In [38]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [39]:
```
my_random_state = 10

bcw_data = pd.read_csv('./breast-cancer-prepared.csv')
bcw_data.sample(5)
```

Out[39]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points
296	10.91	12.35	69.14	363.7	0.08518	0.04721	0.012360	0.013690
361	13.30	21.57	85.24	546.1	0.08582	NaN	0.033440	0.024240
249	11.52	14.93	73.87	406.3	0.10130	0.07808	0.043280	0.029290
334	12.30	19.02	77.88	464.4	0.08313	NaN	0.007756	0.008535
400	17.91	21.02	124.40	994.0	0.12300	0.25760	0.318900	0.119800

5 rows × 31 columns

Random Forst Classification

In [40]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.metrics import classification_report, confusion_matrix, accuracy_sc
```

In [41]:
```
X = bcw_data[bcw_data.columns[:-1]]
y = bcw_data['is_malignant']

# Identify columns with missing values
cols_with_missing_vals = [c for c in X.columns if X[c].isnull().any()]
```

In [ ]:
```
# Split into train, validation, and test sets (70%-15%-15%)

X_train, X_test_full, y_train, y_test_full = train_test_split(X, y,
                                                              random_state=my_ran
                                                              test_size=0.3,
                                                              stratify=y)
X_val, X_test, y_val, y_test = train_test_split(X_test_full, y_test_full,
                                                random_state=my_random_state,
                                                test_size=0.5,
                                                stratify=y_test_full)
```

In [ ]:
```
# Apply imputation with flags
simple_imputer = SimpleImputer(strategy='mean')
```

```
X_train_imputed_plus = X_train.copy()
X_val_imputed_plus = X_val.copy()
X_test_imputed_plus = X_test.copy()
```

In [44]:
```
# Add flag columns for missing values
for curr_col in cols_with_missing_vals:
    X_train_imputed_plus[curr_col + '_was_missing'] = X_train_imputed_plus[curr_
    X_val_imputed_plus[curr_col + '_was_missing'] = X_val_imputed_plus[curr_col]
    X_test_imputed_plus[curr_col + '_was_missing'] = X_test_imputed_plus[curr_co

# Impute missing values
X_train_imputed_plus[cols_with_missing_vals] = simple_imputer.fit_transform(X_tr
X_val_imputed_plus[cols_with_missing_vals] = simple_imputer.transform(X_val_impu
X_test_imputed_plus[cols_with_missing_vals] = simple_imputer.transform(X_test_im
```

In [45]:
```
# Create a function to find the best n_estimators (number of trees)
def find_best_n_estimators(X_train, X_val, y_train, y_val, do_print=True):
    result = None
    accuracy_max = -1

    for n_trees in [10, 50, 100, 200, 300]:
        rf_model = RandomForestClassifier(n_estimators=n_trees, random_state=my_
        rf_model.fit(X_train, y_train)

        y_pred = rf_model.predict(X_val)
        accuracy_score_val = accuracy_score(y_val, y_pred)

        if accuracy_score_val >= accuracy_max:
            accuracy_max = accuracy_score_val
            result = n_trees

        if do_print:
            print(f'n_estimators {n_trees}: {accuracy_score_val:.5%} accuracy on

    if do_print:
        print('-' * 20)
        print(f'Best n_estimators {result} has {accuracy_max:.5%} accuracy.')

    return result

# Find the best number of trees
best_n_estimators = find_best_n_estimators(X_train_imputed_plus, X_val_imputed_p
```

```
n_estimators 10: 96.47059% accuracy on validation set.
n_estimators 50: 96.47059% accuracy on validation set.
n_estimators 100: 96.47059% accuracy on validation set.
n_estimators 200: 96.47059% accuracy on validation set.
n_estimators 300: 96.47059% accuracy on validation set.
--------------------
Best n_estimators 300 has 96.47059% accuracy.
```

In [46]:
```
# Train the final Random Forest model with the best n_estimators
rf_model = RandomForestClassifier(n_estimators=best_n_estimators, random_state=m
rf_model.fit(X_train_imputed_plus, y_train)
```

Out[46]:
```
RandomForestClassifier
RandomForestClassifier(n_estimators=300, random_state=10)
```

In [47]:
```
y_val_pred = rf_model.predict(X_val_imputed_plus)
val_accuracy = accuracy_score(y_val, y_val_pred)
print(f"Validation accuracy: {val_accuracy:.2%}")
```

