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Stock Price Prediction Web Using Time Series Models

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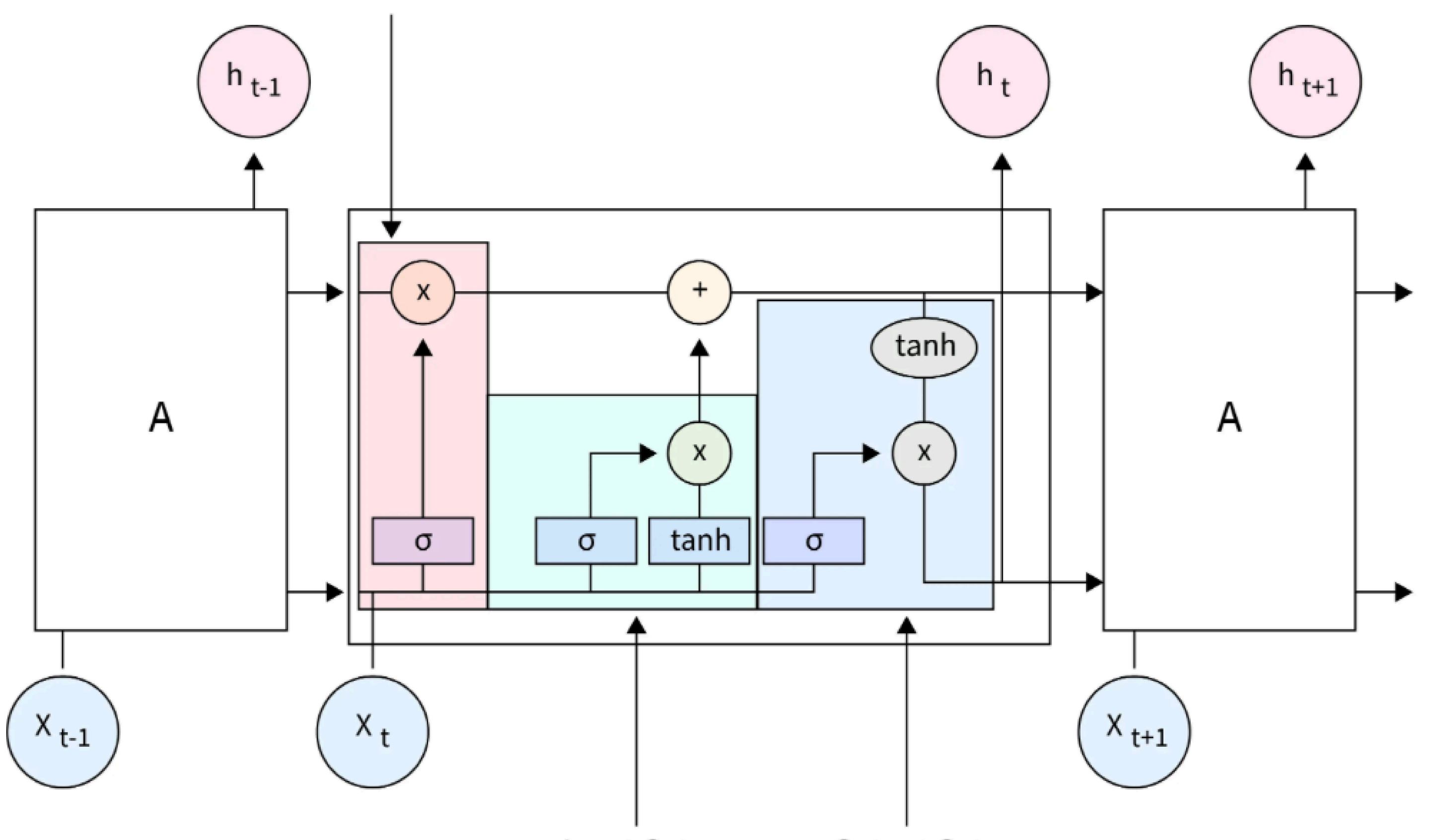
Abstract

In an era of globalization and rapid technological change, financial markets face unprecedented volatility from economic, political, and social events, complicating stock price predictions. Data science enhances market analysis through AI and machine learning time series models that analyze historical data to identify patterns. These models help investors forecast trends and make more informed, data-driven decisions.

