FEATURE_SELECTION

Filter Methods:

Based on statistical test
Correlation Coefficient: Measures the linear relationship between two variables.
Chi-Square Test: Measures the independence between categorical variables.
Mutual Information: Measures the dependency between variables.
Variance Threshold: Removes features with low variance.

Wrapper Methods:

Forward Selection: Starts with no features, adds one at a time based on model performance.
Backward Elimination: Starts with all features, removes the least significant feature one at a time.
Recursive Feature Elimination (RFE): Recursively removes least important features based on model performance.

Embedded Methods:

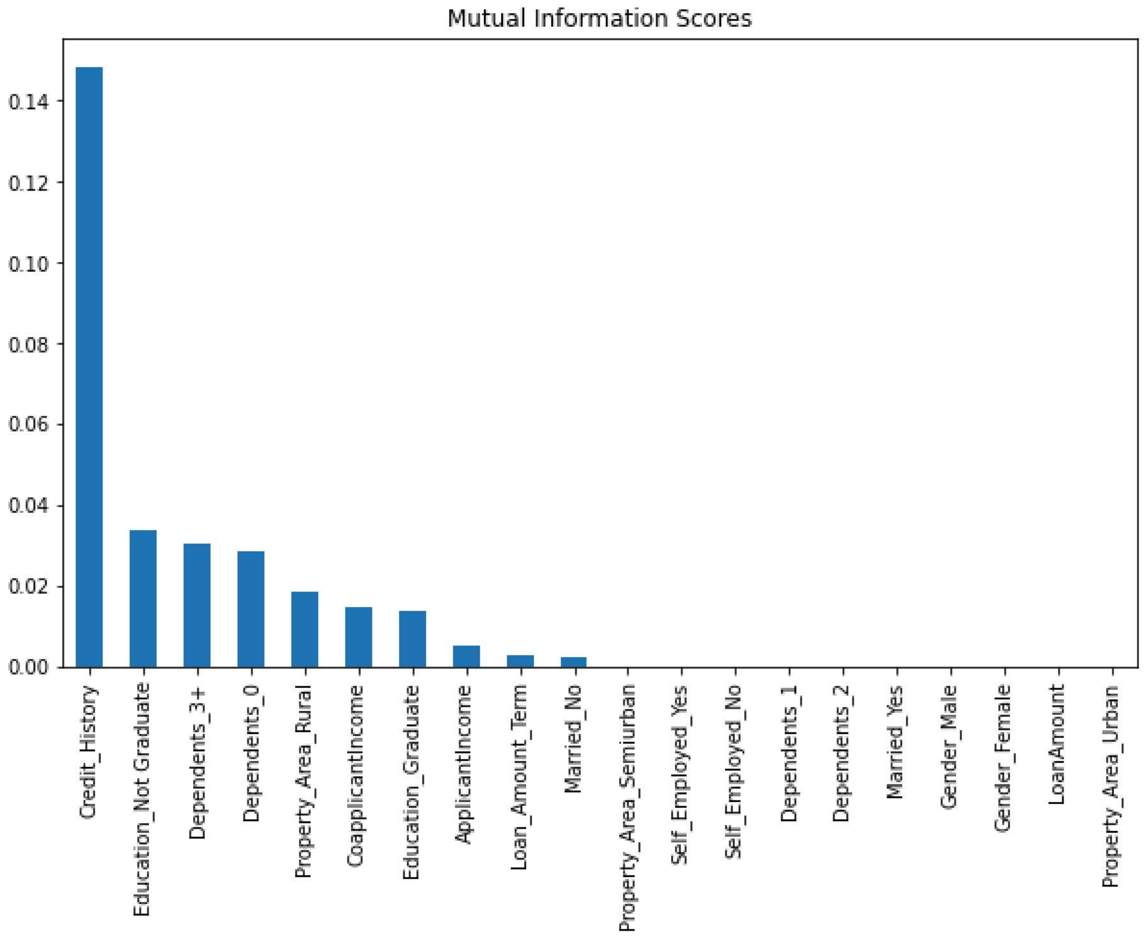
Lasso Regression: Adds a penalty equal to the absolute value of the magnitude of coefficients.
Ridge Regression: Adds a penalty equal to the square of the magnitude of coefficients.
Elastic Net: Combines Lasso and Ridge penalties.
Tree-based Methods: Feature importance based on tree-based models like Random Forests and Gradient Boosting.

