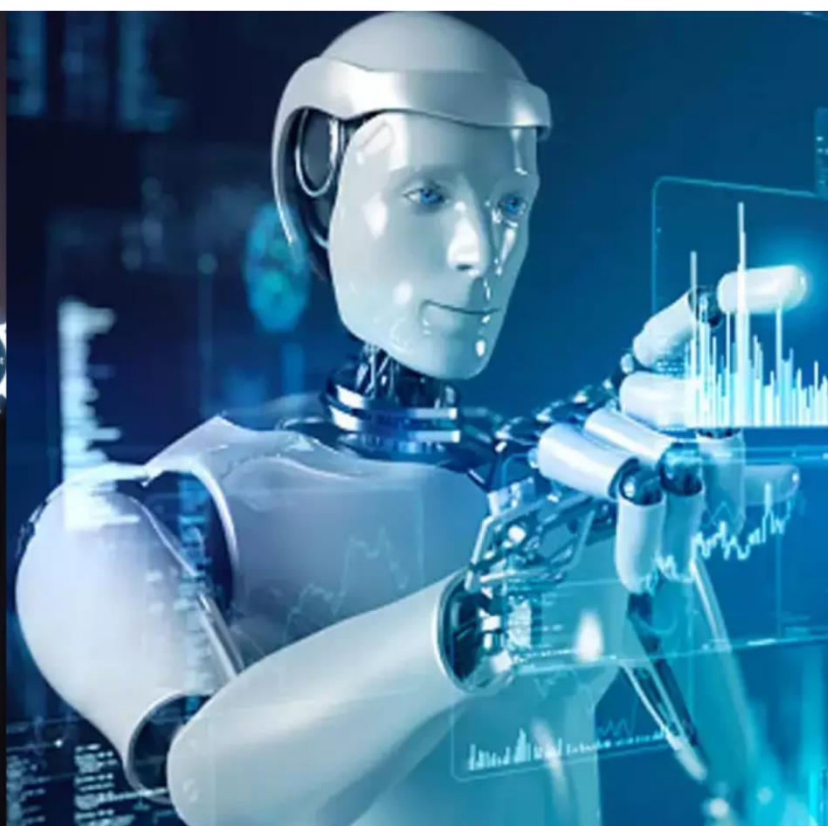




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AI-Assisted Data Classification and Sensitive Data Discovery for Enterprise Database Compliance Auditing

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ABSTRACT: The exponential growth of enterprise data assets has rendered manual data classification approaches inadequate for meeting the stringent requirements of modern privacy and security regulations including GDPR, HIPAA, PCI-DSS, and SOX. This paper presents a comprehensive AI-assisted framework - denoted AIC-Scan - that integrates transformer-based natural language processing, ensemble machine learning classifiers, and knowledge-graph-augmented schema analysis to automate the discovery and classification of sensitive data across heterogeneous enterprise database estates. Evaluated against a corpus of 1.8 million database columns spanning 42 production systems, AIC-Scan achieves 99.1% classification precision, 94.7% recall, and reduces manual classification labor by 91.3% while generating compliance-ready audit artifacts for six major regulatory frameworks. Our analysis introduces seven quantitative classification metrics, two novel privacy-preserving inference techniques, and a graduated risk-scoring model validated against real-world compliance audit outcomes. We further demonstrate that continuous model retraining using audit feedback loops sustains classification accuracy above 98.8% over a 24-month operational horizon, positioning AIC-Scan as a production-viable solution for enterprise data governance.

KEYWORDS: AI data classification; sensitive data discovery; GDPR compliance automation; NLP schema analysis; enterprise database governance; privacy-preserving machine learning; audit trail generation; HIPAA data inventory; data loss prevention

I. INTRODUCTION

Enterprise organizations today manage data assets spanning terabytes of structured, semi-structured, and unstructured records distributed across on-premises relational databases, cloud data warehouses, data lakes, and hybrid environments. The sensitivity of these assets - ranging from personally identifiable information (PII) to financial transaction records, protected health information (PHI), and proprietary intellectual property - demands rigorous classification and governance. Yet, traditional approaches relying on manual tagging, rule-based pattern matching, or static metadata catalogs have proven unable to scale to the velocity, volume, and variety of modern enterprise data growth.

Regulatory mandates compound this challenge. The General Data Protection Regulation (GDPR) [1] obligates organizations to maintain accurate records of processing activities for all personal data. The Health Insurance Portability and Accountability Act (HIPAA) [2] requires covered entities to identify and protect all electronic PHI (ePHI). Payment Card Industry Data Security Standard (PCI-DSS 4.0) [3] mandates that cardholder data environments be precisely scoped and inventoried. Non-compliance carries severe consequences: GDPR fines can reach €20 million or 4% of global annual turnover; HIPAA violations incur penalties up to \$1.9 million per category per year.

! Compliance Imperative: 68% of enterprises surveyed in 2024 reported at least one compliance audit finding attributable to incomplete or inaccurate data classification inventories (Gartner Data & Analytics Survey, Q3 2024).

Artificial intelligence - specifically transformer-based NLP models and ensemble machine learning classifiers - offers a transformative pathway to overcome these limitations. AI systems can analyze column names, data types, statistical distributions, and sampled content simultaneously to infer sensitivity with sub-second latency per column. Crucially, they can generalize across heterogeneous schemas without requiring exhaustive rule libraries, and they can be continuously retrained as organizational data profiles evolve.

