Machine Learning Based Early Warning System for Risk Management

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- **PPT for**: Trimester 7 Internship Report

Introduction

The Challenge: Financial markets are driven by both quantitative price dynamics and qualitative news flows.

The Gap: Traditional metrics like Volatility or Value at Risk (VaR) ignore news, while pure sentiment systems often lack market-derived risk grounding.

The Solution: An integrated early warning system (EWS) that combines:

- Internal Market Data: OHLCV price history.
- External News Data: Real-time sentiment analysis via Gemini API.

Problem

Problem Statement: To design an EWS that classifies trading days into discrete risk levels (Low, Medium, High) accurately.

Core Objectives:

- Collect and preprocess historical data (Amazon/AMZN) using yfinance.
- Engineer "time-series-safe" features using expanding-window statistics.
- Train a multinomial logistic regression pipeline for risk classification.
- Integrate Google Gemini API for structured news sentiment extraction.
- Deploy an interactive dashboard via Streamlit.

System Architecture

Workflow Overview:

- **Data Acquisition**: Yfinance for OHLC market data.
- **Feature Engineering**: Computation of Volatility, VaR, and Sharpe Ratio.
- **Risk Labeling**: A novel rule-based scoring mechanism using distribution quantiles.
- **Modeling**: Multinomial Logistic Regression with L2 Regularization.
- **External Analysis**: News extraction and JSON-structured analysis via Gemini API.

Feature Engineering and Risk Labeling

Time-Series-Safe Features:

- Computed using expanding windows to prevent data leakage.
- Annualized Volatility (σann)
- 95% Value at Risk (VaR): Empirical 5th percenti of past returns.
- Sharpe Ratio: Reward-to-variability ratio.

Risk Scoring Logic:

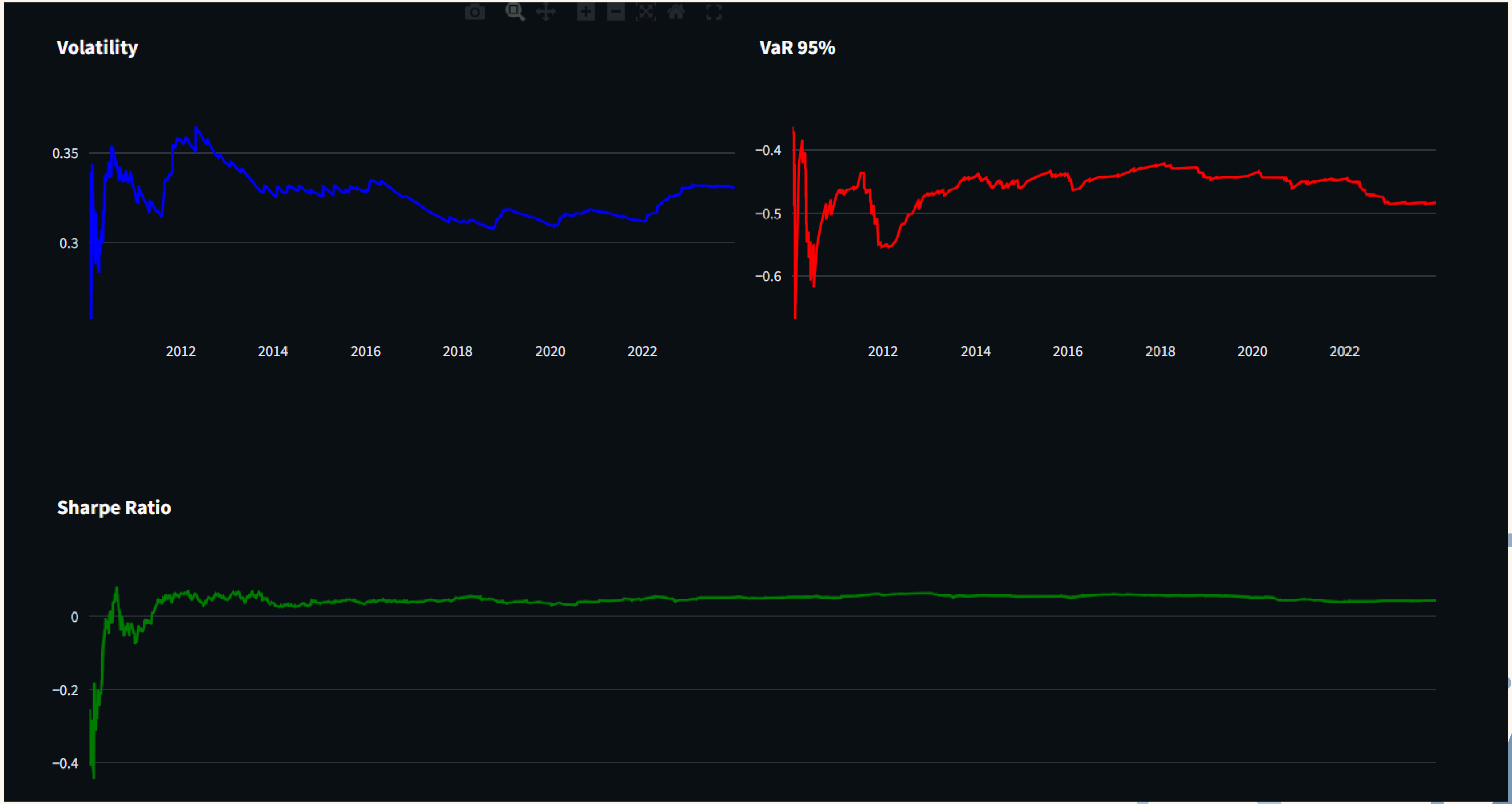
- High Volatility: >75th percentile (+2 points).
- High VaR: Potential loss <−2% (+2 points)
- Negative Sharpe: (+1 point).
- Classes: Low (<2), Medium (2≤score<4), High (≥4).

Experimental Results

Dataset: 3,522 daily observations for AMZN (2010–2023).
Training Protocol: 80/20 chronological split (no random shuffling to maintain time integrity).

Test Metrics:
Accuracy: 0.808
Weighted Precision: 0.918
Weighted Recall: 0.808
F1-Score: 0.835
Insight: The model handles class imbalance effectively, showing high precision for identifying high-risk days.

Visualisations



Conclusion

Conclusion: Successfully built a robust, explainable EWS that combines market data with LLM-based sentiment.

Key Contributions:

- Elimination of look-ahead bias through expanding windows.
- Novel risk-scoring mechanism based on distribution-aware quantiles.
- Practical LLM integration for qualitative risk monitoring.

Thank you