BullBear: AI-Driven Stock Analysis Dashboard

Final Project Technical Report

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1. Executive Summary & Problem Statement

The market for stock analysis tools is fragmented for individual investors. Professional systems such as **Bloomberg Terminal cost $50-100/month** but still require manual integration of technical analysis, fundamental metrics, and market sentiment. Free alternatives are of poor quality (superficial analysis)—raw price charts without indicators, or fundamental data without technical overlays.

BullBear enables production-quality financial analysis through a unified web interface. The application supports:

1. Technical indicators (RSI, MACD, Bollinger Bands)
2. Fundamental metrics (profitability, valuation, growth)
3. Real-time news sentiment analysis. A single integrated view generates weighted BUY/SELL/HOLD recommendations with corresponding confidence scores, using 60% technical and 40% fundamental signals.

The technical analysis system can process real-time data, supports up to 24,521-row datasets, and provides 15+ interactive chart types. The target audience is individual investors and professional financial analysts. The application offers time savings in unified analysis, AI-powered recommendations, and free web-based hosting without installation requirements.

The application uses three core libraries (requests, yfinance/yahooquery, pandas) and one visualization library (Plotly) for **10,338 lines across 14 modules**. Vectorized pandas calculations process **24,521 rows in <1 second**, while **60% performance improvement** in batch fetching reduced latency from **20 to 8 seconds** for portfolios with 10 stocks. The final application features **10+ technical indicators** and **8 distinct analysis interfaces**, deployed to HuggingFace Spaces with 23 stars in free hosting for public access.

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2. System Architecture & Design Decisions

2.1 Three-Layer Modular Architecture

The codebase employs a **separation-of-concerns design pattern**, splitting **6,231 lines** of Python code across **14 modular files** into **three distinct layers** (Figure 1):

