In [7]:
```python
import numpy as np
import sklearn.datasets
import sklearn.linear_model
import sklearn.metrics
```

In [2]:
```python
np.random.seed(42)  # do not change for reproducibility
```

Task and problem statement

In this test we use the Covertype Data Set, a dataset describing cartographic features of areas of land in the USA and also its forest type according to the US Forest Service. There are seven classes (1-7), 581012 samples and 54 features. For this test, we're only interested in cover type 3.

In [4]:
```python
dataset = sklearn.datasets.fetch_covtype()
```

In [6]:
```python
features = dataset.data
target = dataset.target
#feature_names = dataset.feature_names
```

In [7]:
```python
# only use a random subset for speed - pretend the rest of the data doesn't exist
random_sample = np.random.choice(len(dataset.data), len(dataset.data) // 10)
```

In [8]:
```python
len(random_sample)
```

Out[8]:
```
58101
```

In [48]:
```python
COVER_TYPE = 3
features = dataset.data[random_sample, :]
target = dataset.target[random_sample] == COVER_TYPE
```

In [49]:
```python
features.shape
```

Out[49]:
```
(58101, 54)
```

A junior colleague tells you that they're getting 96% accuracy using logistic regression. You review their work and see the following:

In [8]:
```python
classifier = sklearn.linear_model.LogisticRegression(solver='liblinear') # do not change this
```

In [11]:
```python
classifier.fit(features, target)
preds = classifier.predict(features)
acc = sklearn.metrics.accuracy_score(preds, target)
```

In [12]:
```python
print(f'Accuracy: {acc:.3f}')
```

```
Accuracy: 0.961
```

Question 1

Comment on what was done above. Evaluate the accuracy more thoroughly. Do not modify the parameters of the model (the cell marked with the comment). Use the classifier object.

Answer

In the above, the problem is transformed into a binary classification problem, thereby testing if an observation is either of cover type 3 or not. Then a logistic regression model is trained and evaluated, which achieved an accuracy of approximately 96%. However, the trained model is evaluated on the same data it was trained on, which reminds me of a funny ML meme! ;)

title

Further, the model was evaluated w.r.t accuracy metric. However, since the classes are imbalanced, using accuracy will give distorted performance view when we'll take a closer look for individual classes. Therefore, we need to interpret using balanced performance metrics such as f1, MCC, or AUC scores.

So, let's create separate training and test sets: 80:20 ratio. We train the model on training set and evaluate the model on held-out test set to see how accurately we can classify the test samples.

In [53]:
```python
from sklearn.model_selection import train_test_split

def getDataForCoverType3(dataset, COVER_TYPE, to_sampled=False):
    random_sample = np.random.choice(len(dataset.data), len(dataset.data) // 10)

    if to_sampled:
        features = dataset.data
        target = dataset.target == COVER_TYPE

    else:
        features = dataset.data[random_sample, :]
        target = dataset.target[random_sample] == COVER_TYPE

    return features, target
```

In [58]:
```python
COVER_TYPE = 3
features, target = getDataForCoverType3(dataset, COVER_TYPE, False)
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)
```

We train the model and generate predictions on unseen test set:

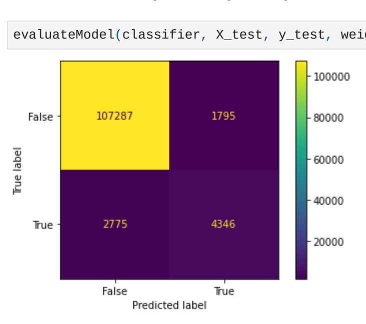
In [14]:
```python
classifier.fit(X_train, y_train)
```

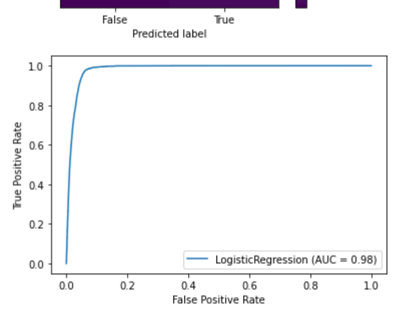
I wrote a method, which generates different metrics to evaluate the predictive power of the model on unseen test set. I could include it as a util, but doing here for the time being.

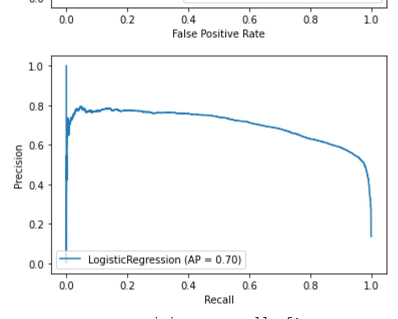
In [16]:
```python
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, accuracy_score, classificat
import matplotlib.pyplot as plt
from sklearn.metrics import plot_confusion_matrix, plot_roc_curve, plot_precision_recall_curve

def evaluateModel(model, X_test, y_test, weighted=False):
    '''This method generates different metrics to evaluate the perdictive power of the model on unseen test set
    y_pred = model.predict(X_test)

    plot_confusion_matrix(model, X_test, y_test)
    plt.show()

    plot_roc_curve(model, X_test, y_test)
    plt.show()

    plot_precision_recall_curve(model, X_test, y_test)
    plt.show()

    print(classification_report(y_test, y_pred))

    if weighted:
        acc = accuracy_score(y_test, y_pred)
        print(f'Accuracy: {acc:.3f}')

        precision = precision_score(y_test, y_pred, average='weighted')
        print(f'Precision: {precision:.3f}')

        recall = recall_score(y_test, y_pred, average='weighted')
        print(f'Recall: {recall:.3f}')

        f1 = f1_score(y_test, y_pred, average='weighted')
        print(f'F1 score: {f1:.3f}')

        auc = roc_auc_score(y_test, y_pred, average='weighted')
        print(f'AUC score: {auc:.3f}')

        mcc = matthews_corrcoef(y_test, y_pred)
        print(f'MCC score: {mcc:.3f}')

    else:
        print(f'Accuracy: {accuracy_score(y_test, y_pred):.3f}')
        print(f'Precision: {precision_score(y_test, y_pred):.3f}')
        print(f'Recall: {recall_score(y_test, y_pred):.3f}')
        print(f'F1: {f1_score(y_test, y_pred):.3f}')
        print(f'AUC score: {roc_auc_score(y_test, y_pred):.3f}')
        print(f'MCC score: {matthews_corrcoef(y_test, y_pred):.3f}')
```

Now if we take the weighted average scoring, we will see very different scenario:

In [39]:
```python
evaluateModel(classifier, X_test, y_test, weighted=True)
```



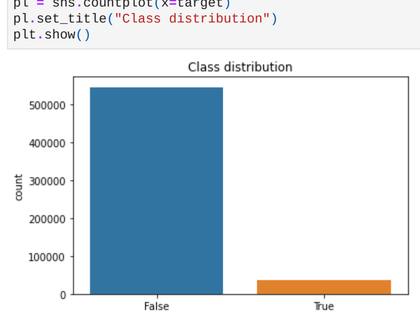





```
              precision    recall  f1-score   support

       False       0.97      0.98      0.98    109082
        True       0.71      0.61      0.66      7121

    accuracy                           0.96    116203
   macro avg       0.84      0.80      0.82    116203
weighted avg       0.96      0.96      0.96    116203

Accuracy: 0.961
Precision: 0.958
Recall: 0.961
F1 score: 0.959
AUC score: 0.797
MCC score: 0.637
```

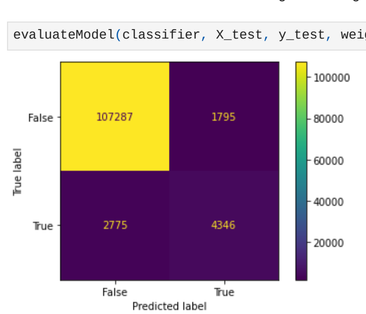
Thus having an weighted f1-score of 95.9% on test set is great. However, if we closely observe at the class-wise classification report, we can see that the classifier has made significant misclassification for the true class (cover type 3), making the scores much lower compared than that of false class. This is obvious because classes are severely imbalanced.

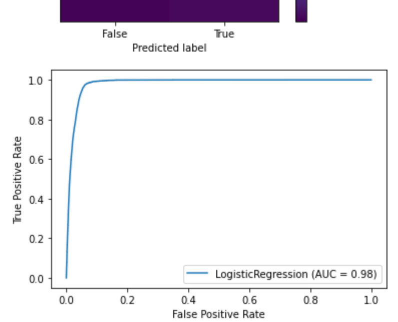
In [40]:
```python
import numpy as np

unique, counts = np.unique(target, return_counts=True)
dict(zip(unique, counts))

#Plotting class membership
import seaborn as sns
pl = sns.countplot(x=target)
pl.set_title("Class distribution")
plt.show()
```

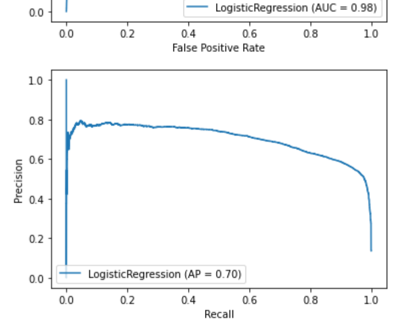


Now let's see the same metrics without weighted averageing:

In [41]:
```python
evaluateModel(classifier, X_test, y_test, weighted=False)
```








```
              precision    recall  f1-score   support

       False       0.97      0.98      0.98    109082
        True       0.71      0.61      0.66      7121

    accuracy                           0.96    116203
   macro avg       0.84      0.80      0.82    116203
weighted avg       0.96      0.96      0.96    116203

Accuracy: 0.961
Precision: 0.708
Recall: 0.610
F1: 0.655
AUC score: 0.797
MCC score: 0.637
```

This is obvious because classes are severely imbalanced.

Now if we take the weighted average scoring, we will see very different scenario:

Question 2

Should you get more training data?

