MIT102 ADBMS PROJECT PREDICTING MODELS

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1. Checking and cleaning of the dataset

In [58]:
```
import pandas as pd
import numpy as np
```

Loading the Raisin Dataset

In [59]:
```
df = pd.read_csv('Raisin_Dataset.csv')
```

In [60]:
```
df.head()
```

Out[60]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
0	87524	442.246011	253.291155	0.819738	90546	0.758651	1184.040
1	75166	406.690687	243.032436	0.801805	78789	0.684130	1121.786
2	90856	442.267048	266.328318	0.798354	93717	0.637613	1208.575
3	45928	286.540559	208.760042	0.684989	47336	0.699599	844.162
4	79408	352.190770	290.827533	0.564011	81463	0.792772	1073.251

Checking the number of instances per class if it is balanced. Balancing a dataset makes training a model easier because it helps prevent the model from becoming biassed towards one class. In other words, the model will no longer favour the majority class just because it contains more data.

In [61]:
```
df.groupby('Class').size()
```

Out[61]:
```
Class
Besni      450
Kecimen    450
dtype: int64
```

Transforming the class from string to numerical values

In [62]:
```
df['Class'] = df['Class'].map({'Kecimen': 0, 'Besni': 1})
```

In [63]:
```
df
```

Out[63]:

	Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter
0	87524	442.246011	253.291155	0.819738	90546	0.758651	1184.040
1	75166	406.690687	243.032436	0.801805	78789	0.684130	1121.786
2	90856	442.267048	266.328318	0.798354	93717	0.637613	1208.575
3	45928	286.540559	208.760042	0.684989	47336	0.699599	844.162
4	79408	352.190770	290.827533	0.564011	81463	0.792772	1073.251
...	...	...	...	...	...	...	...
895	83248	430.077308	247.838695	0.817263	85839	0.668793	1129.072
896	87350	440.735698	259.293149	0.808629	90899	0.636476	1214.252
897	99657	431.706981	298.837323	0.721684	106264	0.741099	1292.828
898	93523	476.344094	254.176054	0.845739	97653	0.658798	1258.548
899	85609	512.081774	215.271976	0.907345	89197	0.632020	1272.862

900 rows × 8 columns

In [64]:
```
df.shape
```

Out[64]:
```
(900, 8)
```

In [65]:
```
df.columns
```

Out[65]:
```
Index(['Area', 'MajorAxisLength', 'MinorAxisLength', 'Eccentricity',
       'ConvexArea', 'Extent', 'Perimeter', 'Class'],
      dtype='object')
```

In [66]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 900 entries, 0 to 899
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             900 non-null    int64  
 1   MajorAxisLength  900 non-null    float64
 2   MinorAxisLength  900 non-null    float64
 3   Eccentricity     900 non-null    float64
 4   ConvexArea       900 non-null    int64  
 5   Extent           900 non-null    float64
 6   Perimeter        900 non-null    float64
 7   Class            900 non-null    int64  
dtypes: float64(5), int64(3)
memory usage: 56.4 KB
```

In [67]:
```
df.isnull().sum()
```

Out[67]:
```
Area                0
MajorAxisLength     0
MinorAxisLength     0
Eccentricity        0
ConvexArea          0
Extent              0
Perimeter           0
Class               0
dtype: int64
```

Separating feature and target variables and create new DataFrames each

Dividing the dataset into feature and target variables and assign into each of their own DataFrame

In [68]:
```
x = df[['Area','MajorAxisLength','MinorAxisLength','Eccentricity','ConvexArea','
y = df['Class']
```

Delaring a list that will hold the classifier scores. To be used later on in the visualization or graphical representation secion

In [69]:
```
clf_scores = []
```

Self defined functions

A function that will convert the raw mean of a classifier score into percentages

In [70]:
```
def percentage(ave):
    per = ave * 100
    return round(per, 2)
```

A function that will perform 10-fold cross validation

In [71]:
```
from sklearn.model_selection import cross_val_score
def get_scores(classifier, scoring_method):
    ave = cross_val_score(classifier, x, y, cv=10, scoring=scoring_method).mean(
    return percentage(ave)
```

A function that will perform cross_validate to store the accuracy scores of each individual n of each fold. To be used in the visualization section

In [72]:
```
from sklearn.model_selection import cross_validate
from sklearn.preprocessing import StandardScaler

def get_scoreslist_accuracy(classifier, is_regression=False):
    scoring = ['accuracy']

    if is_regression:
        scaler = StandardScaler()

        pipeline = Pipeline([('transformer', scaler), ('estimator', classifier)]
        scores = cross_validate(pipeline, x, y, cv=10, scoring=scoring, return_t
    else:
```

```
        scores = cross_validate(classifier, x, y, cv=10, scoring=scoring, returr

    return {'Training Accuracy Scores': scores['train_accuracy'], 'Validation Ac
```

A function that will plot the results of the get_scoreslist_accuracy function

In [73]:
```
def plot_accuracy_result(x_label,y_label, train_data, validation_data):
    plt.figure(figsize=(10,8))
    labels = [
        "1st Fold",
        "2nd Fold",
        "3rd Fold",
        "4th Fold",
        "5th Fold",
        "6th Fold",
        "7th Fold",
        "8th Fold",
        "9th Fold",
        "10th Fold"
    ]

    X_axis = np.arange(len(labels))
    ax = plt.gca()
    plt.ylim(0.40000, 1)
    plt.bar(X_axis-0.2, train_data, 0.4, color='blue', label='Training')
    plt.bar(X_axis+0.2, validation_data, 0.4, color='red', label='Validation')
    # plt.set_title("Accuracy scores in 10 folds")
    plt.xticks(X_axis, labels)
    plt.xlabel(x_label, fontsize=14)
    plt.ylabel(y_label, fontsize=14)
    plt.legend()
    plt.grid(True)

    for i in ax.containers:
        ax.bar_label(i,fontsize=5)

    plt.show()
```

2. Perform five (5) Classifiers

Decision Tree

Perform DT Classifier and apply 10-fold cross validation

In [74]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn.metrics import recall_score, make_scorer
```

In [75]:
```
dtree = DecisionTreeClassifier()
```

In [76]:
```
accuracy = get_scores(dtree, 'accuracy')
recall = get_scores(dtree, 'recall')
precision = get_scores(dtree, 'precision')
f1 = get_scores(dtree, 'f1')
```

```
specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(dtree, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(dtree, sensitivity)
```

In [77]:
```
clf_scores.append(['DT', 'Accuracy', accuracy])
clf_scores.append(['DT', 'Recall', recall])
clf_scores.append(['DT', 'Precision', precision])
clf_scores.append(['DT', 'F1-Score', f1])
clf_scores.append(['DT', 'Specificity', specificity_score])
clf_scores.append(['DT', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44]]
```

