In [106…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_erro
import seaborn as sns
from sklearn.feature_selection import RFE

pd.set_option('display.max_columns', None)
```

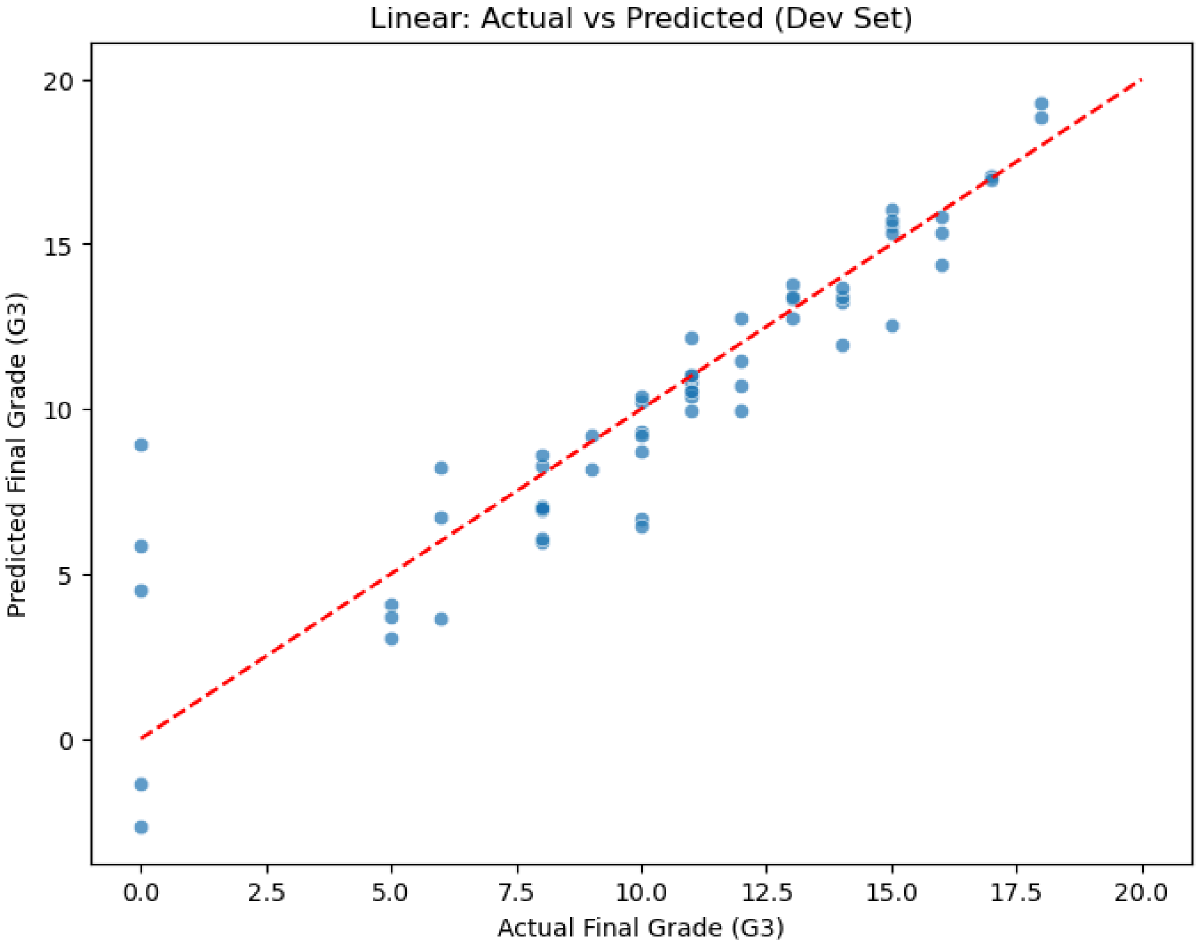
In [73]:

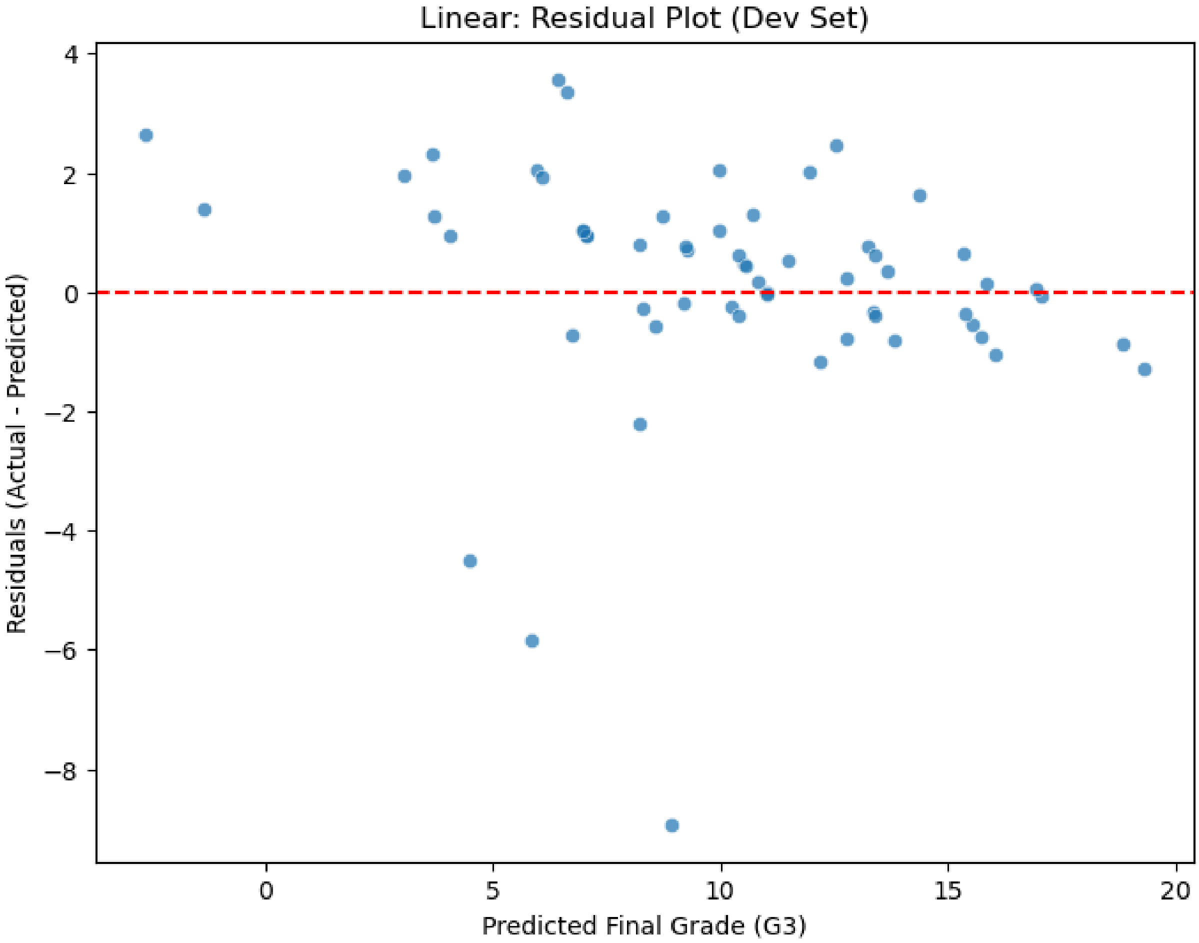
```
df = pd.read_excel('../data/Maths.xlsx')

