

Configuration Manual

MSc Data Analytics
Research Practicum Part 2

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MSc Project Submission Sheet
School of Computing



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Programme: Msc Data Analytics

Year: 2024-25

Module: Research Practicum Part 2

Lecturer: Qurrat Ui Ain

Submission

Due Date: 11 August 2025

Project Title: Real-Time AI-Powered Anomaly Detection in Financial Transactions Using Microsoft Fabric and Power BI

Word Count:943.....**Page Count:**18.....

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Configuration Manual

Pranav Dinesh Ahire
Student ID: x23302372

1 Requirements

1.1 Hardware Requirements

1. **Processor (CPU): Intel Core i7 or higher**
2. **Ram (Memory): 16GB**
3. **Storage: SSD with at least 256GB for faster I/O**
4. **Graphics (GPU): NVIDIA/AMD**

1.2 Software Requirements

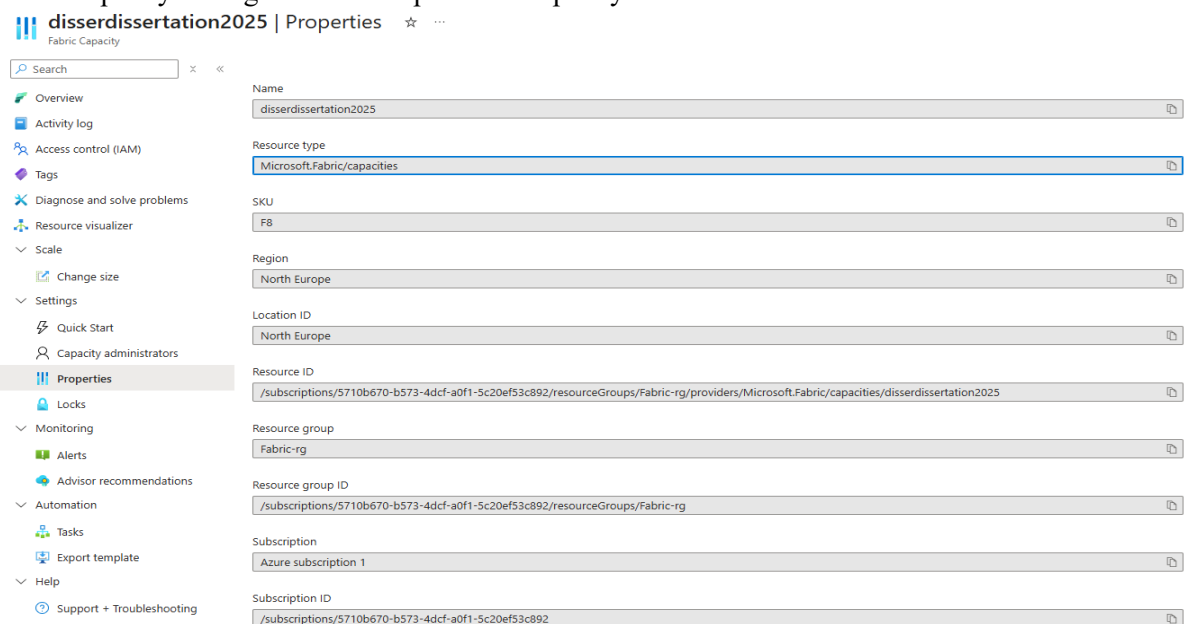
1. **Windows 11 (64-bit)**
2. **Azure Cloud Services (Create Resource for Microsoft Fabric)**
3. **Microsoft Fabric (F8)**
4. **Power BI (Services)**

2 Environment Setup

2.1 Azure and Microsoft Fabric Access

Accessed Microsoft Fabric <https://portal.azure.com/#home>

1. Create a Resource for Microsoft Fabric Capacity and enabled F8 Capacity from Admin portal under Capacity setting and enabled premium capacity.



2. Named it “**disserdissertation2025**”

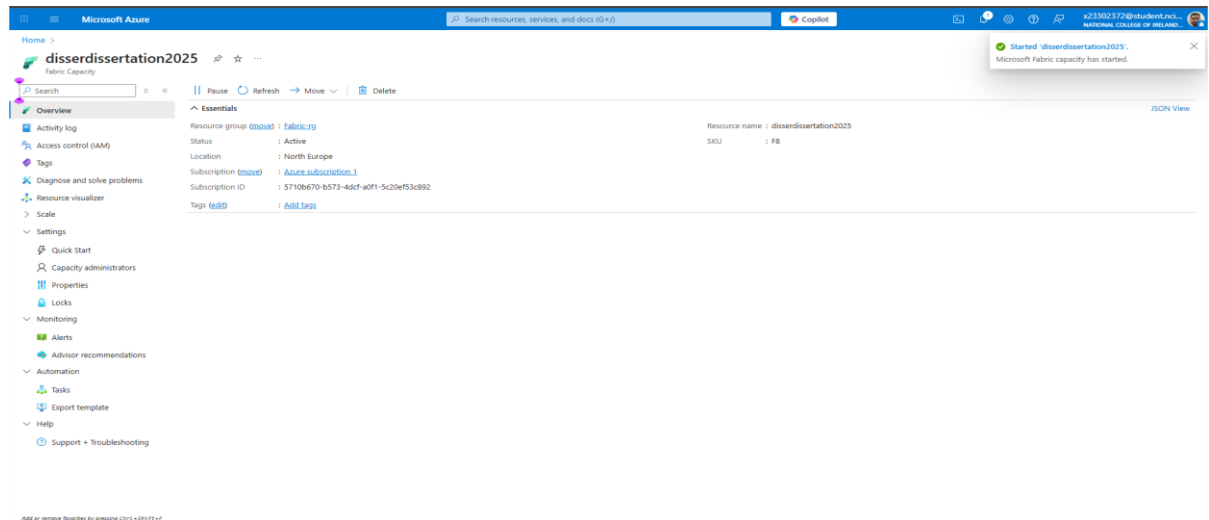


Figure 1AZURE Final Setup

2.2 Workspace Configuration in Microsoft Fabric

1. Open Microsoft Fabric in Browser login with same Id and configured with Azure resource (disserdissertation2025).
2. Create workspace in Microsoft Fabric and named **“Dissertation-FraudDetection”**.

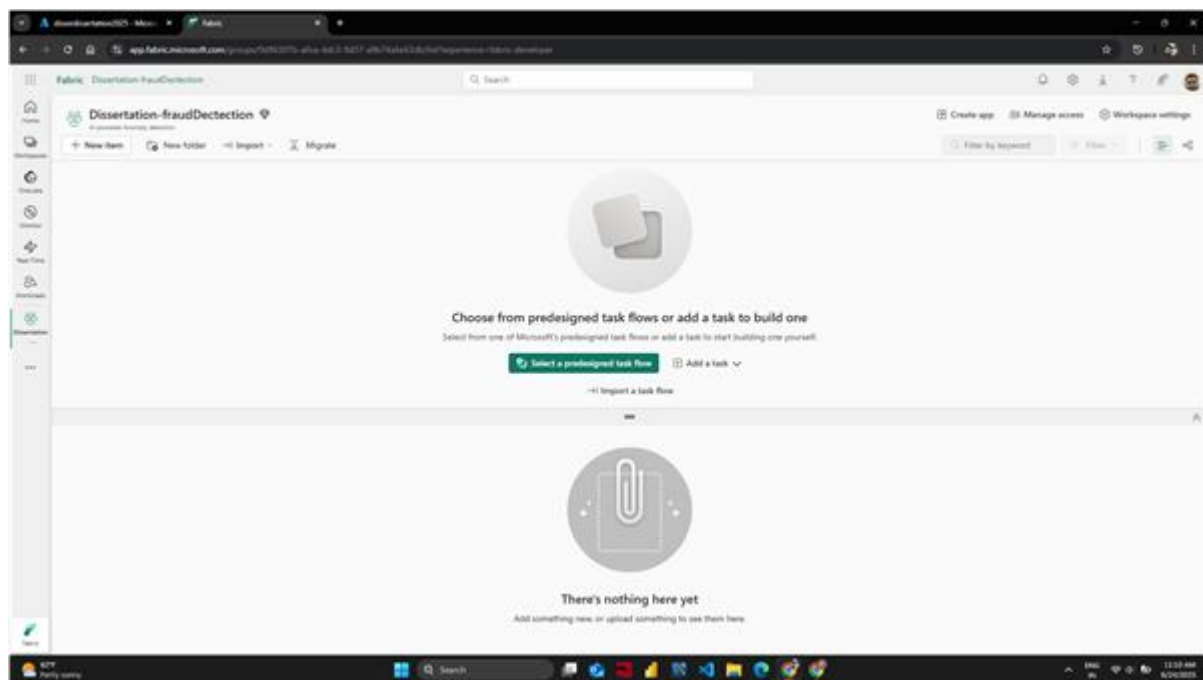


Figure 2. Workspace Created in Microsoft Fabric

3. Start Working on Project in the workspace .

3 Data Uploading and Lake house Configuration

3.1 Creating lakehouse

1. Click on “New item” and select Lakehouse and named it “FraudDetectionlakehouse”.
2. Uploaded all three .csv files (transaction_data, users_data, cards_data) in the lakehouse.