Answer

In my understanding, getting more data in such an imbalanced scenario may not help the classifier. We could go for class balancing, e.g., oversampling or under-sampling. But I'm not gonna do that (that's fairly easy, e.g., using SMOTHE from the imblearn library), as real-life data may not be balanced, e.g., credit card fraud detection, or money laundering use cases, severe imbalance is expected. To prove my hypothesis, let's try training the LR model on full dataset.

In [60]:
```python
COVER_TYPE = 3
features, target = getDataForCoverType3(dataset, COVER_TYPE, False)
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)
```

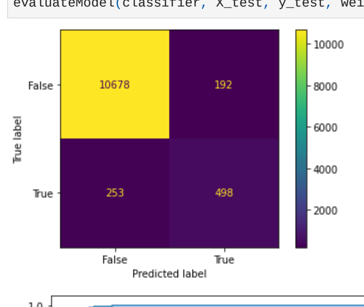
In [61]:
```python
import numpy as np

unique, counts = np.unique(target, return_counts=True)
dict(zip(unique, counts))
```

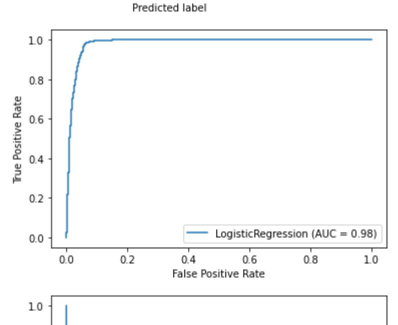
Out[61]:
```
{False: 54615, True: 3486}
```

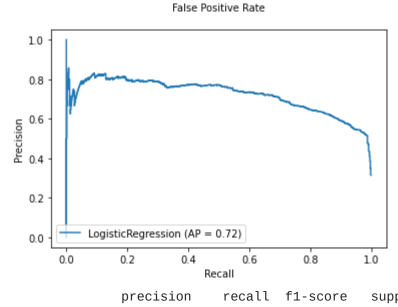
In [62]:
```python
classifier.fit(X_train, y_train)
```

Out[62]:
```
LogisticRegression(solver='liblinear')
```

In [63]:
```python
evaluateModel(classifier, X_test, y_test, weighted=False)
```



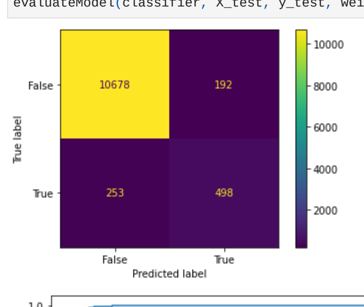


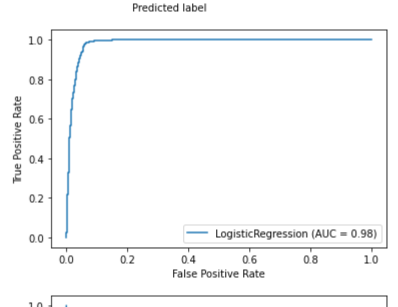


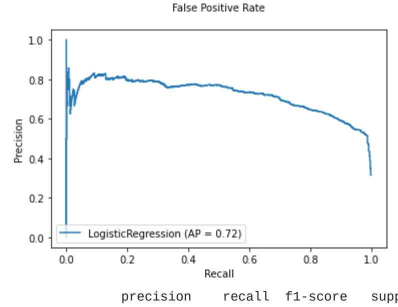

```
              precision    recall  f1-score   support

       False       0.98      0.98      0.98     10870
        True       0.72      0.66      0.69       751

    accuracy                           0.96     11621
   macro avg       0.85      0.82      0.84     11621
weighted avg       0.96      0.96      0.96     11621

Accuracy: 0.962
Precision: 0.722
Recall: 0.663
F1: 0.691
AUC score: 0.823
MCC score: 0.671
```

Now if we take the weighted average scoring, we will see very different scenario:

In [64]:
```python
evaluateModel(classifier, X_test, y_test, weighted=True)
```








```
              precision    recall  f1-score   support

       False       0.98      0.98      0.98     10870
        True       0.72      0.66      0.69       751

    accuracy                           0.96     11621
   macro avg       0.85      0.82      0.84     11621
weighted avg       0.96      0.96      0.96     11621

Accuracy: 0.962
Precision: 0.960
Recall: 0.962
F1 score: 0.961
AUC score: 0.823
MCC score: 0.671
```

Overall, even training with all the available data did not help model perform well due to high data imbalance.

Question 3

How would you decide which features to include in the deployed model?

In [29]:
```python
### Write your code and explanation here.
```

Answer

As not all the features could be of importance or relevant in the predictive modeling, as unimportant features will not only introduce intrinsic noises but also increase the computational complexity of the model. Therefore, it makes sense to identify the most impactful features based on their importance, followed by dropping least important features.

Approach 1: w.r.t coefficients

The very basic thing I'll do is computing and examining the coefficients of the model on standardized parameters, the estimated coefficients, which will be around 1 across features. This then can be used as the feature importance.

In [30]:
```python
# The estimated coefficients will all be around 1:
print(classifier.coef_)
```

```
[[-7.78969185e-03  1.36235296e-03  1.07058098e-01  2.29777736e-03
   2.44569635e-03 -1.69712259e-04  7.35979387e-02 -3.25670700e-02
   5.02677637e-02 -2.90889625e-04 -1.21212524e+00 -1.98535686e-02
   9.97517882e-01  2.94581580e-01 -2.54903123e-01  1.44122040e+00
  -2.69568376e-01  1.95503196e+00 -2.02871637e-01  8.89516511e-01
  -6.03769868e-05 -1.12925989e-04 -6.19693092e-02  4.52815625e-01
   1.51686484e-01 -2.51792650e-01 -6.19950246e-01 -2.17254050e-01
  -1.92025868e-03 -7.72826559e-02 -2.10127252e-01 -5.68384667e-02
  -6.07847471e-03 -1.28183575e-01 -1.96222940e-03 -5.86811567e-02
  -1.91704871e-01 -1.43508877e-01 -4.97215095e-04 -5.61565119e-02
  -6.82231104e-03 -9.58283010e-02 -3.63976449e-01 -3.08464106e-01
  -2.57007677e-01 -2.42228023e-01 -6.64819808e-01 -6.35015223e-02
  -4.36096257e-04 -2.86693616e-04 -2.40138573e-05 -5.55105514e-03
  -7.33344089e-03 -2.44659761e-03]]
```

In [18]:
```python
classifier.fit(X_train / np.std(X_train, 0), y_train)
print((classifier.coef_)*100)
```

```
[[-1.54947372e+02  1.74995761e+01 -1.25349523e+00  4.17641255e+01
   1.13515614e+01 -1.72294093e+01 -9.67104384e+01  8.30804598e+01
  -1.37161869e+02 -3.76210571e+01 -5.69296814e+01 -9.60462612e+00
   3.07460065e+02  1.42936834e+02  5.89271972e+01  1.12306328e+02
   7.56336189e+01  1.44979692e+02  4.06901893e+01  9.80797812e+01
  -2.02722225e-01 -2.83966628e-01 -5.67370926e+00  1.93107259e+02
   1.18013781e+02 -1.33010135e+01  7.79591525e+01  2.18578330e+01
  -1.03334693e+00  5.50628834e+01  5.85776714e+01 -4.90902152e+00
  -6.27388431e+00  4.07123536e+01 -5.05773446e+00 -1.76797358e+01
  -3.33522047e+01 -3.36361709e+01 -1.08908199e+00 -1.46283247e+01
  -8.01688558e+00 -1.42371263e+01 -1.87111829e+01 -1.52104801e+01
  -4.10791988e+01  1.64827303e+02  5.23199799e+01 -1.39337246e+01
  -2.54128698e+00 -2.06841150e+00 -5.70658629e-01 -8.84920202e+00
  -1.12570459e+01 -5.28618147e+00]]
```

In [19]:
```python
import pandas as pd

df = pd.DataFrame(zip(dataset.feature_names, np.transpose(classifier.coef_)), columns=['features', 'coef'])
```

In [20]:
```python
df.sort_values('coef', ascending=False).head(10)
```

Out[20]:

	features	coef
12	Wilderness_Area_2	[3.074600645295881]
23	Soil_Type_9	[1.9310725930866681]
45	Soil_Type_31	[1.6482730289723515]
17	Soil_Type_3	[1.4497969235959864]
13	Wilderness_Area_3	[1.4293683417940954]
24	Soil_Type_10	[1.1801378141985837]
15	Soil_Type_1	[1.1230632773649667]
19	Soil_Type_5	[0.9807978119024735]
7	Hillshade_Noon	[0.8308045980762364]
26	Soil_Type_12	[0.7795915248171168]

As we can see the Wilderness_Area_2, Soil_Type_9, Soil_Type_31, Soil_Type_3, Wilderness_Area_3 are top-k features. However, this will work on sklearn 1.1 version only. Therefore, first I extracted feature and target names from the fetch_covtype() method as follows:

In [ ]:
```python
# dataset = sklearn.datasets.fetch_covtype(return_X_y=False, as_frame=True)
# features = dataset.data
# target = dataset.target
# feature_names = dataset.feature_names
# target_names = dataset.target_names
```

Then I saved the resultant dataframe in a csv file for reusability.

In [12]:
```python
# import pandas as pd

# y = pd.DataFrame(target, columns=target_names)
# data = pd.concat([features, y], ignore_index=False, axis=1).reset_index(drop=True)
# data.to_csv('data.csv', index=False)
```

Approach 2: using permutation feature importance

We know that using tree-based models, we can easily extract the permutation feature importance (PFI). However, the recent version of sklearn has introduced the the permutation_importance, which can be extracted via inspection wrapper for any model that provided coefficients or feature importance.

