```
#Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import f1_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import log_loss


#Loading the dataset
df = pd.read_csv('healthcare-dataset-stroke-data.csv')
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes

```
df.drop('id', axis=1, inplace=True)


df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   gender             5110 non-null   object
 1   age                5110 non-null   float64
 2   hypertension       5110 non-null   int64
 3   heart_disease      5110 non-null   int64
 4   ever_married       5110 non-null   object
 5   work_type          5110 non-null   object
 6   Residence_type     5110 non-null   object
 7   avg_glucose_level  5110 non-null   float64
 8   bmi                4909 non-null   float64
 9   smoking_status     5110 non-null   object
 10  stroke             5110 non-null   int64
dtypes: float64(3), int64(3), object(5)
memory usage: 439.3+ KB
```

```
df['age'].astype(int)
```

	age
0	67
1	61
2	80
3	49
4	79
...	...
5105	80
5106	81
5107	35
5108	51
5109	44

5110 rows × 1 columns

```
#Checking for null values
df.isnull().sum()
```

	0
gender	0
age	0
hypertension	0
heart_disease	0
ever_married	0
work_type	0
Residence_type	0
avg_glucose_level	0
bmi	201
smoking_status	0
stroke	0

```
#replacing the missing values with the most frequent value
df['bmi'].fillna(df['bmi'].mode()[0], inplace=True)
```

```
<ipython-input-7-ba9f48b18358>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col

  df['bmi'].fillna(df['bmi'].mode()[0], inplace=True)
```

Check values and their count in the columns

```
print(df['ever_married'].value_counts())
print(df['work_type'].value_counts())
print(df['gender'].value_counts())
print(df['Residence_type'].value_counts())
print(df['smoking_status'].value_counts())
```

```
ever_married
Yes    3353
No     1757
Name: count, dtype: int64
work_type
Private          2925
Self-employed     819
children          687
```

```
Govt_job          657
Never_worked       22
Name: count, dtype: int64
gender
Female    2994
Male      2115
Other        1
Name: count, dtype: int64
Residence_type
Urban    2596
Rural    2514
Name: count, dtype: int64
smoking_status
never smoked       1892
Unknown            1544
formerly smoked     885
smokes              789
Name: count, dtype: int64
```

Replacing the values in columns with numerical values

Residence Type: Urban = 1, Rural = 0

Smoking Status: formerly smoked = 1, never smoked = 2, smokes = 3,

Unknown = 0

Ever_Maried : Yes = 1, No = 0

Gender : Male = 1, Female = 0, Other = 2

Work Type : Private = 0, Self-employed = 1, children = 2, Govt_job = 3,

Never_worked = 4