Introduction

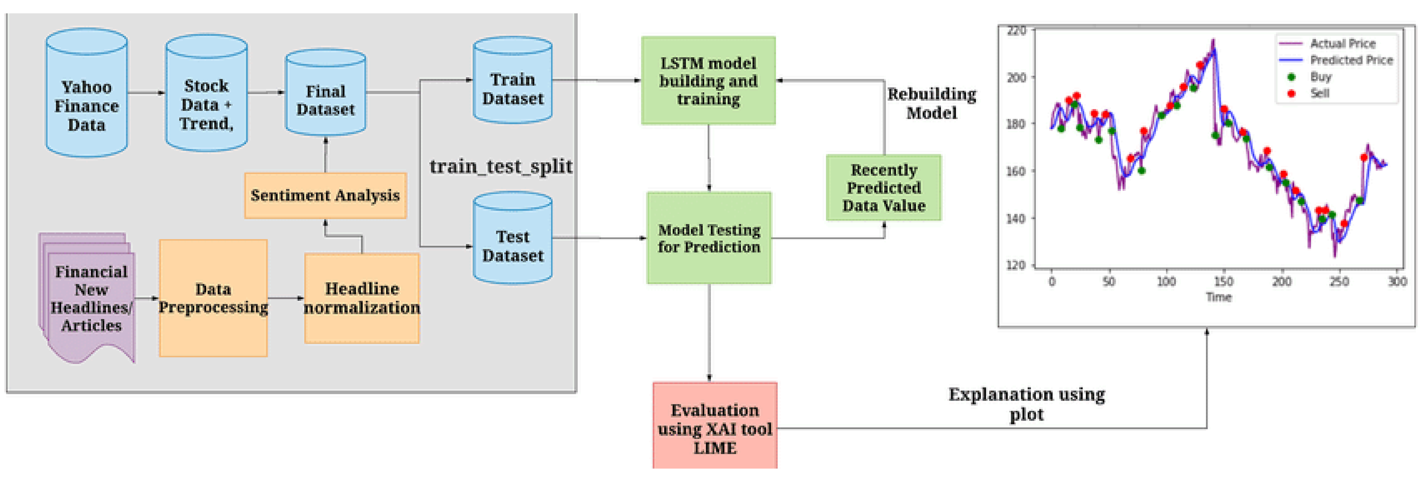
In the rapidly changing global financial markets, predicting stock prices is complex due to economic, political, and social events. Data science and AI, particularly time series forecasting and machine learning, provide new analysis avenues. This research develops a web-based stock price prediction system using advanced models like ARIMA and LSTM. The system processes historical stock data—opening/closing prices, trading volumes, and financial indicators—to forecast future movements. LSTM effectively captures long-term dependencies for accurate predictions. Ultimately, the system aims to support data-driven decision-making for investors through a user-friendly interface that offers insights into market trends and optimizes investment strategies.



Long Short - Term Memory Structure

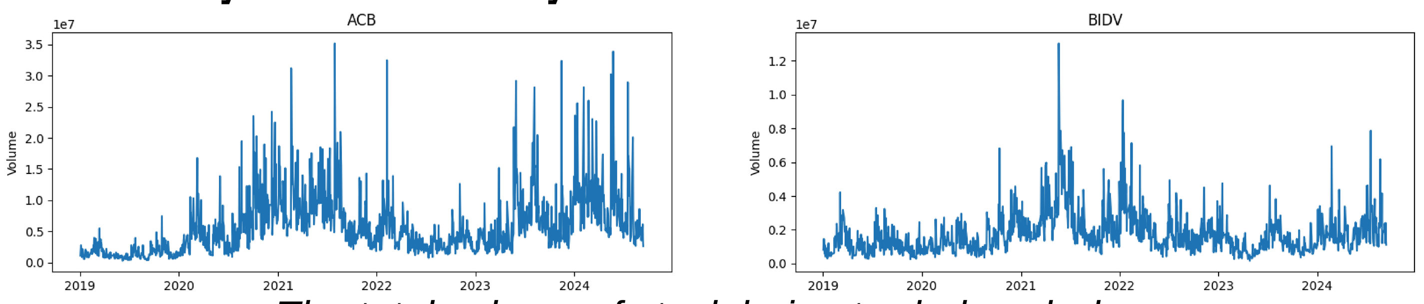
Methods

This study predicts stock prices using ARIMA and LSTM models. Historical stock prices, trading volumes, and preprocessed data are inputs. ARIMA captures linear relationships, while LSTM handles non-linear patterns to **predict 30-day prices based on the past 15 days**. Input is **shaped (5,1)**, with **two LSTM layers (200 nodes, Leaky ReLU)** and **dense layers** reducing to **50 inputs for five forecasted prices**. **Mean Squared Error** is optimized with **ADAM** and a custom learning rate using **Tensorflow's LearningRateScheduler**. Walk-forward validation updates predictions daily.