In [3]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
df = pd.read_csv('data.csv', index_col=None)
df.head()
```

Out[3]:

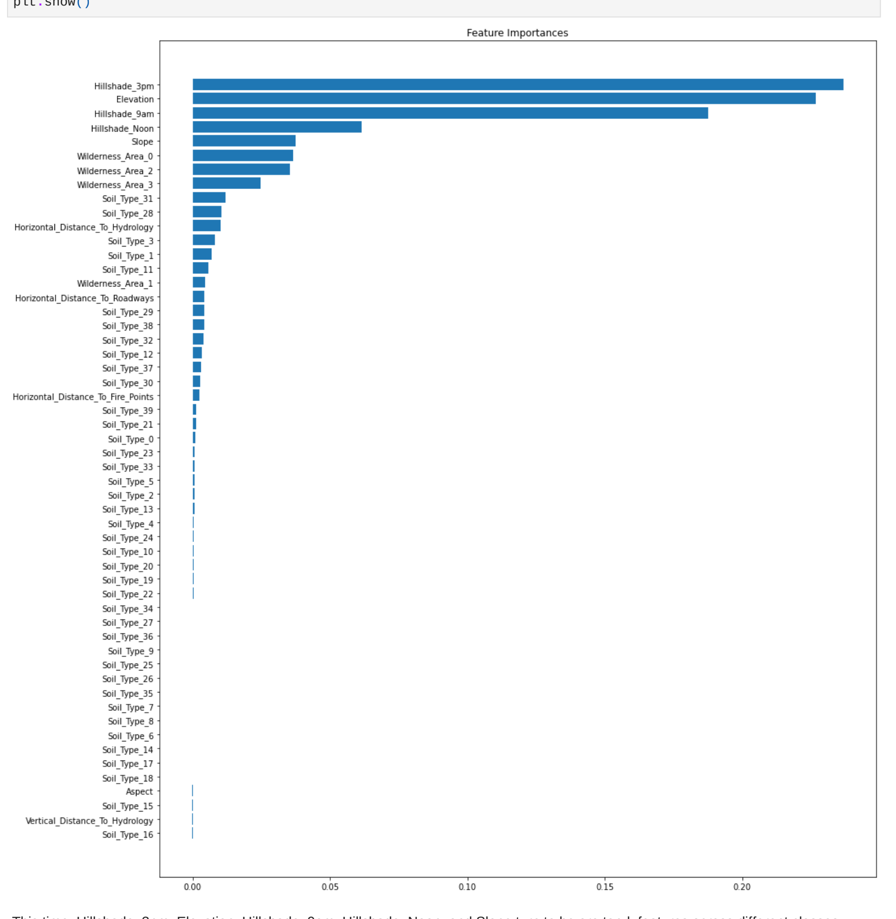
	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	Hillshade_
0	2596.0	51.0	3.0	258.0	0.0	510.0	2
1	2590.0	56.0	2.0	212.0	-6.0	390.0	2
2	2804.0	139.0	9.0	268.0	65.0	3180.0	2
3	2785.0	155.0	18.0	242.0	118.0	3090.0	2
4	2595.0	45.0	2.0	153.0	-1.0	391.0	2

5 rows × 55 columns

In [4]:
```python
# Create a Pandas dataframe with all the features
X = df.loc[:, df.columns != 'Cover_Type']
y = df['Cover_Type']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [ ]:
```python
from sklearn.inspection import permutation_importance
classifier = sklearn.linear_model.LogisticRegression(solver='liblinear')
classifier.fit(X_train, y_train)

pfi = permutation_importance(classifier, X_test, y_test, n_repeats=5, random_state=42)
```

In [27]:
```python
sorted_idx = pfi.importances_mean.argsort()
lr_importances = pd.Series(pfi.importances_mean, index=X_train.columns)

y_ticks = np.arange(0, len(X_train.columns))
fig, ax = plt.subplots(figsize=(15, 15))
ax.barh(y_ticks, lr_importances[sorted_idx])
ax.set_yticks(y_ticks)
ax.set_yticklabels(X_train.columns[sorted_idx])
ax.set_title("Feature Importances")
fig.tight_layout()
plt.show()
```



This time, Hillshade_3pm, Elevation, Hillshade_9am, Hillshade_Noon, and Slope turn to be are top-k features across different classes. This is very different compared to the first approach.

In [ ]:
```python
# from sklearn.inspection import DecisionBoundaryDisplay
# disp = DecisionBoundaryDisplay.from_estimator(classifier, X_test,
#                                               response_method="predict", xlabel="Hillshade_3pm",
#                                               ylabel="Elevation", alpha=0.5)
# disp.ax_.scatter(X_test[:, 0], X_test[:, 1], c=y_test, edgecolor="k")
# plt.show()
```

Approach 3: using SHAP

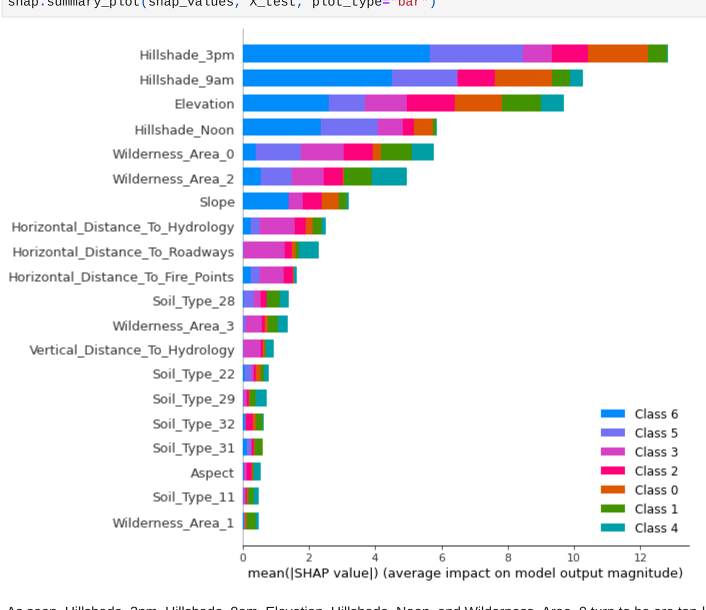
We already generated PFI using LR model, which provides a view on global feature importance and signifies how important a feature is for the model. However, PFI does not necessarily reflect the intrinsic predictive value of a feature by itself, since a feature that seems to have lower importance for an under/overfitted model could be important for a better-fitted model and the order in which a model observes features can affect the predictions. Therefore, I decided to employ SHAP to provide the explanations of the predictions of the model. SHAP uses Shapley values (SVs) as the measure of feature attribution and are based on coalition game theory. Further, as the order in which features are observed by the model matters, SHAP values explain the output of a function as a sum of the effects of each feature being introduced into a conditional expectation. If a feature has no or almost zero effect on the predicted value, it is expected to produce a SV of 0. If two features contribute equally to the prediction, SVs should be the same.

In [2]:
```python
import shap
# Initialize JavaScript visualization - use Jupyter notebook to see the interactive features of the plots
shap.initjs()
```

In [31]:
```python
# Create a TreeExplainer and extract shap values from it - will be used for plotting later
explainer = shap.Explainer(classifier, X_train, feature_names=X_train.columns)
shap_values = explainer.shap_values(X_test)
```

In [52]:
```python
shap_values = explainer(X_test)
```

In [32]:
```python
shap.summary_plot(shap_values, X_test, plot_type="bar")
```



As seen, Hillshade_3pm, Hillshade_9am, Elevation, Hillshade_Noon, and Wilderness_Area_0 turn to be are top-k features across different classes. This is somewhat identical to what we observed using the inspection wrapper.

Approach 4: advanced techniques with AutoML

I used PyCaret - one of my favorite AutoML library. First, I'll compare performance between baseline classifiers and choose a top model whose performance will be evaluated w.r.t different performance metrics.

In [62]:
```python
from pycaret.classification import *
setup(df, target = 'Cover_Type')
```

	Description	Value
0	session_id	844
1	Target	Cover_Type
2	Target Type	Multiclass
3	Label Encoded	None
4	Original Data	(581012, 55)
5	Missing Values	False
6	Numeric Features	10
7	Categorical Features	44
8	Ordinal Features	False
9	High Cardinality Features	False
10	High Cardinality Method	None
11	Transformed Train Set	(406708, 54)
12	Transformed Test Set	(174304, 54)
13	Shuffle Train-Test	True
14	Stratify Train-Test	False
15	Fold Generator	StratifiedKFold
16	Fold Number	10
17	CPU Jobs	-1
18	Use GPU	False
19	Log Experiment	False
20	Experiment Name	clf-default-name
21	USI	6e5d
22	Imputation Type	simple
23	Iterative Imputation Iteration	None
24	Numeric Imputer	mean
25	Iterative Imputation Numeric Model	None
26	Categorical Imputer	constant
27	Iterative Imputation Categorical Model	None
28	Unknown Categoricals Handling	least_frequent
29	Normalize	False
30	Normalize Method	None
31	Transformation	False
32	Transformation Method	None
33	PCA	False
34	PCA Method	None
35	PCA Components	None
36	Ignore Low Variance	False
37	Combine Rare Levels	False
38	Rare Level Threshold	None
39	Numeric Binning	False
40	Remove Outliers	False
41	Outliers Threshold	None
42	Remove Multicollinearity	False
43	Multicollinearity Threshold	None
44	Remove Perfect Collinearity	True
45	Clustering	False
46	Clustering Iteration	None
47	Polynomial Features	False
48	Polynomial Degree	None
49	Trignometry Features	False
50	Polynomial Threshold	None
51	Group Features	False
52	Feature Selection	False
53	Feature Selection Method	classic
54	Features Selection Threshold	None
55	Feature Interaction	False
56	Feature Ratio	False
57	Interaction Threshold	None
58	Fix Imbalance	False
59	Fix Imbalance Method	SMOTE