```
Validation accuracy: 96.47%
```

In [48]:
```
y_test_pred = rf_model.predict(X_test_imputed_plus)
test_accuracy = accuracy_score(y_test, y_test_pred)
print(f"Test accuracy: {test_accuracy:.2%}")
```

```
Test accuracy: 91.86%
```

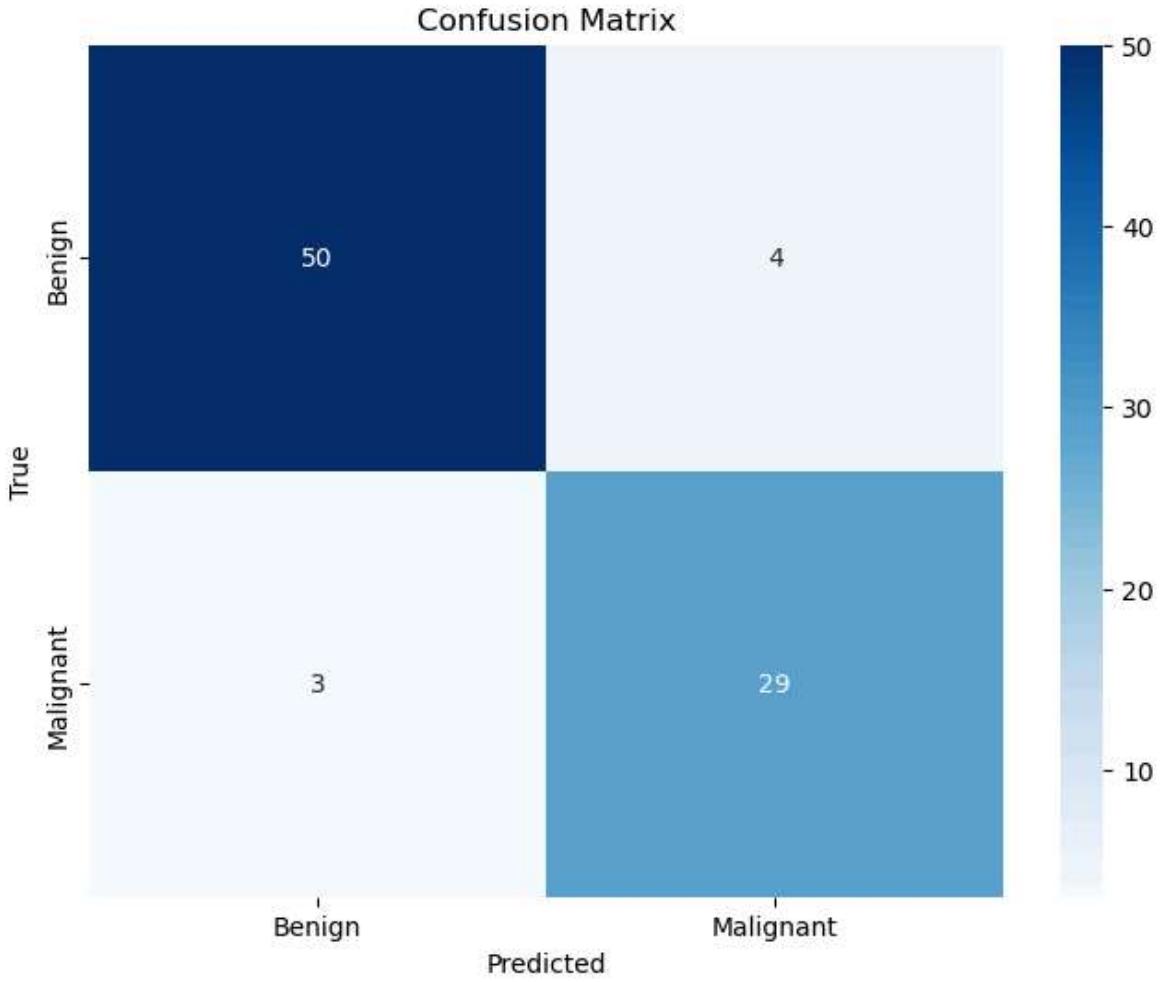
In [49]:
```
dt_accuracy = 0.9419  # Based on the notebook's conclusion
print(f"\nRandom Forest test accuracy: {test_accuracy:.2%}")
print(f"Decision Tree test accuracy: {dt_accuracy:.2%}")