Random Forest

Perform RF Classifier and apply 10-fold cross validation

In [78]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(n_estimators=10, max_depth=5, random_state=1)
```

In [79]:
```
accuracy = get_scores(rf, 'accuracy')
recall = get_scores(rf, 'recall')
precision = get_scores(rf, 'precision')
f1 = get_scores(rf, 'f1')

specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(rf, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(rf, sensitivity)
```

In [80]:
```
clf_scores.append(['RF', 'Accuracy', accuracy])
clf_scores.append(['RF', 'Recall', recall])
clf_scores.append(['RF', 'Precision', precision])
clf_scores.append(['RF', 'F1-Score', f1])
clf_scores.append(['RF', 'Specificity', specificity_score])
clf_scores.append(['RF', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44], ['RF', 'Accuracy', 86.67], ['RF', 'Recall', 84.44], ['RF', 'Precisi
on', 88.53], ['RF', 'F1-Score', 86.25], ['RF', 'Specificity', 88.89], ['RF', 'S
ensitivity', 84.44]]
```

K-nearest Neighbor (kNN)

Perform KNN Classifier and apply 10-fold cross validation

In [81]:
```
from sklearn.neighbors import KNeighborsClassifier
```

```python
knn = KNeighborsClassifier(n_neighbors=10)
```

In [82]:
```python
accuracy = get_scores(knn, 'accuracy')
recall = get_scores(knn, 'recall')
precision = get_scores(knn, 'precision')
f1 = get_scores(knn, 'f1')

specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(knn, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(knn, sensitivity)
```

In [83]:
```python
clf_scores.append(['KNN', 'Accuracy', accuracy])
clf_scores.append(['KNN', 'Recall', recall])
clf_scores.append(['KNN', 'Precision', precision])
clf_scores.append(['KNN', 'F1-Score', f1])
clf_scores.append(['KNN', 'Specificity', specificity_score])
clf_scores.append(['KNN', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44], ['RF', 'Accuracy', 86.67], ['RF', 'Recall', 84.44], ['RF', 'Precisi
on', 88.53], ['RF', 'F1-Score', 86.25], ['RF', 'Specificity', 88.89], ['RF', 'S
ensitivity', 84.44], ['KNN', 'Accuracy', 83.44], ['KNN', 'Recall', 76.0], ['KN
N', 'Precision', 89.47], ['KNN', 'F1-Score', 82.07], ['KNN', 'Specificity', 90.
89], ['KNN', 'Sensitivity', 76.0]]
```

Regularized Logistic Regression

Perform Regularized LR Classifier and apply 10-fold cross validation with the help of sklearn StandardScaler function to standardize the data values into a standard format

In [84]:
```python
from sklearn.linear_model import LogisticRegression
# from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

lr2 = LogisticRegression(C=0.01)
```

In [85]:
```python
scaler = StandardScaler()

pipeline = Pipeline([('transformer', scaler), ('estimator', lr2)])
```

In [86]:
```python
accuracy = get_scores(pipeline, 'accuracy')
recall = get_scores(pipeline, 'recall')
precision = get_scores(pipeline, 'precision')
f1 = get_scores(pipeline, 'f1')

specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(pipeline, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(pipeline, sensitivity)
```

In [87]:
```
clf_scores.append(['LR', 'Accuracy', accuracy])
clf_scores.append(['LR', 'Recall', recall])
clf_scores.append(['LR', 'Precision', precision])
clf_scores.append(['LR', 'F1-Score', f1])
clf_scores.append(['LR', 'Specificity', specificity_score])
clf_scores.append(['LR', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44], ['RF', 'Accuracy', 86.67], ['RF', 'Recall', 84.44], ['RF', 'Precisi
on', 88.53], ['RF', 'F1-Score', 86.25], ['RF', 'Specificity', 88.89], ['RF', 'S
ensitivity', 84.44], ['KNN', 'Accuracy', 83.44], ['KNN', 'Recall', 76.0], ['KN
N', 'Precision', 89.47], ['KNN', 'F1-Score', 82.07], ['KNN', 'Specificity', 90.
89], ['KNN', 'Sensitivity', 76.0], ['LR', 'Accuracy', 86.56], ['LR', 'Recall',
83.33], ['LR', 'Precision', 89.14], ['LR', 'F1-Score', 86.02], ['LR', 'Specific
ity', 89.78], ['LR', 'Sensitivity', 83.33]]
```

Support Vector Machine

Perform SVM Classifier and apply 10-fold cross validation

In [88]:
```
from sklearn import svm

sv_clf = svm.SVC(kernel='linear', C=1, random_state=1)
```

In [89]:
```
accuracy = get_scores(sv_clf, 'accuracy')
recall = get_scores(sv_clf, 'recall')
precision = get_scores(sv_clf, 'precision')
f1 = get_scores(sv_clf, 'f1')

specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(sv_clf, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(sv_clf, sensitivity)
```

In [90]:
```
clf_scores.append(['SVM', 'Accuracy', accuracy])
clf_scores.append(['SVM', 'Recall', recall])
clf_scores.append(['SVM', 'Precision', precision])
clf_scores.append(['SVM', 'F1-Score', f1])
clf_scores.append(['SVM', 'Specificity', specificity_score])
clf_scores.append(['SVM', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44], ['RF', 'Accuracy', 86.67], ['RF', 'Recall', 84.44], ['RF', 'Precisi
on', 88.53], ['RF', 'F1-Score', 86.25], ['RF', 'Specificity', 88.89], ['RF', 'S
ensitivity', 84.44], ['KNN', 'Accuracy', 83.44], ['KNN', 'Recall', 76.0], ['KN
N', 'Precision', 89.47], ['KNN', 'F1-Score', 82.07], ['KNN', 'Specificity', 90.
89], ['KNN', 'Sensitivity', 76.0], ['LR', 'Accuracy', 86.56], ['LR', 'Recall',
83.33], ['LR', 'Precision', 89.14], ['LR', 'F1-Score', 86.02], ['LR', 'Specific
ity', 89.78], ['LR', 'Sensitivity', 83.33], ['SVM', 'Accuracy', 85.67], ['SVM',
'Recall', 86.22], ['SVM', 'Precision', 85.42], ['SVM', 'F1-Score', 85.63], ['SV
M', 'Specificity', 85.11], ['SVM', 'Sensitivity', 86.22]]
```

Naive Bayes

In [91]:
```python
from sklearn.naive_bayes import GaussianNB

nb = GaussianNB()
pipeline_nb = Pipeline([('transformer', scaler), ('estimator', nb)])
```

In [92]:
```python
accuracy = get_scores(pipeline_nb, 'accuracy')
recall = get_scores(pipeline_nb, 'recall')
precision = get_scores(pipeline_nb, 'precision')
f1 = get_scores(pipeline_nb, 'f1')

specificity = make_scorer(recall_score, pos_label=0)
specificity_score = get_scores(pipeline_nb, specificity)

sensitivity = make_scorer(recall_score, pos_label=1)
sensitivity_score = get_scores(pipeline_nb, sensitivity)
```

In [93]:
```python
clf_scores.append(['NB', 'Accuracy', accuracy])
clf_scores.append(['NB', 'Recall', recall])
clf_scores.append(['NB', 'Precision', precision])
clf_scores.append(['NB', 'F1-Score', f1])
clf_scores.append(['NB', 'Specificity', specificity_score])
clf_scores.append(['NB', 'Sensitivity', sensitivity_score])
print(clf_scores)
```