Out[62]:

```
([<pandas.io.formats.style.Styler at 0x7f10cc712f70>],
        Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
103058     2724.0    90.0    4.0                            182.0
335432     3182.0   285.0   13.0                             42.0
128469     2612.0    66.0    8.0                             30.0
304327     3033.0    84.0    4.0                              0.0
284912     3229.0   333.0   16.0                            108.0
...           ...     ...    ...                              ...
273280     2217.0   333.0   29.0                            124.0
46317      3234.0   275.0   11.0                            874.0
368603     3226.0   315.0    1.0                            525.0
242362     2837.0   291.0   33.0                            201.0
17454      2665.0   189.0    5.0                            108.0

        Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
103058                            16.0                           1234.0
335432                             3.0                           4462.0
128469                            -5.0                           1138.0
304327                             0.0                           2850.0
284912                            20.0                           3141.0
...                                ...                              ...
273280                            43.0                           1434.0
46317                             59.0                           4142.0
368603                            42.0                            693.0
242362                            87.0                           1224.0
17454                             22.0                           1500.0

        Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
103058          226.0           233.0          141.0
335432          183.0           240.0          196.0
128469          229.0           224.0          128.0
304327          226.0           232.0          141.0
284912          182.0           218.0          175.0
...               ...             ...            ...
273280          141.0           188.0          179.0
46317           189.0           243.0          193.0
368603          216.0           237.0          159.0
242362          110.0           213.0          233.0
17454           220.0           243.0          159.0

        Horizontal_Distance_To_Fire_Points  ...  Soil_Type_30_0.0  \
103058                              2329.0  ...               1.0
335432                              1702.0  ...               1.0
128469                               430.0  ...               1.0
304327                              2791.0  ...               1.0
284912                              4195.0  ...               1.0
...                                    ...  ...               ...
273280                               808.0  ...               1.0
46317                               2481.0  ...               1.0
368603                              1746.0  ...               0.0
242362                              1289.0  ...               1.0
17454                               6504.0  ...               1.0

        Soil_Type_31_1.0  Soil_Type_32_0.0  Soil_Type_33_0.0  \
103058               0.0               1.0               1.0
335432               0.0               1.0               1.0
128469               0.0               1.0               1.0
304327               0.0               1.0               1.0
284912               0.0               1.0               1.0
...                  ...               ...               ...
273280               0.0               1.0               1.0
46317                0.0               1.0               1.0
368603               0.0               1.0               1.0
242362               0.0               1.0               1.0
17454                0.0               1.0               1.0

        Soil_Type_34_0.0  Soil_Type_35_1.0  Soil_Type_36_0.0  \
103058               1.0               0.0               1.0
335432               1.0               0.0               1.0
128469               1.0               0.0               1.0
304327               1.0               0.0               1.0
284912               1.0               0.0               1.0
...                  ...               ...               ...
273280               1.0               0.0               1.0
46317                1.0               0.0               1.0
368603               1.0               0.0               1.0
242362               1.0               0.0               1.0
17454                1.0               0.0               1.0

        Soil_Type_37_1.0  Soil_Type_38_1.0  Soil_Type_39_0.0
103058               0.0               0.0               1.0
335432               0.0               0.0               1.0
128469               0.0               0.0               1.0
304327               0.0               0.0               1.0
284912               1.0               0.0               1.0
...                  ...               ...               ...
273280               0.0               0.0               1.0
46317                0.0               0.0               1.0
368603               0.0               0.0               1.0
242362               0.0               0.0               1.0
17454                0.0               0.0               1.0

[174304 rows x 54 columns],
        Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
0          2596.0    51.0    3.0                            258.0
1          2590.0    56.0    2.0                            212.0
2          2804.0   139.0    9.0                            268.0
3          2785.0   155.0   18.0                            242.0
4          2595.0    45.0    2.0                            153.0
...           ...     ...    ...                              ...
581007     2396.0   153.0   20.0                             85.0
581008     2391.0   152.0   19.0                             67.0
581009     2386.0   159.0   17.0                             60.0
581010     2384.0   170.0   15.0                             60.0
581011     2383.0   165.0   13.0                             60.0

        Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
0                                  0.0                            510.0
1                                 -6.0                            390.0
2                                 65.0                           3180.0
3                                118.0                           3090.0
4                                 -1.0                            391.0
...                                ...                              ...
581007                            17.0                            108.0
581008                            12.0                             95.0
581009                             7.0                             90.0
581010                             5.0                             90.0
581011                             4.0                             67.0

        Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
0               221.0           232.0          148.0
1               220.0           235.0          151.0
2               234.0           238.0          135.0
3               238.0           238.0          122.0
4               220.0           234.0          150.0
...               ...             ...            ...
581007          240.0           237.0          118.0
581008          240.0           237.0          119.0
581009          236.0           241.0          130.0
581010          230.0           245.0          143.0
581011          231.0           244.0          141.0

        Horizontal_Distance_To_Fire_Points  ...  Soil_Type_31  Soil_Type_32  \
0                                   6279.0  ...           0.0           0.0
1                                   6225.0  ...           0.0           0.0
2                                   6121.0  ...           0.0           0.0
3                                   6211.0  ...           0.0           0.0
4                                   6172.0  ...           0.0           0.0
...                                    ...  ...           ...           ...
581007                               837.0  ...           0.0           0.0
581008                               845.0  ...           0.0           0.0
581009                               854.0  ...           0.0           0.0
581010                               864.0  ...           0.0           0.0
581011                               875.0  ...           0.0           0.0

        Soil_Type_33  Soil_Type_34  Soil_Type_35  Soil_Type_36  Soil_Type_37  \
0                0.0           0.0           0.0           0.0           0.0
1                0.0           0.0           0.0           0.0           0.0
2                0.0           0.0           0.0           0.0           0.0
3                0.0           0.0           0.0           0.0           0.0
4                0.0           0.0           0.0           0.0           0.0
...              ...           ...           ...           ...           ...
581007           0.0           0.0           0.0           0.0           0.0
581008           0.0           0.0           0.0           0.0           0.0
581009           0.0           0.0           0.0           0.0           0.0
581010           0.0           0.0           0.0           0.0           0.0
581011           0.0           0.0           0.0           0.0           0.0

        Soil_Type_38  Soil_Type_39  Cover_Type
0                0.0           0.0           5
1                0.0           0.0           5
2                0.0           0.0           2
3                0.0           0.0           2
4                0.0           0.0           5
...              ...           ...         ...
581007           0.0           0.0           3
581008           0.0           0.0           3
581009           0.0           0.0           3
581010           0.0           0.0           3
581011           0.0           0.0           3

[581012 rows x 55 columns],
False,
        Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
57439      2587.0   130.0    7.0                             90.0
171107     3083.0    32.0    8.0                             30.0
411248     2805.0   296.0   13.0                            170.0
329367     3113.0    32.0    8.0                             30.0
67415      2642.0    77.0   13.0                            277.0
...           ...     ...    ...                              ...
287843     3257.0    82.0   22.0                            537.0
462415     3024.0    50.0   20.0                            560.0
349350     2677.0   122.0   16.0                            277.0
439600     3124.0     7.0   17.0                            510.0
109060     2747.0    87.0    5.0                              0.0

        Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
57439                            -12.0                            892.0
171107                             4.0                           3749.0
411248                            47.0                           2432.0
329367                            -2.0                           1605.0
67415                             -9.0                           1302.0
...                                ...                              ...
287843                            33.0                           1071.0
462415                           211.0                            600.0
349350                             2.0                           1487.0
439600                           128.0                           2343.0
109060                             0.0                           3783.0

        Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
57439           233.0           236.0          136.0
171107          219.0           224.0          141.0
411248          182.0           235.0          193.0
329367          219.0           224.0          141.0
67415           236.0           216.0          108.0
...               ...             ...            ...
287843          244.0           196.0           71.0
462415          225.0           191.0           92.0
349350          245.0           226.0          105.0
439600          196.0           203.0          141.0
109060          227.0           232.0          140.0

        Horizontal_Distance_To_Fire_Points  ...  Soil_Type_30_0.0  \
57439                               2190.0  ...               1.0
171107                              1639.0  ...               1.0
411248                               644.0  ...               1.0
329367                               576.0  ...               0.0
67415                                853.0  ...               1.0
...                                    ...  ...               ...
287843                              2086.0  ...               1.0
462415                               872.0  ...               1.0
349350                               912.0  ...               1.0
439600                              2513.0  ...               1.0
109060                              1140.0  ...               1.0

        Soil_Type_31_1.0  Soil_Type_32_0.0  Soil_Type_33_0.0  \
57439                0.0               1.0               1.0
171107               0.0               1.0               1.0
411248               0.0               1.0               1.0
329367               0.0               1.0               1.0
67415                0.0               1.0               1.0
...                  ...               ...               ...
287843               0.0               1.0               1.0
462415               0.0               0.0               1.0
349350               0.0               1.0               1.0
439600               0.0               1.0               1.0
109060               0.0               1.0               1.0

        Soil_Type_34_0.0  Soil_Type_35_1.0  Soil_Type_36_0.0  \
57439                1.0               0.0               1.0
171107               1.0               0.0               1.0
411248               1.0               0.0               1.0
329367               1.0               0.0               1.0
67415                1.0               0.0               1.0
...                  ...               ...               ...
287843               1.0               0.0               1.0
462415               1.0               0.0               1.0
349350               1.0               0.0               1.0
439600               1.0               0.0               1.0
109060               1.0               0.0               1.0

        Soil_Type_37_1.0  Soil_Type_38_1.0  Soil_Type_39_0.0
57439                0.0               0.0               1.0
171107               0.0               0.0               1.0
411248               0.0               0.0               1.0
329367               0.0               0.0               1.0
67415                0.0               0.0               1.0
...                  ...               ...               ...
287843               0.0               0.0               0.0
462415               0.0               0.0               1.0
349350               0.0               0.0               1.0
439600               0.0               0.0               1.0
109060               0.0               0.0               1.0

[406708 rows x 54 columns],
{'lr': <pycaret.containers.models.classification.LogisticRegressionClassifierContainer at 0x7f10c56cf8b0>,
 'knn': <pycaret.containers.models.classification.KNeighborsClassifierContainer at 0x7f10c56cfd00>,
 'nb': <pycaret.containers.models.classification.GaussianNBClassifierContainer at 0x7f10c56cfd30>,
 'dt': <pycaret.containers.models.classification.DecisionTreeClassifierContainer at 0x7f103f0ed550>,
 'svm': <pycaret.containers.models.classification.SGDClassifierContainer at 0x7f103f0ed0d0>,
 'rbfsvm': <pycaret.containers.models.classification.SVCClassifierContainer at 0x7f1034771190>,
 'gpc': <pycaret.containers.models.classification.GaussianProcessClassifierContainer at 0x7f10347714c0>,
 'mlp': <pycaret.containers.models.classification.MLPClassifierContainer at 0x7f10347715e0>,
 'ridge': <pycaret.containers.models.classification.RidgeClassifierContainer at 0x7f0fccde7ee0>,
 'rf': <pycaret.containers.models.classification.RandomForestClassifierContainer at 0x7f10509bfdf0>,
 'qda': <pycaret.containers.models.classification.QuadraticDiscriminantAnalysisContainer at 0x7f10509bf790>,
 'ada': <pycaret.containers.models.classification.AdaBoostClassifierContainer at 0x7f10509bf070>,
 'gbc': <pycaret.containers.models.classification.GradientBoostingClassifierContainer at 0x7f10cc722970>,
 'lda': <pycaret.containers.models.classification.LinearDiscriminantAnalysisContainer at 0x7f10cc722a00>,
 'et': <pycaret.containers.models.classification.ExtraTreesClassifierContainer at 0x7f10cc722e50>,
 'xgboost': <pycaret.containers.models.classification.XGBClassifierContainer at 0x7f10cc722ee0>,
 'lightgbm': <pycaret.containers.models.classification.LGBMClassifierContainer at 0x7f10cc71e3a0>,
 'dummy': <pycaret.containers.models.classification.DummyClassifierContainer at 0x7f10cc71eb50>},
{'acc': <pycaret.containers.metrics.classification.AccuracyMetricContainer at 0x7f10cc7127f0>,
 'auc': <pycaret.containers.metrics.classification.ROCAUCMetricContainer at 0x7f10cc712850>,
 'recall': <pycaret.containers.metrics.classification.RecallMetricContainer at 0x7f10cc7128e0>,
 'precision': <pycaret.containers.metrics.classification.PrecisionMetricContainer at 0x7f10cc712a30>,
 'f1': <pycaret.containers.metrics.classification.F1MetricContainer at 0x7f10cc712b80>,
 'kappa': <pycaret.containers.metrics.classification.KappaMetricContainer at 0x7f10cc712cd0>,
 'mcc': <pycaret.containers.metrics.classification.MCCMetricContainer at 0x7f10cc712d60>},
-1,
False,
False,
'Cover_Type',
{'parameter': 'Hyperparameters',
 'auc': 'AUC',
 'confusion_matrix': 'Confusion Matrix',
 'threshold': 'Threshold',
 'pr': 'Precision Recall',
 'error': 'Prediction Error',
 'class_report': 'Class Report',
 'rfe': 'Feature Selection',
 'learning': 'Learning Curve',
 'manifold': 'Manifold Learning',
 'calibration': 'Calibration Curve',
 'vc': 'Validation Curve',
 'dimension': 'Dimensions',
 'feature': 'Feature Importance',
 'feature_all': 'Feature Importance (All)',
 'boundary': 'Decision Boundary',
 'lift': 'Lift Chart',
 'gain': 'Gain Chart',
 'tree': 'Decision Tree',
 'ks': 'KS Statistic Plot'},
Pipeline(memory=None, steps=[('empty_step', 'passthrough')], verbose=False),
'clf-default-name',
None,
0         5
1         5
2         2
3         2
4         5
         ..
581007    3
581008    3
581009    3
581010    3
581011    3
Name: Cover_Type, Length: 581012, dtype: int64,
[],
'6e5d',
False,
False,
Pipeline(memory=None,
         steps=[('dtypes',
                 DataTypes_Auto_infer(categorical_features=[],
                                      display_types=True, features_todrop=[],
                                      id_columns=[],
                                      ml_usecase='classification',
                                      numerical_features=[],
                                      target='Cover_Type', time_features=[])),
                ('imputer',
                 Simple_Imputer(categorical_strategy='not_available',
                                fill_value_categorical=None,
                                fill_value_numerical=None,
                                numeric_s...
                ('scaling', 'passthrough'), ('P_transform', 'passthrough'),
                ('binn', 'passthrough'), ('rem_outliers', 'passthrough'),
                ('cluster_all', 'passthrough'),
                ('dummy', Dummify(target='Cover_Type')),
                ('fix_perfect', Remove_100(target='Cover_Type')),
                ('clean_names', Clean_Colum_Names()),
                ('feature_select', 'passthrough'), ('fix_multi', 'passthrough'),
                ('dfs', 'passthrough'), ('pca', 'passthrough')],
         verbose=False),
None,
[],
'box-cox',
{'USI',
 'X',
 'X_test',
 'X_train',
 '_all_metrics',
 '_all_models',
 '_all_models_internal',
 '_available_plots',
 '_gpu_n_jobs_param',
 '_internal_pipeline',
 '_ml_usecase',
 'create_model_container',
 'dashboard_logger',
 'data_before_preprocess',
 'display_container',
 'exp_name_log',
 'experiment__',
 'fix_imbalance_method_param',
 'fix_imbalance_param',
 'fold_generator',
 'fold_groups_param',
 'fold_groups_param_full',
 'fold_param',
 'fold_shuffle_param',
 'gpu_param',
 'html_param',
 'imputation_classifier',
 'imputation_regressor',
 'iterative_imputation_iters_param',
 'log_plots_param',
 'logging_param',
 'master_model_container',
 'n_jobs_param',
 'prep_pipe',
 'pycaret_globals',
 'seed',
 'stratify_param',
 'target_param',
 'transform_target_method_param',
 'transform_target_param',
 'y',
 'y_test',
 'y_train'},
StratifiedKFold(n_splits=10, random_state=None, shuffle=False),
<MLUsecase.CLASSIFICATION: 1>,
5,
False,
[('Setup Config',
                               Description             Value
  0                             session_id               844
  1                                 Target        Cover_Type
  2                            Target Type        Multiclass
  3                          Label Encoded              None
  4                          Original Data      (581012, 55)
  5                         Missing Values             False
  6                       Numeric Features                10
  7                   Categorical Features                44
  8                       Ordinal Features             False
  9              High Cardinality Features             False
  10               High Cardinality Method              None
  11                 Transformed Train Set      (406708, 54)
  12                  Transformed Test Set      (174304, 54)
  13                    Shuffle Train-Test              True
  14                   Stratify Train-Test             False
  15                        Fold Generator   StratifiedKFold
  16                           Fold Number                10
  17                              CPU Jobs                -1
  18                               Use GPU             False
  19                        Log Experiment             False
  20                       Experiment Name  clf-default-name
  21                                   USI              6e5d
  22                       Imputation Type            simple
  23        Iterative Imputation Iteration              None
  24                      Numeric Imputer              mean
  25    Iterative Imputation Numeric Model              None
  26                   Categorical Imputer          constant