print(f"Difference: {test_accuracy - dt_accuracy:.2%}")
```

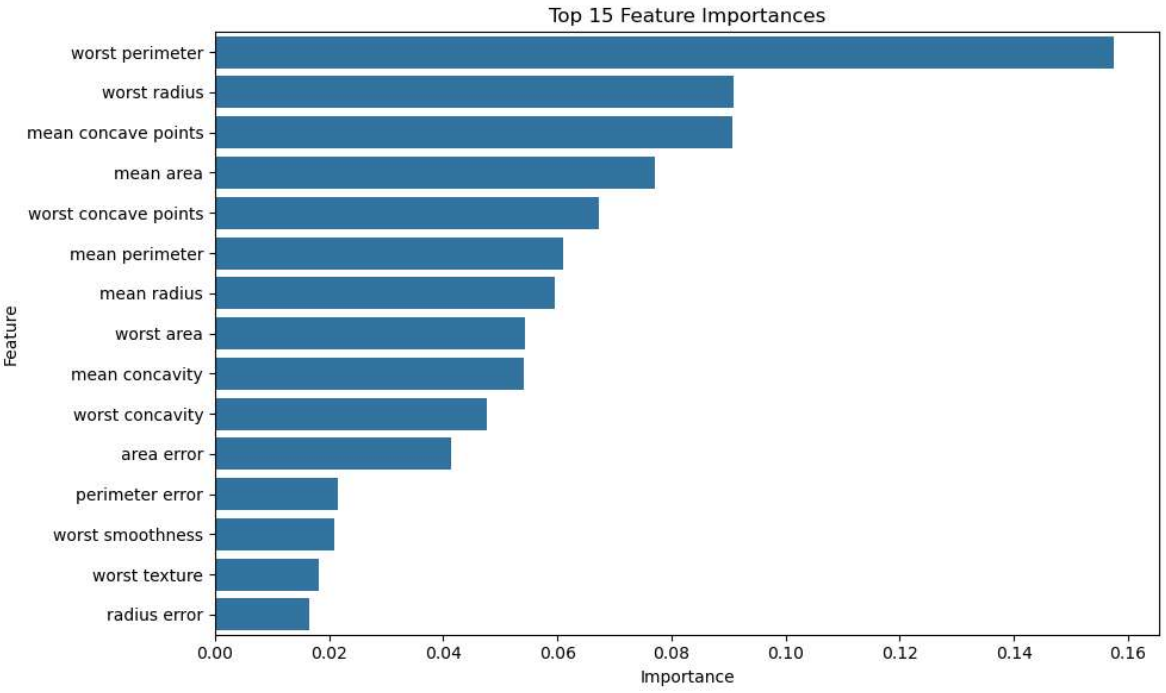
```
Random Forest test accuracy: 91.86%
Decision Tree test accuracy: 94.19%
Difference: -2.33%
```

In [50]:
```
# Print detailed classification report
print("\nClassification Report:")
print(classification_report(y_test, y_test_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.93      0.93        54
           1       0.88      0.91      0.89        32