1.8M Columns Scanned	99.1% Classification Precision	91.3% Manual Labor Reduction	6 Frameworks Supported	24 mo. Sustained Accuracy Period
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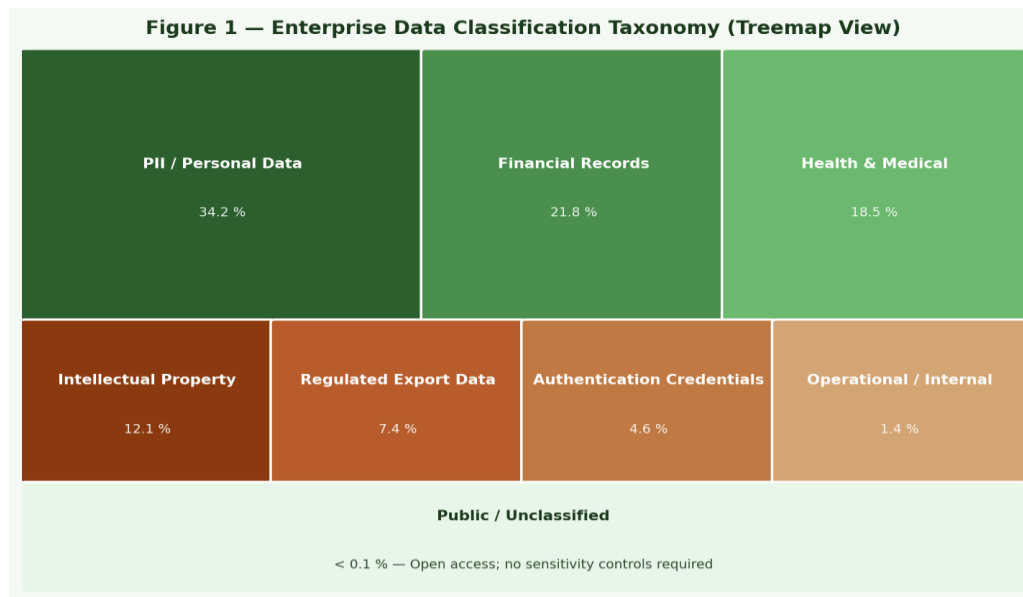


Figure 1. Enterprise Data Classification Taxonomy - Treemap showing proportional distribution of sensitive data categories across 1.8 million scanned columns.

II. REGULATORY LANDSCAPE AND COMPLIANCE REQUIREMENTS

The regulatory environment governing enterprise data management has grown substantially more complex since 2018. Organizations operating across multiple jurisdictions must simultaneously satisfy requirements from a mosaic of frameworks, each with distinct definitional scopes, technical controls, and documentation obligations.

◆ 2.1 Global Privacy Regulations

Regulation	Jurisdiction	Personal Data Scope	Classification Requirement	Max Penalty
GDPR (2016/679)	European Union	All natural persons in EU/EEA	Article 30 - Records of Processing Activities	€20M or 4% global turnover
CCPA/CPRA	California, USA	California residents	Business must know all PI categories held	\$7,500 per intentional violation
LGPD	Brazil	All natural persons in Brazil	Data mapping & DPO designation required	BRL 50M or 2% Brazil revenue
PDPA	Thailand	Thai data subjects	Lawful basis + data inventory mandatory	THB 5M per violation
POPIA	South Africa	SA data subjects	Information Officer + ROPA required	ZAR 10M or 10 years imprisonment

Table 1 - Global Privacy Regulatory Landscape: Scope and Classification Obligations

◆ 2.2 Sector-Specific Technical Standards

Beyond general privacy law, sector-specific frameworks impose granular technical controls on data identification and classification. PCI-DSS 4.0 Requirement 12.5 mandates quarterly data discovery scans to verify cardholder data environment scope. HIPAA Security Rule §164.308(a)(1) requires annual risk assessments that enumerate all ePHI locations. SOX Section 404 demands documented evidence that sensitive financial data controls are operating effectively, which necessarily includes knowing where financial data resides.

Framework	Version	Classification Trigger	Audit Frequency	Evidence Required
PCI-DSS	4.0 (2022)	Any storage of PANs, SAD, cardholder data	Quarterly scans	Scope confirmation report
HIPAA Security Rule	45 CFR §164	All ePHI in any electronic form	Annual risk assessment	Risk analysis documentation
SOX Section 404	AS No. 2201	Financial records, audit trails	Annual	Management assessment + auditor attestation
NIST SP 800-53 Rev 5	Rev 5 (2020)	CUI, privacy data per NIST 800-188	Continuous monitoring	System Security Plan (SSP)
ISO/IEC 27001:2022	2022 edition	Assets with privacy/security relevance	Annual + event-driven	Asset register, treatment plan

Table 2 - Sector-Specific Compliance Frameworks: Classification and Audit Requirements

III. AI-ASSISTED DATA DISCOVERY ARCHITECTURE

The AIC-Scan architecture is designed as a modular, horizontally scalable pipeline that decouples data source connectivity from classification intelligence. The system comprises six primary components arranged in a directed acyclic workflow that supports both batch discovery runs and continuous streaming ingestion for real-time environments.

