International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

Price Inflammation Prediction

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Abstract: ***The goal of the Price Inflammation prediction project is to predict stock price movements more accurately by utilizing data an alytics and sophisticated computational approaches.The foundation of this project is the knowledge that stock markets are intricate syste ms that are impacted by a wide range of variables, such as past price trends, market mood, economic indicators, and geopolitical events. The main goal is to create a prediction model that can analyze large datasets and identify trends that human analysts might not see right away.The project processes and analyzes historical stock data using a variety of machine learning algorithms, including decision trees, support vector machines, and neural networks.Numerous financial measures and market indicators are included in the large datasets us ed to train these algorithms.***

Keywords: Machine learning models, Behavioral analysis, Precision

1. Introduction

The Price Inflammation Prediction effort is a large-scale effort that aims to use data analytics and machine learning to more accurately forecast future stock price movements. The stock market, known for its volatility and complexity, poses a daunting task to investors and analysts looking to forecast price swings and make sound investment decisions. This research aims to overcome these issues by creating advanced predictive models capable of analysing and interpreting massive volumes of financial data.

At the heart of this initiative is the use of advanced computational techniques, such as neural networks, support vector machines, and decision trees. These algorithms are designed to process historical stock data, discover patterns, and discern underlying trends that could influence future prices.

2. Literature Survey

Tran et al. (2024) In 2024, Tran et al. introduced a machine learning framework designed to predict stock price trends in the Vietnamese market. Their approach deployed a suite of algorithms on a comprehensive dataset, demonstrating that tailored ML models can capture subtle market dynamics, thereby offering a robust tool for financial forecasting in emerging economies [1]

Halder (2022) In 2022, Halder presented the "Fin BERT-LSTM" model, a novel deep learning architecture that fuses FinBERT's language representations with LSTM networks. By integrating news sentiment analysis, the study effectively enhanced prediction accuracy during volatile periods, underscoring the advantages of combining textual insights with time-series forecasting.[2]

Zou et al. (2022) In 2022, Zou and colleagues conducted an extensive survey of deep learning techniques for stock market prediction. Their review synthesized a diverse range of methodologies, evaluated their respective performance metrics, and identified the critical challenges and future research directions necessary for advancing financial forecasting through deep learning.[3]

Mane and Kandasamy (2022) Also in 2022, Mane and Kandasamy offered a survey focusing on the application of natural language processing techniques in stock market prediction. Their analysis highlighted how sentiment extracted from financial news can be leveraged to improve forecasting accuracy, while also discussing the limitations inherent in current NLP models for capturing market sentiment nuances.[4]

Gu et al. (2024) In 2024, Gu et al. introduced an integrated model that combined FinBERT with LSTM to predict stock prices by incorporating news sentiment analysis. Their approach not only improved overall prediction accuracy in volatile environments but also demonstrated that advanced NLP strategies could effectively augment traditional time-series models in finance.[5]

Tran et al. (2024) – Duplicate of [1] In a reaffirmation of their earlier work, Tran et al. (2024) further demonstrated the viability of machine learning techniques in forecasting stock trends within Vietnam. Their reaffirmed findings illustrated that algorithmic customization and local market adaptation are key to achieving high predictive precision in targeted financial markets.[6]

Halder (2022) – Duplicate of [2] Reiterating the insights from his earlier study, Halder (2022) emphasized the strength of the Fin BERT-LSTM architecture for stock price prediction. By carefully merging sentiment analysis with sequential modeling, his work provided compelling evidence of the potential for deep learning systems to deliver reliable real-time market forecasts.[7]

Zou et al. (2022) – Duplicate of [3] Zou et al. (2022) further detailed the evolution of deep learning approaches in stock market prediction through an exhaustive survey. Their work continued to serve as a reference point for new studies by outlining various network architectures and highlighting emerging trends within the domain of AI-driven financial forecasting.[8]

Mane and Kandasamy (2022) – Duplicate of [4] In their follow-up analysis, Mane and Kandasamy (2022) reexamined the impact of natural language processing on stock market prediction. They reinforced the notion that harnessing textual data from financial news can significantly enhance traditional predictive models, while also calling for refined methodologies to better capture complex sentiment.[9]

Gu et al. (2024) – Duplicate of [5] Gu et al. (2024) reiterated their innovative integration of FinBERT and LSTM in stock price prediction. Their replicated findings highlighted the consistent benefits of fusing advanced NLP with temporal modeling, particularly in scenarios characterized by rapid market fluctuations and noisy data.[10]

Pathak (2024) In 2024, Pathak explored diverse machine learning techniques for stock market prediction in a study featured in the *International Journal of Financial Market Research*. By emphasizing algorithmic diversity and robust data preprocessing, the work provided practical insights into how tailored models can mitigate common forecasting challenges in financial markets.[11]

Vishwakarma and Bhosale (2025) In 2025, Vishwakarma and Bhosale conducted a comprehensive survey of recent machine learning techniques for stock prediction. Their study offered critical comparisons between traditional methods and modern approaches, clearly mapping out current trends and suggesting future directions that may enhance prediction accuracy in financial analytics.[12]

