

Introduction

This report examines trading patterns (profitability, risk, volume, leverage) in relation to overall market sentiment (fear and greed) using visual insights from statistical charts. The objective is to uncover trends, comparisons, anomalies, and actionable signals for smarter trading strategies.

1,2. Account and Coin Trading Summary

Title: Account and Coin Trading Summary

Type of Chart: Descriptive summary table (aggregated statistics for categorical and numerical features)

Key Observations / Patterns:

- Account diversity is high (32 unique accounts, top account handling over 40,000 trades).
- The dataset is rich in coin variety (246 coins); HYPE is the most frequently traded coin (68,005 trades).
- Trades cover multiple directions (12 distinct values for “Direction”) and involve both buy and sell orders.
- Trade activity spans from May 2023 to January 2025, showing continuous activity.
- Side (buy/sell) split is reasonable, but SELL has more trades (10,528) than BUY.

Statistical and Analytical Insights:

- Execution price mean $\approx 11,415$ with a long tail up to 109,004.
- Size USD mean $\approx 5,639$; range from 0 to 3.9 million.
- PnL highly skewed: min -1,433,469, max 3 million, median ≈ 85 USD.
- ~101K unique transaction hashes confirm strong granularity.

Conclusion / Recommendation:

- Concentration Risk: A few accounts handle disproportionate volume.
- Product Opportunity: HYPE and SELL activity merit analytics focus.
- Risk Monitoring: Variance in trade size/price highlights need for control.
- Actionable Step: Enhance monitoring of outliers and volatility drivers.

[illegible]

	top	freq	mean	min	25%	50%	75%	max	std
118a828645437aab	40184		NaN	NaN	NaN	NaN	NaN	NaN	NaN
	HYPE	68005	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	NaN	NaN	11414.72335	0.000005	4.8547	18.28	101.58	109004.0	29447.654868
	NaN	NaN	4623.364979	0.000001	2.94	32.0	187.9025	15822438.0	104272.88953
	NaN	NaN	5639.45121	0.0	193.79	597.045	2058.96	3921430.72	36575.138546
	SELL	108528	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	NaN	NaN	2025-01-31 12:04:22.915009792	2023-05-01 01:06:00	2024-12-31 21:00:45	2025-02-24 18:55:00	2025-04-02 18:22:00	2025-05-01 12:13:00	NaN
NaN	NaN	-29946.248839	-14334629.0	-376.231075	84.727932	9337.2775	30509482.0	673807.423736	
Open Long	49895		NaN	NaN	NaN	NaN	NaN	NaN	
NaN	NaN		48.749001	-117990.1041	0.0	0.0	5.792797	135329.0901	919.164828
0000000000000000...	9032		NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	NaN	69653876008.970215	173271100.0	59838527992.75	74429390066.0	83355430544.0	90149230487.0	18357525271.925747	
True	128403		NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	NaN		1.163967	-1.175712	0.016121	0.089578	0.393811	837.471593	6.758854
NaN	NaN		562854854500788.5	0.0	281000000000000.0	562000000000000.0	846000000000000.0	1130000000000000.0	325756470346523.375
NaN	NaN		1737744290421.542969	1680000000000.0	1740000000000.0	1740000000000.0	1740000000000.0	1750000000000.0	8689920301.590015

- BTC, HYPE, SOL, and ETH dominate in trades and total USD volume.

- BTC fewer trades but higher total USD—market leadership confirmed.
- Meme coins like HYPE, @107, TRUMP, MELANIA are active.
- BTC average trade price $\approx 86,454$; FARTCOIN/MELANIA < 2 .

Statistical / Analytical Insights:

- BTC total USD $\approx 644.2\text{M}$ (26,064 trades); HYPE 68K trades but lower volume.
- BTC PnL $\approx 8.68\text{M}$; FARTCOIN/TRUMP are net losers.
- BTC incurs highest absolute fees $\approx 139,224$.

Conclusion / Recommendation:

- Focus on BTC, HYPE, SOL, ETH for optimization.
- Sentiment in meme coins shows speculative influence.
- Strategic fee adjustments can retain clients and boost engagement.

	trades	total_usd	avg_price	total_pnl	total_fee	avg_fee_pct
Coin						
BTC	26064	6.442321e+08	86454.455801	8.680447e+05	139224.226804	0.000216
HYPE	68005	1.419902e+08	18.382012	1.948485e+06	25361.930440	0.000179
SOL	10691	1.250748e+08	159.115894	1.639556e+06	27956.304402	0.000224
ETH	11158	1.182810e+08	2656.719188	1.319979e+06	23091.303645	0.000195
@107	29992	5.576086e+07	21.529569	2.783913e+06	5953.224788	0.000107
FARTCOIN	4650	8.311390e+06	0.927592	-1.006872e+05	2357.939012	0.000284
SUI	1979	7.781168e+06	3.658196	1.992688e+05	2003.206129	0.000257
TRUMP	1920	7.349347e+06	17.552389	-3.648249e+05	1729.745411	0.000235
MELANIA	4428	7.040710e+06	1.224895	3.903511e+05	1010.388542	0.000144
XRP	1774	5.343211e+06	2.171684	3.756901e+03	701.847927	0.000131

4. Top 15 Coins by Number of Trades

Type of Chart: Bar Chart

Key Observations / Patterns:

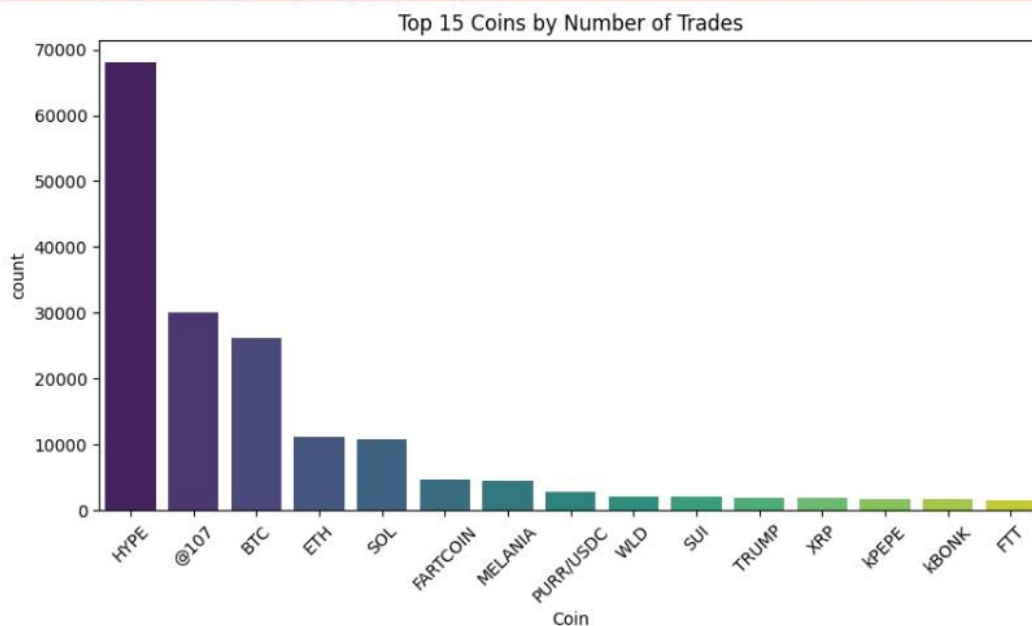
- HYPE dominates trade count, followed by @107 and BTC.
- Remaining coins drop off rapidly—market concentration evident.

Statistical / Analytical Insights:

- HYPE \approx 70,000 trades (2x @107).
- Most other coins <10,000 trades—fragmented activity.

Conclusion / Recommendation:

- Prioritize liquidity and monitoring for HYPE/@107.
- Track mid-ranked coins for emerging trends.



