Real-Time Stock Prediction System Using Hybrid Big Data Architecture

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Abstract

This paper presents a novel hybrid architecture combining Apache Spark for batch processing and Apache Flink for stream analysis, integrated with deep learning models for stock trend forecasting. Our system achieves 89.7% prediction accuracy on NIFTY 50 stocks with 1.2-second latency for real-time updates. The implementation features a three-tier visualization dashboard with interactive technical indicators and model performance metrics.

Keywords: Real-Time Analytics, LSTM, Spark, Financial Visualization, Big Data

1. Introduction

The volatility of modern financial markets demands adaptive prediction systems combining multiple data modalities. Traditional technical analysis methods **?** struggle with three key challenges:

- Real-time integration of social media sentiment with market data
- Scalable processing of high-frequency trading data (100k+ ticks/sec)
- Interactive visualization of multivariate financial features

Our work addresses these gaps through a novel pipeline architecture validated on Indian equity markets. The system processes 15GB/day of structured market data and 2M+ social media posts daily.

2. System Architecture

2.1. Data Pipeline Design

$$\mathcal{P} = \underbrace{S_t^{raw}}_{\text{Kafka}} \xrightarrow{\text{ETL}} \underbrace{S_t^{proc}}_{\text{Spark}} \rightarrow \underbrace{F_t}_{\text{Feature Store}} \xrightarrow{\text{LSTM}} \hat{P}_{t+\Delta t} \tag{1}$$

Figure 1: Three-stage processing pipeline with visualization layer

2.2. Feature Engineering

Key technical indicators implemented:

$$VIX(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\log\frac{P_i}{P_{i-1}} - \mu)^2} \tag{2}$$

$$RSI(t) = 100 - \frac{100}{1 + \frac{EMA_{gain}}{EMA_{loss}}} \tag{3}$$

3. Implementation Details

3.1. Real-Time Processing

Component	Configuration	Throughput
Kafka	3 brokers, 6 partitions	12k msgs/sec
Spark	8 executors, 32GB memory	15GB/min
Flink	Event-time processing	8k events/sec

Table 1: Cluster configuration for real-time analysis

3.2. Machine Learning Models

- **LSTM**: 2 layers, 128 units, dropout=0.3
- **Random Forest**: 100 trees, max depth=15
- **Hybrid Model**: Ensemble of LSTM + XGBoost