In [14]:
```
import numpy as np
import pandas as pd
from sklearn.feature_selection import VarianceThreshold, mutual_info_classif
from sklearn.linear_model import LogisticRegression, Lasso, Ridge, ElasticNe
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.impute import KNNImputer
from sklearn.metrics import r2_score
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
file_path = "D:/Downloads/archive (22)/loan_data_set.csv"
data = pd.read_csv(file_path)

# Drop 'Loan_ID' and separate features and target variable
X = data.drop(['Loan_ID', 'Loan_Status'], axis=1)
y = data['Loan_Status']

# Encode target variable
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

# Encode categorical variables
X_encoded = pd.get_dummies(X)

# Handle missing values
imputer = KNNImputer(n_neighbors=3)
X_imputed = imputer.fit_transform(X_encoded)

# Normalize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_imputed)
print(data)
```

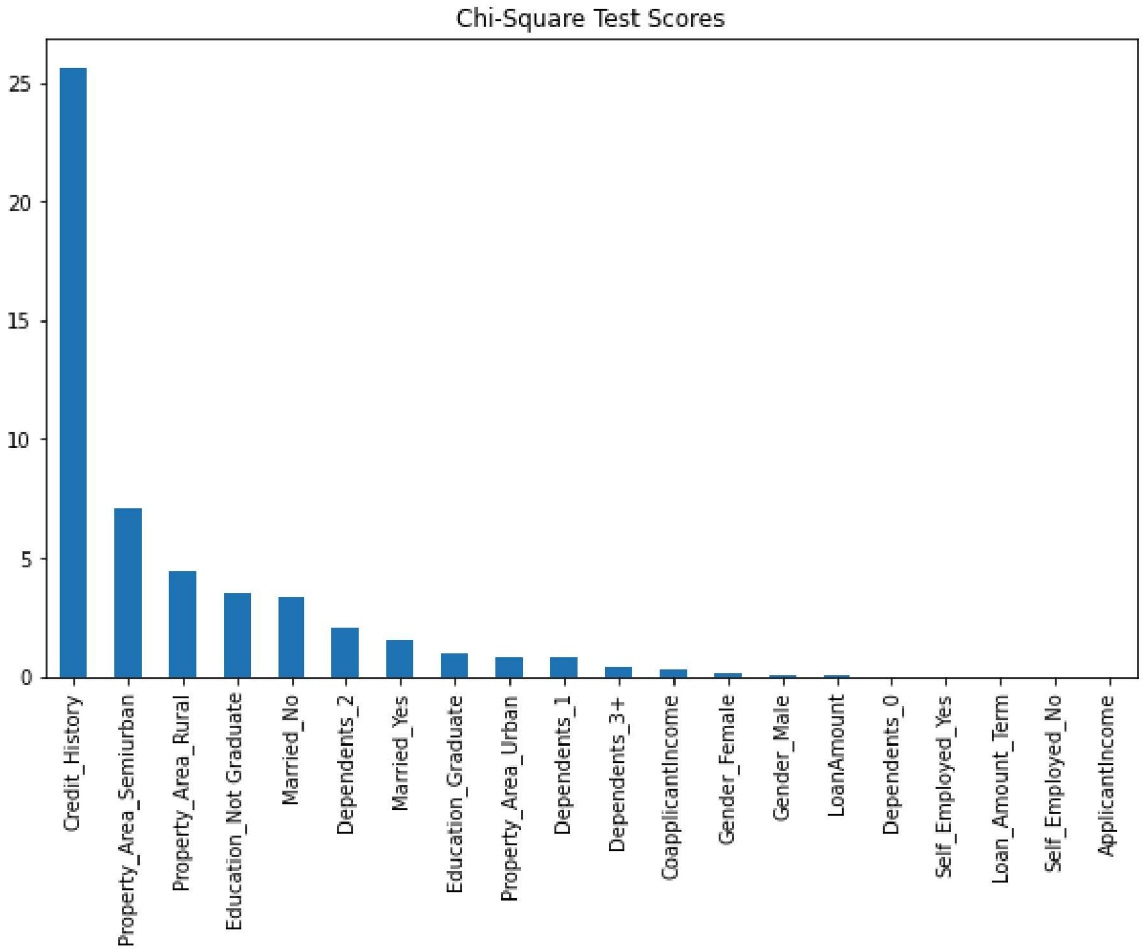
```
      Loan_ID  Gender Married Dependents     Education Self_Employed  \
0    LP001002    Male      No          0      Graduate            No
1    LP001003    Male     Yes          1      Graduate            No
2    LP001005    Male     Yes          0      Graduate           Yes
3    LP001006    Male     Yes          0  Not Graduate            No
4    LP001008    Male      No          0      Graduate            No
..        ...     ...     ...        ...           ...           ...
609  LP002978  Female      No          0      Graduate            No
610  LP002979    Male     Yes         3+      Graduate            No
611  LP002983    Male     Yes          1      Graduate            No
612  LP002984    Male     Yes          2      Graduate            No
613  LP002990  Female      No          0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               ...                ...         ...               ...
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
0               1.0         Urban           Y
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
..              ...           ...         ...
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[614 rows x 13 columns]
```

