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FINX – Stock Market Forecasting Using Data Analytics

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ABSTRACT

Investing in the stock market holds immense potential for wealth creation, yet for many retail investors it remains intimidating and inaccessible due to the complexity and high cost of existing forecasting tools. FinX was conceived to bridge this gap by offering a low-cost, machine learning-based forecasting system that delivers clear, reliable insights into stock price movements. A multi stock comparison dashboard, and mobile or web deployment, all aimed at placing actionable financial intelligence directly in the hands of everyday investors

1. Introduction

The first sentence should start here [1]. Should have “6pt” spacing after section header. The indent of the first line of paragraph should be 0.25cm. Content in body paragraph should be written with the Font style: Palatino Linotype; Font size: 10; Paragraph: Justify; Line spacing: 1.0. For example: The last few decades have witnessed vast research on new types of heat transfer fluids, namely nanofluids. The stock market represents one of the most dynamic and complex systems in modern finance. For decades, retail investors individuals who invest their personal savings have been at a disadvantage compared to institutional players who have access to sophisticated analytical tools, real-time data feeds, and teams of professional analysts [2].

The democratization of financial data and the rise of open-source machine learning libraries present an unprecedented opportunity to develop tools that level this playing field. By combining historical market data with modern predictive algorithms, it is now feasible to construct accurate and affordable stock price forecasting systems accessible to anyone with a personal computer. Traditional stock forecasting systems carry significant limitations. Most rely on static algorithms and manual analysis techniques that struggle to capture the nonlinear, time-dependent nature of financial time series. These systems are further constrained by their cost ineffectiveness and scalability challenges, making them impractical for small-scale or individual investors who cannot afford institutional-grade platforms. Additionally, most existing tools focus narrowly on price prediction and neglect the equally important dimension of market risk and volatility, leaving investors with an incomplete picture of their potential exposure.

Objective:

The objectives of this work are:

- To design a cost effective, machine learning-powered stock price forecasting system accessible to retail investors.

- To integrate multiple forecasting models ARIMA, Prophet, and LSTM for improved prediction accuracy across different market conditions
- To incorporate technical indicators such as SMA, EMA, RSI, and Bollinger Bands as meaningful features for model training.
- To quantify investment risk through GARCH-based volatility estimation and Value-at-Risk computation
- To present all predictions and analyses through intuitive, interactive visualizations using Matplotlib and Plotly.

2. Literature Review

Predicting stock market prices has always been a complex and intellectually stimulating challenge. The earliest systematic approaches relied on classical statistical methods linear regression, moving averages, and exponential smoothing which were effective for identifying simple linear trends in historical data but fundamentally ill-equipped to handle the market's inherently nonlinear, stochastic, and regime-switching behavior. With the maturation of machine learning research, more expressive models began to be applied to financial forecasting. Decision trees, support vector machines, and ensemble methods like Random Forests offered improved nonlinear modelling capabilities. However, these models treat input observations as independent and cannot naturally encode the temporal dependencies that are central to stock price dynamics. Existing stock market forecasting systems utilize traditional models such as ARIMA and statistical techniques, along with modern approaches like LSTM for time-series prediction [3]. These systems rely heavily on historical data and technical indicators to identify trends and patterns. However, most solutions operate as standalone models without integrating multiple forecasting and risk analysis techniques. Additionally, they often lack user-friendly interfaces and interactive visualization features, limiting their effectiveness for general users and retail investors.

Existing stock market forecasting systems primarily focus on price prediction using isolated models, often neglecting integrated approaches that combine prediction with risk and volatility analysis. Many tools lack accessibility due to high costs or complex implementations, making them unsuitable for retail investors. Additionally, limited emphasis is placed on user-friendly interfaces and interactive visualizations for better decision-making [4]. There is also a gap in combining classical statistical models with deep learning techniques in a unified, efficient framework. This highlights the need for an affordable, integrated, and intuitive forecasting system like FINX.