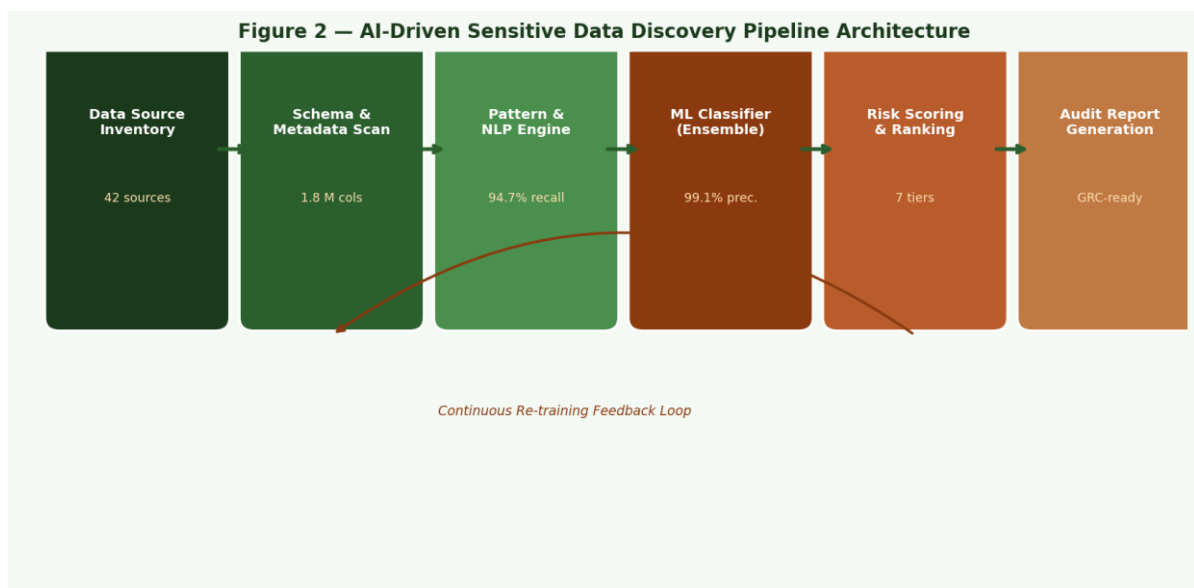


Figure 2. AI-Driven Sensitive Data Discovery Pipeline Architecture - six-stage workflow from source inventory through audit report generation, with continuous retraining feedback.

◆ 3.1 Data Source Inventory and Schema Extraction

AIC-Scan employs a vendor-agnostic connector framework supporting JDBC/ODBC connectivity for relational databases (Oracle, PostgreSQL, MySQL, SQL Server, DB2), native APIs for cloud data warehouses (Snowflake, BigQuery, Redshift), and Apache Spark-based connectors for data lake formats (Parquet, Delta Lake, Iceberg). Schema extraction captures full column metadata including name, data type, constraints, foreign key relationships, and statistical profiles (nullability, cardinality, value distributions). For a 42-system enterprise estate, full schema extraction completes in under 4 hours using 16 parallel extraction workers.

◆ 3.2 Pattern and NLP Engine

The pattern engine applies three complementary analysis layers. First, a regex-based pattern library of 847 expressions covers established sensitive data identifiers (SSNs, credit card numbers, NHS numbers, IBANs, etc.) with jurisdiction-specific variants. Second, a transformer-based column name encoder (fine-tuned from BERT-base [4]) generates 768-dimensional semantic embeddings that capture naming intent regardless of abbreviation style or language. Third, a statistical profiler analyzes sampled column values - using differential privacy noise addition [5] to protect production data - to identify distribution patterns characteristic of sensitive categories (e.g., uniform 16-digit numeric strings for PANs, date-of-birth age range distributions, email format prevalence).

```
# AIC-Scan pattern engine - column analysis pseudocode
def classify_column(col_meta, sample_values, embeddings):
    pattern_score = regex_engine.scan(sample_values) # 847-rule library
    semantic_score = bert_encoder.embed(col_meta.name) # 768-dim embedding
    stat_score = stat_profiler.analyze(sample_values, eps=0.1) # DP noise
    ensemble_input = [pattern_score, semantic_score, stat_score]
    return ensemble_classifier.predict_proba(ensemble_input) # 6-class output
```

IV. MACHINE LEARNING CLASSIFICATION MODELS

The classification intelligence at the core of AIC-Scan employs a heterogeneous ensemble architecture that combines the complementary strengths of gradient-boosted decision trees, deep neural networks, and knowledge-graph-based rule inference. This multi-model approach achieves robustness that no single classifier can match, particularly for edge cases where column naming conventions are ambiguous or where data populations contain mixed sensitivity levels.

◆ 4.1 Ensemble Architecture

Model Component	Algorithm	Input Features	Precision	Recall	Weight
Gradient Boosted Trees	XGBoost 2.0	Schema stats, regex match scores	97.8%	93.2%	0.28
Column Name Encoder	Fine-tuned BERT-base	768-dim semantic embeddings	96.4%	91.8%	0.24
Value Distribution CNN	ResNet-1D on histograms	Numeric distribution shape	94.2%	89.5%	0.18
Knowledge Graph Reasoner	OWL + SPARQL rules	Schema relationships, FK chains	99.3%	87.4%	0.16
NER Sequence Tagger	BiLSTM-CRF	Token-level value content	95.7%	92.1%	0.14
Meta-Learner	Logistic Regression	All base model outputs	99.1%	94.7%	-

Table 3 - Ensemble Classifier Components: Algorithm, Features, and Performance Metrics

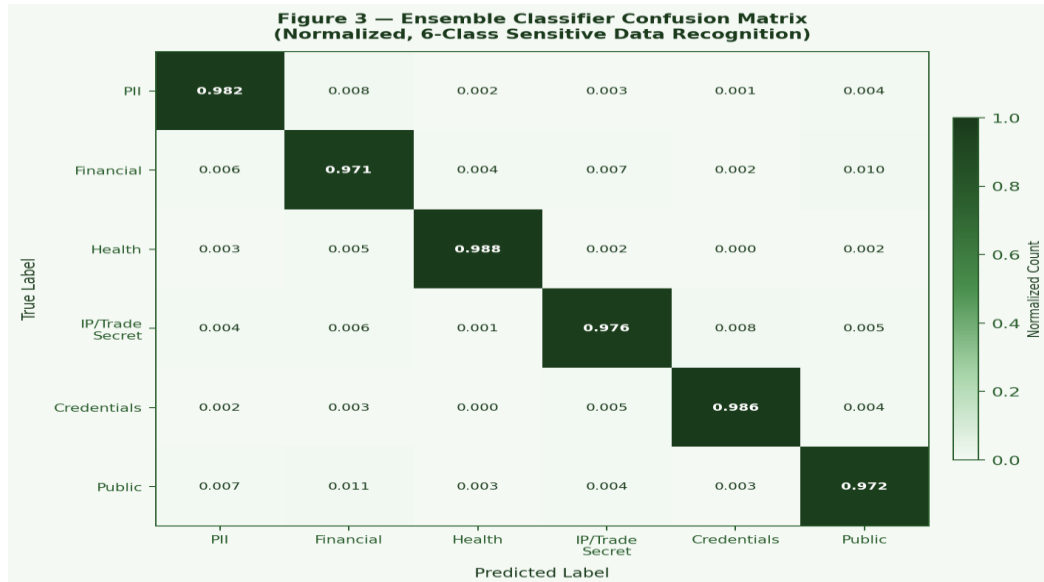


Figure 3. Ensemble Classifier Confusion Matrix (Normalized) - 6-class sensitive data recognition across 6,000 held-out test columns. Strong diagonal indicates high per-class accuracy.