Filter Methods:

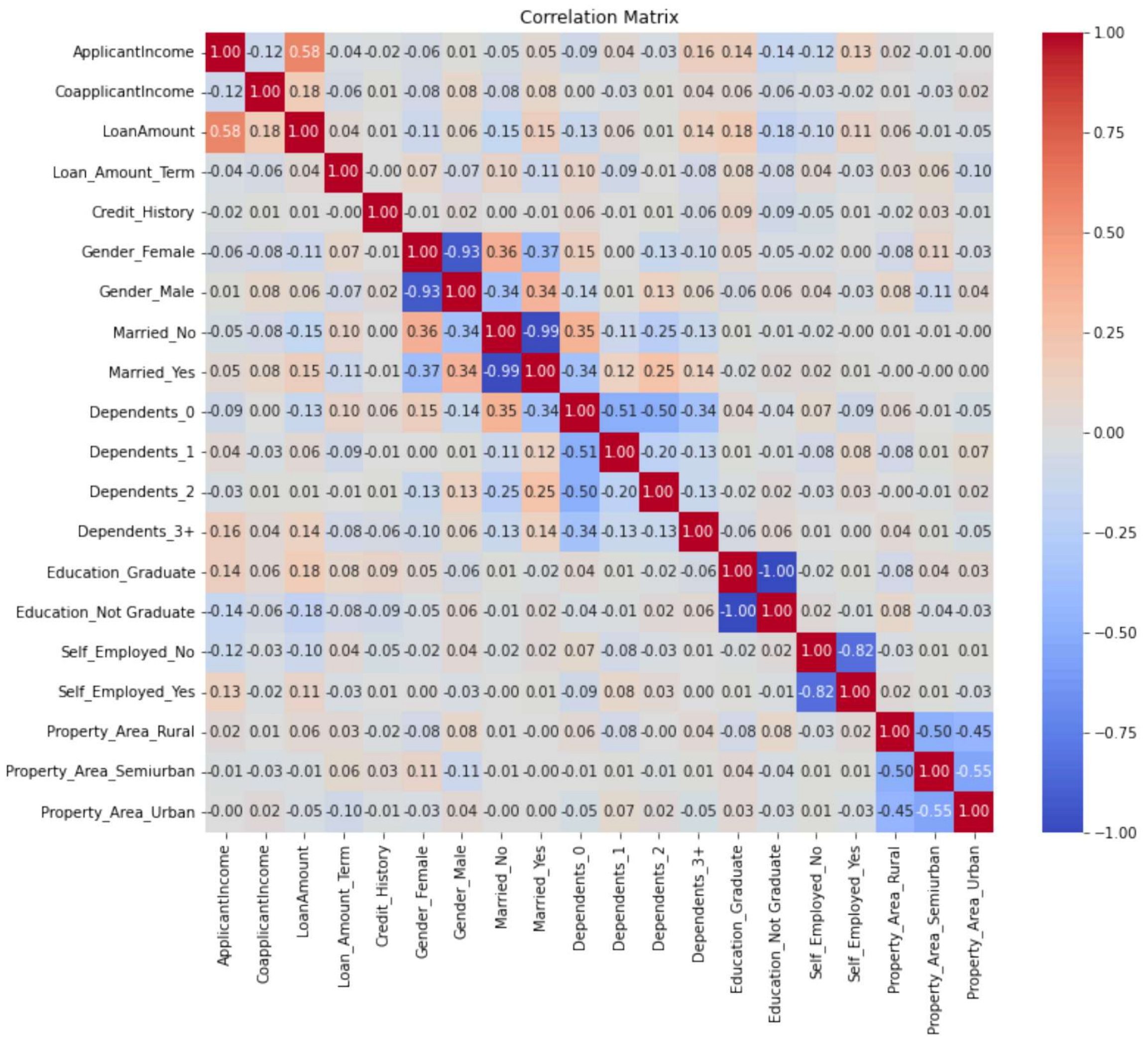
In [2]:
```
# Mutual Information
mi = mutual_info_classif(X_scaled, y)
mi_series = pd.Series(mi, index=X_encoded.columns)


plt.figure(figsize=(10, 6))
mi_series.sort_values(ascending=False).plot.bar()
plt.title('Mutual Information Scores')
plt.show()
```