```
df['ever_married'].replace({'Yes':1, 'No':0}, inplace=True)
df['gender'].replace({'Male':1, 'Female':0,'Other':2}, inplace=True)
df['Residence_type'].replace({'Urban':1, 'Rural':0}, inplace=True)
df['smoking_status'].replace({'formerly smoked':0, 'never smoked':1, 'smokes':2, 'Unknown':3}, inplace=True)
df['work_type'].replace({'Private':0, 'Self-employed':1, 'children':2, 'Govt_job':3, 'Never_worked':4}, inplace=True)
```

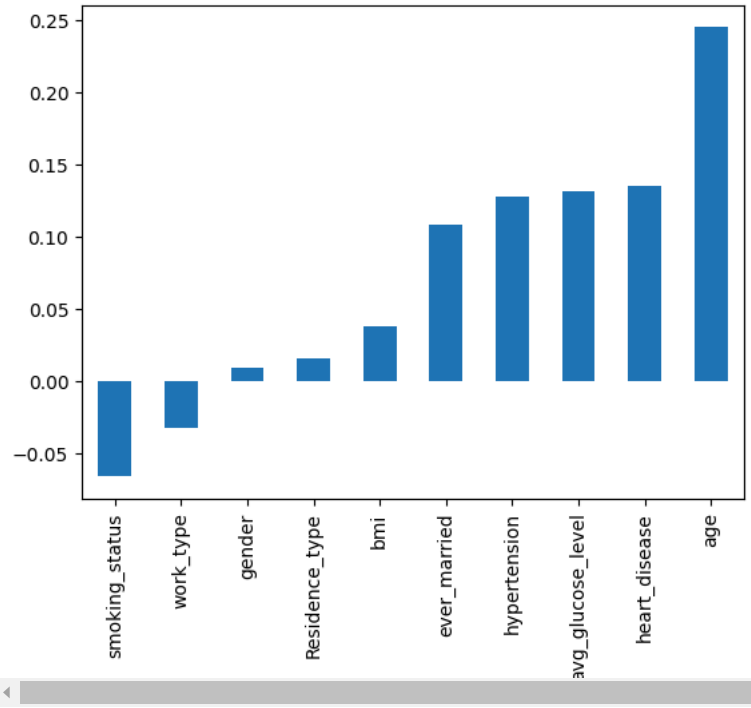
```
<ipython-input-9-93626c79bbd4>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['ever_married'].replace({'Yes':1, 'No':0}, inplace=True)
<ipython-input-9-93626c79bbd4>:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future ver
  df['ever_married'].replace({'Yes':1, 'No':0}, inplace=True)
<ipython-input-9-93626c79bbd4>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['gender'].replace({'Male':1, 'Female':0,'Other':2}, inplace=True)
<ipython-input-9-93626c79bbd4>:2: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future ver
  df['gender'].replace({'Male':1, 'Female':0,'Other':2}, inplace=True)
<ipython-input-9-93626c79bbd4>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['Residence_type'].replace({'Urban':1, 'Rural':0}, inplace=True)
<ipython-input-9-93626c79bbd4>:3: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future ver
  df['Residence_type'].replace({'Urban':1, 'Rural':0}, inplace=True)
<ipython-input-9-93626c79bbd4>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['smoking_status'].replace({'formerly smoked':0, 'never smoked':1, 'smokes':2, 'Unknown':3}, inplace=True)
<ipython-input-9-93626c79bbd4>:4: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future ver
  df['smoking_status'].replace({'formerly smoked':0, 'never smoked':1, 'smokes':2, 'Unknown':3}, inplace=True)
<ipython-input-9-93626c79bbd4>:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assi
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df['work_type'].replace({'Private':0, 'Self-employed':1, 'children':2, 'Govt_job':3, 'Never_worked':4}, inplace=True)
<ipython-input-9-93626c79bbd4>:5: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future ver
  df['work_type'].replace({'Private':0, 'Self-employed':1, 'children':2, 'Govt_job':3, 'Never_worked':4}, inplace=True)
```

Exploratory Data Analysis

Find correlation between the variables

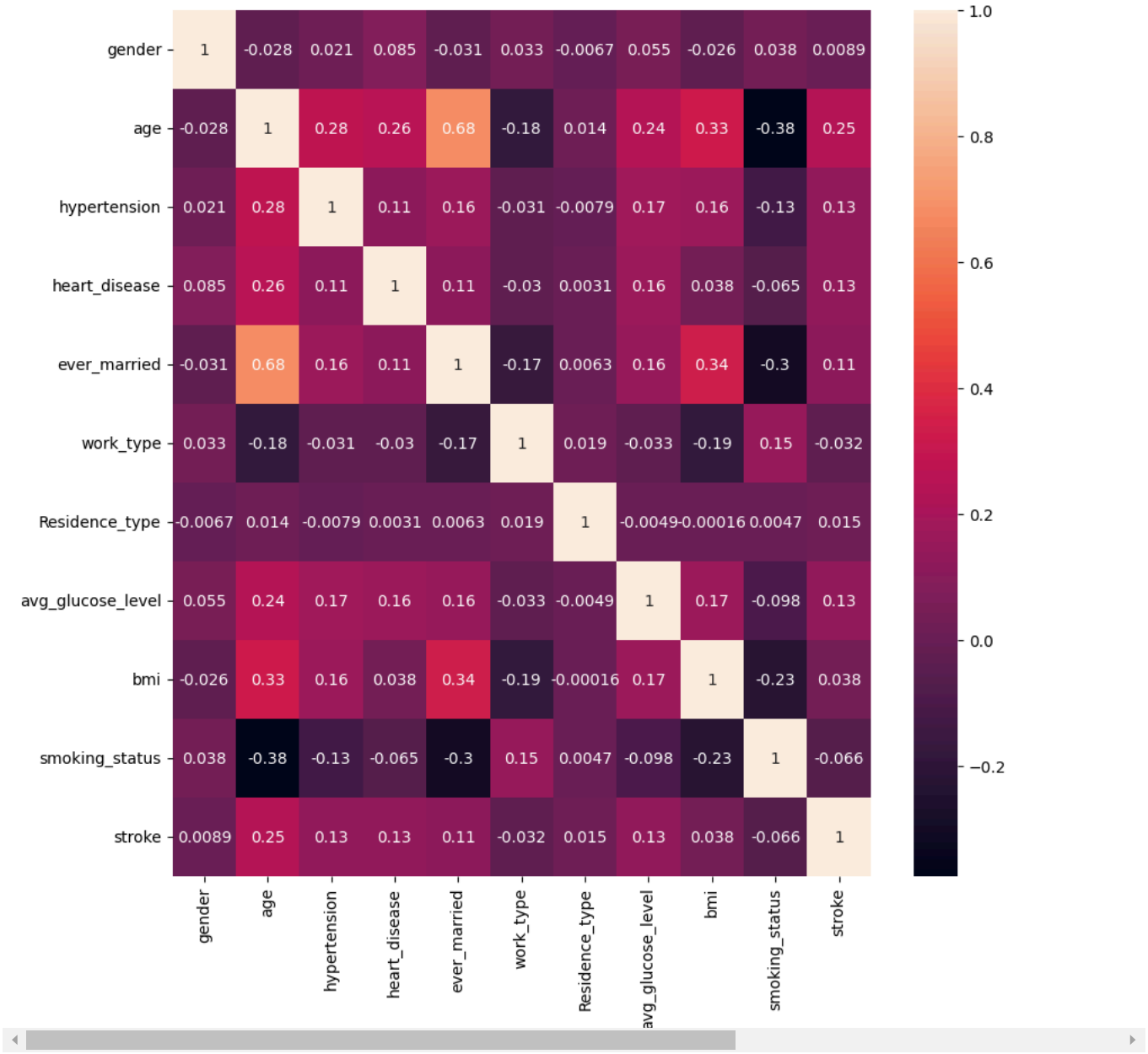
```
df.corr()['stroke'][:-1].sort_values().plot(kind='bar')
```

