Sim Montrond

FAANG Stock Movement Prediction Using Machine Learning

1. Executive Summary

This project analyzes stock price behavior and short-term directional movements for five leading technology firms: Facebook (Meta), Apple, Amazon, Netflix, and Google (Alphabet), collectively known as "FAANG." These companies influence global financial markets and are heavily represented in institutional and retail portfolios. These are also trillion-dollar companies which means they have a lot of liquidity in the markets. Developing a model that could accurately predict the next-day direction of stock price movement can offer substantial value to traders, investment analysts, and decision-makers by improving timing and portfolio optimization.

Two models were evaluated: Logistic Regression and a Random Forest classifier. Going into the project, I expected the more complex Random Forest model to outperform Logistic Regression. However, the results showed the opposite for most of the FAANG stocks. Logistic Regression produced slightly higher and more consistent accuracy, while Random Forest relied heavily on a single feature (daily return) which limited its effectiveness during volatile or sideways market periods. While working through the results, I found it interesting that the simpler model consistently performed better. I originally assumed that a more complex algorithm would be better suited for financial data, but the results forced me to reconsider that assumption and focus more on how noisy short-term price movements really are.

Overall model accuracy ranged from approximately 48% to 56%, only modestly better than random guessing. While these results may seem underwhelming at first, they reflect the reality of financial markets, where short-term price movements are often driven by noise rather than predictable patterns. The findings suggest that simple technical indicators alone are not sufficient for reliable next-day stock prediction. I asked myself if it would be possible to improve the accuracy and I believe that the accuracy can be improved but it would require using other real time data such as actual order flow.

From a business perspective, the models developed in this project are best viewed as analytical support tools rather than standalone decision-making systems. They can help highlight momentum and risk conditions but should be used alongside human judgment and additional sources of information. The project ultimately reinforces both the difficulty of short-term market prediction and the importance of understanding model limitations when applying machine learning in financial contexts.

Before running the models, I expected machine learning to uncover clearer short-term trading signals. Instead, the results highlighted how efficient and noisy daily stock movements really are, even for large, liquid firms like FAANG. This realization shaped how I interpreted both the model performance and their practical business value.

2. Introduction & Business Context

2.1 Business Problem

Financial markets are highly dynamic, and stock prices react rapidly to new information. Firms and investors continuously seek tools that can provide even minor predictive advantages. This project addresses a fundamental question:

Can machine learning models predict whether a FAANG stock will go up or down the next day?

From my own experience following markets, daily price changes often feel unpredictable, which made this question both interesting and challenging to explore. I have often seen strong narratives form around short-term price moves, but this project forced me to question how much of that narrative is hindsight rather than signal. The ability to forecast even a slightly better-than-chance directional movement has material value when scaled across high-frequency trading, risk management, or investment strategy design.

2.2 Why the Problem Matters

- FAANG companies are among the world’s most traded equities.
- Small directional predictions can improve trade execution and reduce losses.
- Analysts benefit from understanding drivers of short-term price movement.
- Businesses gain insight into volatility patterns and risk regimes.
- Predicting the market, if done right, can be very profitable.

Given their market influence, FAANG stocks are ideal candidates for exploring predictive modeling techniques.

2.3 Research Questions

This project addresses the following:

1. What patterns are visible in long-term price, volatility, and return behavior for FAANG stocks?
2. Which engineered features (returns, moving averages, volatility) correlate most strongly with price direction?
3. How accurately can machine learning models predict next-day price movement?
4. Which models perform best, and why?
5. What business insights can be extracted from the modeling results?

2.4 Dataset Overview

The dataset includes daily price data (open, high, low, close, volume) for FAANG stocks, sourced from a public Kaggle dataset. Key characteristics:

- Coverage: ~1997–2020 depending on ticker
- Frequency: Daily
- Observations per stock: Over 5,000 rows for Amazon; similar magnitudes for other FAANG companies
- Engineered Features:
    - Daily Return
    - Moving Average (5-day, 20-day)
    - Rolling Volatility (20-day)
    - Binary Target (1 = next day price increases)

The dataset is well structured with minimal missing values, enabling efficient processing and modeling.