    accuracy                           0.92        86
   macro avg       0.91      0.92      0.91        86
weighted avg       0.92      0.92      0.92        86
```

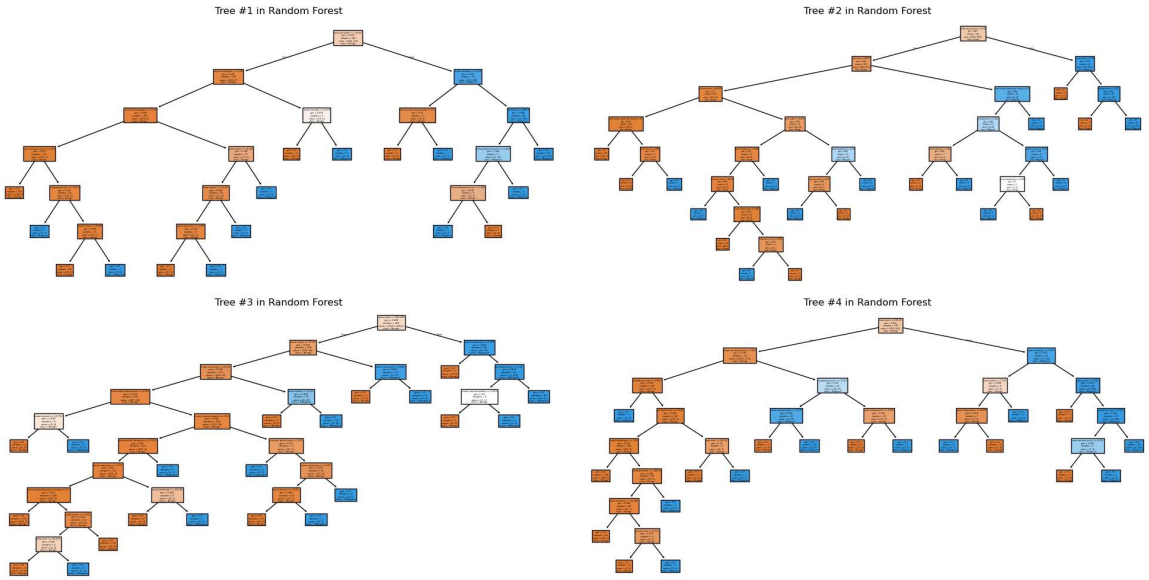
In [51]:
```
# Plot confusion matrix
plt.figure(figsize=(8, 6))
cm = confusion_matrix(y_test, y_test_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Benign', 'Malignant'],
            yticklabels=['Benign', 'Malignant'])
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# Feature importance
feature_importances = pd.DataFrame({
    'Feature': X_train_imputed_plus.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Plot top 15 features
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importances.head(15))
plt.title('Top 15 Feature Importances')
plt.tight_layout()
plt.show()
```





In [ ]:
```
from sklearn import tree
import matplotlib.pyplot as plt
import math

# Function to plot a sample of trees from the forest
def plot_forest_sample(forest, feature_names, class_names, n_trees=4):
    n_rows = math.ceil(n_trees / 2)
    _, axes = plt.subplots(nrows=n_rows, ncols=2, figsize=(20, 5*n_rows))
```

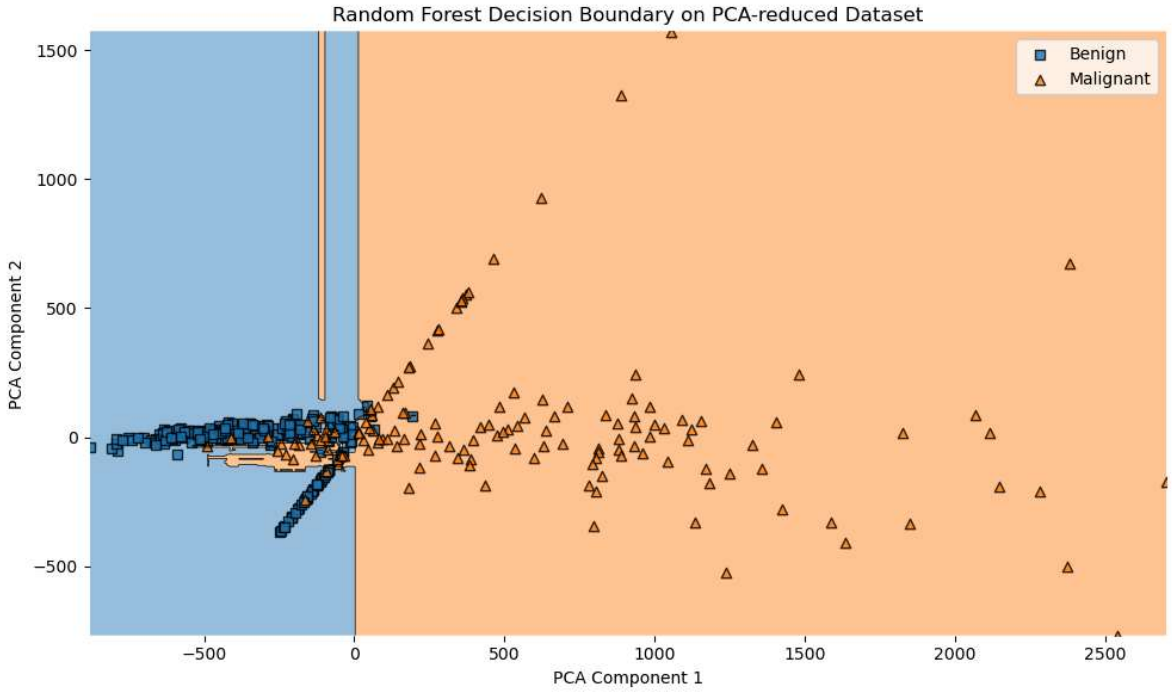
```
    axes = axes.flatten()