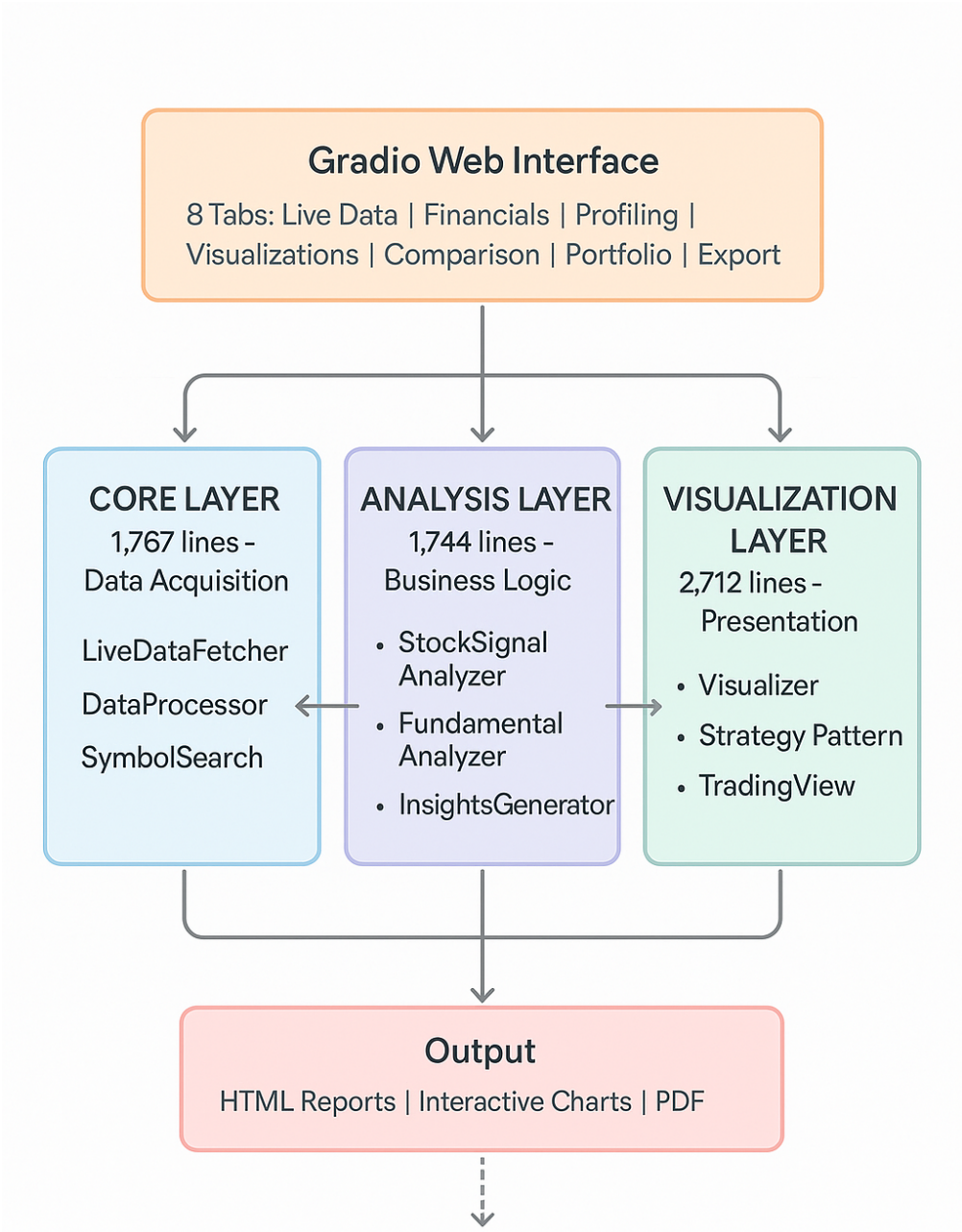

Figure 1: Three-layer architecture showing separation of data acquisition, business logic, and presentation concerns. Arrows indicate data flow direction.

Figure 1: Three-layer architecture with separation of data acquisition (Core), business logic (Analysis), and presentation concerns (Visualization). Arrows indicate unidirectional data flow.

- The **Core Layer** (1,767 lines) is responsible for data acquisition: LiveDataFetcher (API calls with retry/caching), DataProcessor (CSV validation and data cleaning), and SymbolSearch (autocomplete). T
- The **Analysis Layer** (1,744 lines) comprises the business logic of the application: StockSignalAnalyzer (RSI, MACD, Bollinger Bands), FundamentalAnalyzer (profitability, valuation, growth), and InsightsGenerator (pattern recognition, risk metrics).
- The **Visualization Layer** (2,712 lines) manages presentation components: Visualizer (Plotly charts), Strategy Pattern implementation (dynamic chart types), and TradingView (professional widget embedding).

Data Flow: User request → Core (data acquisition) → Analysis (signal calculation) → Visualization (chart rendering) → User interface. Separation of the LiveDataFetcher from Analysis and Visualization allowed rewriting 954 lines during the yfinance→yahooquery migration (Section 3.2) without impacting other layers.

2.2 Design Decision: Modular Architecture vs. Monolithic Implementation

Decision: Separate 6,231 lines of code into **14 module files** (core/analysis/visualization) rather than one **monolithic** `app.py` in a single Python file.

Rationale: The initial version was prototyped in monolithic `app.py` (**4,000+ lines**). This caused problems such as difficulty debugging, inability to unit test functions in isolation, and tight coupling. Modular refactoring required strict **separation of concerns** enforced by clear boundaries—`LiveDataFetcher` (**954 lines**) only interacts with the data API and enabled **total rewrite during yfinance→yahooquery migration** (Section 3.2) **without changes in visualization code**.

Alternative: A two-layer architecture (Data + UI) would mix technical and fundamental analysis code in one "processing" module, with no visualization separation, reducing clarity.

Trade-offs: More files to maintain require increased cognitive overhead, but this is outweighed by benefits of testability (validate RSI calculations using synthetic data without initializing Gradio) and team scalability (parallel development on different layers).