In [12]:
```
# Chi-Square Test
min_max_scaler = MinMaxScaler()
X_minmax = min_max_scaler.fit_transform(X_imputed)
chi2_scores, p_values = chi2(X_minmax, y)
chi2_series = pd.Series(chi2_scores, index=X_encoded.columns)


plt.figure(figsize=(10, 6))
chi2_series.sort_values(ascending=False).plot.bar()
plt.title('Chi-Square Test Scores')
plt.show()
```



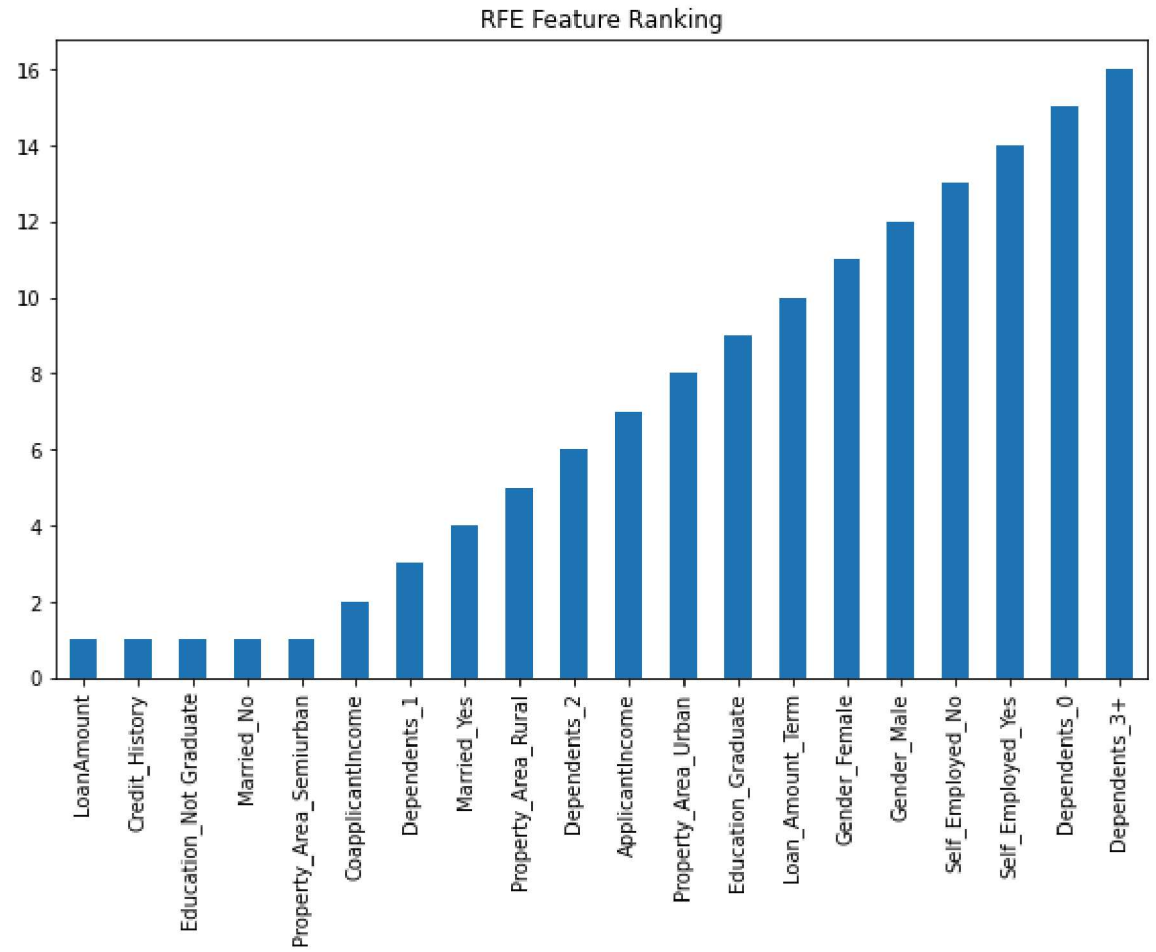
```python
In [15]: # Correlation Coefficient
         correlation_matrix = pd.DataFrame(X_imputed, columns=X_encoded.columns).corr


         plt.figure(figsize=(12, 10))
         sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
         plt.title('Correlation Matrix')
         plt.show()
```



Wrapper Methods:

In [5]:
```
# Recursive Feature Elimination (RFE)
model = LogisticRegression(max_iter=1000)
rfe = RFE(model, n_features_to_select=5)
X_rfe = rfe.fit_transform(X_scaled, y)
print("RFE Selected Features Shape:", X_rfe.shape)


plt.figure(figsize=(10, 6))
rfe_ranking = pd.Series(rfe.ranking_, index=X_encoded.columns)
rfe_ranking.sort_values().plot.bar()
plt.title('RFE Feature Ranking')
plt.show()
```

```
RFE Selected Features Shape: (614, 5)
```