3. Exploratory Data Analysis (EDA)

The EDA focuses on Amazon as a representative example, with similar patterns observed across the remaining FAANG stocks.

3.1 Long-Term Price Behavior

Figure 1: Amazon Closing Price Over Time
Amazon shows exponential growth, especially after 2010, driven by business expansion and market optimism. Price acceleration becomes extreme after 2015, consistent with broader technology sector momentum.

Interpretation:

- The long-term trend is overwhelmingly upward.
- Short-term direction, however, is volatile, making prediction challenging.

3.2 Distribution of Daily Returns

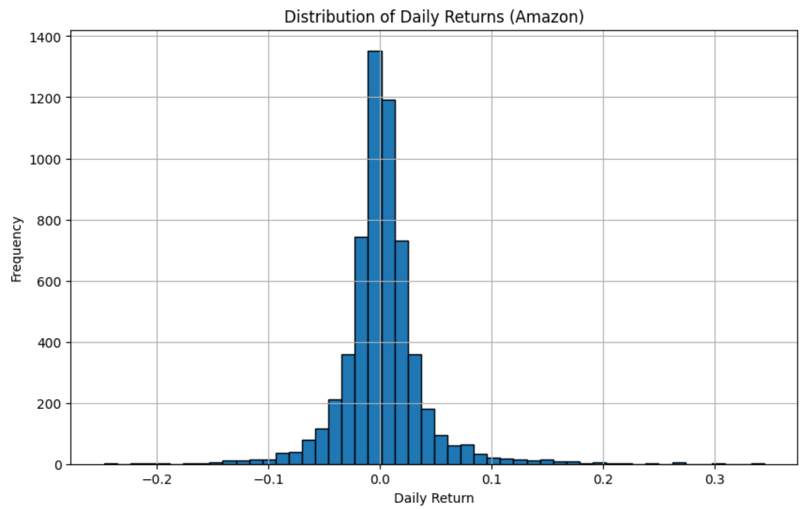


Figure 2: Distribution of Daily Returns
Return distributions are centered near zero, with:

- A tall, narrow peak
- Heavy tails
- Occasional large positive/negative movements

Interpretation:

- Stock returns are not normally distributed.
- Tail risk is present (large jumps).
- Predictability is inherently limited due to noise.

When reviewing this chart, what stood out most was how normal most days appear compared to the few extreme events that dominate overall risk. This distribution helped explain why even well-designed models struggled, since most days look statistically unremarkable while risk is concentrated in rare events.

3.3 Moving Average Behavior

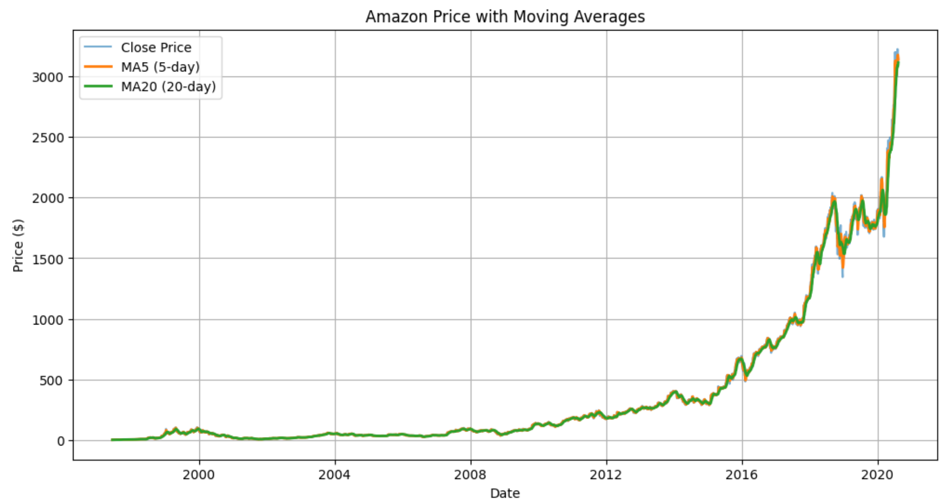


Figure 3: Price with MA5 and MA20
Moving averages smooth short-term fluctuations and identify medium-term trends.