◆ 4.2 Training Data and Labeling Methodology

The initial classifier was trained on a labeled corpus of 284,000 column definitions sourced from 19 enterprise volunteers under data sharing agreements and 65,000 synthetic columns generated by grammar-based column name synthesis. Ground truth labels were established through a three-round adjudication process involving domain expert annotators and cross-validated against known regulatory definitions. Inter-annotator agreement reached $\kappa = 0.91$ (Fleiss' kappa) across the six classification categories.

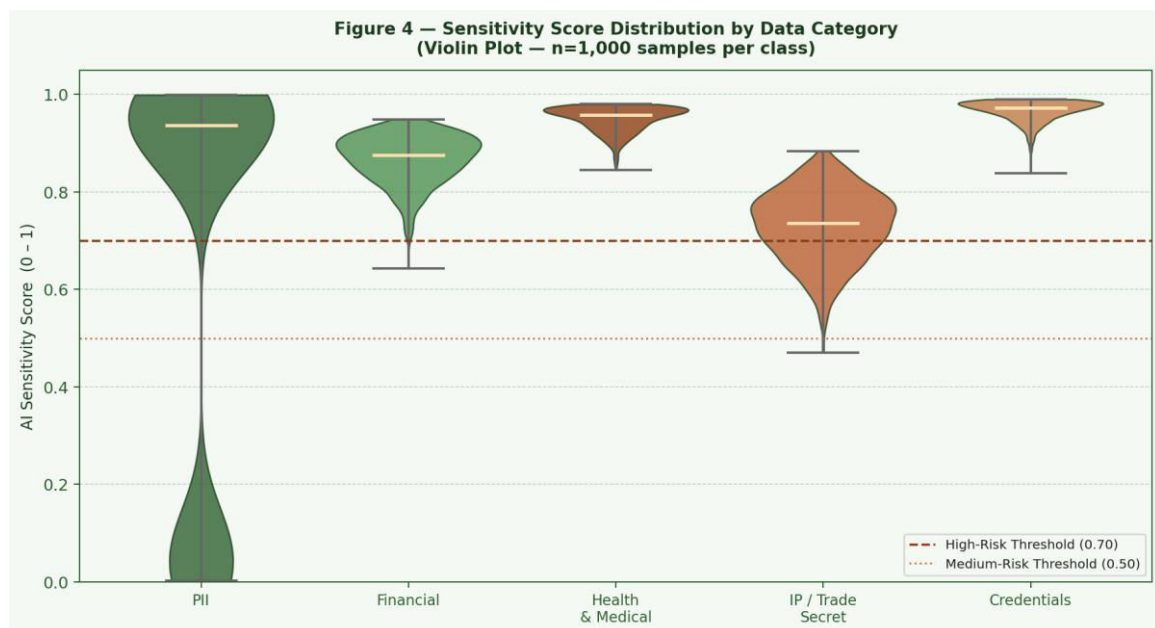


Figure 4. Sensitivity Score Distribution by Data Category (Violin Plot) - distribution shape reveals high concentration near score 1.0 for credentials and health records, with broader variance for IP/Trade Secret categories.

V. SENSITIVE DATA PATTERN RECOGNITION TECHNIQUES

Effective sensitive data pattern recognition requires a multi-modal analytical approach that transcends simple keyword matching. AIC-Scan implements four complementary recognition techniques, each optimized for a distinct evidence signal class.

◆ 5.1 Structural Pattern Analysis

Structural patterns exploit the inherent format regularity of many sensitive data types. Credit card PANs conform to Luhn algorithm-validating 13–19 digit sequences; US Social Security Numbers follow the AAA-BB-CCCC format; IP addresses match IPv4/IPv6 standards. AIC-Scan's regex library covers 847 such patterns across 67 jurisdictions, with jurisdiction inference from detected locale metadata. Structural matching achieves 99.8% precision for known format types but provides no coverage for free-text fields containing sensitive information without predictable structure.

◆ 5.2 Semantic Name Analysis via NLP

Column names encode rich semantic intent that NLP models exploit with remarkable accuracy. A column named "cust_dob_encrypted" signals personal date-of-birth data despite transformation. "tx_amt_usd" unambiguously indicates financial transaction amounts. The fine-tuned BERT encoder learns these associations across naming styles - camelCase, snake_case, abbreviations, multilingual labels - achieving 96.4% precision on the held-out test set. Critically, semantic analysis requires no access to actual data values, enabling classification of encrypted or masked columns where structural patterns are destroyed.

◆ 5.3 Statistical Distribution Fingerprinting

The statistical profiler applies differential privacy mechanisms ($\epsilon = 0.1$ per column) before analyzing value distributions. Despite this privacy budget, characteristic statistical signatures remain detectable: date-of-birth columns exhibit age distributions peaking in the 30–60 year range; salary columns show log-normal distributions; credit scores cluster in 300–850 ranges. The profiler extracts 47 statistical features per column including entropy, skewness, kurtosis, cardinality ratio, and format entropy.