X = df.drop(columns=['G3'])
Y = df['G3'].to_numpy()

X = pd.get_dummies(X, drop_first=True)

# One-hot encode categorical variables (like 'sex', 'address', 'school')
print("Final feature set shape:", X.shape)
print(X.head(5))

X_train, X_temp, Y_train, Y_temp = train_test_split(X, Y, test_size=0.2, ran
X_dev, X_test, Y_dev, Y_test = train_test_split(X_temp, Y_temp, test_size=0.

del X_temp
del Y_temp

print(f"Train: {X_train.shape}, Dev: {X_dev.shape}, Test: {X_test.shape}")
print(f"Train: {Y_train.shape}, Dev: {Y_dev.shape}, Test: {Y_test.shape}")
```

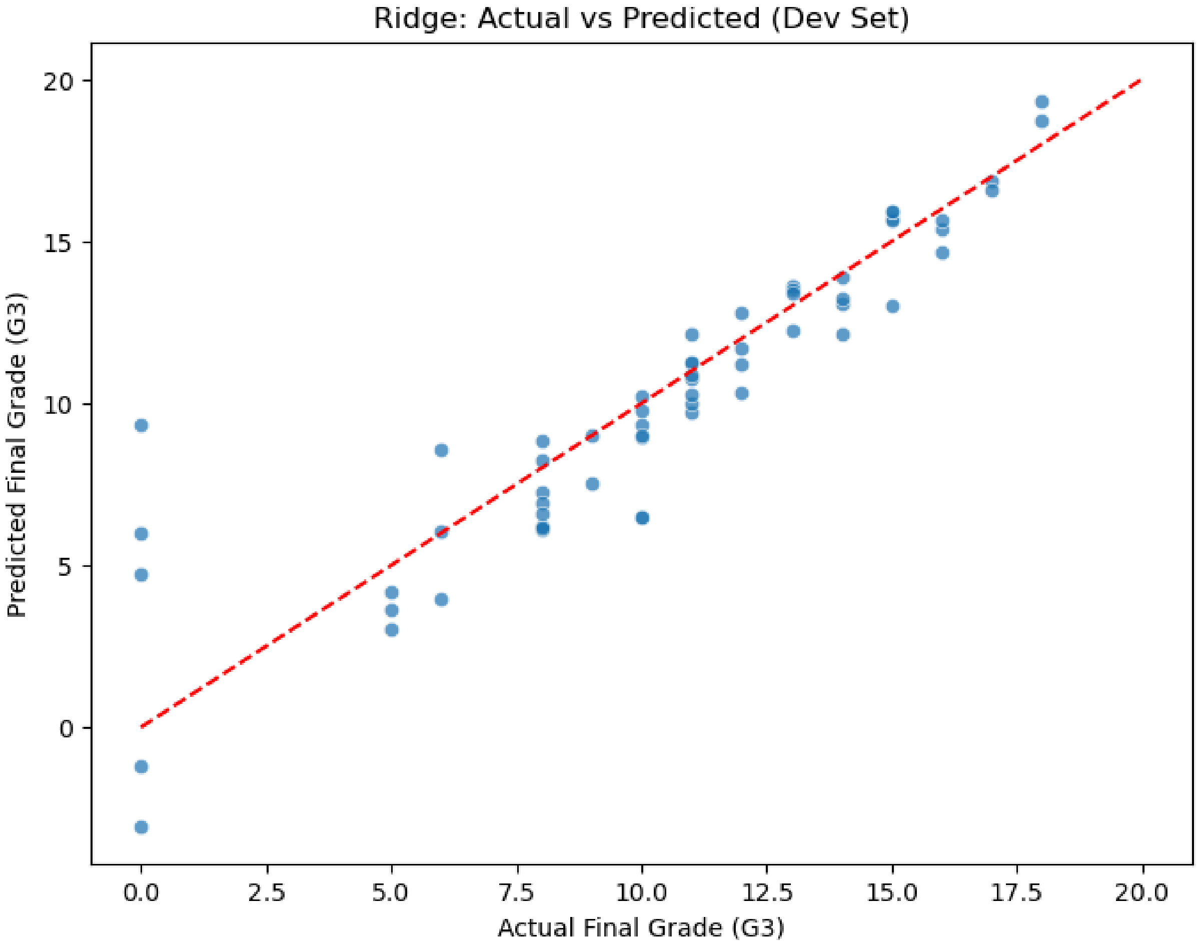
```
Final feature set shape: (397, 41)
   age  Medu  ...  internet_yes  romantic_yes
0   18     4  ...         False         False
1   17     1  ...          True         False
2   15     1  ...          True         False
3   15     4  ...          True          True
4   16     3  ...         False         False

