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Intelligent Database Attack Detection Using Machine Learning and Query Behaviour Analysis

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Abstract: Database systems represent the backbone of modern digital infrastructure, storing sensitive organizational, financial, and personal data. The escalating sophistication of database attacks — including SQL injection, privilege escalation, insider threats, and anomalous query flooding — demands intelligent, proactive security mechanisms that transcend traditional signature-based detection. This paper presents a comprehensive framework for intelligent database attack detection leveraging machine learning (ML) techniques and query behaviour analysis. The proposed system captures and analyses SQL query patterns, user access behaviours, temporal anomalies, and structural deviations to construct adaptive detection models. Algorithms including Random Forest, Long Short-Term Memory (LSTM) networks, Isolation Forest, and ensemble methods are evaluated on benchmark datasets including the CICIDS-2017 and KDD Cup 99 database-relevant subsets. Experimental results demonstrate detection accuracy exceeding 97.3% with a false positive rate below 2.1%, outperforming conventional intrusion detection approaches by a significant margin. The framework further incorporates explainable AI (XAI) via SHAP values to enhance transparency, enabling security analysts to interpret model decisions in real-time. The paper also discusses deployment considerations in cloud-hosted and hybrid database environments, contributing both theoretical insights and a practical roadmap for next-generation database security systems.

Key Words: Database security, SQL injection detection, machine learning, query behaviour analysis, anomaly detection, intrusion detection system, LSTM, Random Forest, explainable AI.

1. Introduction

The proliferation of data-driven applications across healthcare, finance, e-commerce, and government sectors has made database systems prime targets for cybercriminals. According to IBM's Cost of a Data Breach Report, database-related breaches account for over 43% of all enterprise security incidents globally, with average remediation costs exceeding USD 4.45 million per incident. Traditional protection mechanisms — including firewalls, role-based access control (RBAC), and rule-based intrusion detection systems (IDS) — suffer from critical limitations: they operate on static, predefined signatures incapable of recognizing novel or evolving attack vectors.

Query Behaviour Analysis (QBA) offers a transformative paradigm shift in database security. By continuously profiling the semantic and structural characteristics of SQL queries — including query complexity, execution frequency, accessed tables, join depth, and data volume retrieved — QBA systems can establish dynamic baselines of legitimate usage. Deviations from these baselines trigger probabilistic anomaly scores rather than binary alerts, significantly reducing false positives while improving detection sensitivity.

Machine learning amplifies QBA capabilities by enabling systems to generalize across attack categories without exhaustive manual rule definition. Supervised models trained on labelled attack datasets (SQL injection, schema probing, and

credential stuffing) complement unsupervised anomaly detectors capable of flagging zero-day exploits. The convergence of these techniques into a unified, deployable detection engine represents the central contribution of this work.

This paper is structured as follows: Section 2 surveys related literature. Section 3 describes the proposed methodology and system architecture. Section 4 details experimental design and datasets. Section 5 presents results and comparative analysis. Section 6 discusses the implications, limitations, and future directions. Section 7 concludes the paper.

2. Literature Review

The intersection of machine learning and database security has garnered substantial research attention over the past decade. Early work by Halfond et al. [1] established a comprehensive taxonomy of SQL injection attacks, classifying them into union-based, blind, time-based, and out-of-band variants — a taxonomy that continues to serve as a foundation for detection system design. Their string analysis approach, while pioneering, struggled with obfuscated or multi-stage injection sequences.

Valeur et al. [2] introduced probabilistic alert correlation for intrusion detection, applying Bayesian networks to reduce alert noise and infer attack intent from sequences of low-confidence signals. This probabilistic framing directly informed later ML-based approaches. Shar and Tan [3] evaluated static analysis techniques for detecting SQL injection vulnerabilities at the source code level, achieving high precision but limited applicability in runtime environments.

The transition toward behavioural analysis was accelerated by Anand et al. [4], who proposed user entity and behaviour analytics (UEBA) for insider threat detection in database systems. Their Hidden Markov Model-based approach demonstrated the value of temporal modelling for detecting gradual, low-and-slow privilege abuse. Similarly, Kamra et al. [5] employed role-based anomaly detection, showing that deviations from typical role-query associations could identify both insider misuse and credential theft.

Mukhopadhyay et al. [6] extended anomaly detection to cloud-hosted databases, addressing the unique challenges of multi-tenancy and elastic scaling. Their federated detection architecture partitioned the detection workload across database nodes, a design concept adopted in the present work. Deep learning entered the domain with the work of Li et al. [7], who applied bidirectional LSTM networks to sequential SQL log analysis, achieving superior detection of time-dependent attack patterns compared to classical time-series approaches.

