Anomaly Detection for Financial Reconciliation with DeepLearning4J and ServiceNow Integration

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1. Objective

The primary objective of this project is to develop an automated system for detecting anomalies in financial reconciliation data between General Ledger (GL) and iHub systems, enabling financial teams to identify discrepancies efficiently. The system aims to:

- Automate the detection of significant balance differences in real-time financial data by leveraging deep learning techniques.
- Provide actionable insights through a downloadable output CSV file containing anomaly flags and reasons.
- Integrate with ServiceNow to log the anomaly detection process as an incident, ensuring traceability and auditability.
- Lay the foundation for a user-friendly UI dashboard to facilitate file uploads, result visualization, and email notifications.

This solution targets financial organizations that require accurate, scalable, and automated reconciliation processes to reduce manual effort, minimize errors, and enhance decision-making.

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2. What We Achieve

The system successfully achieves the following:

- **Automated Anomaly Detection**: Processes historical financial data (input CSV) and real-time data to detect anomalies using a deep learning-based Autoencoder, flagging rows with significant discrepancies (e.g., balance differences of -15,000, -10,000).
- **Output Generation**: Generates an output CSV file (output_data.csv) with additional columns (is_anomaly, anomaly_reason) to indicate whether each row is an anomaly and the reason for the anomaly (e.g., "Huge spike in outstanding balances").
- **ServiceNow Integration**: Creates an incident in ServiceNow to log the anomaly detection process, including details like the number of rows processed, anomalies detected, and the incident number (e.g., INC0010001), ensuring traceability.
- **Scalability**: Designed to handle large datasets (potentially millions of records) due to the use of DeepLearning4J, a scalable deep learning framework, and Spring Boot, which supports high-performance REST APIs.
- **Proposed UI Dashboard**: Provides a wireframe for a future UI dashboard that allows users to upload CSV files, view the number of anomalies, and trigger email notifications, enhancing user interaction.

The system is accessible via a REST API endpoint (POST /api/anomaly/process), which accepts a CSV file upload and returns the processed output CSV as a downloadable file.

3.2 Components

- **Client**: A user or external system that interacts with the application via the REST API (e.g., using Postman, curl, or a future UI dashboard).
- **Spring Boot Application**:
  - **Controller (AnomalyDetectionController)**: Handles HTTP requests, accepts CSV file uploads, and returns the output CSV as a downloadable file.
  - **Service Layer**:
    - **Anomaly Detection Service (AnomalyDetectionService)**: Processes the input CSV, trains the Autoencoder, detects anomalies, and generates the output CSV.
    - **ServiceNow Service (ServiceNowService)**: Integrates with the ServiceNow API to create an incident and retrieve the incident number.
- **DeepLearning4J (DL4J)**: Implements the Autoencoder for anomaly detection, learning patterns from historical data and flagging anomalies based on reconstruction errors.
- **ServiceNow**: A third-party system used to log incidents, providing traceability for the anomaly detection process.
- **Input/Output**:
  - **Input CSV**: Historical financial data with columns like Date, Company, Account, GL Balance, iHub Balance, Balance Difference, etc.
  - **Output CSV**: Processed real-time data with additional columns (is_anomaly, anomaly_reason) indicating anomalies.

3.3 Data Flow

1. The client uploads a CSV file containing historical financial data via the REST API.
2. The AnomalyDetectionController receives the file and delegates processing to the AnomalyDetectionService.
3. The AnomalyDetectionService:
   - Reads the historical data and trains the Autoencoder using DL4J.
   - Processes hardcoded real-time data (extendable to accept uploads).
   - Detects anomalies using the Autoencoder's reconstruction error.
   - Generates the output CSV with anomaly flags and reasons.
4. The ServiceNowService creates an incident in ServiceNow, logging the process details (e.g., number of rows processed, anomalies detected).
5. The controller returns the output CSV as a downloadable file, with the ServiceNow incident number included in the incident description.

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4. Algorithm Used

The system employs a deep learning-based approach for anomaly detection, specifically using an **Autoencoder** implemented with **DeepLearning4J (DL4J)**. Below are the details of the algorithm:

4.1 Autoencoder Overview

- **Type**: Unsupervised deep learning model.
- **Purpose**: Learns to reconstruct "normal" data patterns and flags anomalies based on high reconstruction errors.
- **Architecture**:
  - **Input Layer**: 3 nodes (features: GL Balance, iHub Balance, Balance Difference).
  - **Hidden Layer**: 2 nodes (compressed representation).
  - **Output Layer**: 3 nodes (reconstructed features).
  - **Activation Functions**: ReLU for the hidden layer, Identity for the output layer.
- **Training**:
  - Trained on historical data for 100 epochs using the Adam optimizer with a learning rate of 0.01.
  - Features are normalized (mean subtraction and division by standard deviation) to improve training performance.

4.2 Anomaly Detection Process

1. **Feature Extraction**: Extracts GL Balance, iHub Balance, and Balance Difference from the historical data.
2. **Normalization**: Normalizes the features to ensure consistent scaling for the Autoencoder.
3. **Training**: The Autoencoder learns to reconstruct the historical data, minimizing the reconstruction error for "normal" patterns.
4. **Inference**:
   - For each real-time row, the Autoencoder computes the reconstruction error (Euclidean distance between input and output).
   - If the reconstruction error exceeds a threshold (0.1), the row is flagged as an anomaly (is_anomaly = Yes).
   - The anomaly_reason is derived from the Comments column or inferred based on the balance difference magnitude (e.g., "Huge spike in outstanding balances" for differences > 10,000).

4.3 Why Autoencoder?

- **Scalability**: Can handle large datasets (millions of records) due to the efficiency of DL4J.
- **Flexibility**: Learns complex, non-linear patterns in financial data, outperforming traditional statistical methods (e.g., Z-score) for anomaly detection.
- **Unsupervised Learning**: Does not require labeled data, making it suitable for financial reconciliation where anomalies are not pre-labeled.

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5. Performance Considerations

The system is designed with performance in mind to ensure scalability and efficiency, especially when handling large datasets. Below are the key performance considerations:

5.1 Scalability

- **DeepLearning4J**: DL4J is optimized for large-scale deep learning tasks and can leverage multi-threading and GPU acceleration (if available) to process millions of records efficiently.
- **Spring Boot**: The REST API is built using Spring Boot, which supports asynchronous processing (via Mono from WebFlux) to handle concurrent requests.
- **File Processing**: CSV processing is done in-memory for small files but can be optimized for large files by using streaming techniques (e.g., reading/writing CSV in chunks).

5.2 Latency

- **Training Time**: Training the Autoencoder on historical data takes approximately 1–2 seconds for small datasets (e.g., 12 rows). For larger datasets (e.g., 1 million rows), training time may increase to a few minutes, depending on hardware.
- **Inference Time**: Anomaly detection for real-time data is fast, with each row processed in milliseconds, ensuring low latency for API responses.
- **ServiceNow API Call**: The API call to create an incident typically takes 1–2 seconds, depending on network latency and ServiceNow instance performance.

5.3 Resource Utilization

- **Memory**: The Autoencoder model is lightweight (3-2-3 layers), requiring minimal memory. However, large datasets may increase memory usage during training and inference.
- **CPU/GPU**: DL4J can utilize CPU or GPU resources. For production, deploying on a GPU-enabled server can significantly improve training and inference performance.
- **File Size**: The system supports CSV files up to 10MB (configurable via spring.servlet.multipart.max-file-size). Larger files can be handled by increasing this limit and optimizing file processing.

5.4 Monitoring and Optimization

- **Logging**: Uses SLF4J for logging key events (e.g., incident creation, errors), enabling performance monitoring.
- **Metrics**: Future enhancements can include Spring Actuator to expose metrics (e.g., API response time, error rates) for monitoring performance.
- **Caching**: Training the Autoencoder for the same historical data can be cached to avoid retraining on subsequent requests, reducing latency.

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6. Future Enhancements

The system is designed with extensibility in mind, and several enhancements can be implemented to improve functionality and user experience:

6.1 Dynamic Real-Time Data Input

- **Current State**: Real-time data is hardcoded in the application.
- **Enhancement**: Extend the API to accept a second CSV file for real-time data, allowing users to upload both historical and real-time data dynamically.

6.2 UI Dashboard Implementation

- **Current State**: The UI dashboard is a wireframe, providing a vision for file uploads, result visualization, and email notifications.
- **Enhancement**: Implement the dashboard using a frontend framework like React, integrating with the Spring Boot backend via REST APIs. Features include:
    - File upload interface for historical and real-time data.
    - Summary view showing total rows processed and number of anomalies.
    - Detailed table view of the output CSV with highlighted anomalies.
    - Button to trigger email notifications.

6.3 Advanced Anomaly Detection

- **Current State**: The Autoencoder uses three features (GL Balance, iHub Balance, Balance Difference).
- **Enhancement**:
    - Incorporate additional features (e.g., rolling averages, account-specific trends) to improve anomaly detection accuracy.
    - Use more advanced models like Variational Autoencoders (VAEs) or Long Short-Term Memory (LSTM) networks to capture temporal patterns in financial data.
    - Implement ensemble methods combining deep learning with statistical techniques for hybrid anomaly detection.

6.4 ServiceNow Enhancements

- **Current State**: Creates a basic incident with a short description and details.
- **Enhancement**:
    - Add more details to the incident, such as a link to the output CSV (if stored in a cloud storage service like AWS S3).
    - Automate incident assignment to a specific team in ServiceNow for follow-up.
    - Use OAuth 2.0 for ServiceNow API authentication in production for enhanced security.

6.5 Performance Optimization

- **Current State**: Processes data in-memory, suitable for small to medium datasets.
- **Enhancement**:
    - Implement streaming for large CSV files to reduce memory usage.
    - Use distributed computing frameworks (e.g., Apache Spark with DL4J) for processing massive datasets.
    - Deploy the application on a Kubernetes cluster with auto-scaling to handle high traffic.

6.6 Email Notifications

- **Current State**: Email notifications are proposed in the UI wireframe but not implemented.
- **Enhancement**: Integrate JavaMail API to send email notifications with the output CSV as an attachment, triggered via the UI dashboard or API.

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7. Assumptions and Constraints

7.1 Assumptions

- The input CSV follows the expected format with columns like Date, Company, Account, GL Balance, iHub Balance, Balance Difference, etc.
- The ServiceNow Personal Developer Instance (PDI) is available for free development and testing, with API access enabled.
- The system is deployed on a server with sufficient CPU and memory resources to handle deep learning tasks.
- Real-time data is currently hardcoded but can be extended to accept uploads in the future.

7.2 Constraints

- **Small Dataset Limitations**: While the system is scalable, very small datasets may lead to overfitting in the Autoencoder, requiring careful tuning of hyperparameters.
- **ServiceNow PDI Limitations**: The free PDI is for development only. Production use requires a licensed ServiceNow instance, which incurs costs.
- **Hardware Dependency**: Deep learning performance depends on hardware capabilities (e.g., CPU/GPU). Without GPU support, training on large datasets may be slow.
- **Network Dependency**: The ServiceNow API call introduces network latency, which may affect API response time if the ServiceNow instance is slow or unavailable.

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8. Conclusion

This High-Level Design document outlines the architecture and implementation strategy for the Anomaly Detection for Financial Reconciliation system. By leveraging DeepLearning4J for anomaly detection, Spring Boot for the REST API, and ServiceNow for incident logging, the system provides an automated, scalable, and traceable solution for financial reconciliation. The use of an Autoencoder ensures flexibility in learning complex patterns, while the modular design allows for future enhancements like UI integration, advanced anomaly detection, and performance optimization. The system is well-positioned to meet the needs of financial organizations, with the potential to scale to millions of records and integrate seamlessly with enterprise workflows.