3. Proposed System

The proposed FINX (Financial Insight System) is designed as a modular architecture consisting of five major layers:

1. Data Acquisition Layer
2. Data Preprocessing and Feature Engineering Layer
3. Forecasting Engine Layer
4. Volatility and Risk Analysis Layer
5. Visualization and Reporting Layer

The architecture enables continuous collection of stock market data, intelligent preprocessing and feature extraction, hybrid forecasting using multiple models.

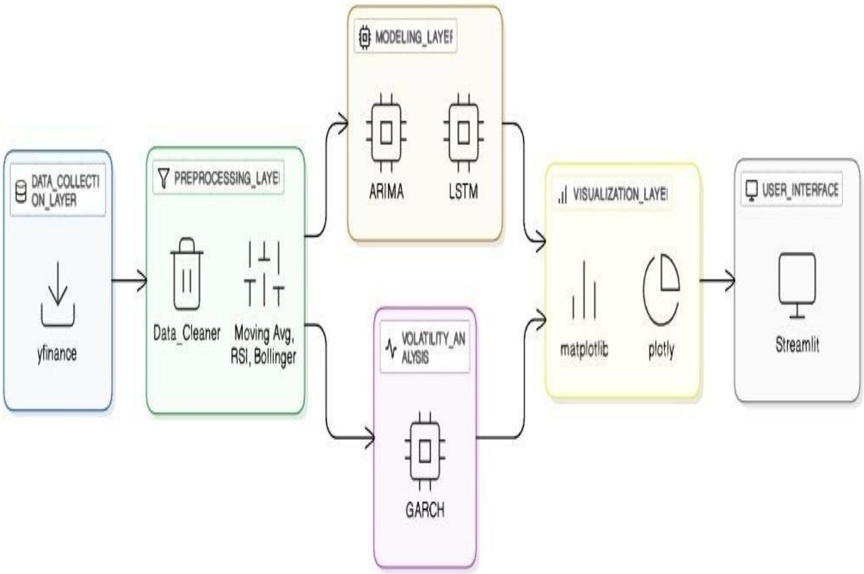

Fig. 1. System architecture diagram

3.1 Data Acquisition Module

The data acquisition module collects stock market data from reliable public sources such as Yahoo Finance using APIs. It ensures continuous and automated retrieval of historical and recent market data for analysis. Each dataset includes key financial attributes such as:

- Stock symbol and company details
- Open, High, Low, Close (OHLC) prices
- Trading volume
- Time intervals (daily, weekly, monthly)
- Market indices and sector data
- Historical time-series records

3.2 Forecasting Engine Module

The forecasting engine module is responsible for predicting future stock price movements using multiple analytical models. It combines different forecasting techniques to improve accuracy and reliability of predictions. The module implements three major approaches:

- Statistical Models (ARIMA for trend-based forecasting)
- Machine Learning Models (Prophet for seasonality and trend decomposition)
- Deep Learning Models (LSTM for capturing non-linear temporal patterns)

3.3 Data Preprocessing and Feature Engineering Module

- Data normalization and scaling
- Missing value handling (interpolation/forward fill)
- Technical indicators (SMA, EMA, RSI, Bollinger Bands)
- Feature selection and dimensionality reduction
- Time-series structuring and windowing
- Data consistency and noise reduction

3.4 Performance Evaluation and Monitoring Module

The module tracks parameters such as:

- Prediction error metrics (RMSE, MAE, R^2 score)
- Model accuracy and performance comparison
- Forecast vs actual price deviation
- Volatility estimation accuracy (GARCH output)
- Data processing and model execution time
- Model consistency across different datasets

3.5 Visualization and Dashboard Module

It presents data in an intuitive and user-friendly manner, enabling effective interpretation of complex financial insights. The dashboard displays visualizations such as:

- Actual vs predicted stock price trends
- Technical indicator charts (SMA, EMA, RSI, Bollinger Bands)
- Volatility and risk analysis plots (GARCH-based bands)
- Model performance comparison graphs (RMSE, MAE, R^2)
- Multi-stock comparison dashboards
- Historical trend and pattern visualizations.