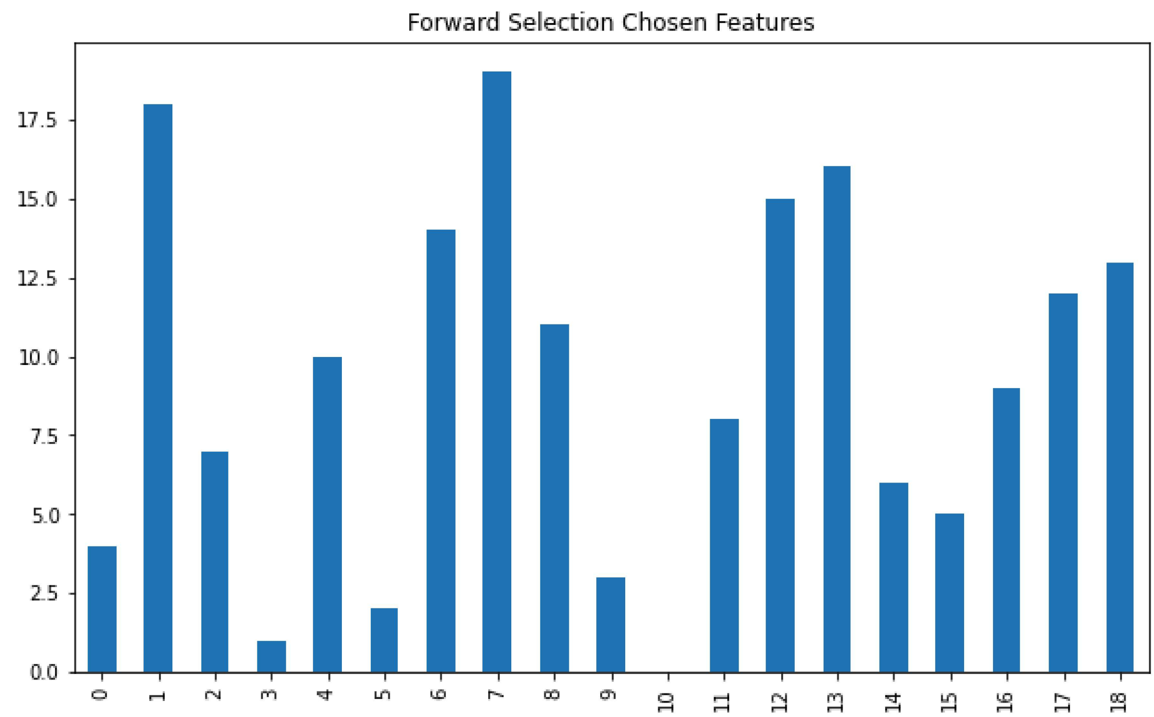


In [6]:
```python
# Backward Elimination
X_with_const = sm.add_constant(pd.DataFrame(X_scaled, columns=X_encoded.colu
model = sm.OLS(y, X_with_const).fit()
print("Initial Model Summary:")
print(model.summary())

while True:
    p_values = pd.Series(model.pvalues, index=X_with_const.columns)
    max_p_value = p_values.max()
    if max_p_value > 0.05:
        excluded_feature = p_values.idxmax()
        print(f"Dropping {excluded_feature}")
        X_with_const = X_with_const.drop(columns=[excluded_feature])
        model = sm.OLS(y, X_with_const).fit()
    else:
        break

print("Final Model Summary:")
print(model.summary())


plt.figure(figsize=(10, 6))
p_values.sort_values().plot.bar()
plt.axhline(y=0.05, color='r', linestyle='--')
plt.title('P-Values of Features After Backward Elimination')
plt.show()
```

```
Initial Model Summary:
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                      y   R-squared:
0.319
Model:                            OLS   Adj. R-squared:
0.299
Method:                 Least Squares   F-statistic:
15.51
Date:                Wed, 05 Jun 2024   Prob (F-statistic):          3.8
9e-39
Time:                        10:02:32   Log-Likelihood:               -2
81.12
No. Observations:                 614   AIC:
600.2
Df Residuals:                     595   BIC:
684.2
Df Model:                          18
```

