```
import pandas as pd

prostate_cancer_data = pd.read_csv("Prostate_Cancer.csv")
```

Data Exploration

```
prostate_cancer_data.head()
```

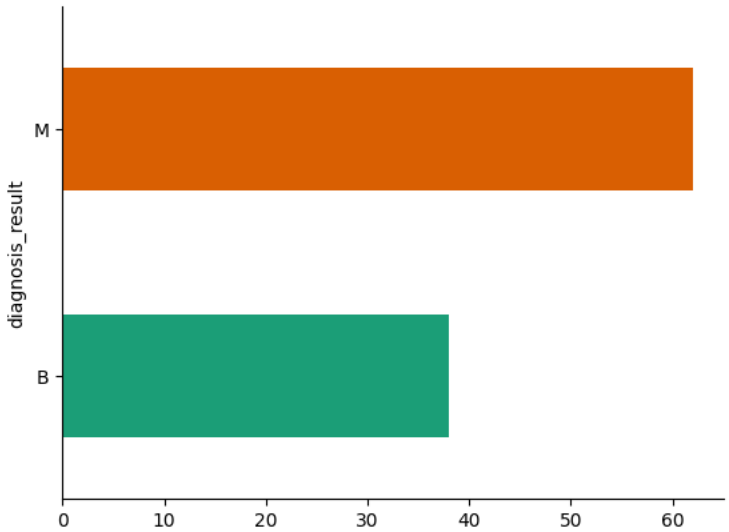
	id	diagnosis_result	radius	texture	perimeter	area	smoothness	compactness	symmetry	fractal_dimension
0	1	M	23	12	151	954	0.143	0.278	0.242	0.079
1	2	B	9	13	133	1326	0.143	0.079	0.181	0.057
2	3	M	21	27	130	1203	0.125	0.160	0.207	0.060
3	4	M	14	16	78	386	0.070	0.284	0.260	0.097
4	5	M	9	19	135	1297	0.141	0.133	0.181	0.059

+ Code + Text

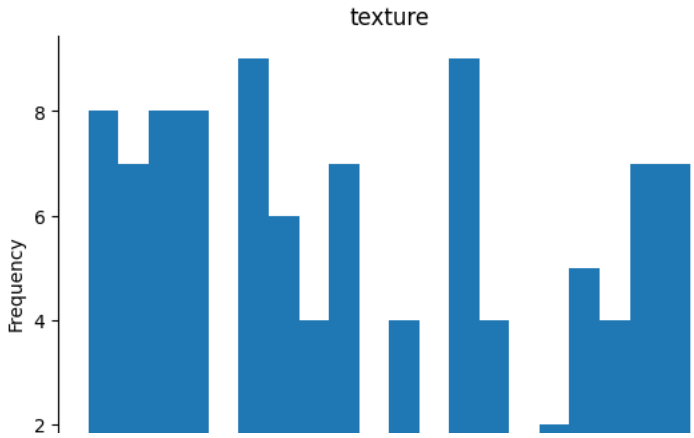
```
print(prostate_cancer_data.isnull().sum())
```

```
id                  0
diagnosis_result    0
radius              0
texture             0
perimeter           0
area                0
smoothness          0
compactness         0
symmetry            0
fractal_dimension   0
dtype: int64
```

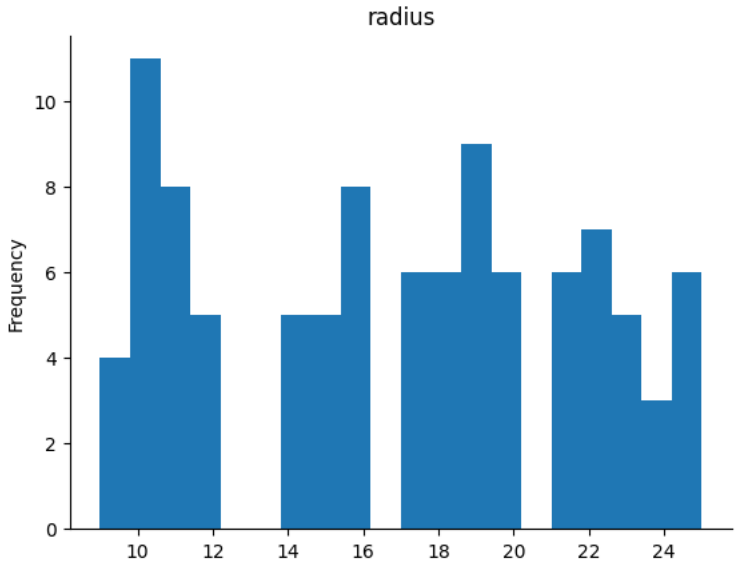
```
# Consideration: unbalanced classes
import seaborn as sns
import matplotlib.pyplot as plt
prostate_cancer_data.groupby('diagnosis_result').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```




