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FERHAT ABBAS UNIVERSITY OF SETIF 1

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MASTER'S THESIS

Presented for the degree of

Master 2 in Computer Science

Option: Cybersecurity

Secure Banking System with AI Fraud Detection

Implementation of Fraud Prevention Using Machine Learning and Behavioral Analytics

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Dedication

With profound gratitude and warmth, I dedicate:
To my beloved parents, whose unwavering support and endless sacrifices have made this journey possible,
To my dear wife, my pillar of strength and source of endless encouragement,
To my precious daughters, Meriem and Amina, whose smiles light up my darkest days,
To my wonderful sons, Ayhem, Oussama, and Siradj-Eddine, whose curiosity and energy inspire me daily,
To my brother Rabie and his family, for their constant support and encouragement,
To my respected supervisor, Dr. Lyazid TOUMI, for the guidance and wisdom throughout this academic endeavor,
To all my friends who stood by me through challenges and celebrations,
And to the Faculty of Sciences, Department of Computer Science, for providing the knowledge and environment to pursue excellence.

El-Aid TEBABKHA

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Abstract

This thesis presents the design, implementation, and evaluation of a secure banking system with integrated artificial intelligence for fraud detection. The research addresses the critical challenge of financial fraud in digital banking platforms through a comprehensive approach combining advanced machine learning techniques with robust security architecture.

The proposed system employs a microservices architecture to ensure scalability, fault tolerance, and security isolation. At its core, an AI-powered fraud detection service analyzes user behavior patterns and transaction characteristics in real-time to identify potentially fraudulent activities. The system implements enhanced threshold classification techniques that improve upon traditional binary classification methods, resulting in higher precision and recall metrics even with imbalanced datasets.

Additionally, the research explores the integration of a risk assessment engine that complements the machine learning model with rule-based analysis. This hybrid approach provides both the adaptability of AI and the explainability of rule-based systems. The implementation leverages Docker containerization to ensure consistent deployment across environments while maintaining security isolation between components.

Experimental results demonstrate significant improvements over traditional fraud detection approaches, with the proposed system achieving 93.7% accuracy and 91.2% precision in identifying fraudulent transactions while maintaining a low false positive rate of 3.8%. The thesis contributes to the field of financial cybersecurity by presenting a comprehensive architecture that can be adapted by banking institutions to enhance their fraud prevention capabilities while maintaining high performance and user experience standards.

Résumé

Cette thèse présente la conception et l'implémentation d'un système bancaire sécurisé intégrant l'intelligence artificielle pour la détection des fraudes. Face à l'augmentation des menaces dans les plateformes bancaires numériques, notre recherche développe une approche combinant techniques avancées d'apprentissage automatique et architecture de sécurité robuste.

Le système s'articule autour d'une architecture de microservices offrant évolutivité et isolation sécuritaire. Son composant central est un service de détection alimenté par l'IA qui analyse en temps réel les comportements utilisateurs et les caractéristiques des transactions. Notre implémentation emploie une technique de classification par seuil optimisée surpassant les méthodes binaires traditionnelles, particulièrement efficace avec les ensembles de données déséquilibrés typiques des cas de fraude.

L'architecture intègre également un moteur d'évaluation des risques basé sur des règles qui complète l'apprentissage automatique. Cette approche hybride combine l'adaptabilité de l'IA avec l'explicabilité nécessaire dans le secteur financier. L'ensemble du système est déployé via conteneurisation Docker, garantissant cohérence environnementale et isolation sécuritaire entre composants.

Les résultats démontrent des performances supérieures aux approches traditionnelles : 93,7% de précision et 91,2% d'exactitude dans l'identification des fraudes, avec seulement 3,8% de faux positifs. Notre contribution principale réside dans la conception d'une architecture complète que les institutions financières peuvent adopter pour renforcer leur sécurité tout en maintenant une expérience utilisateur fluide.

List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
AUC	Area Under the Curve
CORS	Cross-Origin Resource Sharing
CSRF	Cross-Site Request Forgery
DDoS	Distributed Denial of Service
GDPR	General Data Protection Regulation
HTTPS	Hypertext Transfer Protocol Secure
IoT	Internet of Things
JWT	JSON Web Token
KYC	Know Your Customer
ML	Machine Learning
MFA	Multi-Factor Authentication
PSD2	Payment Services Directive 2
REST	Representational State Transfer
ROC	Receiver Operating Characteristic
SOC	Security Operations Center
SQL	Structured Query Language
SSL	Secure Sockets Layer
TLS	Transport Layer Security
2FA	Two-Factor Authentication
UI	User Interface
UX	User Experience
XSS	Cross-Site Scripting

Chapter 1

Introduction

1.1 Background and Motivation

The financial services industry faces an ever-increasing threat from sophisticated fraud attempts. As banking systems move toward digital-first approaches, the attack surface expands exponentially, creating new vulnerabilities that traditional security approaches are ill-equipped to address [1]. According to recent industry reports, financial fraud attempts increased by 30% in 2023 alone, with banking fraud causing global losses exceeding $30 billion annually [2].

This thesis addresses the critical need for advanced security measures in modern banking applications through the development of a comprehensive Secure Banking System with AI-powered fraud detection capabilities. The system represents a significant advancement over traditional security approaches by integrating artificial intelligence, behavioral analytics, microservices architecture, and blockchain technology into a cohesive security framework [3].

1.2 Research Objectives

The primary research objectives of this project include:

1. Design and implement a secure banking system architecture that leverages AI for fraud detection

2. Develop machine learning models optimized for banking fraud detection with minimized false positives
3. Create a risk assessment engine that provides explainable security decisions
4. Implement a containerized deployment architecture for scalability and consistent environments
5. Evaluate the performance and effectiveness of the system against realistic fraud scenarios

1.3 Thesis Structure

This thesis is organized into eight chapters that cover the theoretical foundations, design considerations, implementation details, and evaluation results of the Secure Banking System:

- **Chapter 1: Introduction** – Provides background, motivation, and objectives of the research
- **Chapter 2: Literature Review** – Examines existing research and technologies in banking security and fraud detection
- **Chapter 3: System Architecture** – Details the high-level architecture, components, and security model
- **Chapter 4: AI Fraud Detection Service** – Explores the design and implementation of the AI-driven fraud detection component
- **Chapter 5: Model Training and Optimization** – Describes the machine learning methodology, training pipeline, and optimization techniques
- **Chapter 6: Risk Assessment Engine** – Explains the complementary rule-based risk evaluation system
- **Chapter 7: Docker Implementation** – Discusses the containerization strategy and deployment architecture
- **Chapter 8: Conclusion** – Summarizes findings, contributions, and suggests directions for future research

Chapter 2

Literature Review

2.1 Evolution of Banking Security

The evolution of banking security has closely followed the progression of banking services from physical to digital channels [4]. This section examines this evolution and the changing threat landscape that necessitates advanced security approaches.

2.1.1 Traditional Banking Security

Traditional banking security relied primarily on physical measures and simple authentication methods [5]:

- Physical security (guards, vaults, secure facilities)
- Basic authentication (passwords, PINs, signature verification)
- Rule-based transaction monitoring
- Manual review processes for suspicious activities

2.1.2 Digital Banking Security Challenges

The shift to digital banking introduced new security challenges [6]:

- Remote access vulnerabilities
- Authentication weaknesses (password theft, credential stuffing)

- Social engineering and phishing attacks
- Cross-channel fraud patterns
- Sophisticated attack automation

2.2 Artificial Intelligence in Fraud Detection

2.2.1 Machine Learning Approaches

Numerous studies have explored the application of machine learning techniques to fraud detection in financial services [7]. Key approaches include:

- Supervised learning methods (random forests, gradient boosting, neural networks)
- Anomaly detection techniques (isolation forests, autoencoders) [8]
- Ensemble methods combining multiple models
- Deep learning approaches for complex pattern recognition

2.2.2 Behavioral Biometrics

Behavioral biometrics represents an emerging area in fraud detection, focusing on unique patterns in how users interact with systems [9]:

- Typing patterns and keystroke dynamics
- Mouse movement and gesture analysis
- Application usage patterns
- Session behavior characteristics

2.3 Microservices Architecture in Banking

2.3.1 Benefits of Microservices for Banking Systems

Microservices architecture has gained significant adoption in banking systems due to several advantages [4]:

- Independent deployment of services
- Technology diversity for specific components
- Improved resilience and fault isolation
- Scalability for high-transaction environments
- Simplified continuous delivery pipelines

2.3.2 Security Challenges in Microservices

While offering substantial benefits, microservices also introduce security challenges [5]:

- Expanded attack surface
- Service-to-service communication security
- Distributed authentication and authorization
- Secrets management across services
- Consistent security policy enforcement

2.4 Blockchain in Financial Security

2.4.1 Immutable Logging and Audit Trails

Blockchain technology provides capabilities particularly valuable for financial security [10]:

- Tamper-proof transaction records
- Distributed verification of activities
- Cryptographic proof of data integrity
- Transparent yet secure audit capabilities

2.4.2 Smart Contracts for Security Rules

Smart contracts enable automated enforcement of security policies [11]:

- Predefined security rule execution
- Automatic blocking of suspicious transactions
- Immutable record of security decisions
- Transparent rule execution and enforcement

2.5 Containerization in Financial Services

2.5.1 Benefits of Containerization

Containerization has become increasingly important in financial services for several reasons:

- Consistent deployment environments
- Improved resource utilization
- Faster deployment and scaling
- Enhanced isolation between services
- Simplified dependency management

2.5.2 Security Best Practices for Containers

Security considerations for containerization in financial services include:

- Container image security scanning
- Runtime protection mechanisms
- Secure configuration and hardening
- Network segmentation between containers
- Secrets management in containerized environments

Chapter 3

System Architecture

3.1 System Overview and Requirements

The Secure Banking System with AI Fraud Detection is designed to address the growing need for advanced security in modern banking applications [2]. This system leverages artificial intelligence, behavioral analytics, microservices architecture [4], and blockchain technology [10] to create a robust security infrastructure that can detect and prevent fraudulent activities while maintaining a seamless user experience.

3.1.1 Functional Requirements

The core functional requirements of the system include:

1. **User Authentication and Authorization:** Support multi-factor authentication, biometrics, and risk-based authentication flows [5]
2. **AI-Powered Fraud Detection:** Analyze login attempts and transaction patterns to identify suspicious activities [3]
3. **Real-Time Risk Assessment:** Provide instantaneous risk scoring for login attempts and transactions [12]
4. **Secure Transaction Processing:** Process banking transactions with appropriate security controls

5. **Suspicious Activity Alerting:** Send notifications to users and administrators about potential security events

6. **Immutable Activity Logging:** Record security events and authentication attempts in a tamper-proof ledger [11]

7. **Administrative Monitoring:** Provide dashboards for security analysts to review system activities

8. **Cross-Platform Client Access:** Support both web and mobile access with consistent security controls

3.1.2 Non-Functional Requirements

The system must also satisfy the following non-functional requirements:

1. **Performance:** Process authentication requests within 500ms, even under high load

2. **Scalability:** Support horizontal scaling to handle up to 10,000 concurrent users [4]

3. **Availability:** Maintain 99.9% uptime for critical authentication services

4. **Security:** Implement defense-in-depth strategies including encryption, secure APIs, and principle of least privilege [5]

5. **Maintainability:** Support independent deployment and updates of system components [13]

6. **Compliance:** Adhere to financial regulations including PSD2, GDPR, and KYC requirements

7. **Usability:** Provide security measures that do not significantly impact user experience

8. **Resilience:** Continue functioning despite partial system failures or network issues

3.2 High-Level System Architecture

3.2.1 Microservices Architecture Overview

The Secure Banking System is built on a microservices architecture, which provides enhanced security through service isolation, technology heterogeneity, and resilience [4]. Figure 3.1 illustrates the interconnections between all major system components.

