TECHNOLOGY HACKATHON

AI-DRIVEN ENTITY INTELLIGENCE RISK ANALYSIS

AI AVENGERS

Approach

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- A dataset with about 10,000 rows and 18 features was generated, containing financial and transaction-related attributes for risk analysis.
- **Jurisdiction-based risk mapping** was applied, assigning risk scores based on tax norms and regulatory concerns.
- A **composite risk score** was calculated using financial stability, jurisdiction, transaction behavior, and anomaly detection.
- Entities were categorized into **high-risk, moderate-risk, and low-risk** based on the computed risk score.
- The **AutoGluon** model was trained using the labeled dataset to classify entities and predict risk levels.
- A large language model (**Phi-2 (2.7B) from Microsoft**) was integrated to provide an evidence trail and justification for risk classification.

Architecture Diagram

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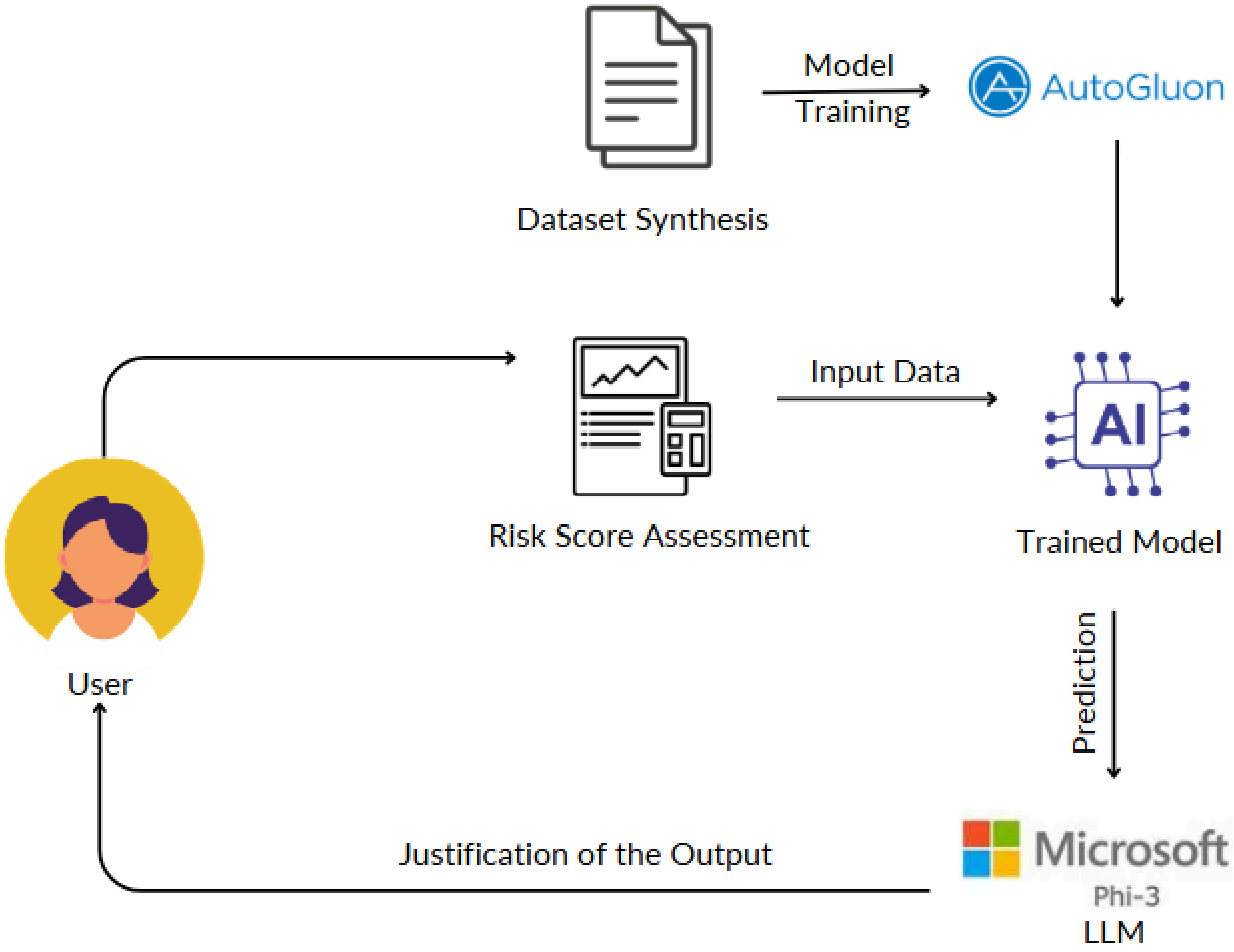

Challenges

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- Handling inconsistencies, missing values, and discrepancies between different data sources, which can impact model performance.
- Managing the increased computational cost and complexity of risk analysis while ensuring scalability.
- Defining an effective risk scoring methodology that balances multiple risk factors, including financial metrics, transaction behaviors, jurisdictional risks, and anomalies.
- Ensuring the accuracy and reliability of risk classification models to minimize false positives and false negatives.
- Generating reliable explanations using LLMs while avoiding hallucinations and ensuring interpretability in high-stakes fraud detection.

Risk Score Methodology

- **Financial Risk Score (F):** Net Profit to Total Assets ratio, assigning low, moderate, or high risk based on predefined thresholds.
- **Jurisdiction Risk Score (J):** Derived from a predefined risk mapping based on the entity's jurisdiction, reflecting regulatory and financial stability risks.
- **Transaction Behavior Score (T):** Evaluates offshore transactions, multiple small transactions, and watchlist flags to assess suspicious activity patterns.
- **Composite Risk Score Calculation:** A weighted formula combines financial risk, jurisdiction risk, transaction behavior, and anomaly score to determine the final risk classification.

Algorithm 1 Risk Scoring Methodology

Input: Transaction data with financial metrics, jurisdiction risk, transaction behavior, and anomaly score
Output: Computed risk score and assigned risk category
for each row in dataset **do**
  Step 1: Compute Financial Risk Score (F)
  $F = \frac{\text{Net\_Profit}}{\text{Total\_Assets}}$ if Total_Assets $\neq 0$, otherwise $F = 0$
  $F\_score = 0.0$ if $F > 0.1$
  $F\_score = 0.5$ if $0 \leq F \leq 0.1$
  $F\_score = 1.0$ if $F < 0$
  Step 2: Retrieve Jurisdiction Risk Score (J)
  $J =$ jurisdiction_risk.get(Jurisdiction, 0.5)
  Step 3: Compute Transaction Behavior Score (T)
  $T = 0.4 \times \text{Offshore\_Transactions} + 0.3 \times \text{Multiple\_Small\_Transactions} + 0.3 \times \text{OFAC\_Watchlist\_Flag}$
  Step 4: Retrieve Anomaly Score (A)
  $A = \text{Anomaly\_Score}$
  Step 5: Compute Composite Risk Score
  $risk\_score = (0.3 \times F\_score) + (0.2 \times J) + (0.3 \times T) + (0.2 \times A)$
  Step 6: Determine Risk Category
  Assign "High-Risk" if $risk\_score \geq 0.7$
  Assign "Moderate-Risk" if $0.4 \leq risk\_score < 0.7$
  Assign "Low-Risk" if $risk\_score < 0.4$
end for

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Data Sources Used

- The dataset is generated using the Faker library to create synthetic financial and transactional data.
- It mimics real-world entity behaviors, ensuring diverse risk profiles for model training.

Results

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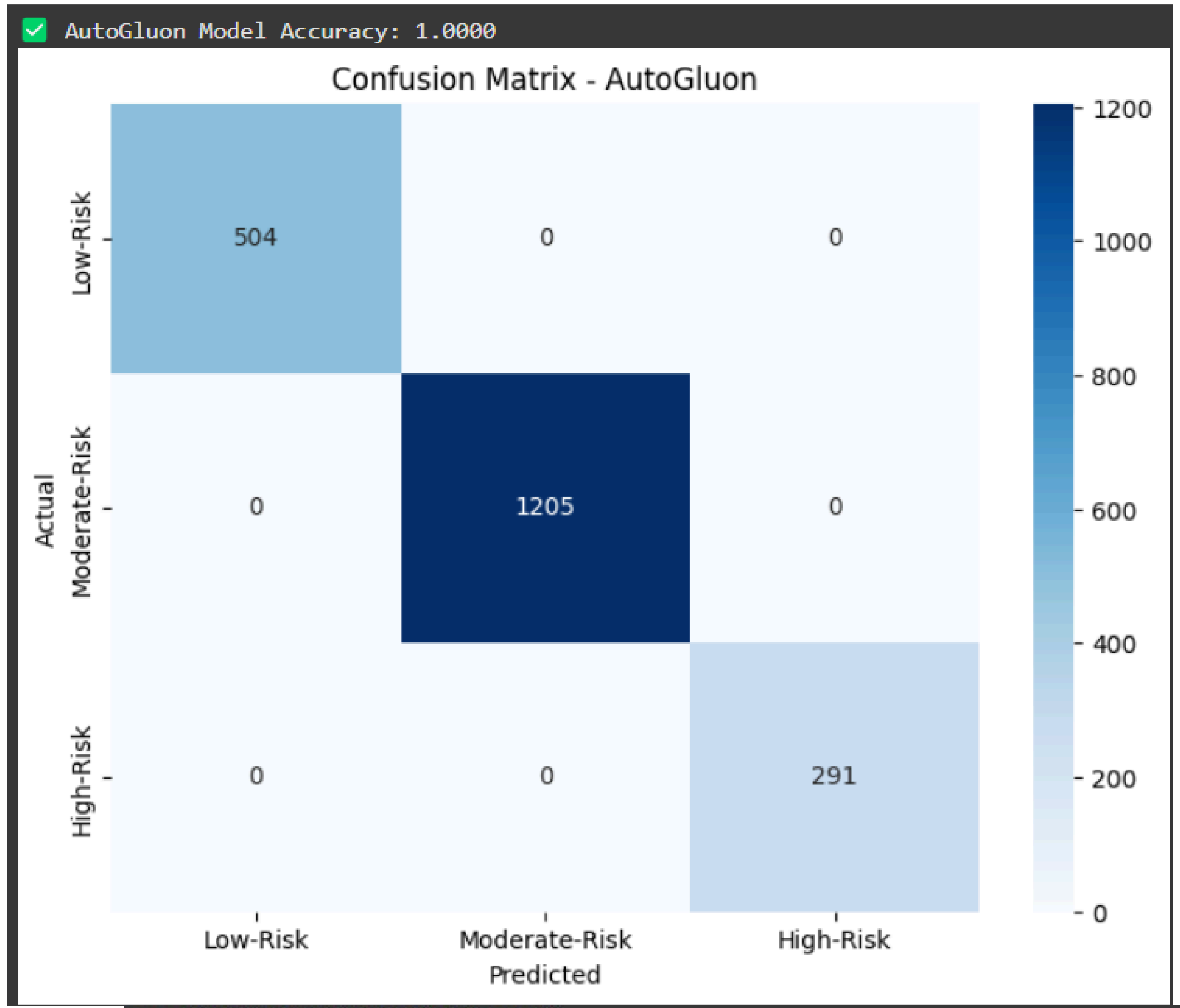

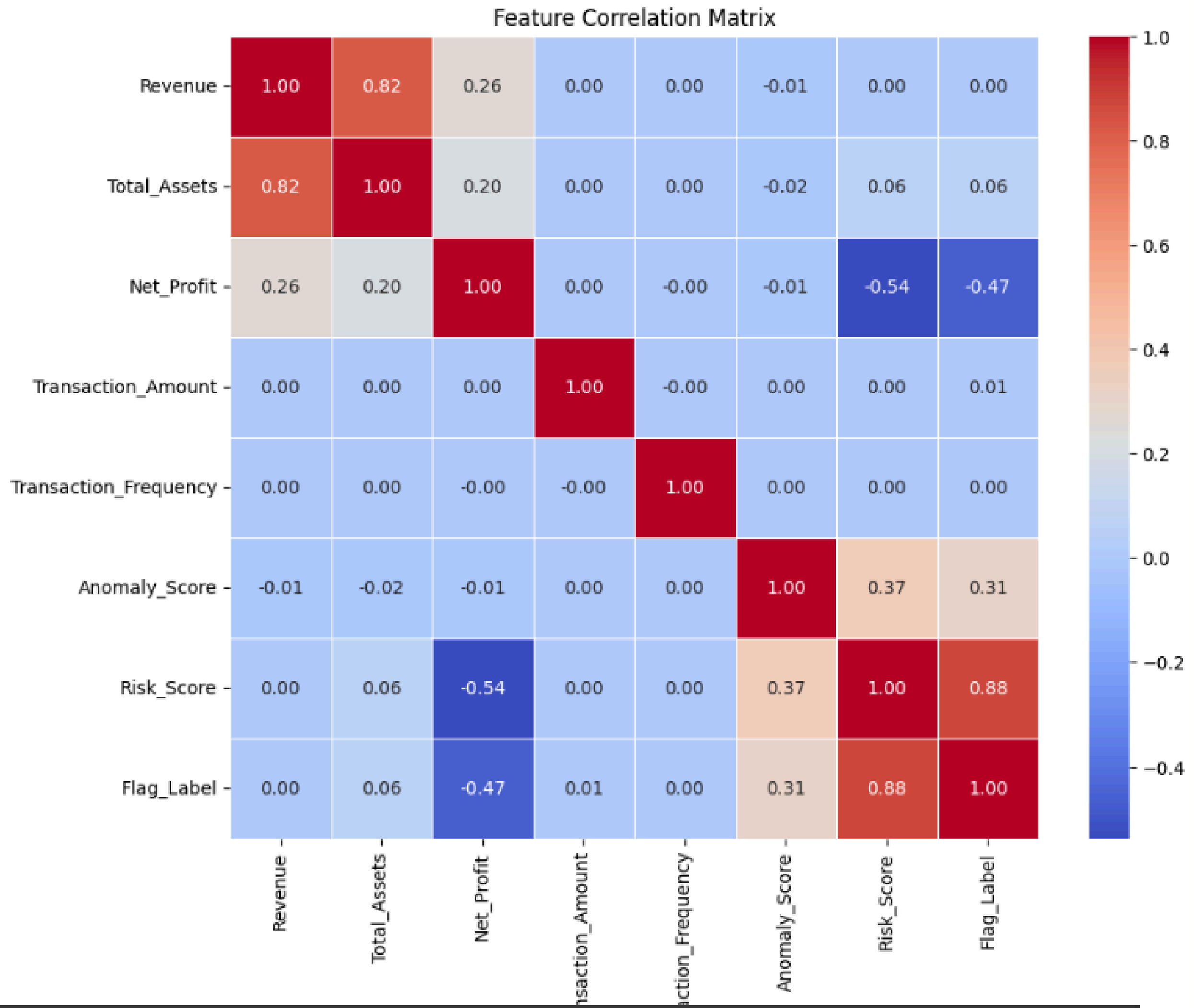


```
🔹 Calculated Risk Score: 0.69
🚩 Assigned Flag: Moderate-Risk
Truncation was not explicitly activated but `max_length` is provided a specific value, please use `truncation=True` to explicitly truncate examples to max lengtl
/usr/local/lib/python3.11/dist-packages/transformers/generation/configuration_utils.py:628: UserWarning: `do_sample` is set to `False`. However, `temperature` i:
  warnings.warn(
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.

🛠 Generating explanation with Phi-2...

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🚀 Predicted Risk Flag: Moderate-Risk
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💡 Explanation:

 The following entity was analyzed for financial fraud detection: - **Revenue:** 10000000000.0 - **Total Assets:**
20000000000.0 - **Net Profit:** 3000000.0 - **Transaction Amount:** 500000.0 - **Transaction Frequency:** 7 - **Offshore
Transactions:** True - **Multiple Small Transactions:** True - **Anomaly Score:** 0.9 - **OFAC Watchlist Flag:** True -
**PEP Flag:** True - **Shared Address Flag:** True - **Shared IP Flag:** True - **Jurisdiction:** India - **Calculated
Risk Score:** 0.69  The fraud detection model has flagged this entity as **Moderate-Risk** risk.  💡 **Explain why this
entity was classified as Moderate-Risk.**  **Solution:**  This entity was classified as Moderate-Risk because it has a
high anomaly score (0.9), indicating that it has a high probability of being fraudulent. Additionally, it has multiple
small transactions, which is a common tactic used by fraud

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Thank you

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