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Stock Price Prediction Web Using Time Series Models

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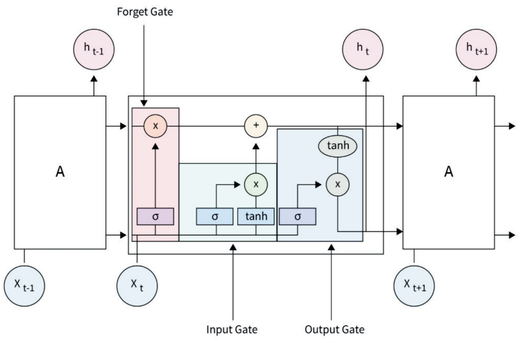
Abstract

In the era of globalization and rapid technological advancement, the financial market is facing unprecedented volatility. Economic, political, and social events have a significant impact on financial assets, making stock price predictions increasingly complex and risky. The stock market, known for its sensitivity to these fluctuations, presents a major challenge for investors striving to optimize profits and protect their portfolios from unexpected changes. The emergence of data science has revolutionized financial market analysis, offering new opportunities through time series prediction models powered by artificial intelligence and machine learning. These models not only analyze historical data but also identify recurring patterns to forecast future trends and stock price movements. By leveraging these advanced methods, investors can move beyond intuition and personal experience, making more informed, data-driven decisions.

Introduction

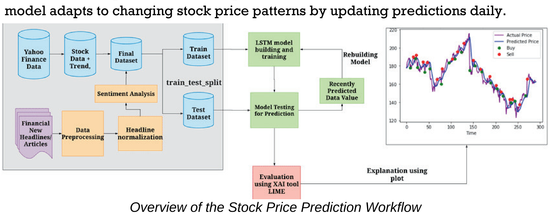
In the rapidly changing global financial markets, influenced by economic, political, and social events, stock market prediction becomes complex and risky. Data science and artificial intelligence, particularly time series forecasting models and machine learning techniques, offer new avenues for analysis and prediction. These models analyze historical data and identify recurring patterns, enabling more accurate stock price movements. This research focuses on developing a web-based stock price prediction system using advanced time series forecasting models, including ARIMA and LSTM. The system processes historical stock data, such as opening and closing prices, trading volumes, and financial indicators, to forecast future price movements. LSTM, due to its ability to capture long-term dependencies, is particularly effective for stock market prediction. The system aims to provide investors with reliable data-driven decision-making tools. By offering accurate predictions, it enables users to gain insights into market trends and optimize their investment strategies. The system is designed with a user-friendly interface, making it accessible to users without technical backgrounds.



Long Short - Term Memory Structure

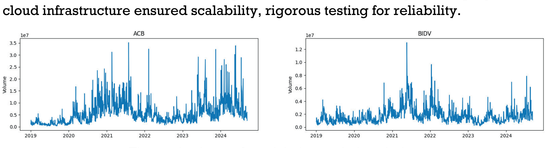
Methods

This study employs time series models, including ARIMA and LSTM, to predict stock prices. Historical stock prices, trading volumes, and preprocessed data are used as inputs. ARIMA, a classical statistical method, captures linear relationships between historical stock prices using autoregression, differencing, and moving averages. Grid search optimizes ARIMA parameters. LSTM, due to its ability to handle non-linear patterns, predicts stock prices for the **next 30 trading days** based on the **previous 15 days' data** with **TensorFlow's LearningRateScheduler** callback to optimize training performance**.** The input is shaped as **(5,1)**, with the past week's data and the closing price as features. **Two LSTM layers** with **200 output nodes** and **Leaky ReLU activation** manage non-linearities. Dense layers reduce the node count progressively, ending with **50 inputs and five outputs** for the forecasted closing prices. **Mean Squared Error** is the loss function, optimized with **ADAM** using a custom learning rate. Walk-forward validation ensures the model adapts to changing stock price patterns by updating predictions daily.

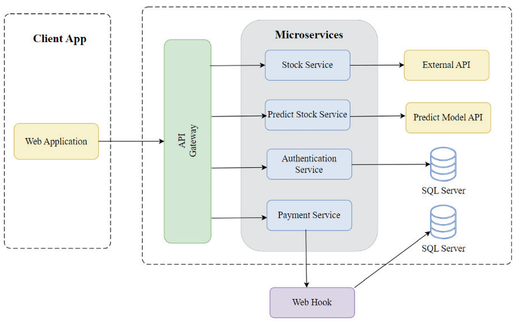


Overview of the Stock Price Prediction Workflow

The microservices architecture ensured scalability and flexibility. Key functionities, such as **user login, stock price predictions, and data comparisons, were mapped using use case, activity, and sequence diagrams**. The architecture included a front-end client application, an API Gateway, and microservices for stock data processing and model execution. **A Microsoft SQL Server** stored user information, historical stock data, and prediction results. Entity-relationship diagrams optimized data retrieval and integration. Angular provided a responsive user interface, while **Fast-API** interacted with machine learning models built in **TensorFlow and Scikit-learn**. The system integrated with real-time financial data APIs for current stock data analysis and prediction. **Matplotlib** displayed prediction results visually. ARIMA and LSTM models trained on historical stock data evaluated using **RMSE and MAPE.** The system deployed on cloud infrastructure ensured scalability, rigorous testing for reliability.