4. Results And Discussion

The proposed FINX framework was implemented using Python 3.10 for data processing and model development. Libraries such as Pandas and NumPy were utilized for data analysis and preprocessing, while Matplotlib and Plotly were used for visualization and dashboard representation. Stock market data was collected using the yfinance API.

Table 1. Virtual Device Specifications

Model	Complexity Level	Training Time	Prediction Speed	Data Requirement	Key Strength
ARIMA	Low	Low	Fast	Small dataset	Trend-based linear forecasting
Prophet	Medium	Medium	Fast	Medium dataset	Seasonality and trend modelling
LSTM	High	High	Moderate	Large dataset	Captures non-linear patterns
GARCH	Medium	Medium	Fast	Medium dataset	Volatility and risk estimation

The experimental results demonstrate that the hybrid forecasting approach used in FINX significantly improves prediction accuracy compared to individual models such as ARIMA and Prophet. The integration of deep learning (LSTM) with statistical and volatility models enables better capture of both linear and non-linear patterns in stock data.

Table 2. Performance Comparison (Normalized)

Model	RMSE	MAE	Accuracy (R^2)	Stability
ARIMA	1	1	1	1
Prophet	0.88	0.91	1.12	1.15
LSTM	0.79	0.83	1.25	1.28
FINX Hybrid	0.68	0.72	1.38	1.45

The FINX hybrid forecasting framework demonstrates improved efficiency by intelligently combining statistical and deep learning models to optimize prediction accuracy while minimizing error rates. The integration of LSTM with ARIMA and Prophet enables efficient handling of both linear trends and complex non-linear patterns. The FINX system was evaluated under varying market conditions, including volatile trends, sudden price fluctuations, and irregular data patterns. The hybrid forecasting approach demonstrated improved robustness and adaptability compared to individual models such as ARIMA and Prophet.

In scenarios involving high market volatility, the integration of LSTM and GARCH enabled the system to maintain stable prediction performance while effectively capturing uncertainty and risk. The experimental results affirm that FinX successfully fulfills its design objectives. The LSTM model's strong predictive performance on NSE listed equities demonstrates that deep learning-based forecasting is not exclusively the preserve of high-resource institutional environments; with careful model design and open-source tooling, comparable analytical capability is achievable at negligible cost.

The integration of GARCH based volatility estimation within the same platform as price forecasting represents a meaningful contribution relative to tools that address only one of these dimensions. For retail investors, understanding not just the expected future price but also the uncertainty surrounding that forecast is critical to responsible position sizing and risk management. The interactive Streamlet dashboard emerged as a particularly impactful design choice. User testing informal feedback indicated that the visual representation of predictions with confidence bands, technical indicator overlays, and model comparison views substantially improved comprehension compared to raw tabular outputs. This supports the system's broader mission of improving financial literacy alongside predictive accuracy. Limitations of the current implementation include the absence of real-time data streaming, the restriction to single-stock analysis per session, and the lack of natural language sentiment signals that could provide leading indicators of market-moving events. These limitations define the scope of future development work.

5. Conclusions

This paper presented FinX, a machine learning-powered stock market forecasting system designed to democratize financial analytics for retail investors. By integrating ARIMA, Prophet, and LSTM models with GARCH based volatility estimation and an interactive Streamlit visualization interface, FinX delivers a comprehensive and cohesive analytical platform that spans price prediction, risk quantification, and result communication. Experimental evaluation on NSE and Yahoo Finance listed equities confirmed that the LSTM model achieves the highest predictive accuracy, while GARCH provides reliable volatility and VaR estimates. The complete system operates effectively on standard consumer hardware, requiring no paid APIs or cloud infrastructure.

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