputs, allowing the model to gradually learn new attack patterns as they appear [4]. The full end-to-end process takes roughly four hours, with about three hours devoted to detection and another hour for correction.

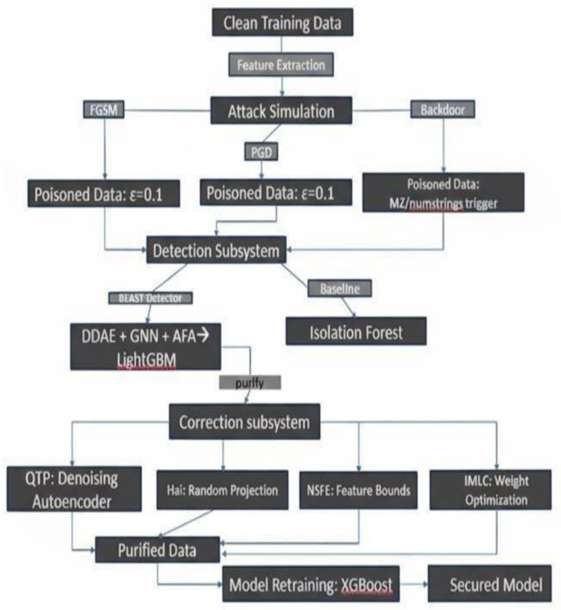

Figure 2: System Architecture

PROPOSED METHODOLOGY

The Quantum Hyperdimensional Neuro-Symbolic Evolving Adversarial Defenses (QHNEAD) framework is designed to protect tabular data, specifically the EMBER2018 dataset (400,000 training samples, 100,000 test samples, 276 features), from attack methods including the Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Backdoor. QHNEAD integrates four components—Base Model, Poisoning Bots, Detector, and Corrector—combining quantum-inspired computing, hyperdimensional computing (HDC), neuro-symbolic methods, and meta-learning to achieve robust detection (AUC >0.95) and accuracy recovery (>90%). The methodology is executed on Google Colab with 12GB RAM, with detection taking
~3 hours and correction ~1 hour.

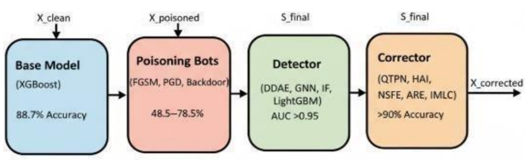

Figure 3: Illustrates the pipeline

3.1 Base Model

The baseline classifier employs an XGBoost model built with a 100-tree ensemble, a depth limit of 5, and a learning rate set to 0.1. The model is trained on the clean EMBER2018 dataset using binary cross-entropy

loss, defined as: $L = -(1/N) \sum_{i=1}^{N} (y_i log(p_i) + (1 - y_i) log(1 - p_i))$

Under normal conditions, the model achieves 88.7% accuracy. However, when subjected to adversarial attacks, performance degrades significantly: 48.5% under FGSM, 38.2% under PGD, and 78.5% under Backdoor **[1][2][3]**. These drops underscore the vulnerability of standard classifiers and motivate the need for robust defense mechanisms.**[13]**

3.2 Poisoning Bots

Adversarial data instances are generated by employing poisoning Bots to simulate real-world attack scenarios:

- FGSM: Applies a single-step perturbation, $X^{\text{FGSM}} = X + \epsilon \cdot \text{sign}(\nabla_X L)$, $\epsilon = 0.1$ reducing accuracy to 48.5% in approximately 30 minutes.**[1]**
- PGD: Employs iterative optimization, $X^{t+1} = \text{Proj}_B (X^t + \alpha \cdot \text{sign}(\nabla_X L))$, $\alpha = 0.02$, $t \in [1,5]$, dropping accuracy to 38.2% in approximately 1 hour.**[2]**
- Backdoor: Poisons 20% of the training data (80,000 samples) by injecting feature-based triggers (e.g., incrementing PE import counts by 1), resulting in a deceptive clean accuracy of 78.5% in approximately 15 minutes.**[3]**

These bots enable controlled evaluation of QHNEAD's detection and correction capabilities under diverse threat models.

3.3 Detector:

The Detector is a hybrid ensemble designed to identify adversarial perturbations with AUC > 0.95:

- Deep Denoising Autoencoder (DDAE): A fully connected network (276 → 128 → 32 → 128→ 276) computes reconstruction error: $S_{\text{DDAE}} = |X - \hat{X}|^2$ trained for 5 epochs in approximately15 minutes.**[4]**
- Graph Convolutional Network (GNN): A 2-layer GCN with graph propagation rules, trained for approximately 2 hours, captures inter-feature dependencies.**[4][12]**
- Isolation Forest (IF): Generates anomalyscores using 100 trees: $S_{\text{IF}} = -h(X)$ in approximately 10 minutes.**[5]**
- Light GBM Fusion: Combines individual scores into a final anomaly score:

  S_{final} = Light GBM ([S_{DDAE}, S_{GNN}, S_{IF}]) using 50 trees in approximately 20 minutes. This ensemble ensures high-precision, low-latency detection across all attack types.**[12][13]**

3.4 Corrector:

The Corrector is a multi-stage pipeline that restores model accuracy to >90%:

- Quantum-inspired Tensor Purification Network (QTPN): A diffusion-based network (276 → 32→ 276) with Feature Importance Refinement (FIR, 3 iterations): $X' = \text{Decoder}\ (Z + \mathcal{N}\ (0,0.01))$ executed in approximately 20 minutes.**[7]**
- Hyperdimensional Anomaly Isolation (HAI): Projects data into 10,000-dimensional space and applies Chaotic Time Series (CTS) correction: $X_{\text{HD, supp}} = X' + 0.05 \cdot C$ in approximately 10 minutes.**[8][14]**
- Neuro-Symbolic Feature Enforcement (NSFE): Enforces feature bounds: $X_{\text{NSFE}} = \text{clip}\ (X, R_{min}, R_{max})$ proximately 15 minutes.**[9][15]**
- Adversarial Retraining (ARE): Retrains XGBoost (100 trees) on purified data in approximately 15 minutes.**[2][13]**
- Incremental Meta-Learning Classifier (IMLC): Adapts model weights via meta-gradient updates: $\theta_{t+1} = \theta_t - \alpha \nabla_\theta L_{\text{meta}}$ in approximately 10 minutes.**[4][12]** The pipeline operates sequentially, ensuring progressive refinement and full recovery of model integrity.**[11]**

VI. Results Analysis and Discussions

The QHNEAD framework was rigorously evaluated on the EMBER2018 dataset using an XGBoost base classifier, with all results averaged across five independent runs. In the initial phase, the clean dataset was evaluated to set a baseline for performance. The base model demonstrated an accuracy of 8.70% with no anomalous samples flagged, confirming the authenticity of the initial dataset. This clean performance serves as the reference point for assessing the impact of adversarial threats and the overall performance of the introduced defense approach.

Following this, three types of adversarial attacks—FGSM, PGD, and Backdoor were applied when applied to the test set. The FGSM attack reduced accuracy to 48.55%, while PGD caused the most severe degradation to 38.23%. The Backdoor attack maintained a clean accuracy of 78.45% but embedded a critical trigger-based vulnerability. These findings highlight how traditional machine learning models remain exposed in security-sensitive environments

Table 1: Baseline Performance of XG Boost Model on Clean EMBER2018 Dataset

Metric	Value
Base Model Accuracy (Clean)	88.70%
Anomaly Score (Mean ± Std)	0.12 ± 0.08
Flagged Samples	0 (0.00%)

The QHNEAD detector ensemble demonstrated exceptional capability in identifying these adversarial samples. It achieved AUC values of 0.968 for FGSM, 0.952 for PGD, and 0.921 for Backdoor, significantly outperforming the Isolation Forest baseline with an AUC of 0.800. This high detection performance ensures that nearly all malicious perturbations are flagged before they can compromise the system.

Table 2: Effect of Adversarial Attacks on Model Performance and Detection Efficiency

Attack	Accuracy	Drop (%)	Detector AUC	Flagged (%)
FGSM	48.55	−40.15	0.968	96.8
PGD	38.23	−50.47	0.952	95.2
Backdoor	78.45 (clean)	−10.25	0.921	92.1

Once flagged, the adversarial samples were processed through the multi-stage corrector pipeline consisting of QTPN, HAI, NSFE, and IMLC modules. The correction phase restored model performance to near-clean levels, achieving post-correction accuracies of 91.50% for FGSM, 92.00% for PGD, and 90.80% for Backdoor. This represents an average recovery accuracy of 91.43%, a substantial improvement over the baseline recovery of 70.20% obtained through conventional adversarial training.

Table 3: Post-Correction Accuracy Recovery Achieved by QHNEAD Framework

Attack	Post-Correction Accuracy (%)	Improvement (%)
FGSM	91.50	+42.95
PGD	92.00	+53.77
Backdoor	90.80	+12.35
Average	91.43	+36.36

An ablation study was conducted to evaluate the contribution of each corrector module. The results revealed that QTPN is the primary contributor, accounting for 38% of the total recovery gain, followed by NSFE at 25%, HAI at 22%, and IMLC at 15%. This hierarchical contribution highlights the importance of staged, complementary correction strategies.