The total volume of stock being traded each day

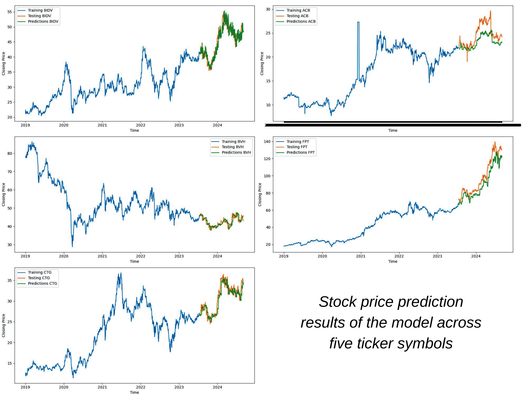


Software Architecture

Result

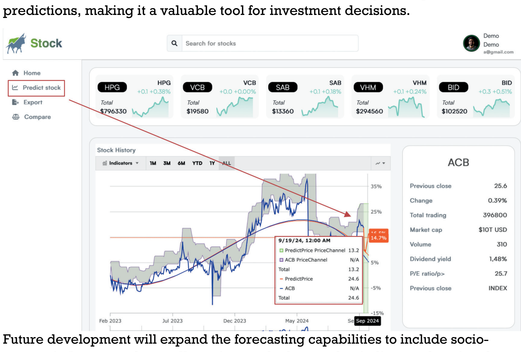
Deep Learning Model Results				
Company/ Digital Currency	RMSE	MAPE	MAE	SEM
ACB	1.6783	5.39%	1.3827	0.0699
BIDV	3.1662	5.46%	2.5834	0.1244
BVH	1.4457	2.58%	1.0944	0.0863
CTG	1.6195	4.00%	1.2687	0.0813
FPT	13.9527	36.71%	11.6538	0.4630
ARIMA Model Results				
Company/ Digital Currency	RMSE	MAPE	MAE	SEM
ACB	6.3428	6.22%	5.5095	0.1868
BIDV	5.1022	6.10%	4.2803	0.2285
BVH	2.9092	2.07%	2.9092	0.1930
CTG	3.3969	5.07%	3.5005	0.2166
FPT	21.0259	14.02%	15.8303	0.8233

There are higher RMSE and MAE in most cases (except FPT), especially for ACB and CTG, which shows that ARIMA is less accurate than Deep Learning in these companies. However, for FPT, ARIMA has **RMSE (21.0259)** and **MAE (15.8303)**, although not small, but still lower than Deep Learning, which shows that this model is more effective for this particular case.Summary:Deep Learning Models are generally superior to ARIMA in terms of accuracy (RMSE, MAPE, MAE) in cases except FPT. ARIMA proved to be ineffective in predicting with high accuracy, except in the case of FPT, where ARIMA has better results than Deep Learning



Stock price prediction results of the model across five ticker symbols

The stock price prediction system successfully integrated historical data with the LSTM algorithm to forecast future stock prices. The LSTM model's ability to capture long-term dependencies in time-series data enabled it to identify patterns and predict trends effectively. It processed key market features, such as opening and closing prices, trading volume, and financial indicators, revealing significant relationships between them for accurate predictions. The system effectively handled noisy data and market volatility, thanks to LSTM's capacity to filter out irrelevant information, focusing on key signals. Optimizations, including a custom learning rate scheduler, improved both training speed and prediction accuracy, making the model suitable for real-time financial forecasting. The system's financial charts offered a clear comparison of historical and predicted data, aiding users in assessing trends through various moving averages. Overall, the LSTM-based approach demonstrated its potential for accurate, robust, and timely stock price predictions, making it a valuable tool for investment decisions.



Future development will expand the forecasting capabilities to include socio-economic factors such as coffee prices and other market indices, enhancing the system's versatility beyond stock price predictions. Integrating advanced models like Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) will further strengthen analytical and predictive capabilities, addressing the critical demands for timeliness and accuracy in predictions. Additionally, the project aims to refine the mobile application and develop a web module for managing publicly listed companies. These enhancements will provide users with a better experience in tracking and analyzing corporate data, facilitating informed investment decisions.

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