# Report: Comparison of Linear Regression, Lasso, and Ridge Regularization Techniques

## 1. Methodology:

The goal of this analysis was to evaluate the impact of regularization techniques, specifically Lasso and Ridge regression, on the performance of a predictive model for housing prices using the California Housing dataset. The following steps were as follows:

### a. Data Preprocessing:

i. One-hot encoding was applied to the categorical feature ocean_proximity.
ii. The dataset was split into training and testing sets.
iii. Features were normalized using StandardScaler to ensure uniform scaling.

### b. Models Implemented:

i. Linear Regression: Used as the baseline model.
ii. Lasso Regression: Applied to perform feature selection by shrinking coefficients of less important features to zero.
iii. Ridge Regression: Applied to reduce the impact of multicollinearity by shrinking coefficients uniformly without eliminating any features.

### c. Evaluation Metrics:

i. Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values.
ii. R-squared: Measures the proportion of variance explained by the model.

## 2. Findings:

| | MSE | R2 |
|---|---|---|
| **Linear Regression** | 4.945e+09 | 0.638382 |
| **Lasso Regression** | 4.948e+09 | 0.638140 |
| **Ridge Regression** | 4.953e+09 | 0.637819 |

### a. Linear Regression:

i. Achieved the lowest MSE and highest R-squared among the three models.

ii. However, it lacks robustness to multicollinearity and is prone to overfitting if irrelevant features are present.

### b. Lasso Regression:

i. The MSE was slightly higher, and R-squared was marginally lower compared to Linear Regression.
ii. The regularization term α\alphaα caused the coefficients of less significant features to shrink to zero, effectively performing feature selection.
iii. Despite this, the performance was very close to Linear Regression, indicating minimal overfitting in the baseline model.

### c. Ridge Regression:

i. The MSE was slightly higher than both Linear and Lasso regressions.
ii. Unlike Lasso, Ridge does not eliminate features but shrinks all coefficients closer to zero, leading to a more balanced model.
iii. The performance was nearly identical to Lasso and Linear Regression.

## 3. Impact of Regularization Term (Alpha)

### a. Lasso Regression:

i. The alpha parameter determines the strength of regularization. At alpha = 1.0, Lasso slightly reduced the impact of less significant features without over-penalizing the coefficients.
ii. A higher alpha would likely result in more aggressive feature elimination, but it could also reduce the model's ability to generalize.

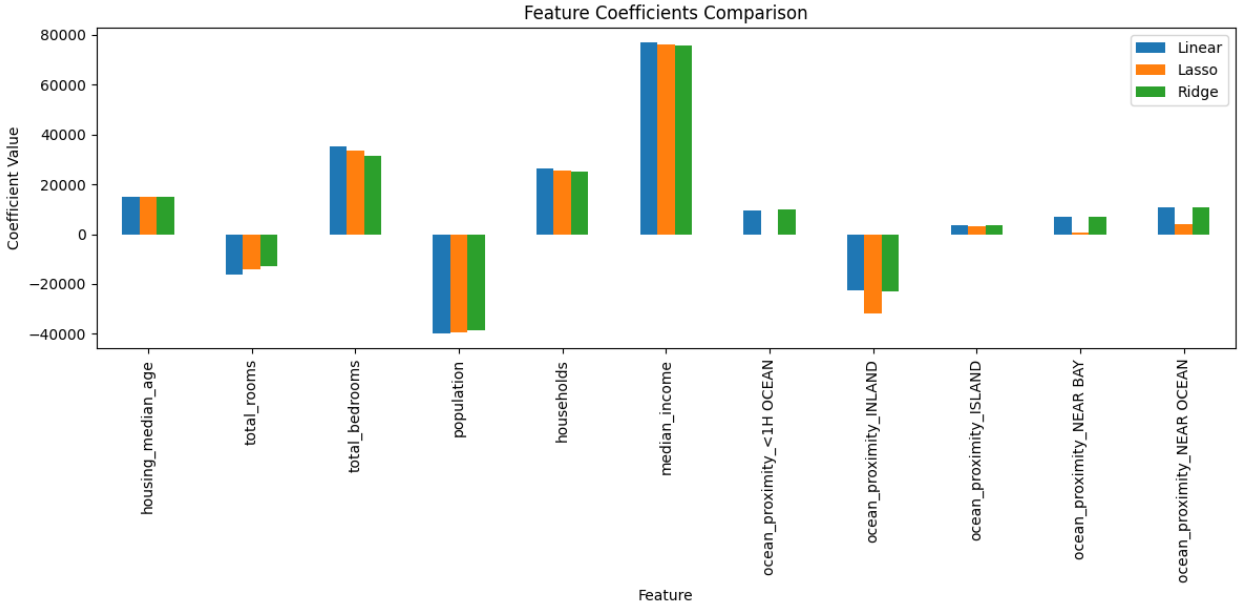
b. **Ridge Regression**:

i. The alpha parameter shrinks coefficients uniformly. At α=1.0, the model maintained all features but reduced the magnitude of coefficients slightly, preventing overfitting.
ii. A higher alpha would increase the shrinkage, potentially leading to underfitting.