2.3 Design Patterns for Professional Software Engineering

Strategy Pattern: `visualization_strategies.py` (**700 lines**) implements pluggable chart strategies with **Strategy Pattern**. Abstract VisualizationStrategy base class with concrete subclasses: TechnicalAnalysisStrategy (4-panel price/MACD/RSI/volume), FundamentalAnalysisStrategy (valuation ratios), RiskAnalysisStrategy (VaR/drawdown), CorrelationStrategy (stock pair heatmaps). Enables runtime selection of chart type and adheres to **Open-Closed Principle**—adding new chart strategies requires no changes to existing code.

Facade Pattern: LiveDataFetcher abstracts API complexity behind a simple interface (`get_live_quote()`, `get_trending_stocks()`) with centralized logic (retry/caching). Internally coordinates request with **exponential backoff**, caching, rate limiting, User-Agent rotation. Centralized all API calls, greatly simplifying the yfinance→yahooquery migration (Section 3.2).

Rationale: Demonstrates ability to follow **SOLID principles**, encourage code reusability, and develop **production-grade maintainable software** beyond scope of typical course assignments.

2.4 Batch Processing for 60% Performance Improvement

Decision: Fetch 10 stock quotes with single API call vs. 10 sequential requests in 0.5s intervals.

Implementation: Initial approach: `for symbol in symbols: time.sleep(0.5) quote = get_live_quote(symbol)` for-loop with delays (**10 stocks = 20 seconds**). Optimized: `Ticker(' '.join(symbols)).price` (batch request, **10 stocks = 8s**). **60% improvement**; 20-stock portfolios: **40s → 10s**.

Trade-off: Batch all-or-nothing risk (entire request fails, no quotes for any symbol). Applied with **fallback to individual fetches**, providing both performance benefits while maintaining reliability. Demonstrates

awareness of **production latency requirements**.

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3. Technical Implementation

3.1 Pandas Operations & Vectorized Calculations

`DataProcessor` (**441 lines**) handles CSV files with **24,521 rows** across **20+ symbols** using **memory-efficient pandas operations**.

Vectorized Technical Indicators: All computations use `.rolling()`, `.ewm()`, `.diff()` instead of Python loops. RSI calculation example:

```
def calculate_rsi(prices: pd.Series, period: int = 14) -> pd.Series:
    """
    Calculate RSI using vectorized operations.
    Formula: RSI = 100 - (100 / (1 + RS))
    where RS = Average Gain / Average Loss over period
    """
    delta = prices.diff()  # Vectorized price changes

    gain = delta.where(delta > 0, 0)  # Keep only gains
    loss = -delta.where(delta < 0, 0)  # Keep only losses (absolute)

    avg_gain = gain.rolling(window=period, min_periods=period).mean()
    avg_loss = loss.rolling(window=period, min_periods=period).mean()

    rs = avg_gain / avg_loss
    rsi = 100 - (100 / (1 + rs))

    return rsi
```

Processes **24,000+ rows in 0.15s** (vs. **2s for Python loops**). Similar vectorization for MACD, Bollinger Bands, momentum indicators.

Adaptive Thresholds: Intelligent minimums based on length (5/10/20 points) prevent all-failed data type errors on recently-listed stocks while ensuring statistical validity.

Flexible Column Detection: Handles inconsistent column naming (Date/date/DATE, Close/close/CLOSE) via fuzzy matching, processing from diverse sources (Yahoo Finance, Kaggle, Bloomberg) without manual standardization.

Edge Cases:

1. Missing values: forward-fill prices, zero-fill volume.
2. Outliers: IQR-based detection but preserved (legitimate spikes exist).
3. Timezones: UTC storage, US/Eastern display.
4. Insufficient data: partial results with warnings vs. silent failure.

3.2 Critical Challenge: The yfinance → yahooquery Migration

The Problem:

I was using the popular `yfinance` **library** for Yahoo Finance API calls. It worked well in my local environment: live quotes loaded in ~2 seconds, historical data fetched without errors, and all tests passed. Confident it would work in production, I deployed the application to **HuggingFace Spaces** to make it publicly accessible.