    for i, ax in enumerate(axes):
        if i < n_trees:
            tree.plot_tree(
                forest.estimators_[i],
                feature_names=feature_names,
                class_names=class_names,
                filled=True,
                ax=ax
            )
            ax.set_title(f'Tree #{i+1} in Random Forest')
        else:
            ax.set_visible(False)

    plt.tight_layout()
    plt.show()

# After training the Random Forest model:
# Visualize a sample of trees
feature_names = X_train_imputed_plus.columns.tolist()
class_names = ['Benign', 'Malignant']

plot_forest_sample(rf_model, feature_names, class_names, n_trees=4)
```



In [53]:

```
from sklearn.decomposition import PCA
from mlxtend.plotting import plot_decision_regions

# Use PCA to reduce to 2 dimensions for visualization
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_imputed_plus)
X_test_pca = pca.transform(X_test_imputed_plus)

# Train a new Random Forest on the reduced dataset for visualization
rf_viz = RandomForestClassifier(n_estimators=best_n_estimators, random_state=my_
rf_viz.fit(X_train_pca, y_train)

# Prepare a meshgrid for visualization
def plot_decision_boundary(X, y, model, title):
    plt.figure(figsize=(10, 6))

    # Plot decision boundary
```

```
    plot_decision_regions(X, y.values.astype(np.int32), clf=model, legend=2)

    # Add axis labels and title
    plt.xlabel('PCA Component 1')
    plt.ylabel('PCA Component 2')
    plt.title(title)

    # Add legend with custom labels
    plt.legend(['Benign', 'Malignant', 'Decision Boundary'])

    plt.tight_layout()
    plt.show()

# Plot decision boundary for Random Forest
plot_decision_boundary(X_train_pca, y_train, rf_viz,
                       'Random Forest Decision Boundary on PCA-reduced Dataset')
```



In [ ]:

```
# Function to visualizse prediction differences between tree
def visualize_tree_differences(forest, X_sample, n_trees=10):
    tree_predictions = []

    # Get predictions from individual trees
    for i in range(min(n_trees, len(forest.estimators_))):
        tree_pred = forest.estimators_[i].predict(X_sample)
        tree_predictions.append(tree_pred)

    # Convert to DataFrame for easier visualization
    tree_preds_df = pd.DataFrame(tree_predictions).T
    tree_preds_df.columns = [f'Tree #{i+1}' for i in range(tree_preds_df.shape[1

    # Add majority vote (ensemble prediction)
    majority_vote = np.array([np.bincount(row.astype(int)).argmax() for row in t
    tree_preds_df['Ensemble'] = majority_vote