```
<Axes: >
```




```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True)
```

<Axes: >



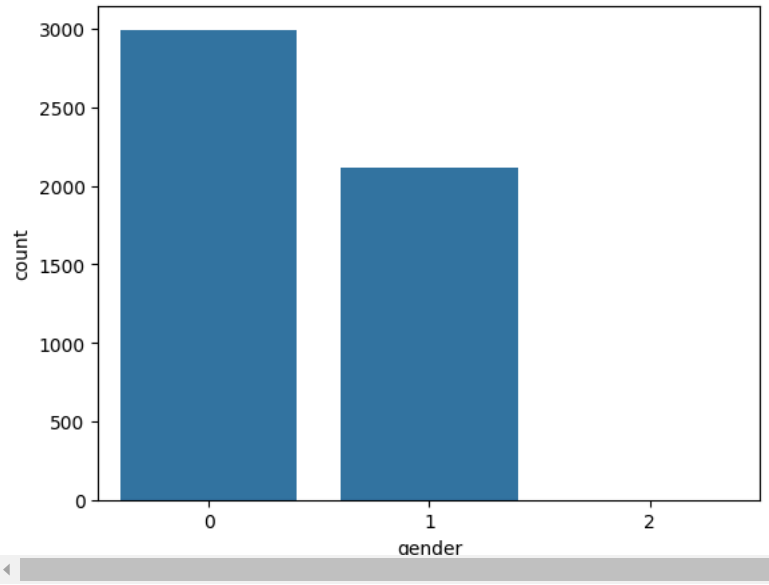

```
# replace age with number wrt to age group
# 0 = 0-12 , 1 = 13-19 , 2 = 20-30 , 3 = 31-60 , 4 = 61-100
df['age'] = pd.cut(x=df['age'], bins=[0, 12, 19, 30, 60, 100], labels=[0, 1, 2, 3,4])
df.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	1	4	0	1	1	0	1	228.69	36.6	0	1
1	0	4	0	0	1	1	0	202.21	28.7	1	1
2	1	4	0	1	1	0	0	105.92	32.5	1	1
3	0	3	0	0	1	0	1	171.23	34.4	2	1
4	0	4	1	0	1	1	0	174.12	24.0	1	1

