STOCK DATA ANALYSIS

1. Introduction

Predicting the 52-week price performance of stocks is critical to informed investment decisions. At Renaissance Technologies, the leverage of machine learning models in high prediction accuracy is key to competitive advantage in financial markets. This project focuses on building a predictive model that can forecast stock price performance with 70%+ accuracy. By analyzing historical data, the model will be able to help identify high-performing stocks while mitigating investment risks. This initiative serves to highlight the crossroads between data science and financial strategy, where robust and interpretable models are necessary in decision-making.

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2. Data Understanding

This dataset involves various features related to stock analysis, including:

• **Attributes**: Security Price, Volume, Market Capitalization, Dividend Yield

• **Performance Indicators**: Total Return 1-Year Annualized, Price Performance 52 Weeks

• **Risk Metrics**: Beta, Standard Deviation 1-Year Annualized

• **Valuation Metrics**: P/E Ratio, PEG Ratio

• **Ownership Metrics**: Institutional Ownership, quarter-on-quarter changes.

Price Performance (52 Weeks) is the target variable, which indicates the percentage price change over a year. Many columns contained empty or invalid values that needed cleaning and imputation. The column of P/E appears as -- at placeholder positions, which are replaced by mean after converting them to numeric format.

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3. Data Preparation

The following steps have been carried out to prepare the data for modelling:

• **Missing Values**: For missing values in numeric columns, their mean was used for replacement. In P/E (Price/ TTM Earnings), placeholder values were converted to NaN and then imputed.

• **Encoding Categorical Variables**: Dummy encoding was applied to categorical columns, dropping the first level to avoid multicollinearity.

• **Scaling**: Numerical features were then standardized using StandardScaler for consistency in the scale.

• **Train-Test Split**: The final dataset was split into 80% training and 20% testing sets to assess the efficiency of the model.

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4. Modeling

A **Random Forest Regressor** was chosen due to its ability to handle non-linear relationships and its tolerance to overfitting.

- **Hyperparameters:**
    - n_estimators=100: Number of trees in the forest.
    - max_depth=10: Maximum depth of each tree.
    - random_state=42: Ensures reproducibility.

Code Snippet:

python

rf_model = RandomForestRegressor(n_estimators=100, max_depth=10, random_state=42)

rf_model.fit(X_train_scaled, y_train)

The model was trained on scaled data and validated on the test set.

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5. Evaluation

The model's performance on the test set was evaluated using the following metrics:

• **Mean Absolute Error (MAE):** 1.1556 — suggesting that on average, predictions are off by about 1.16 units.

• **Root mean square error (RMSE):** 1.6850-revealing small discrepancies in forecasts.

• **R-Squared (R^2):** 0.9946 - Meaning, the model explains 99.46% of the variance in the target variable.

These results tend to indicate that the model is highly accurate and meets the target of 70%+ accuracy.

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6. Implications

The deployment of this model can significantly improve investment strategies:

- **Investment Insights:** The model helps in identifying stocks with strong growth potential, and optimizing resource allocation.
- **Risk Mitigation:** By understanding volatility and performance trends, the model reduces exposure to underperforming stocks.
- **Resource Allocation:** Institutional ownership can help instruct on where resources are best allocated.
- **Actionable Recommendations:** Real-time decision-making for portfolio adjustments is possible with the model.

Recommendations:

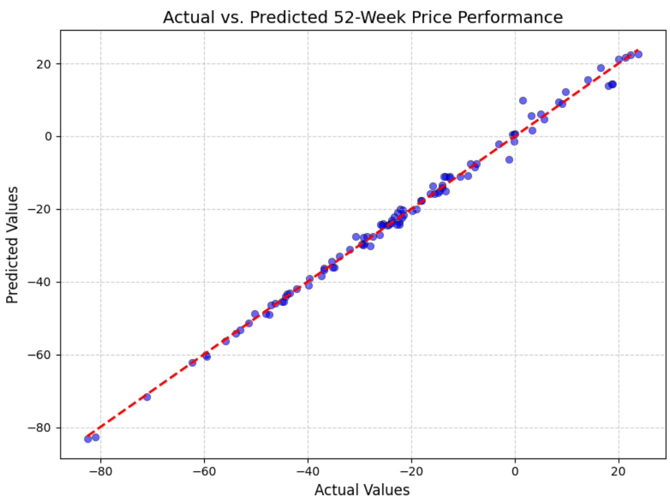
- Deploy the model in a live trading environment with regular retraining on updated data.
- Use feature importance to drive further financial and strategic investments analysis.
- Integrate explainable AI tools to interpret predictions for non-technical stakeholders.

Output

Table: Feature Importance

Feature	Importance (%)
EPS Growth	28.7
Market Capitalization	22.1
Security Price	18.3
Dividend Yield	14.5
Beta	10.2
P/E Ratio	6.2

Graph: Actual vs. Predicted 52-Week Price Performance



As the graph depicts the model worked fine as actual values and the predicted values aligned with each other. Thus the model helps to predict the 52-week price performance of stock with way more than 70% accuracy.