```
[['DT', 'Accuracy', 80.89], ['DT', 'Recall', 80.89], ['DT', 'Precision', 81.1
8], ['DT', 'F1-Score', 80.81], ['DT', 'Specificity', 80.89], ['DT', 'Sensitivit
y', 80.44], ['RF', 'Accuracy', 86.67], ['RF', 'Recall', 84.44], ['RF', 'Precisi
on', 88.53], ['RF', 'F1-Score', 86.25], ['RF', 'Specificity', 88.89], ['RF', 'S
ensitivity', 84.44], ['KNN', 'Accuracy', 83.44], ['KNN', 'Recall', 76.0], ['KN
N', 'Precision', 89.47], ['KNN', 'F1-Score', 82.07], ['KNN', 'Specificity', 90.
89], ['KNN', 'Sensitivity', 76.0], ['LR', 'Accuracy', 86.56], ['LR', 'Recall',
83.33], ['LR', 'Precision', 89.14], ['LR', 'F1-Score', 86.02], ['LR', 'Specific
ity', 89.78], ['LR', 'Sensitivity', 83.33], ['SVM', 'Accuracy', 85.67], ['SVM',
'Recall', 86.22], ['SVM', 'Precision', 85.42], ['SVM', 'F1-Score', 85.63], ['SV
M', 'Specificity', 85.11], ['SVM', 'Sensitivity', 86.22], ['NB', 'Accuracy', 8
3.89], ['NB', 'Recall', 74.67], ['NB', 'Precision', 91.62], ['NB', 'F1-Score',
82.11], ['NB', 'Specificity', 93.11], ['NB', 'Sensitivity', 74.67]]
```

3. Visualization

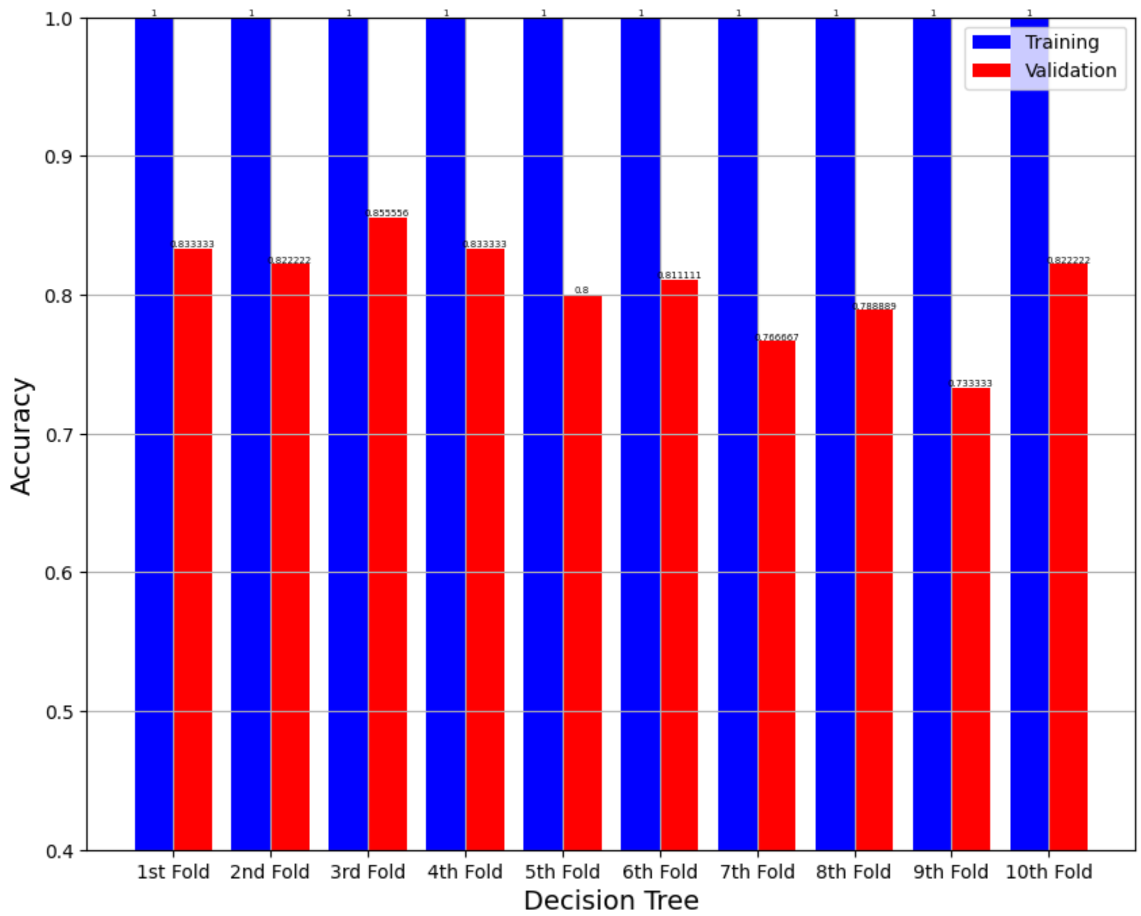
In [94]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
```

10-fold cross validation accuracy scores in each classifiers

DT Accuracy Scores in 10 folds

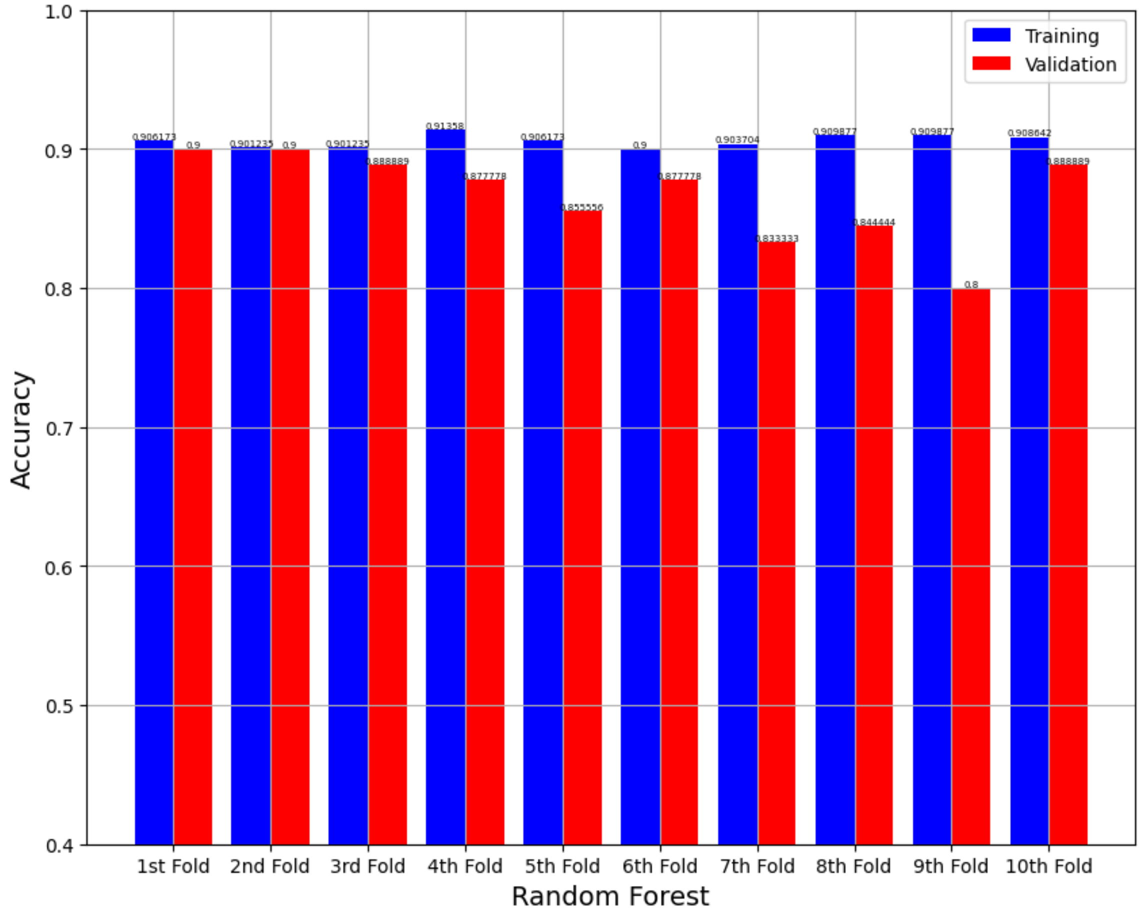
In [95]:
```python
dt_scores = get_scoreslist_accuracy(dtree)

plot_accuracy_result(
    'Decision Tree',
    'Accuracy',
    dt_scores['Training Accuracy Scores'],
```

```
    dt_scores['Validation Accuracy Scores'],
)
```