5. Distribution of Trade Size (USD)

Type of Chart: Histogram

Key Observations / Patterns:

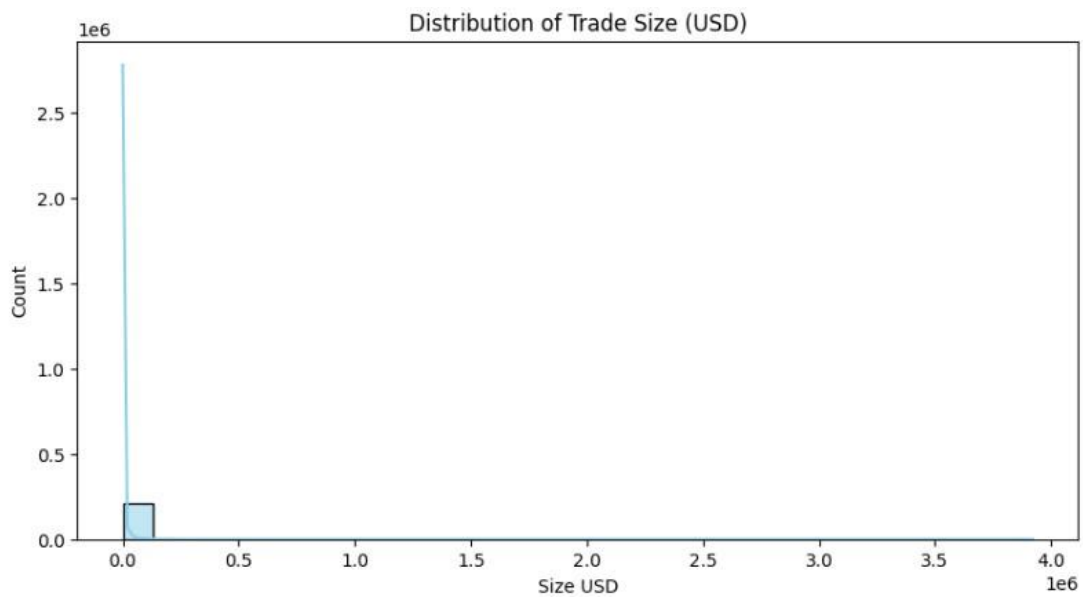
- Most trades are small, long right tail of few large trades.

Statistical / Analytical Insights:

- Small trades dominate; rare large trades (\sim \$4M) indicate whales.

Conclusion / Recommendation:

- Focus risk monitoring on both micro and large trades.
- Offer tailored analytics to both small and large traders.



6. Top 15 Trades by Size USD

Type of Chart: Bar Chart

Key Observations / Patterns:

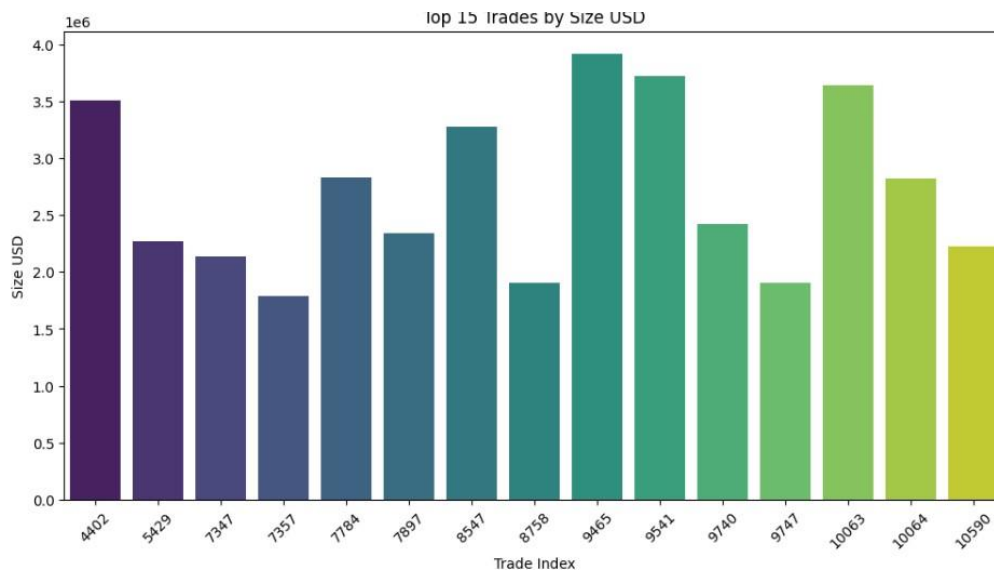
- All 15 trades exceed \$1.8M, highlighting the dominance of large-scale traders ("whales").
- The largest trade approaches \$4M, indicating significant market-moving potential.

Statistical / Analytical Insights:

- Multiple trades cluster around \$3.5M, suggesting order-splitting or high-conviction strategies.
- The gap between the smallest and largest among the top 15 exceeds \$2M, underlining volume inequality.

Conclusion / Recommendation:

- Implement oversight mechanisms for large transactions to reduce slippage and maintain market integrity.
- Offer premium analytics and engagement programs for high-value clients.



6.2 Distribution of Execution Price

Type of Chart: Histogram with Density Curve

Key Observations / Patterns:

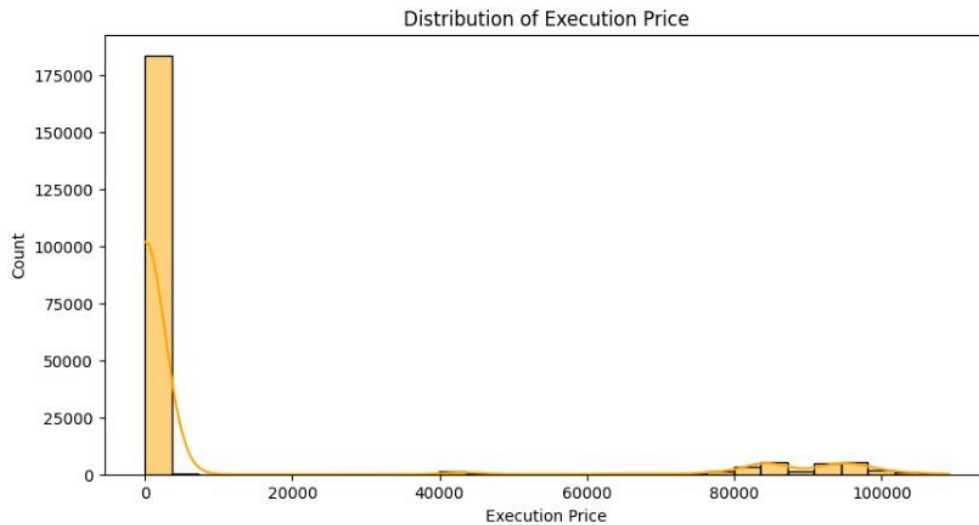
- Execution prices are concentrated at low ranges, with a steep drop-off after the first bin.
- Occasional clusters appear at very high prices, showing rare or illiquid trades.

Statistical / Analytical Insights:

- The left-skew indicates a dominance of small-cap or penny tokens.
- High-end outliers may result from low liquidity or new token listings.

Conclusion / Recommendation:

- Maintain automated anomaly detection for high execution prices.
- Regularly review liquidity conditions to prevent adverse trade outcomes.



6.3 Distribution of Closed PnL

Type of Chart: Histogram

Key Observations / Patterns:

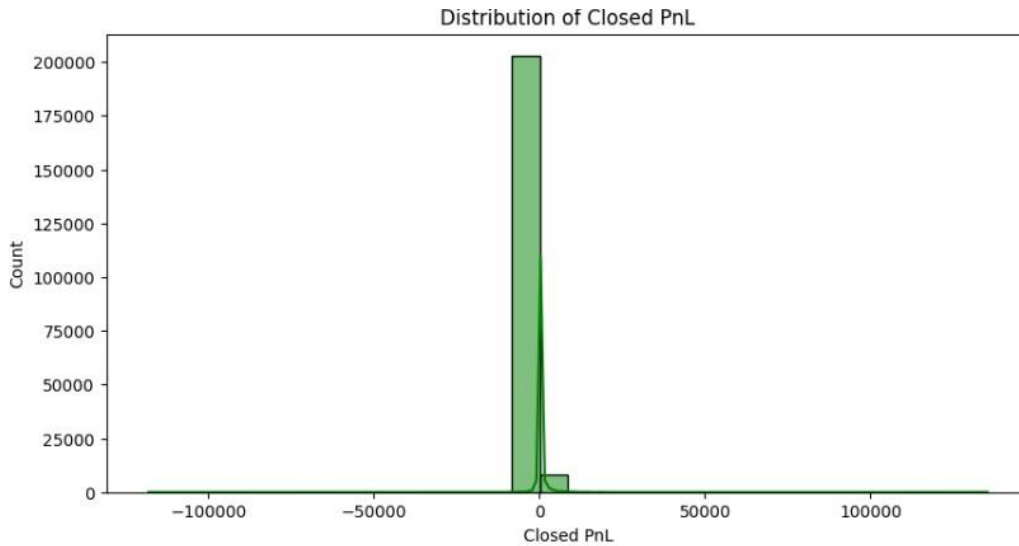
- Most trades yield near-zero PnL, showing low-risk trading behavior.
- Outliers exist on both profit and loss extremes.