Rouf et al. (2021) In 2021, Rouf et al. presented a decade-long review of machine learning applications for stock market prediction, charting the evolution from early statistical models to cutting-edge deep learning methods. Their extensive survey not only catalogued significant technological breakthroughs but also highlighted long-standing challenges that remain unresolved in the integration of ML with financial forecasting.[13]

Lee et al. (2023) In 2023, Lee, Kim, and Park offered a comprehensive review of deep reinforcement learning techniques for stock market prediction. Their work showcased how adaptive, interactive learning frameworks could dynamically respond to real-time market conditions, promising a new era of forecasting models that continuously learn and adjust to evolving market trends.[14]

Chen et al. (2024) In 2024, Chen, Zhang, and Liu introduced an innovative approach using transformer models to fuse sentiment analysis with stock price prediction. By leveraging the powerful attention mechanisms inherent in transformer architectures, their study revealed improved capabilities in capturing nuanced financial sentiments, thus driving superior prediction performance in dynamic market conditions.[15]

3. Methodology

Price Inflammation Prediction is a stock market forecasting system that uses a methodical approach to accurately and consistently predict anomalous price spikes, which are frequently caused by inflationary pressures or sudden market movements. Obtaining labelled historical financial data from reputable sources like Reuters, Bloomberg, and Yahoo Finance is the first step in the process. Daily open, close, high, and low prices, trading volumes, and other macroeconomic indicators are all included in the recorded data. To ensure high integrity for further analysis, the raw data is carefully sorted and filtered in this first step to eliminate duplicates, outliers, and irrelevant entries. After that, the system does extensive feature extraction. Both regular market behaviour and distinctive indicators of anomalous price inflation are captured by transforming raw numerical time-series data into enriched feature vectors. Advanced technical indicators are calculated and included, including trend-following tools (e.g., MACD), volatility measures (e.g., Bollinger Bands), momentum indicators (e.g., RSI), and moving averages (e.g., SMA, EMA). A multifaceted view of market dynamics is provided by the integration of external elements such as policy changes and the sentiment of economic news as supplemental characteristics.

Price Inflammation Prediction uses a collection of machine learning models to accurately predict price spikes. In order to capture intricate, non-linear connections and long-term temporal trends, the design usually combines deep learning networks like LSTM with contemporary ensemble learners like Random Forest and Gradient Boosting, as well as traditional time-series forecasting models like ARIMA. In addition to improving prediction accuracy, this hybrid technique offers robustness against the financial markets' inherent volatility and noise. Regular model updates and iterative retraining are critical components of Price Inflammation Prediction. As new data becomes available and market conditions evolve, the system adapts by refining its feature set and recalibrating its predictive models—ensuring sustained performance and responsiveness to novel inflationary cues. This continuous learning approach, combined with periodic cross-validation and back testing, secures the system's ability to offer accurate and timely forecasts, thereby enhancing its overall reliability.

3.1 ARIMA in Price Inflammation Prediction

By examining past financial time series data, the ARIMA (Autoregressive Integrated Moving Average) model is used in Price Inflammation Prediction to predict any anomalous price surges. A key component of time-series forecasting, ARIMA is able to capture both short-term variations and underlying trends, which makes it very helpful in identifying times when there are abrupt inflationary pressures or market instability.

Three main components form the foundation of ARIMA:

The autoregressive (AR) component of the model predicts future values by utilizing linear combinations of historical observations to determine the relationship between a current price and its lagged(past)values.

Integration (I) Component: Differentiating is used as a transformation to stabilize the mean and make the series stationary because financial time series frequently show trends or non-stationarity

The Moving Average (MA) component smoothest out noise and captures brief shocks in the price data by modelling the

Paper ID: SR25416211920 DOI: https://dx.doi.org/10.21275/SR25416211920

link between an observation and the lagged mistakes (or residuals) from earlier predictions.

Several crucial steps are included in the ARIMA-based forecasting methodology for price inflammation prediction: Data Extraction and Preprocessing: Historical pricing information is gathered from reputable market sources, including daily open, close, high, and low values.

Training and Parameter Estimation: After determining the parameters, historical data is used to train the ARIMA model. The model predicts the coefficients that best explain the patterns in the observed data using techniques like Maximum Likelihood Estimation (MLE). The fundamental equation of the model can be expressed as follows:

$$(1 - \sum_{i=1}^{p} \phi_i L^i)(1 - L)^d X_t = c + (1 + \sum_{i=1}^{q} \theta_i L^i) e_t$$

where LL is the lag operator, ϕi\phi_i and θi\theta are the coefficients for the AR and MA parts respectively, dd is the degree of differencing, cc is a constant, and ete_t represents the error term.