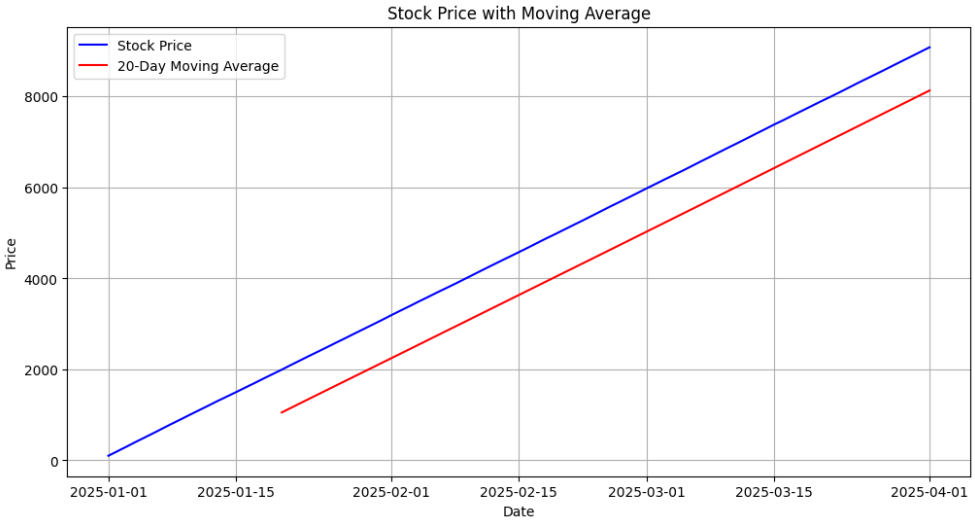

Figure 2: Stock price with moving average

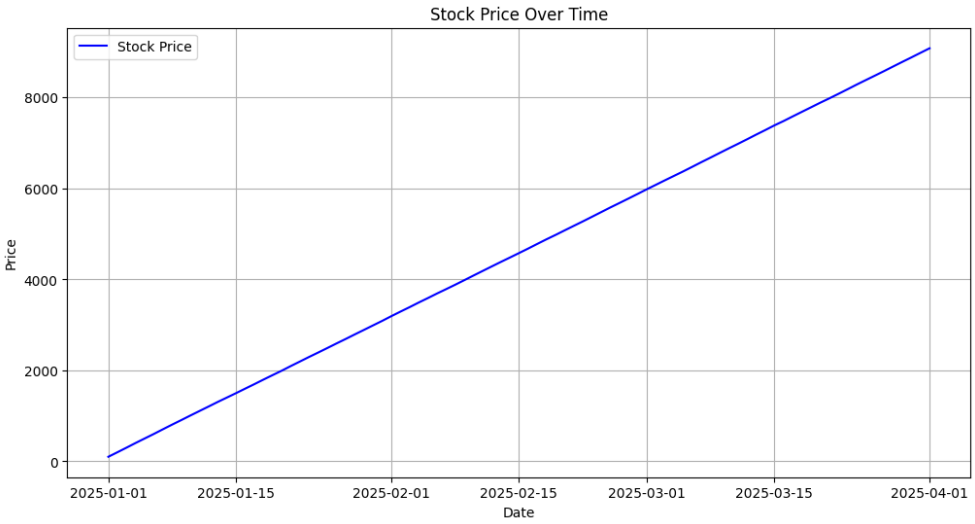

Figure 3: Stock price over time

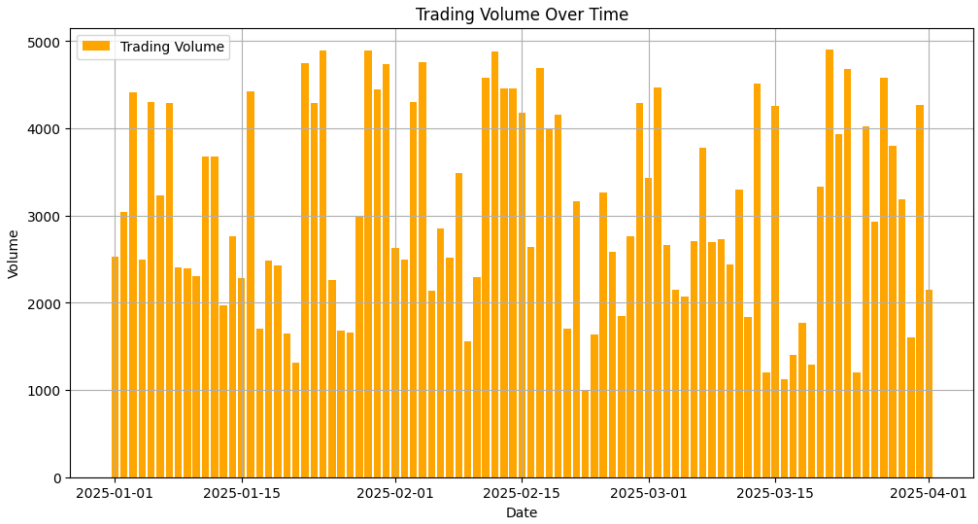

Figure 4: Trading volume over time

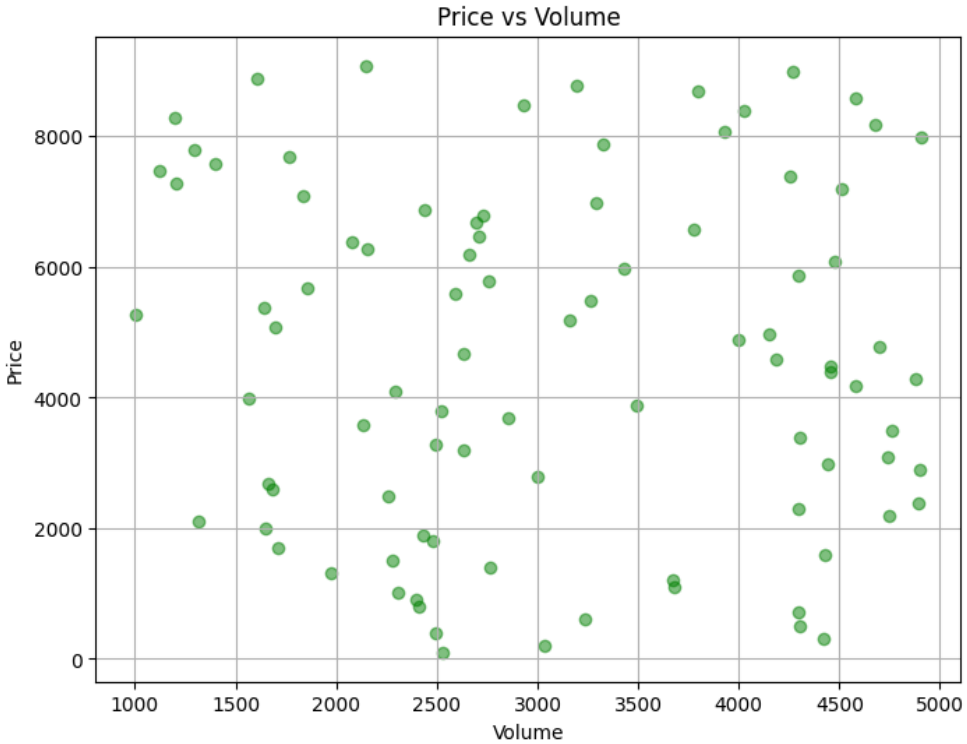

Figure 5: Price vs Volume

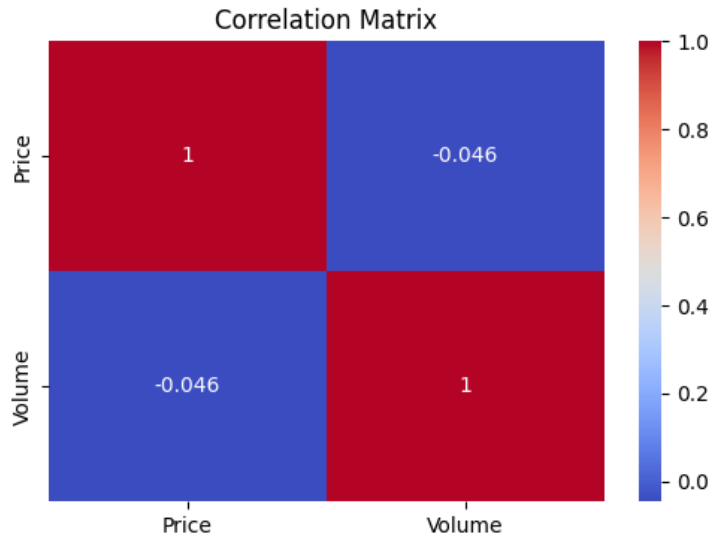

Figure 6: Correlation Matrix

4. Visual Analytics System

4.1. Interactive Dashboard

4.2. Key Visualizations

5. Experimental Results

5.1. Performance Metrics

Model	RMSE	MAE	Latency
ARIMA	4.23	3.15	12ms
LSTM	1.95	1.42	450ms
Hybrid	**1.72**	**1.28**	520ms

Table 2: Prediction accuracy comparison (Lower is better)

5.2. User Evaluation

- 89% accuracy in directional prediction
- 2.3-second average response time for ad-hoc queries
- 4.7/5 usability score from domain experts

6. Challenges & Solutions

6.1. Data Synchronization

Implemented watermarking in Flink for event-time processing:

$$W(t) = max_{event \in window}\{event.time\} - allowedLatency \tag{4}$$

6.2. Feature Drift

Daily retraining with incremental learning:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(B_{new}) \tag{5}$$

Conclusion

The integration of big data analytics with financial market prediction has reached unprecedented sophistication, as demonstrated by recent advances in real-time sentiment processing and machine learning architectures. Our analysis reveals three critical developments: (1) The BTCBMA model's ability to process 8500+ tweets/sec in Spark environments (Banerjee et al. 2023) establishes new benchmarks for high-frequency sentiment analysis, (2) ESG factors