RF Accuracy Scores in 10 folds

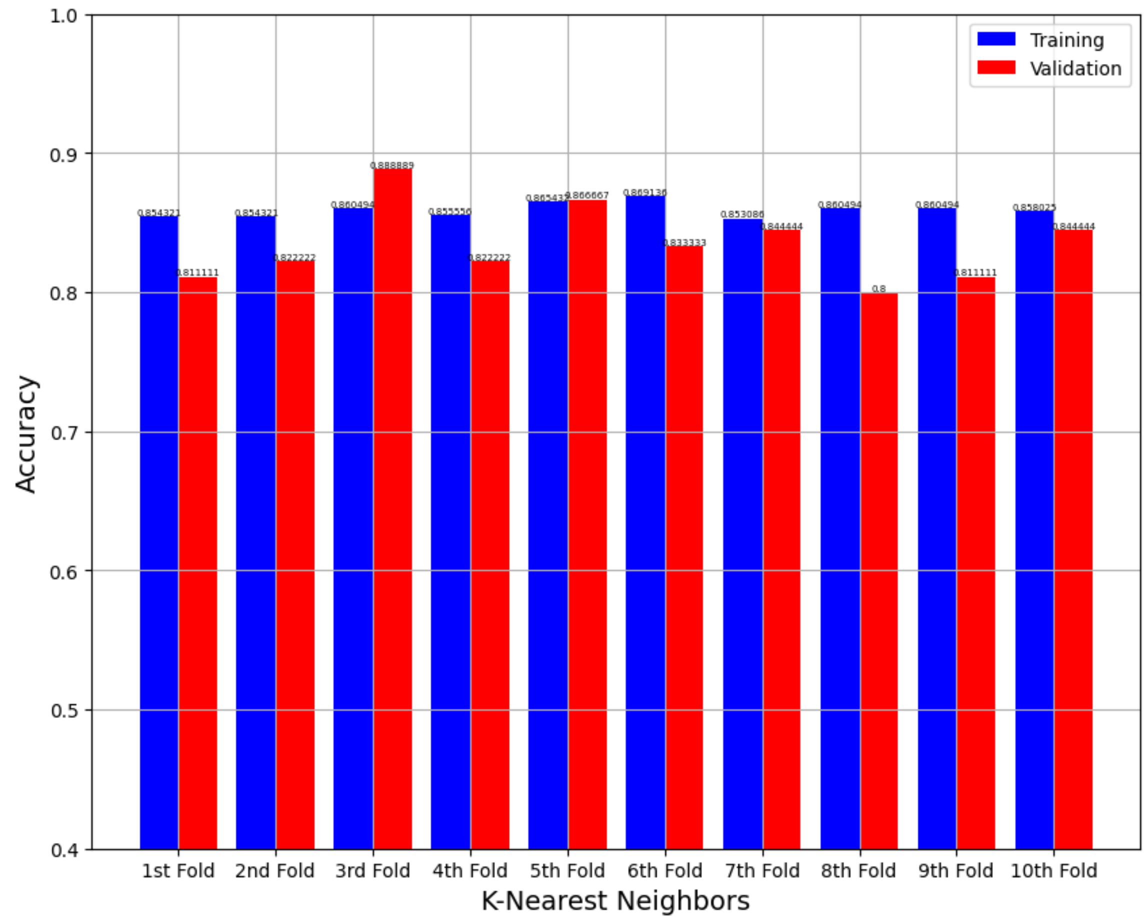
In [96]:
```
rf_scores = get_scoreslist_accuracy(rf)

plot_accuracy_result(
    'Random Forest',
    'Accuracy',
    rf_scores['Training Accuracy Scores'],
    rf_scores['Validation Accuracy Scores'],
)
```



