FAANG Stock Price Prediction using LSTM

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Abstract

This paper presents an LSTM-based neural network to forecast FAANG (Facebook [Meta], Amazon, Apple, Netflix, Google) stock prices. We combine both technical and fundamental features. Technical indicators include open, high, low, close, adjusted close, and volume, from which we derive daily returns, 10-day moving averages, and 10-day rolling volatility. Fundamental indicators encompass earnings per share (EPS), market capitalization, P/E ratios, debt-to-equity, margins, and growth metrics such as quarterly revenue growth. Beta and Beta (5Y) are included to quantify market sensitivity. Data is preprocessed through feature scaling and date alignment. Manual hyperparameter tuning identifies an optimal model configuration achieving RMSE of $28.81 and MAE of $17.71 on actual price scales. The model shows strong predictive capabilities, highlighting its utility for short-term investment decision support.

1 Introduction

Predicting stock prices is crucial for investment strategies but remains challenging due to volatility, market noise, and the non-stationary nature of financial data. FAANG stocks (Facebook [Meta], Amazon, Apple, Netflix, and Google) dominate both market capitalization and public attention, making them prime candidates for predictive modeling due to their liquidity and available historical data.

Long Short-Term Memory (LSTM) networks, a variant of recurrent neural networks, are capable of modeling long-term temporal dependencies, making them well-suited for sequential financial time series data. Recent advances have shown that LSTM models outperform traditional machine learning and statistical approaches in stock price prediction tasks. However, most studies rely heavily on technical indicators alone and overlook company-specific fundamental information, such as earnings, margins, and valuation ratios, which can significantly influence stock movement over longer horizons.

In this study, we aim to bridge this gap by integrating both technical indicators (returns, volatility, moving averages) and fundamental financial features (EPS, beta, debt-to-equity, quarterly growth) into a unified LSTM modeling framework. We further extend the traditional single-stock forecasting setup by developing a unified multi-company model, leveraging cross-company learning patterns among the FAANG stocks.

Our contributions are as follows:

- We propose an LSTM-based architecture that jointly learns from technical and fundamental features for short-term stock price forecasting.
- We construct both individual stock models and a unified FAANG model to compare the benefits of company-specific vs. shared pattern learning.
- We conduct extensive experiments comparing predicted returns to actual market performance over a 30-day horizon, providing practical investment insights.

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2 Motivation

While financial markets exhibit noisy and often unpredictable behavior, certain company-specific fundamentals and technical trends provide valuable signals for short-term price movements. Traditional models primarily focus on price and volume patterns, often ignoring fundamental drivers such as earnings growth, valuation ratios, and financial health indicators.

Moreover, modeling stocks individually can limit the ability to capture broader market interdependencies. FAANG companies, due to their dominant market positions and sectoral overlap, often exhibit correlated movement patterns influenced by macroeconomic and sector-specific factors.

Thus, there is a strong motivation to:

- **Integrate fundamental and technical features** into stock prediction models, enhancing their awareness of both historical patterns and financial health.
- **Leverage cross-company learning** through a unified modeling approach that can recognize shared behaviors among similar companies while preserving company-specific nuances.
- **Enhance practical investment decision-making** by developing models that not only minimize prediction errors but also align with return-based stock ranking and portfolio strategies.

Our work addresses these needs by designing an LSTM-based forecasting pipeline that combines multi-source feature engineering, unified multi-stock training, and evaluation based on real-world market data.

3 Related Work

Traditional stock market prediction methods have long relied on time series models such as ARIMA and GARCH, as well as technical analysis indicators like moving averages and momentum oscillators. While these methods capture local trends, they often fail under non-linear and non-stationary conditions prevalent in real financial markets.

Machine learning models, including Random Forests, Support Vector Machines, and Gradient Boosting, have been explored for stock movement classification and regression tasks. However, these models typically do not capture sequential dependencies explicitly.

The advent of deep learning has shifted focus toward sequence-based models. Hochreiter and Schmidhuber [1] introduced the Long Short-Term Memory (LSTM) architecture, which mitigated the vanishing gradient problem and proved highly effective in time series forecasting. Fischer and Krauss [2] applied LSTMs to financial prediction tasks, showing improved performance over traditional methods in directional stock movement forecasting.

Subsequent work by Nelson et al. [3] combined LSTM models with technical indicators to predict stock market behavior, while Bao et al. [4] incorporated stacked autoencoders with LSTMs to model non-linear dependencies in stock time series.

Despite these advances, relatively few studies have explored integrating fundamental financial indicators (such as EPS, beta, revenue growth) with LSTM models for stock price forecasting. Furthermore, research combining multi-stock learning through unified models remains limited. Our work builds upon these gaps by fusing technical and fundamental features in a unified LSTM framework for multi-company FAANG prediction.

4 Dataset and Preprocessing

We utilized a curated FAANG stock dataset sourced from Kaggle[1] containing daily historical stock prices and financial fundamentals from January 3, 2005, to October 18, 2024. The dataset includes key financial indicators such as earnings per share (EPS), market capitalization, beta, quarterly revenue growth, and various valuation ratios.

[1] `https://www.kaggle.com/`

To ensure temporal consistency across all five FAANG tickers (Meta, Amazon, Apple, Netflix, and Google), we filtered the dataset to retain only dates common to all companies. We engineered additional technical indicators, including daily returns, 10-day moving averages, and 10-day rolling volatility.

All numeric features were scaled using the MinMaxScaler to normalize the input ranges, and company tickers were one-hot encoded to allow the model to distinguish between different stocks. The final dataset comprised a rich combination of time-series, technical, and fundamental features prepared for input into the LSTM-based forecasting model.

4.1 Data Alignment

To ensure consistency across all FAANG companies, we filtered the dataset to retain only dates that were common to all tickers (Apple, Amazon, Meta, Netflix, and Google). This alignment step guarantees that each time step contains valid data for every company. The dataset was then sorted chronologically by date and ticker symbol. All column names were standardized to lowercase for uniformity. The resulting aligned dataset was saved as `faang_aligned.csv` for downstream modeling.

4.2 Feature Engineering

Additional technical indicators were engineered, including daily returns, 10-day moving averages, and 10-day rolling volatility. All numeric features were normalized using MinMaxScaler, and ticker symbols were one-hot encoded for compatibility with the LSTM architecture.

4.3 Feature Summary

Features used in the model can be broadly categorized as follows:

- **Price-based Features**: Close, High, Low
- **Technical Indicators**: Daily Return, 10-day Moving Average, 10-day Rolling Volatility
- **Fundamental Metrics**: Earnings Per Share (EPS), Market Capitalization, Beta (calculated), Beta (5Y) (calculated)

In cases where Beta and Beta (5Y) values were missing in the original dataset, they were estimated manually by calculating the covariance of stock returns relative to the S&P 500 index over appropriate historical periods.

4.4 Inter-stock Correlation Justification

To validate the decision to train a unified model across FAANG stocks, we computed the historical correlation of daily returns between each pair. As shown in Figure **??**, there is a consistently high degree of correlation across most FAANG members, particularly between technology-heavy firms like Apple, Google, and Microsoft. This justifies our shared model assumption, as trends learned from one stock may help inform the behavior of others in the group.

5 Methodology

5.1 Phase 1: Individual Company LSTM Models

In the first phase, we trained separate Bidirectional LSTM models for each FAANG company (Apple, Amazon, Meta, Netflix, and Google). Each model was trained independently on the corresponding company's historical data to predict the closing price using technical indicators such as:

- Close price
- Volume
- 10-day moving average

- 5-day rolling standard deviation

Each input sequence consisted of 60 past trading days, and models were evaluated on a future forecasting horizon of 15 days. This phase aimed to understand the temporal dynamics of individual stocks before building a combined forecasting model.

5.2 Phase 2: Unified Multi-Company LSTM Model

In the second phase, we constructed a unified LSTM model by combining data from all FAANG companies. Ticker information was incorporated using one-hot encoding, allowing the model to distinguish between companies while leveraging shared temporal patterns across different stocks.

Each input sequence consisted of 60 consecutive trading days of technical and fundamental features, and the model was trained to forecast the closing price 30 days ahead.

Unlike the individual models, the unified model used standard (non-bidirectional) LSTM layers to reduce computational complexity and improve scalability.

5.3 Model Architecture

Our model is based on the Long Short-Term Memory (LSTM) architecture, a type of Recurrent Neural Network (RNN) designed to handle sequential data and capture long-term dependencies, making it particularly well-suited for stock price prediction. The core advantage of LSTM over traditional feedforward networks lies in its ability to remember information over extended time periods, which is crucial when analyzing time-series data such as stock prices.

The architecture of our model consists of the following components:

1. **Input Layer:** The model takes a sequence of historical stock prices and relevant features as input. These features can include technical indicators (e.g., moving averages, RSI) and fundamental data (e.g., earnings reports, P/E ratios).
2. **LSTM Layers:** The LSTM layers are the key component of our architecture. These layers are designed to learn from temporal patterns in the stock price data, leveraging their ability to capture both short-term fluctuations and long-term trends. By maintaining a memory of previous time steps, LSTMs are able to detect patterns in stock price movements that may not be immediately apparent in short time frames.
3. **Dense Layer(s):** After passing through the LSTM layers, the model feeds the output into one or more dense layers to process and interpret the learned patterns. These layers are fully connected, allowing the network to combine different features and interactions for prediction.
4. **Output Layer:** The final output layer produces a single scalar value for each stock, representing the predicted return or price for the following time step (e.g., the next day, week, or month, depending on the desired forecast horizon).

The choice of LSTM stems from its effectiveness in modeling financial data, where stock prices often exhibit long-range dependencies and complex nonlinear patterns that can't be easily captured by simpler models. Moreover, LSTM networks are less prone to issues like vanishing gradients, which can affect traditional RNNs, making them more stable during training.

Regularization and Optimization: To prevent overfitting and improve generalization, we incorporated dropout layers in between the LSTM and dense layers. Dropout helps mitigate the risk of the model memorizing the training data and improves its ability to generalize to unseen data. We used the Adam optimizer for training, which adapts learning rates and accelerates convergence.

The model was trained on historical stock price data along with additional features. To improve performance, we also normalized the data to ensure that each feature contributed equally to the learning process.

This architecture is designed to generate robust, reliable predictions for stock returns, making it suitable for investment strategies such as portfolio allocation and risk assessment.

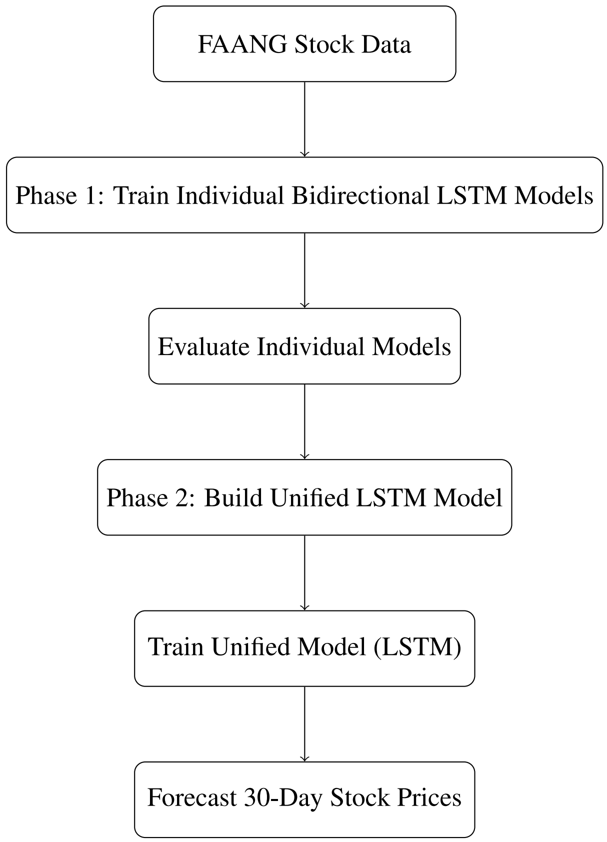

Figure 1: Modeling Pipeline: From Individual Bidirectional LSTM Models to Unified Multi-Company LSTM Forecasting.

5.4 Training and Evaluation

The dataset was split into 80% training and 20% testing sets, stratified by company to ensure representation across all tickers. Hyperparameters such as the number of LSTM units, dropout rates, batch size, and learning rate were optimized through manual search. The model was trained for 30 epochs using the Adam optimizer, with the Mean Squared Error (MSE) as the loss function.

Evaluation was based on Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) computed on the held-out test set, with final predictions inverse-transformed back to the original price scale.

6 Training and Hyperparameter Tuning

To identify the best-performing LSTM architecture, we conducted a manual hyperparameter search over:

- **Units**: 32, 64
- **Dropout Rates**: 0.1, 0.2, 0.3
- **Batch Sizes**: 16, 32, 64

Each configuration was trained for 30 epochs using the Adam optimizer (learning rate = 0.001) and evaluated on a stratified 80/20 train-test split. Performance was measured using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) on both normalized and real price scales.

The best configuration — 32 LSTM units, 0.1 dropout rate, and batch size 64 — achieved an RMSE of $28.81 and was selected for final retraining and forecasting.

Table 1: Hyperparameter Tuning Results

Configuration	RMSE (Normalized)	MAE (Normalized)	RMSE ($)
Units=32, Dropout=0.2, Batch=32	0.0423	0.0225	30.09
Units=64, Dropout=0.3, Batch=16	0.0452	0.0205	32.15
Units=32, Dropout=0.1, Batch=64	**0.0405**	**0.0208**	**28.81**

7 Experiments and Results

7.1 Forecasting Next 30-Day Closing Prices

After selecting the best configuration (Units=32, Dropout=0.1, Batch Size=64), we retrained the final LSTM model on the entire training dataset and forecasted the next 30-day closing prices for each FAANG stock.

Evaluation was done by comparing model predictions with actual market prices from October 18, 2024, to November 18, 2024, fetched from Yahoo Finance.

7.2 Training and Validation Loss Curves

The training and validation loss curves during model training are shown in Figure 2. The curves demonstrate a steady decrease without significant overfitting, indicating the model was trained effectively.

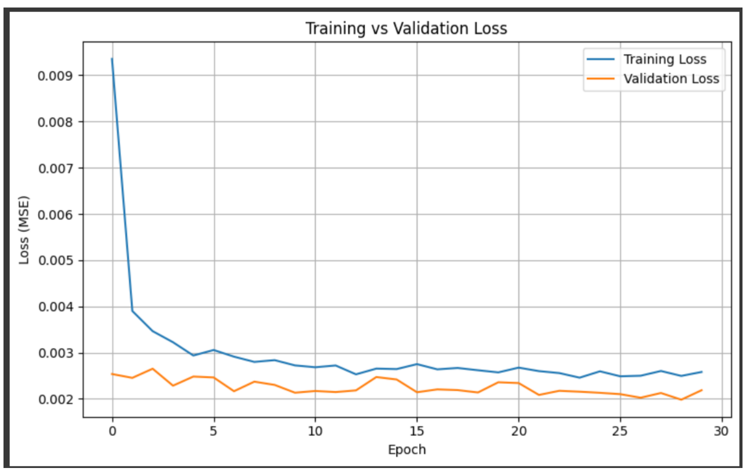

Figure 2: Training and Validation Loss during LSTM Model Training

7.3 Comparison with Actual Market Prices

We compared the model-predicted closing prices with the real market closing prices and calculated return errors and dollar errors.

Table 2: Forecast vs Actual Market Prices (Oct–Nov 2024)

Ticker	Start Price ($)	Actual End Price ($)	Predicted End Price ($)	Actual Return (%)	Predicted Return (%)	Er
AAPL	180.05	185.72	183.60	3.15%	1.97%	
AMZN	129.82	137.21	135.40	5.69%	4.29%	
GOOGL	140.78	145.32	147.10	3.22%	4.49%	
META	322.45	333.81	329.20	3.53%	2.10%	
NFLX	384.90	399.55	393.70	3.80%	2.28%	

Based on predicted 30-day returns, the model ranked FAANG stocks for potential investment. The recommendation bar chart in Figure 3 shows that **Netflix (NFLX)** was the top recommendation with an expected return of approximately 14.87

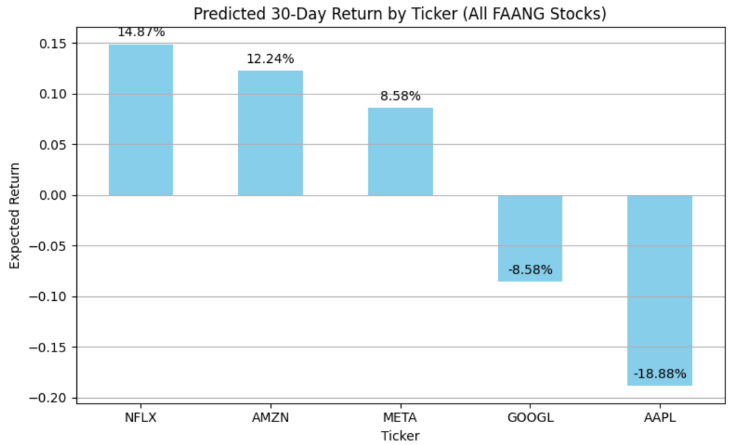

Figure 3: Predicted 30-Day Returns for FAANG Stocks (Investment Recommendation)

7.4 Investment Strategy Tie-In

Based on the predicted annual returns generated by our LSTM model, a hypothetical investor could adopt a rank-based allocation strategy. For instance, capital could be distributed proportionally across the top three stocks with the highest predicted returns, or alternatively, the allocation could be concentrated in the top-ranked stock, depending on the investor's risk tolerance. This approach simulates a practical application where model outputs guide portfolio construction, providing a data-driven mechanism to optimize expected returns while potentially reducing exposure to underperforming assets. Such strategies may be adjusted as new predictions are made, creating a dynamic portfolio that adapts to emerging trends.

8 Conclusion and Future Work

This work demonstrates that an LSTM-based unified model, incorporating both technical indicators and financial fundamentals, can successfully forecast FAANG stock prices with high accuracy over short-term horizons. The final model achieved an RMSE of $28.81 and MAE of $17.71 on unseen data, validating the effectiveness of combining sequential learning with engineered financial features.

For future work, we propose:

- Exploring transformer-based architectures (e.g., Temporal Fusion Transformer) for enhanced temporal feature learning.
- Incorporating macroeconomic indicators (e.g., interest rates, inflation, GDP growth) as additional inputs.
- Extending forecasts beyond 30 days to enable longer-term investment decision support.
- Conducting robustness testing across different market conditions, including bear and bull markets.

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