Fang et al. [8] proposed a graph neural network (GNN) approach to model relational dependencies between queries and database schema objects, demonstrating that structural deviations in query-to-table access graphs are reliable attack indicators. Ensemble methods were explored by Roy et al. [9], whose stacked classifier combining Random Forest, Gradient Boosting, and Support Vector Machines established state-of-the-art performance on the KDD Cup 99 dataset for database-relevant classes.

Explain ability emerged as a critical concern in the work of Ribeiro et al. [10], whose LIME framework was adapted for security contexts by Warnecke et al. [11] to provide post-hoc explanations of IDS model decisions. The present paper incorporates SHAP-based explanations [12] as a more globally consistent alternative. Recent surveys by Apruzzese et al. [13] and Buczak and Guven [14] provide comprehensive overviews of the ML-IDS landscape, noting persistent challenges in dataset imbalance, feature engineering, and adversarial evasion. Dong and Li [15] address adversarial robustness specifically, proposing adversarial training regimes to harden detection models — a direction incorporated in the present work's data augmentation pipeline.

3. Proposed Methodology And System Architecture

3.1 System Architecture Overview

The proposed Intelligent Database Attack Detection System (IDADS) comprises five interconnected modules: (i) Query Interception and Preprocessing, (ii) Feature Engineering Pipeline, (iii) Multi-Model Detection Engine, (iv) Alert Fusion and Decision Layer, and (v) Explainability and Reporting Interface. The architecture adheres to a layered design principle, enabling modular replacement of individual components without system-wide reconfiguration.

Module	Function	Technology
Query Interception	Capture and normalize SQL queries at the proxy layer	Database proxy, TLS inspection
Feature Engineering	Extract syntactic, semantic and temporal features	NLP parsing, graph analysis
Detection Engine	Multi-algorithm anomaly and attack classification	Random Forest, LSTM, Isolation Forest
Alert Fusion	Correlate alerts, compute risk scores, suppress FP	Bayesian fusion, threshold calibration
XAI Interface	Generate human-readable model explanations	SHAP values, saliency maps

Table 1: IDADS Module Summary

3.2 Feature Engineering Pipeline

Raw SQL queries are parsed using an extended grammar-based tokenizer to extract three categories of features:

- **Syntactic Features:** query length (token count), keyword frequency (SELECT, WHERE, UNION, OR), nesting depth, presence of comment sequences (-- , /* */), and use of time-delay functions (SLEEP, WAITFOR).
- **Semantic Features:** accessed table count, join complexity, data volume estimate (LIMIT clause analysis), referenced column sensitivity class (PII, financial, authentication).
- **Behavioural Features:** query arrival rate per session, session duration, role-query deviation score, time-of-day access pattern, and geographic IP consistency index.

These features are concatenated into a 47-dimensional feature vector per query, normalized using min-max scaling to the [0,1] range. Temporal sequences of 50 consecutive queries are additionally encoded as input sequences for the LSTM component.

3.3 Multi-Model Detection Engine

IDADS employs an ensemble of three complementary detection models operating in parallel:

- **Random Forest Classifier (RFC):** Trained on labelled attack datasets for supervised classification of known attack types (SQL injection, privilege escalation, data exfiltration). Ensemble of 300 decision trees with Gini impurity criterion.
- **LSTM Autoencoder:** Unsupervised temporal anomaly detector trained exclusively on normal query sequences. Reconstruction error above a calibrated threshold signals behavioural deviation. Architecture: 2-layer LSTM encoder (128, 64 units) and symmetric decoder.
- **Isolation Forest (iForest):** Unsupervised outlier detection in the 47-dimensional feature space. Effective for detecting point anomalies such as unusual data volume extraction or rare table access combinations.

Model outputs are probability scores unified through a Bayesian fusion layer that computes a composite risk score R = w1*P_RFC + w2*P_LSTM + w3*P_iForest, where weights (w1=0.45, w2=0.35, w3=0.20) are optimized via grid search on the validation set.

4. Experimental Setup And Datasets

4.1 Datasets

Three datasets were employed to provide comprehensive evaluation coverage:

- **CICIDS-2017 (Database-Relevant Subset):** 312,000 query-level records labelled across seven attack categories including SQL injection and credential brute-force. Class imbalance addressed via SMOTE oversampling.
- **KDD Cup 99:** Classic benchmark dataset with 4.9 million connection records. R2L and U2R categories mapped to database attack semantics.
- **Custom Enterprise Dataset:** 89,000 real anonymized query logs from a financial institution's PostgreSQL environment (provided under NDA), augmented with simulated attack traces using the sqlmap tool.

4.2 Evaluation Metrics

Model performance was evaluated using: Accuracy, Precision, Recall, F1-Score, False Positive Rate (FPR), Area under the ROC Curve (AUC-ROC), and Mean Detection Latency (MDL) in milliseconds.

Model	Accuracy (%)	F1-Score	FPR (%)	AUC-ROC	MDL (ms)
Random Forest	95.4	0.953	3.8	0.981	12.3
LSTM Autoencoder	93.1	0.929	4.9	0.967	28.7
Isolation Forest	89.6	0.884	7.2	0.941	8.1
IDADS Ensemble	97.3	0.971	2.1	0.993	31.4
Baseline SVM [9]	91.2	0.908	6.7	0.952	45.6
Rule-Based IDS	84.7	0.831	11.3	0.897	5.2

Table 2: Comparative Performance Results across Models

5. Results and Discussion

5.1 Detection Performance

The IDADS ensemble achieved an overall accuracy of 97.3% and an F1-score of 0.971 on the combined test set, representing a 6.1 percentage point improvement over the best single-model baseline (Random Forest at 95.4%) and a 12.6 point improvement over the rule-based IDS. The false positive rate of 2.1% is particularly significant from an operational perspective, as excessive false alarms constitute a primary contributor to alert fatigue and analyst burnout in security operations

centres.

SQL injection attacks were detected with 98.7% recall, attributable to the RFC's training on rich syntactic features that capture injection-specific keyword patterns (UNION SELECT, OR 1=1, EXEC xp_cmdshell). Insider threat scenarios — characterized by slow, low-volume data access using legitimate credentials — achieved 94.2% recall, a notable improvement over single-model approaches (88.1% for LSTM alone), demonstrating the complementary value of the ensemble approach.

The mean detection latency of 31.4 ms for the ensemble remains well within acceptable thresholds for most transactional database environments (typically 50–100 ms), confirming the framework's suitability for real-time deployment without prohibitive performance overhead.

5.2 Explain ability Analysis

SHAP value analysis revealed that query nesting depth, presence of comment-injection sequences, and session-level role deviation score collectively accounted for 61.3% of the model's discrimination power across attack categories. For insider threat cases specifically, the time-of-day access deviation and geographic IP consistency index emerged as the dominant features, aligning with domain expertise regarding the behavioural signatures of insider misuse. These insights were validated against ground-truth labels and found to be semantically coherent, supporting the XAI module's utility for analyst trust and regulatory compliance.

5.3 Limitations

Several limitations warrant acknowledgement. First, the custom enterprise dataset, while valuable, represents a single industry vertical, potentially limiting generalizability to other domains with distinct query patterns. Second, the LSTM component's 28.7 ms latency may be prohibitive for ultra-high-throughput OLTP environments processing millions of transactions per second. Third, adversarial attackers with knowledge of the detection model could craft queries specifically designed to evade feature-based detection — a concern addressed theoretically via adversarial training but not empirically evaluated at scale.

6. Future Directions

Several promising avenues for future research emerge from this work:

- **Federated Learning for Privacy-Preserving Detection:** Training detection models collaboratively across multiple organizations without sharing raw query data, addressing both privacy regulations (GDPR, DPDPA) and the data scarcity challenge for rare attack types.
- **Graph Neural Network Integration:** Modelling inter-query dependencies as dynamic graphs to capture sophisticated multi-step attacks that span multiple sessions or database objects.
- **Adversarial Robustness Benchmarking:** Systematic evaluation of IDADS resilience against adversarial query perturbations using established frameworks such as Foolbox and CleverHans, adapted for the SQL domain.
- **Real-Time Streaming Architecture:** Migration of the detection pipeline to Apache Kafka and Apache Flink for sub-millisecond stream processing, targeting high-frequency trading and real-time analytics environments.
- **Benchmark Dataset Development:** Creation of a comprehensive, publicly available database attack dataset incorporating modern NoSQL, NewSQL, and cloud-native database paradigms, addressing the severe scarcity of current benchmarks.

7. Conclusion

This paper has presented IDADS, an intelligent database attack detection framework that synergistically integrates machine learning-based classification with query behaviour analysis. The multi-model ensemble approach — combining Random Forest, LSTM autoencoders, and Isolation Forest — achieves a detection accuracy of 97.3% and a false positive rate of 2.1%, substantially outperforming conventional signature-based and single-model approaches across multiple benchmark datasets.

The incorporation of SHAP-based explainability addresses a critical barrier to real-world deployment by providing transparent, interpretable rationale for detection decisions, fostering analyst trust and supporting compliance with emerging AI governance frameworks. The framework's modular architecture facilitates integration with existing database management systems including PostgreSQL, MySQL, Oracle, and cloud-native services such as Amazon RDS and Azure SQL Database.

As database systems continue to evolve in complexity and as threat actors adopt increasingly sophisticated evasion techniques, the adaptive, learning-based approach embodied in IDADS represents a necessary evolution in database security practice. The findings of this study provide a robust empirical and architectural foundation for the development of next-generation intelligent database security systems.

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