Visulaizing the data

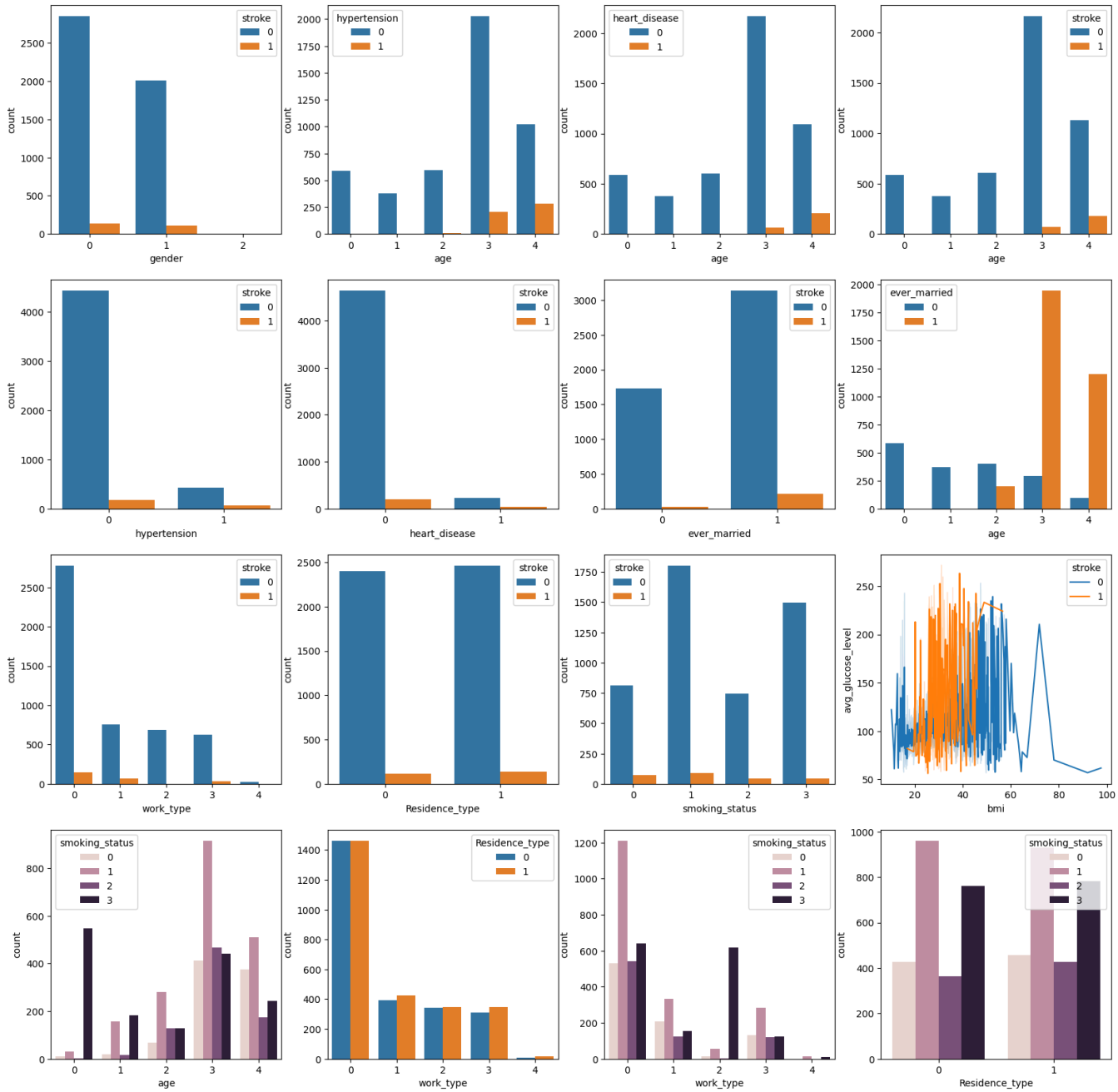
```
sns.countplot(x = 'gender', data = df)
```

```
<Axes: xlabel='gender', ylabel='count'>
```




```
fig, ax = plt.subplots(4,4,figsize=(20, 20))
sns.countplot(x = 'gender', data = df,hue = 'stroke', ax=ax[0,0])
sns.countplot(x = 'age', data = df,hue = 'hypertension', ax=ax[0,1])
sns.countplot(x = 'age', data = df,hue = 'heart_disease', ax=ax[0,2])
sns.countplot(x = 'age', data = df,hue = 'stroke', ax=ax[0,3])
sns.countplot(x = 'hypertension', data = df,hue = 'stroke', ax=ax[1,0])
sns.countplot(x = 'heart_disease', data = df,hue = 'stroke', ax=ax[1,1])
sns.countplot(x = 'ever_married', data = df,hue = 'stroke', ax=ax[1,2])
sns.countplot(x = 'age', data = df,hue = 'ever_married', ax=ax[1,3])
sns.countplot(x = 'work_type', data = df,hue = 'stroke', ax=ax[2,0])
sns.countplot(x = 'Residence_type', data = df,hue = 'stroke', ax=ax[2,1])
sns.countplot(x = 'smoking_status', data = df,hue = 'stroke', ax=ax[2,2])
sns.lineplot(x = 'bmi', y = 'avg_glucose_level', data = df,hue = 'stroke', ax=ax[2,3])
sns.countplot(x = 'age', data = df,hue = 'smoking_status', ax=ax[3,0])
sns.countplot( x = 'work_type', data = df,hue = 'Residence_type', ax=ax[3,1])
sns.countplot(x = 'work_type', data = df,hue = 'smoking_status', ax=ax[3,2])
sns.countplot(x = 'Residence_type', data = df,hue = 'smoking_status', ax=ax[3,3])
```

```
<Axes: xlabel='Residence_type', ylabel='count'>
```