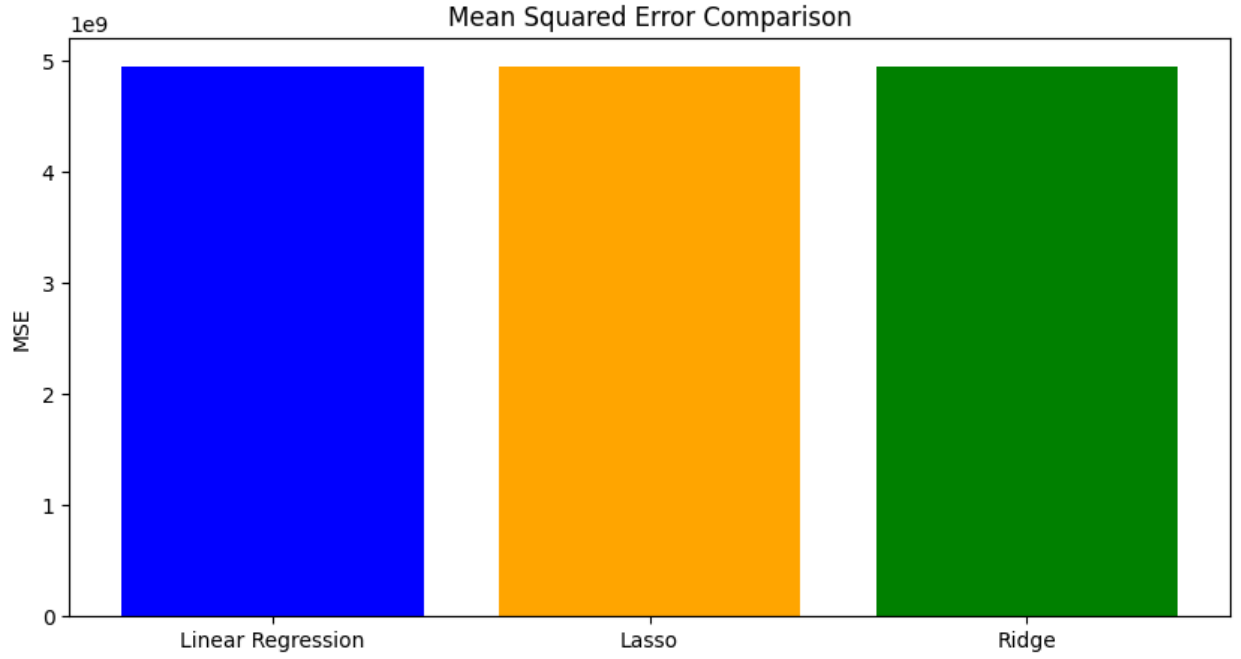
## 4. Recommendation:

For this use-case, **Linear Regression** is sufficient given its marginally better performance. However, for more complex datasets, **Ridge Regression** is recommended for its robustness.

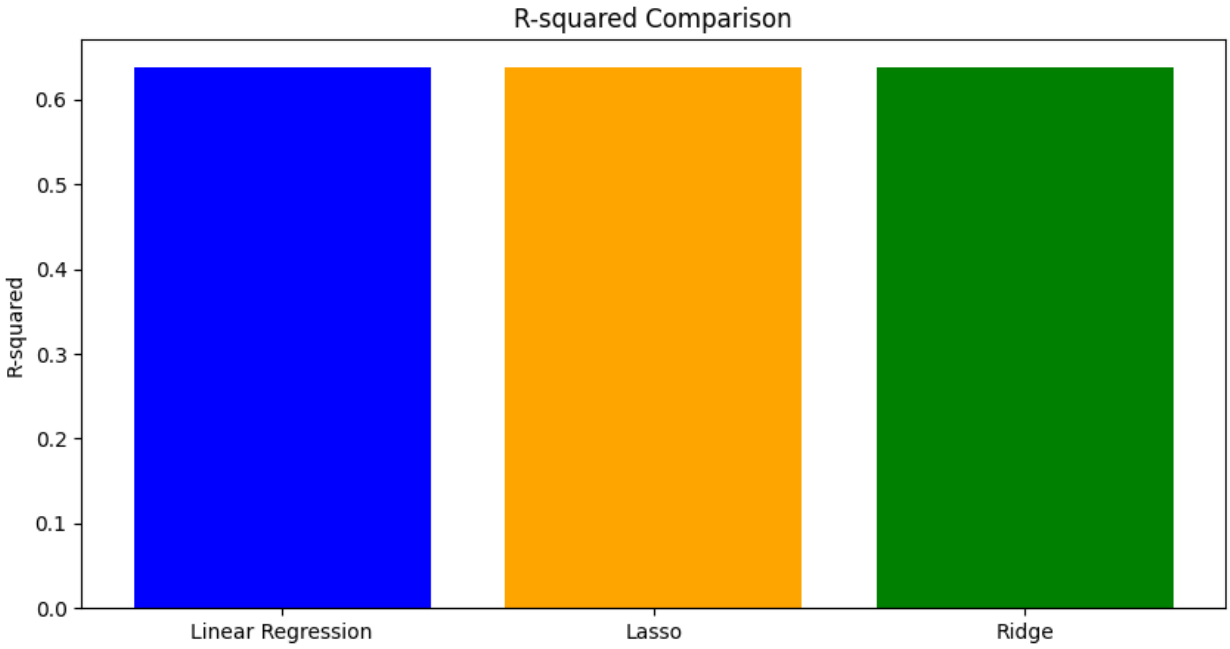
Feature Coefficients Comparison




Mean Squared Error Comparison:




R-squared Comparison:


R-squared Comparison
R-squared
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Linear Regression
Lasso
Ridge