  27 Iterative Imputation Categorical Model              None
  28         Unknown Categoricals Handling    least_frequent
  29                             Normalize             False
  30                      Normalize Method              None
  31                        Transformation             False
  32                 Transformation Method              None
  33                                   PCA             False
  34                            PCA Method              None
  35                        PCA Components              None
  36                   Ignore Low Variance             False
  37                    Combine Rare Levels             False
  38                   Rare Level Threshold              None
  39                       Numeric Binning             False
  40                       Remove Outliers             False
  41                    Outliers Threshold              None
  42              Remove Multicollinearity             False
  43           Multicollinearity Threshold              None
  44           Remove Perfect Collinearity              True
  45                            Clustering             False
  46                  Clustering Iteration              None
  47                   Polynomial Features             False
  48                     Polynomial Degree              None
  49                  Trignometry Features             False
  50                  Polynomial Threshold              None
  51                        Group Features             False
  52                     Feature Selection             False
  53              Feature Selection Method           classic
  54          Features Selection Threshold              None
  55                   Feature Interaction             False
  56                         Feature Ratio             False
  57                 Interaction Threshold              None
  58                         Fix Imbalance             False
  59                  Fix Imbalance Method             SMOTE),
 ('X_training Set',
          Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
  57439      2587.0   130.0    7.0                             90.0
  171107     3083.0    32.0    8.0                             30.0
  411248     2805.0   296.0   13.0                            170.0
  329367     3113.0    32.0    8.0                             30.0
  67415      2642.0    77.0   13.0                            277.0
  ...           ...     ...    ...                              ...
  287843     3257.0    82.0   22.0                            537.0
  462415     3024.0    50.0   20.0                            560.0
  349350     2677.0   122.0   16.0                            277.0
  439600     3124.0     7.0   17.0                            510.0
  109060     2747.0    87.0    5.0                              0.0

          Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
  57439                            -12.0                            892.0
  171107                             4.0                           3749.0
  411248                            47.0                           2432.0
  329367                            -2.0                           1605.0
  67415                             -9.0                           1302.0
  ...                                ...                              ...
  287843                            33.0                           1071.0
  462415                           211.0                            600.0
  349350                             2.0                           1487.0
  439600                           128.0                           2343.0
  109060                             0.0                           3783.0

          Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
  57439           233.0           236.0          136.0
  171107          219.0           224.0          141.0
  411248          182.0           235.0          193.0
  329367          219.0           224.0          141.0
  67415           236.0           216.0          108.0
  ...               ...             ...            ...
  287843          244.0           196.0           71.0
  462415          225.0           191.0           92.0
  349350          245.0           226.0          105.0
  439600          196.0           203.0          141.0
  109060          227.0           232.0          140.0

          Horizontal_Distance_To_Fire_Points  ...  Soil_Type_30_0.0  \
  57439                               2190.0  ...               1.0
  171107                              1639.0  ...               1.0
  411248                               644.0  ...               1.0
  329367                               576.0  ...               0.0
  67415                                853.0  ...               1.0
  ...                                    ...  ...               ...
  287843                              2086.0  ...               1.0
  462415                               872.0  ...               1.0
  349350                               912.0  ...               1.0
  439600                              2513.0  ...               1.0
  109060                              1140.0  ...               1.0

          Soil_Type_31_1.0  Soil_Type_32_0.0  Soil_Type_33_0.0  \
  57439                0.0               1.0               1.0
  171107               0.0               1.0               1.0
  411248               0.0               1.0               1.0
  329367               0.0               1.0               1.0
  67415                0.0               1.0               1.0
  ...                  ...               ...               ...
  287843               0.0               1.0               1.0
  462415               0.0               0.0               1.0
  349350               0.0               1.0               1.0
  439600               0.0               1.0               1.0
  109060               0.0               1.0               1.0

          Soil_Type_34_0.0  Soil_Type_35_1.0  Soil_Type_36_0.0  \
  57439                1.0               0.0               1.0
  171107               1.0               0.0               1.0
  411248               1.0               0.0               1.0
  329367               1.0               0.0               1.0
  67415                1.0               0.0               1.0
  ...                  ...               ...               ...
  287843               1.0               0.0               1.0
  462415               1.0               0.0               1.0
  349350               1.0               0.0               1.0
  439600               1.0               0.0               1.0
  109060               1.0               0.0               1.0

          Soil_Type_37_1.0  Soil_Type_38_1.0  Soil_Type_39_0.0
  57439                0.0               0.0               1.0
  171107               0.0               0.0               1.0
  411248               0.0               0.0               1.0
  329367               0.0               0.0               1.0
  67415                0.0               0.0               1.0
  ...                  ...               ...               ...
  287843               0.0               0.0               0.0
  462415               0.0               0.0               1.0
  349350               0.0               0.0               1.0
  439600               0.0               0.0               1.0
  109060               0.0               0.0               1.0

  [406708 rows x 54 columns]),
 ('y_training Set',
  57439     2
  171107    2
  411248    1
  329367    1
  67415     2
           ..
  287843    1
  462415    2
  349350    3
  439600    1
  109060    1
  Name: Cover_Type, Length: 406708, dtype: int64),
 ('X_test Set',
          Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
  103058     2724.0    90.0    4.0                            182.0
  335432     3182.0   285.0   13.0                             42.0
  128469     2612.0    66.0    8.0                             30.0
  304327     3033.0    84.0    4.0                              0.0
  284912     3229.0   333.0   16.0                            108.0
  ...           ...     ...    ...                              ...
  273280     2217.0   333.0   29.0                            124.0
  46317      3234.0   275.0   11.0                            874.0
  368603     3226.0   315.0    1.0                            525.0
  242362     2837.0   291.0   33.0                            201.0
  17454      2665.0   189.0    5.0                            108.0

          Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
  103058                            16.0                           1234.0
  335432                             3.0                           4462.0
  128469                            -5.0                           1138.0
  304327                             0.0                           2850.0
  284912                            20.0                           3141.0
  ...                                ...                              ...
  273280                            43.0                           1434.0
  46317                             59.0                           4142.0
  368603                            42.0                            693.0
  242362                            87.0                           1224.0
  17454                             22.0                           1500.0

          Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
  103058          226.0           233.0          141.0
  335432          183.0           240.0          196.0
  128469          229.0           224.0          128.0
  304327          226.0           232.0          141.0
  284912          182.0           218.0          175.0
  ...               ...             ...            ...
  273280          141.0           188.0          179.0
  46317           189.0           243.0          193.0
  368603          216.0           237.0          159.0
  242362          110.0           213.0          233.0
  17454           220.0           243.0          159.0

          Horizontal_Distance_To_Fire_Points  ...  Soil_Type_30_0.0  \
  103058                              2329.0  ...               1.0
  335432                              1702.0  ...               1.0
  128469                               430.0  ...               1.0
  304327                              2791.0  ...               1.0
  284912                              4195.0  ...               1.0
  ...                                    ...  ...               ...
  273280                               808.0  ...               1.0
  46317                               2481.0  ...               1.0
  368603                              1746.0  ...               0.0
  242362                              1289.0  ...               1.0
  17454                               6504.0  ...               1.0

          Soil_Type_31_1.0  Soil_Type_32_0.0  Soil_Type_33_0.0  \
  103058               0.0               1.0               1.0
  335432               0.0               1.0               1.0
  128469               0.0               1.0               1.0
  304327               0.0               1.0               1.0
  284912               0.0               1.0               1.0
  ...                  ...               ...               ...
  273280               0.0               1.0               1.0
  46317                0.0               1.0               1.0
  368603               0.0               1.0               1.0
  242362               0.0               1.0               1.0
  17454                0.0               1.0               1.0

          Soil_Type_34_0.0  Soil_Type_35_1.0  Soil_Type_36_0.0  \
  103058               1.0               0.0               1.0
  335432               1.0               0.0               1.0
  128469               1.0               0.0               1.0
  304327               1.0               0.0               1.0
  284912               1.0               0.0               1.0
  ...                  ...               ...               ...
  273280               1.0               0.0               1.0
  46317                1.0               0.0               1.0
  368603               1.0               0.0               1.0
  242362               1.0               0.0               1.0
  17454                1.0               0.0               1.0

          Soil_Type_37_1.0  Soil_Type_38_1.0  Soil_Type_39_0.0
  103058               0.0               0.0               1.0
  335432               0.0               0.0               1.0
  128469               0.0               0.0               1.0
  304327               0.0               0.0               1.0
  284912               1.0               0.0               1.0
  ...                  ...               ...               ...
  273280               0.0               0.0               1.0
  46317                0.0               0.0               1.0
  368603               0.0               0.0               1.0
  242362               0.0               0.0               1.0
  17454                0.0               0.0               1.0

  [174304 rows x 54 columns]),
 ('y_test Set',
  103058    2
  335432    1
  128469    2
  304327    1
  284912    1
           ..
  273280    3
  46317     1
  368603    2
  242362    2
  17454     2
  Name: Cover_Type, Length: 174304, dtype: int64),
 ('Transformation Pipeline',
  Pipeline(memory=None,
           steps=[('dtypes',
                   DataTypes_Auto_infer(categorical_features=[],
                                        display_types=True, features_todrop=[],
                                        id_columns=[],
                                        ml_usecase='classification',
                                        numerical_features=[],
                                        target='Cover_Type', time_features=[])),
                  ('imputer',
                   Simple_Imputer(categorical_strategy='not_available',
                                  fill_value_categorical=None,
                                  fill_value_numerical=None,
                                  numeric_s...
                  ('scaling', 'passthrough'), ('P_transform', 'passthrough'),
                  ('binn', 'passthrough'), ('rem_outliers', 'passthrough'),
                  ('cluster_all', 'passthrough'),
                  ('dummy', Dummify(target='Cover_Type')),
                  ('fix_perfect', Remove_100(target='Cover_Type')),
                  ('clean_names', Clean_Colum_Names()),
                  ('feature_select', 'passthrough'), ('fix_multi', 'passthrough'),
                  ('dfs', 'passthrough'), ('pca', 'passthrough')],
           verbose=False))],
{'lr': <pycaret.containers.models.classification.LogisticRegressionClassifierContainer at 0x7f10cc71ee20>,
 'knn': <pycaret.containers.models.classification.KNeighborsClassifierContainer at 0x7f10cc71ef70>,
 'nb': <pycaret.containers.models.classification.GaussianNBClassifierContainer at 0x7f10cc71ee50>,
 'dt': <pycaret.containers.models.classification.DecisionTreeClassifierContainer at 0x7f10cc71ebb0>,
 'svm': <pycaret.containers.models.classification.SGDClassifierContainer at 0x7f10cc71ec10>,
 'rbfsvm': <pycaret.containers.models.classification.SVCClassifierContainer at 0x7f10701b2490>,
 'gpc': <pycaret.containers.models.classification.GaussianProcessClassifierContainer at 0x7f10701b25b0>,
 'mlp': <pycaret.containers.models.classification.MLPClassifierContainer at 0x7f10701b2670>,
 'ridge': <pycaret.containers.models.classification.RidgeClassifierContainer at 0x7f10701b2910>,
 'rf': <pycaret.containers.models.classification.RandomForestClassifierContainer at 0x7f10701b2a90>,
 'qda': <pycaret.containers.models.classification.QuadraticDiscriminantAnalysisContainer at 0x7f10701b2ca0>,
 'ada': <pycaret.containers.models.classification.AdaBoostClassifierContainer at 0x7f10cc715070>,
 'gbc': <pycaret.containers.models.classification.GradientBoostingClassifierContainer at 0x7f10cc7151f0>,
 'lda': <pycaret.containers.models.classification.LinearDiscriminantAnalysisContainer at 0x7f10cc715250>,
 'et': <pycaret.containers.models.classification.ExtraTreesClassifierContainer at 0x7f10cc7156d0>,
 'xgboost': <pycaret.containers.models.classification.XGBClassifierContainer at 0x7f10cc715730>,
 'lightgbm': <pycaret.containers.models.classification.LGBMClassifierContainer at 0x7f10cc715cd0>,
 'dummy': <pycaret.containers.models.classification.DummyClassifierContainer at 0x7f10cc7124c0>,
 'Bagging': <pycaret.containers.models.classification.BaggingClassifierContainer at 0x7f10cc712460>,
 'Stacking': <pycaret.containers.models.classification.StackingClassifierContainer at 0x7f10cc712610>,
 'Voting': <pycaret.containers.models.classification.VotingClassifierContainer at 0x7f10cc712700>,
 'CalibratedCV': <pycaret.containers.models.classification.CalibratedClassifierCVContainer at 0x7f10cc712760
>},
-1,
True,
103058    2
335432    1
128469    2
304327    1
284912    1
         ..
273280    3
46317     1
368603    2
242362    2
17454     2
Name: Cover_Type, Length: 174304, dtype: int64,
        Elevation  Aspect  Slope  Horizontal_Distance_To_Hydrology  \
0          2596.0    51.0    3.0                            258.0
1          2590.0    56.0    2.0                            212.0
2          2804.0   139.0    9.0                            268.0
3          2785.0   155.0   18.0                            242.0
4          2595.0    45.0    2.0                            153.0
...           ...     ...    ...                              ...
581007     2396.0   153.0   20.0                             85.0
581008     2391.0   152.0   19.0                             67.0
581009     2386.0   159.0   17.0                             60.0
581010     2384.0   170.0   15.0                             60.0
581011     2383.0   165.0   13.0                             60.0

        Vertical_Distance_To_Hydrology  Horizontal_Distance_To_Roadways  \
0                                  0.0                            510.0
1                                 -6.0                            390.0
2                                 65.0                           3180.0
3                                118.0                           3090.0
4                                 -1.0                            391.0
...                                ...                              ...
581007                            17.0                            108.0
581008                            12.0                             95.0
581009                             7.0                             90.0
581010                             5.0                             90.0
581011                             4.0                             67.0

        Hillshade_9am  Hillshade_Noon  Hillshade_3pm  \
0               221.0           232.0          148.0
1               220.0           235.0          151.0
2               234.0           238.0          135.0
3               238.0           238.0          122.0
4               220.0           234.0          150.0
...               ...             ...            ...
581007          240.0           237.0          118.0
581008          240.0           237.0          119.0
581009          236.0           241.0          130.0
581010          230.0           245.0          143.0
581011          231.0           244.0          141.0

        Horizontal_Distance_To_Fire_Points  ...  Soil_Type_30_0.0  \
0                                   6279.0  ...               1.0
1                                   6225.0  ...               1.0
2                                   6121.0  ...               1.0
3                                   6211.0  ...               1.0
4                                   6172.0  ...               1.0
...                                    ...  ...               ...
581007                               837.0  ...               1.0
581008                               845.0  ...               1.0
581009                               854.0  ...               1.0
581010                               864.0  ...               1.0
581011                               875.0  ...               1.0

        Soil_Type_31_1.0  Soil_Type_32_0.0  Soil_Type_33_0.0  \
0                    0.0               1.0               1.0
1                    0.0               1.0               1.0
2                    0.0               1.0               1.0
3                    0.0               1.0               1.0
4                    0.0               1.0               1.0
...                  ...               ...               ...
581007               0.0               1.0               1.0
581008               0.0               1.0               1.0
```

```
581009                 0.0                 1.0                 1.0
581010                 0.0                 1.0                 1.0
581011                 0.0                 1.0                 1.0

         Soil_Type_34_0.0  Soil_Type_35_1.0  Soil_Type_36_0.0  \
0                     1.0               0.0               1.0
1                     1.0               0.0               1.0
2                     1.0               0.0               1.0
3                     1.0               0.0               1.0
4                     1.0               0.0               1.0
...                   ...               ...               ...
581007                1.0               0.0               1.0
581008                1.0               0.0               1.0
581009                1.0               0.0               1.0
581010                1.0               0.0               1.0
581011                1.0               0.0               1.0

         Soil_Type_37_1.0  Soil_Type_38_1.0  Soil_Type_39_0.0
0                     0.0               0.0               1.0
1                     0.0               0.0               1.0
2                     0.0               0.0               1.0
3                     0.0               0.0               1.0
4                     0.0               0.0               1.0
...                   ...               ...               ...
581007                0.0               0.0               1.0
581008                0.0               0.0               1.0
581009                0.0               0.0               1.0
581010                0.0               0.0               1.0
581011                0.0               0.0               1.0

[581012 rows x 54 columns],
844,
None,
'lightgbm',
False,
10,
None,
57439     2
171107    2
411248    1
329367    1
67415     2
         ..
287843    1
462415    2
349350    3
439600    1
109060    1
Name: Cover_Type, Length: 406708, dtype: int64,
'lightgbm')
```