[5 rows x 41 columns]
Train: (317, 41), Dev: (60, 41), Test: (20, 41)
Train: (317,), Dev: (60,), Test: (20,)
```

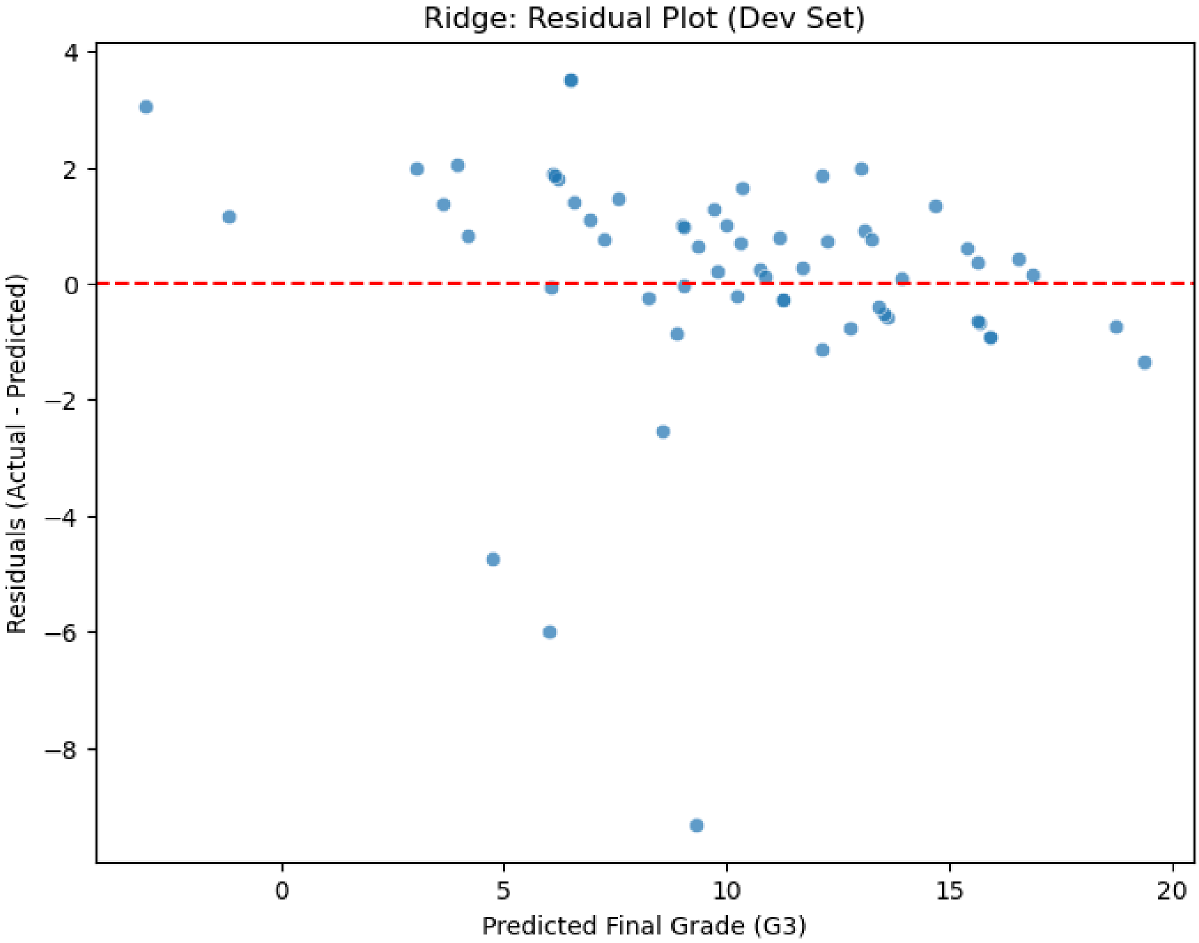
In [109…

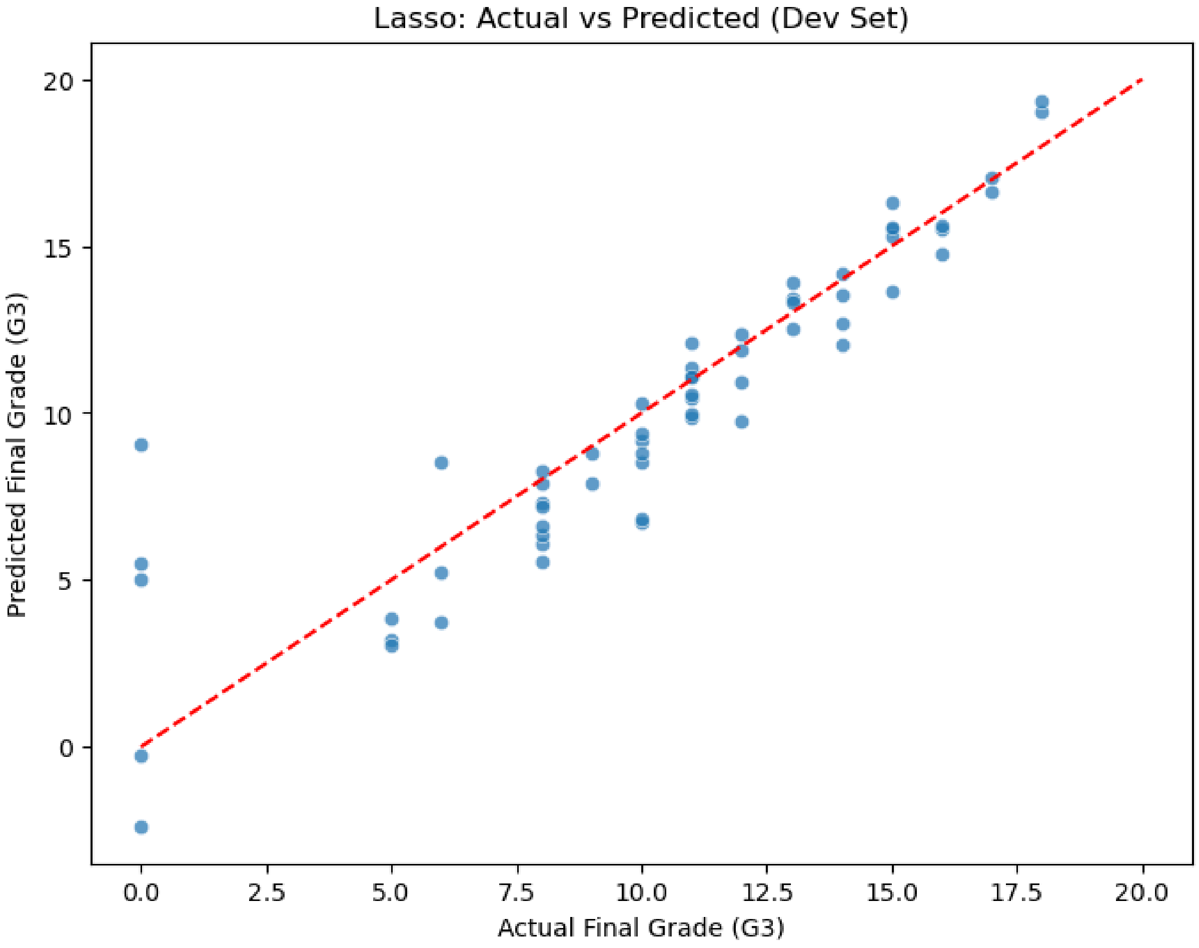
```
models = {
    "Linear": LinearRegression(),
    "Ridge": Ridge(alpha=1.0),
    "Lasso": Lasso(alpha=0.01),
    "Random Forest": RandomForestRegressor(n_estimators=200, random_state=42
}

results = {}

for name,model in models.items():
    rfe = RFE(model, n_features_to_select=15)
    rfe.fit(X_train, Y_train)
    y_dev_pred = rfe.predict(X_dev)

    selected_features = X_train.columns[rfe.support_]

    # Metrics
    mean_squared_error_value = np.sqrt(mean_squared_error(Y_dev, y_dev_pred)
    r2_score_value = r2_score(Y_dev, y_dev_pred)
    mean_absolute_error_value = mean_absolute_error(Y_dev, y_dev_pred)

    # --- Plot: Actual vs Predicted ---
    plt.figure(figsize=(8,6))
    sns.scatterplot(x=Y_dev, y=y_dev_pred, alpha=0.7)
    plt.plot([0,20], [0,20], color="red", linestyle="--")  # perfect predict
    plt.xlabel("Actual Final Grade (G3)")
    plt.ylabel("Predicted Final Grade (G3)")
    plt.title(f"{name}: Actual vs Predicted (Dev Set)")
    plt.show()

    # --- Plot: Residuals ---
    residuals = Y_dev - y_dev_pred
    plt.figure(figsize=(8,6))
    sns.scatterplot(x=y_dev_pred, y=residuals, alpha=0.7)
    plt.axhline(0, color="red", linestyle="--")
    plt.xlabel("Predicted Final Grade (G3)")
    plt.ylabel("Residuals (Actual - Predicted)")
    plt.title(f"{name}: Residual Plot (Dev Set)")
    plt.show()

    results[name] = {
        "selected_features": selected_features,
        "coef_" : model.coef_ if hasattr(model, 'coef_') else None,
        "mean_squared_error": mean_squared_error_value,
        "r2_score": r2_score_value,
        "mean_absolute_error": mean_absolute_error_value
    }

results_df = pd.DataFrame(results).T
print("Dev Set Results:\n", results_df.drop(columns=['coef_', 'selected_feat
```

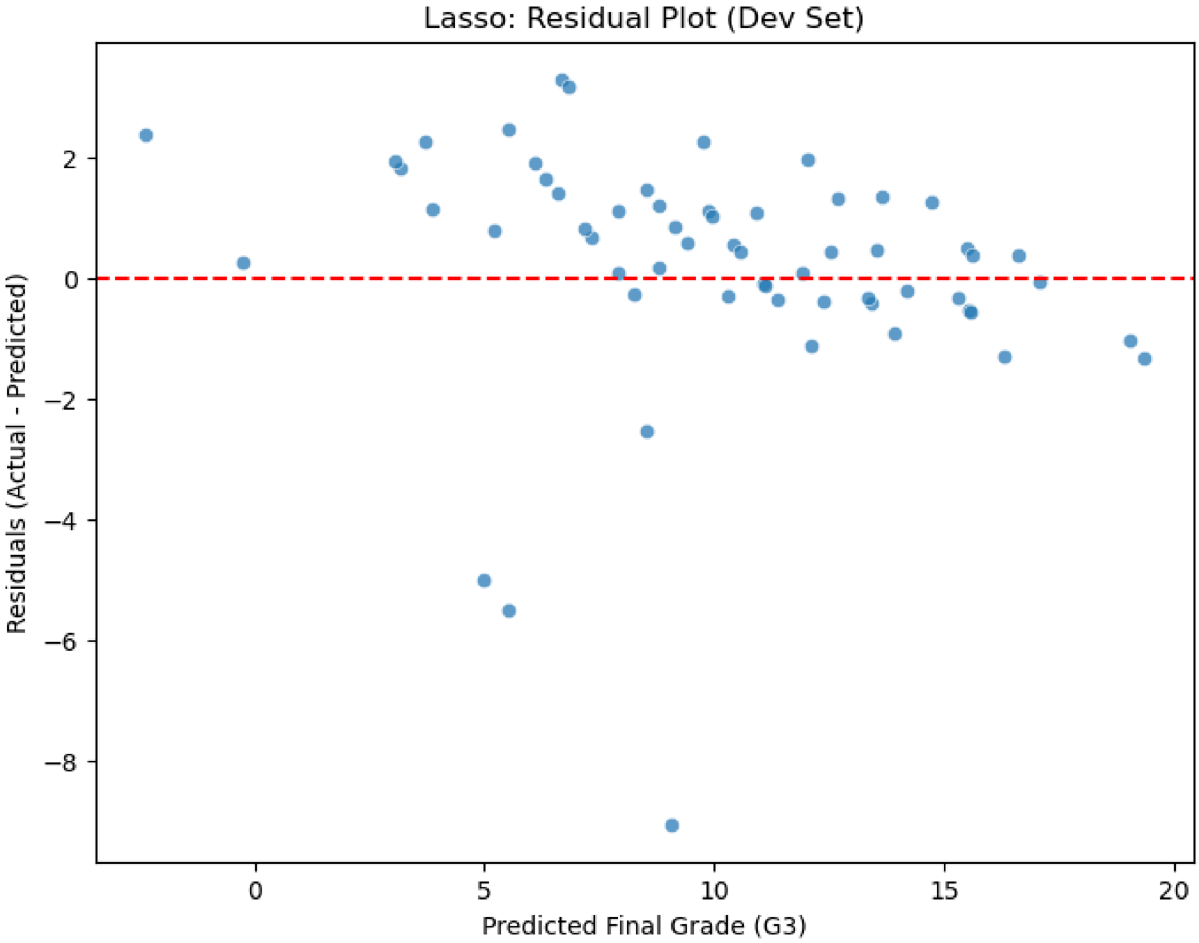

Linear: Actual vs Predicted (Dev Set)
Predicted Final Grade (G3)
Actual Final Grade (G3)
20
15
10
5
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

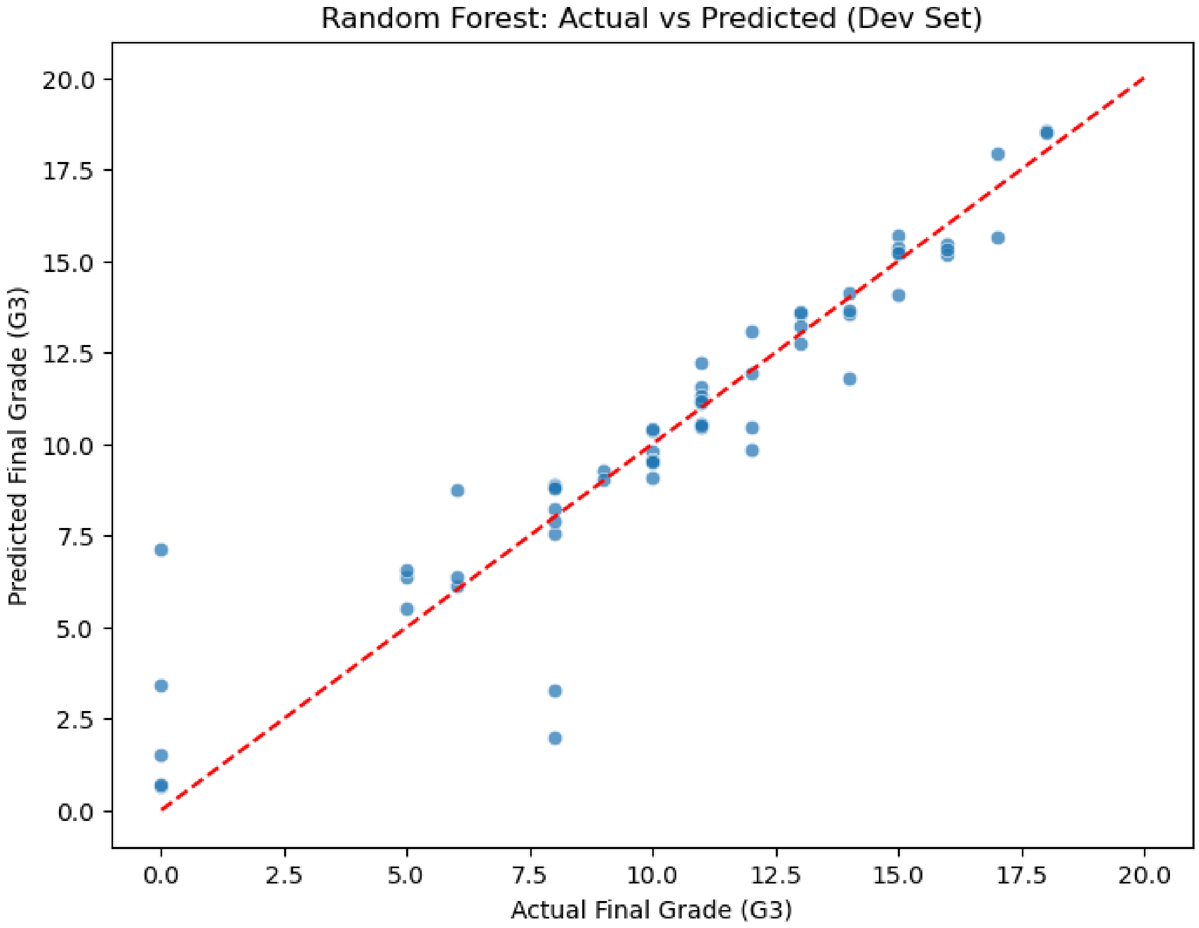

Linear: Residual Plot (Dev Set)
Residuals (Actual - Predicted)
4
2
0
−2
−4
−6
−8
0
5
10
15
20
Predicted Final Grade (G3)

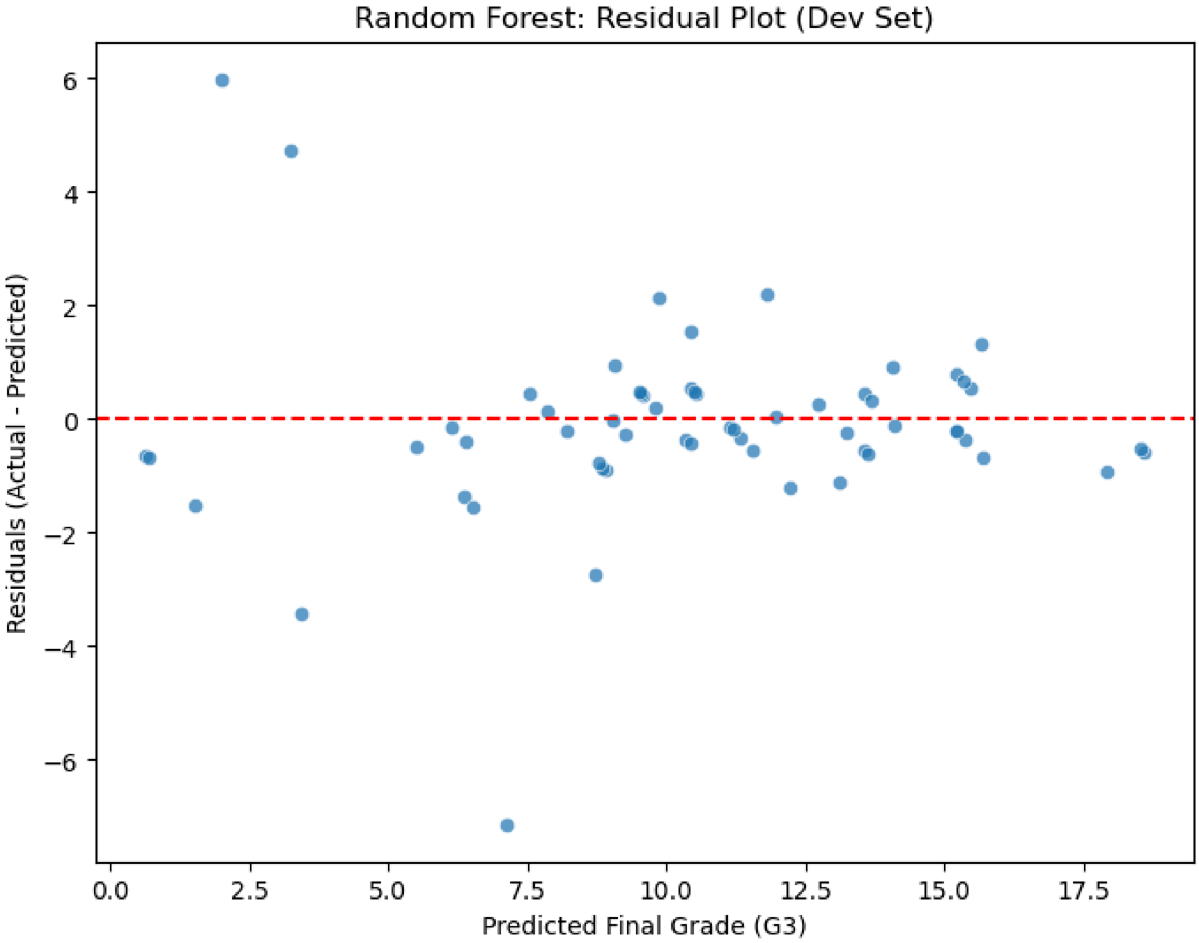

Ridge: Actual vs Predicted (Dev Set)
