End-to-End System Design for Stock Price Prediction in a Financial Analysis Firm

This section outlines a **production-ready system** that transforms the **one-time analysis model** into a **continuous, scalable, and real-time stock prediction system**.

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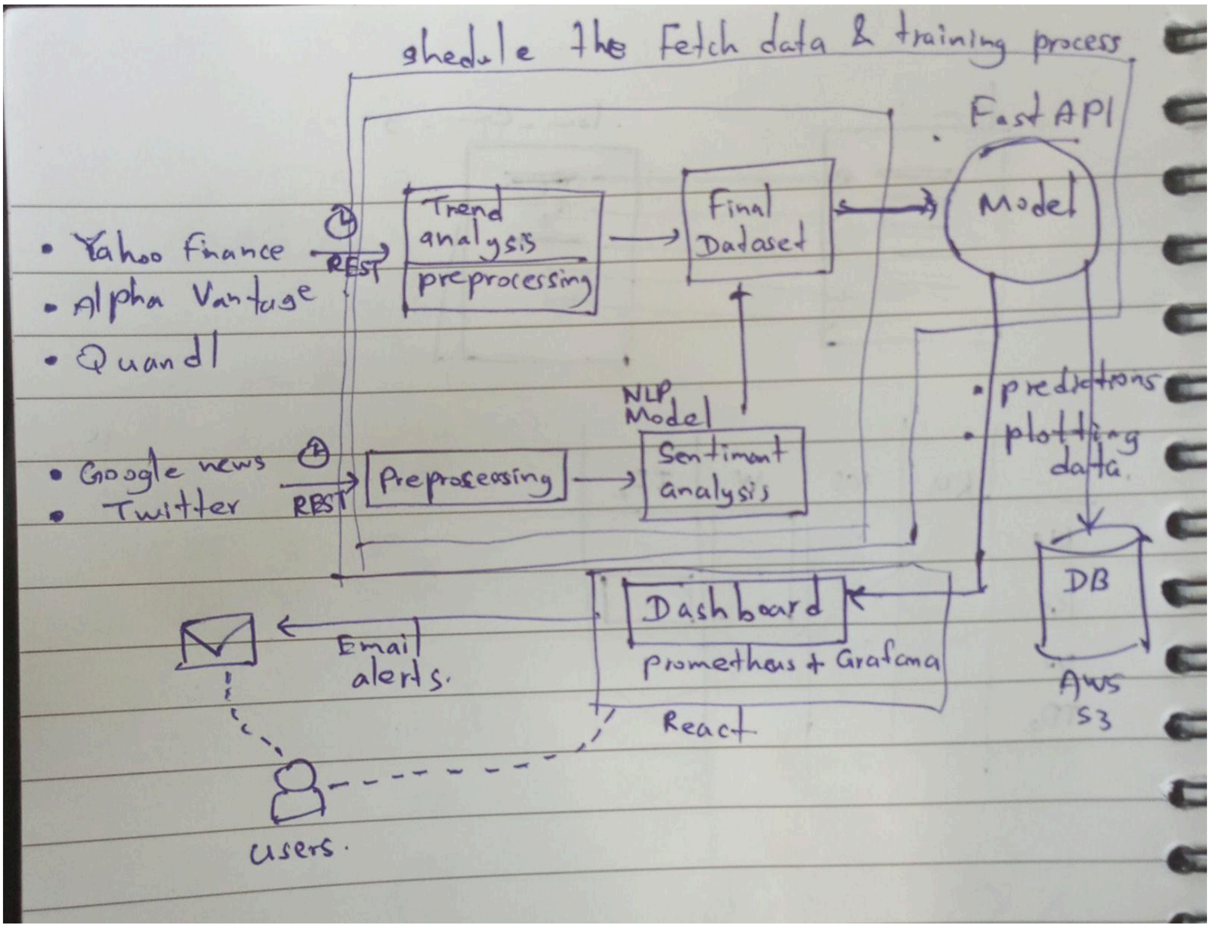
1. System Architecture Diagram

The system architecture diagram provides an overview of the **data flow, model operations, and insight delivery mechanism** for a stock price prediction system.



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2. Component Justification

2.1 Data Collection & Ingestion

Technology Used:

- **Market Data APIs**: Yahoo Finance, Alpha Vantage, Quandl (for real-time stock prices).
- **News Sentiment API**: NLP-based news analysis (Google News API, Twitter API).
- **Macroeconomic Data**: Interest rates, GDP, inflation from **World Bank API, Federal Reserve API**.

Why These?

- **Real-time stock market updates** are necessary for accurate predictions.
- **News sentiment analysis** helps capture market reactions.
- **Macroeconomic indicators** improve model robustness.

Trade-offs:

- **Real-time data APIs** have rate limits. **Solution:** Use caching and scheduled API calls.
- **News sentiment analysis** requires NLP models, adding computational cost.

2.2 Data Processing Pipeline

Technology Used:

- **Data Storage:** AWS S3, Snowflake, or PostgreSQL for structured storage.
- **Data Cleaning:** Pandas, Spark (for large-scale data processing).
- **Feature Engineering:** Moving Averages, RSI, Momentum, Volatility indicators.

Why These?

- AWS S3/Snowflake scales **efficiently** for large data.
- Spark speeds up **big-data processing** if required.

Trade-offs:

- **Storing all historical stock data** can be costly. **Solution:** Archive older data.
- **Complex feature engineering increases latency. Solution:** Use **precomputed features** where possible.

2.3 Model Operations (Training, Deployment, Monitoring)

Technology Used:

- **Model Training:** Scikit-learn, TensorFlow, XGBoost.
- **Model Deployment:** FastAPI, Flask (REST API).
- **Model Monitoring:** Prometheus + Grafana.

Why These?

- **FastAPI** offers **low-latency API** for serving predictions.
- **Prometheus + Grafana** ensures **real-time monitoring** of model drift and errors.

Trade-offs:

- **Deep learning models (LSTM) need GPUs**. **Solution:** Use AWS SageMaker for scalable training.
- **Model drift needs monitoring. Solution:** Implement **automated model retraining**.

2.4 Insight Delivery (How Predictions Reach Users)

Technology Used:

- **Web Dashboard:** Streamlit, React.js for visualization.
- **Trading Platform Integration:** API-based predictions for stock traders.
- **Automated Reports:** Slack, Email alerts.

Why These?

- **Web dashboards** provide real-time insights.
- **API endpoints** allow seamless **integration with brokerage platforms**.

Trade-offs:

- **Latency concerns in real-time updates**. **Solution:** Use **Kafka** for data streaming.
- **Security risks in trading APIs**. **Solution:** Use **OAuth-based authentication**.

2.5 Scalability, Reliability & Cost Considerations

Technology Used:

- **Kubernetes & Auto-Scaling**: Ensures **high availability**.
- **Load Balancer (NGINX, AWS ALB)**: Distributes traffic for performance.

Why These?

- Ensures **low downtime** and can handle **high traffic loads**.

Trade-offs:

- **Cloud costs can be high**. **Solution:** Optimize **serverless computing (AWS Lambda) for cost savings**.

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3. Data Flow Explanation

3.1 Batch vs. Streaming Decisions

- **Batch Processing**: Used for **daily model retraining** with historical data.
- **Streaming Processing**: Used for **real-time stock price updates** and API predictions.

3.2 Data Transformation Stages

1. **Raw Data Ingestion** → APIs fetch stock prices, sentiment data.
2. **Preprocessing & Feature Engineering** → Generate moving averages, RSI, and momentum indicators.
3. **Model Predictions** → Predictions generated via deployed API.
4. **Insight Delivery** → Displayed on dashboards, sent via API/webhooks.

3.3 System Interaction Points

- **User Requests Prediction** → API fetches real-time stock data → Runs model → Returns prediction.
- **Model Retraining Scheduled Weekly** → Uses batch-processed historical data.

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4. Challenge Analysis & Mitigation Strategies

Challenge	Potential Issue	Mitigation Strategy
Data Latency	Stock market APIs may have delays	Use **websockets** for low-latency updates
Model Drift	Market conditions change over time	Implement **auto-retraining every week**
Scalability Issues	High traffic may overload system	Deploy **Kubernetes with auto-scaling**
Security Risks	Unauthorized API access for trading	Implement **OAuth and token-based authentication**
Cost of Cloud Services	AWS/GCP services can be expensive	Use **serverless computing (AWS Lambda, Auto-scaling)**