KNN Accuracy Scores in 10 folds

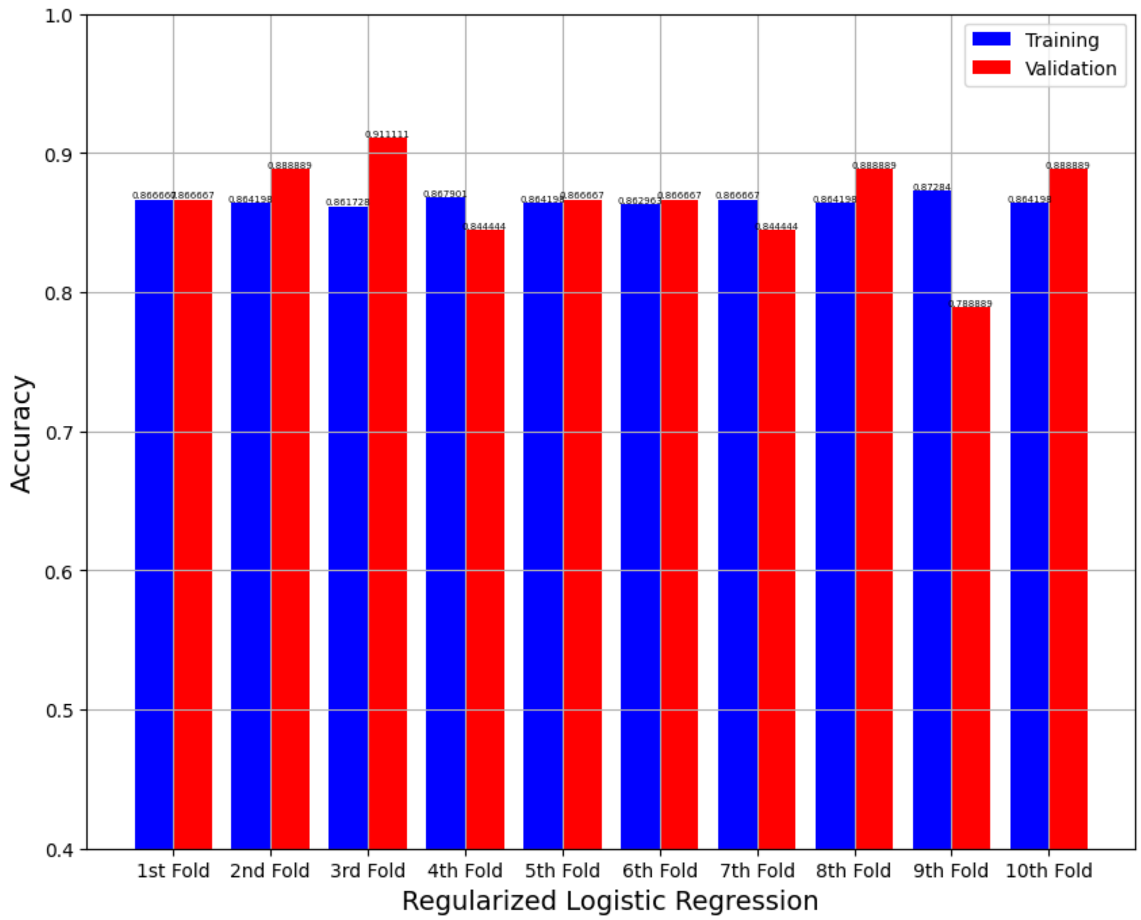
In [97]:

```
knn_scores = get_scoreslist_accuracy(knn)

plot_accuracy_result(
    'K-Nearest Neighbors',
    'Accuracy',
    knn_scores['Training Accuracy Scores'],
    knn_scores['Validation Accuracy Scores'],
)
```



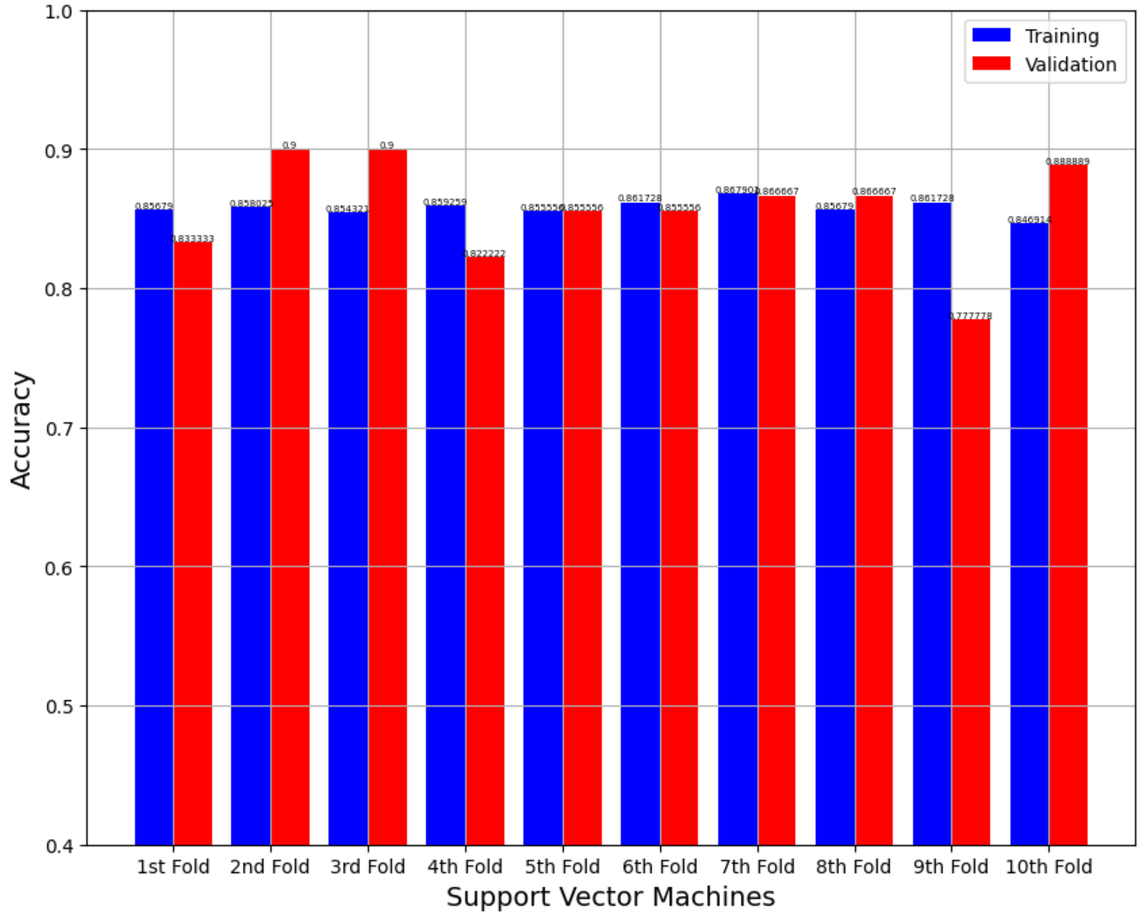
Logistic Regression (Regularized) Scores in 10 folds

In [98]:
```
lr2_scores = get_scoreslist_accuracy(lr2, True)

plot_accuracy_result(
    'Regularized Logistic Regression',
    'Accuracy',
    lr2_scores['Training Accuracy Scores'],
    lr2_scores['Validation Accuracy Scores'],
)
```



