# AI Trading Signal Prediction
# Technical Evaluation & Trading-Oriented Report

## 1. Model Choice Justification

This system was designed around a **dual-model architecture**, separating **profit realization (target hit)** from **risk control (stop hit)**.
This design choice was driven by empirical evidence showing that **the factors leading to profitable trades differ significantly from those leading to losses**.

Rather than optimizing for accuracy, models were selected using **trading-relevant evaluation metrics**, prioritizing precision, stability, and probability reliability.

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### 1.1 Target-Hit Model

The objective of the target-hit model is to **identify high-quality entry signals** with a strong likelihood of reaching the profit target.

- **Model Selection Process**

  Multiple models were trained and evaluated, including **Logistic Regression, Random Forest, XGBoost**, and **LightGBM**. Each model was assessed

  - Precision, Recall, and F1-score
  - Precision@K (top-confidence trades)
  - Train–Validation stability (F1 gap)
  - Probability calibration

- **Why Accuracy Was Not Used**

  In trading, accuracy can be misleading due to class imbalance.
  A model can achieve high accuracy simply by predicting "no trade," while still being useless for real decision-making.

- **Final Model Choice**

  A **Random Forest (calibrated)** model was selected as the final target-hit model due to:

  - **High precision on unseen test data (0.82)**, meaning most executed trades were profitable.
  - **Exceptional Precision@K performance**:

    - Precision@5% ≈ **97%**
    - Precision@10% ≈ **87%**
- **Balanced recall (~55%)**, intentionally allowing missed opportunities to avoid low-quality trades.
- **Low generalization gap (F1 gap ≈ 0.07)**, indicating strong out-of-sample stability.

This demonstrates that the model prioritizes **trade quality over trade quantity**, which is essential in real trading environments.

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### 1.2 Stop-Hit Model

The stop-hit model serves a different purpose: **risk filtering**, not trade selection.
Its role is to identify **only the most dangerous signals** where entering a trade would have an unusually high probability of loss.

- **Class Imbalance Consideration**

  Stop-hit events are rare, resulting in severe class imbalance.
  This makes recall less important than precision.

- **Evaluation Philosophy**

  For stop prediction:
    - **False positives are unacceptable** (blocking good trades is costly).
    - **Low recall is acceptable** if precision is extremely high.

- **Final Model Choice**

  A **calibrated XGBoost model** was selected because it achieved:

    - **Precision = 1.00 on test data**, meaning no good trades were blocked.
    - **Zero false positives** at the chosen threshold.
    - The highest PR-AUC among stable candidates, indicating meaningful risk discrimination.
    - Well-calibrated probabilities after isotonic calibration.

The model is intentionally conservative and only triggers when risk is exceptionally clear.

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### 1.3 Trading Impact Assessment

Based on the evaluation results:
- **Losing trades are reduced** by filtering high-risk entries using the stop-hit model.

- **Bad signals are filtered** by the target-hit model's high precision and confidence thresholds.
- The system favors fewer, higher-quality trades with positive expected value.

**Trust in Real Trading**

This system is suitable for **decision support and semi-automated trading**, provided that:
- Risk limits are enforced
- Models are periodically retrained
- Execution slippage is monitored

It is not intended to operate as a fully autonomous trading system without human oversight.

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## 2. Feature Importance Analysis

Feature importance was analyzed using SHAP values to ensure interpretability and trading relevance.

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### 2.1 Target-Hit Model Drivers

The most influential features for target-hit prediction include:
- Candle body size
- Closing price position
- Price ratios relative to recent ranges
- Moderate volume confirmation

**Interpretation**

The model primarily captures **trend continuation and structural strength**.
Large candle bodies and supportive closing prices signal sustained momentum rather than random volatility.

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### 2.2 Stop-Hit Model Drivers

The stop-hit model relies heavily on:
- Upper wick length
- Wick-to-body ratio
- High–low range ratios
- Overall candle volatility

**Interpretation**

These features represent **price rejection and instability**, commonly associated with false breakouts and sharp reversals.

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### 2.3 Key Structural Insight

The feature importance results confirm a critical trading insight:

> **Profitability is driven by market structure and momentum, while risk is driven by volatility and price rejection.**

This validates the decision to separate profit and risk modeling into two distinct systems.

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## 3. Risks and Limitations

Despite strong empirical performance, the system faces several practical and structural limitations common to real-world trading systems. The following risks were identified along with their mitigation strategies:

| Category | Description | Impact / Mitigation |
|---|---|---|
| Data Bias & Coverage | Models were trained on a limited historical window and a fixed set of instruments. | Periodic retraining and validation across multiple symbols and market conditions are recommended. |
| Class Imbalance | Positive events (target hit / stop hit) represent a minority of samples. | Addressed using class_weight='balanced' instead of artificial resampling to preserve true market distributions. |
| Temporal Leakage Risk | Risk of implicit future information through timestamps or derived time-based features. | Mitigated by removing time-based identifiers (e.g., time_bin, created_at) and validating on strictly forward (time-based) splits. |

| | | |
|---|---|---|
| Market Regime Shift | Model behavior may degrade during volatility regime changes or macroeconomic events. | Deployment should include rolling retraining and regime-aware performance monitoring. |
| Backtest Over-Optimism | Reported backtest ROI (e.g., ~68k%) reflects idealized assumptions and compounding effects. | Results should be interpreted as relative performance indicators, not directly as realizable cash returns. |

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## 4. Evaluation Metrics Rationale

**Accuracy** was intentionally de-emphasized due to strong class imbalance and asymmetric trading costs.
In trading systems, false positives and false negatives do not carry equal financial impact.

- **Precision**:
  Used as the primary metric to ensure that executed trades have a high probability of success, directly protecting capital.

- **Recall**:
  Monitored to understand opportunity coverage, but intentionally sacrificed in favor of higher precision.

- **F1-Score:**
  Used to assess overall balance while monitoring overfitting through train–validation gaps.

- **Precision@K:**
  Applied to simulate real trading behavior, where only top-confidence signals are executed.

- **Confusion Matrix:**
  Used to analyze error types explicitly, particularly false positives in stop-loss prediction.

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# Conclusion

This project demonstrates a **trading-first machine learning approach**, where model decisions are justified by **economic impact rather than raw metrics**.

The combination of:

- High-precision entry filtering
- Conservative risk blocking
- Interpretable feature behavior

results in a system that is **practically deployable**, **risk-aware**, and **aligned with real trading objectives**.