In [7]:
```python
# Forward Selection
remaining_features = list(range(X_scaled.shape[1]))
selected_features = []
current_score, best_new_score = 0.0, 0.0

while remaining_features and current_score == best_new_score:
    scores_with_candidates = []
    for candidate in remaining_features:
        features_to_try = selected_features + [candidate]
        model = LinearRegression()
        model.fit(X_scaled[:, features_to_try], y)
        score = r2_score(y, model.predict(X_scaled[:, features_to_try]))
        scores_with_candidates.append((score, candidate))

    scores_with_candidates.sort(reverse=True)
    best_new_score, best_candidate = scores_with_candidates[0]
    if current_score < best_new_score:
        remaining_features.remove(best_candidate)
        selected_features.append(best_candidate)
        current_score = best_new_score

print("Selected features (indices):", selected_features)


plt.figure(figsize=(10, 6))
forward_selected_features = pd.Series(selected_features)
forward_selected_features.plot(kind='bar')
plt.title('Forward Selection Chosen Features')
plt.show()
```

```
Selected features (indices): [4, 18, 7, 1, 10, 2, 14, 19, 11, 3, 0, 8, 15,
16, 6, 5, 9, 12, 13]
```

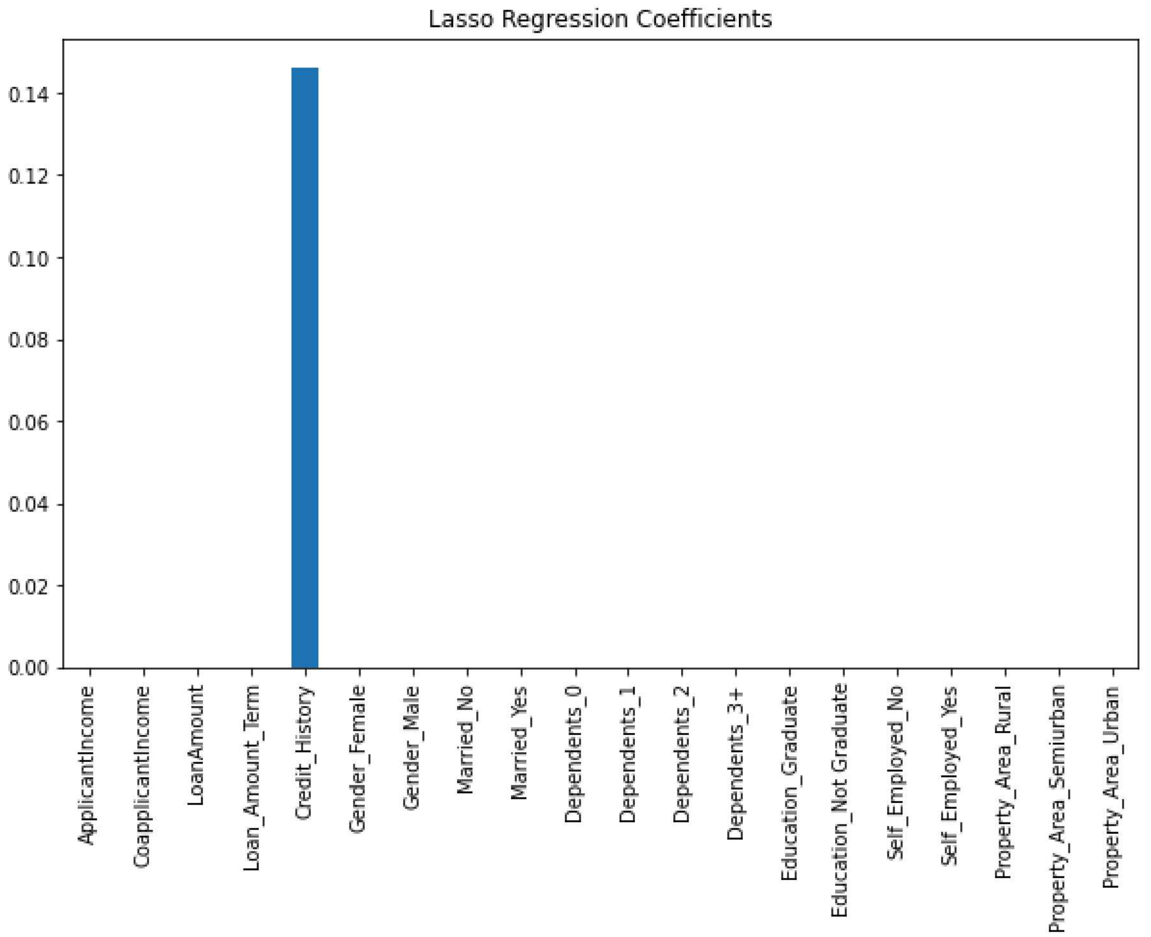


Embedded Methods:

In [8]:

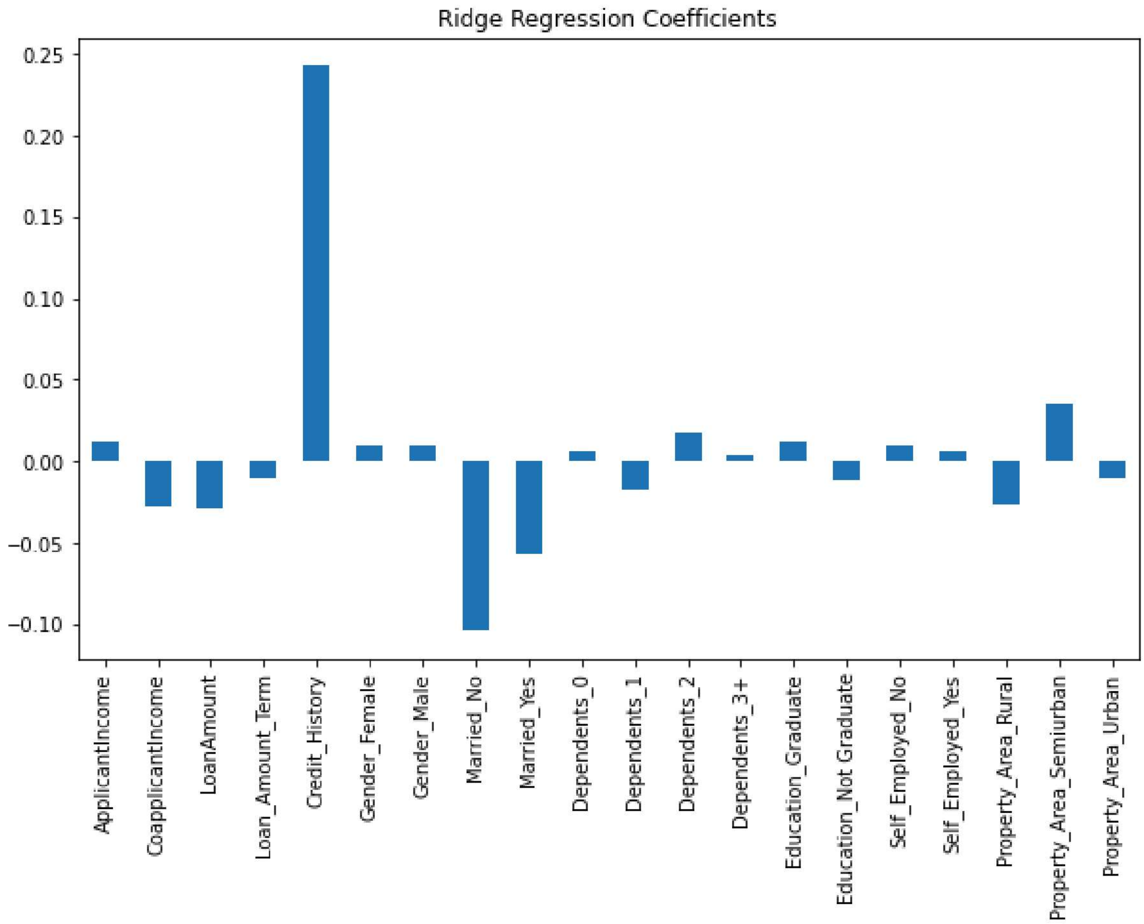
```
# Lasso Regression
lasso = Lasso(alpha=0.1)
lasso.fit(X_scaled, y)
print("Lasso Coefficients:")
print(lasso.coef_)


plt.figure(figsize=(10, 6))
lasso_coefficients = pd.Series(lasso.coef_, index=X_encoded.columns)
lasso_coefficients.plot(kind='bar')
plt.title('Lasso Regression Coefficients')
plt.show()
```

```
Lasso Coefficients:
[ 0.          -0.          -0.          -0.           0.14605572 -0.
  0.          -0.           0.          -0.          -0.           0.
 -0.           0.          -0.           0.          -0.          -0.
  0.          -0.         ]
```



In [9]:
```
# Ridge Regression
ridge = Ridge(alpha=0.1)
ridge.fit(X_scaled, y)


plt.figure(figsize=(10, 6))
ridge_coefficients = pd.Series(ridge.coef_, index=X_encoded.columns)
ridge_coefficients.plot(kind='bar')
plt.title('Ridge Regression Coefficients')
plt.show()
```

