1.Main objective of the analysis that specifies whether your model will be focused on prediction or interpretation and the benefits that your analysis provides to the business or stakeholders of this data

This dataset serves as a foundation for predicting the likelihood of a patient experiencing a stroke, utilizing input parameters such as gender, age, presence of various diseases, and smoking status. Each row in the dataset contains pertinent information about an individual, contributing to the analysis of stroke risk.

The chosen dataset is designed for predicting stroke occurrence based on several input parameters. It includes information on individuals, such as gender, age, presence of various diseases, and smoking status. The primary objective of this analysis is to develop a predictive model that can accurately determine the likelihood of a patient experiencing a stroke. By leveraging the dataset's attributes, we aim to understand the relationships between different factors and stroke risk, ultimately contributing to improved prevention and healthcare strategies.

Data cleaning involved addressing missing values through imputation or removal, handling outliers, and ensuring consistency in the format of categorical variables. Additionally, any duplicate records were identified and removed to maintain data integrity.

```
import numpy as np
import pandas as pd
import seaborn as sns
```

```
df = pd.read_csv('D:/study_extra/coursera/healthcare-dataset-stroke-data.csv', header=0) #data input
```

```
df.head() #data inputs
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5110 non-null   int64
 1   gender             5110 non-null   object
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64
 4   heart_disease      5110 non-null   int64
 5   ever_married       5110 non-null   object
 6   work_type          5110 non-null   object
 7   Residence_type     5110 non-null   object
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object
 11  stroke             5110 non-null   int64
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

```
df.shape
```

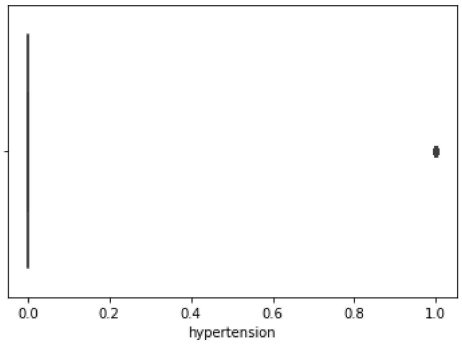
```
(5110, 12)
```

```
df.describe()
```

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
.....							
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000

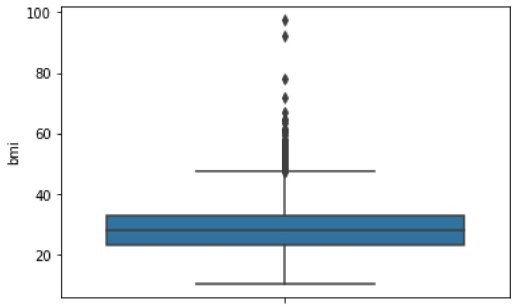
```
sns.boxplot(x="hypertension",  data=df) #finding outliers
```

```
<AxesSubplot:xlabel='hypertension'>
```



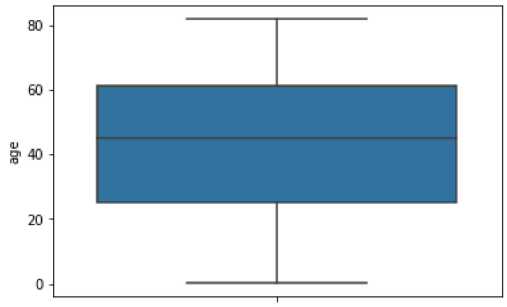

```
sns.boxplot(y="bmi",  data=df)
```

```
<AxesSubplot:ylabel='bmi'>
```




```
sns.boxplot(y="age",  data=df)
```

```
<AxesSubplot:ylabel='age'>
```

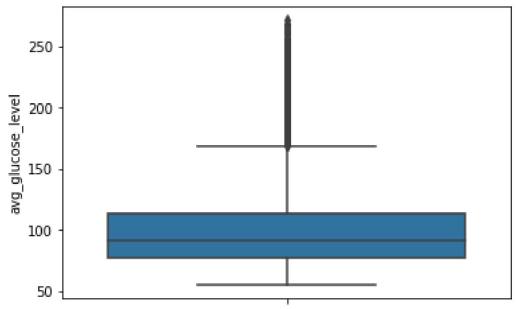



```
sns.boxplot(y="heart_disease",  data=df)
```

```
<AxesSubplot:ylabel='heart_disease'>
```

```
sns.boxplot(y="avg_glucose_level",  data=df)
```

```
<AxesSubplot:ylabel='avg_glucose_level'>
```




```
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	

```
df=pd.get_dummies(df,columns=['smoking_status']) #assign numbers to objective
```

```
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residenc
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self-employed	

