

# CryptoTradeRisk-DSA210: Model Evaluation Results

April 25, 2025

## 1 Introduction

This document presents the model evaluation results for the CryptoTradeRisk-DSA210 project, conducted as part of Step 5 on April 25, 2025. The models were developed to predict trading outcomes and assess risk in cryptocurrency trading, using the dataset `processed_data.csv` and supporting files (`trades.csv`, `news.csv`, `social_media.csv`, `fear_greed.csv`, `portfolio.csv`). The evaluation focuses on three models: Logistic Regression (balanced), Random Forest for predicting `Total_PnL`, and a VAR model for forecasting `Portfolio_Value_USD`, `BTC_Price`, and `ETH_Price`. Additionally, a refined risk metric is presented.

## 2 Model Evaluation Results

### 2.1 Logistic Regression Model for Total\_PnL (Balanced)

The Logistic Regression model predicts whether `Total_PnL` is positive (80) or negative (-40), using features: `News_Sentiment_Avg`, `Lagged_News_Sentiment`, `BTC_Price_Change`, `ETH_Price_Change`, and `BTC_Momentum`. Class weighting (`class_weight='balanced'`) was applied to address class imbalance.

- Mean Cross-Validation Accuracy: 0.500
- Classification Report (on full data):

	precision	recall	f1-score	support
Negative PnL	0.30	0.60	0.40	5
Positive PnL	0.86	0.63	0.73	19
accuracy			0.62	24
macro avg	0.58	0.62	0.56	24
weighted avg	0.74	0.62	0.66	24

- Feature Coefficients:
  - `News_Sentiment_Avg`: 0.054
  - `Lagged_News_Sentiment`: -0.409

- BTC\_Price\_Change: -0.080
- ETH\_Price\_Change: 0.288
- BTC\_Momentum: -0.013

## 2.2 Random Forest Model for Total\_PnL

The Random Forest model uses the same features as Logistic Regression, with `n_estimators=50` and `class_weight='balanced'`.

- Mean Cross-Validation Accuracy: 0.830
- Classification Report (on full data):

	precision	recall	f1-score	support
Negative PnL	1.00	1.00	1.00	5
Positive PnL	1.00	1.00	1.00	19
accuracy			1.00	24
macro avg	1.00	1.00	1.00	24
weighted avg	1.00	1.00	1.00	24

- Feature Importances:
  - News\_Sentiment\_Avg: 0.171
  - Lagged\_News\_Sentiment: 0.212
  - BTC\_Price\_Change: 0.149
  - ETH\_Price\_Change: 0.283
  - BTC\_Momentum: 0.184

## 2.3 VAR Model for Portfolio\_Value\_USD, BTC\_Price, and ETH\_Price

The VAR model forecasts `Portfolio_Value_USD`, `BTC_Price`, and `ETH_Price` using a lag order of 1. The last 5 days (04/14/2025–04/18/2025) are used for testing.

Date	Actual Portfolio Value (USD)	Forecasted Portfolio Value (USD)	Actual PnL
04/14/2025	2607.07	3901.95	
04/15/2025	3850.77	4213.86	
04/16/2025	2560.68	4467.78	
04/17/2025	3885.73	4764.11	
04/18/2025	2622.93	5068.55	

Table 1: Forecasting Results

- Mean Absolute Error (`Portfolio_Value_USD`): 1377.81

## 2.4 Risk Metric

The risk metric uses a 7-day rolling window for volatility, with adjustments for BTC momentum.

- **Latest BTC Volatility (7-day):** 0.0218
- **Latest ETH Volatility (7-day):** 0.0257
- **Latest Risk Score (Normalized):** 0.7445

## 3 Conclusions

The model evaluation highlights the following insights:

- The Logistic Regression model (balanced) achieves a cross-validation accuracy of 0.500, performing no better than random guessing. While recall for **Negative PnL** improved to 0.60, the model's overall performance is poor due to the small dataset.
- The Random Forest model significantly outperforms Logistic Regression, with a cross-validation accuracy of 0.830. However, the perfect performance on the full data (accuracy: 1.00) suggests overfitting, and the cross-validation accuracy may be optimistic given the small dataset.
- The VAR model forecasts **Portfolio.Value.USD** with an MAE of 1377.81, much higher than the previous ARIMA model (MAE: 134.28). The model overestimates portfolio value and fails to capture volatility, likely due to the small dataset and simple lag order.
- The risk metric (score: 0.7445) indicates moderate-to-high risk on the latest day (04/18/2025), driven by recent volatility and positive BTC momentum.

Future steps include deploying the Random Forest model for **Total\_PnL** prediction, improving the VAR model with more data and tuning, and operationalizing the risk metric with actionable thresholds. Collecting more data is critical to enhance model performance.