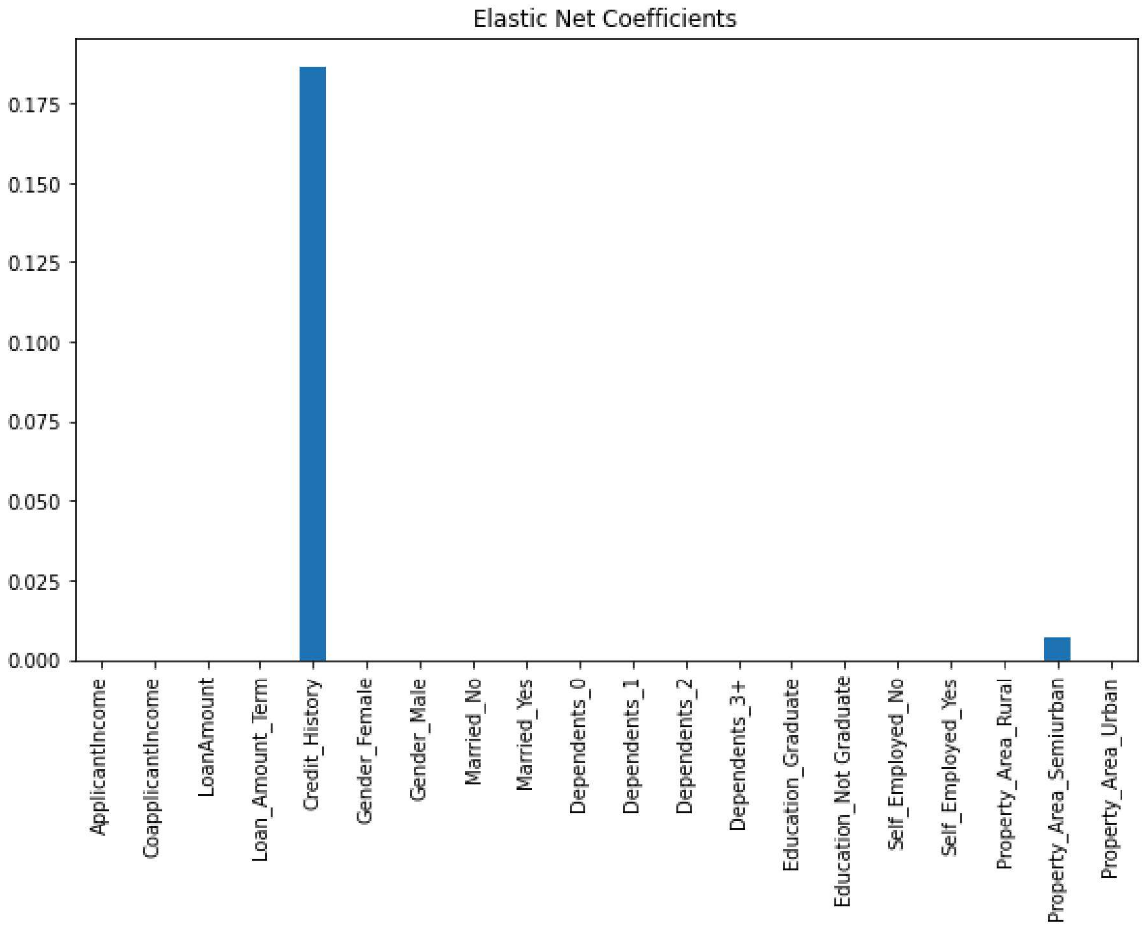
```
Ridge Coefficients:
[ 0.01198102 -0.02818727 -0.02921305 -0.01001761  0.24270978  0.00996648
  0.00999456 -0.10355527 -0.05721514  0.00577958 -0.01763945  0.01724876
  0.00324774  0.01135585 -0.01135585  0.00914944  0.00659059 -0.0267295
  0.03514268 -0.01044077]
```



In [10]:

```
# Elastic Net
elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5)
elastic_net.fit(X_scaled, y)


plt.figure(figsize=(10, 6))
elastic_net_coefficients = pd.Series(elastic_net.coef_, index=X_encoded.colu
elastic_net_coefficients.plot(kind='bar')
plt.title('Elastic Net Coefficients')
plt.show()
```

```
Elastic Net Coefficients:
[ 0.         -0.         -0.         -0.          0.18650781 -0.
  0.         -0.          0.         -0.         -0.          0.
 -0.          0.         -0.          0.         -0.         -0.
  0.00709615 -0.        ]
```



In [16]:
```
# Tree-based Methods
model = RandomForestClassifier()
model.fit(X_scaled, y)
importances = model.feature_importances_
importances_series = pd.Series(importances, index=X_encoded.columns)


plt.figure(figsize=(10, 6))
importances_series.sort_values(ascending=False).plot.bar()
plt.title('Random Forest Feature Importances')
plt.show()
```