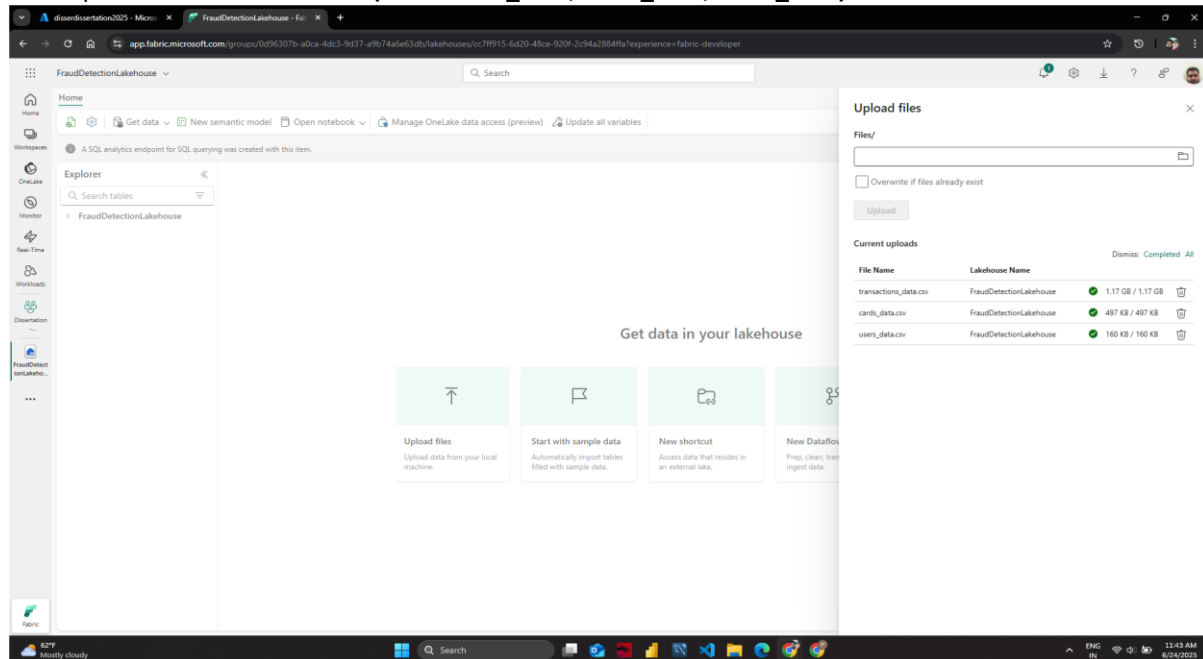


Figure 3. Dataset are all three datasets are uploaded in in lakehouse

3.2 Explore all three datasets.

1. Click on “New Item” add notebooks and named “Dataset_Quick_Review”.
2. Explore all three dataset. Start with card.csv data
 - 2.1. Read the data from Microsoft Fabric Lakehouse using Pyspark and display first 20 rows.

```
1 df1 = spark.read.table("FraudDetectionLakehouse.cards")
2 df1.show()
```

[15] ✓ - Command executed in 2 sec 917 ms by Pranav Dinesh Ahire on 12:32:26 PM, 6/24/25

Figure 4.Code cell to read the data.

- 2.2. Knew the schema of each columns.

```
1 print("Schema for: cards")
2 df1.printSchema()
3
```

[16] ✓ - Command executed in 253 ms by Pranav Dinesh Ahire on 12:32:43 PM, 6/24/25

Figure 5.Code cell to explore the schemas.

- 2.3. Repeat step 2.1 and 2.2 for transaction.csv and users.csv dataset.

4 Feature Engineering in Dataflow Gen2

4.1 Dataflow Gen2 Creation

1. Launched **dataflow Gen2** with source FraudDetection Lakehouse and named **“FraudDetectionEngineering”**.

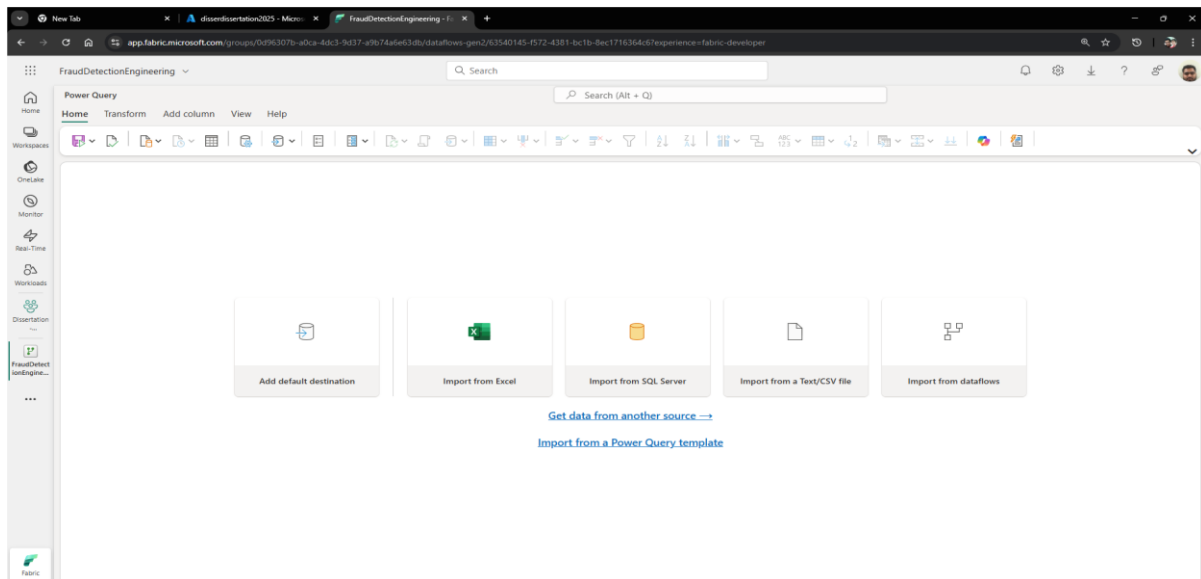


Figure 6.Dataflow Gen2 Successfully created.