    # Add actual labels
    tree_preds_df['True Label'] = y_test.iloc[:len(X_sample)].values

    # Create heatmap - use .astype(int) to ensure integer formatting works
```

```
    plt.figure(figsize=(12, 8))
    sns.heatmap(tree_preds_df.iloc[:20, :-1].astype(int),
                cmap='coolwarm',
                annot=True,
                fmt='d',  # Now safe to use 'd' since we converted to int
                cbar_kws={'label': 'Prediction'})
    plt.title('Predictions from Individual Trees vs. Ensemble')
    plt.ylabel('Sample Index')
    plt.tight_layout()
    plt.show()

    # Show comparison between ensemble prediction and true labels
    comparison_df = tree_preds_df[['Ensemble', 'True Label']].copy()
    comparison_df['Correct'] = comparison_df['Ensemble'] == comparison_df['True

    plt.figure(figsize=(10, 6))
    sns.heatmap(comparison_df.iloc[:20, :2].astype(int),
                cmap='coolwarm',
                annot=True,
                fmt='d',
                cbar_kws={'label': 'Class'})
    plt.title('Ensemble Prediction vs True Labels')
    plt.ylabel('Sample Index')
    plt.tight_layout()
    plt.show()

    return tree_preds_df

# Sample a few test observations and visualize different tree predictions
tree_diff_df = visualize_tree_differences(rf_model, X_test_imputed_plus.iloc[:20
```

```
c:\Users\fabia\anaconda3\Lib\site-packages\sklearn\base.py:486: UserWarning: X ha
s feature names, but DecisionTreeClassifier was fitted without feature names
  warnings.warn(
c:\Users\fabia\anaconda3\Lib\site-packages\sklearn\base.py:486: UserWarning: X ha
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```