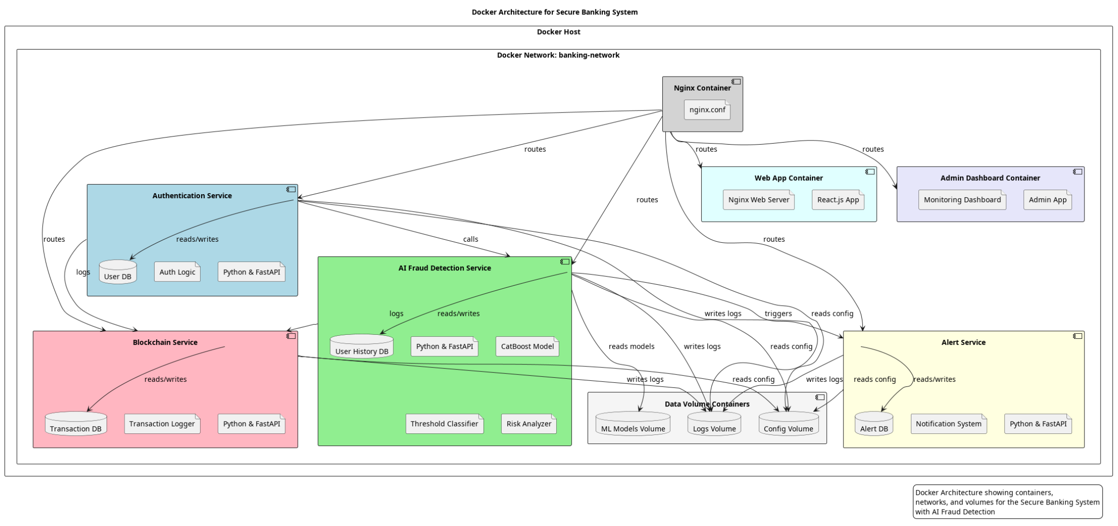

Figure 3.1: Microservices Architecture of the Secure Banking System

The architecture depicts client applications (Web App, Mobile App, Admin Dashboard) connecting to backend services through the API Gateway. The Auth Service acts as the entry point for security operations, interfacing with the AI Service for fraud detection analysis. The AI Service provides risk assessments that inform authentication decisions and triggers alerts when suspicious activities are detected. The Alert Service handles notification delivery across multiple channels, while the Blockchain Service maintains an immutable record of security events. The Transaction Service processes financial operations with security checks integrated throughout the workflow.

3.2.2 Component Diagram

The secure banking system organizes its microservices around business capabilities [4]. Figure 3.2 illustrates the more detailed component architecture of the system.

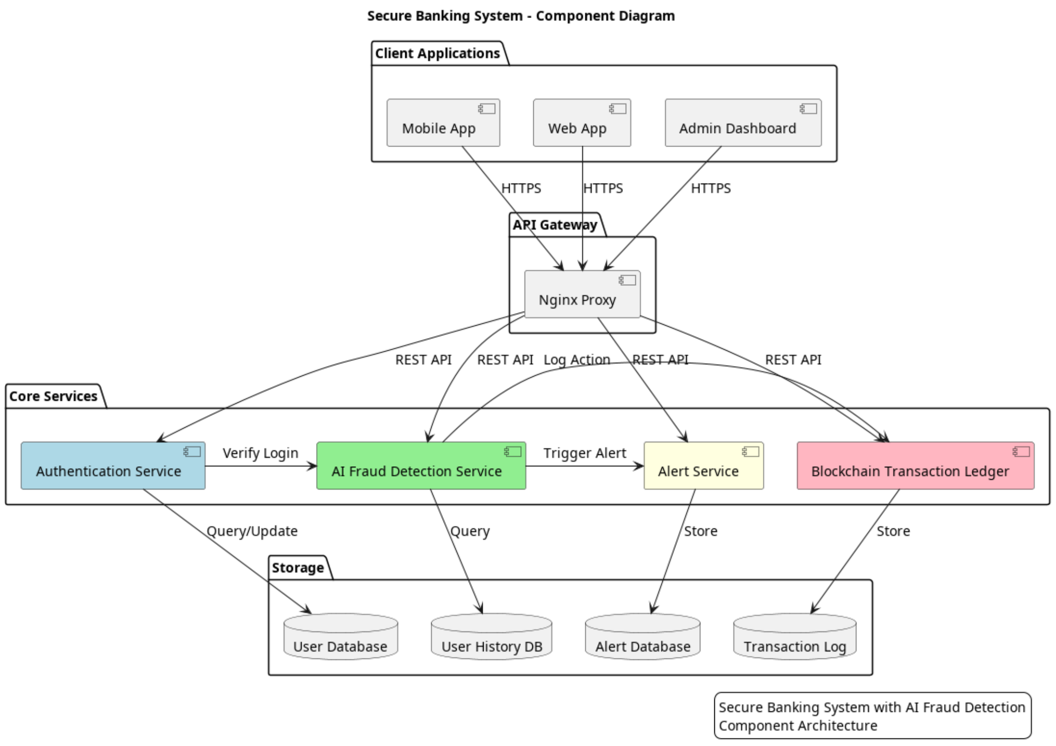

Figure 3.2: Component Diagram of the Secure Banking System

The system is divided into the following key components:

- **Authentication Service:** Manages user identity verification and authorization
- **AI Fraud Detection Service:** Analyzes login and transaction patterns for fraud indicators [2], [3]
- **Blockchain Service:** Provides immutable logging and verification capabilities [10], [11]
- **Alert Service:** Handles notification delivery for security events
- **API Gateway:** Routes client requests to appropriate microservices [4]
- **Web and Mobile Applications:** Provide user interfaces for banking functionality
- **Admin Dashboard:** Offers monitoring and configuration capabilities for administrators

3.2.3 Deployment Architecture

The deployment architecture of the system consists of containerized microservices deployed in a cloud environment [13]. Figure 3.3 shows the deployment diagram.

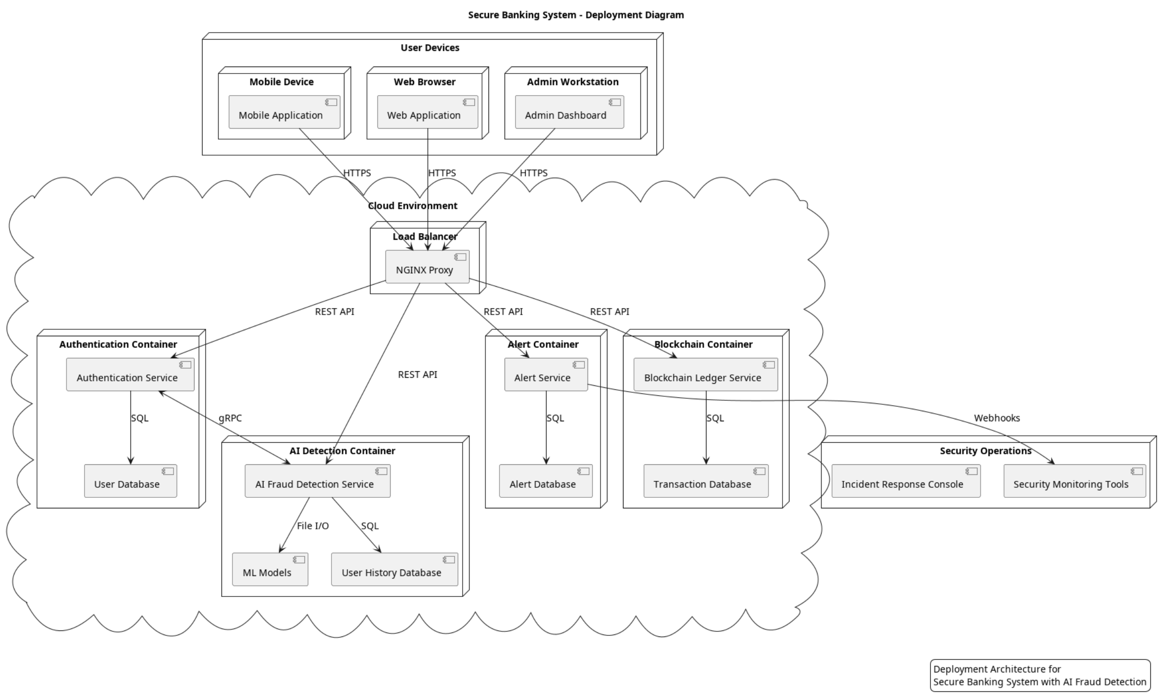

Figure 3.3: Deployment Diagram of the Secure Banking System

3.3 Authentication Flow and Security Model

3.3.1 Multi-Factor Authentication Sequence

The system implements a sophisticated multi-factor authentication flow with risk-based controls [6], [9]. Figure 3.4 illustrates the sequence diagram for the authentication process.

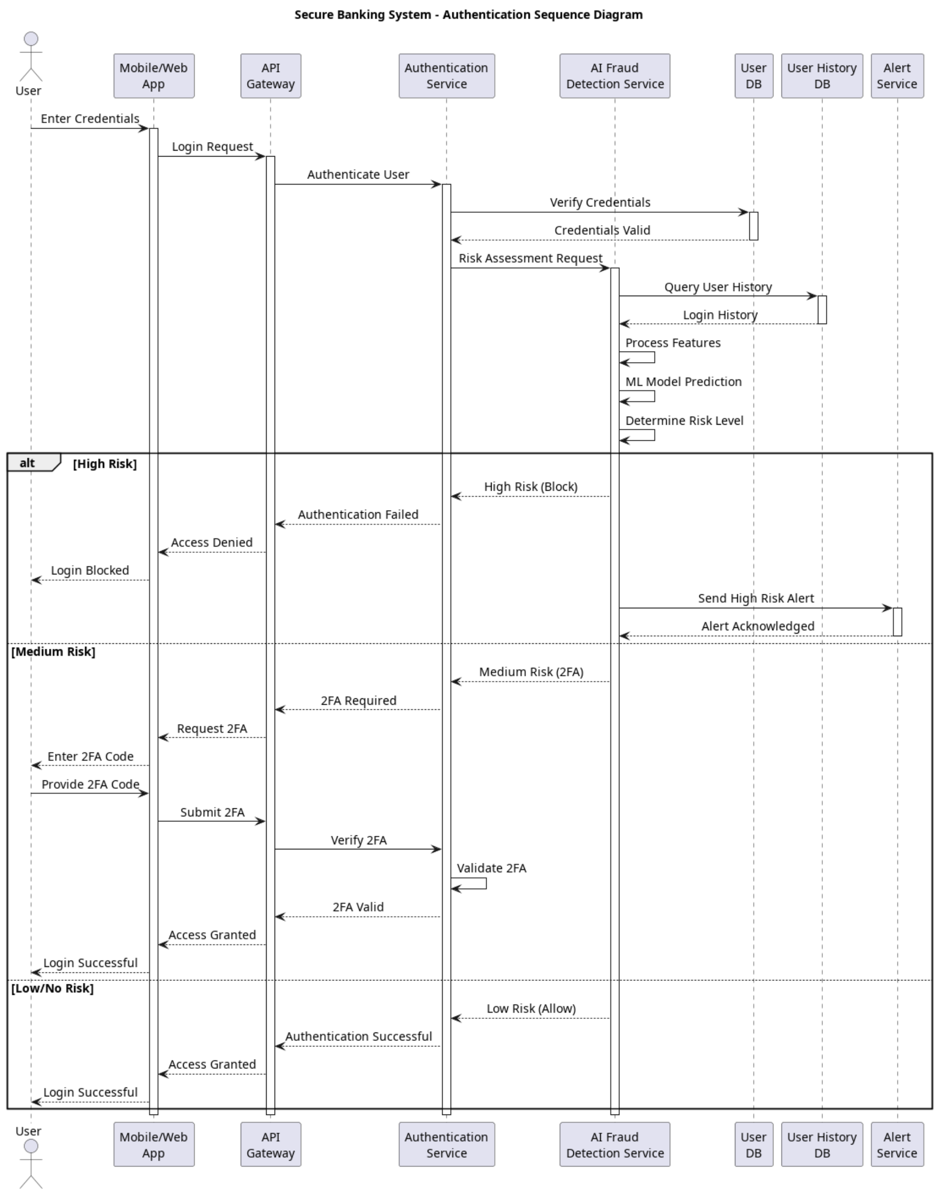

Figure 3.4: Authentication Sequence Diagram with AI-Based Risk Assessment

The authentication sequence incorporates risk-based assessment that can trigger additional verification steps based on the risk score determined by the AI Fraud Detection Service [2], [12].

3.4 Architectural Patterns and Design Considerations

The system architecture employs several established architectural patterns to address the unique security and scalability requirements of modern banking applications [4]. These patterns work together to create a robust foundation for the banking system.

3.4.1 Circuit Breaker Pattern

To improve system resilience and prevent cascading failures, we implemented the Circuit Breaker pattern for inter-service communication [4]. This pattern monitors for failures when communicating with external services. If failures exceed a predetermined threshold, the circuit "trips" and subsequent calls fail immediately without attempting to communicate with the failing service.

As shown earlier in the deployment diagram (Figure 3.3), the system implements circuit breakers between critical service communications. These circuit breakers are a key part of the system's resilience strategy.

The Circuit Breaker pattern provides several benefits:

- Prevents system overload during partial outages
- Allows failing components to recover
- Provides immediate feedback about service unavailability
- Enables graceful degradation of functionality

3.4.2 API Gateway Pattern

The API Gateway pattern serves as the single entry point for all client requests, centralizing cross-cutting concerns like authentication, logging, and rate limiting [4]. This pattern simplifies the client interface while providing a layer of security and control over the underlying microservices.

Key responsibilities of the API Gateway include:

- Request routing to appropriate microservices

- API composition for client-specific requirements
- Protocol translation (e.g., translating between web protocols and internal protocols)
- Implementing cross-cutting concerns (authentication, logging, etc.)