In [63]:
```python
# This model will be used to compare all the model along with the cross validation
best = compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
knn	K Neighbors Classifier	0.9635	0.9959	0.9202	0.9635	0.9635	0.9414	0.9414	1.3810
rf	Random Forest Classifier	0.9503	0.9944	0.8974	0.9504	0.9500	0.9198	0.9200	2.4210
et	Extra Trees Classifier	0.9492	0.9938	0.9019	0.9493	0.9489	0.9181	0.9183	2.9000
dt	Decision Tree Classifier	0.9317	0.9450	0.8909	0.9318	0.9318	0.8905	0.8905	0.8010
lightgbm	Light Gradient Boosting Machine	0.8516	0.9523	0.8091	0.8527	0.8515	0.7606	0.7610	2.1520
gbc	Gradient Boosting Classifier	0.7725	0.9065	0.6495	0.7718	0.7687	0.6282	0.6289	73.2880
ridge	Ridge Classifier	0.7007	0.0000	0.3716	0.6797	0.6779	0.5032	0.5055	0.2610
lr	Logistic Regression	0.6840	0.8353	0.3465	0.6503	0.6572	0.4648	0.4680	17.8680
lda	Linear Discriminant Analysis	0.6794	0.8369	0.5763	0.6941	0.6825	0.4963	0.4977	0.8170
svm	SVM - Linear Kernel	0.5326	0.0000	0.3238	0.6019	0.4838	0.2672	0.3134	19.4620
ada	Ada Boost Classifier	0.5190	0.6042	0.3673	0.6222	0.5348	0.2993	0.3150	2.4090
dummy	Dummy Classifier	0.4875	0.5000	0.1429	0.2377	0.3195	0.0000	0.0000	0.2410
nb	Naive Bayes	0.4571	0.7814	0.5877	0.6451	0.4153	0.2631	0.3076	0.2890
qda	Quadratic Discriminant Analysis	0.4542	0.5375	0.3036	0.4383	0.3569	0.0761	0.1080	0.3470

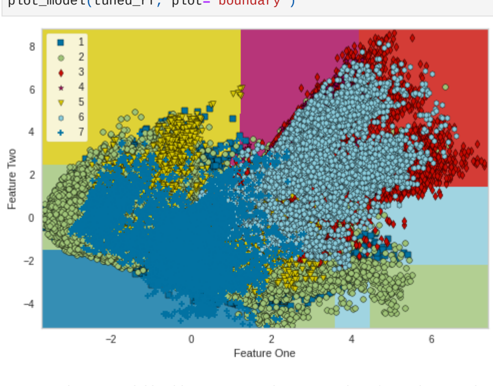
In [71]:
```python
# Build random forest classifier.
#I picked it eventhough it trankoed 2 due to the fact that we can extract feature importance
rf=create_model('rf')
```

Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.9493	0.9942	0.8912	0.9493	0.9489	0.9182	0.9183
1	0.9509	0.9945	0.8992	0.9510	0.9506	0.9207	0.9210
2	0.9502	0.9941	0.8978	0.9502	0.9498	0.9196	0.9198
3	0.9492	0.9944	0.8899	0.9493	0.9488	0.9180	0.9182
4	0.9512	0.9947	0.9045	0.9514	0.9510	0.9213	0.9216
5	0.9507	0.9944	0.8973	0.9509	0.9504	0.9205	0.9207
6	0.9502	0.9945	0.8990	0.9503	0.9500	0.9197	0.9199
7	0.9511	0.9947	0.9088	0.9511	0.9508	0.9211	0.9213
8	0.9491	0.9938	0.8828	0.9492	0.9488	0.9179	0.9181
9	0.9510	0.9948	0.9038	0.9511	0.9508	0.9211	0.9212
Mean	0.9503	0.9944	0.8974	0.9504	0.9500	0.9198	0.9200
Std	0.0008	0.0003	0.0073	0.0008	0.0008	0.0013	0.0013

In [72]:
```python
# Whenenver we compare different models or build a model, the model uses deault
#hyperparameter values. Hence, we need to tune our model to get better performance

tuned_rf=tune_model(rf)
```

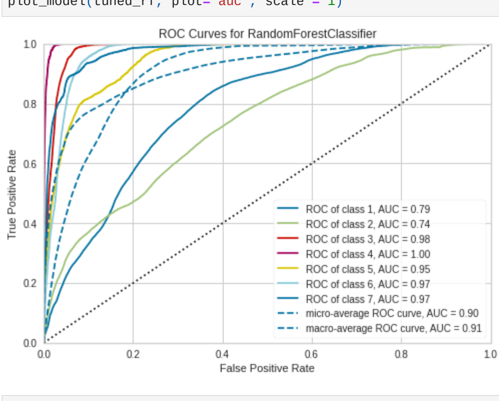
Fold	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.5197	0.7917	0.7069	0.6875	0.5476	0.3512	0.3782
1	0.5218	0.7910	0.7056	0.6831	0.5497	0.3515	0.3772
2	0.5230	0.7889	0.7110	0.6827	0.5512	0.3526	0.3778
3	0.5188	0.7885	0.7043	0.6816	0.5469	0.3486	0.3745
4	0.5291	0.7894	0.7145	0.6900	0.5575	0.3610	0.3872
5	0.5212	0.7890	0.7062	0.6895	0.5502	0.3530	0.3799
6	0.5177	0.7889	0.7017	0.6850	0.5468	0.3490	0.3758
7	0.5241	0.7876	0.7104	0.6872	0.5519	0.3553	0.3818
8	0.5204	0.7879	0.7081	0.6826	0.5491	0.3510	0.3768
9	0.5183	0.7915	0.7106	0.6826	0.5461	0.3484	0.3748
Mean	0.5214	0.7894	0.7079	0.6852	0.5497	0.3521	0.3784
Std	0.0032	0.0014	0.0036	0.0030	0.0032	0.0036	0.0036

In [73]:
```python
plot_model(tuned_rf, plot='boundary')
```

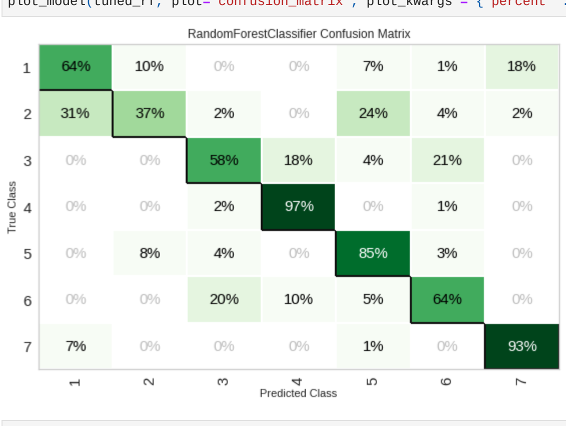


It seems the RF model is able to create a clear seperation of samples w.r.t decision boundary.

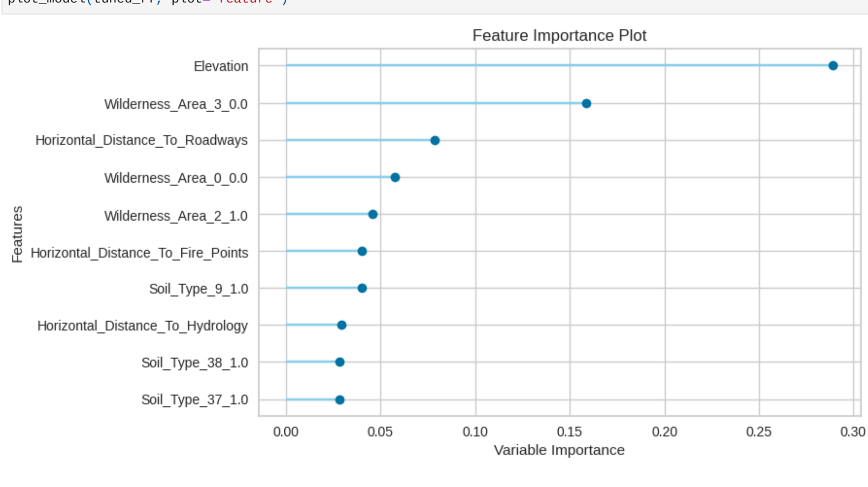
In [74]:
```python
plot_model(tuned_rf, plot='auc', scale = 1)
```



In [75]:
```python
plot_model(tuned_rf, plot='confusion_matrix', plot_kwargs = {'percent' : True})
```



In [76]:
```python
plot_model(tuned_rf, plot='feature')
```



As seen, Elevation, Wilderness_Area_0, Horizontal_Distance_To_Roadways, Wilderness_Area_0, and Wilderness_Area_2 turn to be are top-k features across different classes. This is somewhat identical to what we observed using the inspection wrapper.

Approach 5: using SHAP stacking ensemble

First, we train the StackingClassifier from sklearn, which is technically blending or stacking predictions from logistic regression, decision tree, and extra tree classifiers, where the random forest classifier works as the base estimator.

In [6]:
```python
import shap
import sklearn
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import ExtraTreesClassifier