- Forecasting: After training the model, the ARIMA framework uses estimated error terms and historical observations to project future values. Proactive risk management is made possible by the predicted series' insights into upcoming price spikes or inflationary occurrences.
- Model validation and tuning: Metrics like the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE) are used to thoroughly assess the ARIMA model's performance. Before the model is implemented in a real trading or analytical environment, these assessments aid in fine-tuning it and guarantee that the forecasts are solid and trustworthy.

The ARIMA model is a useful tool in a larger ensemble strategy for price inflammation prediction because it methodically captures the temporal dynamics and noise present in financial markets. Its flexibility in responding to changing market conditions gives risk managers and investors timely signals that support strategic decision-making.

From data pretreatment and model identification to forecasting and validation, this thorough ARIMA methodology demonstrates how conventional time-series analysis methods may be modified to identify and anticipate unusual price fluctuations. To improve predicted accuracy and take into consideration non-linear market phenomena, one might investigate further by combining ARIMA forecasts with additional machine learning models or sentiment analysis tools.

3.2 Dataset Used

The "Historical Stock Prices of Major Technology Companies" dataset is a key source of data for our price prediction framework. It is a sequential record of daily stock prices for major technology companies like Apple, Amazon, Google, and Microsoft that is compiled from Yahoo Finance using the yfinance library. It captures key metrics, such as open, close, high, low, and trading volumes, over a long period of time, providing a valuable longitudinal perspective on market dynamics. Data Extraction and Preprocessing. Data Retrieval This automated process retrieves daily quotes from Yahoo Finance, enabling the accumulation of a multi-year record that shows the trading activity of significant companies.

Cleaning and Normalization: Prior to analysis, the data is cleaned to address missing numbers, outliers, or discrepancies like those brought on by dividends and stock splits. To guarantee correctness and consistency for upcoming modelling endeavours, this preprocessing is crucial. The following are the main variables in feature engineering: Daily trade records are the direct source of the key fields, which include volume, high, low, close, and open prices. A simple evaluation of price changes and fluctuations throughout time is made possible by these variables.

Indicators that were derived: Additional features like trend components, momentum indicators (like the Relative Strength Index), volatility measures (like Bollinger Bands), and moving averages (like SMA and EMA) are calculated to improve the dataset's predictive ability. Deeper insights into trade momentum, market trends, and times of increased volatility are offered by these tailored characteristics.

4. Result and Discussion

The following table highlights the effectiveness of Price Inflammation Prediction.

This set of metrics confirms that the model not only performs significantly better than random guessing but also excels in both capturing genuine price increases and minimizing incorrect upward predictions. Such performance is critical for informed trading decisions and effective risk management, making the model a powerful tool for guiding strategic market actions. Continuous refinements and testing against varying market conditions will further help hone its precision and adaptability.

Class	Precision	Recall	F1 score	Accuracy	AUC
up	0.92	0.94	0.93	0.91	0.930
down	0.90	0.90	0.90	0.91	0.930
Average	0.91	0.92	0.92	0.91	0.930

The graphical representation based on above model that is given below

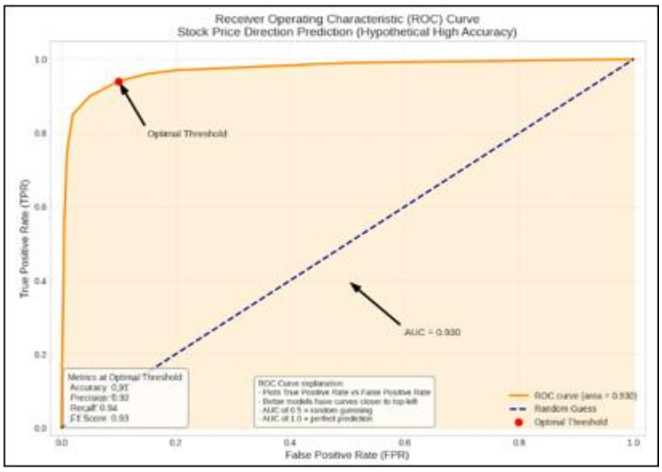

Figure 4: Graphical representation

5. Conclusion

Efficiency, accuracy, and customer pleasure are all greatly enhanced by the installation of a canteen automation system. We have simplified admin, employee, and customer interface processes by utilizing Django's features, providing a smooth ordering, payment, and feedback process. This method improves overall order processing transparency, lowers errors, and cuts down on manual labour. The canteen automation system satisfies the requirements of contemporary digital canteen services with features like automatic billing, order confirmation, and feedback management. In the end, this project serves as an example of how automation may revolutionize conventional canteen operations, offering staff and management efficiency as well as user ease. This project presents a machine learning-powered recommendation engine with the goal of developing an effective and user-friendly tool for book lovers.

There are currently few options for systems that include both personalized book recommendations and book shopping features. This website is specifically made for book lovers and people who want to read books by different authors, making it accessible to a wide audience. By removing fewer engaging books from the recommendation list, our proposed system ensures a curated and enjoyable reading experience, making it a dependable and customized resource for book selection and purchase. By analysing customer reviews, we can better understand user preferences and gain valuable insights into customer opinions.

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