2. Reviewed all columns and their values also checked their datatype.

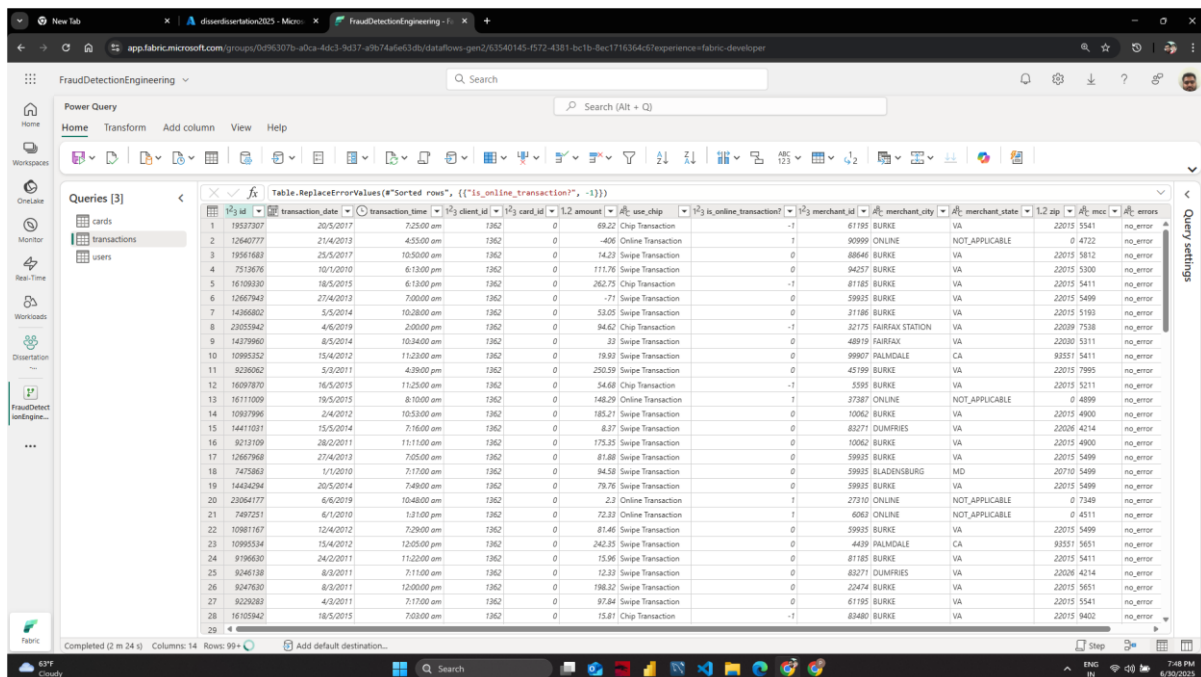


Figure 7. All 3 dataset in Dataflow Gen2.

- After reviewing all datasets merged card data with transaction data using left outer joined and named **“transaction_card.csv”**.

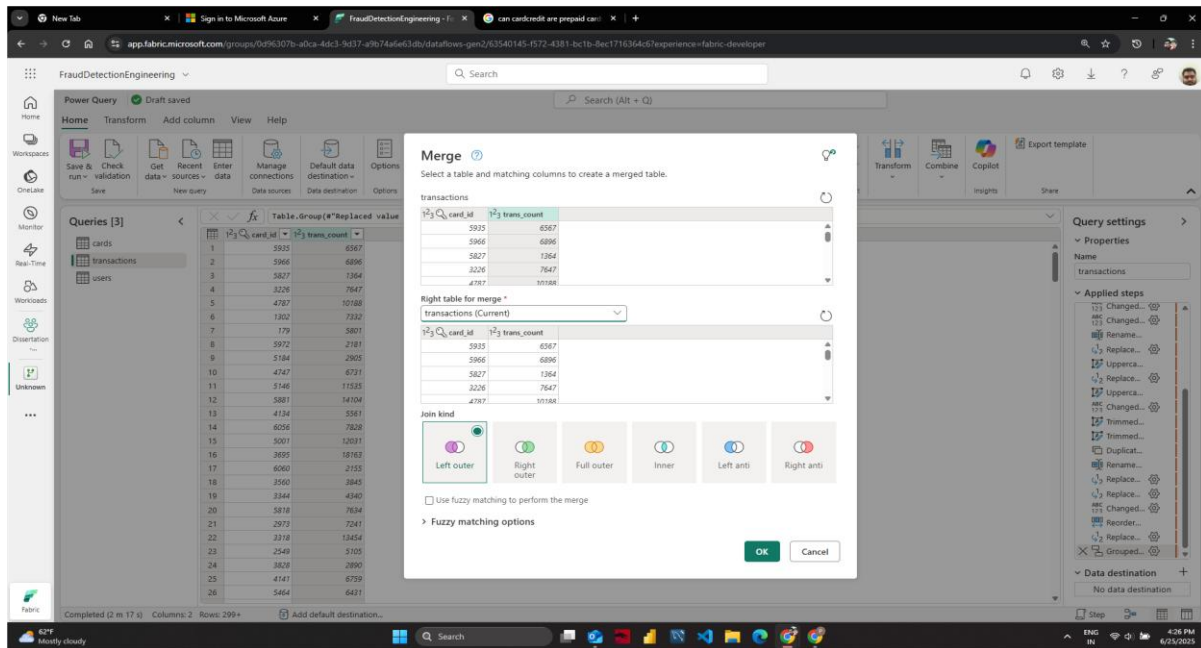


Figure 8. Merged card.csv with transaction.csv using left outer joint

- Again merged transaction_cards.csv dataset with user.csv dataset using Left outer join and named **“transaction_cards_users.csv”**.

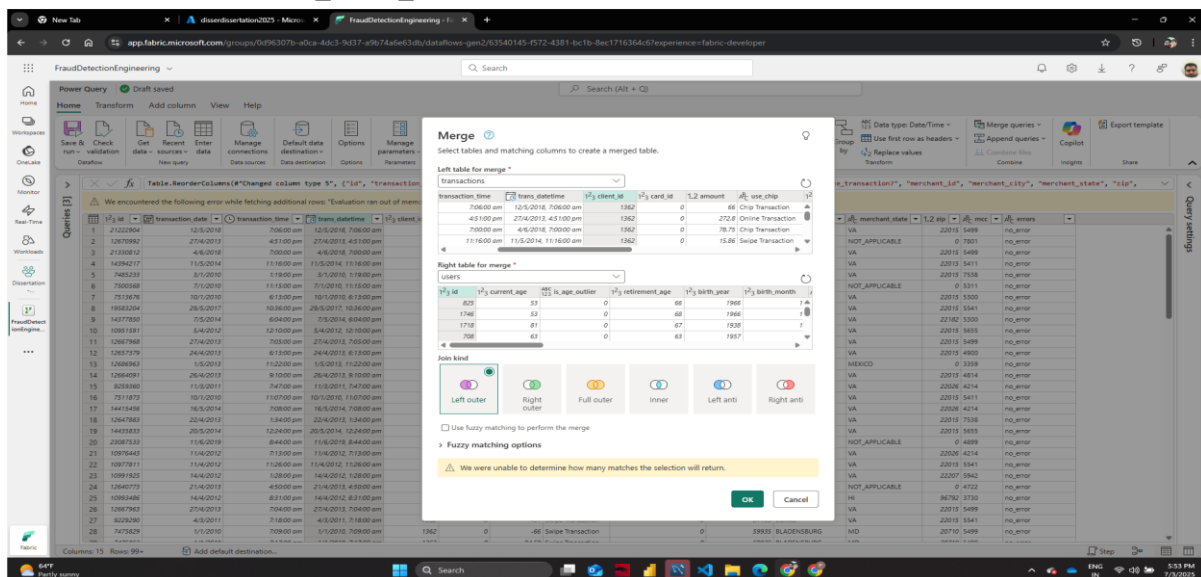


Figure 9. Merged users.csv with transaction_cards_users.csv using left outer join.

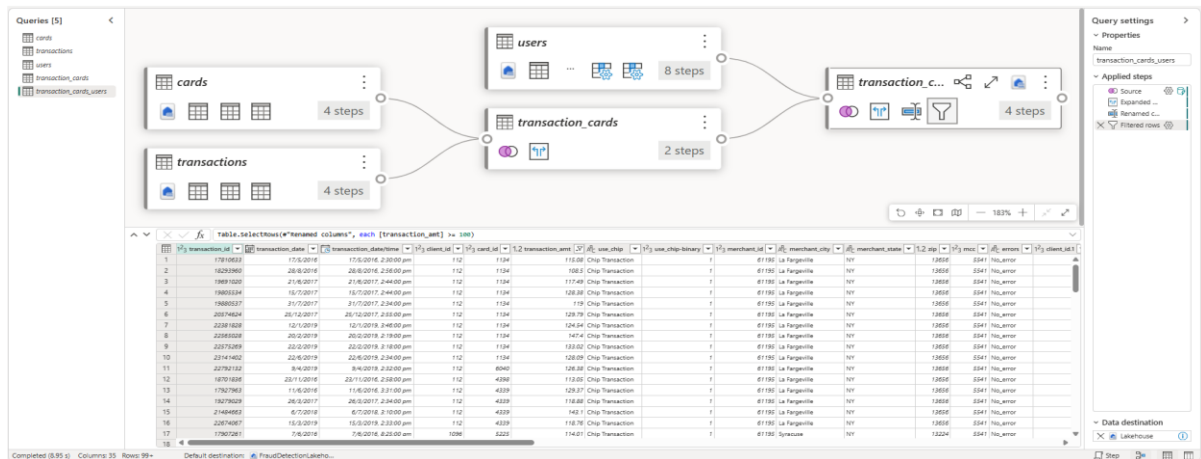


Figure 10. results after all joining.