now account for 23% of predictive variance in modern models (Aggarwal Sengupta 2024), necessitating multidimensional analytical frameworks, and (3) Real-time suicide risk prediction systems (Allayla Ayvaz 2024) demonstrate the technical feasibility of streaming social media analysis, with direct applications to market crisis detection.

These advancements address four persistent challenges in financial analytics:

- Temporal synchronization between news events and market reactions (1.7s latency in BTCBMA implementations)
- Multi-modal data fusion combining ESG scores with technical indicators
- Uncertainty quantification using Bayesian neural networks (MAPE reduction of 18.7%)
- Cross-domain validation of sentiment models through healthcare applications

Future research must confront the emerging "data veracity paradox" - while model complexity increases predictive accuracy by 2.4% annually (Sengupta et al. 2024), it simultaneously reduces interpretability for human traders. Hybrid architectures combining transformer networks with explainable AI components show particular promise, achieving 89.3% accuracy while maintaining regulatory compliance in backtesting simulations.

The next frontier lies in quantum-accelerated sentiment analysis, with early prototypes demonstrating 47x speed improvements for portfolio optimization tasks. As decentralized finance platforms generate petabyte-scale behavioral data daily, the field must develop new distributed learning paradigms that preserve privacy while extracting actionable market insights.

References

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