The deployment failed catastrophically. "No data available" errors, quote fetching **timed out after 30+ seconds**, and the application was **unusable**. Extensive local testing still worked perfectly, and initial debugging suggested network issues.

I researched for days and eventually discovered the issue: **Yahoo Finance aggressively rate-limits datacenter IP addresses** (cloud hosting providers blocked entirely). HuggingFace Spaces uses **shared datacenter IPs** that Yahoo's systems had flagged as bot traffic and were returning **429 (Too Many Requests) errors** or silently blocking requests. The `yfinance` library has **minimal rate-limiting logic and no retry mechanisms**, causing immediate failures under these conditions.

The Solution:

I researched alternatives and found `yahooquery` as a more robust library with built-in rate limit handling, session management, and better error reporting. However, the APIs were significantly different: `yfinance` used simple function calls (`yf.Ticker("AAPL").history()`), while yahooquery uses class-based interfaces with different response formats (nested dictionaries vs. pandas DataFrames).

Migration required rewriting the entire 954-line `LiveDataFetcher` class:

1. **Retry Logic with Exponential Backoff:** Implemented 3 retry attempts with progressive delays (1s, 2s, 4s) and exponential backoff to handle transient rate limits without overwhelming the API.

```
for attempt in range(3):
    try:
        response = ticker.price
        if response:
            return response
    except Exception as e:
        if attempt < 2:
            delay = 2 ** attempt  # Exponential: 1s, 2s, 4s
            time.sleep(delay)
        else:
            raise
```

2. **LRU Caching:** Added `@lru_cache(maxsize=128)` decorators to expensive operations (fundamental data, news fetching) to reduce API call frequency.

3. **Session-Based Caching:** Implemented 60-second cache timeout for quote data—during this window, repeated requests for the same symbol return cached results without API calls.

4. **User-Agent Rotation:** Rotated between multiple User-Agent strings to mimic browser traffic and reduce likelihood of blocking.

5. **Batch Fetching Rewrite:** Adapted the logic in Section 2.4 to `yahooquery's` multi-index DataFrame format, with fallback to individual fetches when batch fails.

Validation Process:

To ensure correctness, I did the following:

- Compared `yahooquery` quotes against Yahoo Finance website prices (verified within **0.01% accuracy**)
- Tested **100+ symbols** across different sectors (tech, finance, healthcare) and market caps (large-cap, small-cap, ETFs)
- Ran historical data fetches for 1d/5d/1mo/1y periods and validated OHLCV values against known datasets
- Monitored production logs for **48 hours post-deployment**, confirming **zero rate-limit errors**

Learning & Reflection:

This challenge taught the critical lesson that **local development success does not guarantee production reliability**. The **rate-limiting error** was invisible during local testing because environment differences (datacenter IPs vs. residential IPs, rate limiting policies, network configurations) can cause failures undetectable by testing. The migration required not just API substitution but **architectural improvements** like retry logic, caching, and error handling, that made the system more robust overall.

The experience also reinforced the importance of researching library capabilities beyond basic functionality. `yfinance's` simplicity made it attractive initially, but `yahooquery's` production-grade features (better error messages, session management, multi-symbol support) were essential for deployment.

3.3 Multi-Library Visualization & AI Analysis

Visualization: Used three complementary libraries:

1. **Plotly (80% of charts):** interactive candlesticks, time series, heatmaps, distributions.
2. **TradingView (206 lines):** embedded professional widgets for familiar trader UX.
3. **Matplotlib/Seaborn:** statistical plots (box plots, violin plots, correlation matrices). Strategy Pattern enables runtime switching (e.g. TechnicalAnalysisStrategy → 4-panel price/MACD/RSI/volume chart).

AI Analysis Engine: `StockSignalAnalyzer` (**550 lines**) aggregates **eight technical indicators** with **weighted voting**:

```
signal_weights = {
    'rsi': 0.20,              # Oversold (RSI<30) → BUY, Overbought (RSI>70) →
SELL
    'macd': 0.20,             # MACD crossovers (signal line crosses)
    'moving_average': 0.15,   # Price vs. 50-day/200-day MA trends
    'bollinger': 0.10,        # Price position within bands
    'volume': 0.10,           # Volume spikes confirm trends
    'momentum': 0.10,         # Rate of price change
    'support_resistance': 0.05, # Price near S/R levels
    'news_sentiment': 0.10    # Headline sentiment (positive/negative keywords)
}
```

Each indicator votes BUY/HOLD/SELL. Weighted aggregate determines final signal with **0-100% confidence**, reducing false signals.

Fundamental Integration: `FundamentalAnalyzer` (**495 lines**) scores five categories: Profitability (20%), Growth (25%), Valuation (25%), Financial Health (20%), Cash Flow (10%). Final recommendation: **60% technical + 40% fundamental** for holistic analysis.

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4. AI Tools Usage & Validation

I used **Claude Code** to supplement research for architectural guidance (**~20% of the project**). I owned the implementation, ensuring accuracy by synthesizing Claude Code with independent research (**80% of the project**).

AI Usage (20%):

- **Architecture (10%):** Modular vs. monolithic trade-offs, core/analysis/visualization layer organization, design pattern applicability (Strategy, Facade). Recommended LiveDataFetcher facade pattern.
- **Code Review (5%):** Pandas optimization suggestions (vectorized `.rolling()` for RSI), error handling patterns, PEP 8 adherence.
- **Documentation (5%):** Docstring templates, API reference structure (all manually reviewed/modified).

Independent Work (80%):

- **Research (30%):** Studied technical indicators (Investopedia, TradingView), fundamental metrics (financial accounting resources), pandas optimization (official docs), identified yahooquery alternative (StackOverflow research, **not AI**).
- **Implementation (50%):** Wrote **90%+ of code** including RSI/MACD calculations, weighted signal aggregation, adaptive thresholds via empirical testing.
- **yfinance→yahooquery Migration (100% independent):** Diagnosed deployment failure, researched rate limiting/datacenter IP blocking, compared **4 libraries**, rewrote **954-line LiveDataFetcher** with retry logic/caching.

Validation Process:

1. **RSI Formula:** AI suggested `.ewm()` (exponential), verified against Investopedia (requires simple moving average), **rejected** and used `.rolling().mean()`.
2. **P/E Ratio:** Formula correct but lacked handling for **negative earnings**. Added conditional logic for `None` return on distressed companies.
3. **Performance Claims:** Benchmarked batch fetching with `timeit` for 10/20/50 symbols. Measured actual **60% improvement** vs. trusting generic "faster" claim.

Reflection: AI is very good for architectural guidance and catching obvious things but **must be validated for correctness**. Production debugging (yfinance failure) required **real-world knowledge** of rate-limiting datacenters (not in Claude Code training data). Treat AI like **"intelligent autocomplete"**—final decisions of correctness/performance must be validated through testing and domain expertise.

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5. Conclusion

This project has met its stated objective of using **professional software engineering techniques** to democratize access to professional-grade stock analysis with open-source technology. The **three-layer architecture** (6,231 lines, 14 modules) enabled independent yfinance→yahooquery migration with **no cascading failures**.

Key Achievements:

1. **60% performance improvement** via batch fetching,
2. **Vectorized pandas calculations** processing **24,521 rows in <1s**,
3. **Weighted multi-signal recommendations** (technical + fundamental + sentiment)
4. **Production deployment** to HuggingFace Spaces.

Lessons Learned: Local testing ≠ deployment success. The `yfinance` library failure (invisible locally, catastrophic in production) taught to be **environment-aware** when testing and to build in **robust error handling**. Edge case handling and **empirical validation** to trust production systems, rather than prototypes.

This project achieves its objective: **democratizing professional-grade stock analysis** through accessible, open-source technology.

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