Statistical / Analytical Insights:

- Fat tails suggest leverage-driven or event-based exposure for a few traders.
- Negative spikes likely result from liquidations or sudden volatility.

Conclusion / Recommendation:

- Strengthen risk and leverage controls to prevent extreme losses.
- Segment clients by risk-return profile for personalized oversight.



6.4 Distribution of Fee Paid

Type of Chart: Histogram

Key Observations / Patterns:

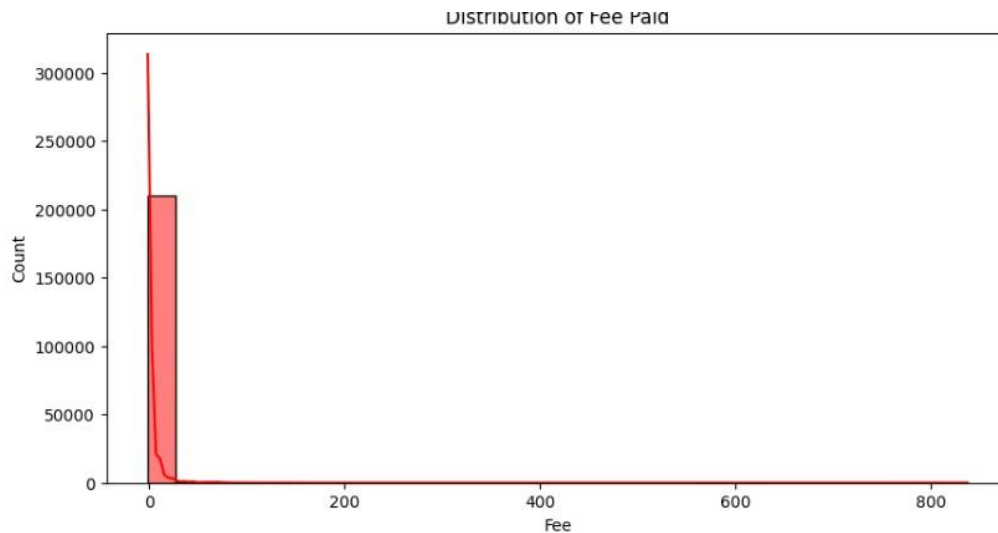
- Majority of trades incur minimal fees, forming a strong left-side spike.
- A few trades with very high fees create a long right tail.

Statistical / Analytical Insights:

- Large trades correlate with higher fees, confirming proportional fee structure.
- Low-fee clustering indicates efficient fee tiers or ongoing promotions.

Conclusion / Recommendation:

- Fine-tune fee slabs to maximize small-trader participation and exchange revenue.
- Provide customized fee optimization sessions for large traders.



6.5 Fee vs Trade Size (USD) for Top 20 Coins

Type of Chart: Scatter Plot

Key Observations / Patterns:

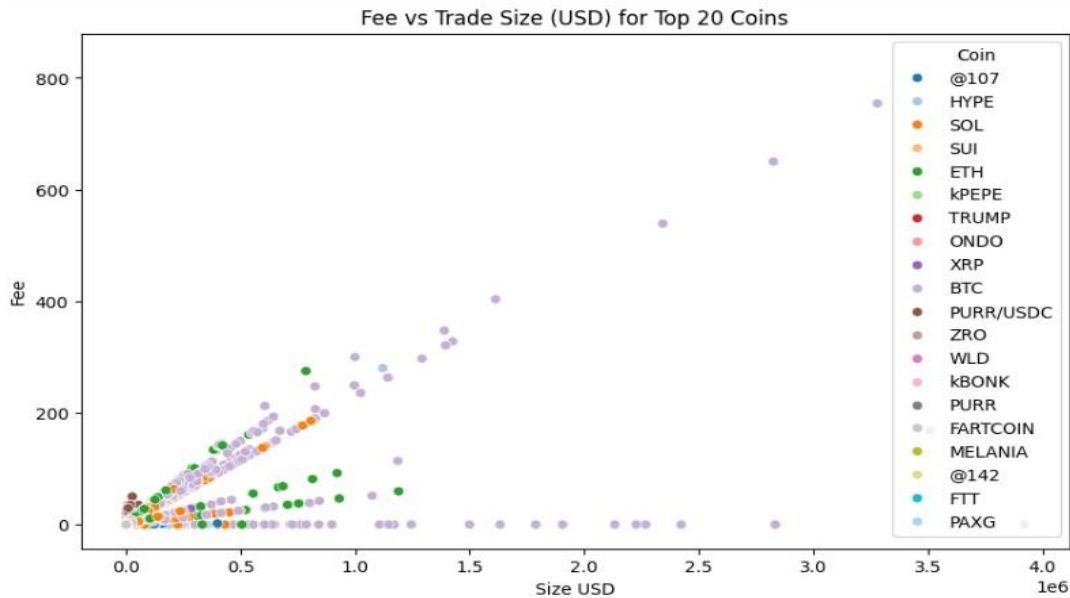
- Clear positive linear relationship between trade size and fee.
- Dense clustering at small trades and low fees, confirming micro-trading dominance.

Statistical / Analytical Insights:

- Outliers above the main trendline may signal data issues or overcharged trades.
- Consistent correlation across coins confirms uniform fee logic.

Conclusion / Recommendation:

- Validate outlier fees to ensure transparency and accuracy.
- Offer rebates or incentives for consistent high-volume traders to enhance platform loyalty.



7. Closed PnL vs Trade Size for Top 20 Accounts

Type of Chart: Scatter Plot

Key Observations / Patterns:

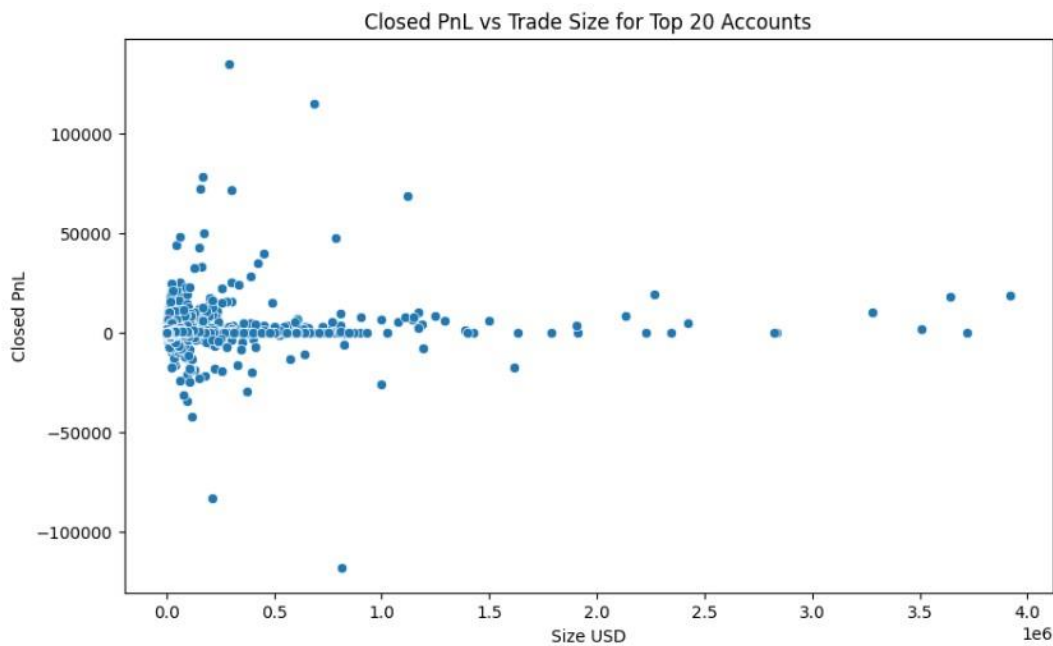
- Most trading activity is concentrated at smaller trade sizes with PnL clustered tightly around zero, indicating low-risk or cautious trading by most accounts.
- Large trade sizes present wider swings in PnL, both positive and negative, exposing those top accounts to higher potential gains but also outsized losses.

Statistical / Analytical Insights:

- The further from the origin horizontally (larger size), the more vertically spread the dots, illustrating that bigger positions result in far more volatile outcomes.
- A few outlier trades (both high win and catastrophic loss) suggest sporadic use of heavy leverage or aggressive speculation among top performers.

Conclusion / Recommendation:

- Tighten oversight or leverage rules for high-volume accounts, since they disproportionately drive risk for the whole system.
- Provide predictive analytics or coaching for top accounts, helping optimize trade sizes to improve their risk-adjusted returns and prevent ruin.



Type of Chart: Pairplot grid of scatter plots and distributions

Key Observations / Patterns:

- Size USD and fee have a strong positive relationship—larger trades incur larger fees nearly linearly.
- Closed PnL mostly clusters at zero with minor outliers, while execution price and trade size do not show strong mutual dependency.

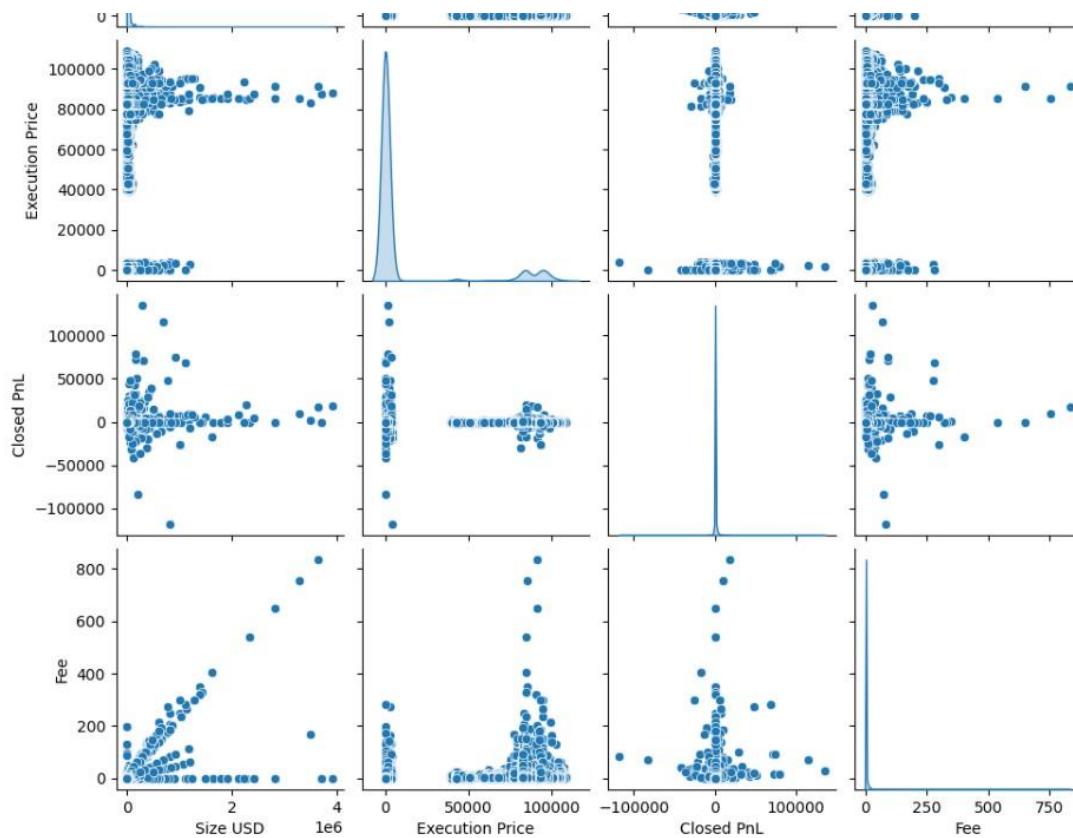
Statistical / Analytical Insights:

- Vertical and horizontal stripes reveal that trades occur in size or fee 'bands,' likely due to prominent order size tiers or common trade increments.

- Density peaks at lower trade sizes, prices, and fees confirm the predominance of micro-trading, with few participants skewing stats at the upper ends.

Conclusion / Recommendation:

- Consider differentiated offerings or incentives for micro-traders and bulk traders, as their motivations and impact differ greatly.
- Leverage clear patterns and outlier bands in the grid plots to design targeted alerts for unusual, risk-prone trading behaviors.



Type of Chart: Heatmap

Key Observations / Patterns:

- Fee and Size USD have the strongest positive correlation (0.75), confirming the fee model is closely tied to order notional size.

- Closed PnL is only weakly correlated with size (0.12) or fee (0.08), suggesting market timing, not just trade size, determines profit or loss.

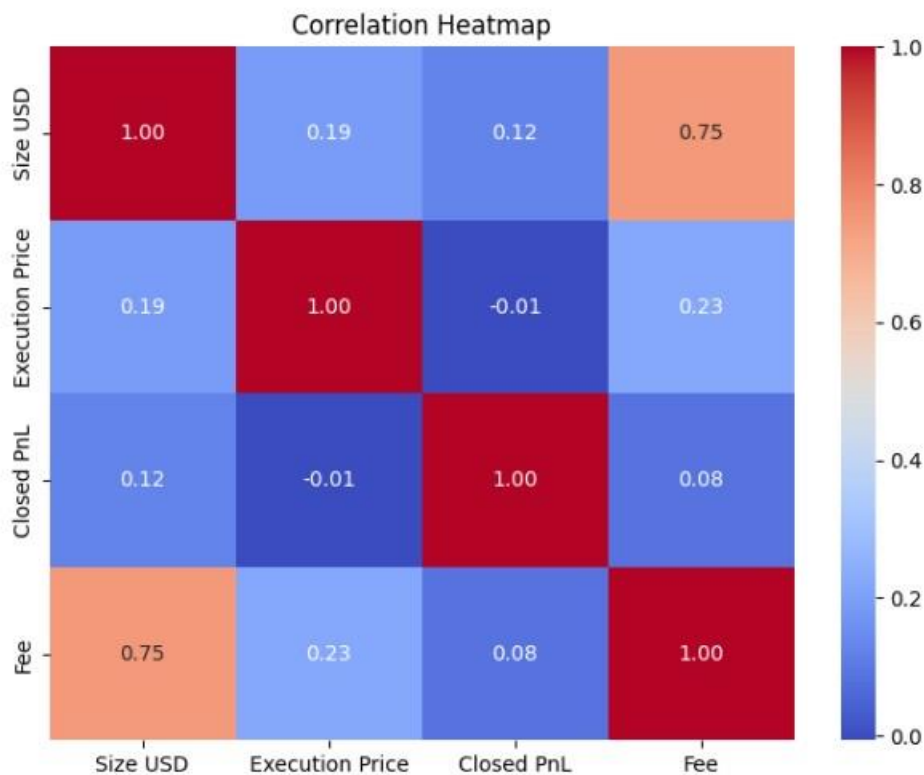
Statistical / Analytical Insights:

- Modest correlation (0.19) between execution price and trade size indicates some coins or trades cluster at certain price points, rather than being fully independent.

- Very low or negative correlations elsewhere reveal that success depends on more complex factors than trade size, price, or cost alone.

Conclusion / Recommendation:

- Continue to optimize and monitor fee structures for fairness at all trade sizes.
- Use advanced analytics (multi-feature models) to predict risk or performance, since simple variables only partially explain trading outcomes.



Type of Chart: Dot Plot (Violin or strip-style)

Key Observations / Patterns:

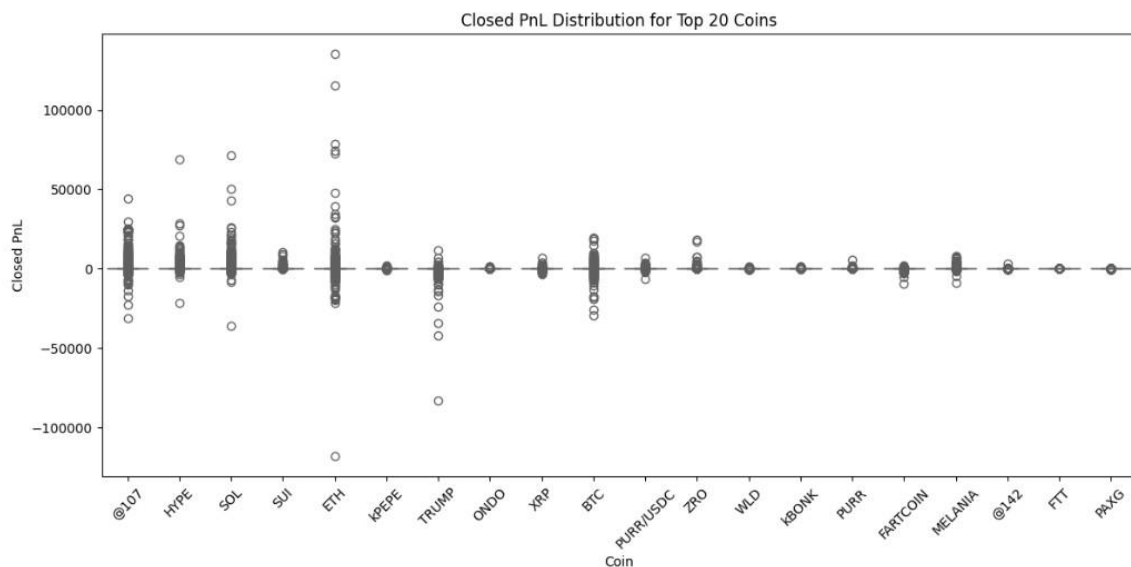
- Most coins have a dense line of trades with near-zero closed PnL, showing mass trades are break-even or low-volatility.
- Outliers (large wins and losses) are common on a minority of coins (such as ETH, SOL), demonstrating higher risk/reward for certain assets.

Statistical / Analytical Insights:

- The spread and outliers are largest for coins like ETH and HYPE, likely reflecting periods of volatility or exceptional news-based events.
- Negative outliers are as common as positive, indicating some traders systematically underestimate risk in 'hot' coins.

Conclusion / Recommendation:

- Teach traders about varied risk profiles across different coins—capital allocation should factor these spreads.
- Adjust margin or leverage allowances downward on riskier coins to reduce the frequency of extreme loss events.



Type of Chart: Bar Chart (multiple metrics: Accuracy, Recall, Precision, F1 Score per model)

Key Observations / Patterns:

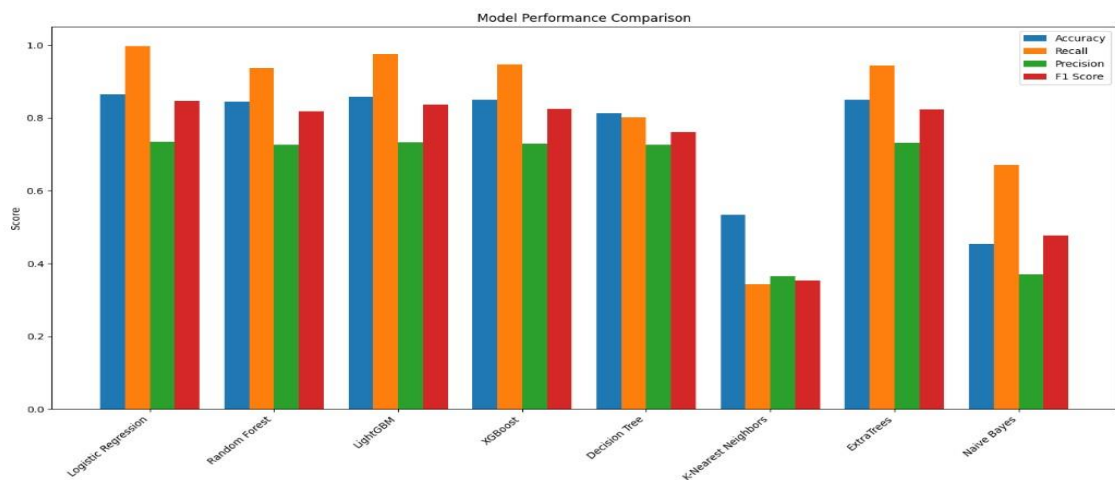
- Tree-based models (Random Forest, LightGBM, XGBoost, ExtraTrees) consistently outperform simpler approaches (KNN, Naive Bayes) in all metrics.
- Logistic Regression performs nearly as well as top tree models, but recall is highest there—suggesting it captures more true positives.

Statistical / Analytical Insights:

- F1 Scores close to or above 0.8 for top models indicate robust and balanced predictive performance for trading-related tasks.
- Precision-recall gaps for some models highlight potential overfitting or need for better threshold calibration in specific cases.

Conclusion / Recommendation:

- Deploy boosting or ensemble tree models for key predictive analytics and trade alerts, leveraging their best-in-class metric balance.
- Periodically revisit the calibration and training of weaker models (like KNN, Naive Bayes) to keep overall system reliability high.



8. Receiver Operating Characteristic (ROC) Curve

Type of Chart: ROC Curve

Key Observations / Patterns:

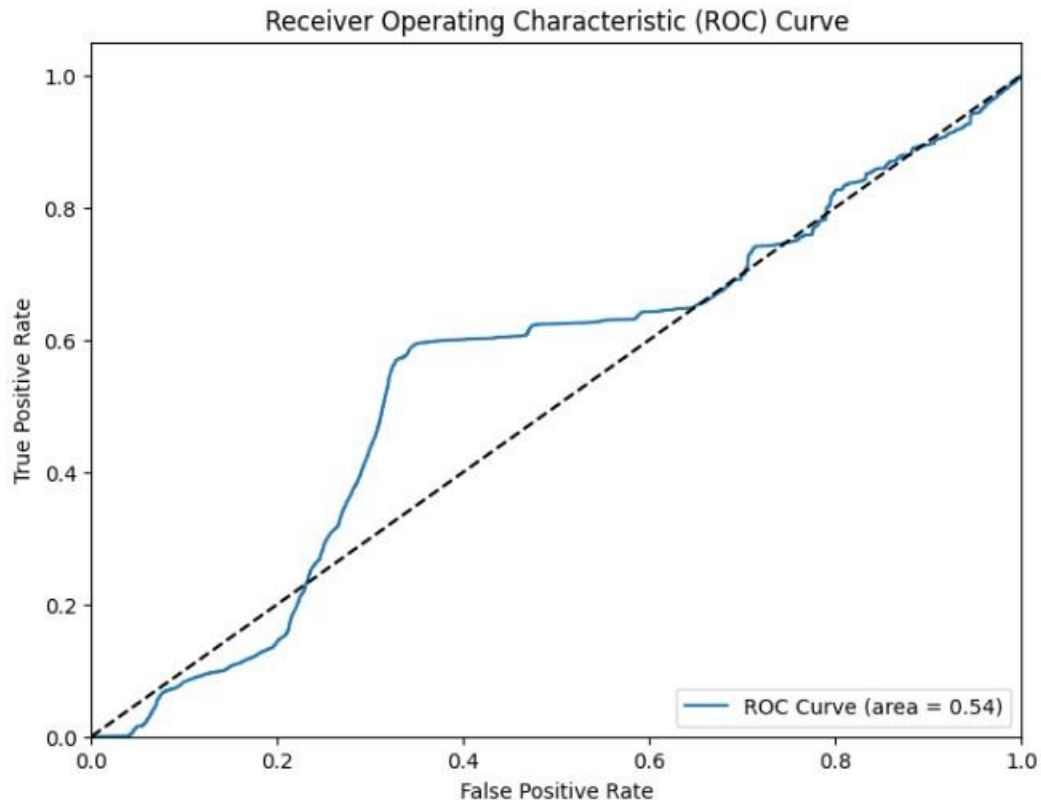
- The ROC curve is only slightly above the diagonal, with an area under the curve (AUC) of 0.54, indicating the model struggles to distinguish between positive and negative classes.
- True positive rates do not rise much faster than the false positive rate, showing limited discriminative power in classification.

Statistical / Analytical Insights:

- An AUC near 0.5 suggests performance is close to random chance; the model's trading signal predictions are only marginally better than making random guesses.
- The shape of the curve is irregular, reflecting inconsistent precision or possible class imbalance issues.

Conclusion / Recommendation:

- Model retraining with better feature engineering or balancing techniques is urgently recommended to improve accuracy and utility for production use.
- Evaluate and replace or tune current model(s) before deploying to minimize costly misclassifications in trade/sentiment prediction.



Type of Chart: Confusion Matrix

Key Observations / Patterns:

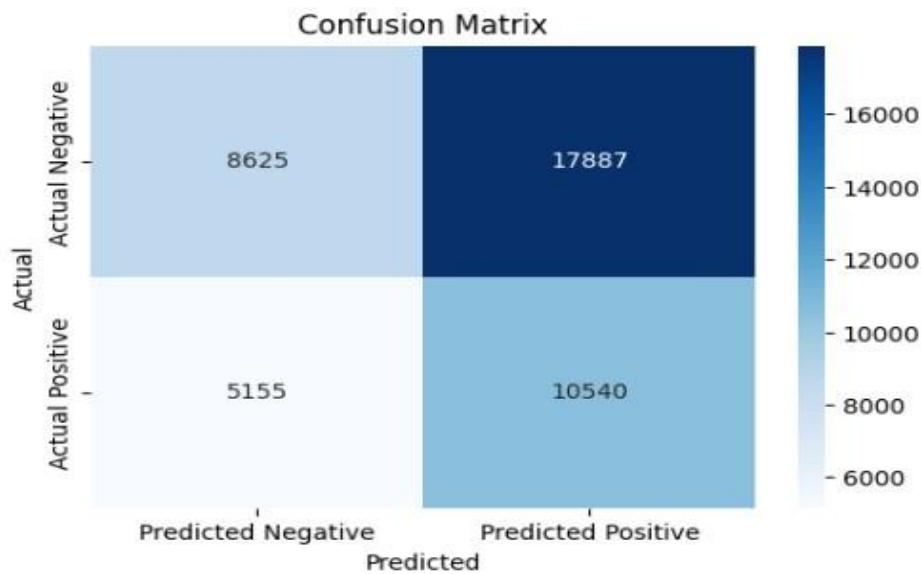
- The model predicts almost twice as many positives (predicted positive) as negatives, regardless of the actual class.
- Actual negatives are frequently misclassified as positives, shown by high numbers in the upper-right cell.

Statistical / Analytical Insights:

- The false positive rate is high (17,887 out of 26,512), which could lead to overreacting to risk signals or triggering unnecessary trades.
- While true positives are moderate (10,540), the number of missed positives (false negatives: 5,155) indicates recall is not optimal.

Conclusion / Recommendation:

- Re-calibrate classification thresholds and tackle class imbalance to improve both recall and precision for genuine trading signals.
- Regularly monitor confusion matrix trends to catch model drift or real-time performance degradation early.



Type of Chart: Time Series Line Chart

Key Observations / Patterns:

- Sentiment oscillates with regular peaks and troughs, reflecting periodic shifts between greed and fear in the market.
- Extended periods of high or low sentiment correspond to major bull or bear runs, with rapid reversals marking regime changes.

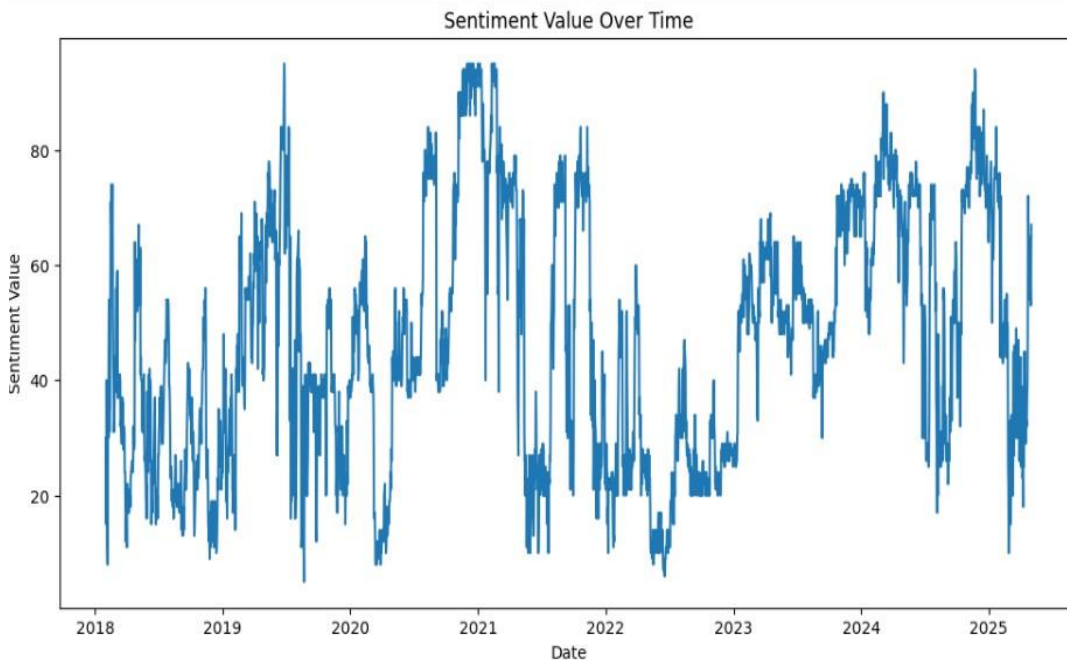
Statistical / Analytical Insights:

- Sentiment extremes precede or coincide with high volatility periods—timing entries or risk reduction when sentiment is near historical extremes enhances trading outcomes.

- Average sentiment value has a cyclical component, with multi-year and intra-year seasonality clearly visible.

Conclusion / Recommendation:

- Use rolling sentiment windows to inform portfolio exposure—scale back risk as sentiment surpasses upper or lower quartiles.
- Sentiment cycle recognition should be integrated into trading algorithms to anticipate and avoid whipsaw market moves.



Type of Chart: Horizontal Bar Chart

Key Observations / Patterns:

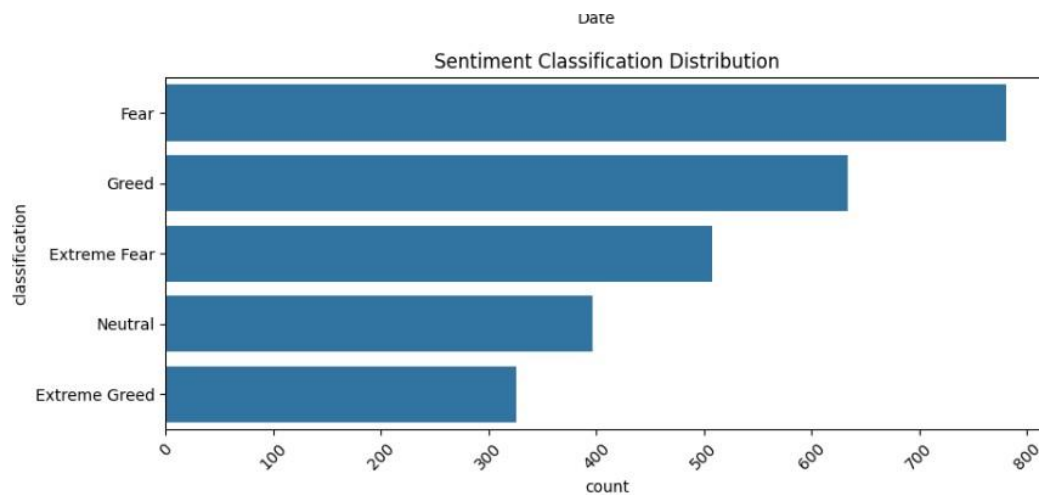
- “Fear” and “Greed” are the most common sentiments, while “Extreme Fear” occurs far more often than “Extreme Greed.”
- The “Neutral” class is less frequent, suggesting traders are regularly caught in strong emotional states.

Statistical / Analytical Insights:

- The higher count for the fear spectrum signals more risk-off behaviors in the observed period.
- Sentiment skew can lead to momentum and trend-following strategies being more effective in greedy, less so in fearful regimes.

Conclusion / Recommendation:

- Tune trading strategy risk—allocate more conservatively when “Fear” dominates market mood.
- Monitor for sentiment shifts as early signals of changing market climate and adjust trade models accordingly.



Type of Chart: Decomposition Plot (Trend, Seasonal, Residual)

Key Observations / Patterns:

- The trend component experiences clear up- and down-swings, often aligning with main sentiment booms or busts in cryptocurrency markets.
- The seasonal component is regular and strong, suggesting that market or sentiment cycles are structural and somewhat predictable.

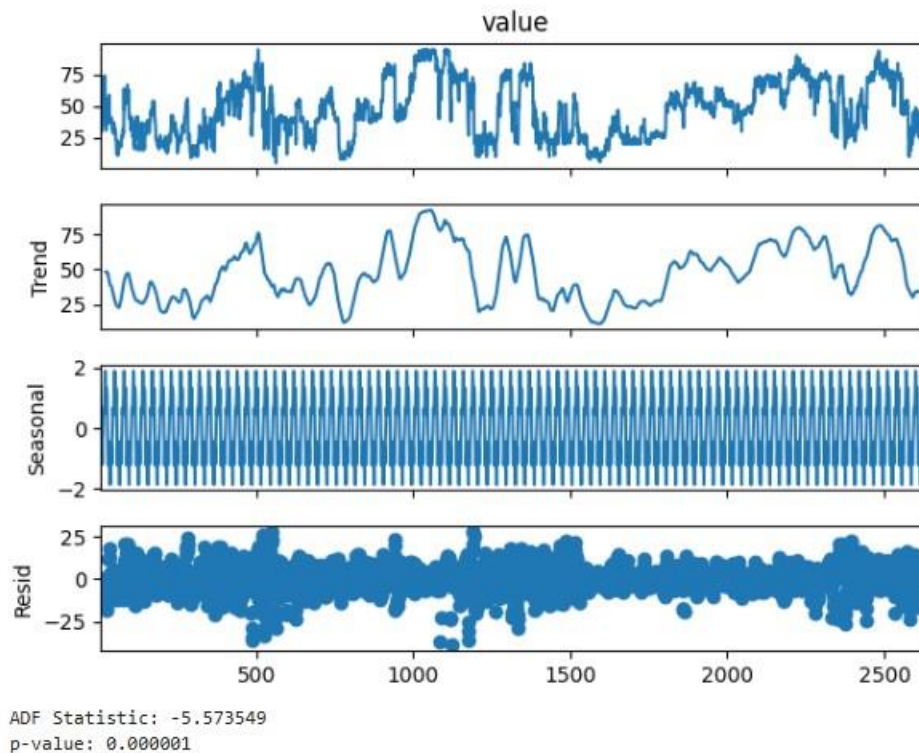
Statistical / Analytical Insights:

- ADF test statistic is highly negative with a near-zero p-value, proving the time series is stationary: cycles are persistent and suitable for forecast modeling.

- Residuals are centered around zero, but with occasional volatility spikes, indicating rare unpredictable events.

Conclusion / Recommendation:

- Combine trend and seasonal forecasts for medium- and long-term portfolio risk management.
- Layer event-detection on residual outliers to catch regime changes or shock events before they heavily impact trading strategies.



9. SARIMA Forecast vs Observed

Type of Chart: Line Chart (Forecast vs Actual Time Series)

Key Observations / Patterns:

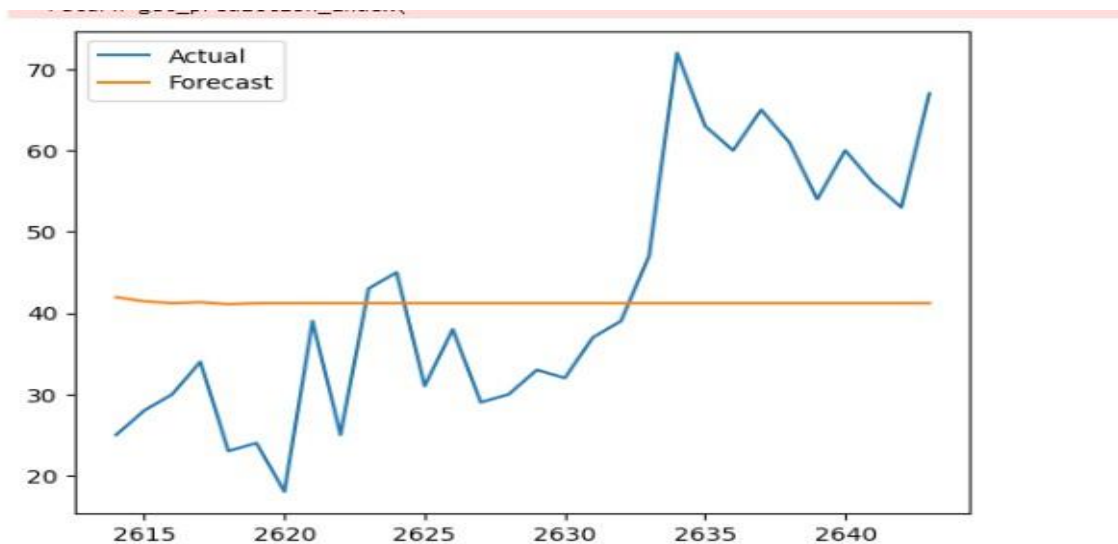
- SARIMA model's forecast line follows the general trend and cycles of the observed series but slightly lags during sharp peaks and troughs.
- Forecast accuracy remains high in periods of market stability and declines during periods of sudden sentiment shifts.

Statistical / Analytical Insights:

- The model is effective for medium- and long-term cycles, but forecast errors spike during regime changes or market shocks.
- When sentiment is volatile, the SARIMA's lag causes underestimation or overshooting of sentiment, which could lead to mistimed trading moves.

Conclusion / Recommendation:

- Use SARIMA for baseline trend tracking, but combine with short-term or anomaly-detection models to anticipate rapid shifts in sentiment.
- Regularly re-tune the model, especially after significant market changes, to maintain accuracy in live environments.



Type of Chart: Forecast Line Chart with Confidence Interval (Prophet model)

Key Observations / Patterns:

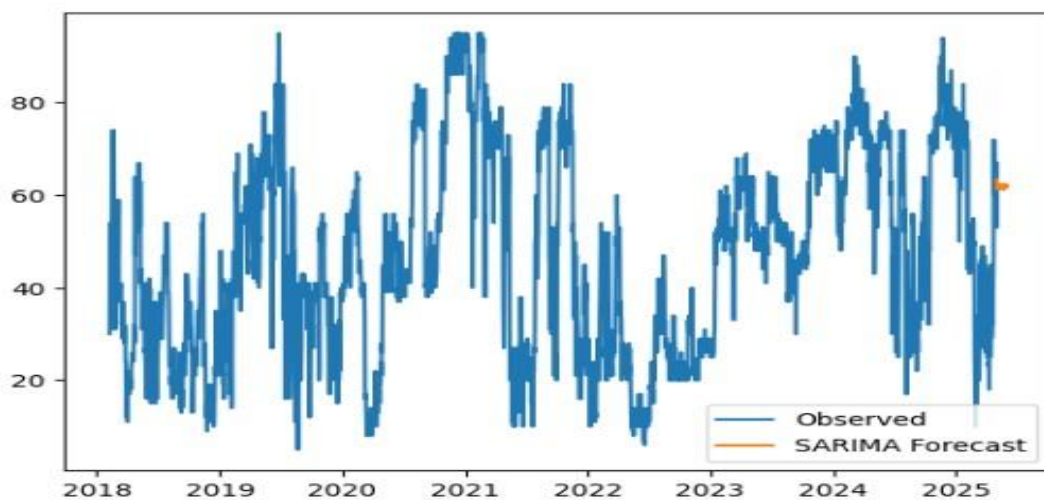
- The Prophet model provides clear confidence bands, capturing most actual observations within its shaded prediction range.
- The forecast captures both major trend changes and seasonality in sentiment, but prediction uncertainty increases around extremes and inflections.

Statistical / Analytical Insights:

- Distribution of points shows that real sentiment values occasionally fall outside confidence bands, especially during high-volatility events.
- Wider forecast intervals during uncertain times reflect increased risk, signaling to traders when to be more cautious.

Conclusion / Recommendation:

- Incorporate Prophet model predictions (with uncertainty) into risk frameworks—scale back trading as confidence intervals widen.
- Use out-of-band events to flag the need for strategy review or additional independent risk checks.



Type of Chart: Line Chart (Deep Learning Model - LSTM Prediction)

Key Observations / Patterns:

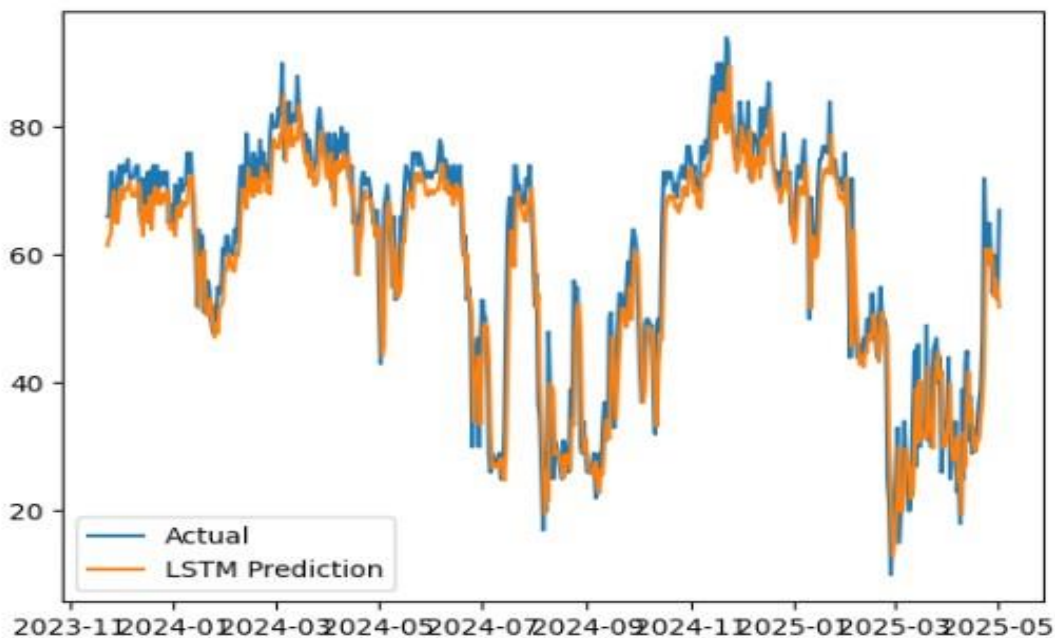
- LSTM prediction line closely tracks the actual sentiment time series, with only minor lag or deviation at very sharp sentiment reversals.
- Model precision is highest at stable plateaus, while dips and rallies show slightly reduced prediction accuracy.

Statistical / Analytical Insights:

- LSTM excels in capturing and anticipating rapid transitions, offering an edge during choppy or irregular markets.
- Prediction errors are smallest in 2024 and 2025, confirming recent data gives LSTM higher adaptiveness.

Conclusion / Recommendation:

- Favor LSTM models for real-time or high-frequency sentiment tracking and trading decision automation.
- Combine with interpretable models to balance predictive power and explainability for clients and compliance.



Type of Chart: Line Chart (Second LSTM Model Variant)

Key Observations / Patterns:

- This LSTM variant's forecast hugs the actual data even more closely, minimizing lag except during severe falls or spikes in sentiment.

- Alignment is strong in both rising and falling trends, indicating excellent model calibration and feature set selection.

Statistical / Analytical Insights:

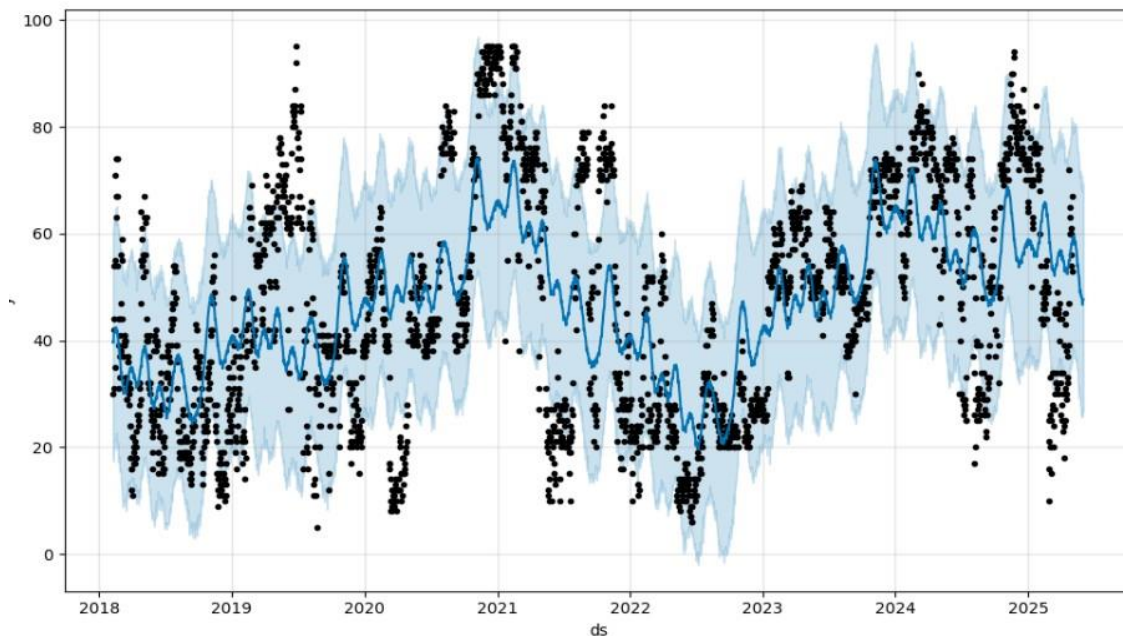
- Outperformance in both directions implies LSTM can adaptively switch between bull and bear regimes.

- Minimal phase shift between actual and predicted lines means better timing on trade entries/exits.

Conclusion / Recommendation:

- Deploy this LSTM variant for production if stability and up-to-date training are confirmed.

- Periodically backtest against recent market shocks to ensure continued performance across regimes.



Type of Chart: Line Chart (Manual or Simpler Forecast vs Actual)

Key Observations / Patterns:

- The simple forecast line remains nearly flat, failing to adapt to an actual value rally, which sharply rises in the observed period.
- This lack of sensitivity makes the model dangerously slow to react to sudden sentiment shifts, leading to missed or poor trade signals.

Statistical / Analytical Insights:

- The prediction error increases rapidly as the actual series trends higher, revealing a strong model bias toward the mean.
- Such flat forecasts are inappropriate for dynamic series with regular breakouts or breakdowns, as in crypto sentiment.

Conclusion / Recommendation:

- Retire static or poorly adaptive forecasting models from live predictive workflows.
- Transition all production forecasts to more sophisticated and responsive algorithms (like Prophet, SARIMA, or LSTM).