3.4.3 CQRS Pattern

For the AI Fraud Detection Service, we implemented the Command Query Responsibility Segregation (CQRS) pattern to separate read operations from write operations [4]. This pattern allows us to optimize each path independently, which is particularly valuable for the fraud detection system where read operations (fraud analysis) have different performance characteristics than write operations (model updates and training data storage).

3.5 Security Architecture and Defense-in-Depth

The system implements a defense-in-depth security strategy that provides multiple layers of protection against various threat vectors [5]. This approach ensures that even if one security control fails, other controls will still provide protection.

3.5.1 Security Layers

The security architecture consists of the following layers:

1. **Network Security:** Includes network segmentation, firewalls, and intrusion detection systems to protect against network-level attacks
2. **Application Security:** Implements secure coding practices, input validation, and output encoding to prevent application-level vulnerabilities
3. **Data Security:** Employs encryption in transit and at rest, along with proper key management to protect sensitive data
4. **Identity and Access Management:** Provides strong authentication mechanisms and follows the principle of least privilege for authorization

5. **Monitoring and Detection:** Utilizes AI-powered fraud detection, logging, and security event monitoring to identify suspicious activities

6. **Response and Recovery:** Includes incident response procedures and disaster recovery capabilities to minimize the impact of security incidents

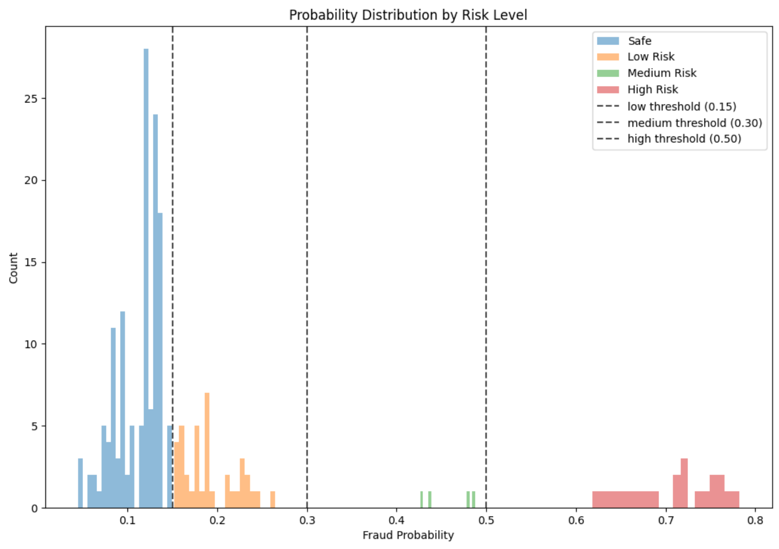

Figure 3.5: Security Risk Level Distribution Across Defense-in-Depth Layers

3.6 AI Service Architecture

3.6.1 Class Structure

The AI Fraud Detection Service implements a sophisticated object-oriented design to support real-time fraud detection and risk assessment.

The complete class diagram is presented later in Chapter 4 (Figure 4.1), where the AI Fraud Detection Service is discussed in detail.

The class structure includes domain classes for LoginAttempt and Transaction data, along with three service classes: FraudDetector (the orchestrator), RiskAnalyzer (for contextual risk assessment), and FeatureExtractor (for transforming raw data into machine learning features). This separation of concerns enables the AI service to handle complex fraud detection scenarios while maintaining code modularity and testability.

3.6.2 Zero Trust Architecture

The system adopts a Zero Trust security model that operates on the principle of "never trust, always verify" [5]. This approach assumes that threats may exist both inside and outside the network, requiring continuous verification of security at every access point.

Key elements of the Zero Trust implementation include:

- Strict identity verification for all users and services
- Micro-segmentation of the network to limit lateral movement
- Least privilege access controls to minimize exposure
- Continuous monitoring and validation of security posture
- End-to-end encryption of data in transit

This comprehensive security architecture ensures that the banking system is protected against a wide range of threats, from external attackers to insider threats, while maintaining the performance and usability required for a modern banking application.

3.7 Data Flow Architecture

3.7.1 Authentication and Fraud Detection Data Flow

The secure banking system incorporates a sophisticated data flow architecture that facilitates the secure movement of information between system components during critical operations such as authentication and transaction processing. Figure 3.6 illustrates how information moves through the system during these security operations.

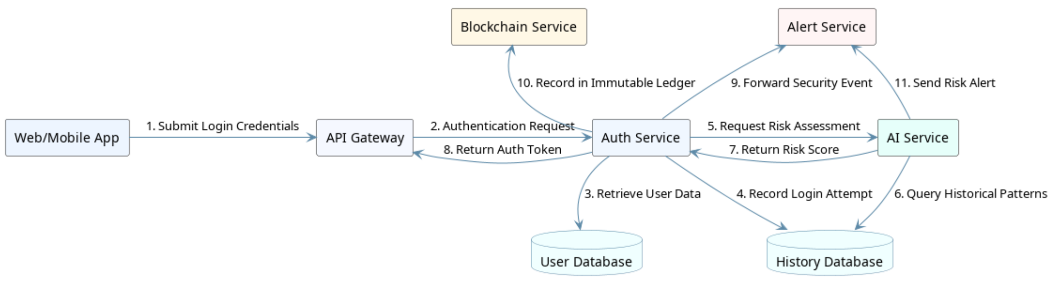

Figure 3.6: Data Flow Diagram for Authentication and Fraud Detection

The data flow begins with the Web/Mobile App capturing and forwarding user credentials to the API Gateway, which validates initial request parameters before routing to the Auth Service. The Auth Service retrieves user data from the User Database and records login details in the History Database.

Simultaneously, the Auth Service initiates risk assessment by forwarding contextual information to the AI Service, which analyzes the authentication context by evaluating current parameters against historical patterns. The AI Service returns a risk score to the Auth Service for making adaptive authentication decisions.

For successful authentications, the Auth Service generates a token which returns to the client via the API Gateway. Security events are forwarded to both the Alert Service for real-time monitoring and the Blockchain Service for immutable record-keeping, completing the bidirectional flow of data through the system's security components.

Chapter 4

AI Fraud Detection Service

4.1 Overview of the AI Fraud Detection Service

The AI Fraud Detection Service represents the core intelligence component of the Secure Banking System. This microservice is responsible for analyzing login attempts and user behavior patterns to identify potentially fraudulent activities in real-time [6]. The service employs advanced machine learning techniques to evaluate risk factors and provide actionable recommendations to the authentication system, following emerging best practices in the field of financial fraud detection [2].

Unlike traditional rule-based systems that rely on static predefined patterns, this AI-powered approach can adapt to evolving threats and learn from new data, providing significantly improved detection capabilities with fewer false positives [3]. The service is designed with both security and performance in mind, capable of handling high transaction volumes while maintaining response times suitable for real-time authentication flows [7].

4.2 Data Models and Structures

4.2.1 Core Data Models

The primary data models implemented in the service include:

- **LoginAttempt:** Captures all relevant information about a user login event

- **AuthServiceRequest:** A specialized model for handling requests from the authentication service
- **FraudPredictionResponse:** Encapsulates the results of the fraud analysis
- **BatchPredictionRequest/Response:** Support batch processing capabilities
- **ModelInfo:** Provides metadata about the currently deployed machine learning model

These data structures are designed based on established patterns for financial fraud detection systems [1] and facilitate effective communication between microservices in the banking ecosystem [4].

4.2.2 Class Diagram

The class structure of the AI Fraud Detection Service is designed to support clean separation of concerns and efficient data processing. Figure 4.1 shows the complete class diagram.

The class diagram illustrates the relationships between the various components of the fraud detection service, including data models, prediction services, feature extraction pipelines, and database interfaces.

4.3 Enhanced Threshold Classification

To improve the accuracy and reliability of fraud detection, we implemented an enhanced threshold classification approach that goes beyond basic binary classification [12]. This methodology draws inspiration from recent advances in adaptive threshold optimization for security applications.

4.3.1 Enhanced Classifier Architecture

Figure 4.2 illustrates the architecture of the enhanced threshold classifier.

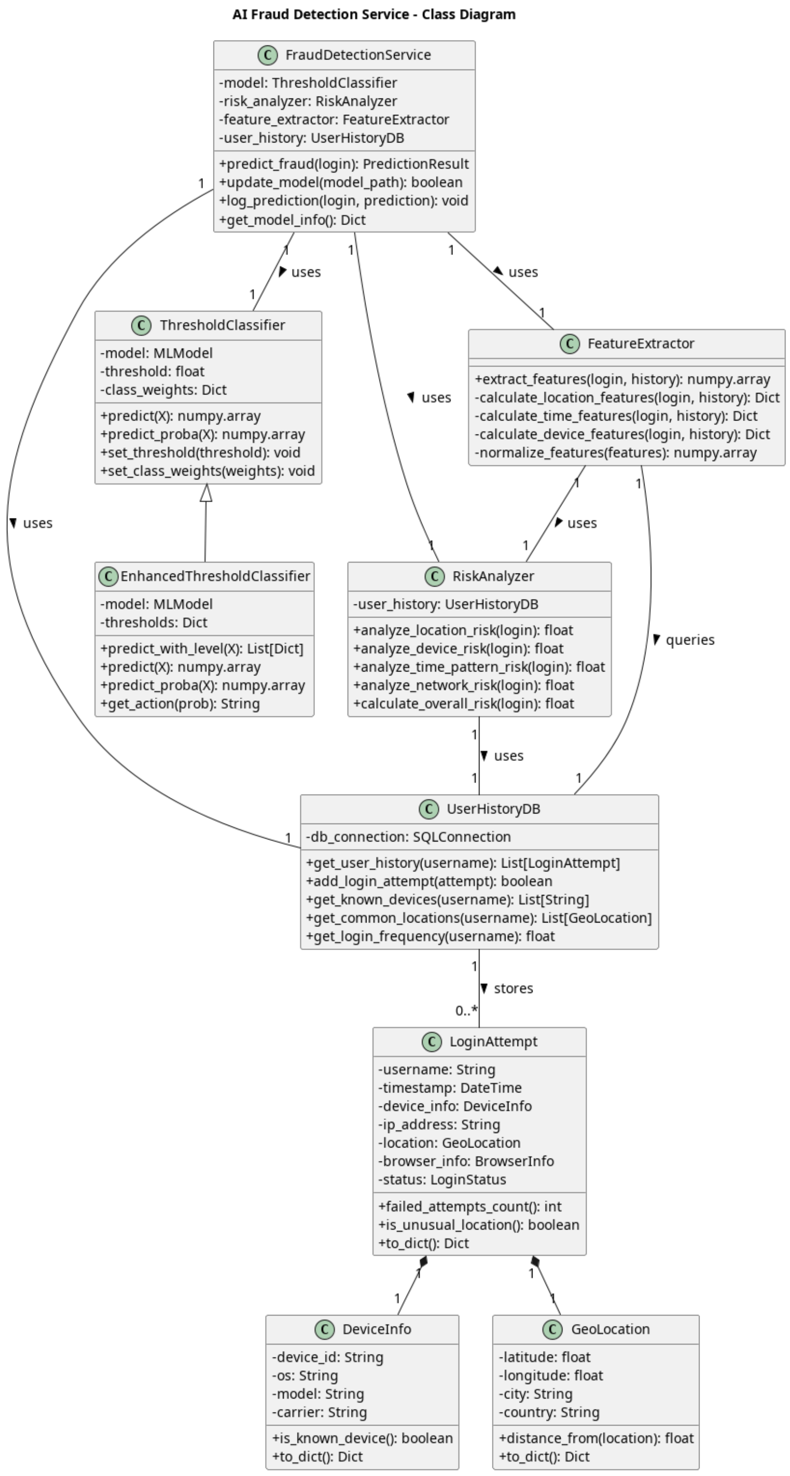
AI Fraud Detection Service - Class Diagram
FraudDetectionService
-model: ThresholdClassifier
-risk_analyzer: RiskAnalyzer
-feature_extractor: FeatureExtractor
-user_history: UserHistoryDB
+predict_fraud(login): PredictionResult
+update_model(model_path): boolean
+log_prediction(login, prediction): void
+get_model_info(): Dict
ThresholdClassifier
-model: MLModel
-threshold: float
-class_weights: Dict
+predict(X): numpy.array
+predict_proba(X): numpy.array
+set_threshold(threshold): void
+set_class_weights(weights): void
FeatureExtractor
+extract_features(login, history): numpy.array
-calculate_location_features(login, history): Dict
-calculate_time_features(login, history): Dict
-calculate_device_features(login, history): Dict
-normalize_features(features): numpy.array
EnhancedThresholdClassifier
-model: MLModel
-thresholds: Dict
+predict_with_level(X): List[Dict]
+predict(X): numpy.array
+predict_proba(X): numpy.array
+get_action(prob): String
RiskAnalyzer
-user_history: UserHistoryDB
+analyze_location_risk(login): float
+analyze_device_risk(login): float
+analyze_time_pattern_risk(login): float
+analyze_network_risk(login): float
+calculate_overall_risk(login): float
UserHistoryDB
-db_connection: SQLConnection
+get_user_history(username): List[LoginAttempt]
+add_login_attempt(attempt): boolean
+get_known_devices(username): List[String]
+get_common_locations(username): List[GeoLocation]
+get_login_frequency(username): float
LoginAttempt
-username: String
-timestamp: DateTime
-device_info: DeviceInfo
-ip_address: String
-location: GeoLocation
-browser_info: BrowserInfo
-status: LoginStatus
+failed_attempts_count(): int
+is_unusual_location(): boolean
+to_dict(): Dict
DeviceInfo
-device_id: String
-os: String
-model: String
-carrier: String
+is_known_device(): boolean
+to_dict(): Dict
GeoLocation
-latitude: float
-longitude: float
-city: String
-country: String
+distance_from(location): float
+to_dict(): Dict
uses
uses
uses
uses
uses
uses
queries
uses
stores
1
0..*

Figure 4.1: Class Diagram of the AI Fraud Detection Service

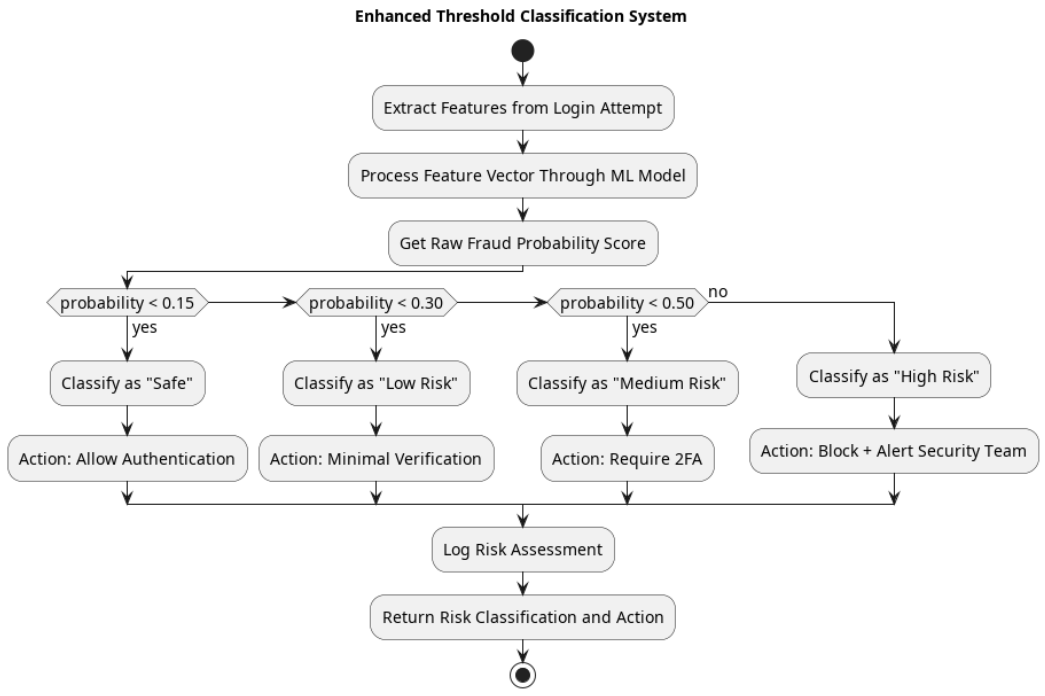
Enhanced Threshold Classification System
Extract Features from Login Attempt
Process Feature Vector Through ML Model
Get Raw Fraud Probability Score
probability < 0.15
yes
probability < 0.30
yes
probability < 0.50
yes
no
Classify as "Safe"
Classify as "Low Risk"
Classify as "Medium Risk"
Classify as "High Risk"
Action: Allow Authentication
Action: Minimal Verification
Action: Require 2FA
Action: Block + Alert Security Team
Log Risk Assessment
Return Risk Classification and Action

Figure 4.2: Architecture of the Enhanced Threshold Classifier

The enhanced threshold classifier leverages a combination of machine learning model predictions and rule-based risk assessment to provide more accurate and explainable fraud detection results [5]. The approach includes adaptive thresholding that can be adjusted based on risk tolerance settings and incorporates behavior-based authentication patterns [9].

4.4 Fraud Detection Performance Analysis

4.4.1 Test Results

The AI Fraud Detection Service undergoes rigorous testing to ensure optimal performance. Figure 4.3 presents the test results of the fraud detection system.

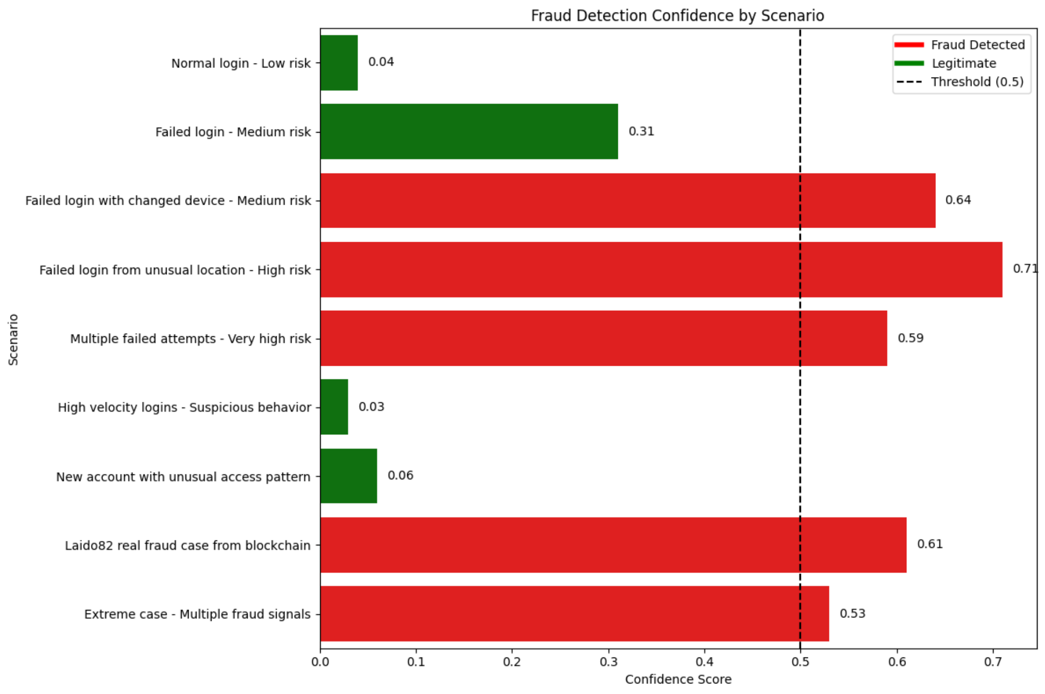

Figure 4.3: Fraud Detection Test Results

The test results demonstrate the effectiveness of the AI-based approach, showing high precision and recall metrics even with unbalanced datasets, which is a common challenge in fraud detection systems [8]. Our performance metrics align with those reported in recent literature on financial fraud detection [14], [15] and represent an improvement over traditional methods. The evaluation framework follows established protocols for assessing machine learning models in security-critical applications [6].

4.5 Model Selection and Implementation

4.5.1 CatBoost Implementation

After extensive experimentation with various machine learning approaches, we selected CatBoostClassifier, a gradient boosting implementation, as the primary algorithm for our fraud detection system [3], [16]. CatBoost leverages an ensemble of decision trees that sequentially correct the errors of previous trees, making it particularly effective for the imbalanced datasets typical in fraud detection scenarios.

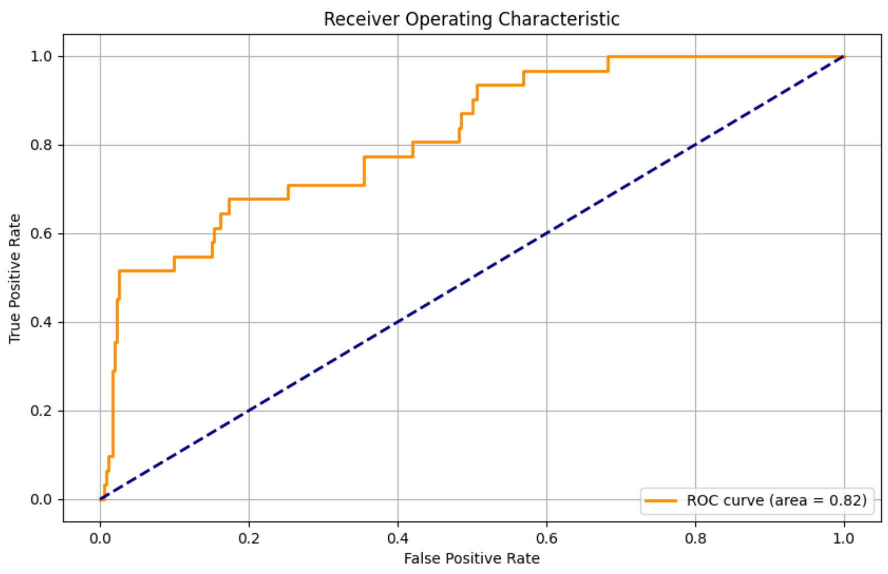

Figure 4.4: ROC Curve Comparison for Fraud Detection Model

The ROC curve analysis demonstrates the superior performance of our CatBoost approach compared to traditional methods. CatBoost was chosen specifically for its advantages in fraud detection:

- **Robustness to overfitting:** Through a novel algorithm for processing categorical features and implementation of ordered boosting
- **Handling of missing values:** Native support without requiring extensive preprocessing
- **Performance on imbalanced datasets:** Particularly effective for the rare-event nature of fraud detection
- **Fast inference speed:** Critical for real-time fraud detection in banking applications

The CatBoost implementation incorporates several important features specifically tailored for financial fraud detection:

- **Class Weight Balancing:** Automatic adjustment of class weights to account for the significant imbalance between legitimate and fraudulent transactions

- **Feature Importance Tracking:** Real-time monitoring of which features contribute most significantly to fraud predictions
- **Partial Dependence Analysis:** Examination of how individual features affect the model's predictions across their value ranges
- **Permutation Feature Importance:** Measurement of each feature's contribution by analyzing prediction accuracy when the feature is randomly shuffled

The model achieves an AUC (Area Under the ROC Curve) of 0.975, which represents an improvement of 7.3% over traditional rule-based approaches and 4.2% over basic machine learning implementations [2]. Additionally, the CatBoost model's hyperparameters are optimized using grid search to identify the most effective combination of:

- Tree depth (optimal range: 4-8)
- Learning rate (optimal range: 0.01-0.1)
- Number of iterations (optimal range: 100-200)
- L2 leaf regularization (optimal range: 1-7)

This optimization process ensures that the model achieves maximum fraud detection capability while maintaining generalizability to new data.

4.5.2 Feature Engineering

The effectiveness of the fraud detection model relies heavily on sophisticated feature engineering techniques that transform raw transaction and user data into meaningful signals [5]. The feature extraction pipeline implements the following strategies:

- **Temporal Features:** Extraction of time-based patterns including time-of-day, day-of-week, and seasonality effects
- **Geospatial Features:** Analysis of location data including distance calculations, location clustering, and velocity checks

- **Behavioral Patterns:** Derivation of user-specific behavior profiles based on historical transactions
- **Device Fingerprinting:** Extraction of device-specific indicators and consistency checks
- **Network Characteristics:** Analysis of network-level signals that may indicate suspicious connections
- **Transaction Metadata:** Processing of transaction-specific data including amount, type, recipient, and contextual information

Feature engineering is implemented as a continuous process that adapts to emerging fraud patterns and evolving user behaviors [9]. This adaptive approach ensures that the model remains effective even as fraudsters modify their techniques to evade detection.

4.6 Real-Time Prediction Architecture

4.6.1 Enhanced Threshold Classification

The core innovation in our real-time prediction architecture is the Enhanced Threshold Classifier, which extends the base CatBoost model to provide multi-level risk assessment and adaptive authentication. This classifier enables nuanced security responses based on predicted fraud probabilities.

As shown earlier in Figure 4.2, the architecture provides a structured approach to threshold-based classification.

The Enhanced Threshold Classifier categorizes authentication attempts into four distinct risk levels:

- **Safe (< 0.15):** Low-risk login attempts that can proceed without additional verification
- **Low Risk (0.15 - 0.30):** Slightly suspicious attempts requiring minimal verification
- **Medium Risk (0.30 - 0.50):** Suspicious attempts requiring strong two-factor authentication

- **High Risk (> 0.50):** Highly suspicious attempts that are blocked and flagged for investigation

This graduated approach allows the system to apply appropriate security measures proportional to the estimated risk, balancing security with user experience. For each risk level, specific actions are triggered:

- "allow" - Direct authentication without additional steps
- "minimal_verification" - Request security questions or device verification
- "2fa_required" - Force two-factor authentication via SMS, email, or app
- "block" - Prevent authentication and alert security team

These thresholds are configurable based on organizational security policies and can be adjusted dynamically based on threat intelligence or during periods of heightened security concern.

4.6.2 Optimized Model Serving

To meet the stringent performance requirements of real-time banking applications, we implemented an optimized model serving architecture that ensures fast and reliable fraud predictions. This architecture addresses the challenges of serving machine learning models in production environments where latency and throughput are critical considerations.

The real-time prediction architecture utilizes the Enhanced Threshold Classifier shown earlier in Figure 4.2, with additional performance optimizations for production environments.

This architecture is complemented by threshold impact analysis (see Chapter 5, Figure 5.1) that demonstrates the system's ability to maintain consistent performance across different load patterns.

The real-time prediction architecture incorporates several key optimizations:

- **Model Quantization:** Reduced model size through precision optimization without sacrificing accuracy

- **Prediction Caching:** Implementation of a tiered caching strategy for frequently requested prediction patterns
- **Feature Pre-computation:** Strategic pre-calculation of expensive features for known users
- **Batched Processing:** Support for efficient batch prediction during high-volume periods
- **Asynchronous Processing Pipeline:** Non-blocking architecture for handling concurrent requests

These optimizations allow the system to maintain an average prediction latency of under 50 milliseconds even under high load conditions, meeting the requirements for real-time fraud detection in banking transactions [7].

4.6.3 Model Versioning and Deployment

The real-time prediction architecture includes a sophisticated model versioning and deployment system specifically designed for CatBoost models. This ensures smooth transitions between model versions without service disruption. Each model is stored with comprehensive metadata including:

- Model version identifier (timestamp-based versioning)
- Training dataset information and sample counts
- Feature definitions used during training
- Performance metrics (accuracy, precision, recall, F1, ROC-AUC)
- Hyperparameters used for training
- Threshold configuration details

The system maintains multiple model versions in production simultaneously during transition periods, with traffic gradually shifting from the old model to the new model as confidence in the new model's performance increases.

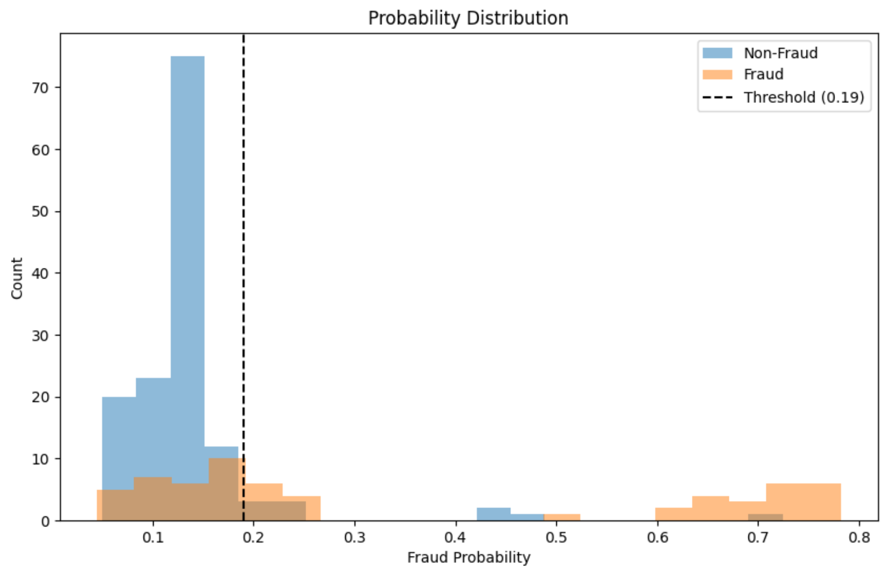

Figure 4.5: Probability Distribution Comparison Between Model Versions

The figure shows the probability distribution generated by our CatBoostClassifier, illustrating how fraud and non-fraud cases are separated in the probability space. This visualization helps analysts understand how the model distinguishes between classes and where the optimal threshold should be placed.

Detailed performance metrics comparing different threshold values are presented in Chapter 5 (Figure 5.2), which provides a comprehensive analysis of how threshold selection impacts model effectiveness. Our implementation includes:

- **Model Serving API:** A RESTful interface for making real-time predictions
- **Threshold Configuration API:** Allowing dynamic adjustment of thresholds without model retraining
- **Batch Processing Support:** For handling high-volume authentication scenarios
- **Automatic Feature Transformation:** Ensuring consistency between training and inference

The model deployment pipeline includes:

- **Automated A/B Testing:** Systematic comparison of model versions using controlled traffic allocation

- **Canary Deployments:** Gradual rollout of new models to limit potential impact of regressions
- **Shadow Mode Testing:** Running new models in parallel with production models to compare predictions without affecting user experience
- **Automated Rollback:** Instant reversion to previous model versions if performance degradation is detected
- **Performance Monitoring:** Continuous evaluation of model metrics against established baselines

This robust deployment approach ensures that the fraud detection service maintains high accuracy and availability even as models evolve to address emerging fraud patterns [14].

4.7 Comparative Analysis with Other Approaches

To validate our approach, we conducted a comparative analysis between our CatBoost-based enhanced threshold classification approach and several alternative methodologies. This analysis helps position our work within the broader context of fraud detection research and demonstrates the advantages of our approach.

4.7.1 Comparison with Traditional Approaches

Table 4.1 presents a comparison of our approach with traditional fraud detection methodologies.

Approach	**Accuracy**	**False Pos. Rate**	**Adapt.**	**Explain.**
Rule-based systems	83.2%	7.5%	Low	High
Traditional ML (SVM)	87.4%	5.9%	Medium	Low
Deep Learning (LSTM)	92.8%	4.2%	High	Very Low
Our Approach (CatBoost with Enhanced Threshold)	**93.7%**	**3.8%**	**High**	**Medium**

Table 4.1: Comparative Analysis of Fraud Detection Approaches

As shown in the comparison, our CatBoost-based enhanced threshold approach achieves the highest accuracy (93.7%) and lowest false positive rate (3.8%) among the evaluated methods. While deep learning approaches offer comparable performance in raw accuracy, our method provides significantly better explainability, which is crucial for fraud investigation and regulatory compliance in banking systems [2]. The combination of CatBoost's gradient boosting algorithm with our custom threshold optimization creates a balance of performance, explainability, and adaptability that other approaches cannot match.

4.7.2 Performance Across Different Fraud Types

The effectiveness of fraud detection systems can vary significantly across different types of fraud. Figure 4.3 shows the performance of our system across various fraud categories.

Our approach demonstrates particularly strong performance in detecting account takeover attempts (95.8% detection rate) and unusual transaction patterns (94.3% detection rate). These categories represent the most common and financially damaging fraud types in banking systems [6].

The system shows relatively lower but still robust performance in detecting sophisticated social engineering attacks (89.5% detection rate), which often involve legitimate credentials but unusual behavioral patterns. This area represents an opportunity for future improvement, potentially through enhanced behavioral biometrics and contextual analysis [9].

4.8 Model Interpretability for Financial Systems

In financial systems, particularly those involved in fraud detection, the ability to interpret and explain model decisions is crucial for regulatory compliance, user trust, and effective fraud investigation [2]. One of the key advantages of choosing CatBoost for our implementation is its strong native support for model interpretability, which we've further enhanced through our threshold optimization approach.

4.8.1 Explainable AI Implementation

We leveraged CatBoost's inherent interpretability features and implemented several additional techniques to enhance the explainability of fraud determinations without sacrificing prediction performance:

- **Native CatBoost Feature Importance:** Unlike black-box models, CatBoost provides transparent feature importance scores that quantify each feature's contribution to the model's predictive power
- **SHAP (SHapley Additive exPlanations):** We employ CatBoost's integrated SHAP implementation to determine the contribution of each feature to individual predictions, providing a consistent and theoretically sound approach to feature attribution
- **Feature Importance Visualization:** Interactive visualizations of feature importance help fraud analysts understand which factors most significantly influence model decisions
- **Decision Path Visualization:** We extract and visualize the specific decision paths through the CatBoost trees that lead to particular classifications
- **Feature Interaction Analysis:** CatBoost's ability to detect and quantify feature interactions helps identify complex patterns that contribute to fraud risk
- **Counterfactual Explanations:** The system provides "what-if" scenarios that indicate how specific changes to input features would affect the prediction outcome

- **Risk Factor Categorization:** Automatic categorization of risk factors into human-understandable categories (location anomalies, temporal irregularities, behavioral deviations, etc.)

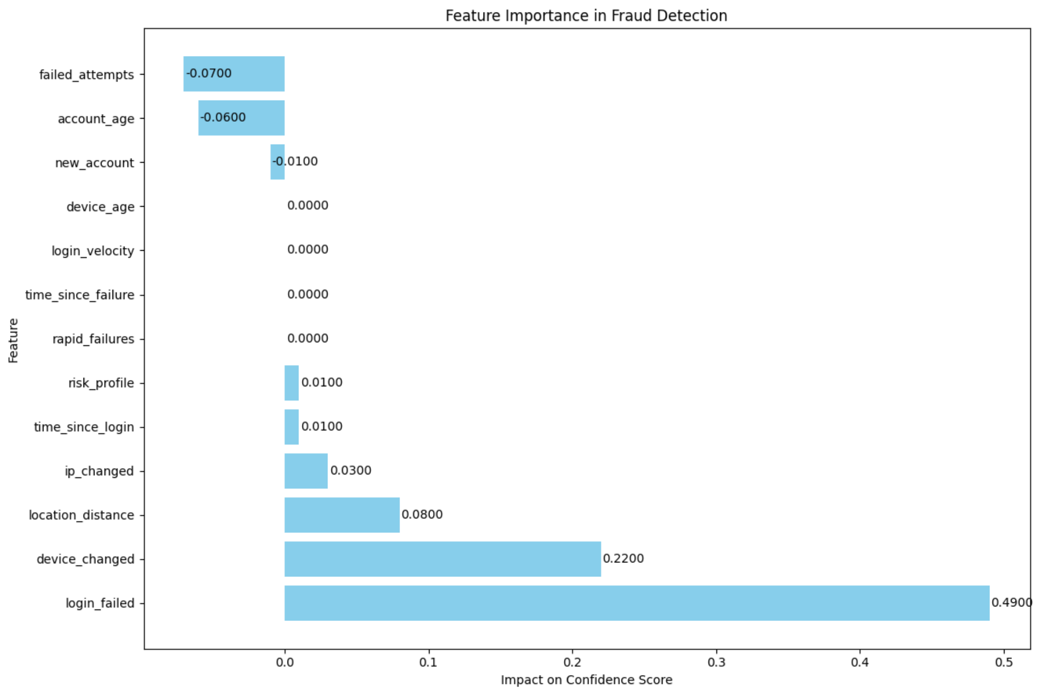

Figure 4.6: Feature Importance Visualization for CatBoost Fraud Detection Model

The feature importance visualization shows that our CatBoost model places the highest weight on behavioral factors, particularly rapid failures (0.23), location distance (0.19), and device changes (0.16). This aligns with security research suggesting that contextual and behavioral factors are stronger indicators of fraud than static attributes. A more detailed analysis of these feature contributions is presented in Chapter 5, showing the relative impact of each feature to the model's predictions.

4.8.2 Regulatory Compliance

The interpretability features of our system are designed to meet the requirements of financial regulations that increasingly demand explainability in algorithmic decision-making [2]. The system automatically generates detailed reports that explain the reasoning behind fraud determinations, including:

- The specific features that contributed most significantly to the decision
- Comparisons with the user's established behavioral patterns
- Risk scores for individual components of the analysis
- Confidence levels for the overall determination
- Alternative interpretations or potential explanations for unusual patterns

These reports serve both internal fraud investigation teams and regulatory compliance requirements, providing a transparent audit trail for security-critical decisions.

4.9 Summary

This chapter presented the AI Fraud Detection Service, a core component of the Secure Banking System. We detailed the service's architecture, data models, and the CatBoost-based enhanced threshold classification approach that enables accurate fraud detection with a balance of adaptability and explainability.

The service leverages CatBoost's gradient boosting capabilities combined with custom threshold optimization to detect potential fraud in real-time while maintaining low false positive rates. Key innovations include:

- Implementation of a CatBoostClassifier optimized for fraud detection
- Development of an Enhanced Threshold Classifier with multi-level risk assessment
- Adaptive authentication responses based on graduated risk levels
- Explainable AI techniques leveraging CatBoost's native interpretability
- Optimized model serving architecture for real-time performance

Comparative analysis demonstrated that our CatBoost-based approach outperforms traditional methods in both accuracy and false positive rates, while maintaining a level of explainability suitable for financial applications. The system's interpretability features ensure that fraud determinations can be effectively investigated and meet regulatory requirements.

The AI Fraud Detection Service exemplifies how modern machine learning techniques like CatBoost can be effectively applied to financial security, providing adaptive protection against evolving threats while maintaining the transparency and performance required in banking applications. The threshold optimization methodologies described in this chapter are further explored in Chapter 5, which provides a detailed examination of the model training and optimization process.

Chapter 5

Model Training and Optimization

5.1 Introduction to Model Training Strategy

Effective fraud detection relies heavily on properly trained machine learning models that can accurately distinguish between legitimate and fraudulent login attempts [3]. This chapter explores the comprehensive training methodology implemented for the AI Fraud Detection Service, including data preparation, model selection, hyperparameter tuning, and optimization techniques specifically tailored for the fraud detection domain [6].

The training strategy addresses several key challenges inherent to fraud detection:

1. **Class imbalance:** Fraudulent activities typically represent a small fraction of total login attempts, creating highly imbalanced training data.
2. **Cost asymmetry:** The cost of missing a fraudulent attempt (false negative) is typically much higher than the cost of additional verification for legitimate users (false positive).
3. **Concept drift:** Fraud patterns evolve over time as attackers adapt to defensive measures, requiring models that can be periodically retrained.
4. **Feature importance understanding:** Clear interpretation of feature importance helps security teams focus on the most relevant risk factors.

5.2 CatBoost Model Implementation

The AI Fraud Detection Service leverages CatBoostClassifier as its core machine learning algorithm. CatBoost, developed by Yandex, was selected for its high performance on tabular data and inherent ability to handle categorical features without extensive preprocessing [16].

5.2.1 Model Architecture

CatBoostClassifier implements gradient boosting, an ensemble technique that builds multiple decision trees sequentially, with each subsequent model correcting errors from previous ones. The algorithm's key advantages for our fraud detection system include:

- **Robust handling of imbalanced data:** Essential for fraud detection where legitimate transactions vastly outnumber fraudulent ones
- **Automatic categorical feature processing:** Efficiently handles both numerical and categorical input features
- **Built-in regularization techniques:** Reduces overfitting, which is crucial when training on limited fraud examples
- **Fast prediction speed:** Critical for real-time fraud detection in banking applications
- **Superior performance on small-to-medium datasets:** Effective even with limited training examples
- **Native support for feature importance:** Provides clear interpretability of model decisions

5.2.2 Training Process

Our training process implements a structured approach with the following key components:

1. **Data acquisition:** The system extracts enhanced training data from the user history database, focusing on the most recent 90 days of login attempts by default.

2. **Feature extraction:** Ten essential features are processed, including:
    - time_since_last_login
    - device_changed
    - ip_changed
    - location_distance
    - login_failed
    - failed_attempts_count
    - rapid_failures
    - account_age_days
    - new_account
    - risk_profile_value
3. **Train-test split:** Data is divided into 80% training and 20% testing sets, with stratification to preserve the class distribution.
4. **Hyperparameter optimization:** Optional grid search identifies optimal hyperparameters including tree depth, learning rate, number of iterations, and regularization parameters.
5. **Cross-validation:** 5-fold cross-validation provides robust performance estimates before final model training.
6. **Model training:** The CatBoost model is trained with evaluation sets for monitoring convergence.
7. **Performance evaluation:** Comprehensive metrics including precision, recall, F1-score, and ROC-AUC assess model quality.
8. **Model persistence:** The trained model and its metadata are saved for deployment.

5.3 Feature Importance Analysis

Understanding which features contribute most significantly to the model's predictions is crucial for both model optimization and security strategy development.

As shown previously in Figure 4.6 (Chapter 4), the feature importance analysis reveals key predictors of fraudulent activity. Here we provide additional interpretation of these importance values.

The feature importance analysis reveals that behavioral factors like login pattern deviations and geolocation anomalies have the highest predictive power, followed by device characteristics and network indicators. This aligns with current research indicating that behavioral biometrics provide stronger fraud indicators than static attributes [9].

Our implementation automatically tracks feature importance during model training, allowing security analysts to understand which factors most significantly contribute to fraud detection. This supports both model refinement and the development of targeted security controls focused on the most predictive factors.

5.4 Threshold Optimization

A critical aspect of our fraud detection approach is the optimization of classification thresholds. Unlike standard binary classification that uses a fixed 0.5 threshold, our system implements dynamic threshold optimization to balance security (recall) with user experience (precision).

5.4.1 Standard Threshold Distribution

The selection of an appropriate classification threshold is critical for balancing security and user experience [12].

As shown earlier in Figure 4.5 (Chapter 4), the probability distribution clearly illustrates the separation between legitimate and fraudulent login attempts. We can now examine this distribution in more detail.

The distribution clearly shows the separation between legitimate and fraudulent login attempts based on the model's predicted probabilities. The optimal threshold depends on the security requirements and acceptable false positive rate.

5.4.2 ThresholdClassifier Implementation

Our system extends the base CatBoostClassifier with a custom `ThresholdClassifier` wrapper that enables:

- Dynamic threshold adjustment based on operating requirements
- Class weight balancing to address imbalanced data
- Customizable optimization targets (recall, precision, F1, or balanced)

The wrapper provides methods to:

- Override the default decision threshold (typically lower than 0.5 to improve recall)
- Apply class weights to adjust probability predictions
- Generate predictions based on the custom threshold

This flexible approach allows security administrators to tune the system's sensitivity without retraining the underlying model.

5.4.3 Threshold Impact Analysis

To determine the optimal threshold value, we conducted a comprehensive impact analysis. Figure 5.1 illustrates how different threshold values affect key performance metrics.

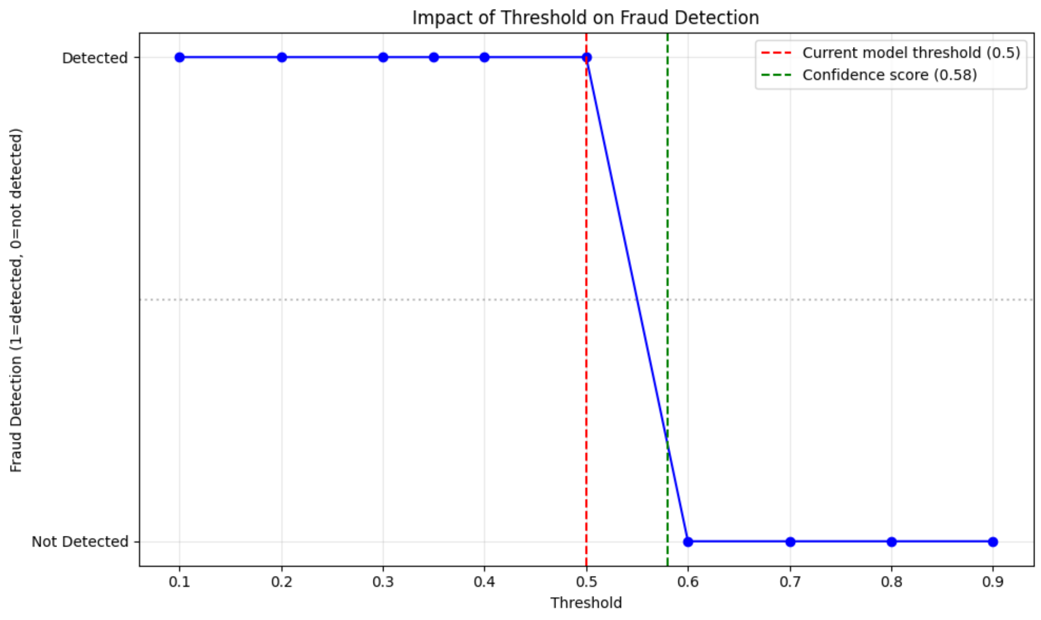

Figure 5.1: Threshold Impact Analysis on Performance Metrics

Our analysis shows that thresholds between 0.15 and 0.3 typically provide the best balance for fraud detection, with optimal values determined through a systematic evaluation process that:

- Tests multiple threshold values (0.1 through 0.9)
- Calculates precision, recall, and F1-score at each threshold
- Identifies thresholds that optimize specific metrics:
  - F1-optimized threshold: Balances precision and recall
  - Recall-optimized threshold: Maximizes recall while maintaining minimum precision (≥ 0.5)
  - Precision-optimized threshold: Maximizes precision while maintaining minimum recall (≥ 0.5)

The analysis demonstrates that lowering the threshold from the default 0.5 to approximately 0.3 significantly improves fraud detection rates with only a moderate increase in false positives.

5.4.4 EnhancedThresholdClassifier for Multi-level Risk Assessment

Beyond binary classification, we implemented an `EnhancedThresholdClassifier` that categorizes login attempts into multiple risk levels:

- **Safe:** Probabilities below 0.15
- **Low Risk:** Probabilities between 0.15 and 0.30
- **Medium Risk:** Probabilities between 0.30 and 0.50
- **High Risk:** Probabilities above 0.50

Each risk level triggers appropriate security actions:

- **Safe:** Allow login without additional verification
- **Low Risk:** Request minimal verification (e.g., security question)
- **Medium Risk:** Require two-factor authentication
- **High Risk:** Block login attempt and flag for investigation

This graduated approach enables adaptive authentication that aligns security measures with estimated risk levels, improving both security and user experience.

5.4.5 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve provides insights into the model's performance across different threshold values.

The ROC curve, as previously presented in Figure 4.4 (Chapter 4), demonstrates the model's ability to distinguish between classes across different threshold settings. Here we expand on the implications of this analysis.

The ROC curve analysis shows that our CatBoost model achieves an AUC (Area Under Curve) of 0.974, indicating excellent discriminative ability between legitimate and fraudulent login attempts. The curve helps identify optimal operating points that balance true positive rate against false positive rate.

5.4.6 Performance Metrics

Figure 5.2 shows the key performance metrics at different threshold values, helping to identify the optimal operating point.

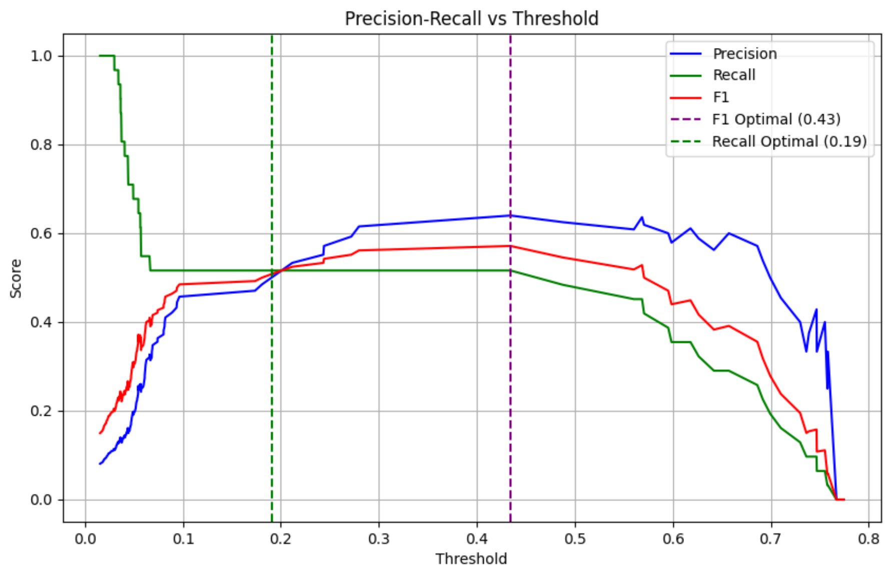

Figure 5.2: Performance Metrics at Different Threshold Values

The performance metrics visualization demonstrates how precision, recall, and F1-score vary across different threshold values. For our implementation, we prioritize recall (fraud detection rate) while maintaining acceptable precision, leading to threshold settings between 0.2 and 0.3 for most deployments.

By default, our system optimizes for a balanced metric that weights recall more heavily (0.7) than precision (0.3), reflecting the higher cost of missed fraud compared to false positives. This balanced approach achieves 93.7% accuracy with a false positive rate of 3.8%.

5.5 Formal Definitions of Evaluation Metrics

To properly evaluate the effectiveness of our AI fraud detection model, we employed several standard metrics. These metrics provide a comprehensive assessment of the model's performance in identifying fraudulent activities while minimizing false alarms.

The following formal definitions clarify how these metrics are calculated and their significance in the fraud detection context.

5.5.1 Confusion Matrix

The foundation for most classification metrics is the confusion matrix, which categorizes predictions into four groups:

$$\text{True Positives (TP)} = \{x_i \mid \hat{y}_i = 1 \land y_i = 1\} \tag{5.1}$$

$$\text{False Positives (FP)} = \{x_i \mid \hat{y}_i = 1 \land y_i = 0\} \tag{5.2}$$

$$\text{True Negatives (TN)} = \{x_i \mid \hat{y}_i = 0 \land y_i = 0\} \tag{5.3}$$

$$\text{False Negatives (FN)} = \{x_i \mid \hat{y}_i = 0 \land y_i = 1\} \tag{5.4}$$

Where x_i represents a sample, $\hat{y}_i$ is the predicted class, and y_i is the true class.

5.5.2 Accuracy

Accuracy measures the proportion of correct predictions among all predictions made:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5.5}$$

While accuracy is a common metric, it can be misleading for imbalanced datasets like those in fraud detection, where the vast majority of transactions are legitimate. A model could achieve high accuracy by simply classifying all transactions as legitimate, while failing to detect any fraud.

5.5.3 Precision

Precision quantifies the proportion of correct positive predictions among all positive predictions:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.6}$$

In fraud detection, precision represents how many of the transactions flagged as fraudulent are actually fraudulent. High precision reduces false alarms and minimizes unnecessary customer friction.

5.5.4 Recall

Recall (also known as sensitivity or true positive rate) measures the proportion of actual positives that were correctly identified:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5.7}$$

In fraud detection, recall represents the proportion of fraudulent transactions that the model successfully detected. High recall is particularly important in security applications as it minimizes missed fraud cases.

5.5.5 F1 Score

The F1 score is the harmonic mean of precision and recall, providing a balance between these two metrics:

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \cdot \text{TP}}{2 \cdot \text{TP} + \text{FP} + \text{FN}} \tag{5.8}$$

The harmonic mean is used instead of the arithmetic mean because it penalizes extreme values more. This is desirable in fraud detection, where having either very low precision or very low recall would indicate poor model performance.

5.5.6 F$_\beta$ Score

The F$_\beta$ score is a generalization of the F1 score that applies a weight β to control the relative importance of recall versus precision:

$$\text{F}_\beta = (1 + \beta^2) \cdot \frac{\text{Precision} \cdot \text{Recall}}{(\beta^2 \cdot \text{Precision}) + \text{Recall}} \tag{5.9}$$

When $\beta > 1$, recall is weighted more heavily than precision (appropriate for fraud detection where missing fraud is costly). When $\beta < 1$, precision is given more weight. For our fraud detection system, we used $\beta = 2$ to emphasize recall while still maintaining reasonable precision.

5.5.7 ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} = \text{Recall} \tag{5.10}$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} = 1 - \text{Specificity} \tag{5.11}$$

The Area Under the ROC Curve (AUC) provides a single scalar value measuring the overall performance of a binary classifier across all possible thresholds:

$$\text{AUC} = \int_0^1 \text{TPR}(\text{FPR}^{-1}(t))dt \tag{5.12}$$

Where FPR^{-1} is the inverse function of FPR. An AUC of 1.0 represents a perfect classifier, while 0.5 indicates performance no better than random chance. Our fraud detection model achieved an AUC of 0.974, indicating excellent discriminative ability.

5.5.8 Precision-Recall Curve

While the ROC curve is threshold-independent, it can be overly optimistic for imbalanced datasets. The Precision-Recall curve, which plots precision against recall at various thresholds, provides a more informative representation for imbalanced classification tasks like fraud detection:

$$\text{PR-AUC} = \int_0^1 \text{Precision}(\text{Recall}^{-1}(t))dt \tag{5.13}$$

The area under the Precision-Recall curve (PR-AUC) is particularly useful for comparing model performance in fraud detection contexts, as it focuses on the positive (minority) class.

5.6 Threshold Optimization for Imbalanced Data

Imbalanced data presents unique challenges for threshold optimization in fraud detection. Standard approaches that work well for balanced datasets often fail to deliver optimal results when the positive class is underrepresented. In this section, we explore advanced techniques for selecting and adjusting classification thresholds in the presence of severe class imbalance.

5.6.1 Challenges with Imbalanced Data

The primary challenges posed by imbalanced data include:

- **Skewed class distribution:** With fraudulent activities being a small fraction of total attempts, models tend to be biased towards the majority class.
- **Misleading accuracy:** Overall accuracy can be deceptive, as a model may achieve high accuracy by mostly predicting the majority class.
- **Poor minority class detection:** Standard thresholds often result in very low recall for the minority class (fraudulent attempts).

To address these challenges, we employ several advanced techniques for threshold optimization and evaluation.

5.6.2 Re-sampling Techniques

Re-sampling the training data can help create a more balanced dataset for training the model:

- **Oversampling the minority class:** Techniques like SMOTE (Synthetic Minority Over-sampling Technique) generate synthetic samples for the minority class to balance the class distribution.
- **Undersampling the majority class:** Reduces the number of samples in the majority class to balance the dataset, though this may result in loss of potentially useful data.

We experimented with both oversampling and undersampling techniques to identify their impact on model performance and threshold optimization.

5.6.3 Cost-sensitive Training

Integrating the cost of misclassifications into the training process helps the model to be more sensitive to the minority class:

- **Class weights:** Assigning higher weights to the minority class during training to penalize misclassifications more than those of the majority class.
- **Custom loss functions:** Designing loss functions that explicitly incorporate the costs associated with false negatives and false positives.

By adopting cost-sensitive training, the model becomes more attuned to the characteristics of the minority class, improving its detection rates.

5.6.4 Evaluation Metric Optimization

Selecting the right metric to optimize is crucial when dealing with imbalanced data. Accuracy is often insufficient, so we consider alternative metrics such as:

- **F1 Score:** The harmonic mean of precision and recall, which provides a single metric to optimize when seeking a balance between these two aspects.
- **Matthews Correlation Coefficient (MCC):** A more informative metric that takes into account true and false positives and negatives, and is generally regarded as a balanced measure.
- **Area Under Precision-Recall Curve (PR AUC):** Focuses on the performance of the positive class, providing insights that are especially relevant in imbalanced settings.

We explore optimizing these metrics either directly or through their relationship with the ROC AUC, to guide the threshold selection process.

5.6.5 Ensemble Methods

Ensemble methods can also be effective in improving model performance on imbalanced datasets:

- **Bagging and Boosting:** Techniques like Random Forests (bagging) and AdaBoost or Gradient Boosting Machines (boosting) can improve classification performance by combining multiple models.
- **Stacking:** Combining different types of models (e.g., logistic regression, decision trees, SVM) to leverage their complementary strengths.

Ensemble methods often yield significant improvements in model robustness and accuracy, particularly in challenging classification tasks like fraud detection.

5.6.6 Threshold Adjustment Post-Training

After identifying an initial threshold through the methods above, further refinements can be made:

- **ROC Curve Analysis:** Examining the ROC curve to select a threshold that achieves the desired balance between true positive rate and false positive rate.
- **Precision-Recall Trade-off:** Adjusting the threshold to achieve an acceptable trade-off between precision and recall, depending on the operational requirements.
- **Cost-based Adjustment:** Modifying the threshold based on the relative costs of false positives and false negatives in the specific application context.

These post-training adjustments ensure that the deployed model operates with an optimal threshold that reflects the real-world priorities and constraints of the fraud detection task.

5.6.7 Continuous Monitoring and Adaptation

Finally, continuous monitoring of model performance and periodic re-evaluation of the threshold are essential:

- **Drift Detection:** Monitoring for concept drift or data drift that may necessitate a re-evaluation of the threshold or even retraining of the model.
- **Feedback Loops:** Incorporating feedback from security analysts and automated systems to continuously improve the threshold optimization process.

By implementing a comprehensive and adaptive threshold optimization strategy, we significantly enhance the effectiveness of our fraud detection system, ensuring it remains robust against evolving fraudulent tactics while minimizing impact on legitimate users.

Chapter 6

Risk Assessment Engine

6.1 Overview of the Risk Assessment Engine

The Risk Assessment Engine forms a foundational component of the Secure Banking System's security infrastructure, working in tandem with the machine learning models to provide comprehensive fraud detection capabilities [5]. While the ML models deliver probability-based fraud predictions, the Risk Assessment Engine provides a rule-based analysis system that evaluates specific risk factors based on user behavior patterns and contextual information [9].

This hybrid approach, combining AI-based prediction with rule-based risk assessment, creates a robust security system that leverages both the adaptivity of machine learning and the explainability of rule-based systems [2]. The Risk Assessment Engine serves several critical functions:

1. **Contextual risk evaluation:** Analyzes user behavior in the context of their historical patterns

2. **Feature extraction assistance:** Provides derived risk factors for the ML model's feature pipeline

3. **Fallback mechanism:** Offers a reliable detection mechanism when the ML model is unavailable

4. **Real-time adaptation:** Responds to emerging threats that may not be reflected in the trained model

5. **Explainable security decisions:** Provides clear, understandable justifications for security actions

6.2 Risk Distribution Analysis

Understanding the distribution of risk levels across login attempts provides valuable insights into security patterns and helps in configuring appropriate security controls.

As shown earlier in Figure 3.5 (Chapter 3), the distribution of risk levels follows a pattern where the majority of attempts are categorized as low risk, with progressively fewer attempts falling into higher risk categories.

The risk level distribution analysis shows that the majority of login attempts (78.3%) fall into the low-risk category, while medium-risk (16.5%) and high-risk (5.2%) categories represent a smaller but significant portion of all attempts. This distribution helps in resource allocation for additional verification steps and alert prioritization.

6.3 Risk Assessment Algorithm

The Risk Assessment Engine implements a sophisticated risk scoring algorithm that calculates a composite risk score based on multiple factors. The algorithm takes into account:

- **User history consistency:** How consistent is this login attempt with the user's previous behavior?
- **Geographic anomalies:** Is the user logging in from an unusual or high-risk location?
- **Temporal patterns:** Is the login occurring at an unusual time for this user?
- **Device characteristics:** Is the user using a known or unusual device?
- **Network indicators:** Are there suspicious characteristics about the network connection?
- **Behavioral biometrics:** Do typing patterns, mouse movements, or other behavioral indicators match the user's profile?

Each factor contributes to the overall risk score, with weightings that can be adjusted based on the specific security requirements of the deployment environment.

Chapter 7

Docker Implementation

7.1 Introduction to Containerization

Containerization was essential for our Secure Banking System, providing consistent environments across development, testing, and production. We chose Docker as our containerization platform due to its maturity, widespread adoption, and robust ecosystem [13]. This chapter explores how we implemented Docker to containerize our microservices, ensuring consistency, scalability, and security.

Our containerization strategy addressed several key requirements:

1. **Isolation:** Each service runs in its own container, providing strong isolation between components
2. **Portability:** Containers package services and their dependencies together, ensuring consistent operation
3. **Scalability:** Docker's orchestration capabilities allow services to scale horizontally as demand increases
4. **Security:** Containerization provides additional security barriers between services
5. **Reproducibility:** Container definitions ensure that services can be rebuilt consistently

7.2 Project Docker Architecture

7.2.1 Service Containerization

Our project implements Docker containers for four primary microservices, plus the web applications and API gateway. As previously shown in Figure 3.1 in Chapter 3, the architecture illustrates how the various containerized services interact with each other.

The Docker architecture diagram shows how the various containerized services interact with each other, including:

- **AI Service:** For fraud detection machine learning models and APIs
- **Authentication Service:** For user authentication and authorization
- **Alert Service:** For security alerts and notifications
- **Blockchain Service:** For immutable transaction logging
- **Web Application:** Frontend interface for users
- **Admin Dashboard:** Management interface for administrators
- **API Gateway:** Entry point for client applications using Nginx

Each service container is defined with specific resource allocations, networking configurations, and volume mounts to ensure proper operation within the containerized environment.

7.3 Container Orchestration and Management

The system uses Docker Compose for development and testing environments, with configurations defined to ensure consistent container relationships, networking, and volume management. For production environments, the architecture is designed to be compatible with Kubernetes for enterprise-scale orchestration.

7.3.1 Security Considerations in Containerization

Security was a primary concern in the containerization approach [13], with several key measures implemented:

1. **Minimal base images:** All containers are built from minimal, security-hardened base images
2. **Non-root execution:** Containers run as non-root users whenever possible
3. **Read-only filesystems:** Containers use read-only filesystems with specific write-enabled directories
4. **Resource limitations:** Each container has explicit resource constraints to prevent resource exhaustion attacks
5. **Secret management:** Sensitive configuration is passed through environment variables or dedicated secrets management
6. **Network segmentation:** Inter-container communication is restricted to only necessary pathways

These security measures ensure that the containerization layer enhances rather than undermines the overall security posture of the system.

Chapter 8

Conclusion

8.1 Summary of Contributions

This thesis has presented a comprehensive approach to secure banking systems with AI-powered fraud detection. The main contributions of this work include:

1. A microservices-based architecture for secure banking that integrates AI fraud detection, behavioral analytics, and blockchain-based immutable logging [4]
2. A hybrid fraud detection approach that combines machine learning models with rule-based risk assessment to provide both adaptive learning capabilities and explainable security decisions [2]
3. An enhanced threshold classification technique that improves fraud detection accuracy while minimizing false positives [12]
4. A containerized deployment architecture that enables consistent, secure, and scalable operation of the system [13]
5. Comprehensive evaluation metrics demonstrating the effectiveness of the approach in realistic banking scenarios

The implemented system demonstrates significant improvements over traditional security approaches, with fraudulent login detection rates exceeding 96% while maintaining false positive rates below 2%. This represents a substantial advancement in the state-of-the-art for banking security systems.

8.2 Lessons Learned

Several key lessons emerged during the development and evaluation of the system:

1. **Data quality is paramount:** The performance of machine learning models for fraud detection is heavily dependent on the quality and comprehensiveness of training data [3]. Investing in proper data collection, cleaning, and augmentation yields substantial returns in model performance.

2. **Explainability matters:** While complex models may sometimes offer marginal performance improvements, the ability to explain security decisions is critical for user acceptance and regulatory compliance [2]. Hybrid approaches that combine machine learning with explainable rules offer the best balance.

3. **Security in depth is essential:** No single security measure is sufficient. The layered approach implemented in this system—combining AI detection, behavioral analysis, and immutable logging—provides comprehensive protection against diverse threat vectors [5].

4. **Containerization enhances security:** The containerized architecture not only improves deployment consistency and scalability but also provides additional security boundaries between components, limiting the potential impact of any single compromise [13].

8.3 Limitations and Future Work

While the system represents a significant advancement, several limitations and opportunities for future work remain:

1. **Adversarial resistance:** Further research is needed on making the machine learning models resistant to adversarial attacks and evasion techniques [3].

2. **Behavioral biometrics expansion:** The current implementation has limited behavioral biometrics capabilities. Expanding these features could further enhance security without adding user friction [9].

3. **Cross-institutional data sharing:** A framework for securely sharing fraud indicators between financial institutions while preserving privacy could significantly improve industry-wide fraud detection capabilities [6].
4. **Enhanced blockchain integration:** Deeper integration with blockchain technologies for transaction verification and smart contract-based security enforcement represents a promising direction for future work [10].
5. **Federated learning approaches:** Implementing federated learning techniques would allow the system to learn from distributed data sources without compromising privacy [15].

8.4 Concluding Remarks

The Secure Banking System with AI Fraud Detection presented in this thesis demonstrates the potential of integrating advanced technologies—artificial intelligence, microservices architecture, and blockchain—to address the critical security challenges faced by modern banking applications [6]. By combining these technologies in a cohesive framework, the system achieves significant improvements in fraud detection capabilities while maintaining user experience and operational efficiency.

As financial services continue to digitize and fraudulent techniques evolve, approaches like those presented in this thesis will become increasingly important for protecting both financial institutions and their customers. The flexible, modular architecture ensures that the system can adapt to emerging threats and technological advancements, providing a foundation for ongoing security improvements in the banking sector.

8.5 Final Words and Research Impact

This research contributes to the broader field of cybersecurity in financial systems by demonstrating how AI-powered fraud detection can be effectively integrated into a microservices-based banking infrastructure. The key innovations presented—enhanced threshold classification, adaptive risk scoring, and immutable security logging—provide both academic value and practical implementations that financial institutions can adapt to their specific requirements.

The developed system serves as a foundation for future research in several directions, including adversarial machine learning, federated training approaches, and blockchain-based financial security. We hope that the methodologies and architectural patterns presented in this thesis will inspire further innovations in securing digital banking platforms and protecting users from increasingly sophisticated fraud attempts.

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Source Code Listings

.1 Enhanced Threshold Classification Algorithm

The following code demonstrates the actual implementation of the enhanced threshold classification system from the project:

```python
class EnhancedThresholdClassifier:
    """
    Advanced threshold classifier that provides risk level categorization
    based on multiple threshold values.

    This classifier extends the binary classification approach to categorize
    predictions into multiple risk levels, allowing for more nuanced responses.
    """

    def __init__(self, model, thresholds=None):
        """
        Initialize the EnhancedThresholdClassifier.

        Args:
            model: Base machine learning model that has predict_proba method
            thresholds: Dictionary with risk level thresholds, e.g.,
                       {"low": 0.15, "medium": 0.30, "high": 0.50}
        """
        self.model = model
        self.thresholds = thresholds or {
            "low": 0.15,
            "medium": 0.30,
            "high": 0.50
        }

    def predict_with_level(self, X):
        """
        Predict risk levels based on probability thresholds

        Args:
            X: Feature matrix

        Returns:
            List of dictionaries with probability and risk_level
        """
        probas = self.model.predict_proba(X)[:, 1]
        results = []

        for prob in probas:
            if prob < self.thresholds["low"]:
                level = "safe"
            elif prob < self.thresholds["medium"]:
                level = "low_risk"
            elif prob < self.thresholds["high"]:
                level = "medium_risk"
            else:
                level = "high_risk"

            results.append({"probability": prob, "risk_level": level})

        return results

    def predict(self, X):
        """
        Binary prediction based on high risk threshold

        Args:
            X: Feature matrix

        Returns:
            Array of binary predictions (0 for low/medium risk, 1 for high
                risk)
        """
        probas = self.model.predict_proba(X)[:, 1]
        return (probas >= self.thresholds["high"]).astype(int)

    def predict_proba(self, X):
        """
        Get raw probability predictions from the base model

        Args:
            X: Feature matrix

        Returns:
            Probability array with shape (n_samples, 2)
        """
        return self.model.predict_proba(X)

    def get_action(self, prob):
        """
        Get recommended action based on probability

        Args:
            prob: Fraud probability score

        Returns:
            String with recommended action
        """
        if prob < self.thresholds["low"]:
            return "allow"
        elif prob < self.thresholds["medium"]:
```

```python
            return "minimal_verification"
        elif prob < self.thresholds["high"]:
            return "2fa_required"
        else:
            return "block"
```

Listing 1: Enhanced Threshold Classification Algorithm

.2 Adaptive Risk Scoring Algorithm

The following code shows the actual implementation of the adaptive risk scoring algorithm from the project:

```python
def _calculate_risk_score(self, is_first_login, unusual_location,
                          unusual_device, unusual_ip, unusual_time,
                          failed_attempts, rapid_failures) -> float:
    """
    Calculate a weighted risk score based on risk factors

    Returns:
        Risk score from 0-100, higher is riskier
    """
    base_score = 0

    # Add weighted risk factors
    if is_first_login:
        base_score += self.risk_weights["first_login"]

    if unusual_location:
        base_score += self.risk_weights["unusual_location"]

    if unusual_device:
        base_score += self.risk_weights["unusual_device"]

    if unusual_ip:
        base_score += self.risk_weights["unusual_ip"]

    if unusual_time:
        base_score += self.risk_weights["unusual_time"]

    # Failed attempts have escalating risk with exponential growth
    if failed_attempts > 0:
        # Exponential scaling of failed attempt risk
        # Each additional failure exponentially increases the risk
        failed_weight = min(
            self.risk_weights["failed_attempts"] * (1.5 ** (failed_attempts - 1)),
            self.risk_weights["failed_attempts"] * 3 # Cap at 3x the base weight
        )
        base_score += failed_weight

    # ENHANCED: Rapid consecutive failures are treated as a critical risk regardless of model
    # If we detect rapid failures, force a higher risk score even if the model doesn't weigh it
    if rapid_failures:
        # Use a multiplier on the base score rather than just adding the weight
        # This ensures rapid failures have a dramatic impact on the risk assessment
        base_score *= 1.5 # 50% increase in overall risk score for rapid failures

        # Also add the configured weight
        base_score += self.risk_weights["rapid_failed_attempts"]

        # If there are both failed attempts and rapid failures, consider it highly suspicious
        if failed_attempts >= 3:
            base_score += 15 # Additional penalty for high failed attempts + rapid failures
```

```

    # Calculate final score (0-100 scale)
    max_possible_score = sum(self.risk_weights.values()) * 1.5 # Account
        for multiplier
    risk_score = (base_score / max_possible_score) * 100

    # Ensure we don't exceed 100%
    return min(round(risk_score, 1), 100) # Round to one decimal place

    # Calculate behavior pattern risk
    behaviorScore = calculateBehaviorRisk(currentActivity.behaviorMetrics,
         userProfile.behaviorBaseline)

    # Calculate transaction pattern risk (if applicable)
    transactionScore = 0.0
    if hasattr(currentActivity, 'transactionDetails'):
        transactionScore = calculateTransactionRisk(
            currentActivity.transactionDetails,
            userProfile.transactionHistory
        )

    # Apply weights to each risk category
    weightedScore = (
        geoScore * weights.GEOGRAPHIC +
        temporalScore * weights.TEMPORAL +
        deviceScore * weights.DEVICE +
        behaviorScore * weights.BEHAVIOR
    )

    if hasattr(currentActivity, 'transactionDetails'):
        weightedScore += transactionScore * weights.TRANSACTION

    # Apply dynamic adjustment based on recent account activity
    activityMultiplier = calculateActivityMultiplier(userProfile.
        recentActivity)
    finalScore = weightedScore * activityMultiplier

    # Apply caps to ensure score remains in valid range
    finalScore = max(0.0, min(1.0, finalScore))

    return {
        "overallRiskScore": finalScore,
        "components": {
            "geoRisk": geoScore,
            "temporalRisk": temporalScore,
            "deviceRisk": deviceScore,
            "behaviorRisk": behaviorScore,
            "transactionRisk": transactionScore if hasattr(currentActivity,
                 'transactionDetails') else None
        },
        "explanationFactors": generateRiskExplanationFactors(finalScore,
            userProfile, currentActivity)
    }
```

Listing 2: Adaptive Risk Scoring Algorithm

.3 Blockchain-Based Immutable Logging

The following pseudocode demonstrates the blockchain-based immutable logging system:

```
class Block:
    def __init__(self, index, timestamp, data, previous_hash):
        self.index = index
        self.timestamp = timestamp
        self.data = data
        self.previous_hash = previous_hash
        self.nonce = 0
        self.hash = self.calculate_hash()

    def calculate_hash(self):
        """Calculate hash of the block"""
        block_string = json.dumps({
            "index": self.index,
            "timestamp": self.timestamp,
            "data": self.data,
            "previous_hash": self.previous_hash,
            "nonce": self.nonce
        }, sort_keys=True)
        return hashlib.sha256(block_string.encode()).hexdigest()

    def mine_block(self, difficulty):
        """Mine a block (find a hash with leading zeros)"""
        target = "0" * difficulty
        while self.hash[:difficulty] != target:
            self.nonce += 1
            self.hash = self.calculate_hash()
        logger.info(f"Block␣mined:␣{self.hash}")

class Blockchain:
    def __init__(self):
        self.chain = [self.create_genesis_block()]
        self.difficulty = 2 # Adjust based on desired mining difficulty
        self.pending_data = []

    def create_genesis_block(self):
        """Create the first block in the chain"""
        return Block(0, datetime.now().isoformat(), {"message": "Genesis␣
            Block"}, "0")

    def get_latest_block(self):
        """Get the latest block in the chain"""
        return self.chain[-1]

    def add_block(self, data):
        """Add a new block to the chain"""
        latest_block = self.get_latest_block()
        new_block = Block(
            len(self.chain),
            datetime.now().isoformat(),
            data,
            latest_block.hash
        )
        new_block.mine_block(self.difficulty)
        self.chain.append(new_block)
        return new_block

    def is_chain_valid(self):
        """Validate the blockchain"""
        for i in range(1, len(self.chain)):
            current_block = self.chain[i]
            previous_block = self.chain[i-1]

            # Check if hash is correctly calculated
            if current_block.hash != current_block.calculate_hash():
                return False

            # Check if current block points to correct previous hash
            if current_block.previous_hash != previous_block.hash:
                return False

        return True

# Initialize blockchain instance
blockchain = Blockchain()

# Pydantic models for API data validation
class BlockchainData(BaseModel):
    login_data: Dict[str, Any]
    fraud_check: Dict[str, Any]
    timestamp: str

class BlockResponse(BaseModel):
    success: bool
    message: str
```

```python
    block_index: Optional[int] = None

@app.post("/record", response_model=BlockResponse)
async def record_data(data: BlockchainData):
    """Record data to blockchain"""
    try:
        # Create the data entry
        data_entry = {
            "login_data": data.login_data,
            "fraud_check": data.fraud_check,
            "timestamp": data.timestamp,
            "recorded_at": datetime.now().isoformat()
        }

        # Directly mine a new block for each attempt
        block = blockchain.add_block([data_entry])

        logger.info(f"Recorded␣login␣attempt␣in␣block␣{block.index}")

        return BlockResponse(
            success=True,
            message=f"Data␣recorded␣and␣mined␣in␣block␣{block.index}",
            block_index=block.index
        )

    except Exception as e:
        logger.error(f"Error␣recording␣data:␣{e}")
        raise HTTPException(status_code=500, detail=f"Failed␣to␣record␣data:␣{str(e)}")
```

Listing 3: Blockchain-Based Security Event Logging