# knn = KNeighborsClassifier()
# knn.fit(X_train, y_train)

lr = sklearn.linear_model.LogisticRegression(solver='liblinear')
lr.fit(X_train, y_train)

dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

et = ExtraTreesClassifier()
et.fit(X_train, y_train)

# svc_linear = sklearn.svm.SVC(kernel='linear', probability=True)
# svc_linear.fit(X_train, y_train)

rf = sklearn.ensemble.RandomForestClassifier()

# stacking_model = sklearn.ensemble.StackingClassifier([('knn', knn), ('svc', svc_linear)], rf)
stacking_model = sklearn.ensemble.StackingClassifier([('lr', lr), ('dt', dt), ('et', et)], rf)

stacking_model.fit(X_train, y_train)
```

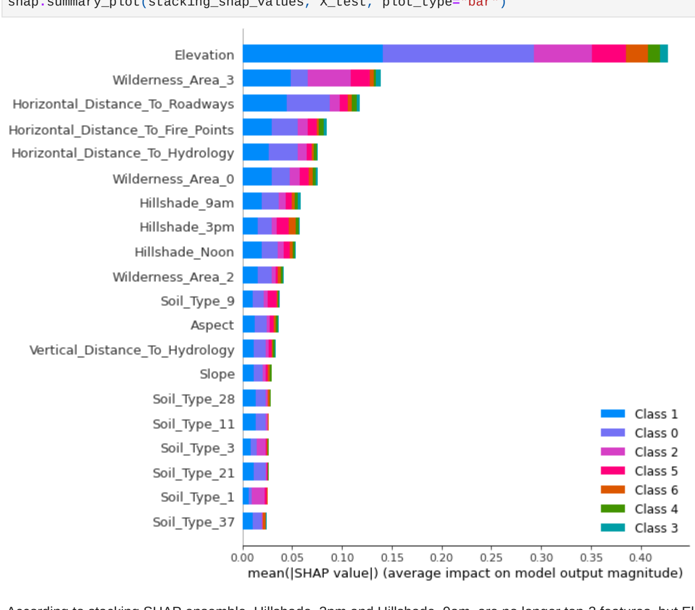
Out[6]:
```
StackingClassifier(estimators=[('lr', LogisticRegression(solver='liblinear')),
                               ('dt', DecisionTreeClassifier()),
                               ('et', ExtraTreesClassifier())],
                   final_estimator=RandomForestClassifier())
```

Then I employ SHAP to provide the explanations of the predictions made by StackingClassifier. RF is an ensemble technique that takes a subset of observations and a subset of variables to build decision trees that creates an ensemble of decision trees. RF first builds decision trees then integrates them to get a more accurate and stable prediction. This is a direct consequence since by maximum voting from a panel of independent juries, we get the final prediction better, fair, and trustworthy than the best jury.

In [10]:
```python
# Create a TreeExplainer and extract shap values from it - will be used for plotting later
stacking_explainer = shap.KernelExplainer(stacking_model.predict_proba, shap.sample(X_test, 100))

stacking_shap_values = stacking_explainer.shap_values(shap.sample(X_test, 100))
```

```
  0%|          | 0/100 [00:00<?, ?it/s]
```

In [11]:
```python
shap.summary_plot(stacking_shap_values, X_test, plot_type="bar")
```

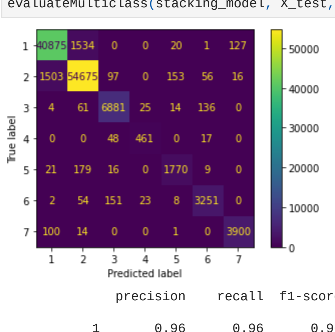


According to stacking SHAP ensemble, Hillshade_3pm and Hillshade_9am, are no longer top-2 features, but Elevation and Wilderness_Area_3 are across classes. Besides, we can see that features Horizontal_Distance_To_Roadways, Horizontal_Distance_To_Fire_Points, and Horizontal_Distance_to_Hydrology are included in top-5 important feature list. In summary, even if we rely on multiple models, we may end up with slightly different feature importance.

By the way, did we observe how does the stacking classifier performs on the test set? I wrote a method, which generates different metrics to evaluate the predictive power of the model on unseen test set in multi-class classification setting.

In [24]:
```python
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, accuracy_score, classificat
import matplotlib.pyplot as plt
from sklearn.metrics import plot_confusion_matrix, plot_roc_curve, plot_precision_recall_curve

def evaluateMulticlass(model, X_test, y_test):
    '''This method generates different metrics to evaluate the perdictive power of the model on unseen test set
    y_pred = model.predict(X_test)

    plot_confusion_matrix(model, X_test, y_test)
    plt.show()

    print(classification_report(y_test, y_pred))

    acc = accuracy_score(y_test, y_pred)
    print(f'Accuracy: {acc:.3f}')

    precision = precision_score(y_test, y_pred, average='micro')
    print(f'Precision: {precision:.3f}')

    recall = recall_score(y_test, y_pred, average='micro')
    print(f'Recall: {recall:.3f}')

    f1 = f1_score(y_test, y_pred, average='micro')
    print(f'F1 score: {f1:.3f}')

    mcc = matthews_corrcoef(y_test, y_pred)
    print(f'MCC score: {mcc:.3f}')
```

In [25]:
```python
evaluateMulticlass(stacking_model, X_test, y_test)
```




```
              precision    recall  f1-score   support

           1       0.96      0.96      0.96     42557
           2       0.97      0.97      0.97     56500
           3       0.96      0.97      0.96      7121
           4       0.91      0.88      0.89       526
           5       0.90      0.89      0.89      1995
           6       0.94      0.93      0.93      3489
           7       0.96      0.97      0.97      4015

    accuracy                           0.96    116203
   macro avg       0.94      0.94      0.94    116203
weighted avg       0.96      0.96      0.96    116203

Accuracy: 0.962
Precision: 0.962
Recall: 0.962
F1 score: 0.962
MCC score: 0.939
```

Feature selection

We can also use ELI5's feature selection method (well, of course, I could go for other approaches such as RFE), as it may be useful for introspection too. That is, once we compute feature importances, we can drop unimportant features.

In [ ]:
```python
import eli5
from eli5.sklearn import PermutationImportance
from sklearn.svm import SVC
from sklearn.feature_selection import SelectFromModel

import numpy as np
from eli5.permutation_importance import get_score_importances

perm = PermutationImportance(classifier, cv=5)
perm.fit(X_train, y_train)
```

Now that the PFI attribute is available, we can use it for feature selection. Besides, in order to avoid wanted feature, let's e.g. select only those features for which the accuracy is increase by at least 0.05:

In [ ]:
```python
sel = SelectFromModel(perm, threshold=0.05, prefit=True)
X_trans = sel.transform(X_train)
```

Note on feature selection by dropping less important ones

Research has suggested to use permutation feature importance (as well as other feature importance measures) very carefully. The reasoning is that, if several features are correlated, and the estimator uses them all equally, their corresponding permutation importance can be low for all of these features: dropping one of the features may not affect the result, as estimator still has an access to the same information from other features. Therefore, if features are dropped based on importance threshold, such correlated features could be dropped all at the same time, regardless their usefulness.

In [ ]: