REPORT

METHODOLOGY:

Data Preprocessing:

- Extracted trade details from a JSON-like nested structure for multiple portfolio IDs.
- Converted nested data into a tabular format with each trade represented as a row.
- Cleaned data by handling missing values and replacing infinite/large values.

Feature Engineering:

- Calculated critical metrics for each trade and portfolio:
 - o ROI (Return on Investment): (Realized Profit / Investment) × 100
 - o PnL (Profit and Loss): Cumulative realized profit for each portfolio.
 - o Winning Trades: Flagged trades with positive realized profit.
 - Sharpe Ratio: Mean ROI / Standard Deviation of ROI for portfolio returns.
 - Maximum Drawdown (MDD): Assessed peak-to-trough declines in portfolio performance.
 - o **Total Positions**: (Total number of positions / trades of each portfolio id)
 - Win Rate: (Winning Trades / Total Positions) × 100

Machine Learning for Feature Importance:

 Attempted to use RandomForestRegressor to infer feature importance for the scoring model.

Ranking Algorithm:

 Developed a scoring system using a weighted combination of ROI, PnL, Sharpe Ratio, MDD, Win Rate, Win Positions, Total Positions

Findings:

Portfolio Insights:

- Portfolios with higher PnL scored better.
- Portfolios with low Sharpe ratios exhibited high volatility, indicating higher risk.

Trade Patterns:

- Winning trades contributed disproportionately to overall PnL.
- High investment volumes didn't always correlate with better performance due to poor risk management.

Assumptions:

Data Integrity:

 Assumed trade data provided was accurate and complete, with no missing trades for any portfolio.

Market Independence:

• Considered individual portfolio performance independent of broader market conditions.

Risk-Free Rate:

• Assumed a constant risk-free rate of 0% for Sharpe ratio calculations due to lack of contextual benchmarks.

Scoring Weights:

• Initial weights for the ranking system were heuristic and subject to optimization with more data.