Train Test Split

```
X_train, X_test, y_train, y_test = train_test_split(df.drop('stroke', axis=1), df['stroke'], test_size=0.2, random_state=42)
```

Model Training

Logistic Regression

```
lr = LogisticRegression()
lr
```

```
LogisticRegression()
```

```
#training the model
lr.fit(X_train, y_train)
lr.score(X_test, y_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to converge (status=
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

```
Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
0.9393346379647749
```

```
#testing the model
lr_pred = lr.predict(X_test)
accuracy_score(y_test, lr_pred)
```

```
0.9393346379647749
```

Support Vector Machine (SVM)

```
from sklearn.svm import SVC
svm = SVC()
svm
```

```
SVC()
```

```
#training the model
svm.fit(X_train, y_train)
svm.score(X_test, y_test)
```

```
0.9393346379647749
```

```
#testing the model
sv_pred = svm.predict(X_test)
accuracy_score(y_test, sv_pred)
```

```
0.9393346379647749
```

Decision Tree Classifier

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt
```

```
DecisionTreeClassifier()
```

```
#training the model
dt.fit(X_train, y_train)
dt.score(X_test, y_test)
```

```
0.9060665362035225
```

```
#testing the model
dt_pred = dt.predict(X_test)
accuracy_score(y_test, dt_pred)
```

```
0.9060665362035225
```

K-Nearest Neighbors (KNN)

```
knn = KNeighborsClassifier()
knn
```

```
KNeighborsClassifier
KNeighborsClassifier()
```

```
#training the model
knn.fit(X_train, y_train)
knn.score(X_test, y_test)
```

```
0.9373776908023483
```