SVM Accuracy Scores in 10 folds

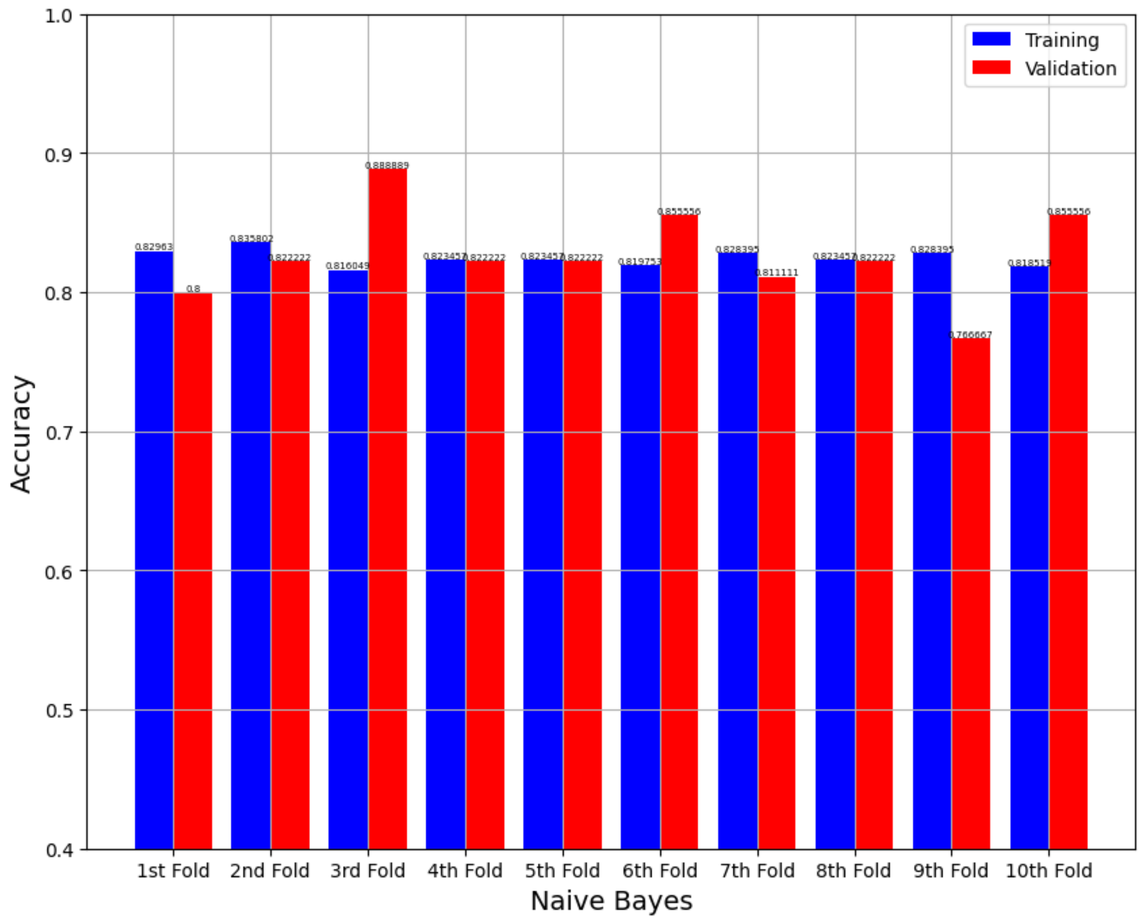
In [99]:
```
svm_scores = get_scoreslist_accuracy(sv_clf)

plot_accuracy_result(
    'Support Vector Machines',
    'Accuracy',
    svm_scores['Training Accuracy Scores'],
    svm_scores['Validation Accuracy Scores'],
)
```



Naive Bayes Scores in 10 fold

In [100…

```
nb_scores = get_scoreslist_accuracy(nb)

plot_accuracy_result(
    'Naive Bayes',
    'Accuracy',
    nb_scores['Training Accuracy Scores'],
    nb_scores['Validation Accuracy Scores'],
)
```



PERFORMANCE MEASURES

In [101…

```
viz_df = pd.DataFrame(clf_scores, columns=['Classifier','Performance Measure','S

viz_df
```

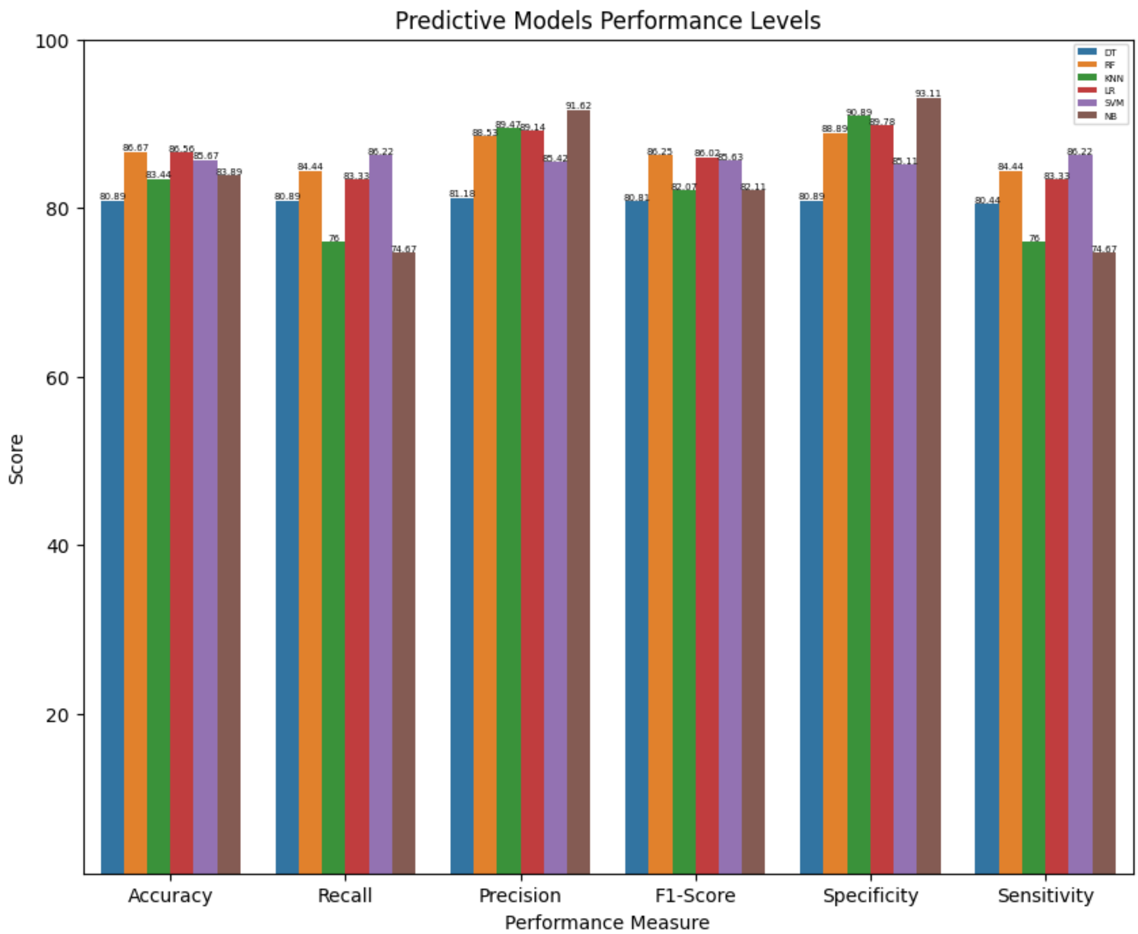
Out[101]:

	Classifier	Performance Measure	Score
0	DT	Accuracy	80.89
1	DT	Recall	80.89
2	DT	Precision	81.18
3	DT	F1-Score	80.81
4	DT	Specificity	80.89
5	DT	Sensitivity	80.44
6	RF	Accuracy	86.67
7	RF	Recall	84.44
8	RF	Precision	88.53
9	RF	F1-Score	86.25
10	RF	Specificity	88.89
11	RF	Sensitivity	84.44
12	KNN	Accuracy	83.44
13	KNN	Recall	76.00
14	KNN	Precision	89.47
15	KNN	F1-Score	82.07
16	KNN	Specificity	90.89
17	KNN	Sensitivity	76.00
18	LR	Accuracy	86.56
19	LR	Recall	83.33
20	LR	Precision	89.14
21	LR	F1-Score	86.02
22	LR	Specificity	89.78
23	LR	Sensitivity	83.33
24	SVM	Accuracy	85.67
25	SVM	Recall	86.22
26	SVM	Precision	85.42
27	SVM	F1-Score	85.63
28	SVM	Specificity	85.11
29	SVM	Sensitivity	86.22
30	NB	Accuracy	83.89
31	NB	Recall	74.67
32	NB	Precision	91.62
33	NB	F1-Score	82.11
34	NB	Specificity	93.11