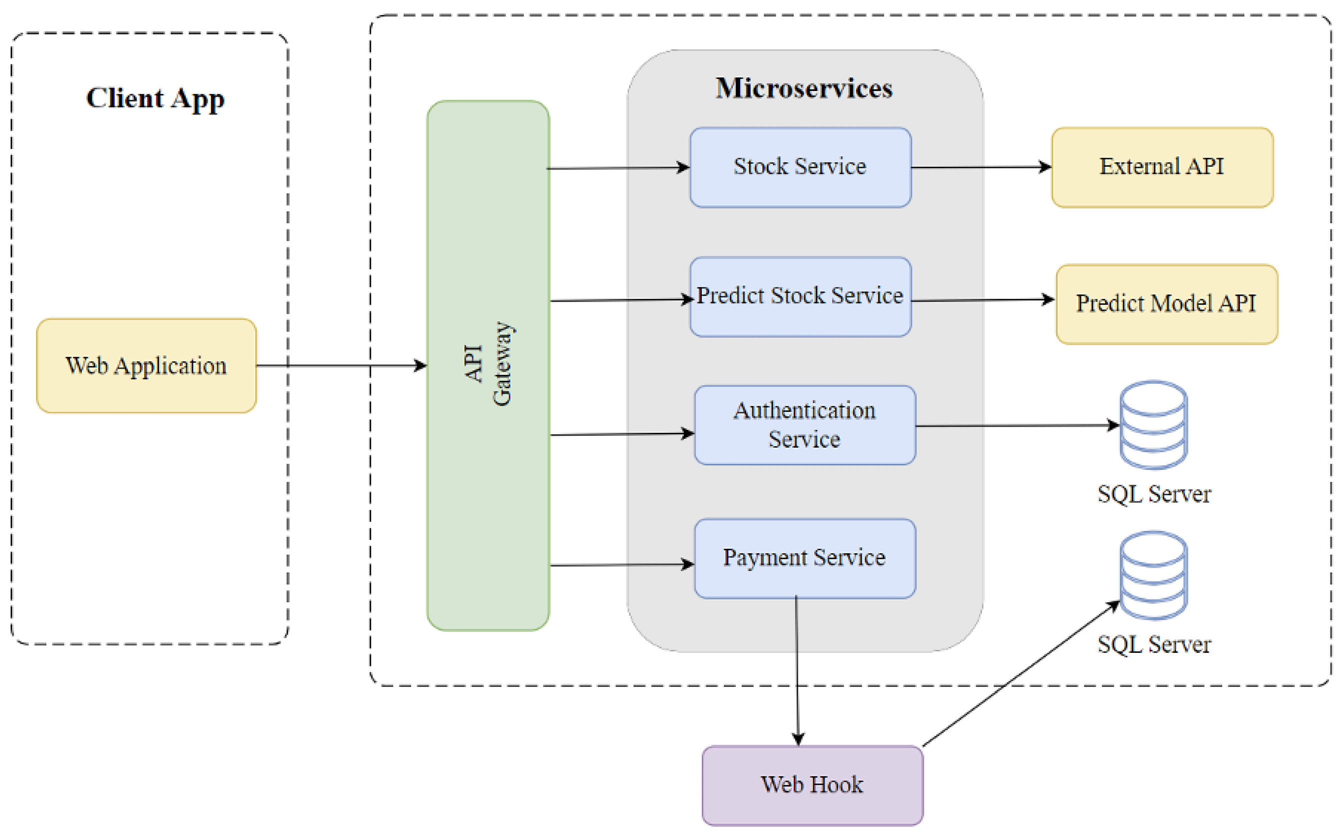


Overview of the Stock Price Prediction Workflow

The microservices architecture ensured scalability and flexibility, with features like **user login, stock predictions, and data comparisons**. It used a **front-end client, API Gateway**, and **microservices** for data processing. **Microsoft SQL Server** stored data, **Angular** powered the UI, and **FastAPI** connected to **TensorFlow and Scikit-learn models**. **Real-time financial APIs** enabled stock analysis, visualized with **Matplotlib**. ARIMA and LSTM models, evaluated with RMSE and MAPE, were **deployed on cloud** infrastructure for scalability and reliability.



The total volume of stock being traded each day

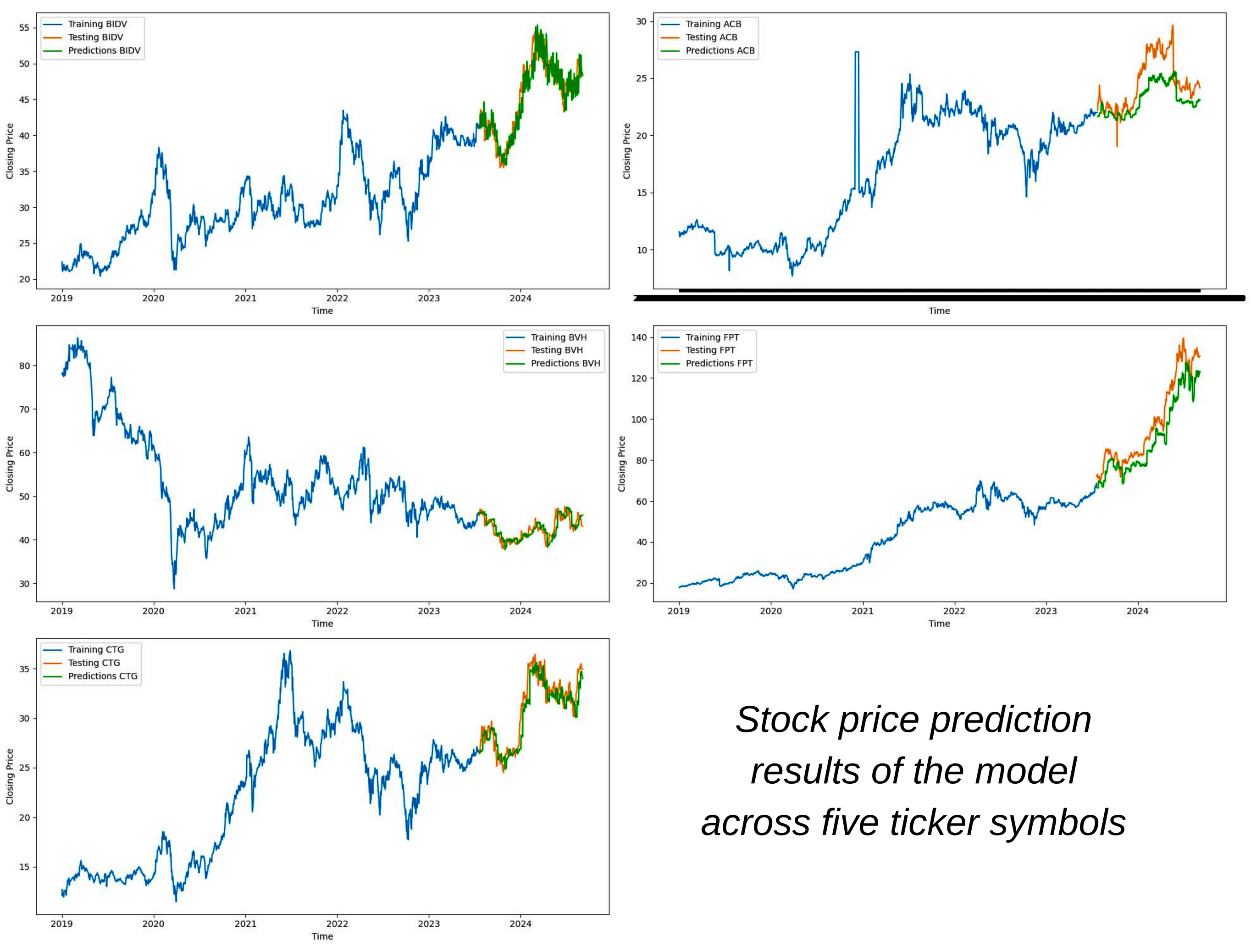


Software Architecture

Result

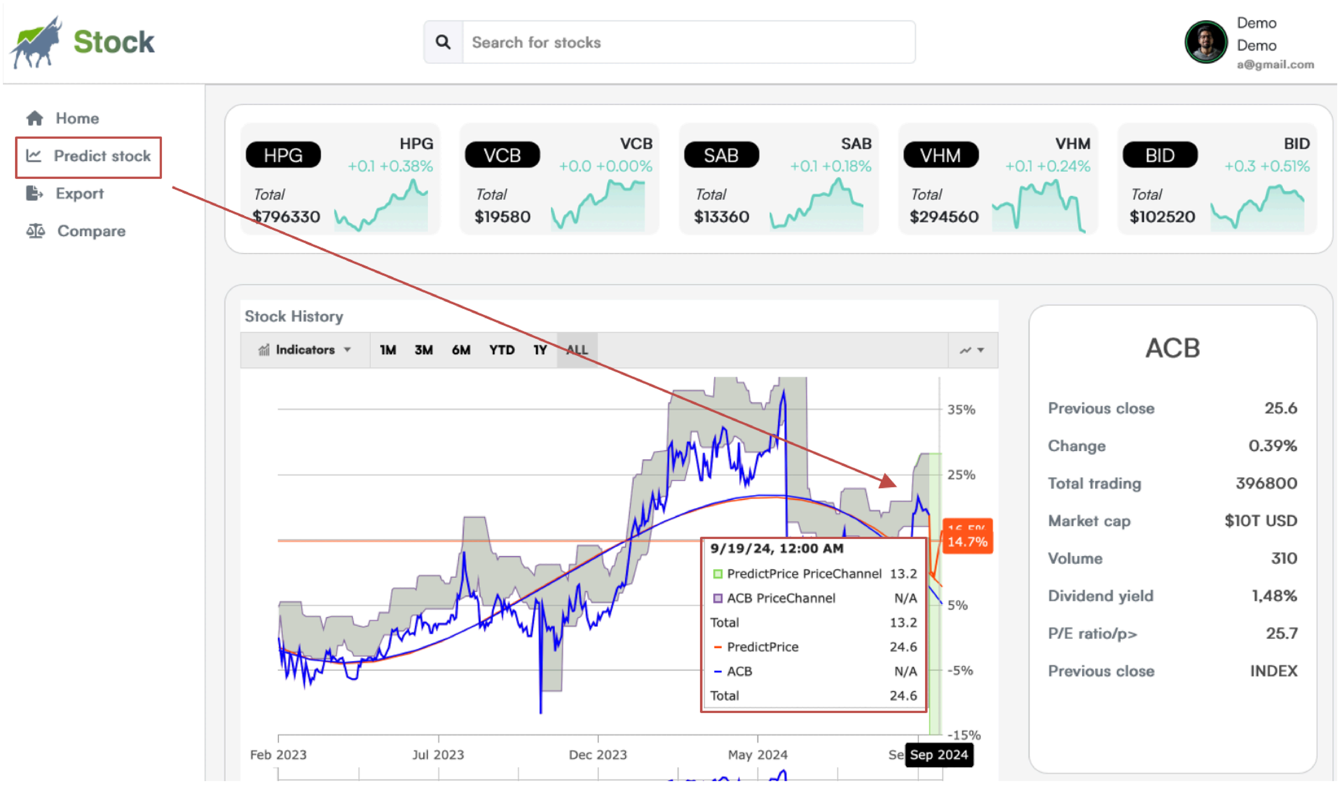
Deep Learning Model Results				
Company/ Digital Currency	RMSE	MAPE	MAE	SEM
ACB	1.6783	5.39%	1.3827	0.0699
BIDV	3.1662	5.46%	2.5834	0.1244
BVH	1.4457	2.58%	1.0944	0.0863
CTG	1.6195	4.00%	1.2687	0.0813
FPT	13.9527	36.71%	11.6538	0.4630
ARIMA Model Results				
Company/ Digital Currency	RMSE	MAPE	MAE	SEM
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

- ARIMA shows higher RMSE and MAE compared to Deep Learning in most cases, especially for ACB and CTG, indicating its **lower accuracy.**
- However, for FPT, ARIMA achieves **RMSE of 21.0259** and **MAE of 15.8303**, which, while not small, are lower than those of Deep Learning, making ARIMA more effective for this specific case.
- Deep Learning models generally **outperform ARIMA in accuracy (RMSE, MAPE, MAE)**, except for FPT, where ARIMA delivers better results.



Stock price prediction results of the model across five ticker symbols

The stock price prediction system leveraged LSTM to forecast future prices by capturing long-term dependencies in time-series data and processing key market features like opening/closing prices, trading volume, and financial indicators. LSTM effectively handled noisy data and market volatility, boosting prediction accuracy. Optimizations improved training speed, and financial charts offered clear comparisons between historical and predicted prices to aid trend assessment.



Future development will expand forecasts to include socio-economic factors like coffee prices and market indices. Adding SVM and RNN models will improve accuracy and timeliness. Enhancing the mobile app and building a web module for managing listed companies will boost user experience and support better investment decisions.

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