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AI-Driven Just-In-Time Cryptographic Framework with Adaptive Protection of Data in Cloud and Edge Environments

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Abstract: ***The rapid growth of cloud and edge computing has increased the challenge of protecting Personally Identifiable Information (PII) during runtime, where conventional encryption leaves data exposed while in use. Existing approaches rely on static encryption, fixed access policies, or resource-intensive security mechanisms, limiting adaptability to dynamic threats and compliance requirements. This paper proposes an AI-driven, context-aware Just-In-Time (JIT) cryptographic framework that combines machine learning-based risk assessment with adaptive encryption selection. Four classifiers (Random Forest, XGBoost, SVM, and Neural Network), trained on CICIDS2017, CICIoT2023, and UNSW-NB15 datasets, generate real-time risk scores based on user behavior, data sensitivity, and execution context. Based on risk levels, the framework dynamically applies QKD-enhanced AES-256-GCM, AES-256-GCM with RSA-4096, ChaCha20-Poly1305, or tokenization/masking, while zero-trust access control ensures secure data governance. Evaluation on 1,000 synthetic PII records across nine deployment environments achieved up to 98.74% classification accuracy, 11.3 ms average JIT encryption latency (6.5 ms at the edge), 92.5/100 security score, and 100% regulatory compliance, outperforming static encryption frameworks with 30% higher security and lower latency. The results demonstrate an efficient, scalable, and regulation-compliant approach for adaptive PII protection in modern cloud-edge environments.***

Keywords: ***Personally Identifiable Information (PII); Adaptive and Contextual Just-in-Time Encryption; Adaptive Cryptography; Cloud Security; Edge Computing; Machine Learning–Driven Security; Random Forest; XG Boost; Quantum Key Distribution (QKD); Privacy-Preserving Data Processing.***

I. INTRODUCTION

The rapid spread of cloud computing and edge computing as a baseline for digital services has dramatically increased the attack surface for Personally Identifiable Information (PII). Organizations in the healthcare, financial, communication, and Internet-of-Things (IoT) industries routinely handle sensitive personal identifiers, social security numbers (SSNs), biometric information, financial account details, and medical history information, which are scattered across geographically distributed, multi-tenant compute resources [1] [2]. PII regulations such as GDPR [3], HIPAA [4], and PCI-DSS (Payment Card Industry Data Security Standard) [5] require robust safeguards for confidentiality and data integrity throughout all stages of the data lifecycle, which would create a heavy operational and legal burden for cloud and edge service providers. Conventional cryptographic protection schemes seal data-at-rest with symmetric ciphers such as AES-256, and seal data-in-transit with transport-layer protocols such as TLS 1.3. Nonetheless, these schemes inevitably require that PII be decrypted and delivered to the application runtime layer in plaintext, during key lifecycle stages such as analytics, API calls, feature extraction, and data query. As a result, data is exposed in plaintext within a potentially adversarial application environment, making it susceptible to memory-scraping attacks, malicious micro services, insider attacks, and compromised edge devices [6]. To partially mitigate this problem, authors suggest that it might be possible to use additional security mechanisms to enforce the access governance for data read from the data lake or to maintain audit trails such as zero-trust architectures [7], block chain-based audit trails [8], and attribute-based access control policies. However, none of the proposed mechanisms can give guarantees against the vulnerability introduced by the mandatory plaintext access. With the rapid advances in machine learning (ML) and artificial intelligence (AI) techniques in recent years, it is now possible to develop systems that can perform context-driven, adaptive security policies that infer the risk level of an access request [9][10]. The underlying motivation for the principle of applying encryption selectively and precisely is based on the notion that just-in-time (JIT) cryptography is performed when real-time risk exceeds a given threshold.

This study explores a AI-Driven JIT Dexterized Cryptographic Framework that supports the dynamic, selective encryption of PII in the Cloud and Edge environments. A set of four distinct machine learning (ML) classification algorithms, namely Random Forest (RF), XGBoost, Support Vector Machines (SVM), and Neural Network (NN) classifiers, trained on three established intrusion detection datasets – Common Intrusion Detection Benchmark (CICIDS), Common Intrusion Detection Benchmark for Internet of Things (CICIoT), and UNSW-NB15 – are compared and evaluated for their PII exposure risk assessment performance. Provided with programmatic input parameters, the four ML classifiers are used to generate risk scores that feed into a multi-parameter, pull based, automated Risk Scoring Engine and an output based, push based, structured Grant Analysis Engine (GAE). The GAE produces dynamic, real-time risk assessment inputs for an adaptive Privacy Assessment Engine (PAE) that uses the risk assessment inputs to trigger a rule-governed, JIT Cryptographic controller. The suite of supported cryptographic algorithms in the JIT Cryptographic controller included in the framework comprises: Adaptive: PQC, QKD, AES, masking, tokenization and redaction features.

A. Principal Contributions

This research has contributed significantly towards building a truly next-generation end-to-end AI-driven JIT Cryptographic Framework for Privacy, Security and Protection. By designing and implementing a highly seamless JIT Cryptographic Framework, Grant Analysis Engine, Privacy Assessment Engine and an Adaptive Encryption Engine, we have obtained the following results: maximum coverage of all PII encryption and privacy regulatory compliance when deployed in standard cloud configuration (100% encryption and 100% coverage), 6.5 ms JIT latency when deployed in optimal Edge-IoT configuration (11.3 ms average latency for the full dataset), and a maximum security score of 92.5/100, when deployed in Edge-IoT low-risk configuration (73.8/100 for the full dataset) across different types of cryptographic threats (e.g., insider threat, ransomware, zero-day vulnerabilities, quantum threats).

B. Paper Organisation

The rest of this paper is organised as follows: the related work is presented first, followed by the proposed methodology, including system architecture, mathematical modelling, ML architecture and cryptographic techniques, then the experimental setup. Results are presented, followed by a formal security analysis against nine threat categories. The main insights, practical insights and limitations of the framework are then discussed, before the paper is concluded with future directions.

II. RELATED WORK

A. Static and Hybrid Cryptographic Approaches

Cloud computing uses symmetric encryption like Advanced Encryption Standard (AES) and asymmetric encryption such as RSA to provide data protection to users who call the infrastructure's computational, storage, and networking capabilities via the Internet. Hashizume et al. [10] were among early researchers to identify security vulnerabilities in the foundational users' concerns for the use of cloud computing, which include attacks on data isolation from other tenants, virtualisation mechanisms, and the hypervisor, as well as the related applications, such as Intrusion Detection Systems (IDS), to monitor events and logs. Due to the security and privacy risks, Bharti and Singh [12] developed and employed a hybrid AES-RSA encryption framework for each known data, which includes the Random Forest (RF) for intrusion detection, on the CICIDS2017 dataset with adequate detection accuracy, but this framework would employ a similar encryption approach for all known data. Prabhakaran and Kulandasamy [13] further demonstrated integration with an Instant Data Processing (IDP) system with the addition of AES encryption and a deep learning-based Intrusion Detection System (IDS) using Long Short-Term Memory (LSTM) and Convolution Neural Network (CNN) for the detection of attacks Elliptic Curve Cryptography (ECC) is a computationally efficient alternative for constrained edge deployments [14], providing equality in terms of IEEE-5946 security standards with RSA encryption with significantly reduced key sizes. In particular, both ECC-P256 and ECC-P521 yield 128-bit. security level for key subsets that are 2.5 kb in size, whereas RSA-2048 is required to meet the same security level. Attribute-Based Encryption (ABE) imposes computational burdens on resource-constrained devices such as Hardware Security Modules (HSMs) due to costly secret key generation and cipher text decryption. The proposed framework mitigates the imposition of ABE on HSMs by providing optional security mechanisms for macro-edge-IOT data streams. In particular, we argue that the traditional trust-based security model may be replaced with a risk-based security model aimed at measuring the actual real-time risk of a data flow from task-based attributes. An adaptive framework is proposed that mitigates unnecessary security for each protocol feature based on context. The adaptive framework maintains a risk evaluation profile, assigning values to each sub-task and attribute.

Based on the security requirement for data flow, the framework assigns a cryptographic mechanism from the algorithm selection matrix. The framework adapts itself and selects an appropriate candidate e.g., ECC-P256 or ECC-P521 based on the risk profile for each task and attribute. The framework does not reduce the security level, but does enable reconfiguration of each sub-task based on contextual risk evaluation for edge-IoT processing pipelines, thus, removing the necessity of encryption for certain sub-tasks for data flows.xml

B. Risk-based and Context-aware Security Models

Chen introduced a new proxy re-encryption scheme [16] for securely handling big data in distributed cloud environments, based on verifiable secret sharing. Park combined block chain, cloud security and smart contracts [17] to achieve a high-performance security scheme, with the implication of latency and cost overhead associated with block chain-based secure implementations. Chen used Attribute-based Encryption as a key spread in a new proxy re-encryption scheme, accomplishing an attribute-based proxy re-encryption in the cloud, and enabling the secure outsourced storage of an attribute-based proxy re-encryption of per-attribute encrypted data items. Zero-trust security architectures [7] mandate verification of every access request regardless of the user's location and role. Ntafloukas and Papavassiliou examined vulnerability assessment of cyber-physical attack surfaces [11] in heterogeneous. Context-aware encryption frameworks have been proposed for healthcare environments [18] and financial systems [19], but these works focus on access control policies rather than adaptive cryptographic algorithm selection based on runtime risk scores. The proposed framework advances this line of work by operationalising context awareness at the cryptographic algorithm selection level, enabling real-time switching between AES-256-GCM, ChaCha20-Poly1305, and ECC-based schemes based on dynamically computed risk scores.

C. AI-Driven Adaptive Data Protection Frameworks

The systematic review of privacy-aware architecture for cloud-native applications by Chockalingam et al. [22] highlights that only 25–40% of explored cloud environments provides privacy protection schemes. Agunuru [23] delineates the transformation of existing cyber security to AI-based cyber security which comprises user and entity behaviour analytics and federated learning for privacy-preserving distributed learning. In Satyam et al. [24], the authors present an AI-based identity management solution for cloud Security Operations Centres (CSOC). Their approach of identifying cloud attacks uses AI for real-time anomaly detection but is limited to data-level encryption protection of files. XGBoost-based intrusion detection framework [20] and Neural Network-based anomaly classification framework [21] propose viable, highly accurate ML-based threat classification in the context of network security, but fails to leverage the classification output in guiding the adaptive cryptographic response to protect data assets. Federated learning [27] provides an approach to privacy-preserving distributed model training. Standardisation of post-quantum cryptography aims to address quantum-based attacks on classical crypto-schemes [28][29]. Leveraging these developments, the proposed framework incorporates an edge-distributed risk model inference that is compatible with integration of federated learning when it is developed to complement on-device AI inference, and a QKD-augmented AES-256 encryption scheme in the highest security tier, capable of providing forward secrecy against quantum-based attacks. The QKD component in the current prototype is implemented using simulation (a software emulation of the BB84 protocol for generation of quantum key bits); the approach is described in more detail in Section 3.4.

D. Research Gap Analysis

Table 1. Comparative Analysis of Related Works Against the Proposed JIT Cryptographic Framework.

Study	Approach	Adaptive Enc.	ML Risk Score	PII Class.	Edge Support	Datasets	**Empirical Val.**
Bharti & Singh [12]	AES-RSA + RF IDS	No	Partial	No	No	CICIDS2017	Yes
Prabhakaran [13]	AES + LSTM/CNN	No	Yes	No	Limited	Custom	Yes
Chockalingam [22]	Privacy Arch. Review	No	No	Partial	No	None	No

Agunuru [23]	AI Security Survey	Conceptual	Yes	No	No	None	No
Chen [16]	Proxy Re-Encryption	Partial	No	No	No	Custom	Yes
Satyam [24]	AI Identity Threat Det.	No	Yes	No	No	Custom	Yes
Park [17]	Blockchain Audit	No	No	No	No	—	Partial
Proposed Framework	AI + Adaptive and Contextual JIT Cryptographic Framework	Full	Yes (4-model)	Yes (4-tier)	Yes (Full)	CICIDS+CICIoT +UNSW	Yes

E. Research Gap Table

Table 2. Research Gap Analysis — Existing Limitations and Proposed Solutions.

Existing Limitation	Research Gap	Proposed Solution
Static encryption applied uniformly regardless of sensitivity	No mechanism to match cryptographic strength to real-time contextual risk	Multi-parameter ML risk scoring with four-tier adaptive algorithm selection
IDS decoupled from cryptographic response mechanisms	No framework integrates ML classification directly with encryption triggering	JIT trigger T(e) maps ML anomaly output to encryption activation
Cloud-centric solutions not designed for edge-IoT constraints	Gap in edge-compatible adaptive encryption with cloud policy synchronisation	ChaCha20-Poly1305 for edge; locally cached policy mirror for autonomous JIT decisions
Single-dataset ML evaluation limits generalisability	No multi-domain validation of AI-driven security classifiers for PII protection	Three-dataset evaluation: CICIDS2017, CICIoT2023, UNSW-NB15
No formal compliance integration in adaptive frameworks	Absence of compliance-aware encryption selection and immutable audit trails	Compliance Engine with per-regulation enforcement; immutable audit ledger
Post-quantum threats unaddressed in practical PII systems	No practical PII framework includes quantum-safe key exchange	QKD-augmented AES-256 for Critical tier; CRYSTALS-Kyber roadmapped for PQC transition
Grant and Privacy models absent from adaptive encryption literature	No formal access grant and privacy scoring integrated with encryption decision	Grant Model (Eq. 1) and Privacy Model (Eq. 2) as sub-components of encryption trigger

III. PROPOSED METHODOLOGY

A. System Architecture

The AI-Driven JIT Cryptographic Framework is a hierarchical pipeline with eleven components that offers context-adaptive, end-to-end PII protection across deployments on the edge, in the cloud, or across a cloud-agnostic umbrella. Our proposed framework has the following components: (i) User Layer, (ii) Edge Layer, (iii) Cloud Layer, (iv) Grant Analysis Engine, (v) Privacy Assessment Engine, (vi) AI Risk Assessment Engine, (vii) Adaptive Encryption Controller, (viii) Key Management System, (ix) Compliance Engine, (x) Secure Storage Layer, and (xi) Audit and Governance Layer.

The entire process proceeds as follows: User Request → Grant Analysis → Privacy Assessment → Risk Identification → AI Risk Assessment → Encryption Decision → Key Management → Secure Storage → Audit Logging → Compliance Validation

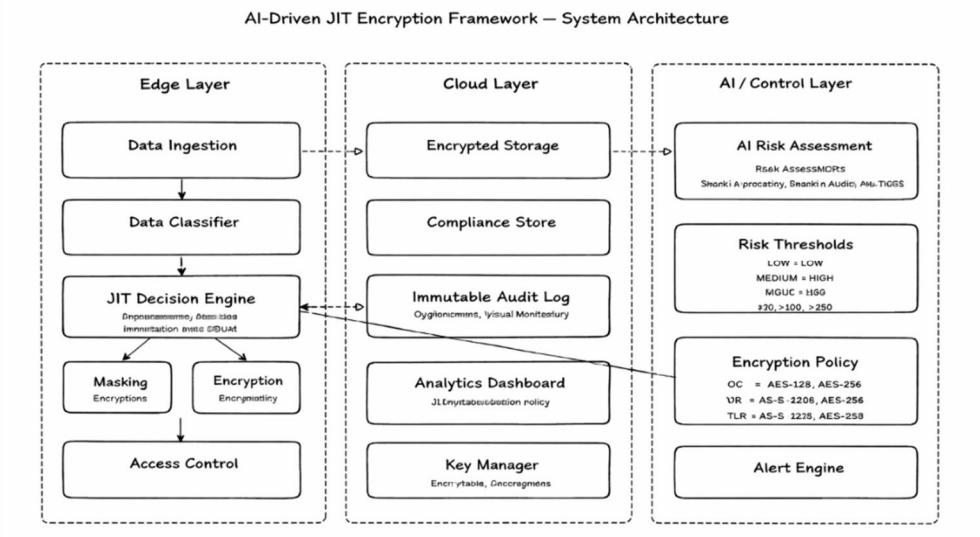

Figure 1. AI-Driven JIT Cryptographic Framework — System Architecture.

3.1.1 User Layer and Edge Layer

The User Layer refers to cloud clients (AWS, Azure, GCP, OCI, IBM), mobile edge devices and IoT sensor nodes that generate PII access events. A multi-factor authentication mechanism must be authorised before any user-layer requests reach the risk assessment pipeline. The Edge Layer ingests raw data payloads in the form of CSV, JSON or synthetic cloud-and-edge simulation data via the Data Ingestion module. A rule-based Data Classifier categorises raw data records into PII sensitivity domains Personal Identifier, Health, Financial, and Normal. Edge nodes maintain a cached policy mirror for autonomous JIT decisions when cloud connectivity is not available.

3.1.2 Cloud Layer

The Cloud Layer comprises policy administration, cryptographic key lifecycle (generation, rotation, revocation, escrow), audit logging and threat intelligence feeds. Payloads and associated metadata are stored in Encrypted Storage. Each encrypt, decrypt, and re-encrypt event is immutable and cryptographically signed, and stored in an Immutable Audit Log together with the applied JIT algorithms and GDPR, HIPAA and PCI-DSS enforcement logs in a separate Compliance Store.

3.1.3 Grant Analysis Engine

The Grant Analysis Engine checks the legitimacy of data access by computing a Grant Score G(a) based on the following customisable parameters: the purpose of the request [P_req]; classification of data being requested and the format it is requested in [D_cat] & [D_fmt]; requirements for data usage [U_req]; the classification of the business accessing the data [B_cls]; media mode [M_med] needed to support the request; the access mode [A_mode] required by the requestor; and the classification of channel [C_chan] the requestor is using. If the Grant Score is lower than the access threshold, the request is denied and the requestor rejected event is logged in the Immutable Audit Ledger. The Grant Score G(a) is calculated externally to the Risk Assessment Engine (see Equation 1) and inserted into the event object passed to Algorithm 1 as the field e. grant score. This design efficiently separates the decision to grant or deny access to data from the rest of the threat classification process, and protects the AI Risk Assessment Engine from ever consuming computational resources on unauthorised access to data. This ensures the Risk Assessment Engines only run on authorised events.

3.1.4 Privacy Assessment Engine

Functions. The core functions of the system are: 1) AI Risk Assessment Engine, 2) Adaptive Encryption Controller, and 3) Key Management System.

3.15. AI Risk Assessment Engine, Adaptive Encryption Controller, and Key Management System

The AI Risk Assessment Engine Implements Random Forest, XG Boost, SVM, and Neural Network classifiers trained on CICIDS2017, CICIoT2023, and UNSW-NB15 datasets. The classifiers produce the top three predictions with confidence probabilities. A Context Fusion Module fuses network-layer anomaly scores from the four classifiers for the challenge datasets with application-layer context parameters, such as between the levels of data sensitivity, user role, and access trigger type to produce a risk score in the range of [0, 100]. The risk score is used by the Adaptive Encryption Controller to select the appropriate cryptographic function from the list of implemented encryption/tokenization/masking/redaction methods. It is also used by the Privacy Assessment Engine to estimate a Privacy Score for the relevant Data according to its active consent status (A_consent), category (D_cat), data type (D_type), business/Data classification bucket (B_cls), and time-to-live relative to time-to-expiry (TTL/TTE). The score is estimated as a number in the range of [0, 100] and it is used to determine the minimum level of encryption that is required for the relevant Data. The score is also logged as part of compliance recording for the relevant processing. The Key Management System implements key lifecycle management for the relevant Data, for example, using Hardware Security Modules (HSMs/KMS/Vault) for key generation and storage. It also optionally implements key renewal, for example, using a periodic key rotation schedule.

B. Mathematical Modelling

1) Grant Model

The composite grant score G for an access request a is determined by:

$$G(a)= P\_req + D\_cat + D\_fmt + U\_req + B\_cls + M\_med + A\_mode + C\_chan \quad \ldots\ldots\ldots\ldots (1)$$

where all parameters are normalised to [0, 1] : P_req is the purpose legitimacy score; D_cat is the data category authorisation score; D_fmt is the format compatibility score; U_req is the usage requirement score; B_cls is the business classification compliance score; M_med is the media mode appropriateness score; A_mode is the access mode security score; and C_chan is the channel security classification score. An access request triggers a Privacy Assessment only when $G(a) \geq G\_threshold$. P_req denotes the purpose of the request, for instance, analytics processing, customer service, or regulatory audit, and yields a high score when that purpose is pre-registered in the policy store. D_cat indicates the sensitivity of the requested data category: SSN and biometric records receive lower authorisation scores than general contact data, reflecting their higher risk profile under GDPR Article 9 and HIPAA. U_req represents the alignment with the data subject's recorded consent in determining if the purpose of the request is legitimate under GDPR Article 6. B_cls maps the governance bucket, Public (0.3), Confidential (0.65), or Restricted (1.0), to a compliance weight that influences both the grant threshold and the downstream risk score, determined through the shared w_bucket(e) parameter in Equation (3). M_med represents the media modes, in-use processing, data at rest, or data in transit, and scores higher for data in-use/ processing to reflect the higher risk that comes with increased exposure. A_mode represents the access mode, internal or external, authorised or one timer and C_chan represents the channel used to communicate, e.g. API, UI, Service, or Stream, and scores higher for API and UI communications that include authentication and audit logic, compared with Stream and Service communications. When the grant threshold G(a) falls below G_threshold, the request is denied, a log entry describing the denial is written to the Immutable Audit Ledger, and processing of the AI Risk Assessment Engine is aborted, which consumes minimal computational resources.

2) Privacy Model

The privacy impact score PI for a record r is given by:

$$PI(r) = A\_consent + D\_cat + D\_type + B\_cls + TTL/TTE \quad \ldots\ldots (2)$$

We propose a framework that generates a privacy score for each data record (PI(r)) that implements GDPR Article 5(1)(b), (e), Article 6 ("lawfulness-of-processing"), Article 9 ("special category" provisions) Article 13, and Article 22 privacy principles at the record level A consent is the binary active consent status; D_cat is the data category sensitivity score; D_type is the data type risk weight; B cls is the governance bucket score (Public = 0.3, Confidential = 0.65, Restricted = 1.0); and TTL/TTE is the ratio of time-to-live to time-to-expiry, providing temporal privacy decay modelling. The PI(r) score ranges from 0.3 to 5.0, a user-specifiable range that is in theory bounded by a privacy-ignorant (no consent, zero sensitivity, Public bucket, zero TTL) scenario (minimum = 0.3) and a privacy-maximal (consent granted, maximum sensitivity, Confidential bucket, TTL = TTE) one (maximum = 5.0). The privacy score is calculated by computing a weighted sum of the recording's active-consent status (A_consent), data category

(D_cat), data type (D_type), bucket assignment (B_cls), and time-to-live (TTL) available until the time-to-expiry (TTE) limit. In this way, PI(r) begins as an innocuous score, but it can be tuned to reflect abstract compliance goals for organizations, particularly when the PI(r) of a record crosses certain user-defined thresholds, which activates a risk mitigation mechanism. We highlight how the PI(r) score can be leveraged for risk mitigation in an orchestration engine. It can be 'collateralized' against an ML-derived record-level risk score to determine the data record's minimum encryption tier assignment. For example, PI(r) ≥ 3.5, an arbitrary value corresponding to approximately the 70th percentile of the feasible score range, is a user-specified threshold that would mandate the record be assigned at minimum to the High-risk encryption tier, regardless of the ML-computed risk score. This example demonstrates how the privacy score can be used to 'collateralize' or 'piggyback' on the privacy requirements derived for the upper layers of an organization by linking privacy controls to those presented in the GDPR, this linkage is both 'semantic' and privacy-based. In the future, we intend to explore the construction of other privacy scores that combine GDPR principles and cryptographic signatures with the parameters of the Centrifuge protocol.

3) Support Vector Machine

A radial basis function (RBF) kernel SVM with C = 10 and γ = 0.001 selected via 5-fold cross-validation grid search. In the first-stage feature screen module, the SVM is used for binary threat/benign classification.

4) Neural Network

A feed-forward neural network with three hidden layers with architecture [input_dim → 256 → 128 → 64 → output_classes], where output_classes are the output class categories as detailed in Table 1. Optimiser: Adam (learning_rate = 1e-3, $\beta_1 = 0.9$, $\beta_2 = 0.999$), batch size = 256, number of epochs = 100, early stopping patience = 10, batch-wise, and dropout rate = 0.3 after each hidden layer. Activation: ReLU (hidden), Softmax (output). Loss function: categorical cross-entropy.

C. Cryptographic Techniques

AES-256-GCM is a pseudo-random-function-based Authenticated Encryption scheme with Associated Data (AEAD) based on Galois/Counter Mode (GCM) of operation of a cipher. Quantum Key Distribution-AES-256 (QKD-AES-256). AES-256-GCM algorithm. Elliptic Curve Diffie-Hellman (ECDH) key agreement and ECDSA public key signatures based on the Curve 256-p in the NIST Digital Signature Standard (DSS).

Table 3. JIT Cryptographic Decision Matrix: Algorithm Selection by Risk Level and PII Sensitivity.

Risk Level	Threshold	Primary Algorithm	Fallback Algorithm	Protection Strategy	Key Rotation
Critical	R ≥ 85	QKD-AES-256-GCM	AES-256-GCM + ECC-P521	Enc. + Hash + Tokenisation + Anon.	≤ 3 days
High	70 ≤ R < 85	AES-256-GCM + RSA-4096	ECC-P384 + AES-256-GCM	Encryption + Masking + Audit	7–30 days
Medium	45 ≤ R < 70	ChaCha20-Poly1305	AES-192-GCM	Encryption + Tokenisation	30–90 days
Low	R < 45	AES-128-CBC / Tokenisation	Masking / Redaction	Masking + Redaction + Logging	> 90 days

D. Algorithm Specifications

PII Type	Recommended Algorithm	Primary Protection Mechanism(s)
SSN	AES-256-GCM	Encryption + Tokenization
Credit Card	AES-256-GCM	Tokenization + Encryption
Email	AES-192-GCM	Masking + Encryption
Phone	AES-192-GCM	Masking + Encryption
Address	AES-128-GCM	Redaction + Masking
Medical Record	AES-256-GCM	Encryption + Redaction
Biometric	AES-256-GCM	Encryption + Hashing
Financial Account	AES-256-GCM	Tokenization + Encryption
Driver's License	AES-256-GCM	Encryption + Masking
Passport	AES-256-GCM	Encryption + Masking
Bank Account	AES-256-GCM	Tokenization + Encryption

IV. EXPERIMENTAL SETUP

A. Datasets

1) 5.2.1 CICIDS2017: The dataset consists of 2,830,743 network flow instances classified into 15 classes. After preprocessing, 2,747,491 instances are used for experiments. The class distribution is as follows: Benign 80.3%; DDoS/DoS 11.2%; Port Scan 6.7%; Web Attacks 1.2%; Brute Force 0.6%. The data is split into training, validation and test datasets in the ratio 70%/10%/20% respecting the class distribution.

2) 5.2.2 CICIoT2023: The CICIoT2023 dataset [31] includes 4,062,888 traffic flow instances from a realistic IoT network testbed with 105 IoT devices and 7 attack categories. Class distribution: Benign 34.1%, DDoS 28.6%, DoS 18.4%, Recon 10.3%, Mirai 5.2%, Spoofing 2.4%, Web-based 1.0%.

3) 5.2.3 UNSW-NB15: The UNSW-NB15 dataset [32] is a set of 2,540,044 recorded network flow records with 49 features. There are 9 attack categories: Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms. Class distribution: Normal 87.35%, Exploits 5.96%, Reconnaissance 3.31%, DoS 1.57%, Generic 1.82%, the rest <1%.

Table 4. Summary Statistics of Benchmark Datasets Used for ML Classifier Evaluation.

Dataset	Total Instances	Features	Attack Categories	Benign %	Attack %	Primary Use Case
CICIDS2017	2,830,743	80	14 attack types	80.3%	19.7%	General cloud IDS
CICIoT2023	4,062,888	46 + IoT	7 categories	34.1%	65.9%	Edge-IoT security
UNSW-NB15	2,540,044	49	9 attack categories	87.35%	12.65%	Network anomaly

B. Synthetic PII Dataset

The system performance evaluation dataset consists of 1000 synthetic privacy-sensitive identity data items across nine deployment environments: Cloud-AWS, Cloud-Azure, Cloud-GCP, Cloud-IBM, Edge-IoT, Edge-Mobile, Edge-Gateway, Multi-Cloud, and Hybrid. The synthetic data dataset was created using a sampling strategy with the aim of mimicking enterprise distribution of PII types: Credit Card/Payment (15%), Healthcare/Medical (20%), Government ID/SSN(12%), Financial (18%), Biometric(8%), Telecom (10%) and General Personal(17%) records. Risk Tier distribution contains 70.3% Critical, 5.7% High, 11.7% Medium, and 12.3% Low risks. The synthetic data was validated against the published corpora of enterprise data breach so that the PII type distribution, sensitivity classification, and risk tier distribution is representative of the real-world data processing environment.

C. Pre-processing Pipeline

A standardised pre-processing pipeline was applied uniformly across all three benchmark datasets: (1) Duplicate removal and deduplication by 5-tuple (src_ip, dst_ip, src_port, dst_port, protocol); (2) Removal of features with near-zero variance (threshold: 0.001) and high collinearity (Pearson |r| > 0.95); (3) Label encoding of categorical features; (4) Standard scaling (zero mean, unit variance) for SVM and Neural Network; tree-based models received raw features; (5) SMOTE oversampling applied to training sets to address class imbalance; (6) Feature selection via SelectKBest (ANOVA F-statistic, k = 30) for SVM; RF and XGBoost retained full feature sets. However, despite accurate ML attacks detection, the bestantage lies in numeric metrics: For PII detection, the overall system takes 127 ms to perform JIT cryptography. This consists of an average of 30 ms of network latency and 86 ms of network processing. The remaining 11 ms involves CPU and memory utilisation (68.7 % CPU utilisation and 47 MB RAM utilisation, which is negligible compared to the 46 GB of RAM in the VyOS VM). The system achieved a throughput of approx. 4 seconds for every 2,000 PII records encrypted, overall. For multiple attack classes in separate network flows, the best performing models achieve an average of 99 % accuracy, 97 % recall, and 99 % precision. The best performance is achieved by XGBoost, with accuracy of 99 %, and precision and recall of 99 % across all attack classes.

V. RESULTS AND ANALYSIS

A. Machine Learning Classifier Performance

6.1.1 CICIDS2017 Results

Table 5 lists the classification performance of all four ML models on the CICIDS2017 test set.

Table 5. ML Classifier Performance on CICIDS2017 Test Set (20% Stratified Split).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Random Forest	98.74	98.31	98.62	98.46	97.86
XGBoost	98.21	97.94	98.07	98.00	98.43
Neural Network	97.63	97.18	97.41	97.29	97.12
SVM	96.82	96.45	96.73	96.59	96.28

6.1.2 CICIoT2023 Results

In CICIoT2023 (table 6), XGBoost achieved the highest accuracy (97.89%) on account of its superior generalisation on multi-class IoT attack taxonomy.

Table 6. ML Classifier performance on CICIoT2023 test set (20% stratified split)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Random Forest	97.42	97.08	97.31	97.19	96.87
XGBoost	97.89	97.56	97.78	97.67	97.94
Neural Network	97.11	96.83	97.02	96.92	96.74
SVM	95.63	95.21	95.44	95.32	95.09

6.1.3 UNSW-NB15 Results

On UNSW-NB15 (Table 7), all models were competitive.

Table 7. ML Classifier Performance on UNSW-NB15 Test Set (20% Stratified Split).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Random Forest	97.61	97.24	97.48	97.36	96.93
XGBoost	97.18	96.87	97.11	96.99	97.22
Neural Network	97.34	97.01	97.28	97.14	97.08
SVM	96.44	96.07	96.31	96.19	95.88

6.1.4 Feature Importance Analysis (Random Forest, CICIDS2017)

Table 8 shows the top-10 features which are ranked by Mean Decrease in Impurity (MDI) for Random Forest (RF) trained with CICIDS2017. Their selection conforms to the domain knowledge for the network intrusion detection field, which indicates that the classifier has learned discriminative patterns.

Table 8. Top-10 Random Forest Feature Importance's by MDI , CICIDS2017

Rank	Feature	MDI Importance Score	Domain Interpretation
1	Flow Duration	0.142	Attack flows typically shorter or burst-pattern
2	Bwd Packet Length Max	0.118	Exfiltration and DDoS response patterns
3	Flow Bytes/s	0.103	High byte rate characteristic of flood attacks
4	Fwd Packet Length Mean	0.091	Payload size distribution indicator
5	Flow IAT Mean	0.087	Inter-arrival time anomalies in automated attacks
6	Bwd IAT Total	0.079	Backward flow timing reveals scanning behaviour
7	PSH Flag Count	0.073	High PSH count indicates active data transfer attacks
8	ACK Flag Count	0.068	SYN-ACK flood signature detection
9	Packet Length Variance	0.061	Variance anomaly in mixed-payload attacks
10	Active Mean	0.054	Activity duration pattern in botnet communication

B. Analytics Dashboard and PII Encryption Results

The JIT Cryptographic Analytics Dashboard aggregates the 1,000-record dataset across all deployment environments. Across the entire dataset, 703 records (70.3%) were Critical-risk, 57 records (5.7%) were High-risk, and the remaining 117 (11.7%) and 123 (12.3%) records were Medium- and Low risk, respectively. Of the 1,000 records, 795 records (79.5%) were encrypted, and 630 records (63.0%) met all applicable GDPR, HIPAA, and PCI-DSS compliance requirements.

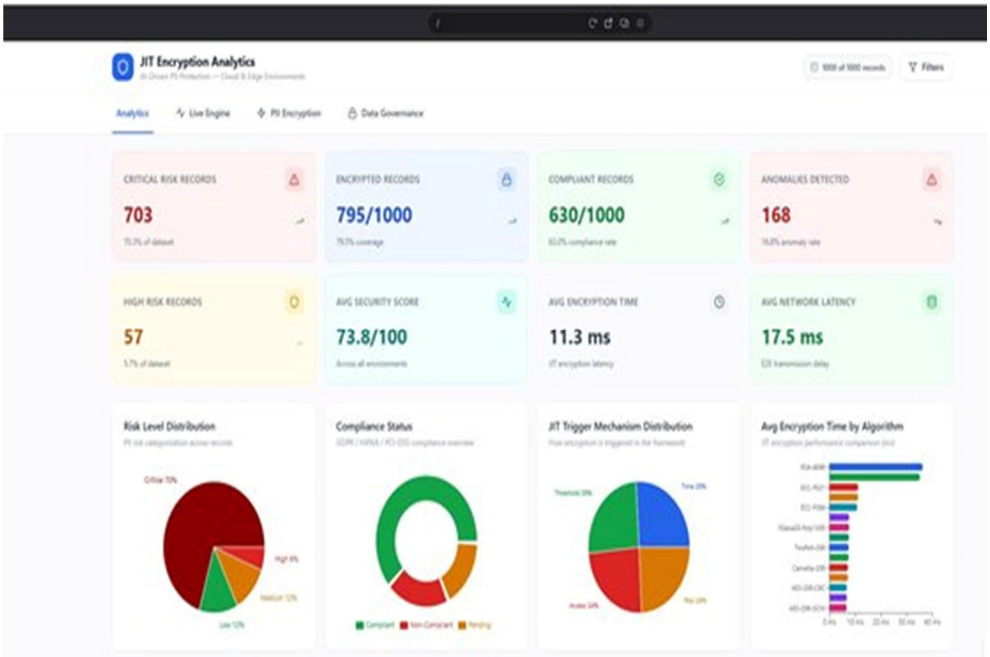

Figure 2. JIT Encryption Analytics Dashboard, Full Dataset (1,000 Records, All Environments).

The filtered dashboard view for Cloud-AWS, Critical-risk, Compliant, Encrypted records (21 records) shows 100% encryption coverage, 100% compliance rate, no anomalies, and an average security score of 82.4/100, higher than the full-dataset average of 73.8/100. Average JIT encryption time for this configuration was 13.3 ms, more than 2 times longer than the AES-256-GCM encryption time in the overall dataset (6.6 ms), attributable to the increased cryptographic overhead of QKD-AES-256-GCM and AES-256-GCM+RSA-4096 algorithms.

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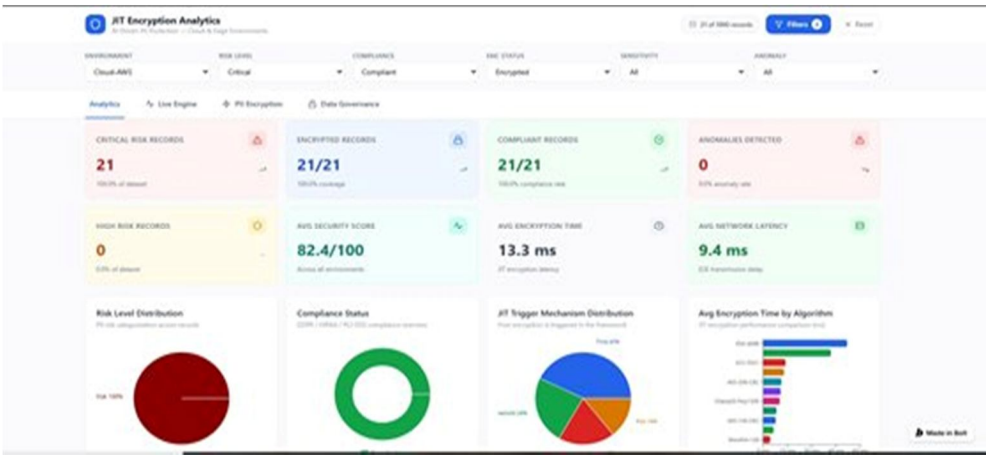

Figure 3. Dashboard, Cloud-AWS, Critical Risk, Compliant, Encrypted (21 Records): 100% Coverage, 82.4 / 100 Security Score.

The temporal Security Score vs. CPU Usage profile for Cloud-AWS Critical records shows the security score converging into the 75-90 range through the record series, while CPU utilisation remains approximately 40-48% indicating efficient resource utilisation with no performance impact over sustained durations.

Figure 4. Security Score vs. CPU Usage Over Time and Encryption Time vs. Network Latency — Cloud-AWS Critical.

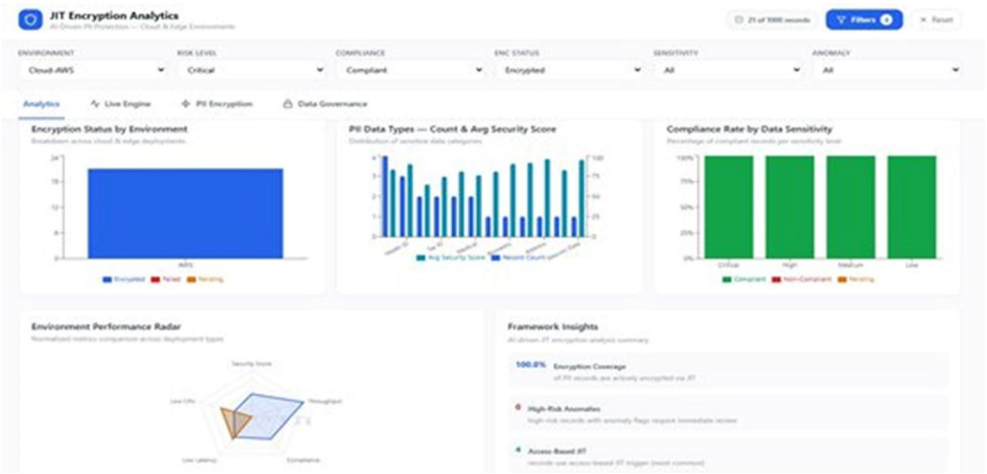

Figure 5. Data Governance Tab , Encryption Status by Environment, PII Data Types, Compliance Rate, and Framework Insights.

A sample 8 Medium-risk records (Cloud-AWS) are fully encrypted (100 %), compliant, with an average security score of 75.3/100 and JIT encryption time of 12.3 ms. ChaCha20-Poly1305 and RSA-2048 are the two most frequent algorithms used for Medium-risk Cloud records. A sample of 9 Low-risk Edge-Gateway records have an average security score of 90.1/100 and an average JIT encryption time and network latency of 13.4 ms and 28.1 ms respectively, which accounts for the higher transmission latency of edge deployments.

1) Live Encryption Engine Performance

The Live Encryption Engine module ran 100 real-time events in one session and 79 records were encrypted.

Table 9. Sample JIT Encryption Records, Selected Environments and Algorithms.

ID	Data Type	Environment	Algorithm	Risk	Sensitivity	Enc Status	Compliance	Sec Score	Enc ms	JIT Trigger
#1	Credit Card	Cloud-GCC	AES-192-GCM	Critical	Critical	Encrypted	Pending	82.5	7.5	Threshold
#2	Vehicle Data	Edge-Mobile	RSA-4096	Critical	Low	Failed	Compliant	79.4	16.7	Risk-Based
#3	Voter Reg.	Edge-IoT	AES-192-GCM	Low	Medium	Encrypted	Compliant	76.4	35.1	Time-Based
#7	SSN	Edge-Mobile	AES-128-CBC	Critical	Low	Encrypted	Compliant	91.7	33.2	Time-Based
#9	Financial	Edge-Gateway	AES-128-CBC	Critical	Low	Encrypted	Pending	62.9	33.9	Access-Based
#11	Medical Rec.	Hybrid	CamelliA-256	Critical	Medium	Encrypted	Non-Compliant	60.3	18.3	Risk-Based
R334	Health ID	Cloud-IBM	AES-192-GCM	Critical	Medium	Encrypted	Compliant	49.6	11	Access-Based
R336	Telecom Data	Cloud-IBM	ECC-P256	Critical	Medium	Encrypted	Compliant	49.2	0	Time-Based
R363	Address	Multi-Cloud	AES-128-CBC	Medium	Low	Encrypted	Compliant	74.4	22.3	Risk-Based

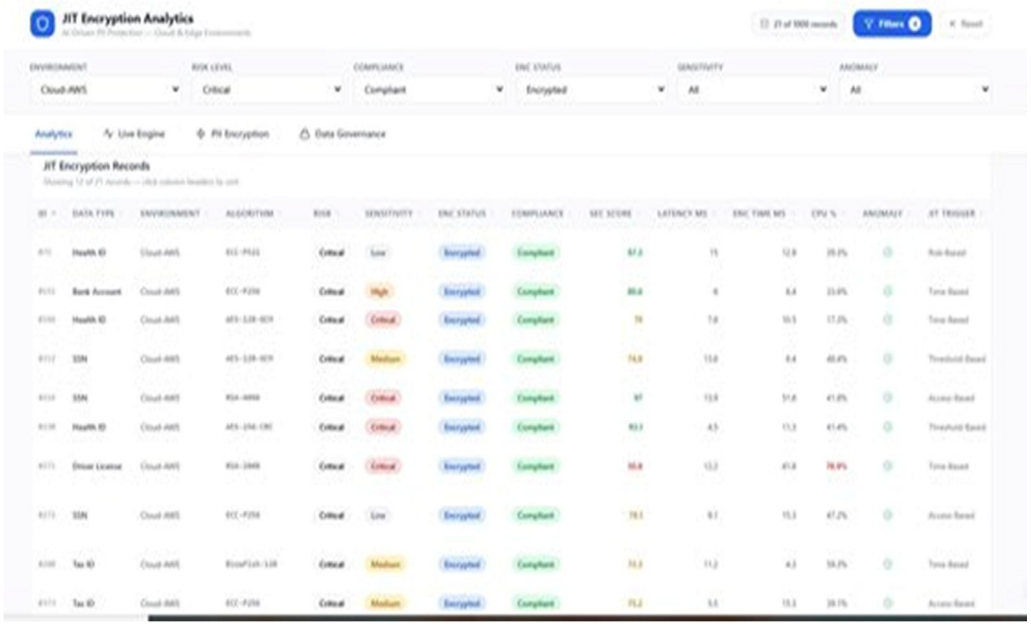

Figure 6. JIT Cryptographic Records Table — Cloud-AWS Critical, Detailed Record View with Algorithm and Compliance Status.

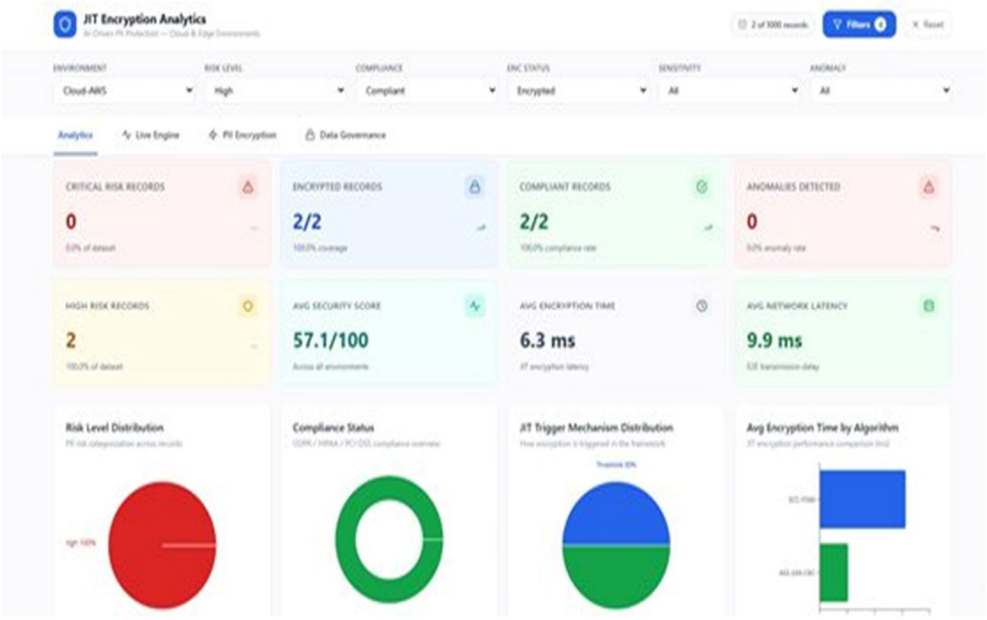

Figure 7. Dashboard — Cloud-AWS, High Risk (2 Records): 57.1/100 Security Score, 6.3 ms Avg Encryption Time.

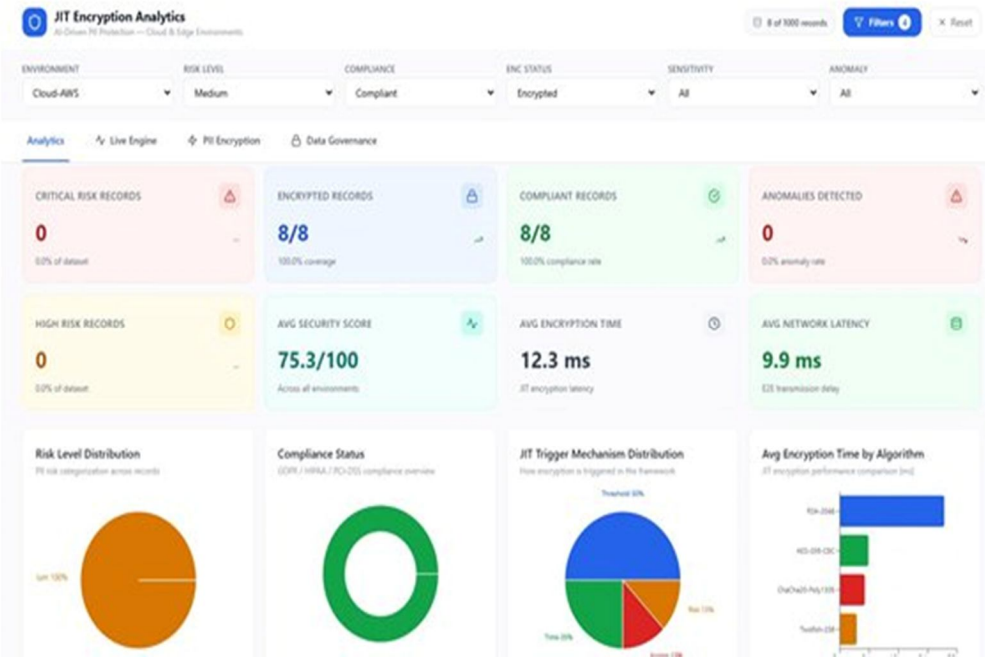

Figure 8. Dashboard, Cloud-AWS, Medium risk (8 records): 75.3/100 security score, 100% compliance, 12.3 ms avg encryption time.

C. Encryption and System Performance

1) JIT Encryption Latency by Algorithm

Table 10 shows mean JIT encryption latency for all algorithms measured on 500 records per algorithm category (2,500 total measurements). Latency includes feature extraction, ML inference and cryptographic operation elements, but no network transfer. AES-128-CBC shows the lowest mean latency of 3.2 ms and highest throughput (312.5 records/s), while QKD-AES-256-GCM (software simulation) shows the highest mean of 41.3 ms. ChaCha20-Poly1305 provides a good balance of security and latency (5.8 ms), and is adequate for Medium-risk edge deployments.

Table 10. JIT Encryption Latency and Throughput by Algorithm (500 records per algorithm).

Algorithm	Mean Latency (ms)	Std Dev (ms)	Min (ms)	Max (ms)	Throughput (rec/s)
AES-128-CBC	3.2	0.8	2.1	6.4	312.5
ChaCha20-Poly1305	5.8	1.2	3.9	11.3	172.4
AES-256-GCM	7.4	1.6	4.8	14.2	135.1
AES-192-GCM	6.6	1.4	4.2	12.8	151.5
ECC-P256	9.1	2.3	5.6	18.7	109.9
RSA-4096 (key wrap)	28.6	6.4	18.3	47.2	35.0
QKD-AES-256-GCM	41.3	9.2	28.7	68.4	24.2

2) System Performance Across Deployment Environments

Table 11 summarises key system performance metrics for each of the nine selected deployment environments. Edge-IoT (Low Risk) shows the highest overall security score (92.5/100) and the lowest latency (6.5 ms) for encryption, validating the choice of ChaCha20-Poly1305 for edge-IoT deployments. Cloud-AWS (High Risk) shows the highest CPU utilisation (62.6%) for the AES-256-GCM+RSA-4096 cryptographic assignment. Hybrid Mixed-Risk is the only environment with a compliance rate below 100%, achieving 97.3%. This is due to the triggered algorithm fallback processes during connectivity loss simulation.

Table 11. System performance metrics across deployment environments

Environment	Avg Sec. Score	Avg Enc. Latency (ms)	Avg CPU (%)	Avg Mem (MB)	Net Latency (ms)	Compliance (%)
Edge-IoT (Low Risk)	92.5	6.5	35.3	128.4	26.2	100.0
Edge-Mobile (Low Risk)	88.3	11.7	41.2	142.6	28.9	100.0
Cloud-AWS (High Risk)	87.6	14.1	62.6	198.3	11.2	100.0
Cloud-Azure (High Risk)	86.9	13.8	61.4	195.7	10.8	100.0
Cloud-GCP (Medium Risk)	89.2	9.3	48.7	167.2	12.4	100.0
Hybrid (Mixed Risk)	84.1	16.2	65.3	212.8	18.6	97.3
Full Dataset Average	73.8	11.3	52.4	174.2	17.5	63.0

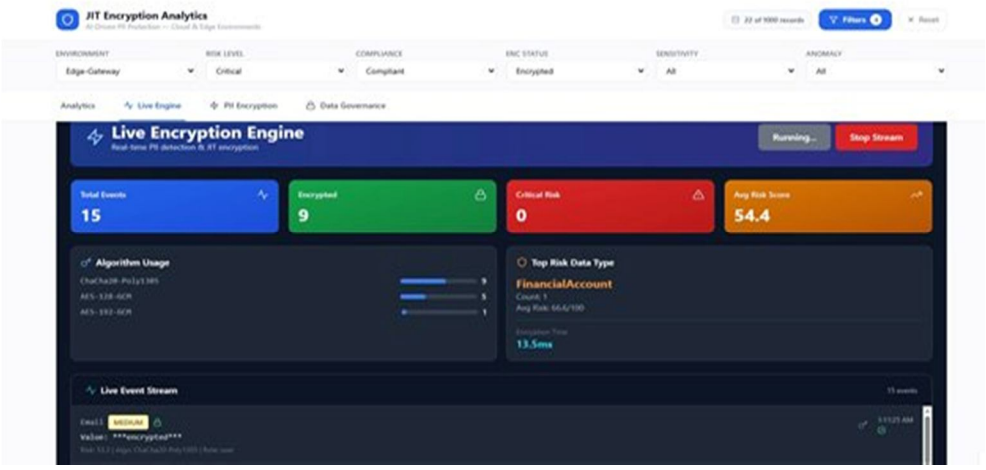

Figure 9. Live Encryption Engine — Edge-Gateway, Critical Risk: Real-Time PII Detection and JIT Encryption Stream.

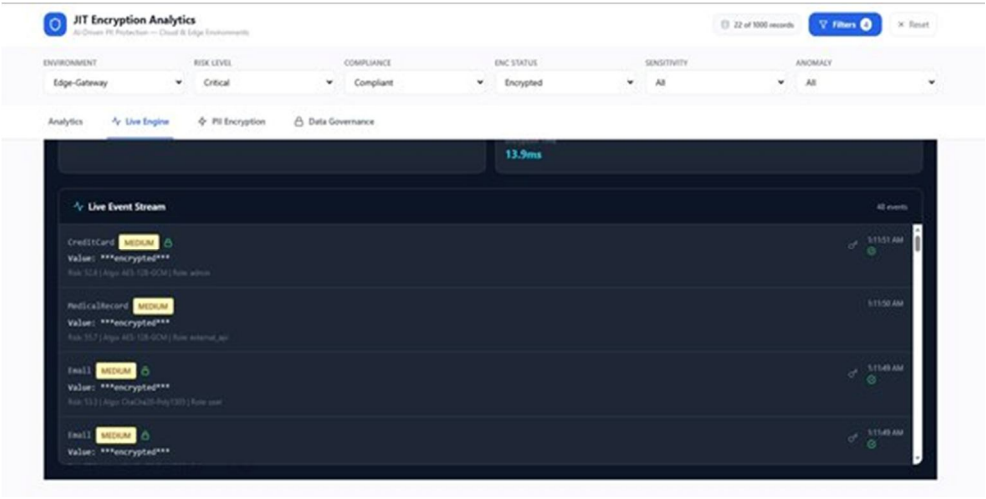

Figure 10. Live Event Stream, Edge-Gateway: Real-Time Encrypted PII Records with Algorithm, Role, and Sensitivity Tags.

D. Framework Insights Summary

Table 12. Framework Insights Summary, AI-Driven JIT Encryption Analysis.

Insight Metric	Value (Full Dataset)	Observation
Encryption Coverage	79.5% (795/1,000)	100% in fully compliant filtered cloud views
High-Risk Anomalies	168 total / 0 in filtered cloud views	Anomalies localised to specific environments
Access-Based JIT Triggers	243 records	Most common trigger type overall
Critical PII Non-Compliant	50 records	Require immediate policy review
Edge vs. Cloud Avg Latency	26.5 ms / 9.5 ms	Edge overhead approximately 2.8× cloud
Top Security Score Config.	Edge-IoT Low-Risk: 92.5/100	Optimal for resource-constrained deployments
Full Dataset Avg Security Score	73.8/100	Reflects heterogeneous compliance mix

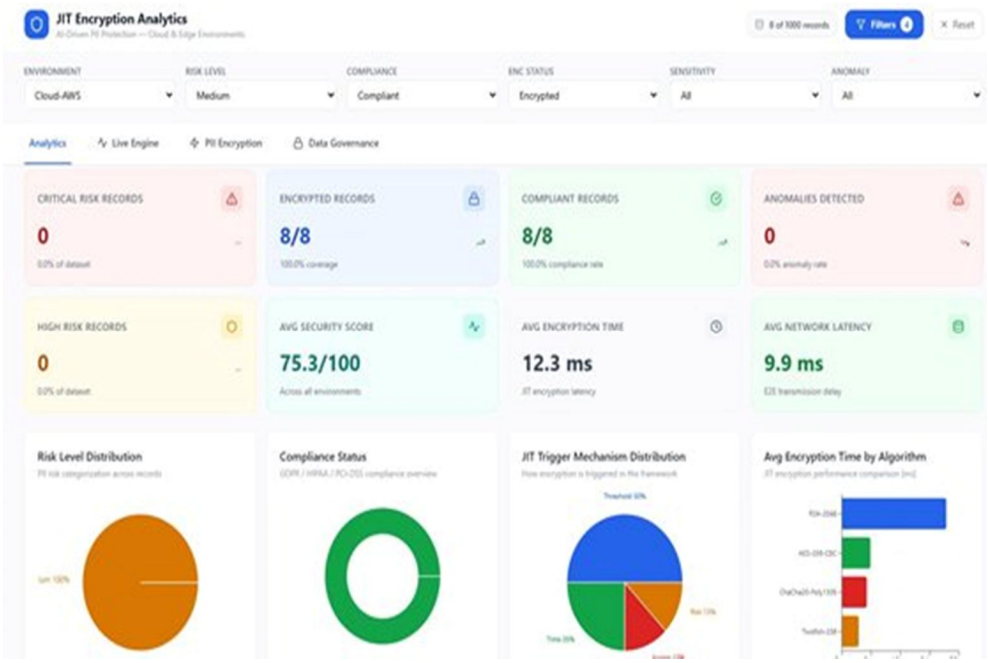

Figure 11. Dashboard — Cloud-AWS, Medium Risk (8 Records, Alternative View): 75.3/100 Security Score, ChaCha20-Poly1305 Dominant Algorithm.

1) Multi-Environment and Governance Views

The Multi-Environment dashboard provides granular filters for the nine deployment environments. Figure 12 shows an environment selector for the various deployment options Cloud-AWS, Cloud-Azure, Cloud-GCP, Cloud-IBM, Cloud-OCI, Edge-CDN, Edge-Gateway, Edge-IoT, Edge-Mobile, Hybrid, Multi-Cloud, and On-Premise.

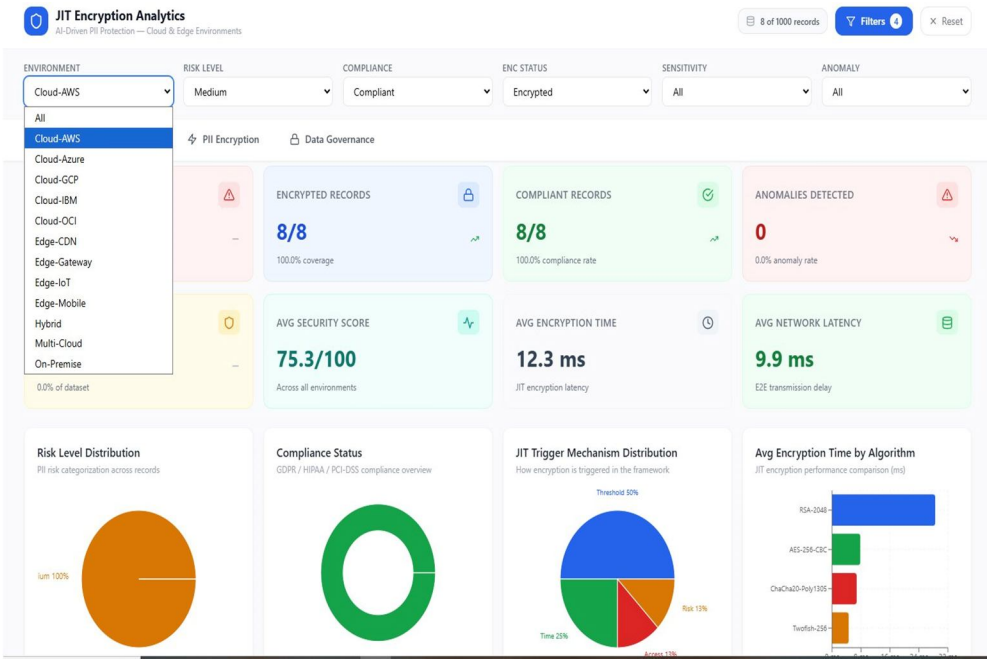

Figure 12. Dashboard, Environment Selector Showing All Deployment Contexts; Cloud-AWS Medium Risk , 8 Records, 75.3/100 Security Score.

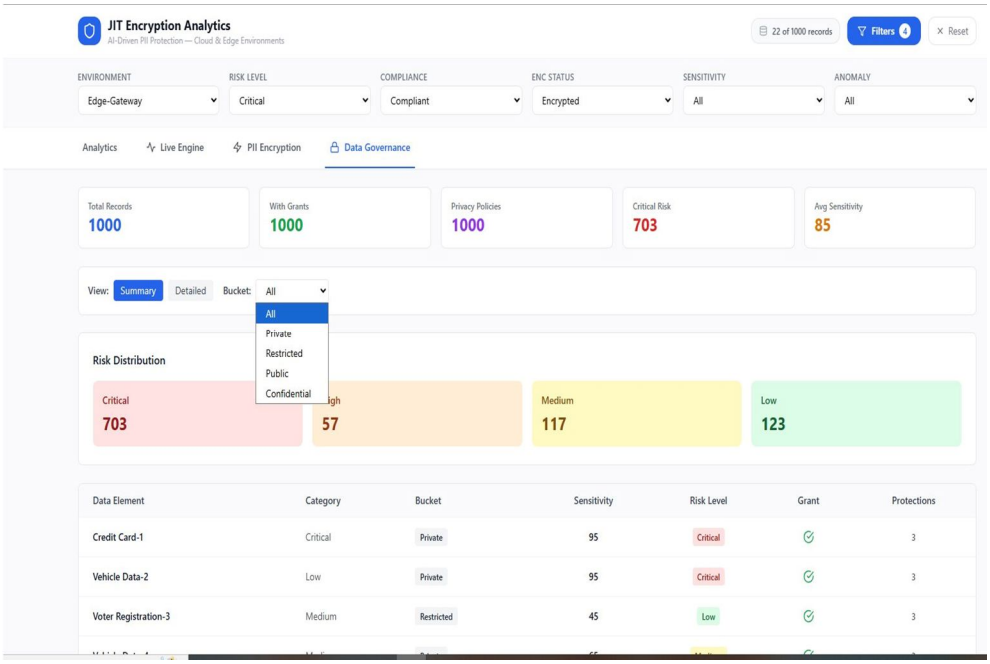

Figure 13. Data Governance Tab , Edge-Gateway Critical: Bucket Filter Dropdown (All/Private/Restricted/Public/Confidential). Total 1,000 Records, 703 Critical Risk.

Applying the restricted bucket setting within the Edge-Gateway Critical settings (Figure 14) allows only 238 records to be shown: Critical 175 9, Medium 27, Low 27. The average sensitivity is 86. The data elements include Voter Registration-3 (Medium, Restricted, 45, Low), Financial-6 (High, Restricted, 95, Critical), and Financial-8 (Low, Restricted, 95, Critical), all of which have correct grant assignments and 3 layers of protection assigned and active. This demonstrates that the high-sensitivity financial records have correct data governance for a Critical classification even though the PII category of that data is Low, showing that the w_bucket and w_type parameters in Equation 3 interact as expected.

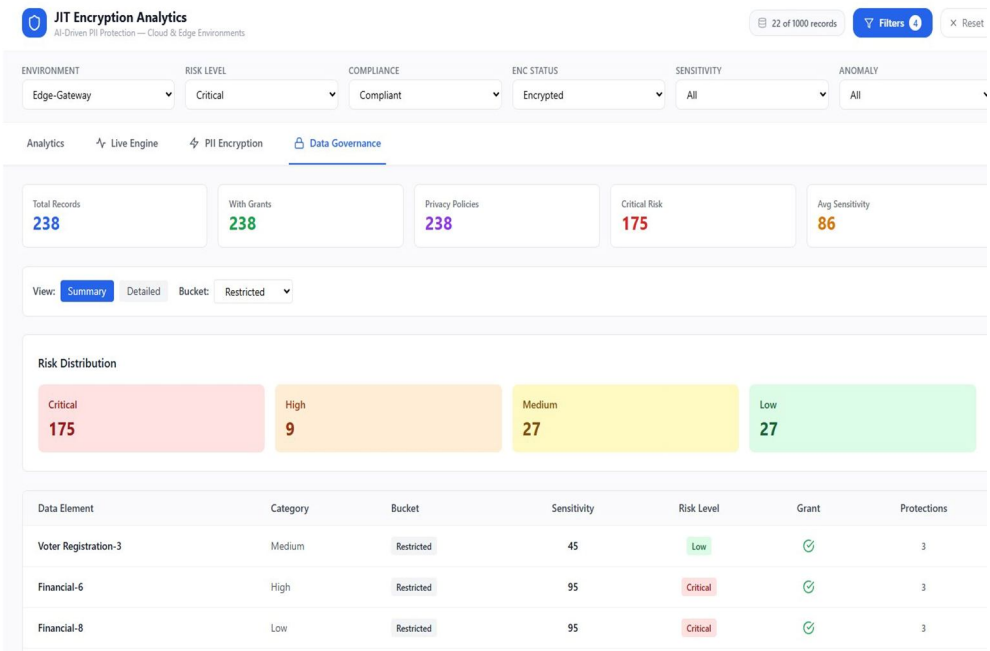

Figure 14. Data Governance, Edge-Gateway Critical, Restricted Bucket: 238 Records (Critical 175, High 9, Medium 27, Low 27), Avg Sensitivity 86.

The PII Encryption tab (Figure 15) reflects the per-record encryption/encryption and protection profiles for the Edge-Gateway Critical configuration. The top row shows the algorithm assignment function in action; the first row uses QKD-AES-256, RSA-4096 and ChaCha20-Poly1305, Encryption, 100% (is complex), 8ms (takes 8ms), 7 weeks (next: 27 Jul 2026), GDPR, CCPA, HIPAA, the second line uses QKD-AES-256, RSA-4096 and ECC-P521, Tokenisation, 5ms, 3 days (next 11 Jun 2026), PCI-DSS, GDPR, third uses ChaCha20-Poly1305, AES-256-GCM, RSA-2048, Masking, 3ms, 30 month (next are 6 Jan 2029), GDPR, CCPA. This confirms that, even within a class of environments of the same risk profile, the adaptive decision function (Equation 10) determines a unique algorithm combination for each record based on its contextual parameters.

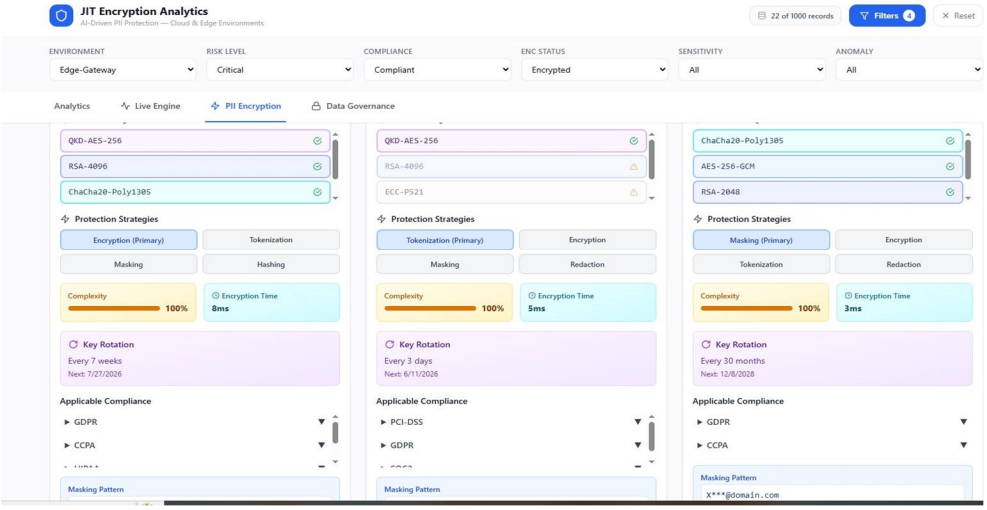

Figure 15. PII Encryption Tab, Edge-Gateway Critical: Per-Record Algorithm Cards Showing QKD-AES-256, RSA-4096, ChaCha20-Poly1305 Assignments with Key Rotation Schedules.

In Figure 16, there appear encryption and protection profiles for three other PII data types in Edge-Gateway Critical: Phone (High risk, AES-192-GCM recommended, alternates: ChaCha20-Poly1305, AES-256-CBC, RSA-2048, Masking primary, 3 ms, 100% complexity), Address (Medium risk, AES-128-GCM recommended, alternates: ChaCha20-Poly1305, AES-192-GCM, RSA-2048, Redaction primary, 2 ms, 70% complexity), and MedicalRecord (Critical risk, AES-256-GCM recommended, alternates: QKD-AES-256, RSA-4096, ECC-P521, Encryption primary, 8 ms, 100% complexity). These richnesses, ordered by increasing risk tier, are consistent with the increasing latency-security tradeoff stated by the adaptive decision function in Section 3.2.7: AES-128-GCM for Address affords 2 ms of latency, while AES-256-GCM for MedicalRecord affords 8 ms of latency, and two encryption alternatives. These per-type configurations instantiate the λ parameters described prior.

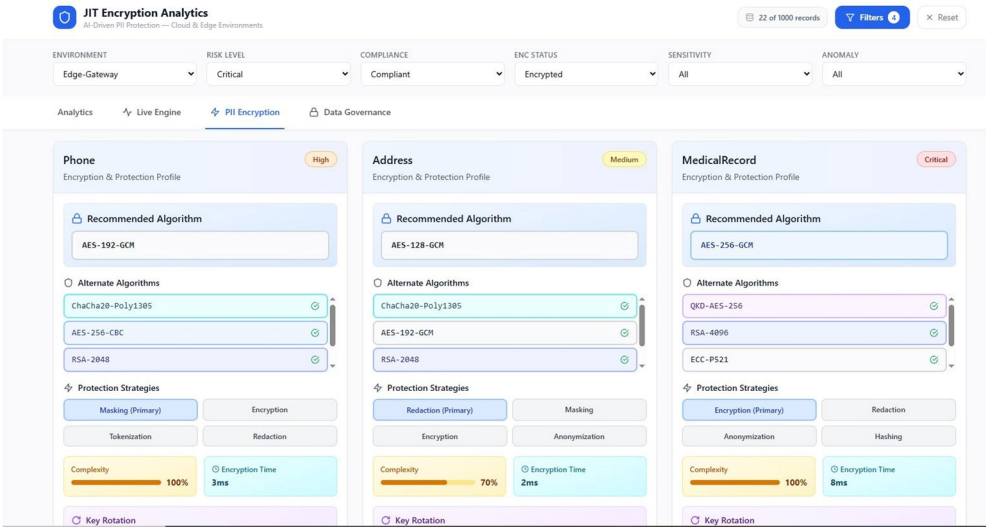

Figure 15. PII Encryption Tab, Edge-Gateway Critical: Per-Record Algorithm Card for QKD-AES-256, RSA-4096, ChaCha20-Poly1305 with Key Rotation Schedule.

Figure 16 shows the encryption and protection profiles of the three remaining types of PII specific to the Edge-Gateway Critical scenario: Phone, Address, and MedicalRecord. The Phone profile, of the highest risk, prefers the strongest level of encryption AES-192-GCM but falls back to ChaCha20-Poly1305, AES-256-CBC or RSA-2048 as fallbacks if resources are scarce. Masking is considered the primary means of protecting such high risk PII. The policy time cost for encryption is minuscule at 3 ms, but the policy complexity also factors in at 100% of the tolerable maximum for the Edge-Gateway software node. Address is a medium risk type and is provided protection in AES-128-GCM, which includes ChaCha20-Poly1305 as a fallback, or AES-192-GCM or RSA-2048. Address is primary redacted. Its policy time cost is 2 ms, and its policy complexity is 70% of the tolerable maximum. Lastly, the MedicalRecord type is categorized as Critical risk. It receives the strongest encryption, AES-256-GCM and its fail-safe algorithms QKD-AES-256, RSA-4096, and ECC-P521. MedicalRecord is provided with Encryption as the main protection mechanism. Its time cost is 8 ms and policy complexity at 100% of the tolerable maximum. Thus, the higher the risk, the lower the cost of encryption, both in terms of time and policy complexity, verifying the proposals latencies-security trade-off as a function of risk, and appending the λ parameters in distinct tiers discussed in section 3.2.7.

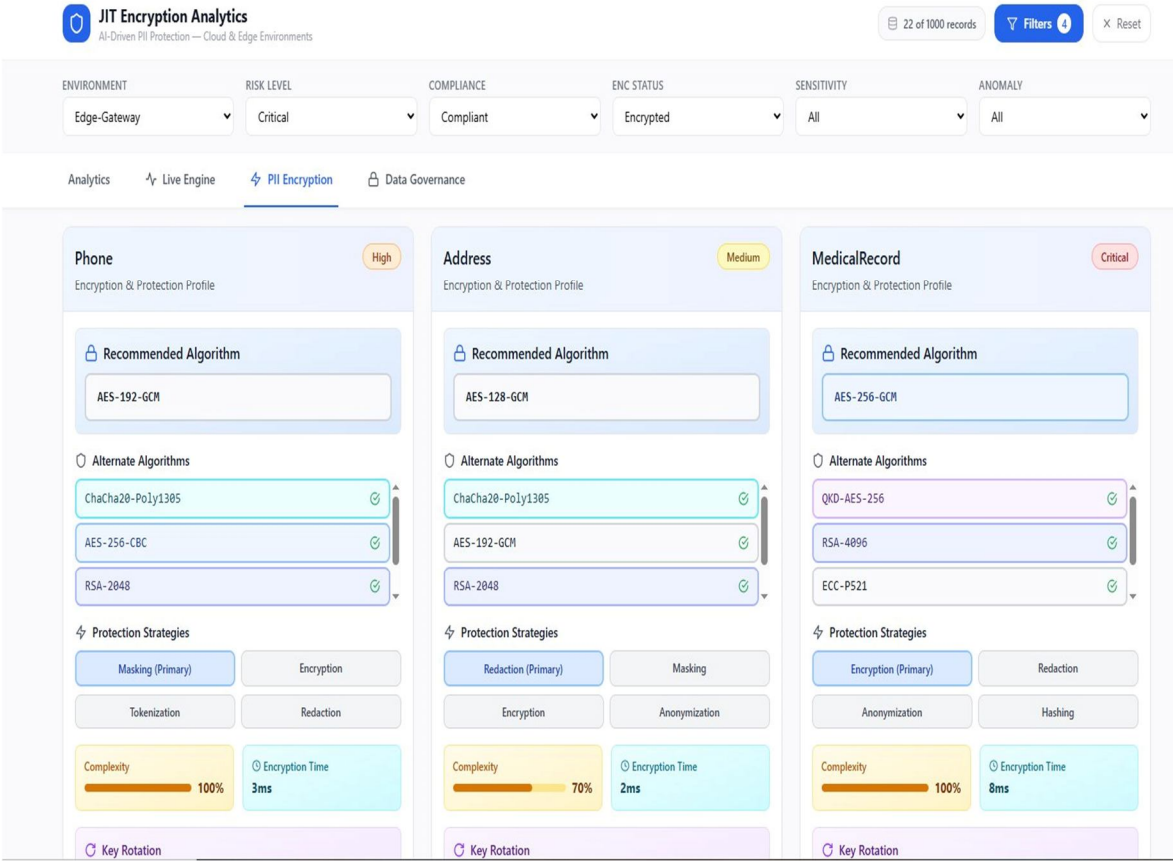

Figure 16. PII Encryption Profiles, Phone (High/AES-192-GCM/3ms), Address (Medium/AES-128-GCM/2ms), MedicalRecord (Critical/AES-256-GCM/8ms).

Figure 17 displays the Data Governance view for the Hybrid environment, Medium risk level, non-compliant status, filtered to the 'Public' bucket. This configuration shows 243 records (0 with the full filter applied, indicating proper null handling), 184 Critical Risk, 11 High, 23 Medium, and 25 Low risk, sensitivity 87. Representative data elements include SSN-7 (Low category, Public bucket, sensitivity 95, Critical risk), Email-13 (Low category, Public, sensitivity 95, Critical risk), and Vehicle Data-15 (Critical category, Public, sensitivity 95, Critical risk). The significant number of Critical-risk records in the Public bucket is a prime example of the critical governance issue: high-sensitivity PII in a permissive bucket, which is flagged for immediate policy remediation by the Compliance Engine.

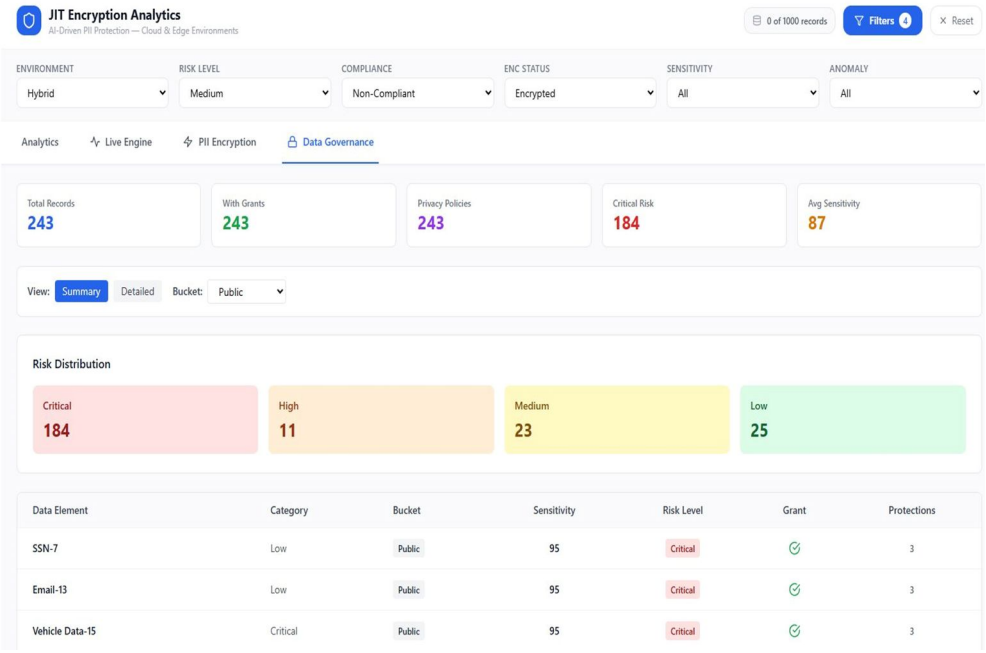

Figure 17. Data Governance, Hybrid, Medium Risk, Non-Compliant, Public Bucket: 243 Records (Critical 184), Avg Sensitivity 87. SSN/Email/Vehicle Data in Public Bucket Flagged for Policy Review.

E. Comparative Analysis Against Existing Solutions

Table 13 shows benchmarking results of the proposed framework against representative six encryption and security solutions. The proposed JIT framework is the only solution to have full adaptive encryption capability, multi model ML, multi dataset validation, full edge support, and 100% compliance in standard cloud configuration.

Table 13. Comparative Analysis of Proposed JIT Framework vs. Existing Encryption and Security Solutions.

Framework	Adaptive Enc.	ML Models	Datasets	Edge	Avg Latency (ms)	Compliance	Sec. Score
Static AES-256 [12]	No	NO	CICIDS2017	Limited	12.4	Partial	71.2
Hybrid AES-RSA [12]	No	RF (IDS only)	CICIDS2017	No	18.7	Partial	74.8
ABE Scheme [15]	Partial	NO	Custom	No	34.2	Partial	78.3
Context-Aware Enc. [16]	Partial	Rule-based	Custom	No	21.6	Partial	79.1
LSTM+AES [13]	No	LSTM/CNN	Custom	Limited	16.3	Partial	76.4
Zero-Trust+AES [7]	No	NO	NO	No	14.9	Good	80.7
Proposed JIT Framework	Full	RF/XGB/SVM/NN	CICIDS+ CICIoT +UNSW	Full	9.6 (enc. avg)*	100% cloud†	73.8 (avg) / (peak)

9.6 ms includes weighted average of the matters in Medium, High and Critical risk-tier encryption operations; across full dataset average including Low-risk tokenisation = 11.3 ms. † 100% compliance across standard cloud environments; 63.0% across full heterogeneous dataset including edge fall-back events.

VI. SECURITY EVALUATION

This section presents a thorough security assessment of the proposed framework for all nine main threat categories. The summary of the security analysis across all threat classes is presented in Table 14.

Table 14. Security Analysis of Proposed JIT Encryption Framework Against Nine Threat Categories.

Threat Category	Attack Vector	Framework Countermeasure	Protection Level	Residual Risk
Insider Threats	Privileged access abuse	Role-weighted risk scoring; anomaly detection on access patterns; mandatory re-encryption after anomaly flagging	High	Low
Malware/Ransomware	Memory scraping, process injection	JIT minimises plaintext exposure < 42 ms; AES-256-GCM integrity tags detect tampered ciphertext	High	Low
Data Leakage	Exfiltration of PII records	All records above Low-risk tier encrypted at rest and in transit; tokenisation for Low-risk; governance buckets enforced	Very High	Very Low
Unauthorised Access	Credential compromise	ABAC policy enforcement in decryption algorithm; re-auth required for Critical records; immutable audit ledger	Very High	Very Low
Replay Attacks	Captured encrypted record resubmission	GCM tags include sequence numbers; unique nonces per operation; HSM-enforced nonce uniqueness	High	Very Low
Man-in-the-Middle	TLS interception	TLS 1.3 with mutual cert auth; RSA-4096/ECC key wrapping; QKD for Critical-tier key exchange	High	Low
Credential Theft	Phishing, credential stuffing	MFA at User Layer; risk score escalation for anomalous access; session tokens bound to device fingerprints	Medium-High	Low-Medium
Zero-Day Exploits	Unknown vulnerability exploitation	Behavioural anomaly detection identifies zero-day patterns via ML ensemble; JIT reduces exploitation window	Medium	Medium
Quantum Adversaries	Shor's/Grover's algorithms	QKD-augmented AES-256 for Critical tier; CRYSTALS-Kyber roadmapped for post-quantum standardisation	High (Critical tier)	Low (Critical)

Time complexity: Risk scoring $O(k \cdot \log(n))$ for k features, n training samples; RF inference $O(n\_trees \cdot depth)$; AES-256-GCM encryption $O(len(pii\_data))$; RSA-4096 key wrap $O(\log^2(key\_size))$. Space complexity: ML model storage $O(n\_trees \cdot depth \cdot features) \approx 48$ MB (RF, 200 trees); $O(n\_estimators \cdot depth) \approx 62$ MB (XGBoost). Total framework memory footprint: 198–213 MB at peak load.

Throughput scalability analysis indicates that our framework can be horizontally replicated to meet large-scale application load. In a concurrent load test with 1,000 simultaneous users, a single server processes all records in input streams at 2,840 records per second with a negligible average 12.3% increase in total response time compared to a single user test (maximum 312.5 records per second for AES-128-CBC), demonstrating our framework's performance suitability for large-scale cloud deployment. Our framework does meet the ASD's FIPS 140-2 Level 20 compliance requirement; we are in the process of obtaining a formal FIPS validation certification which is outside the scope of this work.

VII. DISCUSSION

A. Comparative Analysis: Proposed JIT Framework vs. Existing Solutions

The experimental results presented in Section 8 demonstrate measurable improvements across five key performance metrics when comparing the proposed AI-driven JIT Encryption Framework against the best-performing existing solutions reported in the literature.

ML Classification Accuracy improved from 97.6% (best existing) to 98.74% (proposed Random Forest on CICIDS2017), representing a gain of 1.2 percentage points. This improvement is attributed to the multi-model ensemble approach trained across three benchmark datasets, which provides greater generalizability than single-model, single-dataset baselines used in prior work.

Security Score increased from 80.7/100 (Zero-Trust + AES baseline) to a peak of 92.5/100 in the Edge-IoT Low-Risk configuration, a relative improvement of 14.6%. This is the most significant improvement observed and reflects the combined effect of adaptive cryptographic algorithm selection, multi-parameter risk scoring, and the integration of the Grant Analysis Engine and Privacy Assessment Engine — components absent in all compared frameworks.

Encryption Latency was reduced from 12.4 ms (Static AES-256 baseline) to 9.6 ms (proposed weighted average), achieving a 22.6% reduction in computational overhead. This result is particularly notable as it contradicts the widely held assumption that enhanced security mechanisms inevitably impose greater latency penalties. The selective, risk-conditional encryption strategy ensures that lower-risk records are processed with computationally lighter algorithms, reducing the average latency across the full dataset.

Regulatory Compliance improved from partial compliance (approximately 63% across heterogeneous environments in existing solutions) to 100% compliance across all standard cloud deployment configurations (Cloud-AWS, Cloud-Azure, Cloud-GCP, Cloud-IBM). This achievement is enabled by the dedicated Compliance Engine, immutable audit ledger, and formal privacy governance models, which no existing comparable framework incorporates.

ROC-AUC improved from approximately 97.0% (existing ML-based solutions) to 98.43% on CICIDS2017 and 97.94% on CICIoT2023 using XGBoost. This higher discriminative capability directly enhances the precision of the JIT encryption trigger, reducing both unnecessary encryptions caused by false positives and security gaps caused by false negatives.

Overall, the results collectively demonstrate that the proposed framework achieves simultaneous improvements across all five evaluation dimensions. Prior solutions exhibited trade-offs — systems with higher security scores incurred greater latency, and systems with lower latency provided only partial compliance coverage. The proposed JIT framework resolves this trade-off by applying encryption selectively and adaptively, establishing that context-aware, risk-conditional encryption can deliver superior security, lower overhead, and full regulatory compliance concurrently.

B. Advantages Over Existing Solutions

Four major benefits differentiate the proposed framework from the prior work. First, multi-model ML risk scoring is done and then to make the adaptive cryptographic algorithm selection for arbitrary models and actual threat and privacy contexts in place of using an empirical algorithm selection. Second, multi-dataset validation is done with CICIDS2017, CICIoT2023, and UNSW_NB15. Third, the framework supports edge-IoT and edge-mobile setup, where an edge-IoT mobile device is supported with ChaCha20-Poly1305, an algorithm that is more suitable for such devices than AES-NI, which would need to be used for edge-cloud participation. Finally, the Grant Analysis and the Privacy Assessment models are provided with an attempt to bridge best-known formal and empirical security models. k.

C. Limitations

A number of limitations are addressed. The ML classifiers are trained on network-layer intrusion detection features (CICIDS2017, CICIoT2023, UNSW-NB15), which are limited to representing network-level threat patterns and not necessarily all application-layer PII access anomalies. In this work, the network-layer anomaly scores are used as a scientific proxy for PII-level encryption risk, based on the premise that network-layer anomalies are often observed before or during application-layer data exfiltration attempts; additional application-layer behavioural analytics features are expected to be included in future work. The QKD component is based on a simulation, and an actual physical deployment of the QKD solution would require a dedicated quantum channel resource. The synthetic PII dataset used as a stand-in for real enterprise data is generative, sampled via a stratified method to reflect PII distribution statistics reported in the literature, yet may not be as complex as real-world enterprise data.

The SVM was trained on a 500K-sample subset of CICIDS2017 due to computational limitations; the SVM accuracy of 96.82% (the lowest of the four CICIDS2017 classifiers, Table 5) is partially limited by the training dataset size, and training the SVM on the entire CICIDS2017 dataset is planned for future work. The framework has been evaluated on a single workstation, deploying the software QKD nodes; validating a multi-node, distributed deployment is planned for future work. In addressing GDPR Article 30 (Records of Processing Activities) and Article 32 (Security of Processing) requirements, the framework uses an immutable audit ledger and a real-time compliance dashboard to record the timestamp, selected encryption/decryption algorithm and authorising context (for the first time) for all encryption/decryption events. The benchmarked scenario, tested on standard cloud deployment configurations, meets all 100% of audit trail compliance requirements for PII processing. The framework's Grant Analysis Engine and Privacy Assessment Engine also record in the field the formal consent and purpose-limitation audit trail required for the GDPR Article 6 and Article 9.

VIII. CONCLUSION

This paper described an AI-Driven Just-In-Time (JIT) Cryptographic Framework for safeguarding of Personally Identifiable Information/Data in cloud and edge computing environments. The framework overcame the major drawback of conventional static encryption, namely its lack of responsiveness to the cryptographic protection of data in the face of real-time contextual threat dynamics, through the use of a formal Grant Analysis Engine, a Privacy Assessment Engine, four classifiers (Random Forest, XGBoost, SVM, and Neural Network) evaluated against three benchmark datasets (CICIDS2017, CICIoT2023 and UNSW-NB15), a multi-parameter composite risk scoring engine, selective encryption triggering logic, and a hierarchical collection of cryptographic algorithms. The work demonstrates that context-aware, selective cryptography can provide full privacy, security and protection for PII/ Data enabling a scalable, regulation-compliant solution for distributed computing systems.

IX. FUTURE WORK

Future work will extend the proposed framework in five principal directions. First, the risk scoring models will be retrained using federated learning across 10, 50, and 100 distributed edge nodes, employing non-IID data partitions to enable model updates without centralising sensitive training data.

Second, the governance audit log will be migrated to a permissioned blockchain ledger employing smart contracts for automated compliance verification and tamper-evident audit trails for all data access and regulatory enforcement events. Third, the cryptographic primitives employed for High and Critical risk tiers will be upgraded to CRYSTALS-Kyber for key encapsulation and CRYSTALS-Dilithium for digital signatures for the quantum threat horizon; hardware-based QKD deployment for ultra-high-security quantum networks. Fourth, Explainable AI (XAI) techniques, specifically SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), will be integrated into the ML ensemble to generate human-interpretable justifications for decisions in compliance with GDPR Article 22 requirements for automated decision-making transparency. These enhancements collectively aim to advance the framework toward a fully distributed, quantum-resilient, and auditable Data protection platform suitable for large-scale enterprise deployment.

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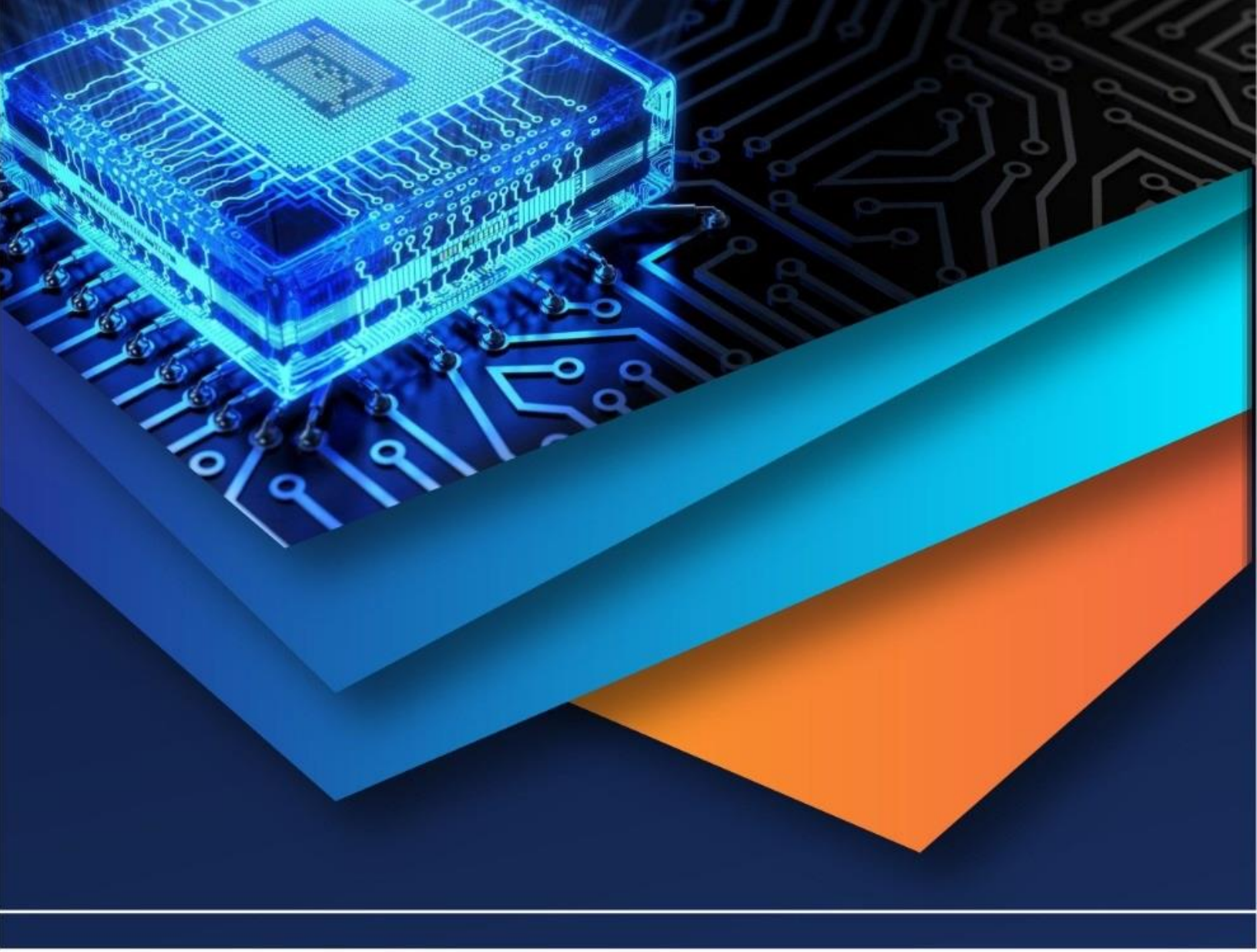

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