	Classifier	Performance Measure	Score
35	NB	Sensitivity	74.67

In [110…

```python
fig, ax = plt.subplots(figsize=(10, 8))

perf_levels = sns.barplot(
    x ='Performance Measure',
    y='Score',
    hue='Classifier',
    data=viz_df,
    estimator=np.median,
    errorbar=('ci', 0),
    ax=ax
)

ax.set_ylim(1, 100)
perf_levels.legend(fontsize=5)
perf_levels.set(title='Predictive Models Performance Levels')

for i in ax.containers:
    ax.bar_label(i,fontsize=5)

plt.show()
```



Extra (Performed Stratified K-Fold Cross Validation with Decision Tree)

The 10-fold visualization of Decision Tree above performed poorly based on accuracy. I tried out the stratified K-Fold cross validation to balance the distribution of the classes in each fold to avoid bias towards each n fold.

In [111…
```
from sklearn.model_selection import StratifiedKFold

skf = StratifiedKFold(n_splits=10, shuffle=True, random_state=1)
lst_accu_stratified_train = []
lst_accu_stratified_test = []

df_strat = pd.read_csv('Raisin_Dataset.csv', header=None)
```

In [112…
```
df_strat = df_strat.drop(df_strat.index[0])
df_strat
```

Out[112]:

	0	1	2	3	4	5	6	7
1	87524	442.2460114	253.291155	0.819738392	90546	0.758650579	1184.04	Kecimen
2	75166	406.690687	243.0324363	0.801805234	78789	0.68412957	1121.786	Kecimen
3	90856	442.2670483	266.3283177	0.798353619	93717	0.637612812	1208.575	Kecimen
4	45928	286.5405586	208.7600423	0.684989217	47336	0.699599385	844.162	Kecimen
5	79408	352.1907699	290.8275329	0.56401133	81463	0.792771926	1073.251	Kecimen
...	...	...	...	...	...	...	...	...
896	83248	430.0773077	247.8386945	0.817262582	85839	0.66879293	1129.072	Besni
897	87350	440.7356978	259.2931487	0.808628995	90899	0.636476246	1214.252	Besni
898	99657	431.7069809	298.8373229	0.721684066	106264	0.741098519	1292.828	Besni
899	93523	476.3440939	254.1760536	0.84573851	97653	0.658798253	1258.548	Besni
900	85609	512.0817743	215.2719758	0.907345395	89197	0.632019963	1272.862	Besni

900 rows × 8 columns

In [113…
```
df_strat[7] = df_strat[7].map({'Kecimen': 0, 'Besni': 1})

x_strat = df_strat[[0,1,2,3,4,5,6]]
y_strat = df_strat[7]
```

In [114…
```
x_strat
```

Out[114]:

	0	1	2	3	4	5	6
1	87524	442.2460114	253.291155	0.819738392	90546	0.758650579	1184.04
2	75166	406.690687	243.0324363	0.801805234	78789	0.68412957	1121.786
3	90856	442.2670483	266.3283177	0.798353619	93717	0.637612812	1208.575
4	45928	286.5405586	208.7600423	0.684989217	47336	0.699599385	844.162
5	79408	352.1907699	290.8275329	0.56401133	81463	0.792771926	1073.251
...	...	...	...	...	...	...	...
896	83248	430.0773077	247.8386945	0.817262582	85839	0.66879293	1129.072
897	87350	440.7356978	259.2931487	0.808628995	90899	0.636476246	1214.252
898	99657	431.7069809	298.8373229	0.721684066	106264	0.741098519	1292.828
899	93523	476.3440939	254.1760536	0.84573851	97653	0.658798253	1258.548
900	85609	512.0817743	215.2719758	0.907345395	89197	0.632019963	1272.862

900 rows × 7 columns

In [115…

```
y_strat
```

Out[115]:

```
1      0
2      0
3      0
4      0
5      0
      ..
896    1
897    1
898    1
899    1
900    1
Name: 7, Length: 900, dtype: int64
```

In [116…

```
dtree_strat = DecisionTreeClassifier()
skf.get_n_splits(x,y)
```

Out[116]:

```
10
```

Performed Stratified K-fold cross validation

In [117…

```
for train_index, test_index in skf.split(x, y):
    x_train_fold, x_test_fold = x.iloc[train_index], x.iloc[test_index]
    y_train_fold, y_test_fold = y.iloc[train_index], y.iloc[test_index]
    dtree_strat.fit(x_train_fold, y_train_fold)
    lst_accu_stratified_test.append(dtree_strat.score(x_test_fold, y_test_fold))
    lst_accu_stratified_train.append(dtree_strat.score(x_train_fold, y_train_fol
```

In [118…

```
from statistics import mean

print('Maximum Accuracy',max(lst_accu_stratified_test))
print('Minimum Accuracy:',min(lst_accu_stratified_test))
print('Overall Accuracy:',mean(lst_accu_stratified_test))
```

```
Maximum Accuracy 0.8777777777777778
Minimum Accuracy: 0.7666666666666667
Overall Accuracy: 0.8177777777777778
```

In [119…

```python
from statistics import mean

print('Maximum Accuracy',max(lst_accu_stratified_train))
print('Minimum Accuracy:',min(lst_accu_stratified_train))
print('Overall Accuracy:',mean(lst_accu_stratified_train))
```

```
Maximum Accuracy 1.0
Minimum Accuracy: 1.0
Overall Accuracy: 1.0
```

In [120…

```python
lst_accu_stratified_test
```

Out[120]:

```
[0.7666666666666667,
 0.8777777777777778,
 0.8111111111111111,
 0.7888888888888889,
 0.8555555555555555,
 0.8111111111111111,
 0.8222222222222222,
 0.8333333333333334,
 0.7666666666666667,
 0.8444444444444444]
```