```
df=pd.get_dummies(df,columns=['Residence_type'])
```

```
df.head()
```

	id	gender	age	hypertension	heart_disease	ever_married	work_type	avg_gluc
0	9046	Male	67.0	0	1	Yes	Private	
1	51676	Female	61.0	0	0	Yes	Self-employed	
2	31112	Male	80.0	0	1	Yes	Private	
3	60182	Female	49.0	0	0	Yes	Private	
4	1665	Female	79.0	1	0	Yes	Self-employed	

```
df['bmi'].fillna(df['bmi'].mean(), inplace=True) #missing value replcement
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 16 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   id                             5110 non-null   int64
 1   gender                         5110 non-null   object
```

```
 2   age                              5110 non-null   float64
 3   hypertension                     5110 non-null   int64
 4   heart_disease                    5110 non-null   int64
 5   ever_married                     5110 non-null   object
 6   work_type                        5110 non-null   object
 7   avg_glucose_level                5110 non-null   float64
 8   bmi                              5110 non-null   float64
 9   stroke                           5110 non-null   int64
 10  smoking_status_Unknown           5110 non-null   uint8
 11  smoking_status_formerly smoked   5110 non-null   uint8
 12  smoking_status_never smoked      5110 non-null   uint8
 13  smoking_status_smokes            5110 non-null   uint8
 14  Residence_type_Rural             5110 non-null   uint8
 15  Residence_type_Urban             5110 non-null   uint8
dtypes: float64(3), int64(4), object(3), uint8(6)
memory usage: 429.3+ KB
```

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

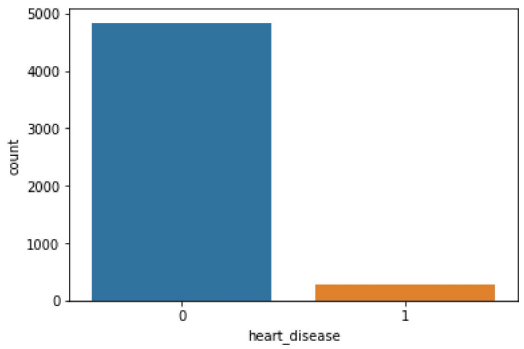
```
df.head()
```

	gender	age	hypertension	heart_disease	ever_married	work_type	avg_glucose_lev
0	Male	67.0	0	1	Yes	Private	228
1	Female	61.0	0	0	Yes	Self-employed	202
2	Male	80.0	0	1	Yes	Private	105
3	Female	49.0	0	0	Yes	Private	171
4	Female	79.0	1	0	Yes	Self-employed	174

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score
```

```
sns.countplot(x="heart_disease", data=df)
```

```
<AxesSubplot:xlabel='heart_disease', ylabel='count'>
```




```
df = pd.get_dummies(df, columns=['ever_married'])
```

```
df = pd.get_dummies(df, columns=['work_type'])
```

```
df = df.replace('Male', 1)
df = df.replace('Female', 2)
df = df.replace('Other', 3)
```

```
x=df.drop("stroke",axis=1)
y=df["stroke"]
```

```
y
```

```
0       1
1       1
2       1
3       1
4       1
       ..
5105    0
5106    0
```

```
5107    0
5108    0
5109    0
Name: stroke, Length: 5110, dtype: int64
```

```
def replace_outliers_with_median(column):
    median = column.median()
    std = column.std()
    outliers = (column - median).abs() > 3 * std
    column[outliers] = median
    return column
```

```
df['bmi'] = replace_outliers_with_median(df['bmi'])
```

```
C:\Users\nanth\AppData\Local\Temp\ipykernel_22248\2210063658.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  column[outliers] = median
```

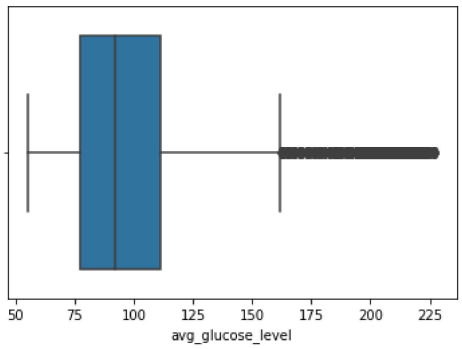
```
df['avg_glucose_level'] = replace_outliers_with_median(df['avg_glucose_level'])
```

```
C:\Users\nanth\AppData\Local\Temp\ipykernel_22248\2210063658.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
  column[outliers] = median
```

```
sns.boxplot(x="avg_glucose_level",  data=df)
```

```
<AxesSubplot:xlabel='avg_glucose_level'>
```




```
x.head()
```

	gender	age	hypertension	heart_disease	avg_glucose_level	bmi	smoking_st
0	1	67.0	0	1	228.69	36.600000	
1	2	61.0	0	0	202.21	28.893237	
2	1	80.0	0	1	105.92	32.500000	
3	2	49.0	0	0	171.23	34.400000	
4	2	79.0	1	0	174.12	24.000000	

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

```
model = LogisticRegression()
```

```
df["gender"]
```

```
0       1
1       2
2       1
3       2
4       2
       ..
5105    2
5106    2
5107    2
5108    1
```

```
5109    2
Name: gender, Length: 5110, dtype: int64
```

```
x.head()
```

	gender	age	hypertension	heart_disease	avg_glucose_level	bmi	smoking_st
0	1	67.0	0	1	228.69	36.600000	
1	2	61.0	0	0	202.21	28.893237	
2	1	80.0	0	1	105.92	32.500000	
3	2	49.0	0	0	171.23	34.400000	
4	2	79.0	1	0	174.12	24.000000	

```
model.fit(x_train, y_train) #train the model
```

```
f:\Python\lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning
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(
```

▾ LogisticRegression

LogisticRegression()

```
y_pred = model.predict(x_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
```

```
accuracy
```

```
0.9393346379647749
```

```
confusion_matrix(y_test,y_pred)
```

```
array([[960,   0],
       [ 62,   0]], dtype=int64)
```

Support Vector Machine (SVM) -classification

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(x_train)
X_test_scaled = scaler.transform(x_test)
```

```
from sklearn.svm import SVC
svm_classifier = SVC(kernel='rbf', C=1.0, gamma='scale')
```

```
svm_classifier.fit(X_train_scaled, y_train)
```

▾ SVC

SVC()

```
y_pred1 = svm_classifier.predict(X_test_scaled)
```

```
accuracy = accuracy_score(y_test, y_pred1)
```

```
accuracy # accuracy
```

```
0.9393346379647749
```

```
confusion_matrix(y_test,y_pred1)
```

```
array([[960,   0],
       [ 62,   0]], dtype=int64)
```

random forest

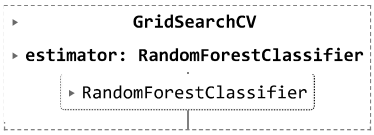
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV


params_grid = {"max_features" : [3,4,5,6,7,8,9,10],
               "min_samples_split": [2, 3, 10, 15],
               }


rf_clf = RandomForestClassifier(n_estimators=250,random_state=42)


grid_search = GridSearchCV(rf_clf, params_grid,
                           n_jobs=-1, cv=5, scoring='accuracy')


grid_search.fit(x_train, y_train)
```




```
grid_search.best_params_
```

```
{'max_features': 3, 'min_samples_split': 10}
```

```
cvrf_clf = grid_search.best_estimator_


y_pred_rand=cvrf_clf.predict(x_test)


confusion_matrix(y_test,y_pred_rand)
```

```
array([[960,   0],
       [ 62,   0]], dtype=int64)
```

```
accuracy_score(y_test,y_pred_rand)
```

```
0.9393346379647749
```

for this data three model's accuracy rate nearly equal

Next steps include analyzing feature importance, exploring correlations, and conducting model evaluation and tuning. Stratifying the data based on relevant features, considering temporal trends, and consulting domain experts are recommended for deeper insights.