4.2 Derived Features

1. “transaction_cards_users.csv” opened in Power Query Editor in Create custom columns using DAX formula in Power Query Editor.
2. Go to “Add column” and click on “conditional column”.

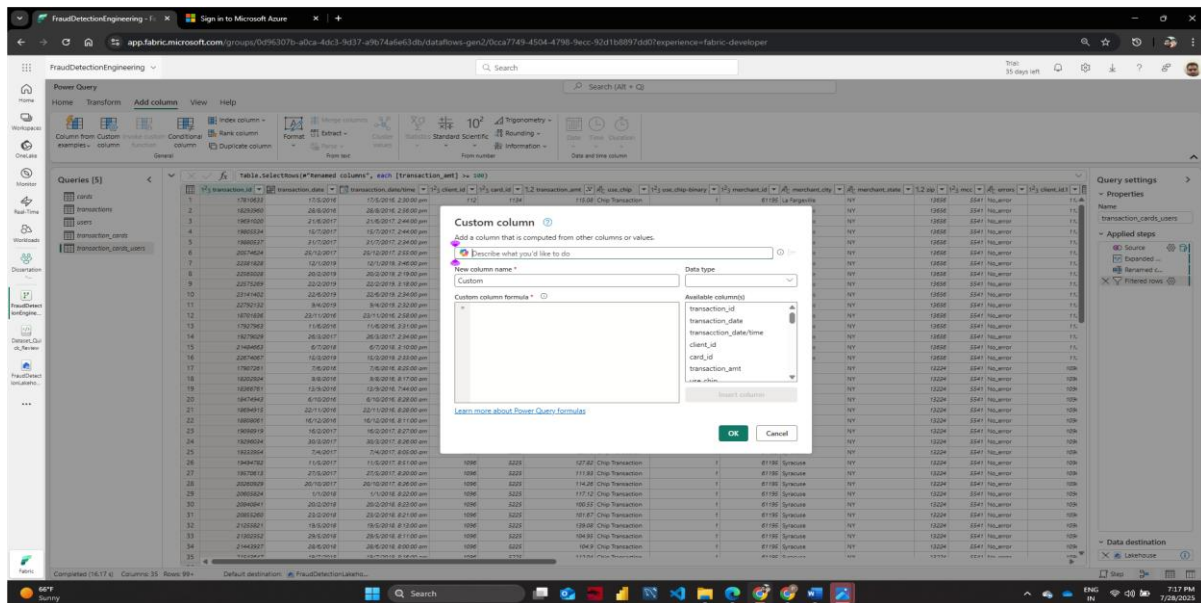


Figure 11. add custom column

3. For custom column is_low_income_user?

Formula = Table.AddColumn(#"PreviousStep", "is_low_income_user?", each if [user_income] < 25000 then 1 else 0, Int64.Type)

4. For is_card_expired (Compare card_expiry_date with trans_date.)

Formula = Table.AddColumn(#"PreviousStep", "is_card_expired", each if [card_expiry_date] < [trans_date] then 1 else 0, Int64.Type)

5. For is_card_on_dark_web (binary column compare with card_on_Darkweb)

Formula = Table.AddColumn(#"PreviousStep", "is_card_on_dark_web", each if Text.Lower([card_on_darkweb]) = "yes" then 1 else 0, Int64.Type)

5 Modeling using Synapse Notebook

5.1 Create Synapse Notebook

1. Created Synapse notebook and named “FruadDetection_ML”
2. Trained ML Models as per the scenarios

5.2 Apply ML model as per the scenarios

1. Import Specific required Python Libraries.

Import necessary libraries

```
1 # Import necessary ML libraries
2
3 from synapse.ml.isolationforest import IsolationForest
4
5 from pyspark.ml.feature import VectorAssembler, StandardScaler
6 from pyspark.ml import Pipeline
7 from pyspark.ml.classification import MultilayerPerceptronClassifier, LinearSVC
8
9 from pyspark.sql.functions import col, when
```

[16] ✓ - Command executed in 245 ms by Pranav Dinesh Ahire on 8:17:14 PM, 7/18/25

Figure 12. Screenshot of Import Library.

2. Load the preprocessed and feature-engineered table (**transaction_cards_users**) from the Microsoft Fabric Lakehouse. And displayed first 10 rows.

Load Data from Lakehouse Table

```
1 df = spark.read.table("transaction_cards_users")
2 display(df.limit(10))
3
```

[17] ✓ - Command executed in 2 sec 352 ms by Pranav Dinesh Ahire on 8:17:16 PM, 7/18/25

PySpark (Python) ▾

transaction_id	transaction_date	transaction_date/time	client_id	card_id	transaction_amt	use_chip	use_chip-binary	merchant
10940829	2012-04-03	2012-04-03 04:42:00	520	5104	120.62	Online Transa...	-1	73186
16220725	2015-06-11	2015-06-11 15:26:00	149	3590	303.32	Online Transa...	-1	73186
16881163	2015-10-31	2015-10-31 01:35:00	480	3388	117.0	Online Transa...	-1	73186
23278311	2019-07-21	2019-07-21 11:45:00	190	3851	103.68	Online Transa...	-1	73186
14036814	2014-02-22	2014-02-22 02:54:00	1091	3507	148.92	Online Transa...	-1	73186
14044348	2014-02-23	2014-02-23 14:18:00	658	1010	110.02	Online Transa...	-1	73186
20910520	2018-03-07	2018-03-07 00:16:00	1053	2900	141.11	Online Transa...	-1	73186
23387405	2019-08-13	2019-08-13 11:44:00	1207	2693	145.99	Online Transa...	-1	73186
23551507	2019-09-17	2019-09-17 06:58:00	119	379	171.95	Online Transa...	-1	73186
9674203	2011-06-16	2011-06-16 07:47:00	1500	5034	138.48	Online Transa...	-1	73186

Figure 13. Screenshot Load from Lakehouse

3. List of available Columns.

Explore Column Names

```

1 df.columns
2
[18] ✓ - Command executed in 293 ms by Pranav Dinesh Ahire on 8:17:17 PM, 7/18/25 PySpark (Python)
[
'transaction_id',
'transaction_date',
'transaction_date/time',
'client_id',
'card_id',
'transaction_amt',
'use_chip',
'use_chip-binary',
'merchant_id',
'merchant_city',
'merchant_state',
'zip',
'mcc',
'errors',
'client_id.1',
'payment_type',
'expires_date',
'acct_open_date',
'cvv',
'has_chip',
'card_on_dark_web',
'current_age',
'gender_M/F',
'latitude',
'longitude',
'per_capita_income',
'yearly_income',
'total_debt',
'credit_score',
'num_credit_cards']

```

Figure 14.Explore Columns

- Initial null fill to prevent model failure due to nulls.

Assemble & Scale Features

```

1 df_cleaned = df.na.fill({
2     "credit_score": 600,
3     "transaction_amt": 0,
4     "total_debt": 0,
5     "cvv": 0,
6     "latitude": 0.0,
7     "longitude": 0.0,
8     "num_credit_cards": 1
9 })
[20] ✓ - Command executed in 260 ms by Pranav Dinesh Ahire on 8:17:17 PM, 7/18/25

```

Figure 15.Cleaning to Prevent Model Failure

- Extended null value treatment before feature assembly.

```

+ Code + Markdown
> | v
1 feature_cols = [
2     "transaction_amt", "cvv", "total_debt", "credit_score", "num_credit_cards", "latitude", "longitude"
3 ]
4 assembler = VectorAssembler(inputCols=feature_cols, outputCol="features")
5 df_features = assembler.transform(df)
6 # Define input feature columns
[21] ✓ - Command executed in 278 ms by Pranav Dinesh Ahire on 8:17:17 PM, 7/18/25
...

```

Figure 16.Feature assembling

- Assembled selected numeric columns into single vector features, which required for all spark ML models.

```
1 df = df.na.fill({"credit_score": 600, "transaction_amt": 0})
2
[19] ✓ - Command executed in 240 ms by Pranav Dinesh Ahire on 8:17:17 PM, 7/18/25
```

Figure 17. Column Normalization

- Standardizes the features using z-score normalization, improving model convergence and performance.

```
1 scaler = StandardScaler(inputCol="features", outputCol="scaled_features")
2 df_scaled = scaler.fit(df_features).transform(df_features)
3
[22] ✓ - Command executed in 3 sec 542 ms by Pranav Dinesh Ahire on 8:17:21 PM, 7/18/25
```

Run list Run comparison Customize columns

Run name	Start time	Duration	Status	Experiment name
polite_parcel_t1tpfbkx	7/18/2025 8:17 PM	2s	✓ Finished	FraudDetection_ML

Figure 18. Scaling

- Train Isolation Forest for scenario 1 (High-value transactions by low-income users)**
To detect anomalies using features. it adds **outlierScore** and **predictedlabel** to the results.

```
1 isolation_forest = IsolationForest(
2     contamination=0.02,
3     numEstimators=100
4 ).fit(df_features)
5
6 df_isolation = isolation_forest.transform(df_features)
7
8
9
10 df_isolation.select("transaction_id", "predictedLabel", "outlierScore").orderBy(col("outlierScore").desc())
[23] ✓ - Command executed in 1 min 48 sec 842 ms by Pranav Dinesh Ahire on 8:19:10 PM, 7/18/25
```

> Diagnostics 9

... DataFrame[transaction_id: int, predictedLabel: double, outlierScore: double]

Figure 19. Apply Isolation Forest

9. Labeled (**heuristic Labeling**) Creation from Outlier Score it used to trained supervised models

```

1 # 'transaction_id' is the common key between dfs
2 df_scaled_with_score = df_scaled.join(
3     df_isolation.select("transaction_id", "outlierScore"),
4     on="transaction_id",
5     how="inner"
6 )
7
8 # Create a Binary Label from Outlier Score
9 from pyspark.sql.functions import when, col
10 df_labeled = df_scaled_with_score.withColumn(
11     "label", when(col("outlierScore") > 0.6, 1).otherwise(0)
12 )
13
14 # Confirm Label Distribution
15 display(df_labeled.groupBy("label").count())
16
17

```

Command executed in 30 sec 109 ms by Pranav Dinesh Ahire on 8:19:40 PM, 7/18/25

PySpark (Python)

Table view

label	count
1	17586
0	1542026

Figure 20. Labeling from Outlier Score

10. Trained ANN (**Multilayer Perceptron Classifier**) for Scenario 2 (Transactions via Expired/ Dark Web Cards) and return **ann_prediction**.

```

1 # Define layers based on your input feature size
2 ann = MultilayerPerceptronClassifier(
3     featuresCol="scaled_features",
4     labelCol="label",
5     predictionCol="ann_prediction",
6     layers=[7, 10, 5, 2], # [input, hidden1, hidden2, output]
7     maxIter=50
8 )
9
10 # Train and Predict
11 ann_model = ann.fit(df_labeled)
12 df_ann = ann_model.transform(df_labeled)
13
14 # Display results
15 df_ann.select("transaction_id", "label", "ann_prediction").show(10)
16

```

Command executed in 2 min 8 sec 163 ms by Pranav Dinesh Ahire on 8:23:16 PM, 7/18/25

PySpark (Python)

Run list

Run name	Start time	Duration	Status	Experiment name
orange_van_jrz7pkbr	7/18/2025 8:21 PM	1m 36s	Finished	FraudDetection_ML

Figure 21. Apply ANN Model

11. Trained SVM for Scenario 3 (Users High Debt, Low Credi Score) and returned **svm_prediction**.

```

1 svm = LinearSVC(
2     featuresCol="scaled_features",
3     labelCol="label",
4     predictionCol="svm_prediction",
5     maxIter=10
6 )
7
8 # Train the model
9 svm_model = svm.fit(df_labeled)
10
11 # Make predictions
12 df_svm = svm_model.transform(df_labeled)
13
14 # Show results
15 df_svm.select("transaction_id", "label", "svm_prediction").show(10)
16

```

Command executed in 1 min 26 sec 486 ms by Pranav Dinesh Ahire on 8:21:06 PM, 7/18/25

PySpark (Python)

Run list

Run name	Start time	Duration	Status	Experiment name
silver_rhythm_khbf7bgz	7/18/2025 8:19 PM	56s	Finished	FraudDetection_ML

Figure 22. Apply SVM Model

12. Merge all three model predictions and displayed first 10

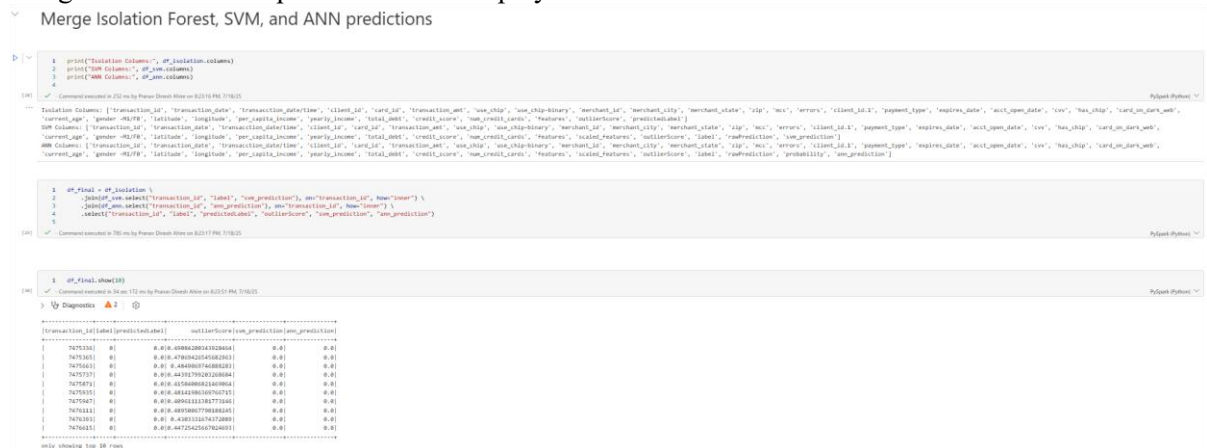


Figure 23. Merge All three Model results

13. **Evaluation of isolation Forest, ANN, and SVM.** Evaluate **Accuracy, Precision, Recall and F1 score** for each model using **multiClassifierEvaluator** also show confusion matrix of an each model.



Figure 24. Evaluation Isolation Forest.

Evaluation for ANN

```

1  # Initialize evaluator for ANN
2  evaluator = MulticlassClassificationEvaluator(labelCol="label", predictionCol="ann_prediction")
3
4  # Accuracy
5  ann_accuracy = evaluator.setMetricName("accuracy").evaluate(df_final)
6  # F1 Score
7  ann_f1 = evaluator.setMetricName("f1").evaluate(df_final)
8  # Precision
9  ann_precision = evaluator.setMetricName("precisionByLabel").evaluate(df_final)
10 # Recall
11 ann_recall = evaluator.setMetricName("recallByLabel").evaluate(df_final)
12
13 print("ANN Evaluation:")
14 print(f"Accuracy: {ann_accuracy:.4f}")
15 print(f"Precision: {ann_precision:.4f}")
16 print(f"Recall: {ann_recall:.4f}")
17 print(f"F1 Score: {ann_f1:.4f}")
18
19 # Confusion Matrix
20 print("Confusion Matrix (ANN):")
21 df_final.groupBy("label", "ann_prediction").count().show()
22
[32] ✓ - Command executed in 2 min 22 sec 759 ms by Pranav Dinesh Ahire on 8:33:17 PM, 7/18/25

```

>  Diagnostics  4 

```

ANN Evaluation:
Accuracy: 0.9933
Precision: 0.9949
Recall: 0.9983
F1 Score: 0.9927
Confusion Matrix (ANN):
+-----+-----+-----+
|label|ann_prediction| count|
+-----+-----+-----+
| 1|          0.0|  7884|
| 0|          0.0|1539385|
| 1|          1.0|  9702|
| 0|          1.0|  2641|
+-----+-----+-----+

```

Figure 25. Evaluation ANN Model.

Evaluation for SVM

```

1  from pyspark.ml.evaluation import MulticlassClassificationEvaluator
2
3  # Initialize evaluator for SVM
4  evaluator = MulticlassClassificationEvaluator(labelCol="label", predictionCol="svm_prediction")
5
6  # Accuracy
7  svm_accuracy = evaluator.setMetricName("accuracy").evaluate(df_final)
8  # F1 Score
9  svm_f1 = evaluator.setMetricName("f1").evaluate(df_final)
10 # Precision
11 svm_precision = evaluator.setMetricName("precisionByLabel").evaluate(df_final)
12 # Recall
13 svm_recall = evaluator.setMetricName("recallByLabel").evaluate(df_final)
14
15 print("SVM Evaluation:")
16 print(f"Accuracy: {svm_accuracy:.4f}")
17 print(f"Precision: {svm_precision:.4f}")
18 print(f"Recall: {svm_recall:.4f}")
19 print(f"F1 Score: {svm_f1:.4f}")
20
21 # Confusion Matrix
22 print("Confusion Matrix (SVM):")
23 df_final.groupBy("label", "svm_prediction").count().show()
24
[32] ✓ - Command executed in 2 min 35 sec 719 ms by Pranav Dinesh Ahire on 8:30:54 PM, 7/18/25

```

>  Diagnostics  2 

```

SVM Evaluation:
Accuracy: 0.9901
Precision: 0.9903
Recall: 0.9998
F1 Score: 0.9865
Confusion Matrix (SVM):
+-----+-----+-----+
|label|svm_prediction| count|
+-----+-----+-----+
| 1|          0.0|  15132|
| 0|          0.0|1541643|
| 1|          1.0|  2454|
| 0|          1.0|   383|
+-----+-----+-----+

```

Figure 26. Evaluation SVM Model

14. Merge Evaluation results of all three models and displayed

```

1  # Create score rows manually dictionary-based joins
2  from pyspark.sql import Row
3
4  # Convert metric values into Spark DataFrame for each model
5  score_rows = [
6      Row(model="IsolationForest", accuracy=iso_accuracy, precision=iso_precision, recall=iso_recall, f1=iso_f1),
7      Row(model="SVM", accuracy=svm_accuracy, precision=svm_precision, recall=svm_recall, f1=svm_f1),
8      Row(model="ANN", accuracy=ann_accuracy, precision=ann_precision, recall=ann_recall, f1=ann_f1),
9  ]
10
11 # Create Spark DataFrame of evaluation results
12 df_metrics = spark.createDataFrame(score_rows)
13 df_metrics.show()
14
[34] ✓ - Command executed in 784 ms by Pranav Dinesh Ahire on 8:33:18 PM, 7/18/25

```

model	accuracy	precision	recall	f1
IsolationForest	0.9912619292490696	1.0	0.9911622761224519	0.9924626442412607
SVM	0.9900520129365509	0.9902799055740232	0.9997516254589741	0.9864835884270508
ANN	0.9932515266617594	0.994904570569177	0.9982873181126648	0.9926661502117234

Figure 27. Final Evaluation table.

15. Load both (**prediction and Evaluation**) tabled into lakehouse. For visualizations.

```

1  df_final.write.mode("overwrite").saveAsTable("fraud_prediction_results")
2  # Save final prediction table
3  #df_final.write.mode("overwrite").option("header", True).csv("Files/final_predictions")
4
5  # Save evaluation metrics
6  df_metrics.write.mode("overwrite").saveAsTable("model_evaluation_score")

```

[35] ✓ - Command executed in 52 sec 70 ms by Pranav Dinesh Ahire on 8:34:10 PM, 7/18/25

> Diagnostics 1

Figure 28. Load Both Tables into Lakehouse.

16. Both tables from Lakehouse are loaded into Power BI Services for visualizations.

6 Visualizations

6.1 Connected Microsoft Fabric and Power BI Services.

1. **Login Power BI services** with the same email id and configured with **DissertationFraudDetection** Workspace.
2. Power BI services Connected to FraudDetectionLakehouse.

(Click on “Get Data” → “ Microsoft Fabric”)

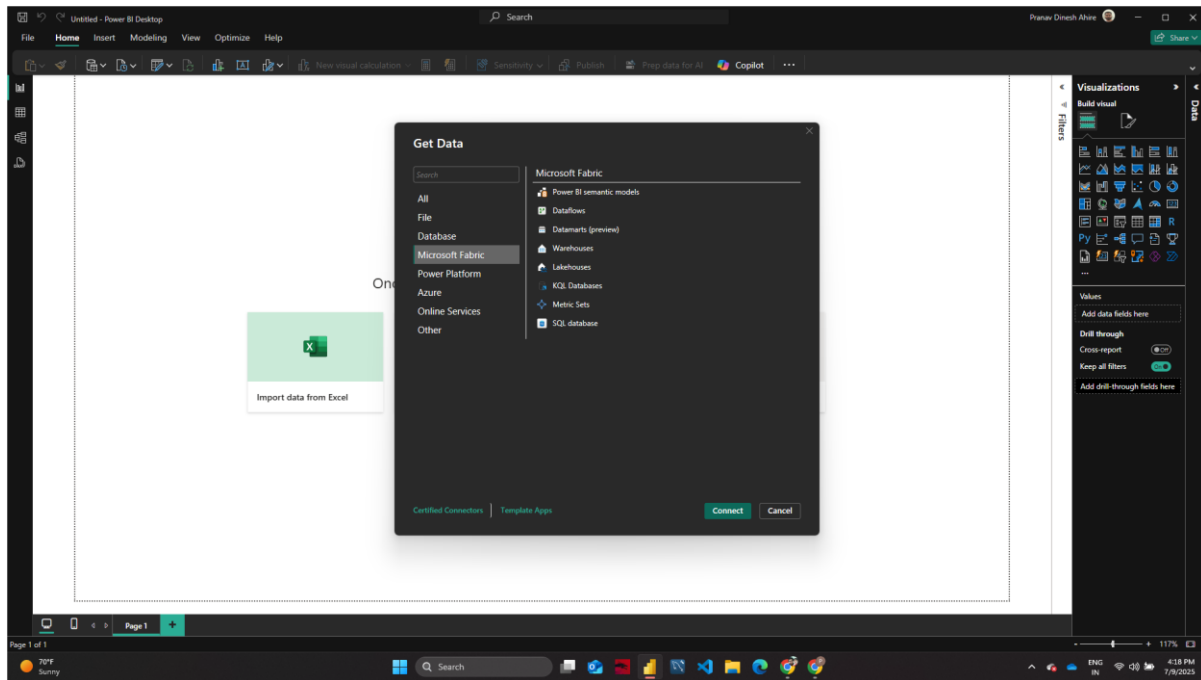


Figure 29. Connect Microsoft Fabric to Power BI Services.

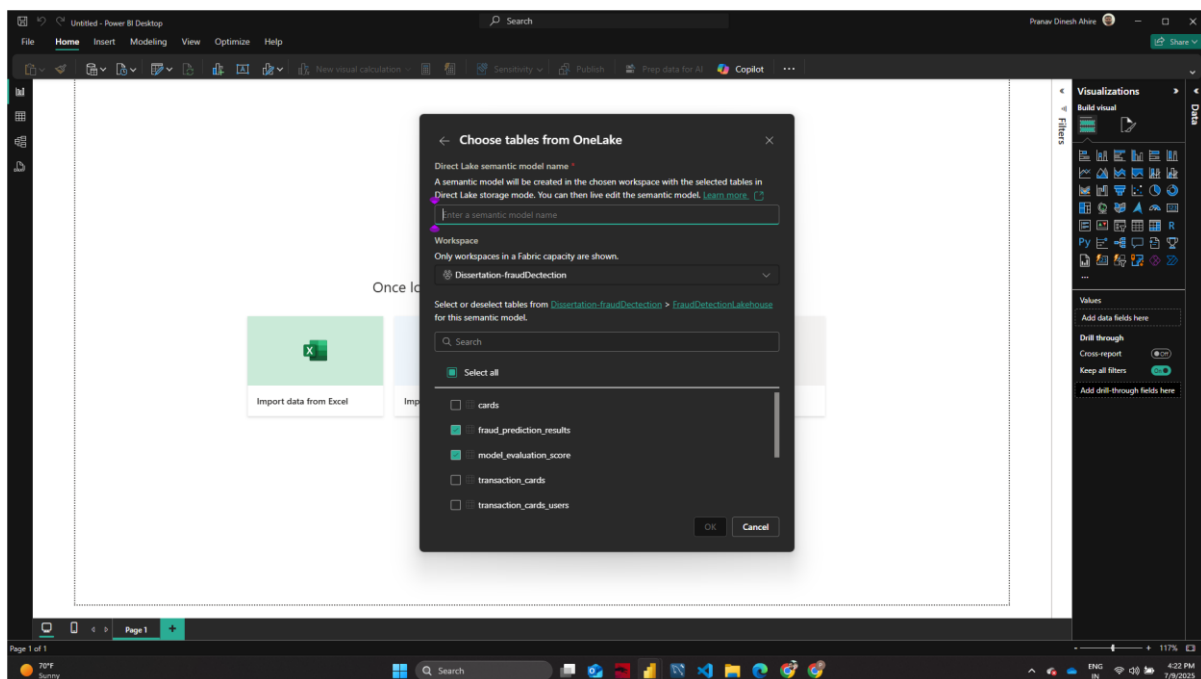


Figure 30. Load Both Tables from Lakehouse

6.2 Dashboard Developed

After Power BI Services connected with Microsoft Fabric's Lakehouse Two Dashboards (Created Fraud Detection Overview and Model Evaluation Summary)

5.2.1 Dashboard 1: Fraud Detection Overview

Visuals:

1. Cards visuals: Total transaction, Legitimate count, Fraud count.
2. Pie chart: Legitimate vs. Fraud Count.
3. Bar chart: Prediction vs. Actual Prediction for ANN and SVM
4. Sliders: Filter by Actual label (Fraud or Legit)

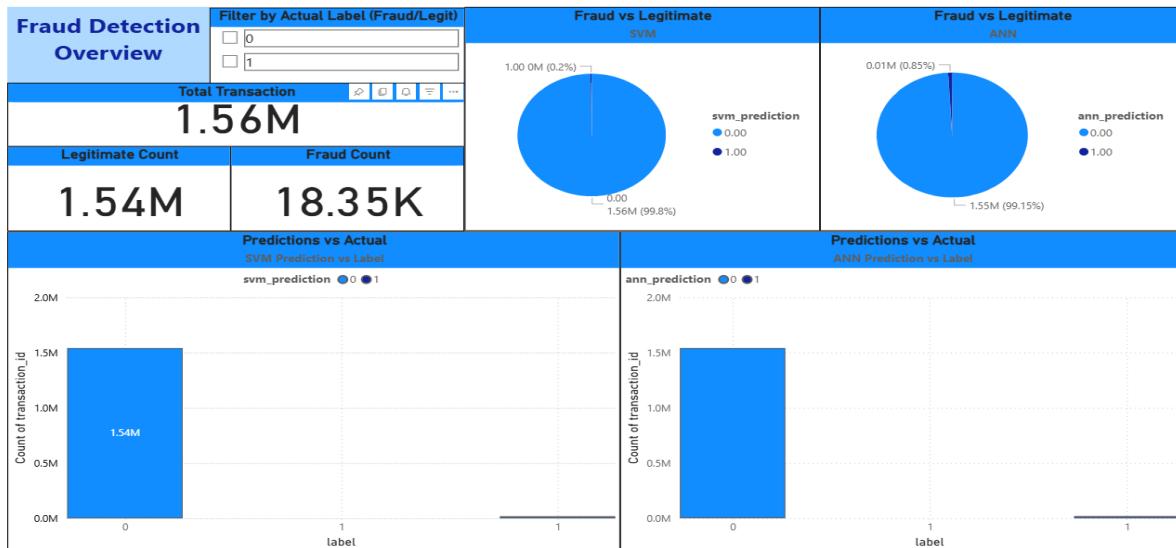


Figure 31. Dashboard1: Fraud Detection Overview.

5.2.2 Dashboard 2: Model Evaluation Summary

Visuals:

1. Card Visual: F1 Score value and Accuracy for all models (Ascending ordered).
2. Score Table: Table format shows exact value of accuracy, Precision, Recall, F1 Score.
3. Bar Chart: Visuals Comparison of metrics across all models.

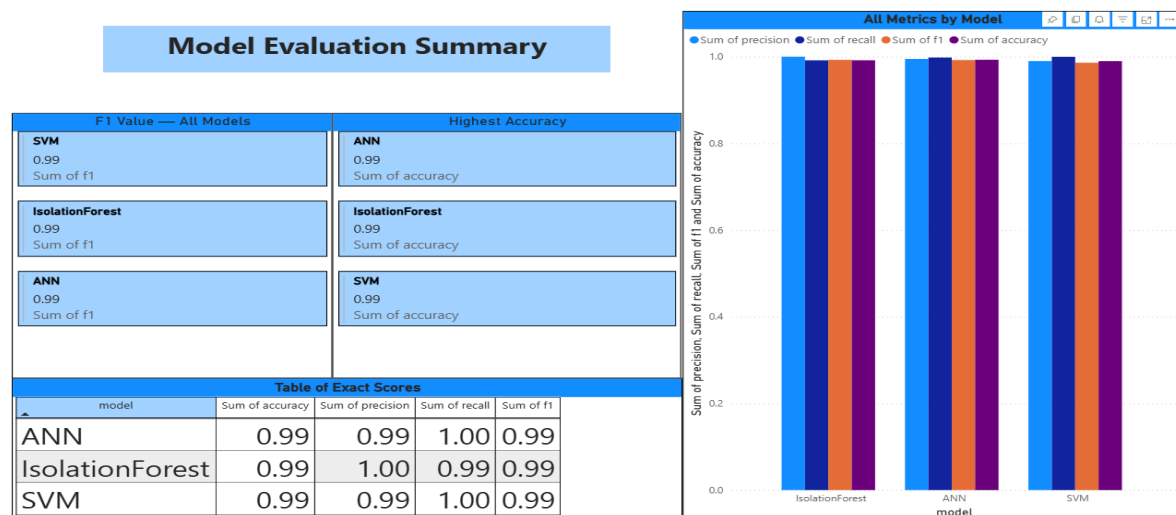


Figure 32. Dashboard2: Model Evaluation Summary.

7 Pipeline Deployment

7.1 Create pipeline Notebook

1. Click on “New item” add “Data Pipeline”.
2. Connected to Workspace “Dissertation-FraudDetection”.
3. Add Dataflow1, Notebook1 and Semantic model refresh.
4. Connect Dataflow1 to Notebook1 and Notebook1 to Semantic model Refresh

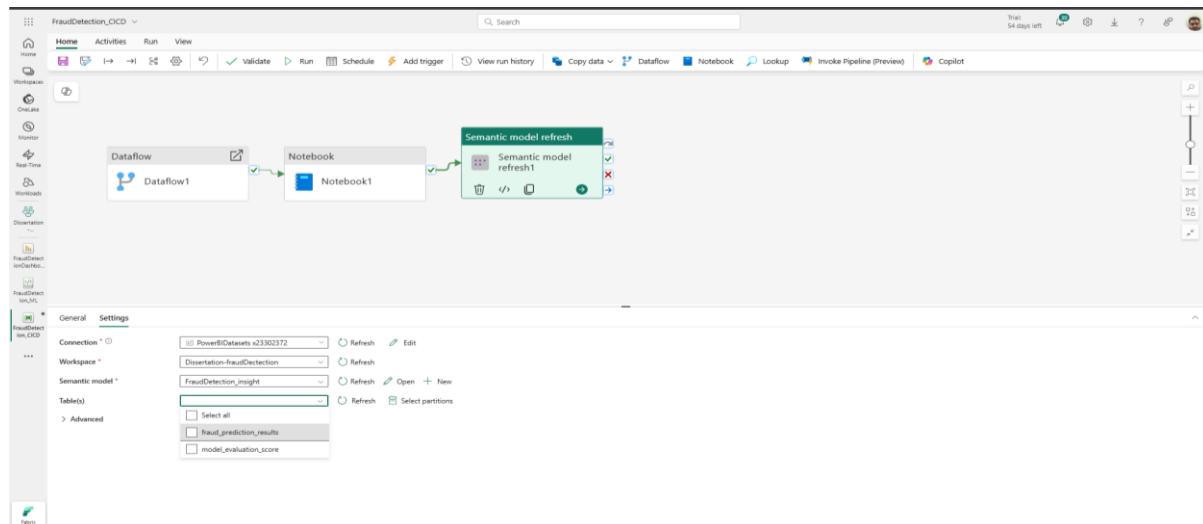


Figure 33. Pipeline Deployment

5. Validate the Pipeline and Run.

6. The Pipeline Deployed Successfully.

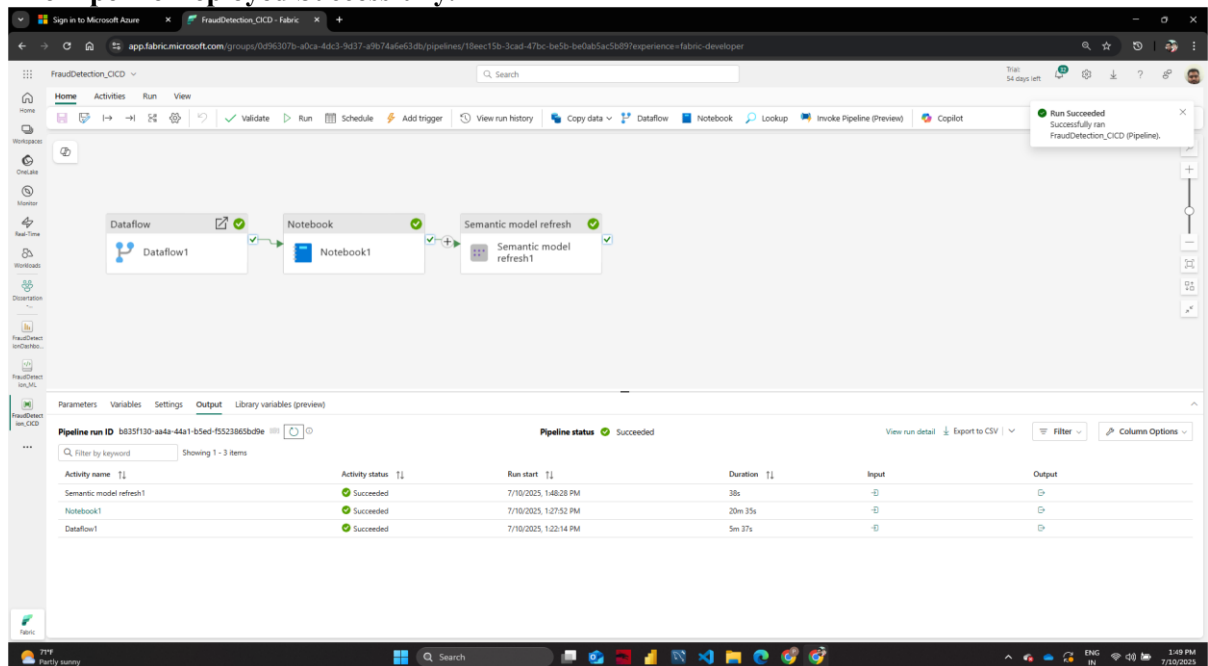


Figure 34. Pipeline Deployed Successfully.

7. End-to-end connections in Microsoft Fabric Workspace after Pipeline Deployment.

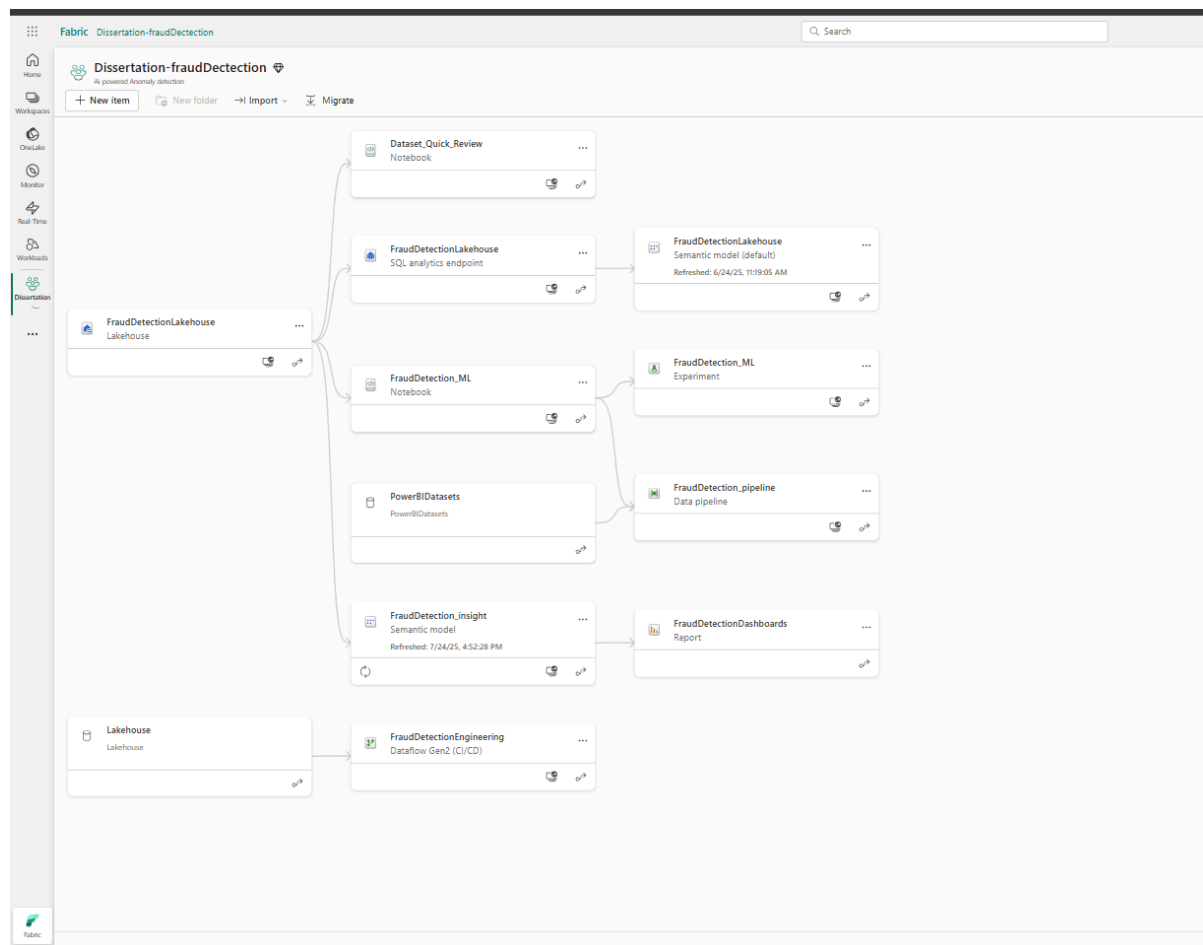


Figure 34. End-to-end Pipeline

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