```
from matplotlib import pyplot as plt
prostate_cancer_data['texture'].plot(kind='hist', bins=20, title='texture')
plt.gca().spines[['top', 'right',]].set_visible(False)
```




```
prostate_cancer_data['radius'].plot(kind='hist', bins=20, title='radius')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



Data Preprocessing

```
trim_prostate_cancer_data = prostate_cancer_data.drop("id", axis=1)
unlabled_data = trim_prostate_cancer_data.drop("diagnosis_result", axis = 1)

label_mapping = {'M': 1, 'B': 0}
labels = trim_prostate_cancer_data["diagnosis_result"].map(label_mapping)
```

Basic Decision Tree

Intuition: Decision Trees work well with smaller datasets and are less likely to overfit. Random forest improves on the generalization further by using an ensemble model.

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

X_train, X_test, y_train, y_test = train_test_split(unlabled_data, labels, test_size=0.2)
dt_model = DecisionTreeClassifier()
dt_model.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

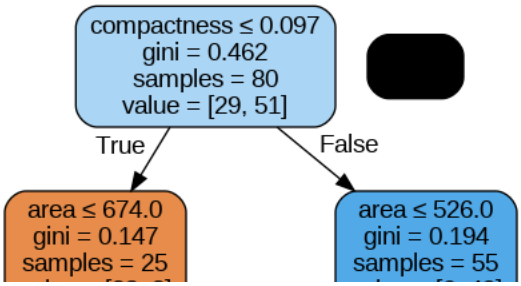
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
y_pred = dt_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.75
Confusion Matrix:
 [[8 1]
 [4 7]]
Classification Report:
              precision    recall  f1-score   support

           0       0.67      0.89      0.76         9
           1       0.88      0.64      0.74        11

    accuracy                           0.75        20
   macro avg       0.77      0.76      0.75        20
weighted avg       0.78      0.75      0.75        20
```

```
pip install graphviz pydotplus
```

```
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (0.20.1)
Requirement already satisfied: pydotplus in /usr/local/lib/python3.10/dist-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /usr/local/lib/python3.10/dist-packages (from pydotplus) (3.1.1)
```

```
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import pydotplus

dot_data = StringIO()
export_graphviz(dt_model, out_file=dot_data, filled=True, rounded=True, special_characters=True, feature_names=unlabled_data.columns)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



Tuning Hyperparameters (making it shallower)

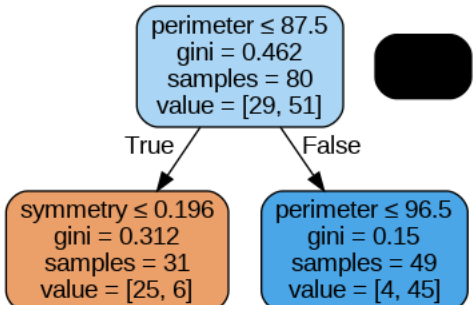
Looking at the visualization above, I suspect the model is overfitting.

```
# from sklearn.model_selection import GridSearchCV

# # Define the parameter grid
# param_grid = {
#     'criterion': ['gini', 'entropy'],
#     'max_depth': [None, 6, 7, 8, 4, 3, 5],
#     'min_samples_split': [2, 5, 10],
#     'min_samples_leaf': [1, 2, 4],
#     'max_features': ['sqrt', 'log2']
# }

# dt_model = DecisionTreeClassifier()
# grid_search = GridSearchCV(dt_model, param_grid, cv=5, scoring='accuracy')
# grid_search.fit(X_train, y_train)
# print("Best Hyperparameters:", grid_search.best_params_)
```

```
best_dt_model = DecisionTreeClassifier(criterion = 'gini', max_depth = 6, max_features = 'sqrt', min_samples_leaf = 4, min_samples_split = 1
best_dt_model.fit(X_train, y_train)
y_pred = best_dt_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.65
Confusion Matrix:
 [[8 1]
 [6 5]]
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.89      0.70         9
           1       0.83      0.45      0.59        11

    accuracy                           0.65        20
   macro avg       0.70      0.67      0.64        20
weighted avg       0.72      0.65      0.64        20
```

```
dot_data = StringIO()
export_graphviz(best_dt_model, out_file=dot_data, filled=True, rounded=True, special_characters=True, feature_names=unlabled_data.columns)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```



Random Forest

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8
Confusion Matrix:
 [[8 1]
 [3 8]]
Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.89      0.80         9
           1       0.89      0.73      0.80        11

    accuracy                           0.80        20
   macro avg       0.81      0.81      0.80        20
weighted avg       0.82      0.80      0.80        20
```