Healthcare Claims Fraud Detection

Capstone Project – Databricks with Delta Live Tables

Problem Statement

- Traditional ETL lacks scalability, governance, and real-time insights.
- Objective: Build a scalable, governed pipeline to detect fraud in claims data.

Solution Overview

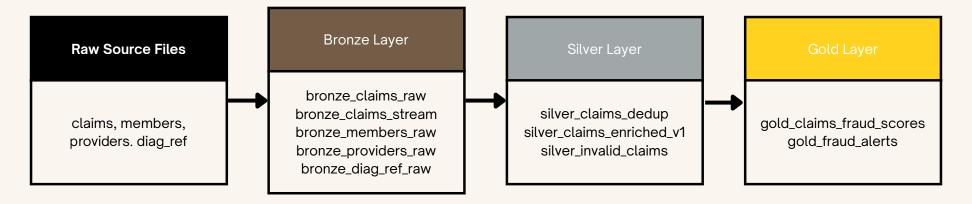
- Built using Databricks + Delta Live Tables
- Applied Medallion Architecture (Bronze → Silver → Gold)
- Ingested batch + streaming data
- Enforced governance (quality checks, history, restore, z-order)
- Produced fraud scores and alerts

Medallion Architecture

Bronze keeps raw fidelity for auditing.

Silver provides clean, consistent, validated data.

Gold delivers business-ready insights (fraud scores & alerts).



Healthcare_pipeline



Bronze Layer (Raw Ingestion)

- Ingested raw files (CSV, JSON) into Bronze tables:
 - bronze_claims_raw
 - bronze_members_raw
 - bronze_providers_raw
 - bronze_diag_ref_raw

Bronze Layer: This layer ingests raw, unprocessed data, including claims, members, providers, and diagnosis references, preserving its original fidelity for auditing purposes.

Silver Layer (Cleaning & Enrichment)

Silver Layer: Here, data is cleaned, validated, and enriched. Key steps include:

- Deduplication: Claims are deduplicated based on ClaimID, keeping the latest record by ingest_ts.
- Enrichment: Claims data is joined with member, provider, and diagnosis reference information.
- Validation: Flags such as member_exists, provider_exists, diagnosis_high_risk, and is_valid are added to claims.

Gold Layer (Fraud Scoring & Alerts)

- gold_claims_fraud_scores: Fraud score = score_amount + score_diag + score_provider
- Risk buckets: High / Medium / Low
- gold_fraud_alerts: high-risk claims for monitoring.

Gold Layer: This final layer delivers business-ready data, producing fraud scores and alerts.

Fraud Scoring Logic

The pipeline calculates a multi-signal

fraud_score for each claim in the gold_claims_fraud_scores table. This score is based on a combination of factors:

- score_amount: A score of 0.6 is added if the claim's Amount exceeds a \$1,000 threshold.
- score_diag: A score of 0.3 is added if the diagnosis_description contains keywords like "CANCER," "MALIGNANT," or "CRITICAL," or if the Diagnosis_Code is on a fallback high-risk list ("D123", "X999").
- score_provider: A score of 0.4 is added if the provider is flagged as inactive.

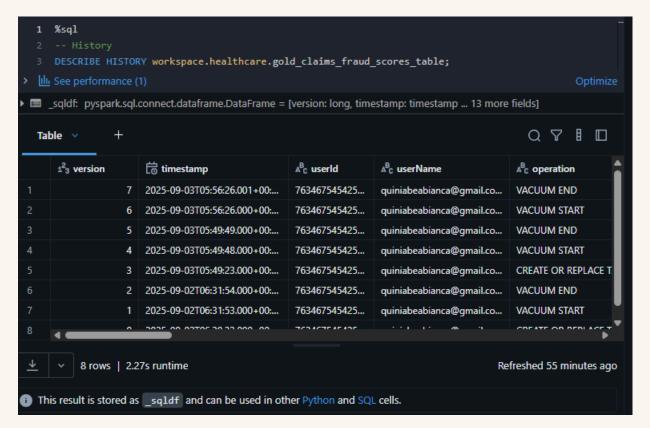
The total: fraud_score is the sum of these individual scores. Claims are then assigned to a risk_bucket (High, Medium, or Low) based on the total score.

- High Risk: fraud_score >= 0.7
- Medium Risk: fraud score >= 0.3
- Low Risk: fraud_score < 0.3

A separate table, gold_fraud_alerts, is generated to capture and flag claims in the "high" risk bucket for immediate monitoring.

Governance & Optimization

- Data Quality: dlt.expect and dlt.expect_or_drop are used to define quality expectations for tables, ensuring data integrity
- Auditability: The DESCRIBE HISTORY command is used on Delta tables to view the history of changes, providing a complete audit trail.



Governance & Optimization

• Performance: The OPTIMIZE ... ZORDER command is used to co-locate related data by risk_bucket, which improves query performance for the gold_claims_fraud_scores

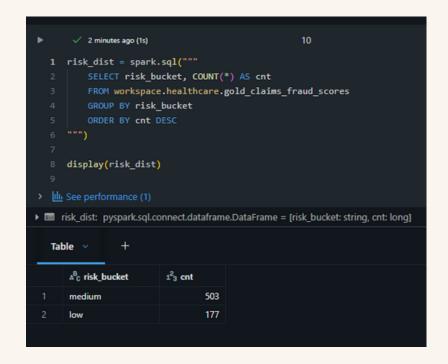


Demo Results

• This query would retrieve the state of the gold_claims_fraud_scores table from its initial creation, which is useful for auditing and ensuring data lineage. The ability to restore a table to an earlier version is a critical part of the pipeline's governance and recovery capabilities.

1 2 3	Time trave		care.gold_claims_f	raud_scores_table V	ERSION AS OF 0 LIMI	Т 10;			
Ш	<u>see performance</u>	2 (1)				Optim			
Table ∨ + Q ♥ ▮ □									
	ABC ClaimID	△B _C MemberID	△B _C ProviderID	1.2 Amount	△B Diagnosis_Code	△ ^B c diag			
	CL000031	M00459	P0036	1256.4	A69.9	Month v			
10	CL000035	M00311	P0112	2082.47	A76.3	Let arm			
11	CL000036	M00415	P0103	2261.35	A55.6	Rest cul			
12	CL000037	M00062	P0046	3476.32	A73.7	Leave d			
13	CL000040	M00297	P0023	304.63	A80.7	Rise pro			
14	CL000045	M00445	P0009	1300.14	A53.6	Rich fine			
15	CL000053	M00468	P0073	1090.14	A25.9	Measur			
16	CL000057	M00425	P0096	1475.98	A64.9	Other o			
17	CL000058	M00400	P0089	2185.69	A21.8	Small o			
18	CL000065	M00278	P0055	909.88	A45.4	Laugh s			
19	CL000069	M00114	P0007	2343.78	A44.8	Rich bu			
20	CL000075	M00136	P0016	2374.39	A66.1	Its ever			
21	CL000078	M00203	P0084	403.7	A14.1	Despite			
22	CL000079	M00107	P0116	3567.81	A91.4	Show in			

PIPELINE VALIDATION TESTS



There are no fraud alerts since there are no high risk count.

DATA QUALITY CHECKS

```
# Example: % of claims missing MemberID

2 missing_members = spark.sql("""

3 SELECT COUNT(*) AS cnt

4 FROM default.silver_claims_enriched_v1

5 WHERE MemberID IS NULL

6 """).collect()[0]["cnt"]

7

8 print(f" ▲ Claims missing MemberID: {missing_members}")

> Шь See performance (1)

▲ Claims missing MemberID: 0
```

- In the silver_claims_enriched_v1 table, all rows have a valid MemberID.
- There are no claims missing a MemberID, so every claim could be joined back to a member record from bronze_members_raw.

DATA QUALITY CHECKS

```
# Example: Claims with invalid FK (is_valid = false)
invalid_claims = spark.sql("""

SELECT COUNT(*) AS cnt
FROM default.silver_invalid_claims
""").collect()[0]["cnt"]

print(f" X Invalid claims flagged: {invalid_claims}")

Invalid claims flagged: 0
Invalid claims flagged: 0
```

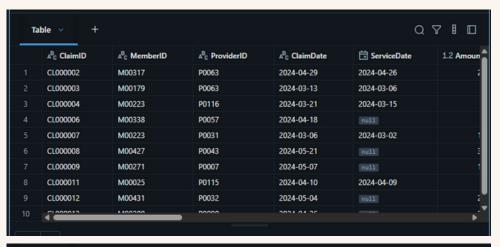
• The validation check for invalid claims in the silver_invalid_claims table returned a count of zero. This indicates that no claims were flagged as invalid, suggesting that the dataset maintains high data integrity with respect to the defined validation rules. Consequently, there are no immediate concerns regarding the quality or validity of the claims data.

silver_claims_dedup

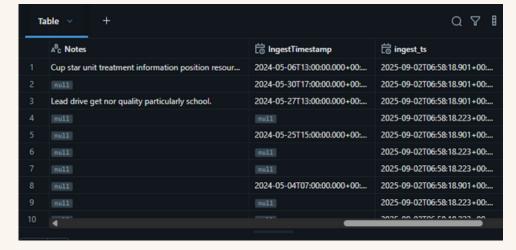
```
1 %sql
2 DESCRIBE TABLE workspace.default.silver_claims_dedup;
3 SELECT * FROM workspace.default.silver_claims_dedup LIMIT 20;
> Ill See performance (2)
```

Reads:

- · Reads bronze claims raw.
- Deduplicates on claim_id (keeps latest by ingest_ts).
- Ensures there's one row per claim.







gold_claims_fraud_scores

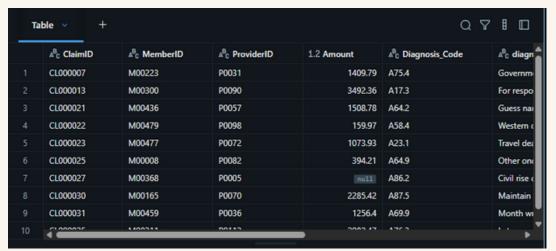
```
| SQL ☐ ❖ [] :

1 %sql
2 SELECT * FROM workspace.default.gold_claims_fraud_scores LIMIT 10;

3
```

Multi-signal fraud scoring:

- score_amount: credit for high claim amounts
- score_diag: credit for high-risk diagnosis codes
- score_provider: credit if provider_flagged is True (if provider metadata includes it)
 - score_amount = 0.6 if claim_amount > threshold
 - score_diag = 0.3 if diagnosis_high_risk
 - score_provider = 0.4 if provider_flagged
 - fraud_score = score_amount + score_diag+ score_provider
 - risk_bucket = high / medium / low
 - high: If fraud_score is greater than or equal to 0.7.
 - medium: If fraud_score is greater than or equal to 0.3.
 - o low: If fraud_score is less than 0.3



Tal	ble v	_ +			Q7IE
		A ^B C diagnosis_description	1.2 fraud_score	A ^B C risk_bucket	ingest_ts
1		Government citizen investment.	0.6	medium	2025-09-02T06:58:18.901+00:
		For responsibility oil.	0.6	medium	2025-09-02T06:58:18.223+00:
3		Guess name report decision.	0.6	medium	2025-09-02T06:58:18.901+00:
		Western open thousand.	0	low	2025-09-02T06:58:18.223+00:
		Travel deal degree fact door protect.	0.6	medium	2025-09-02T06:58:18.901+00:
		Other once apply interesting.	0	low	2025-09-02T06:58:18.223+00:
		Civil rise civil nor sister.	0	low	2025-09-02T06:58:18.901+00:
		Maintain first seek wear.	0.6	medium	2025-09-02T06:58:18.223+00:
		Month writer whose course.	0.6	medium	2025-09-02T06:58:18.901+00:
0		4.0		e e	2025 00 02705 50 40 004 00

Conclusion

- Delivered end-to-end pipeline with:
 - Medallion Architecture (Bronze, Silver, Gold), which ensures raw data fidelity for auditing, provides clean and consistent data, and delivers business-ready insights, respectively. The pipeline effectively handled both batch and streaming data ingestion.
 - Data Governance: The pipeline incorporated crucial governance features like data quality checks (dlt.expect, dlt.expect_or_drop), auditability via data history, and the ability to restore to previous versions.
 - Fraud Detection: A multi-signal scoring model was developed to calculate a
 fraud_score based on factors such as claim amount, diagnosis codes, and provider
 status. This enabled the categorization of claims into High, Medium, and Low risk
 buckets, with high-risk claims flagged for alerts
- Future work: Integrate ML models, external alerting systems.