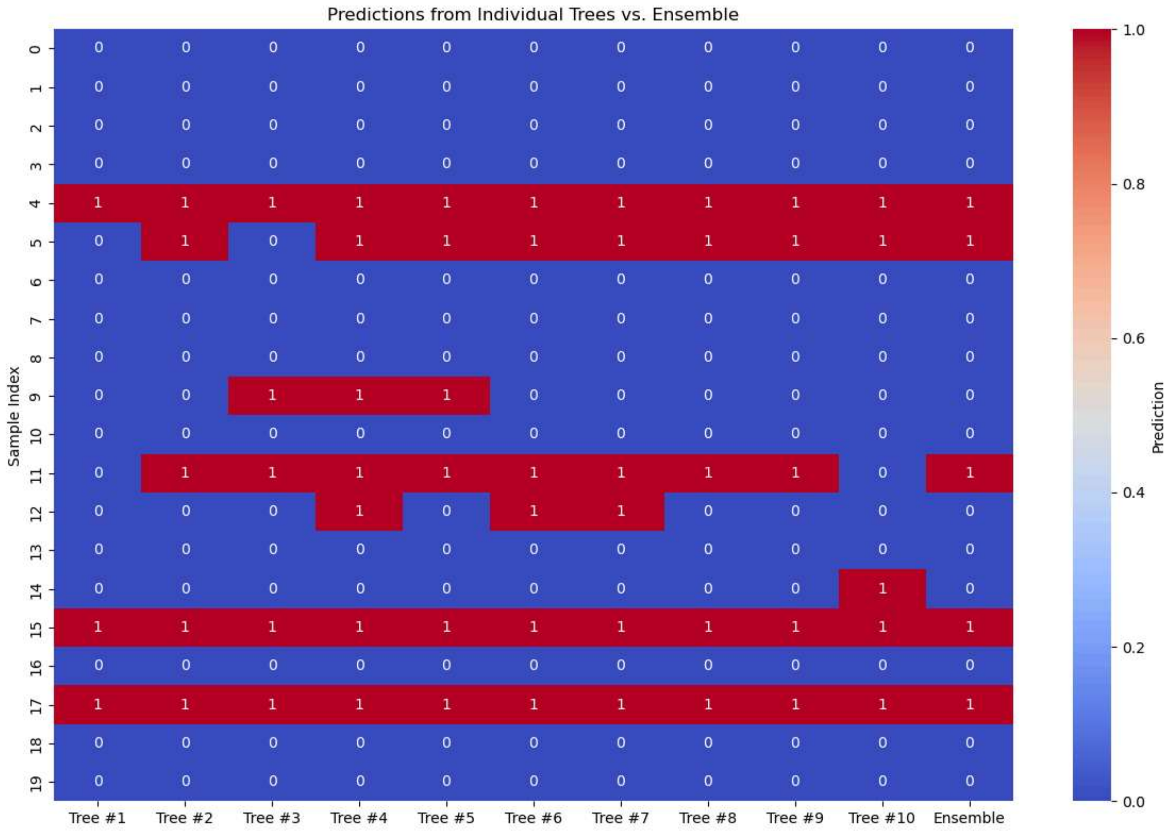

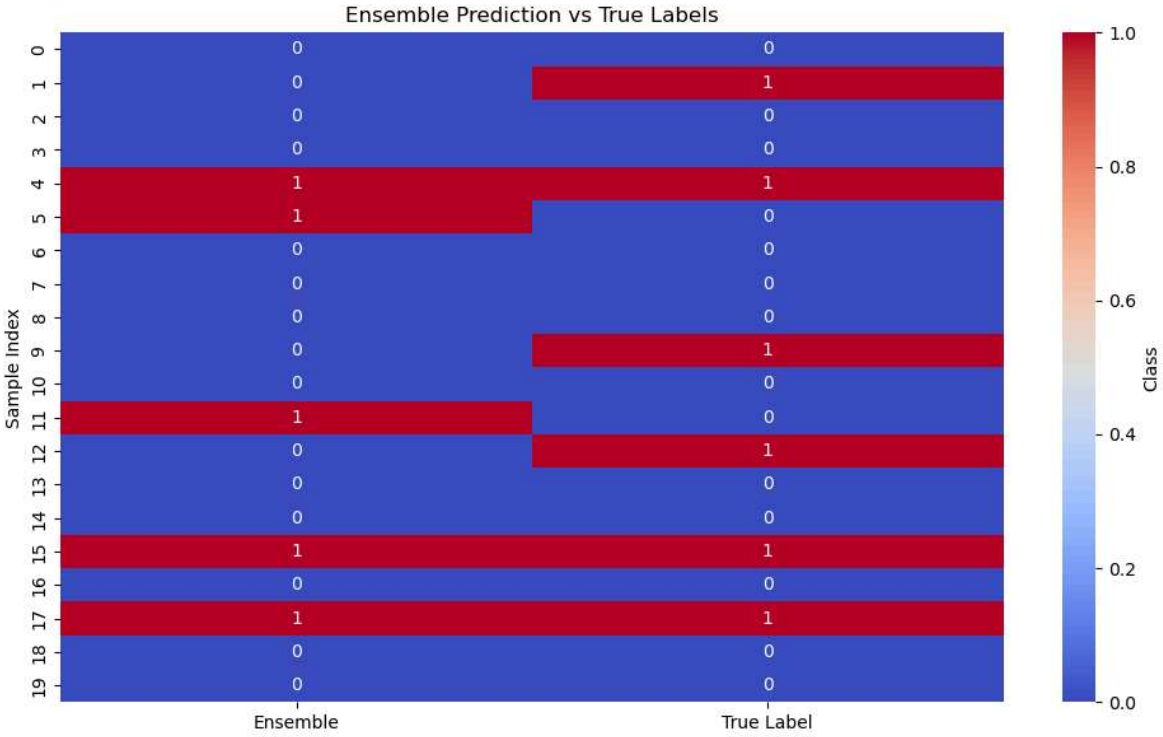

Conclusion

We have a general accuracy of

- Random Forest test accuracy: 91.86%
- Decision Tree test accuracy: 94.19%
- Validation accuracy: 96.47%

Compared to the other approach, we can't really see a difference, other than that the approach is a bit more complex. Even through we don't have to prepare the data as much as we did in the other approach, since we combine multiple descision trees.