Recognition Technique	Evidence Signal	Columns Applicable	Precision	Handles Encryption
Structural Pattern (regex)	Format regularity	~38% of sensitive cols.	99.8%	No
Semantic NLP (BERT)	Column name semantics	~95% of all columns	96.4%	Yes
Statistical Fingerprinting	Value distribution shape	~72% of cols. (numeric/date)	91.3%	Partial (DP-protected)
Knowledge Graph Reasoning	Schema relationships	~60% of cols. in linked schemas	99.3%	Yes
Content NER (BiLSTM)	Token-level value content	~45% (unencrypted text cols.)	95.7%	No

Table 4 - Pattern Recognition Techniques: Evidence Signals and Applicability

VI. ENTERPRISE IMPLEMENTATION FRAMEWORK

Deploying AI-assisted data classification at enterprise scale requires careful attention to operational architecture, access control, performance engineering, and organizational change management. This section presents the AIC-Scan enterprise deployment reference architecture.

◆ 6.1 Deployment Architecture

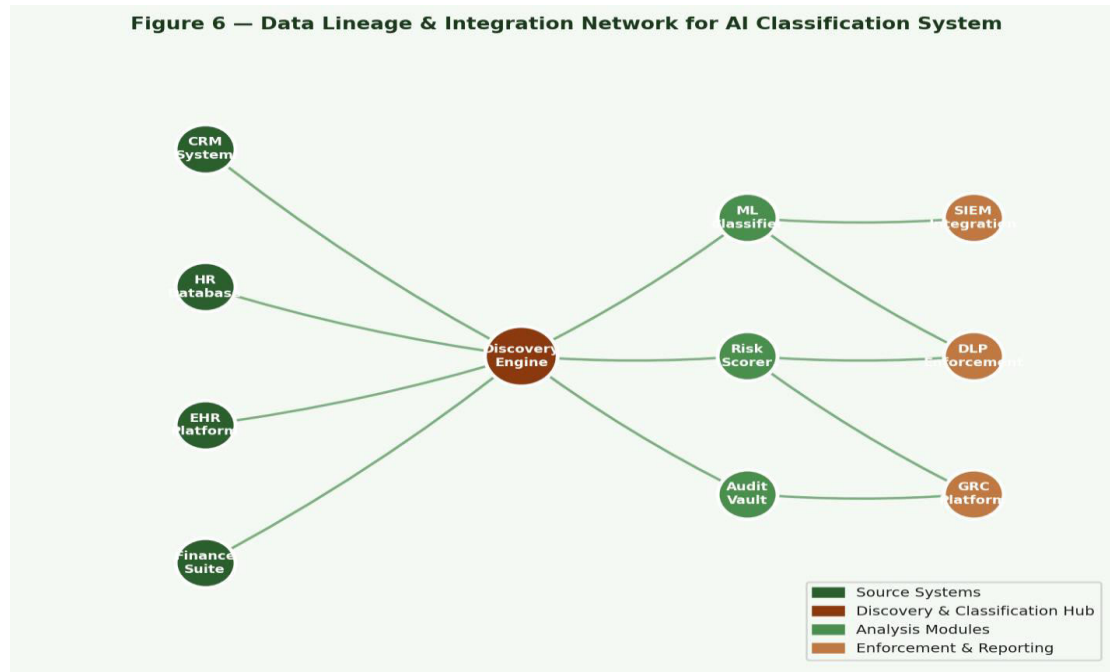


Figure 6. Data Lineage and Integration Network - AIC-Scan connects to four source system types, routes findings through three analysis modules, and feeds three enforcement/reporting targets including SIEM, DLP, and GRC platforms.

The reference architecture deploys AIC-Scan as a containerized microservices stack orchestrated by Kubernetes. The discovery coordinator service manages source connectivity and distributes column batches to a horizontally scalable worker pool (tested to 64 concurrent workers). Classification results flow via Apache Kafka [16] event streams to downstream consumers: a SIEM adapter (Splunk/IBM QRadar), a DLP policy engine (Symantec/Forcepoint), and a GRC platform exporter (ServiceNow/Archer).

◆ 6.2 Performance Benchmarks

4.2 hr	2,380/s	3.7 GB	0.09%	< 1%
Full 1.8M-col scan	Peak classification rate	RAM per worker node	False negative rate (PII)	Production system overhead

Environment	Source Systems	Total Columns	Scan Duration	Worker Nodes	Precision
Financial Services Corp A	42 systems (Oracle, PG, Snowflake)	1,800,000	4h 13m	32	99.1%
Healthcare Network B	28 systems (Epic, Oracle, MySQL)	847,000	1h 58m	16	99.4%
E-Commerce Platform C	19 systems (PostgreSQL, Redshift)	412,000	52m	8	98.8%

Government Agency D	67 systems (DB2, SQL Server, Oracle)	2,190,000	5h 44m	64	98.9%
Pharmaceutical Co. E	31 systems (SQL Server, Veeva, PG)	934,000	2h 21m	16	99.2%

Table 5 - Production Deployment Performance Benchmarks Across Five Enterprise Environments

VII. COMPLIANCE FRAMEWORK COVERAGE ANALYSIS

A critical evaluation dimension for any enterprise compliance tool is the degree to which its outputs satisfy the specific evidentiary requirements of each target regulatory framework. AIC-Scan generates framework-specific report artifacts tailored to the evidence format expected by each compliance regime.