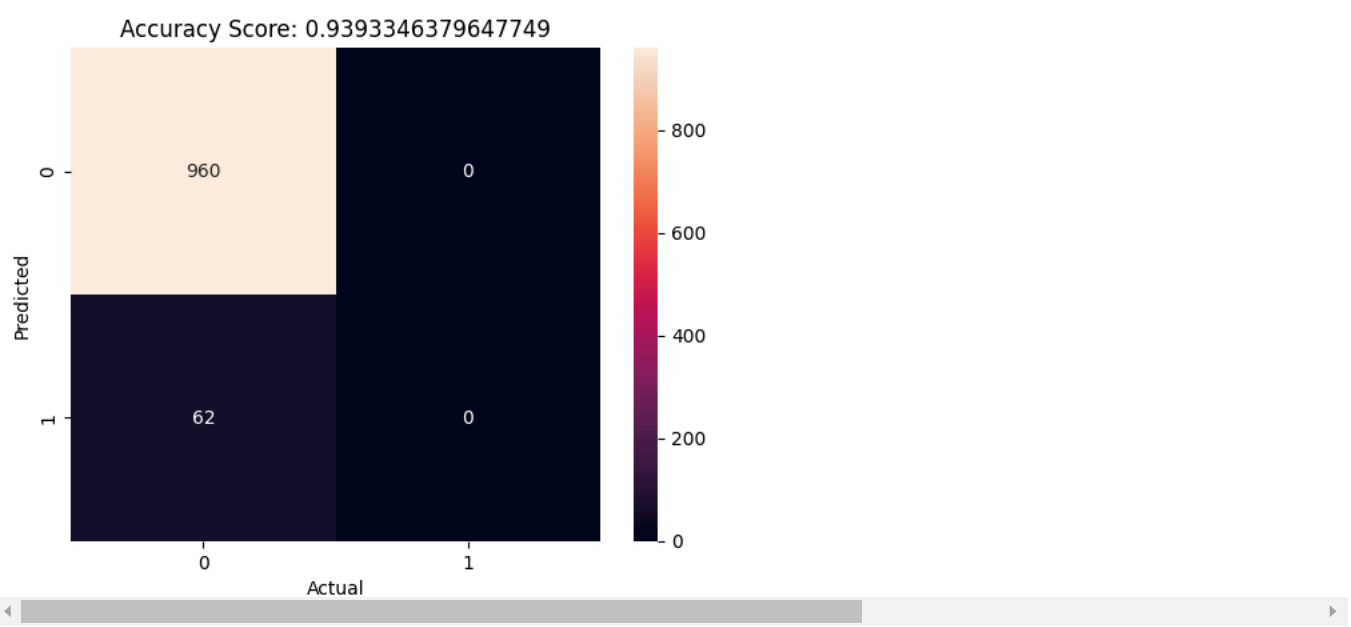
```
#testing the model
knn_pred = knn.predict(X_test)
accuracy_score(y_test, knn_pred)
```

```
0.9373776908023483
```

Model Evaluation

Logistic Regression

```
sns.heatmap(metrics.confusion_matrix(y_test, lr_pred), annot=True, fmt='d')
plt.title('Accuracy Score: {}'.format(accuracy_score(y_test, lr_pred)))
plt.ylabel('Predicted')
plt.xlabel('Actual')
plt.show()
```

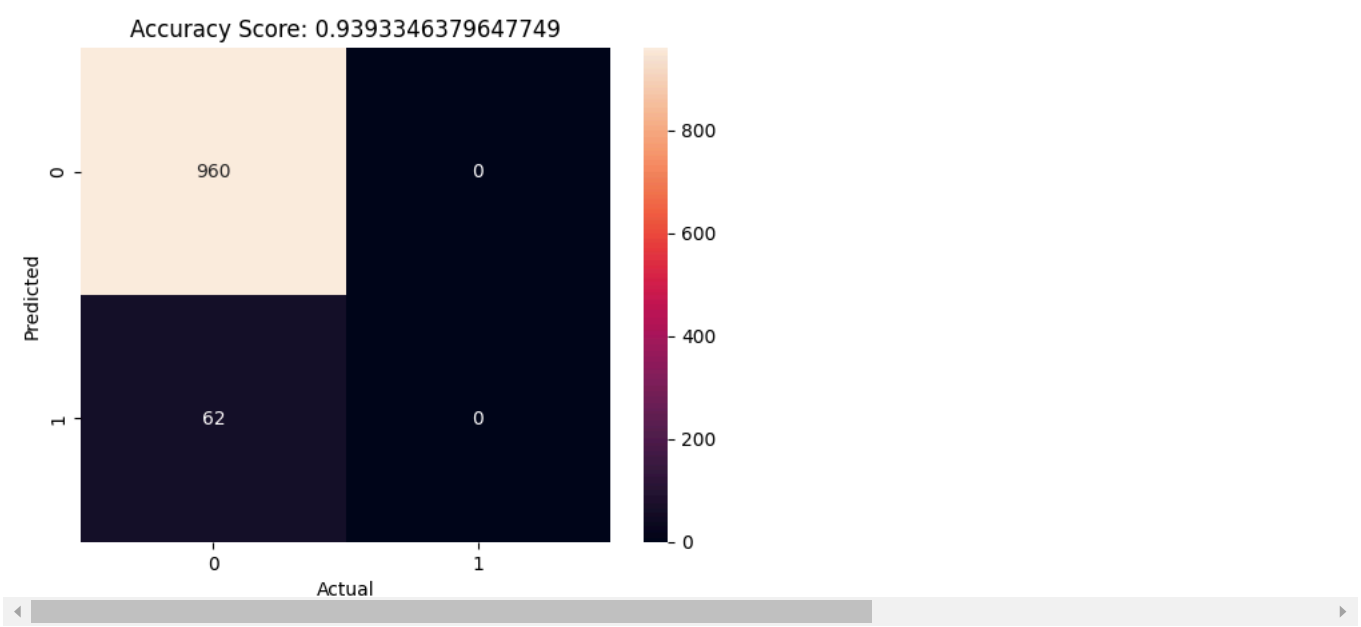



```
print('Logistic Regression Model Accuracy Score:',accuracy_score(y_test, lr_pred))
print('Logistic Regression Model F1 score: ',metrics.f1_score(y_test, lr_pred))
print('Logistic Regression Model Mean Absolute Error: ',metrics.mean_absolute_error(y_test, lr_pred))
print('Logistic Regression Model Mean Squared Error: ',metrics.mean_squared_error(y_test, lr_pred))
print('Logistic Regression Model log loss: ',log_loss(y_test, lr_pred))
```

```
Logistic Regression Model Accuracy Score: 0.9393346379647749
Logistic Regression Model F1 score:  0.0
Logistic Regression Model Mean Absolute Error:  0.060665362035225046
Logistic Regression Model Mean Squared Error:  0.060665362035225046
Logistic Regression Model log loss:  2.1866012819229588
```

Support Vector Machine (SVM)

```
sns.heatmap(metrics.confusion_matrix(y_test, sv_pred), annot=True, fmt='d')
plt.title('Accuracy Score: {}'.format(accuracy_score(y_test, sv_pred)))
plt.ylabel('Predicted')
plt.xlabel('Actual')
plt.show()
```

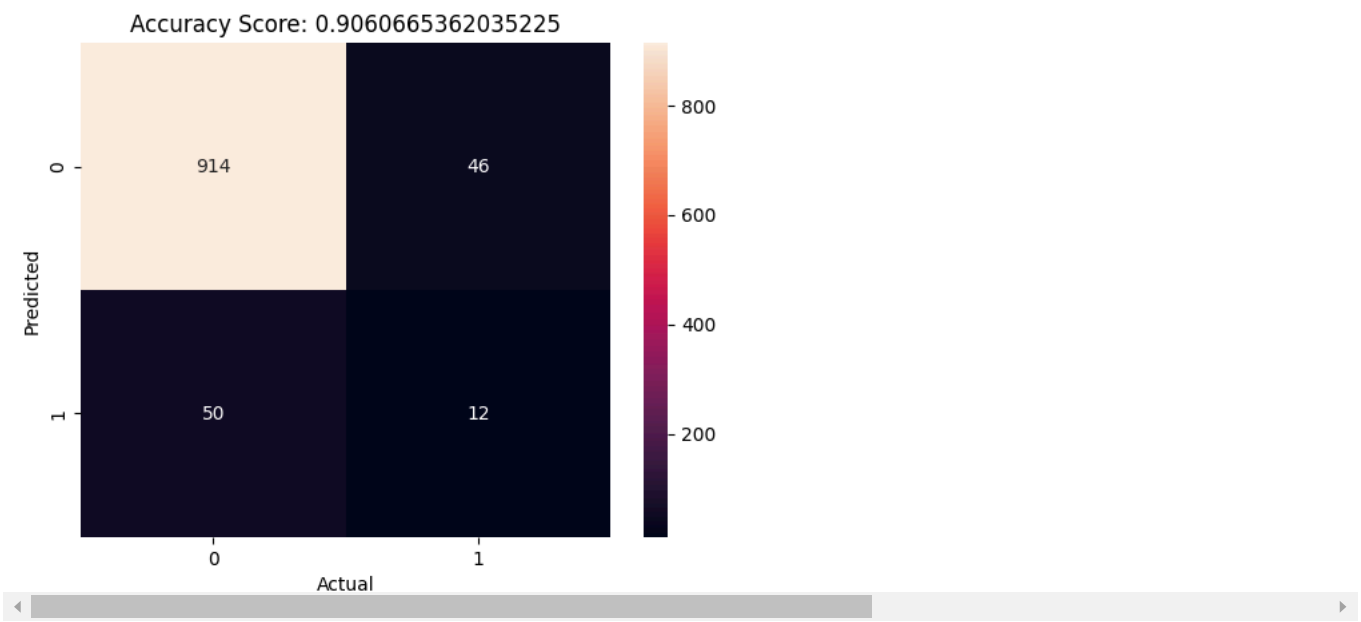



```
print('SVM Model Accuracy Score:',accuracy_score(y_test, sv_pred))
print('SVM Model F1 score: ',metrics.f1_score(y_test, sv_pred))
print('SVM Model Mean Absolute Error: ',metrics.mean_absolute_error(y_test, sv_pred))
print('SVM Model Mean Squared Error: ',metrics.mean_squared_error(y_test, sv_pred))
print('SVM Model log loss: ',log_loss(y_test, sv_pred))
```

```
SVM Model Accuracy Score: 0.9393346379647749
SVM Model F1 score:  0.0
SVM Model Mean Absolute Error:  0.060665362035225046
SVM Model Mean Squared Error:  0.060665362035225046
SVM Model log loss:  2.1866012819229588
```

Decision Tree Classifier

```
sns.heatmap(metrics.confusion_matrix(y_test, dt_pred), annot=True, fmt='d')
plt.title('Accuracy Score: {}'.format(accuracy_score(y_test, dt_pred)))
plt.ylabel('Predicted')
plt.xlabel('Actual')
plt.show()
```



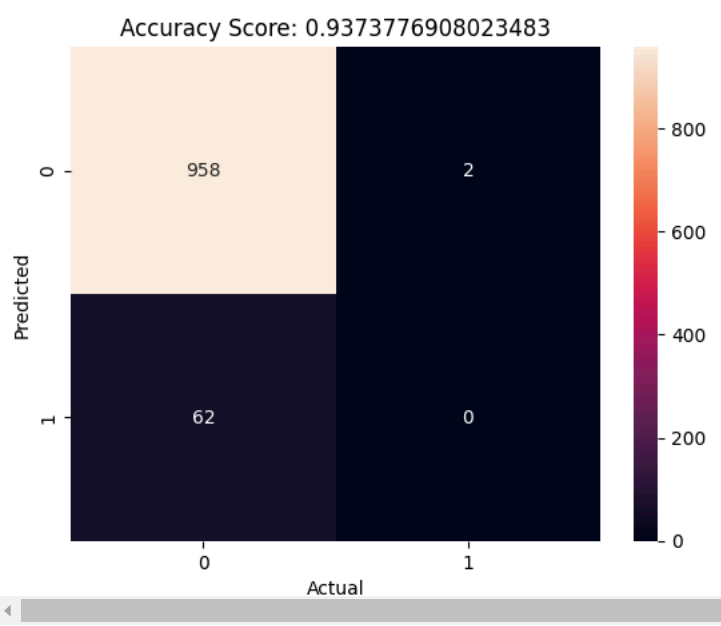

```
print('Decision Tree Model Accuracy Score:',accuracy_score(y_test, dt_pred))
print('Decision Tree Model F1 score: ',metrics.f1_score(y_test, dt_pred))
print('Decision Tree Model Mean Absolute Error: ',metrics.mean_absolute_error(y_test, dt_pred))
print('Decision Tree Model Mean Squared Error: ',metrics.mean_squared_error(y_test, dt_pred))
print('Decision Tree Model log loss: ',log_loss(y_test, dt_pred))
```

```
Decision Tree Model Accuracy Score: 0.9060665362035225
Decision Tree Model F1 score:  0.2
Decision Tree Model Mean Absolute Error:  0.09393346379647749
```

```
Decision Tree Model Mean Squared Error:  0.09393346379647749
Decision Tree Model log loss:  3.385705210719419
```

K-Nearest Neighbors (KNN)

```
sns.heatmap(metrics.confusion_matrix(y_test, knn_pred), annot=True, fmt='d')
plt.title('Accuracy Score: {}'.format(accuracy_score(y_test, knn_pred)))
plt.ylabel('Predicted')
plt.xlabel('Actual')
plt.show()
```



Model Comparison

```
models = ['Logistic Regression', 'SVM', 'Decision Tree', 'KNN']
accuracy = [accuracy_score(y_test, lr_pred), accuracy_score(y_test, sv_pred), accuracy_score(y_test, dt_pred), accuracy_score(y_test, kı
plt.figure(figsize=(10,5))
plt.bar(models, accuracy, color = 'Maroon', width = 0.4)
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.title('Model Accuracy')
plt.show()
```