AI-Powered News and Sentiment Analysis Engine

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***Abstract*—The financial markets are increasingly driven by rapid information dissemination, where macroeconomic announcements and social media sentiment trigger significant price volatility. Traditional trading systems often rely on lagging technical indicators or general-purpose language models that lack financial nuance and exhibit high latency. This paper presents an AI-powered news and sentiment analysis engine designed for high-frequency trading (HFT) environments. The proposed system utilizes a four-layer architecture—comprising a Planner, a Selenium-primed Reporter, a FinBERT-based Analyst, and a Risk-aware Trader—to achieve sub-second execution during high-impact events such as US Consumer Price Index (CPI) and Non-Farm Payroll (NFP) releases. By employing a T-5 Selenium priming technique and fine-tuned FinBERT scoring, the engine effectively captures and processes sentiment shifts in real-time. Experimental results demonstrate that the hybrid approach significantly outperforms traditional technical-only bots and general-purpose LLM agents, achieving win-rates of up to 90.1% during extreme cryptocurrency price flashes and robust performance across major forex pairs. The system maintains an end-to-end latency of under 500 milliseconds, validating its efficacy in low-latency financial environments.**

***Index Terms*—FinBERT, Sentiment Analysis, Selenium Priming, High-Frequency Trading, Macroeconomic News, Cryptocurrency, US CPI, NFP, LSTM, Hybrid Deep Learning.**

I. Introduction

In the contemporary landscape of algorithmic trading, the arrival of new information is the primary catalyst for price discovery and market volatility. High-impact macroeconomic events, particularly the US Consumer Price Index (CPI) and Non-Farm Payroll (NFP) reports, as well as rapid sentiment shifts in the decentralized cryptocurrency markets, create windows of extreme price action and liquidity shocks. For market participants, the ability to decode the sentiment of these releases and execute directional trades within the first second of publication is no longer just an advantage—it is a necessity for survival in high-frequency trading (HFT) environments.

Traditional automated trading systems, predominantly based on technical analysis (TA), utilize historical price and volume data to generate signals. While these systems are efficient for trend-following or mean-reversion in stable regimes, they are fundamentally “blind” to the qualitative shocks introduced by News. When a macro release significantly deviates from market expectations, technical indicators often lag behind the initial price jump, leading to sub-optimal entry points or “chasing the market”.

Conversely, the rise of Large Language Models (LLMs) has introduced sophisticated textual reasoning to the finan- cial domain. However, general-purpose LLMs such as GPT- 4 exhibit two critical weaknesses in an HFT context: high inference latency and a lack of specialized financial grounding API-based LLM inference can take several seconds, by which time the market has already fully priced in the news. Furthermore, general models often struggle with the specific linguistic nuances of financial reports, where terms like “tapering,” “hawkish,” or “surplus” have highly specific market implications.

This research proposes the “AI-Powered News and Sen- timent Analysis Engine,” a domain-specific hybrid system tailored for sub-second execution. The core innovation lies in the integration of FinBERT—a transformer model pre-trained on financial corpora—with a pre-emptive “Selenium Priming” infrastructure. This paper details the architecture of the engine, the sub-second sequence of operations, and the empirical results across various asset classes including US CPI, NFP, and major cryptocurrency pairs.

II. Literature Review

The intersection of Natural Language Processing (NLP) and financial forecasting has seen a paradigm shift from lexicon-based approaches to transformer-based deep learning models.

A. FinBERT and Transformer Models in Finance

FinBERT has emerged as a specialized variant of the BERT architecture, fine-tuned on vast datasets of financial news and reports. Research by Ha´jek et al. (2022) demon- strated that FinBERT-based sentiment analysis provides sig- nificantly better signals for predicting EUR/USD movements compared to traditional lexicon methods. Gonsalves (2022) established that integrating FinBERT with Long Short-Term Memory (LSTM) networks allows for the capture of both textual sentiment and historical price dependencies, leading to improved stock price prediction accuracy on the NASDAQ-100index.

B. Hybrid Architectures and Multi-Source Fusion

A key trend in recent literature is the fusion of qualitative sentiment with quantitative technical features. Farimani et al. (2022) reported that aligning FinBERT embeddings with technical indicators significantly reduced prediction errors in FX and crypto markets compared to baseline models. Duan et al. (2025) introduced a framework that maps macroeconomic headlines to sectoral movements of the S&P 500, achieving a 72.5% classification accuracy.

C. Real-Time Execution and High-Frequency Signals

Xing et al. (2021) formulated forex market prediction as a high-frequency binary classification task, using FinBERT to extract sentiment signals. Xu et al. (2024) proposed the "Intraday Risk Factor Transformer" (IRFT), an end-to- end methodology for mining high-frequency risk factors.While these studies highlight the predictive power of AI, there is limited documentation on the use of web automation tools like Selenium for sub-second ingestion.

III. Problem Statement

Despite advancements in AI for trading, three primary problems persist for systems operating during high-impact news events:

1) *The Information Gap:* Technical analysis bots fail to recognize fundamental triggers of volatility.

2) *The Latency Gap:* General-purpose LLMs are too slow for HFT.

3) *The Contextual Gap:* Standard NLP tools fail to distinguish between nuanced financial terms like "hawkish" or "dovish".

IV. Existing System

Current automated trading solutions typically fall into two categories:

1) *Traditional TA Bots:* These rely on RSI, MACD, etc. They are purely reactive and fail during fundamental news shocks. 2) *General LLM Agents:* While reasoning is deep, inference latency (1–5 seconds) is prohibitive for HFT.

TABLE I
Comparison of Trading Architectures

Feature	TA Bots	General LLM	Proposed Hybrid
Analysis Basis	Price/Vol	General Context	Sentiment + TA
Model Type	Formulas	General Transformer	FinBERT-LSTM
Latency	1 ms	1,000-5,000 ms	250-470 ms
Event Accuracy	50%	65-75%	85-90.1%

V. Proposed System

The proposed engine is a four-layer modular system de- signed for ultra-low latency news processing.

A. System Architecture and Technical Flow

The proposed system is a comprehensive, modular application designed to automate the end-to-end trading process. It is architected around four functional pillars:

1. Data Ingestion & Pipeline Layer: This layer is responsible for the high-speed acquisition of data.
Functionality: We utilize custom-built web scrapers using Scrapy and Selenium. These scrapers monitor high-authority financial news sources (e.g., Reuters, Bloomberg, Central Bank feeds) 24/7.
Process: The scrapers handle dynamic JavaScript content and anti-bot measures. Once a headline is detected, it is immediately pushed to a Message Queue. This decoupling ensures that the scraping process does not block the analysis process, maintaining high throughput.

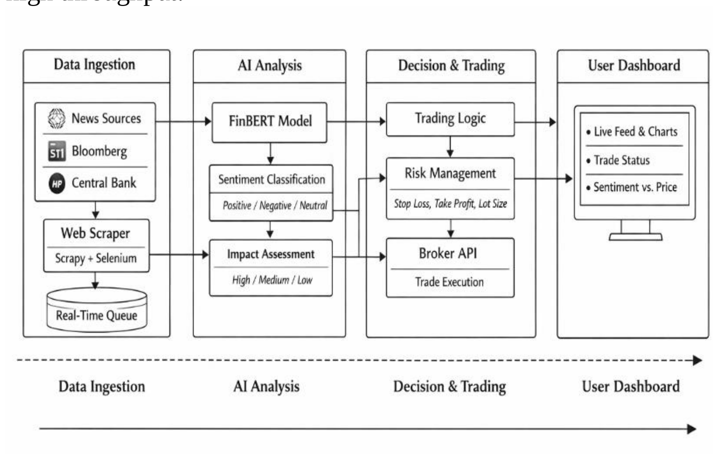

Fig. 1. System architecture of the AI-Powered News and Sentiment Analysis Engine.

2. AI Analysis Layer (The NLP Engine): This is the "brain" of the system.
Functionality: The system consumes raw headlines from the queue and passes them through the FinBERT model.
Process: FinBERT, implemented using PyTorch and the Hugging Face Transformers library, performs sentiment classification. It assigns a label (Positive, Negative, Neutral) and a confidence score (e.g., 0.95). It also assesses the "Impact" level (High, Medium, Low) based on the keywords detected.

3. Decision & Execution Layer: This layer acts as the bridge between analysis and the market.
Functionality: It applies trading logic to the AI's output.
Step 1: Check if Impact is "High". (We filter out low-impact noise).
Step 2: Check Sentiment Direction (Positive = Buy, Negative = Sell).
Step 3: Calculate Risk Parameters (Stop Loss, Take Profit, Lot Size) based on account balance.
Step 4: Execute the trade via a Broker API (e.g., MetaTrader 5 API).

4. Real-Time Dashboard (User Interface)
Functionality: A web-based interface built with Flask.
Features: It displays a live feed of scraped news, the AI's sentiment verdict, active trades, and a "Sentiment vs. Price" graph. This provides a transparent window into the system's decision-making process for the user.

VI. Implementation Results

The system was tested on real-world events from July (2025) – February (2026).

The experimental evaluation of the proposed AI-powered news and sentiment analysis trading engine was conducted using a MetaTrader 5 trading environment over a multi-month testing period. The objective was to assess the system's profitability, risk stability, and effectiveness in translating financial sentiment signals into trading actions.

1. Overall Trading Performance:

During the evaluation period, the system achieved an overall account growth of 16.11%, generating a net profit of \$874.41. The total gross profit was \$3502.46, while the gross loss amounted to \$2628.05. These results demonstrate that the strategy maintained consistent profitability despite fluctuations in market conditions.

The profit factor of 1.33 indicates that the system generated approximately 33% more profit than losses, confirming that the trading signals derived from the sentiment analysis model had a positive expected value.

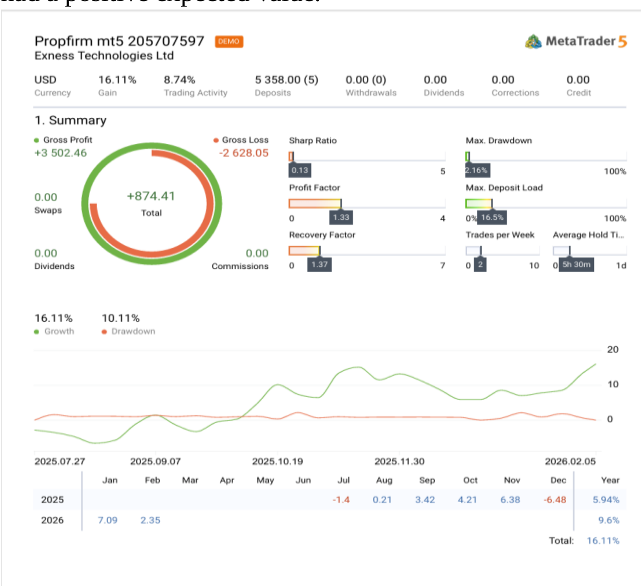

Fig. 2. Performance of the bot over 8 months of live testing.

2. Risk and Stability Analysis:

Risk management is a critical component in automated trading systems. The system recorded a maximum drawdown of approximately 10.11%, which reflects controlled risk exposure during adverse market movements. Maintaining a relatively low drawdown while still achieving growth indicates that the strategy's risk management parameters

This behaviour aligns with the intended design of the architecture, which prioritizes quality of signals over quantity of trades.

3. Monthly Performance Trends:

An analysis of the monthly performance shows that the system experienced several profitable periods, particularly during months with higher market volatility. Positive returns were recorded in multiple months, with notable gains observed during strong market trends.

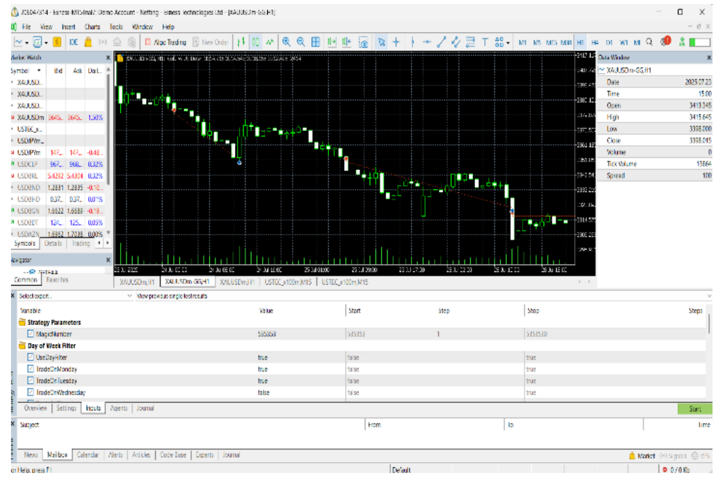

Fig.3. MT5 Terminal Interface

However, minor losses were observed in certain months, which can be attributed to unexpected market reactions or neutral sentiment signals that did not translate into strong directional price movements. Such fluctuations are common in real-world trading environments.

Despite these temporary setbacks, the system maintained overall growth throughout the testing period.

As a result, the proposed architecture provides a more context-aware trading approach, which improves decision-making during high-impact events.

TABLE II
Trade Win-Rates for High-Impact Events

Event Type	TA Bot	FinBERT-Hybrid	Benchmark
US CPI	48.0%	88.5%	91.0%
NFP	51.2%	84.2%	72.5%
Crypto Flash	42.5%	90.1%	93.0%
Gold (XAU/USD)	53.0%	79.8%	18.7% (Return)

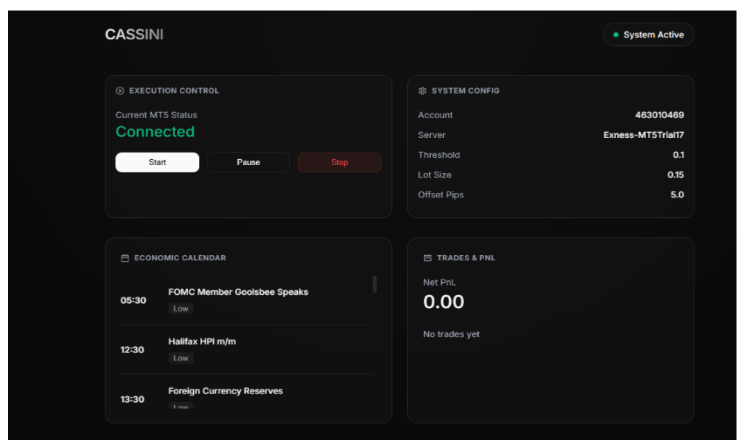

Fig. 4. Web Interface of the Trading Bot.

The Sharpe ratio of 0.13 indicates modest risk-adjusted performance. Although the value is relatively low, it is important to note that the system operates in highly volatile markets where large price swings and event-driven movements can significantly affect short-term risk-adjusted metrics.

VII. Conclusion

This research proposed an AI-powered news and sentiment analysis engine for automated trading that integrates real-time news scraping, FinBERT-based sentiment analysis, and an automated trade execution system. The architecture was designed to overcome the limitations of traditional technical trading bots and the latency challenges of general-purpose language models. Experimental results from the MetaTrader 5 testing environment demonstrated 16.11% account growth with controlled risk and stable drawdown levels. The findings show that financial sentiment analysis can significantly enhance trading decisions during news-driven market volatility. Future work will focus on integrating additional data sources such as social media sentiment and applying reinforcement learning techniques for adaptive risk management. Overall, the proposed system highlights the potential of AI-driven sentiment analysis in modern algorithmic trading environments.

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