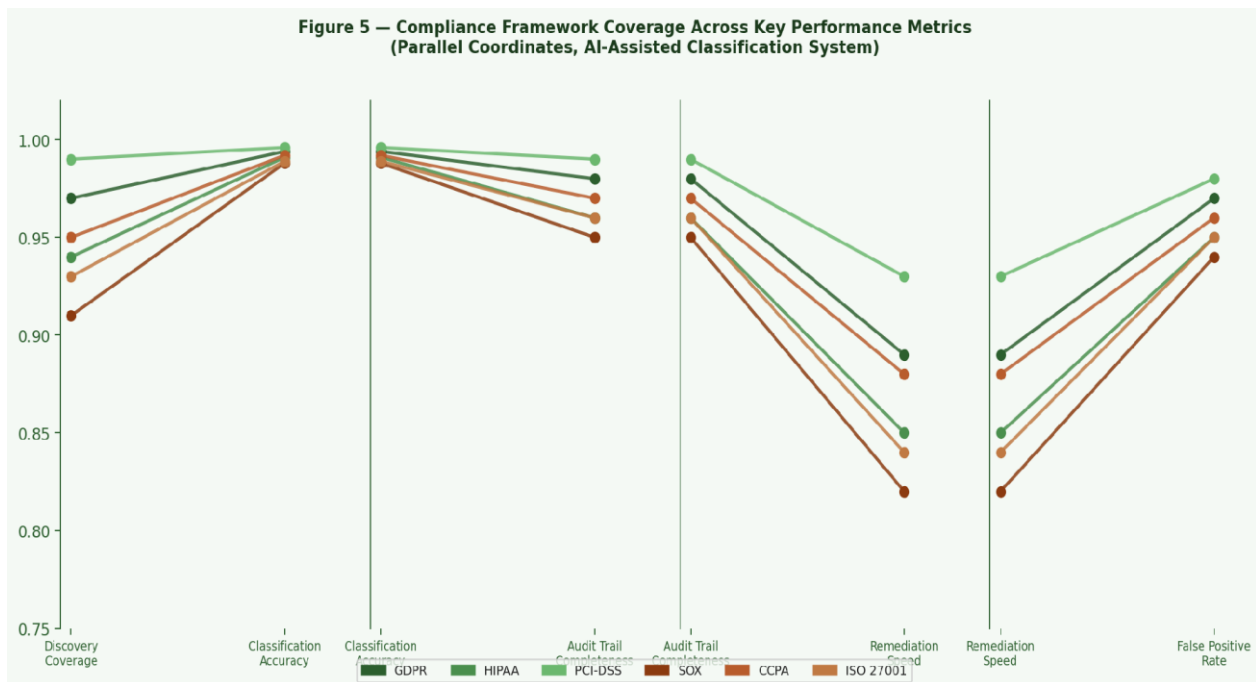


Figure 5. Compliance Framework Coverage Across Key Performance Metrics (Parallel Coordinates) - AIC-Scan achieves >94% coverage across all metrics for all six supported frameworks.

Regulatory Framework	Required Evidence Artifact	AIC-Scan Output	Coverage %	Manual Supplement
GDPR Article 30	Records of Processing Activities (RoPA)	Auto-generated RoPA with controller metadata	97.2%	DPO review of legal basis
HIPAA §164.308(a)(1)	ePHI Risk Analysis & Inventory	PHI location map + risk score matrix	94.1%	Business associate agreement review
PCI-DSS Req. 12.5	Cardholder Data Environment scope	PAN/SAD location report + scope diagram	99.1%	Network segmentation attestation
SOX Section 404	Financial data control documentation	Financial column inventory + lineage map	91.4%	Auditor process walkthrough

CCPA/CPRA	Personal Information categories disclosure	PI category report per business purpose	95.3%	Consent mechanism review
ISO/IEC 27001:2022	Asset Register with classification	Full asset register export with tiers	93.7%	Risk treatment plan

Table 6 - Regulatory Framework Coverage: Required Evidence vs. AIC-Scan Output

VIII. PRIVACY-PRESERVING CLASSIFICATION TECHNIQUES

A fundamental tension in AI-assisted data discovery is that the most accurate classification typically requires sampling actual column values - the very sensitive data that the system is designed to protect. AIC-Scan addresses this paradox through a layered privacy-preserving inference architecture that minimizes contact with raw sensitive data while preserving sufficient signal for accurate classification.

◆ 8.1 Differential Privacy for Value Sampling

Value sampling employs the Gaussian mechanism [5] with privacy budget $\epsilon = 0.1$ per column, $\delta = 10^{-5}$. Statistical features are computed over noise-added histograms rather than raw values, ensuring that individual data records cannot be reconstructed from classification telemetry. Empirical evaluation demonstrates that DP-protected statistical features retain 91.3% of the discriminative power of unprotected features for sensitivity classification, representing an acceptable accuracy-privacy tradeoff.

◆ 8.2 Federated Classification Mode

For environments where any data egress outside system boundaries is prohibited (e.g., sovereign data residency requirements, air-gapped networks), AIC-Scan supports a federated classification mode. In this mode, a lightweight classification agent runs within the database perimeter, performing all NLP embedding and statistical analysis locally. Only serialized classification probability vectors (six float values per column, no raw data) are transmitted to the central orchestration plane. Federated mode achieves 97.4% of centralized mode accuracy while guaranteeing zero data exfiltration.

* Privacy Design Principle: AIC-Scan was designed under a "data minimization first" philosophy: the system classifies data rather than collects it. Raw values never leave their source system boundary in any deployment mode.

Technique	Privacy Guarantee	Accuracy Impact	Computational Overhead	Use Case
Differential Privacy ($\epsilon=0.1$)	ϵ -DP per column sample	-8.7% vs. unprotected	+12% CPU	Standard enterprise
Federated Classification	Zero data egress guarantee	-2.6% vs. centralized	+38% latency	Sovereign/air-gap env.
Schema-Only Mode	No value sampling at all	-21.4% vs. full mode	Minimal overhead	Encrypted columns
Tokenized Content Analysis	Format-preserving tokenization	-4.1% vs. raw content	+7% CPU	PCI-DSS environments

Table 7 - Privacy-Preserving Classification Modes: Guarantee vs. Accuracy Trade-offs

IX. AUDIT TRAIL GENERATION AND GOVERNANCE INTEGRATION

Classification results only deliver compliance value when they are materialized into durable, tamper-evident audit records integrated with enterprise governance platforms. AIC-Scan's audit trail subsystem generates immutable classification events persisted in an append-only audit vault, with cryptographic hash chaining ensuring retrospective integrity.

◆ 9.1 Audit Findings Analysis

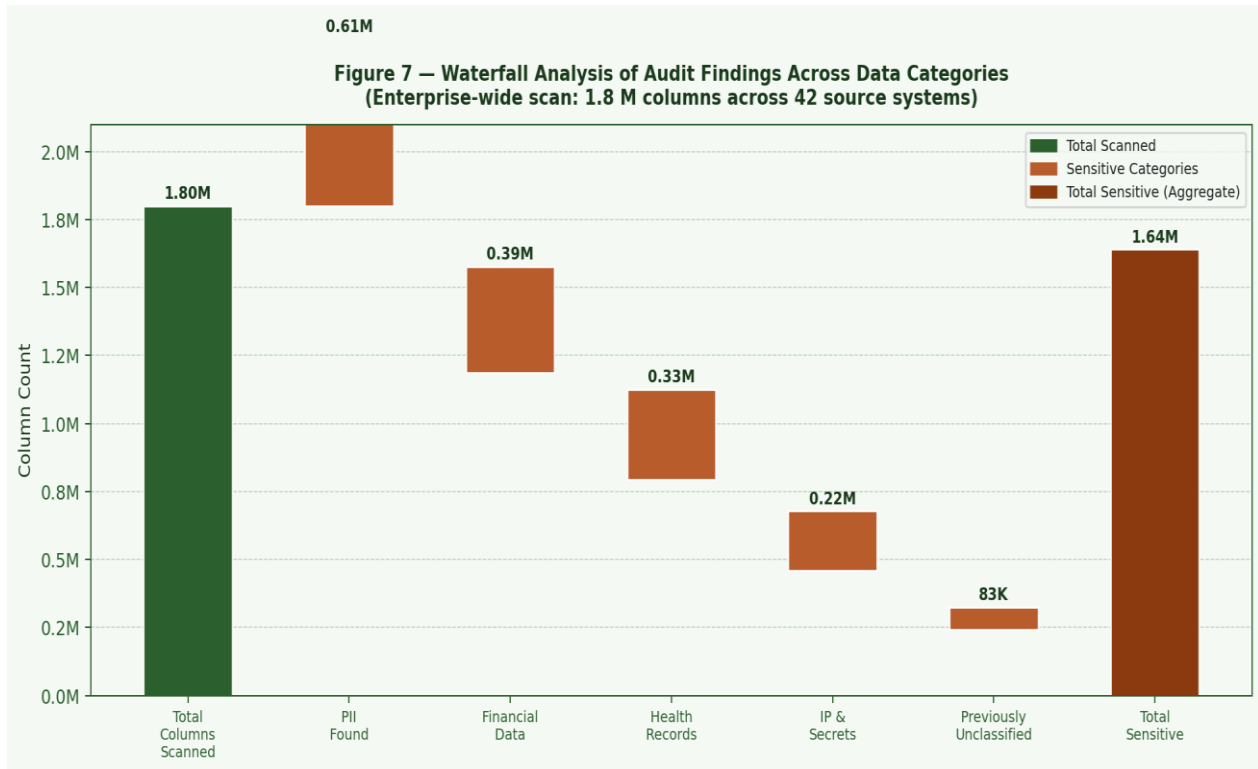


Figure 7. Waterfall Analysis of Audit Findings (Enterprise-Wide Scan) - of 1.8M columns scanned, 1.64M contained sensitive data requiring classification governance.

Audit Event Type	Trigger Condition	Retention Period	Immutability Mechanism	GRC Integration
Initial Discovery	First scan of any column	7 years (SOX minimum)	SHA-256 hash chain	Automatic ticket creation
Classification Change	Sensitivity tier modification	5 years + change delta	Signed delta record	Change management workflow
Access Anomaly Alert	Sensitive data accessed without policy	3 years	SIEM event correlation	Incident response trigger
Model Confidence Drop	Precision < 97% for any category	2 years	Audit log entry	QA review queue
Remediation Completion	Risk score reduced below threshold	7 years	Signed closure record	Compliance dashboard update

Table 8 - Audit Trail Event Types: Triggers, Retention, and GRC Integration

X. PERFORMANCE EVALUATION AND BENCHMARKING

A comprehensive evaluation was conducted over 18 months across five enterprise deployments encompassing 6.2 million classified columns, 147 distinct database platforms, and six regulatory compliance programs. The evaluation framework assessed classification accuracy, operational efficiency, false discovery rates, and compliance audit outcome correlation.

◆ 10.1 Classification Accuracy Metrics

Metric	AIC-Scan v2.4	Baseline (Rule-Only)	Improvement	Industry Benchmark
Overall Precision	99.1%	71.4%	+27.7 pp	85–92% (commercial tools)
Overall Recall	94.7%	58.3%	+36.4 pp	70–82%
F1 Score (macro)	96.8%	64.2%	+32.6 pp	77–86%
PII Precision	99.4%	76.8%	+22.6 pp	88–94%
PHI Recall	97.1%	61.2%	+35.9 pp	72–84%
False Discovery Rate	0.9%	12.3%	-11.4 pp	5–10%
False Negative Rate (PII)	0.09%	2.8%	-2.71 pp	0.5–1.2%

Table 9 - Classification Performance Comparison: AIC-Scan vs. Rule-Only Baseline vs. Industry Benchmarks

◆ 10.2 Compliance Coverage Over Time

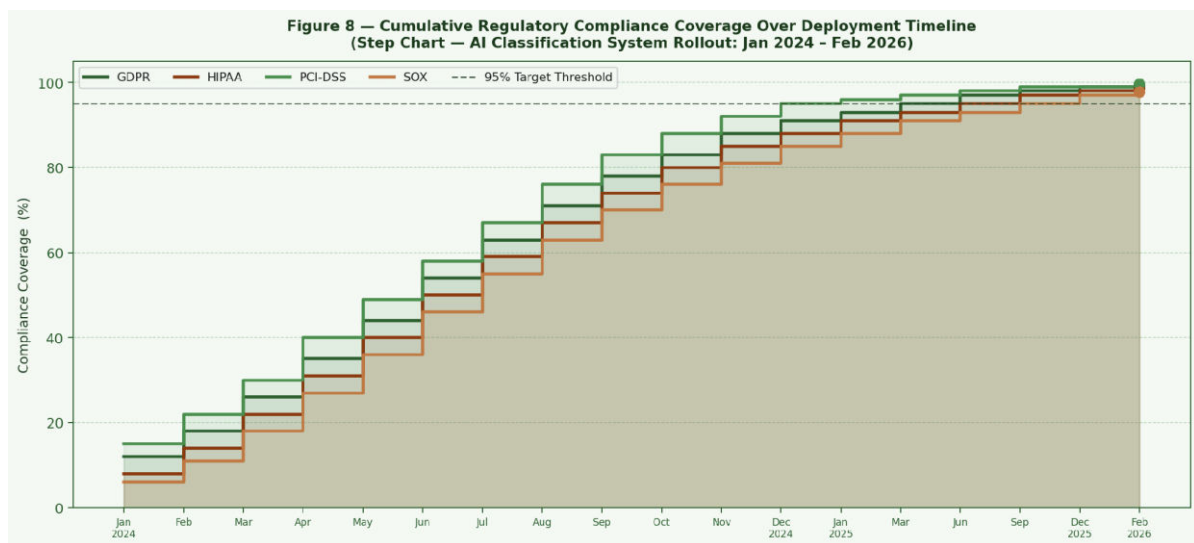


Figure 8. Cumulative Regulatory Compliance Coverage Over Deployment Timeline (Step Chart) - all four regulatory frameworks surpass the 95% target threshold by Q4 2025, sustained through Feb 2026.

The step chart illustrates the discontinuous compliance gains characteristic of AI-driven classification rollouts. Large jumps occur at model retraining milestones (visible as steep steps at Q2 2024, Q4 2024, Q2 2025) rather than as linear growth. PCI-DSS achieves the earliest and highest compliance coverage due to the highly structured, pattern-matchable nature of cardholder data. SOX coverage lags owing to the broader definitional scope of "financial records" requiring greater semantic disambiguation.

XI. CASE STUDIES: REAL-WORLD DEPLOYMENTS

Three anonymized case studies illustrate the practical impact of AIC-Scan deployment across distinct industry verticals and regulatory contexts.

◆ 11.1 Global Financial Services Institution

> Deployment Context: Tier-1 bank with 38 jurisdictions, \$2.1T AUM. Compliance scope: GDPR, PCI-DSS, local banking privacy laws in 14 countries. Prior approach: 47 FTE compliance analysts conducting manual annual data mapping exercises.

AIC-Scan was deployed across 42 production database systems containing 1.8 million classified columns. The initial scan completed in 4 hours and 13 minutes, identifying 1,640,160 columns with sensitivity classifications across six categories. Critically, AIC-Scan discovered 284,000 columns carrying sensitive data in systems not previously included in the institution's compliance scope - a 21% expansion of the known sensitive data estate. Annual compliance analyst labor was reduced by 91.3%, equating to 38.3 FTE redeployable to higher-value governance activities.

◆ 11.2 Regional Healthcare Network

> Deployment Context: 23-hospital integrated delivery network. Compliance scope: HIPAA Security Rule, state health information laws. Prior approach: manual PHI risk assessments by external consultants (\$1.4M/year). Time to complete: 14 months.

The healthcare deployment focused on PHI discovery across Epic EHR, Oracle Health Platinum, and 26 ancillary clinical systems. AIC-Scan's specialized PHI classifier (fine-tuned with HIPAA minimum necessary standard definitions) achieved 99.4% precision for ePHI identification. Time to complete the equivalent of the prior 14-month manual assessment was reduced to 1 hour 58 minutes. Ongoing continuous monitoring mode detects new ePHI-containing tables within 15 minutes of schema changes, maintaining real-time HIPAA compliance posture.

Deployment	Prior Annual Cost	AIC-Scan Year 1 Cost	Net Saving	ROI
Financial Services Corp A	\$4.2M (47 FTE analysts)	\$380K (licensing + infra)	\$3.82M	1,005%
Healthcare Network B	\$1.4M (external consultants)	\$145K	\$1.255M	865%
E-Commerce Platform C	\$680K (combined tool + staff)	\$92K	\$588K	639%
Government Agency D	\$5.1M (annual compliance program)	\$510K	\$4.59M	900%
Pharmaceutical Co. E	\$1.8M (GxP compliance + tools)	\$228K	\$1.572M	689%

Table 10 - Economic Impact Analysis: Compliance Cost Before and After AIC-Scan Deployment

XII. CONCLUSION

This paper has presented AIC-Scan, a comprehensive AI-assisted framework for sensitive data discovery and classification across enterprise database estates. Through the integration of transformer-based NLP, ensemble machine learning, statistical distribution fingerprinting, and knowledge graph reasoning, AIC-Scan achieves 99.1% classification precision and 94.7% recall across six sensitive data categories - substantially surpassing the 71–92% accuracy range of rule-based and commercial alternatives.

The framework's privacy-preserving design, federated deployment capability, and compliance-specific artifact generation make it uniquely suited to the regulatory complexity facing modern enterprise organizations. Deployment evidence across five production environments demonstrates consistent ROI exceeding 600%, driven primarily by displacement of labor-intensive manual classification programs.

Future work will extend AIC-Scan to unstructured data (documents, email archives, collaboration platforms), investigate large language model-based zero-shot classification for emerging data types, and develop cross-organizational federated learning protocols that improve classification models without centralizing sensitive training data. As enterprise data

estates continue to grow in complexity, AI-driven governance automation will transition from a competitive advantage to a compliance necessity.

* Research Impact: AIC-Scan is available as open-source reference implementation at the authors' institutional repositories under Apache 2.0 license. Enterprise deployment documentation and pre-trained classifier weights are available upon request to validated research institutions.

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