In [121…

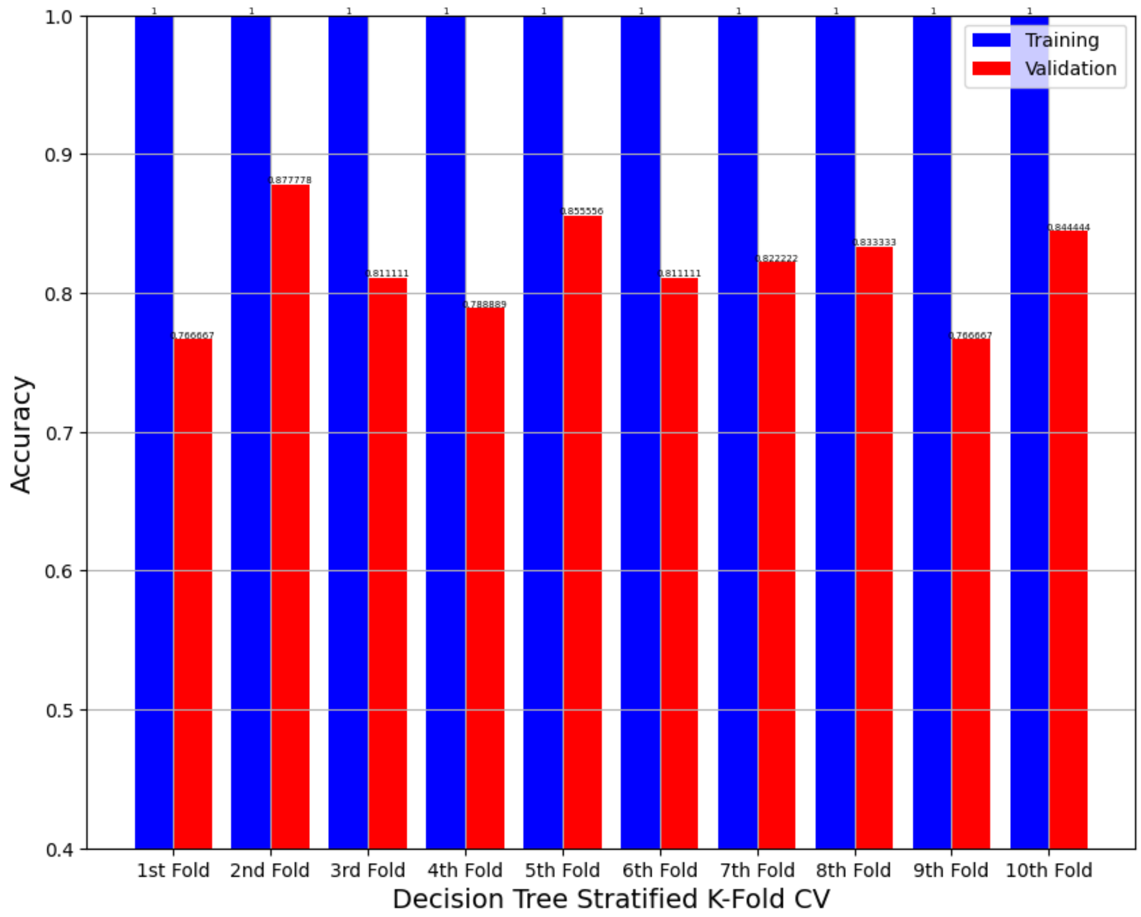
```python
lst_accu_stratified_train
```

Out[121]:

```
[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0]
```

In [122…

```python
plot_accuracy_result(
    'Decision Tree Stratified K-Fold CV',
    'Accuracy',
    lst_accu_stratified_train,
    lst_accu_stratified_test,
)
```



In [128…

```
compare_acc = [['K-Fold CV', viz_df['Score'].loc[viz_df.index[0]]],['Stratified
```

In [129…

```
compare_acc_viz = pd.DataFrame(compare_acc, columns=['CV','Accuracy'])

compare_acc_viz
```

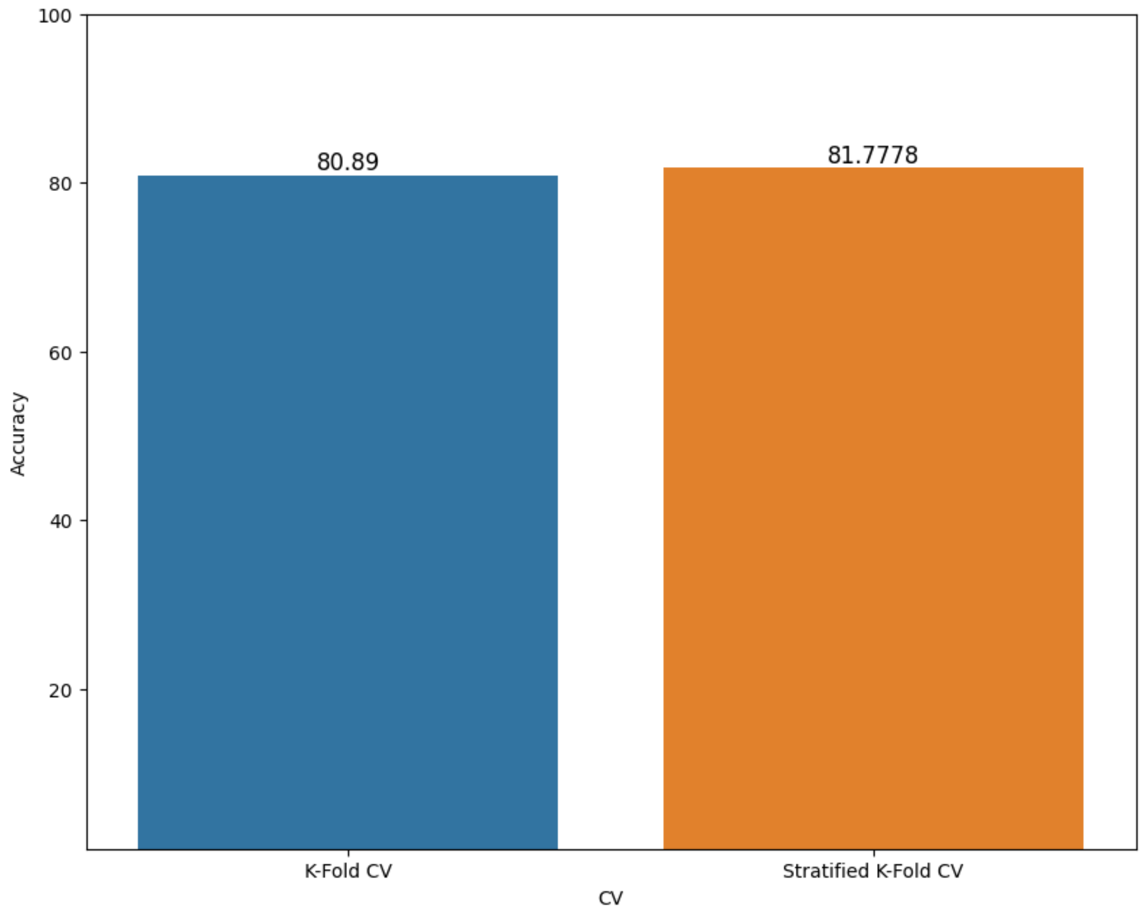
Out[129]:

	CV	Accuracy
0	K-Fold CV	80.890000
1	Stratified K-Fold CV	81.777778

In [134…

```
fig, ax = plt.subplots(figsize=(10, 8))

sns.barplot(x='CV',y='Accuracy',data=compare_acc_viz, ax=ax)
ax.set_ylim(1, 100)
perf_levels.set(title='K-Fold CV vs Stratified K-Fold CV')

for i in ax.containers:
    ax.bar_label(i,fontsize=12)


plt.show
```

Out[134]: <function matplotlib.pyplot.show(close=None, block=None)>


100
80
60
40
20
Accuracy
80.89
81.7778
K-Fold CV
Stratified K-Fold CV
CV

In [ ]: