**40/60 Split Insights**

The model achieves an overall accuracy of 77.7%, showing balanced precision and recall for both classes. With a relatively small training set (40%), the model still performs reasonably well, suggesting the decision tree can capture key patterns with limited training data.

The confusion matrix shows 79 true negatives (correctly identified no-disease cases) and 60 true positives (correctly identified disease cases), which represents good performance in both classes. However, there are 23 false negatives, where patients with heart disease were incorrectly classified as healthy, which is concerning from a medical perspective since these missed diagnoses could have serious consequences.

The model shows slightly better precision for disease detection (0.78) than for no-disease (0.77), but better recall for no-disease cases (0.82) than for disease cases (0.72). This indicates that while the model is slightly more confident when predicting disease, it's more likely to miss some disease cases.

**60/40 Split Insights**

With 60% of data used for training, the model reaches an accuracy of 74.8%, which is slightly lower than the 40/60 split. This unexpected result may indicate that the additional training examples introduced more complexity that the model struggled to generalize from, or possibly that the particular test set in this split contained more challenging cases.

Looking at the confusion matrix, we see 55 true negatives and 34 true positives, but also 21 false negatives and 9 false positives. The model shows significantly higher recall for no-disease cases (0.86) than for disease cases (0.62), indicating a tendency to classify borderline cases as no-disease, which is problematic for a medical application where failing to identify disease carries greater risk.

The precision for disease detection (0.79) is higher than for no-disease (0.72), suggesting that when the model predicts disease, it's often correct, but it's missing too many positive cases overall.

**80/20 Split Insights**

The 80/20 split model achieves an accuracy of 76.7%, with a more balanced performance across classes. This split provides the model with substantial training data while maintaining a reasonable test set size.

The confusion matrix reveals 24 true negatives and 22 true positives, with 8 false positives and 6 false negatives. The model shows comparable precision for both classes (0.80 for no-disease and 0.73 for disease) and similar recall rates (0.75 for no-disease and 0.79 for disease).

This represents the most balanced model performance across all metrics, with an F1-score of 0.77 for no-disease and 0.76 for disease, suggesting this split provides sufficient data for both training a robust model and maintaining a representative test set.

**90/10 Split Insights**

With the largest training set (90%), the model achieves only 70% accuracy, which is the lowest among all splits. This could indicate potential overfitting to the training data, or it might simply reflect the small test set size (30 samples) being less representative of the overall data distribution.

The confusion matrix shows 13 true negatives and 8 true positives, with 3 false positives and 6 false negatives. The model shows a clear bias toward the no-disease class, with better precision (0.68 vs 0.73) and recall (0.81 vs 0.57) for no-disease cases.

The high number of false negatives relative to the test set size is particularly concerning, as it means nearly half of the actual disease cases were missed. This suggests that despite having the most training data, the model fails to effectively identify many positive cases, making this split potentially dangerous for real-world application.