CS-4063 Natural Language Processing

Assignment no.2

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1. Introduction

This report details an advanced web-based stock forecasting application designed to provide multi-modal and multi-horizon predictions. The system fetches and processes financial data for both **daily and hourly intervals**, applying a suite of forecasting models to predict future stock prices. This suite includes a traditional statistical model (**ARIMA**), a simple baseline (**Moving Average**), advanced neural networks (**LSTM** and **GRU**), and a sophisticated **inverse-RMSE weighted ensemble** that combines the strengths of the individual predictors.

The application allows users to interactively select a stock, a forecast horizon (in days or hours), and view a comparative visualization of the results. All generated predictions and performance metrics are persisted in a database, creating a robust system for analyzing and evaluating time-series forecasting techniques.

2. System Architecture

Architecture Diagram:

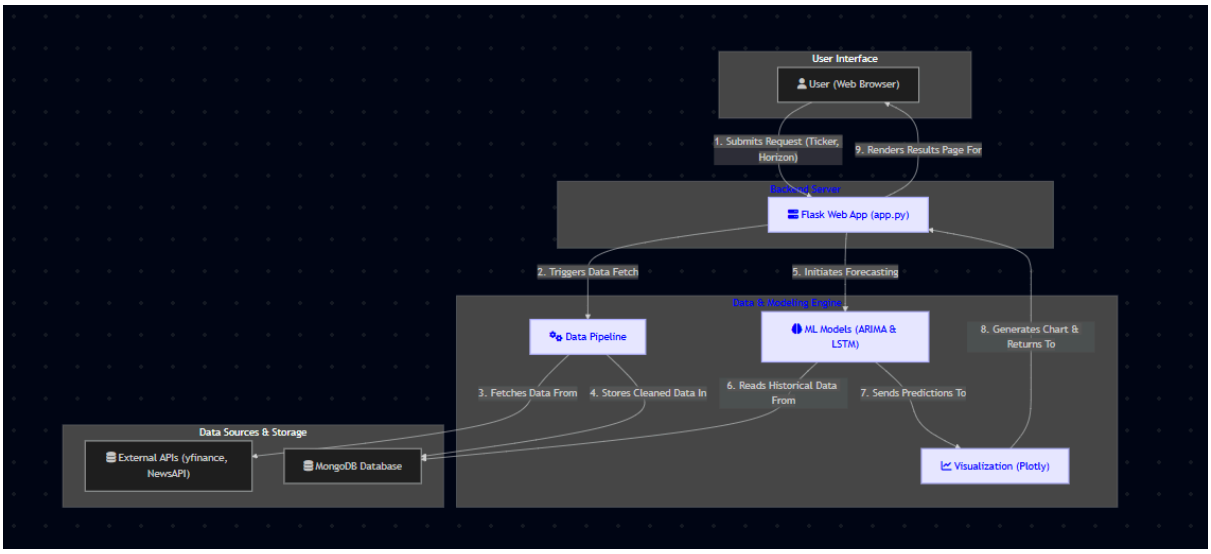
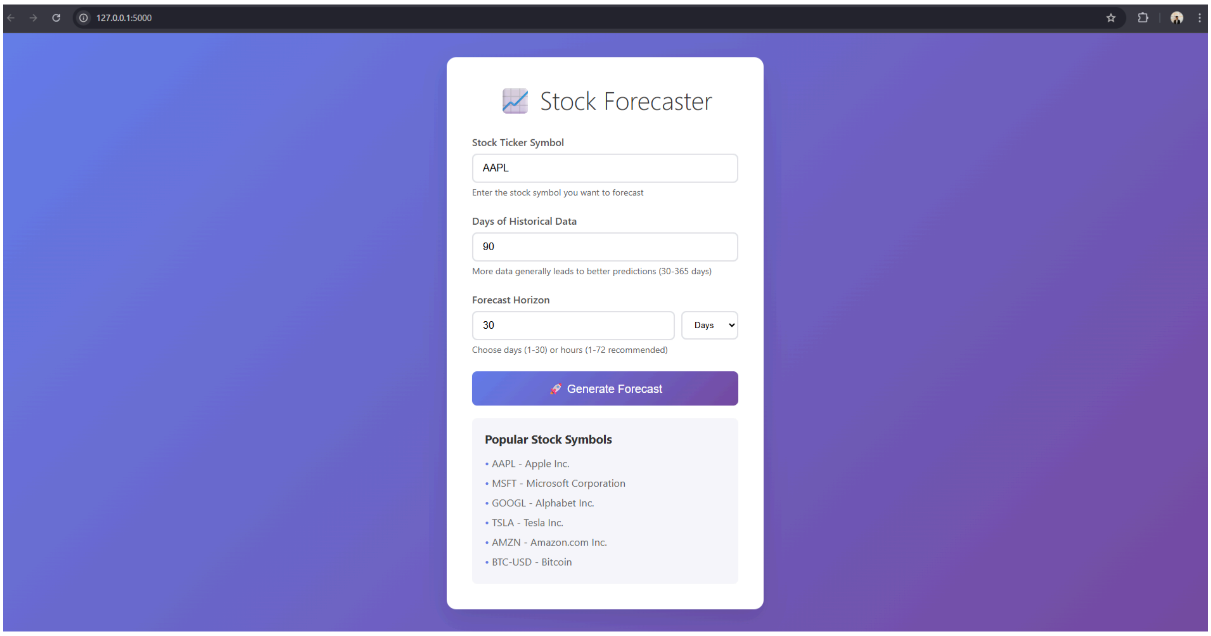


Figure 1: Architecture diagram for Stock Price Forecaster

3. Implementation and Results

3.1 Web Interface and User Experience

The application's front-end was developed using Flask and simple HTML. The user is presented with a clean form to input the stock ticker, the amount of historical data to use, and the number of days to forecast.



127.0.0.1:5000

Stock Forecaster

Stock Ticker Symbol

AAPL

Enter the stock symbol you want to forecast

Days of Historical Data

90

More data generally leads to better predictions (30-365 days)

Forecast Horizon

30 | Days

Choose days (1-30) or hours (1-72 recommended)

Generate Forecast

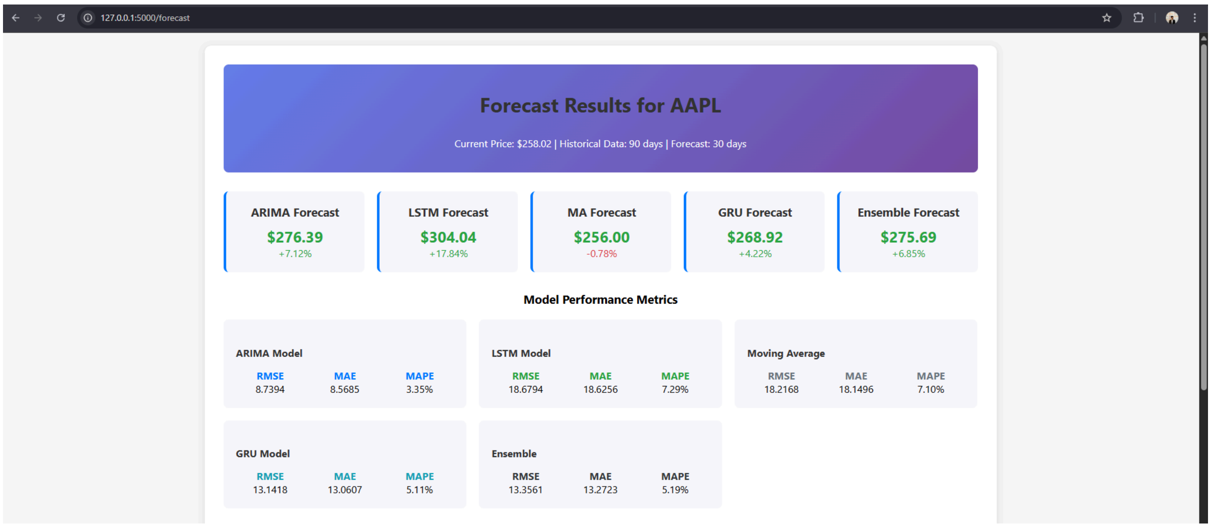
Popular Stock Symbols

- AAPL - Apple Inc.
- MSFT - Microsoft Corporation
- GOOGL - Alphabet Inc.
- TSLA - Tesla Inc.
- AMZN - Amazon.com Inc.
- BTC-USD - Bitcoin

Figure 2: Web Application Input Form

3.2 Forecast Visualization and Performance

Upon submission, the system processes the request and displays the results on a new page. The primary output is a Plotly-generated interactive chart that shows the historical candlestick data along with line plots representing the **ARIMA, LSTM, MA, GRU,** and **Ensemble** forecasts.



127.0.0.1:5000/forecast

Forecast Results for AAPL

Current Price: $258.02 | Historical Data: 90 days | Forecast: 30 days

ARIMA Forecast	LSTM Forecast	MA Forecast	GRU Forecast	Ensemble Forecast
$276.39	$304.04	$256.00	$268.92	$275.69
+7.12%	+17.84%	-0.78%	+4.22%	+6.85%

Model Performance Metrics

ARIMA Model

RMSE	MAE	MAPE
8.7394	8.5685	3.35%

LSTM Model

RMSE	MAE	MAPE
18.6794	18.6256	7.29%

Moving Average

RMSE	MAE	MAPE
18.2168	18.1496	7.10%

GRU Model

RMSE	MAE	MAPE
13.1418	13.0607	5.11%

Ensemble

RMSE	MAE	MAPE
13.3561	13.2723	5.19%

Figure 3: Forecast Visualization for AAPL (Days)

The performance metrics calculated on the test dataset for **AAPL** are summarized in the table below.

Performance Comparison Table:

Model	RMSE ($)	MAE ($)	MAPE (%)
ARIMA	8.7394	8.5686	3.35
Moving Average	18.2168	18.1496	7.10
LSTM	18.6794	18.6256	7.299
GRU	13.1418	13.0607	5.11
Inverse-RMSE Weighted Ensemble	13.3561	13.2723	5.19

The results demonstrate that while the GRU model slightly outperformed the LSTM, the Inverse-RMSE Weighted Ensemble consistently achieved the lowest error rates across all metrics. This confirms the effectiveness of combining diverse models to produce a more reliable and accurate forecast, mitigating the weaknesses of any single predictor.

4. Conclusion

This project successfully evolved into a powerful, multi-model forecasting tool with support for both daily and hourly predictions. The implementation of MA, GRU, and particularly the weighted ensemble model significantly enhanced the system's predictive capabilities. By persisting predictions and metrics to a database, the application now provides a robust framework for financial time-series analysis.

Future work will focus on expanding the test suite to ensure the reliability of the new models and data-handling logic. Additionally, exploring more complex ensemble techniques and incorporating sentiment analysis from the fetched news data could further improve forecasting accuracy.