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## **Model Performance Report**

## **Dataset Summary**

The dataset contains **1,000 samples** and **15 features**, with a target variable named "Target2". The data was split into:

• **Training Set**: 70% (700 samples)

• **Testing Set**: 30% (300 samples)

### **Models Evaluated**

The following regression models were trained and evaluated:

- 1. Linear Regression
- 2. Random Forest Regressor
- 3. Gradient Boosting Regressor
- 4. Decision Tree Regressor
- 5. K-Nearest Neighbors Regressor
- 6. Support Vector Regressor

#### **Model Performance Metrics:**

## **Linear Regression:**

Mean Squared Error: 0.1062

Mean Absolute Error: 0.2683

R^2 Score: 0.6356

## **Random Forest Regressor:**

Mean Squared Error: 0.1116

Mean Absolute Error: 0.2746

R^2 Score: 0.6169

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## **Gradient Boosting Regressor:**

Mean Squared Error: 0.1134

Mean Absolute Error: 0.2766

R^2 Score: 0.6106

## **Decision Tree Regressor:**

Mean Squared Error: 0.1765

Mean Absolute Error: 0.3230

R^2 Score: 0.3940

## K-Nearest Neighbors Regressor:

Mean Squared Error: 0.3704

Mean Absolute Error: 0.5185

R^2 Score: -0.2714

## **Support Vector Regressor:**

Mean Squared Error: 0.2956

Mean Absolute Error: 0.4763

R^2 Score: -0.0145

#### Conclusion

Based on the evaluation metrics:

- Models like **Linear Regression** or **Gradient Boosting Regressor** may perform better for certain datasets due to their balance of complexity and accuracy.
- Ensemble methods like **Random Forest** and **Gradient Boosting** typically provide robust results with complex patterns.

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•	Simpler models like K-Nearest Neighbors or Decision Tree Regressors
	can be used for quick, interpretable solutions.