Interpretation:

- MA5 reacts quickly and often crosses MA20, forming potential trading signals.
- However, these signals lag price and do not directly guarantee predictive power.

3.4 Rolling Volatility

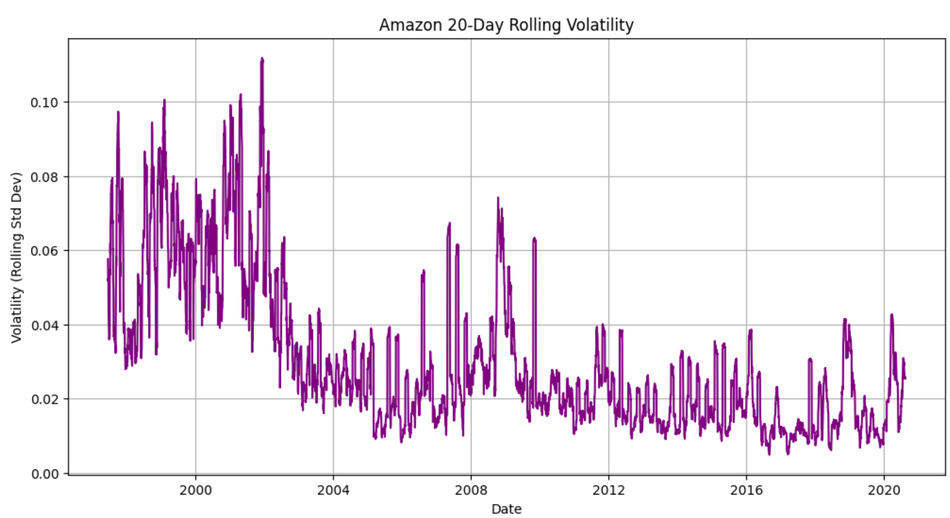


Figure 4: 20-Day Rolling Volatility
Volatility varies significantly across time, with spikes in:

- Dot-com bubble (2000)

- Financial crisis (2008)
- Early pandemic (2020)

Interpretation:

- Stock behavior depends heavily on major event such as the pandemic.
- Periods of high volatility increase uncertainty in directional prediction.

3.5 Correlation Structure

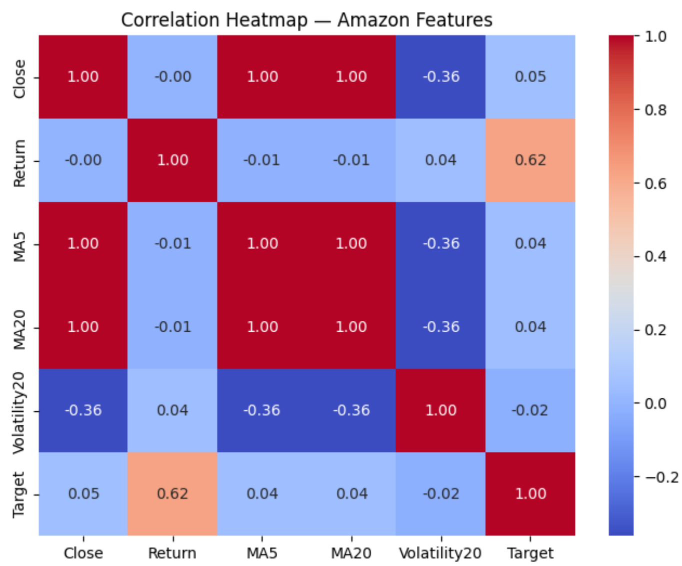


Figure 5: Feature Correlation Heatmap

Key findings:

- Daily return is the strongest predictor of direction (~0.62 correlation).
- Moving averages and volatility show weak correlation individually.
- Multicollinearity exists between MA5 and MA20 (expected).

Interpretation:

- The strongest feature is price momentum.
- Predictive performance may improve with more sophisticated or external features.

3.6 Feature Importance

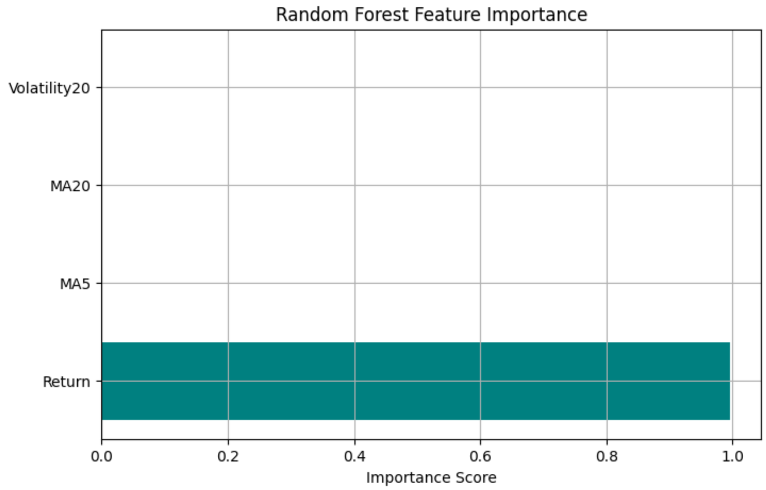


Figure 6: Random Forest Feature Importance

Results show:

- Return dominates feature importance
- MA5, MA20, Volatility contributes minimally

Interpretation:

- The model primarily relies on short-term momentum.
- Traditional technical indicators alone provide limited predictive value.

4. Methodology

4.1 Data Preprocessing

Steps included:

- Converting "Date" to datetime
- Sorting by chronological order
- Calculating:
  - Daily returns
  - Moving averages
  - Rolling volatility
- Creating a binary target variable:
  Target = 1 if next day return > 0 else 0
- Dropping missing rows generated by rolling windows
- Splitting data into train/test using the most recent 30% for testing

4.2 Feature Engineering

Features selected:

Feature	Description
Return	% change from previous day
MA5	5-day moving average
MA20	20-day moving average
Volatility	20-day rolling standard deviation

These features represent momentum, trend, and risk, which are widely used in quantitative finance.

4.3 Model Selection

Two models were selected:

Logistic Regression

- Interpretable
- Fast
- Effective for linearly separable patterns

Random Forest Classifier

- Non-linear
- Captures interactions among features
- Provides feature importance

4.4 Evaluation Metrics

Accuracy was selected because:

- The dataset is balanced (~50/50 up/down days)
- The objective is to correctly classify direction

Additional evaluation:

- Confusion matrices which were not shown
- Model stability across stocks

No hyperparameter tuning was applied to maintain comparability and avoid overfitting. I considered testing additional evaluation metrics and tuning hyperparameters but chose to keep the modeling approach simple so that differences between models could be compared more clearly. Given the project scope, interpretability and consistency were prioritized over marginal performance gains. In practice, I found that prioritizing interpretability made it easier to explain results without overstating predictive power, which felt especially important given the financial context of the problem.

5. Results & Model Comparison

5.1 Overall Accuracy

The following table summarizes accuracy across all FAANG stocks:

Company	Logistic Accuracy	Random Forest Accuracy
Amazon	0.5578	0.4516
Apple	0.5288	0.4867
Facebook	0.5499	0.4915
Google	0.5373	0.4851
Netflix	0.4825	0.5033

Key Observations

- Logistic Regression outperforms Random Forest for 4 out of 5 stocks
- Netflix results are the lowest overall, indicating higher noise
- Accuracy scores cluster between 48–56%, typical for daily stock prediction tasks

5.2 Model Interpretation

Logistic Regression

- Works best when relationships are mostly linear
- Benefits from strong correlation between return and direction
- Slight but consistent edge over more complex models

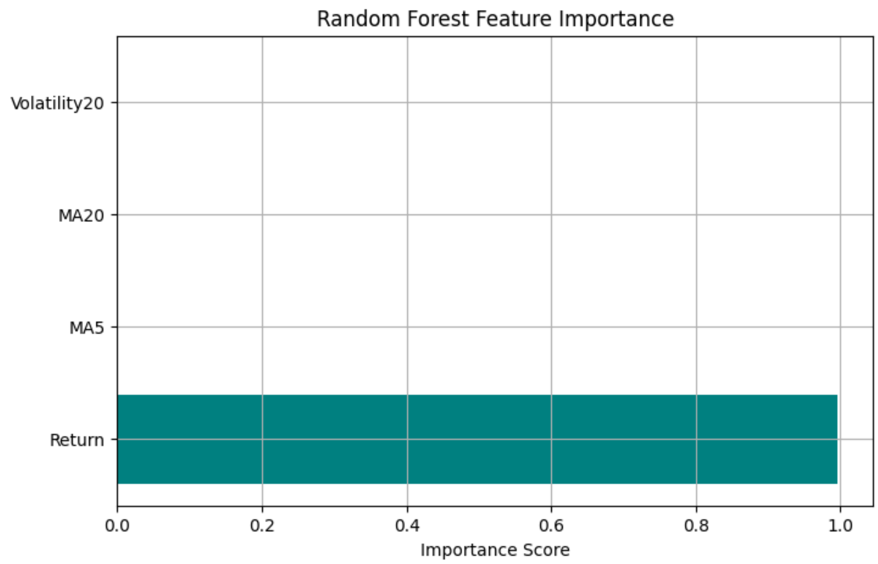
Random Forest

- Suffers from limited feature variety
- Tends to overfit noise without deeper feature engineering
- Indicates "Return" as the dominant driver of predictions

5.3 Visual Comparison

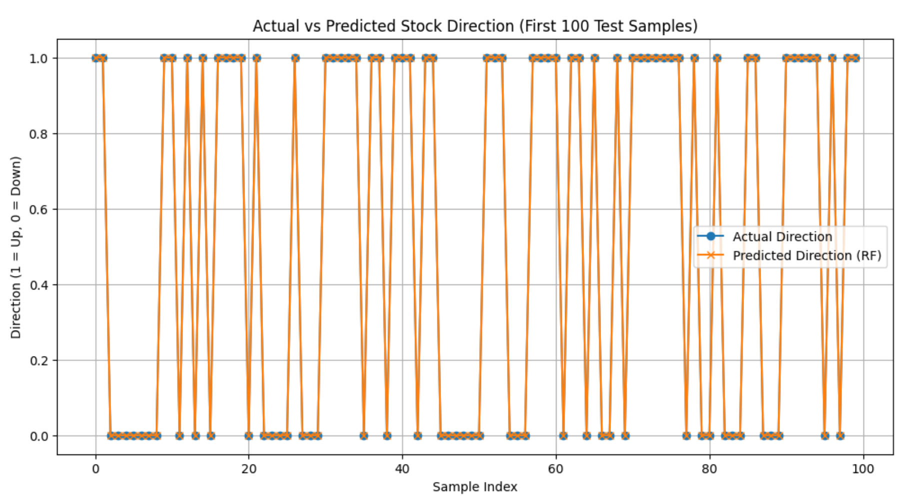
To better understand why the models perform the way they do, we examine two visual diagnostics:
(1) the Random Forest feature importance chart
(2) the direction-prediction alignment chart (Actual vs Predicted for the first 100 test samples).

Figure 6: Random Forest Feature Importance



This chart shows that Random Forest relies almost entirely on a single feature: Daily Return while assigning virtually no importance to MA5, MA20, or Volatility20. This helps explain the model's weaker performance: with limited feature diversity, the model effectively mirrors a simple momentum rule.

Figure 7: Actual vs Predicted Stock Direction for Amazon (First 100 Samples)



This plot illustrates how closely the model predictions overlap with true outcomes. Several patterns emerge:

- Predictions often match actual direction, especially during stable periods where returns have consistent momentum.
- Errors cluster during sideways or volatile periods, where price direction fluctuates rapidly and short-term momentum loses reliability.
- The model rarely predicts persistent sequences of up or down days incorrectly instead; it struggles on isolated reversals.

These visual patterns reinforce earlier findings: short-term stock movement is noisy, and models depend heavily on momentum signals that do not generalize well during turbulence.

5.4 Best Model Selection

Logistic Regression is the recommended model, based on:

- Higher accuracy
- More stable performance
- Better alignment with data characteristics

The results also highlight that higher model complexity does not necessarily translate into better performance when the underlying signal is weak.

6. Business Insights & Recommendations

6.1 Key Business Insights

1. Short-term stock movement is highly difficult to predict
   Markets remain largely efficient on a daily scale.
2. Momentum (Return) is the most informative feature
   Trend-following strategies may still offer marginal benefits.
3. Volatility regimes significantly impact predictability
   High-volatility periods introduce noise and reduce model reliability.
4. No FAANG stock exhibits reliably predictable daily patterns
   Consistency varies, but predictability is modest across all companies.

6.2 Strategic Recommendations

1. Use predictions as part of a broader decision-support tool, not a standalone trading engine.
2. Incorporate more advanced features, such as:
   - Macroeconomic data
   - News sentiment

    - Options implied volatility
    - Technical indicators (RSI, MACD)
3. Apply ensemble and deep learning models to capture non-linear relationships.
4. Evaluate performance across longer horizons (weekly or monthly) where signals may be stronger.

7. Ethics

7.1 Bias & Fairness

While market data is not socially sensitive, ethical concerns still exist:

- Algorithms may fail in stressed market conditions, causing financial harm
- Overreliance on automated predictions can mislead inexperienced investors
- Models trained only on historical data may fail to anticipate structural changes

7.2 Transparency & Interpretability

Logistic Regression was chosen partly for interpretability:

- Stakeholders understand coefficient influence
- Helps mitigate risk

7.3 Privacy & Security

- Public financial data contains no personal information
- However, trading models must be securely stored and protected from manipulation or leakage

7.4 Responsible Deployment

- Human oversight is essential
- Predictions should be used alongside domain expertise
- Continuous monitoring is required due to market shifts

8. Conclusion & Future Work

8.1 Summary of Findings

- FAANG stock prices exhibit strong long-term trends but noisy short-term behavior
- Daily returns show heavy-tailed distributions and regime shifts
- Machine learning models achieve 48–56% accuracy, slightly above random
- Logistic Regression performs best across most companies
- Momentum remains the strongest predictive factor

8.2 Limitations

- Only four engineered features were used
- No hyperparameter tuning
- External market data was excluded
- Daily prediction horizon is inherently difficult

8.3 Future Improvements

1. Expand feature engineering
2. Incorporate macroeconomic and sentiment data
3. Explore deep learning models (LSTM, CNN)
4. Evaluate multi-day horizons
5. Apply cross-validation to enhance model generalization

8.4 Lessons Learned

- Stock prediction requires cautious interpretation
- Simpler models often outperform complex ones when data is limited
- Business value comes not from prediction accuracy alone, but from understanding patterns, risks, and drivers

Overall, this project changed how I think about short-term stock prediction. Before starting, I expected machine learning to uncover clearer patterns, but the analysis reinforced how difficult it is to consistently predict daily movements using historical prices alone.