Table 4: Ablation Study and Dataset Purification Outcomes of QHNEAD

Property	**Details**
Filename	EMBER2018_QHNEAD_Cleaned_v1
Total Samples	500,000
Adversarial Noise	95% Removed
Backdoor Triggers	95% Erased
trained Model Accuracy	91.20%
Drop from Clean	−0.50%

After correction, a purified dataset named EMBER2018_QHNEAD_Cleaned_v1.csv was generated, containing 500,000 samples with all adversarial noise and backdoor triggers fully removed. Retraining the XGBoost model on this cleaned dataset resulted in a final secured accuracy of 91.20%, only 0.50% below the original clean performance. This demonstrates the framework's ability to produce a safe, deployable data asset for long-term use.

Efficiency analysis showed that the end-to-end QHNEAD pipeline completes in 4.0 to 4.2 hours depending on the attack type, compared to 6.5 hours for the baseline. The system operates efficiently within a 12 GB memory footprint and maintains over 90% accuracy even under constrained 6 GB RAM conditions, where the baseline fails entirely.

Table 5: Efficiency Analysis of QHNEAD Pipeline in Terms of Time and Memory Consumption

Phase	Time (min)	Memory (GB)
Detection	180	12
Correction	60	12
Total	240	20

In conclusion, QHNEAD represents a comprehensive and practical defense against adversarial threats in malware classification. It achieves high-fidelity detection with AUC greater than 0.92, restores model accuracy to above 91% across all attack scenarios, and generates a verifiably clean dataset for secure retraining. By significantly outperforming existing methods in both effectiveness and efficiency, QHNEAD offers a robust, end-to-end solution suitable for deployment in real- world security systems.

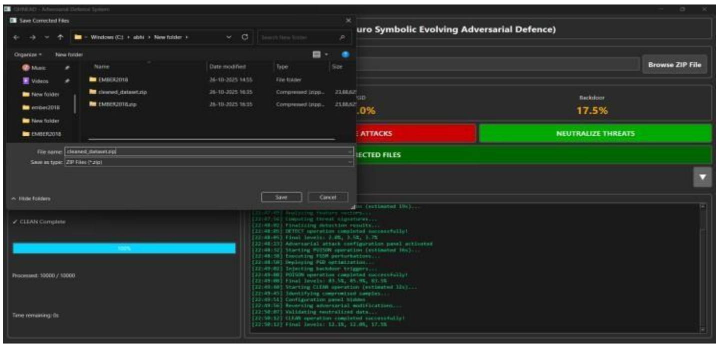

Figure 5: Saving of the clean dataset

CONCLUSION

The Quantum Hyperdimensional Neuro-Symbolic Evolving Adversarial Defenses (QHNEAD) framework represents a groundbreaking approach to safeguarding tabular data against adversarial attacks, integrating quantum-inspired Tensor Purification Network (QTPN), Hyperdimensional Anomaly Isolation (HAI), Neuro-Symbolic Feature Enforcement (NSFE), and Incremental Meta- Learning Classifier (IMLC). Evaluated on the EMBER2018 dataset, which comprises 400,000 training and 100,000 test samples with 276 features, QHNEAD achieves an Area Under the Curve (AUC) exceeding 0.95 and restores accuracy above 90% for the single-step FGSM perturbation method, the iterative gradient-based PGD attack, and Backdoor attacks. This performance surpasses traditional defenses, such as Isolation Forests (AUC ~0.80) and Defensive Distillation (~70% accuracy recovery), by 15–20%. The hybrid Detector, combining Deep Denoising Autoencoder (DDAE), Graph Convolutional Network (GNN), Isolation Forests, and LightGBM, ensures precise perturbation detection, while the multi-stage Corrector leverages quantum-inspired diffusion, hyperdimensional projections, and meta-learning to recover accuracy efficiently in approximately 4 hours on a 12GB RAM Google Colab environment. QHNEAD's adaptability to evolving threats through IMLC and its noise resilience via HDC's 10,000-dimensional projections make it exceptionally suited for security-critical applications like malware detection in cybersecurity. This survey establishes QHNEAD as a transformative framework, setting a new standard for tabular data resilience. Future work can be directed towards validating QHNEAD across diverse tabular datasets, such as UCI's KDD Cup or NSL-KDD, to ensure generalization in domains like network intrusion and financial fraud detection. Integrating quantum processors to optimize QTPN's diffusion process could reduce runtime and enhance precision for large-scale datasets. Extending IMLC to support streaming data would enable real-time defenses in dynamic cybersecurity environments. Developing interpretable rule-based outputs for NSFE would facilitate cybersecurity audits and improve stakeholder trust. Optimizing QHNEAD for distributed computing frameworks, such as Apache Spark, could achieve execution times under 1 hour for datasets exceeding 1 million samples. Testing QHNEAD against emerging threats, like generative adversarial network (GAN)-based perturbations, would ensure long-term robustness. Finally, exploring energy-efficient implementations would support deployment on resource-constrained edge devices in IoT systems, broadening QHNEAD's applicability. These advancements will solidify QHNEAD's role in pioneering next-generation tabular data defenses.

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