Predicted Final Grade (G3)
Actual Final Grade (G3)
20
15
10
5
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


Ridge: Residual Plot (Dev Set)
Residuals (Actual - Predicted)
Predicted Final Grade (G3)
4
2
0
−2
−4
−6
−8
0
5
10
15
20


Lasso: Actual vs Predicted (Dev Set)
Predicted Final Grade (G3)
20
15
10
5
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Actual Final Grade (G3)


Lasso: Residual Plot (Dev Set)
Residuals (Actual - Predicted)
2
0
−2
−4
−6
−8
0
5
10
15
20
Predicted Final Grade (G3)


Random Forest: Actual vs Predicted (Dev Set)
Predicted Final Grade (G3)
Actual Final Grade (G3)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0



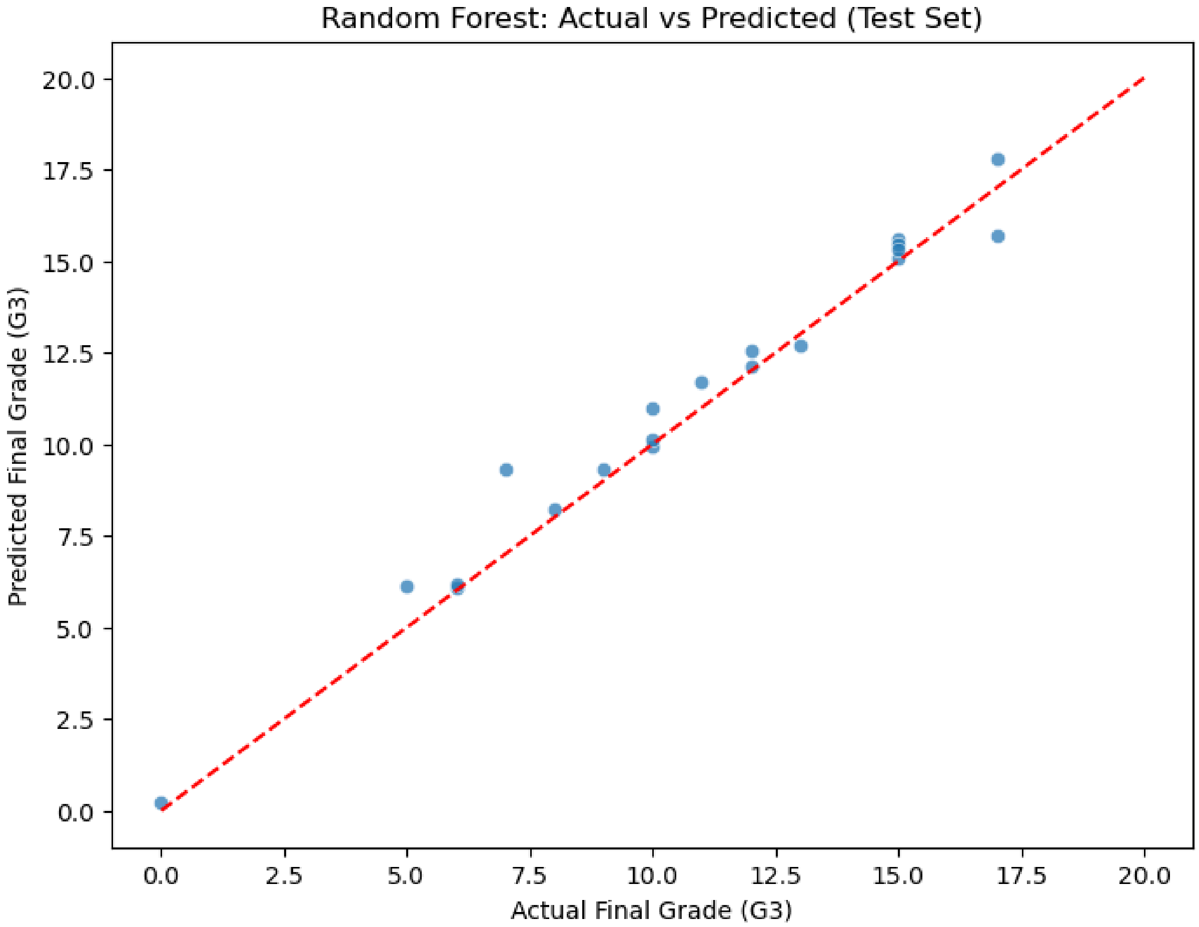
```
Dev Set Results:
               mean_squared_error  r2_score mean_absolute_error
Linear                   1.956986  0.813474            1.281224
Ridge                    2.016186  0.802018            1.321125
Lasso                    1.972581  0.810489            1.297025
Random Forest            1.651189  0.867212               0.982
```

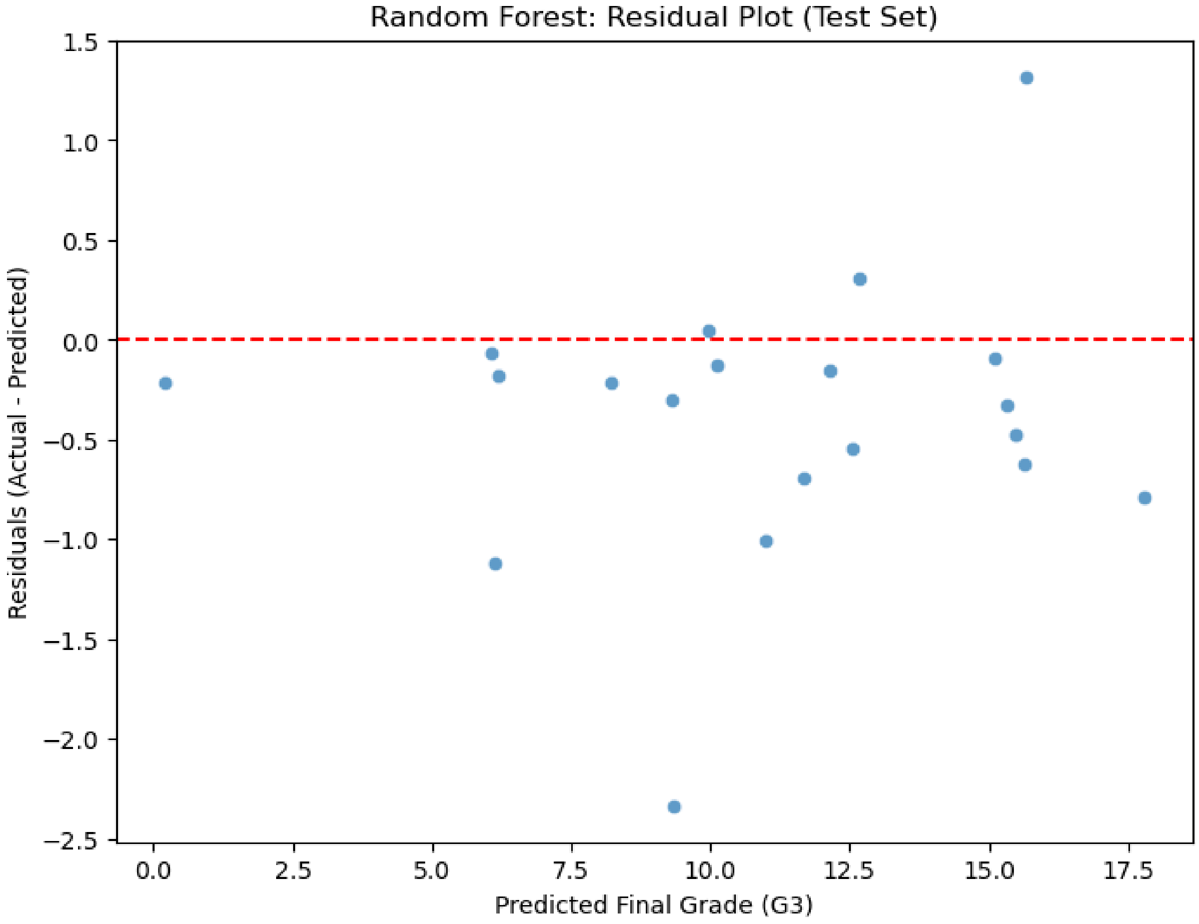
In [113…

```
# Step 2: Pick best model (highest R2)
best_model_name = results_df['r2_score'].idxmax()
best_model_info = results[best_model_name]
best_features = list(best_model_info["selected_features"])  # convert Index

print(f"Best Model: {best_model_name}")
print(f"Selected Features: {best_features}")

# Step 3: Retrain best model on Train+Dev with selected features
X_train_dev = pd.concat([X_train, X_dev])
Y_train_dev = np.concatenate([Y_train, Y_dev])

best_model = models[best_model_name]
rfe_final = RFE(best_model, n_features_to_select=len(best_features))
rfe_final.fit(X_train_dev[best_features], Y_train_dev)

# Step 4: Evaluate on Test set
y_test_pred = rfe_final.predict(X_test[best_features])

mae_test = mean_absolute_error(Y_test, y_test_pred)
```

```
rmse_test = np.sqrt(mean_squared_error(Y_test, y_test_pred))
r2_test = r2_score(Y_test, y_test_pred)

print("Test Set Performance:")
print(f"MAE: {mae_test:.2f}")
print(f"RMSE: {rmse_test:.2f}")
print(f"R2: {r2_test:.2f}")

# --- Plot: Actual vs Predicted (Test set) ---
plt.figure(figsize=(8,6))
sns.scatterplot(x=Y_test, y=y_test_pred, alpha=0.7)
plt.plot([0,20], [0,20], color="red", linestyle="--")
plt.xlabel("Actual Final Grade (G3)")
plt.ylabel("Predicted Final Grade (G3)")
plt.title(f"{best_model_name}: Actual vs Predicted (Test Set)")
plt.show()

# --- Plot: Residuals (Test set) ---
residuals_test = Y_test - y_test_pred
plt.figure(figsize=(8,6))
sns.scatterplot(x=y_test_pred, y=residuals_test, alpha=0.7)
plt.axhline(0, color="red", linestyle="--")
plt.xlabel("Predicted Final Grade (G3)")
plt.ylabel("Residuals (Actual - Predicted)")
plt.title(f"{best_model_name}: Residual Plot (Test Set)")
plt.show()
```

```
✅ Best Model: Random Forest
Selected Features: ['age', 'Medu', 'Fedu', 'studytime', 'famrel', 'freetim
e', 'goout', 'Walc', 'health', 'absences', 'G1', 'G2', 'reason_home', 'schoo
lsup_yes', 'activities_yes']

📊 Test Set Performance:
MAE: 0.55
RMSE: 0.77
R2: 0.97
```


Random Forest: Actual vs Predicted (Test Set)
Predicted Final Grade (G3)
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Actual Final Grade (G3)


Random Forest: Residual Plot (Test Set)
Residuals (Actual - Predicted)
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Predicted Final Grade (G3)