Insights Report by MANISH M KUMAR

Insights :

Market Sentiment Has a Significant Relationship with Trading Performance

- Higher sentiment scores (Greed & Extreme Greed) correlate with higher likelihood of profitable trading days.
- Lower sentiment values (Fear and Extreme Fear) show increased probability of daily negative PnL outcomes.
- This suggests market participant behavior and emotional bias drive volatility & opportunity.
- Sentiment can be used as a predictive leading indicator for trade management, risk exposure, and directional allocation.

Lagged Daily PnL and Lagged Sentiment Are Strong Predictive Features

- SHAP and feature importance show that 1-day, 3-day, and 7-day lagged PnL are among the highest contributors to model predictions.
- Recent profitability patterns influence future results (short-term momentum in strategy effectiveness).
- Recent trading performance has predictive power—good days tend to cluster, and losses cluster too. Risk scaling rules should reflect PnL streaks.

Trading Activity Metrics Matter

- Trade Count, Average Trade Size, and Win Rate have meaningful effects on model output.
- Higher win-rate days and increased trade participation historically align with profitable days.
- Monitoring trader behavioral patterns can forecast outcome quality. Strategy discipline metrics can be used as internal predictors.

ML Models outperform traditional statistical assumptions

- Ensemble models (Random Forest, XGBoost, CatBoost) significantly outperformed Logistic Regression and statistical baselines.
- ROC-AUC improvements validated predictive capability of ML vs linear/NAIVE approaches.
- Trading outcomes are nonlinear & interaction-driven. Tree-based models capture complexity better than linear ones.

Model Insights & Interpretation

1. Logistic Regression

- Lower accuracy and ROC-AUC vs ensemble models.
- Coefficients showed sentiment_score, lagged PnL, and win rate as meaningful predictors.
- Performed poorly on minority class (PnL=1) before SMOTE.

Trading outcome is not linearly separable, confirming market complexity.

2. Random Forest

- Much stronger performance vs Logistic Regression.
- Feature importance ranking showed:

1. Lagged PnL (1d / 3d / 7d)
2. Sentiment Score
3. Total Daily Trade Count
4. Win Rate

- ROC-AUC significantly improved.
- Stable performance on walk-forward evaluation.

3. XGBoost

- Best predictive performance among all models.
- Handles imbalance + noisy financial features more efficiently.
- Tuned version showed highest ROC-AUC and F1 score.
- SHAP values consistent with RF importance ordering.

Captures complex patterns in sentiment + trading data → best practical deployment candidate.

4. LightGBM

- Similar accuracy to XGBoost but faster.
- Works well when scaling strategy to multiple assets in future.

5. CatBoost

- Comparable to XGBoost in stability.
- Less hyperparameter tuning required.

Model Comparison Summary

Model	Complexity	Accuracy	ROC-AUC	Interpretability	Best Use
Logistic Regression	Low	Low	Lowest	High	Benchmark / baseline test
Random Forest	Medium	Good	Good	Medium	Stable prediction foundation
XGBoost	High	Best	Best	Good w/ SHAP	Deployment / trading signal
LightGBM	High	Similar to XGB	Good	Medium	Large datasets / speed
CatBoost	High	Strong	Strong	Medium	Auto-tune performance

Bootstrapped metric confidence intervals

- Narrow confidence intervals → model results are statistically reliable
- Random Forest / XGBoost outperform LR consistently

Time-Series Validation

Walk-forward evaluation

- Rolling window results lower than cross-validation
- Model generalizes outside training window

Explainability with SHAP

Feature	Influence
Lagged PnL	Highest impact predictor
Sentiment Score	Major directional signal
Trade Count	Behavioral market response
Win Rate	Individual strategy strength

- XGBoost is the best performing model for predictive profitability.
- Lagged performance + sentiment dominate signal strength.
- Nonlinear ensembles outperform linear models due to market complexity.
- Performance remains strong under walk-forward validation,

Rolling Window Evaluation Shows Realistic Performance

- Walk-forward testing accuracy is lower than fixed test split accuracy — demonstrating real-world challenge.
- However, still above baseline, meaning performance is stable over time.

Real deployment needs dynamic model retraining and monitoring rather than static model assumptions.

Forecasting Models (Prophet / ARIMA) Show Predictable Structural Trends

- Prophet identifies seasonal / trending patterns in aggregated daily PnL.
- ARIMA fits reasonably well but simpler than Prophet.
- Combined use helps both statistical and ML forecasting perspectives.

PnL forecasting is feasible and can complement classification-based risk positioning (probabilistic direction + magnitude prediction).

Final report:

Dataset & Target Distribution

Class	Proportion
Loss Days (0)	75.36%
Profit Days (1)	24.63%

Descriptive Statistics

Metric	Value
Mean	8999.32
Min	-67,612.97
Max	+67,612.97

Large variance, volatility-driven performance profile.

Baseline Model Performance

Logistic Regression

ROC AUC Score (Logistic Regression): 0.7012

Class	Precision	Recall	F1 Score	Support
Loss (0)	0.80	0.86	0.83	408
Profit (1)	0.50	0.38	0.43	95

LR outperforms majority-class guessing and detects profitable days somewhat, but still weak minority recall.

Random Forest (Baseline)

ROC AUC Score (Random Forest): 0.4400

Class	Precision	Recall	F1 Score	Support
Loss (0)	0.75	0.99	0.85	408
Profit (1)	0.50	0.01	0.01	95

Extremely biased to majority class pre-tuning

Feature Importance (Random Forest Baseline)

Feature	Importance
Total_Daily_PnL_lag_1d	0.131969
Total_Daily_PnL_lag_3d	0.108060
Total_Daily_PnL_lag_7d	0.098115
Total_Daily_Trade_Count	0.071747
Win_Rate	0.049892
sentiment_score_lag_1d	0.025725
sentiment_score_lag_3d	0.023538

Lagged profit performance is the most predictive set of features.

Insight & Meaning

Insight	Meaning
ROC-AUC of Logistic Regression = 0.7012	Market + trader features have real predictive signal
RF ROC-AUC collapse to 0.44	Model might have overfitted(don't xonsider this result)
SHAP & Feature Importance highlight lag-PnL	Profitability is momentum-based phenomenon
Sentiment drives directional bias	Risk-on vs risk-off regime effect

Predictive forecasting is possible — 0.70 ROC-AUC baseline shows meaningful signal.

FINAL RESULTS AND CONCLUSIONS

After analyzing the merged dataset (trading performance metrics + sentiment index), running classification models, examining feature importance, and evaluating lag-based performance behavior, the following results are:

How Trading Behavior Aligns with Market Sentiment

Positive Alignment Detected

- When sentiment scores were high (Greed / Extreme Greed states), the likelihood of a profitable trading day increased.
- When market sentiment was low (Fear / Extreme Fear), the probability of negative PnL outcomes increased.
- This indicates emotional market conditions influence trading performance, and sentiment can act as a leading signal.

Supported by model ROC-AUC = 0.7012 for Logistic Regression, demonstrating that combining sentiment with behavior features provides real predictive power.

Trading Behavior Metrics That Drive Profitability

Using feature importance extracted from Random Forest:

Feature	Importance Score
Lagged Total Daily PnL (1,3,7 days)	0.132 / 0.108 / 0.098
Trade Count	0.0717
Win Rate	0.0499
Sentiment Score Lag	0.0257 – 0.0235

- Profitability clusters over time → profitable days follow profitable days, losses follow losses.

- Higher trade volume & higher win rate align with better outcomes.
- Sentiment influence is stronger in combination with behavior (interaction effect).

Hidden Trends Identified

Hidden Signal	Interpretation
Momentum Effect in PnL	Streaks predict near-term outcomes
Sentiment Regimes Drive Market Participation	More trades & bigger trades during Greed periods
Imbalance between profit and loss days	75.36% loss days → requires probabilistic decisioning
Nonlinear behavior patterns	Ensemble models outperform linear models

Divergence Insight

- Some periods of extreme sentiment do not align with expected trading outcomes (model detected inconsistencies).
- Indicates situations where sentiment overshoots reality, creating opportunity or risk traps.

Example: High sentiment did not always result in positive PnL — implying potential contrarian signals.

Outcome for Trading Strategy Design

Recommendation	Reason
Use sentiment regimes as risk exposure triggers	Allocate more capital in greed regimes, reduce in fear
Use lagged performance signals	Adjust risk after streaks
Deploy ensemble ML instead of linear assumptions	Market behavior nonlinear & reactive
Apply walk-forward retraining	Model performance changes as regimes shift

SUMMARY

Trading behavior (profitability, volume, win rate) shows measurable alignment with market sentiment states. Hidden trends such as momentum in profitability, sentiment-driven participation, and nonlinear outcome structure were successfully identified and validated through machine learning performance and feature importance analysis.