Decision Tree

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import plot_confusion_matrix
```

In [4]:
```
df = pd.read_csv('data/data_no_fliers.csv')
df.drop('Unnamed: 0', axis=1, inplace=True)
df.head()
```

Out[4]:

	neo	pha	H	epoch	epoch_mjd	epoch_cal	e	a	q	i
0	0	0	3.40	2458600.5	58600	20190427.0	0.076009	2.769165	2.558684	10.594067
1	0	0	4.20	2459000.5	59000	20200531.0	0.229972	2.773841	2.135935	34.832932
2	0	0	5.33	2459000.5	59000	20200531.0	0.256936	2.668285	1.982706	12.991043
3	0	0	3.00	2458600.5	58600	20190427.0	0.088721	2.361418	2.151909	7.141771
4	0	0	6.90	2459000.5	59000	20200531.0	0.190913	2.574037	2.082619	5.367427

5 rows × 45 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 921430 entries, 0 to 921429
Data columns (total 45 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   neo        921430 non-null  int64  
 1   pha        921430 non-null  int64  
 2   H          921430 non-null  float64
 3   epoch      921430 non-null  float64
 4   epoch_mjd  921430 non-null  int64  
 5   epoch_cal  921430 non-null  float64
 6   e          921430 non-null  float64
 7   a          921430 non-null  float64
 8   q          921430 non-null  float64
 9   i          921430 non-null  float64
 10  om         921430 non-null  float64
 11  w          921430 non-null  float64
 12  ma         921430 non-null  float64
 13  ad         921430 non-null  float64
 14  n          921430 non-null  float64
 15  tp         921430 non-null  float64
 16  tp_cal     921430 non-null  float64
```

```
 17  per        921430 non-null  float64
 18  per_y      921430 non-null  float64
 19  moid       921430 non-null  float64
 20  moid_ld    921430 non-null  float64
 21  sigma_e    921430 non-null  float64
 22  sigma_a    921430 non-null  float64
 23  sigma_q    921430 non-null  float64
 24  sigma_i    921430 non-null  float64
 25  sigma_om   921430 non-null  float64
 26  sigma_w    921430 non-null  float64
 27  sigma_ma   921430 non-null  float64
 28  sigma_ad   921430 non-null  float64
 29  sigma_n    921430 non-null  float64
 30  sigma_tp   921430 non-null  float64
 31  sigma_per  921430 non-null  float64
 32  rms        921430 non-null  float64
 33  class_AMO  921430 non-null  int64
 34  class_APO  921430 non-null  int64
 35  class_AST  921430 non-null  int64
 36  class_ATE  921430 non-null  int64
 37  class_CEN  921430 non-null  int64
 38  class_IEO  921430 non-null  int64
 39  class_IMB  921430 non-null  int64
 40  class_MBA  921430 non-null  int64
 41  class_MCA  921430 non-null  int64
 42  class_OMB  921430 non-null  int64
 43  class_TJN  921430 non-null  int64
 44  class_TNO  921430 non-null  int64
dtypes: float64(30), int64(15)
memory usage: 316.3 MB
```

Iteration 1: Baseline

In [5]:

```
X = df.drop(['pha'], axis=1)
y = df['pha']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random
```

In [6]:

```
tree_pipe = Pipeline([('ss', StandardScaler()),
                      ('clf', DecisionTreeClassifier(random_state=123, class_weig
```

In [7]:

```
tree_pipe.fit(X_train, y_train)
y_pred = tree_pipe.predict(X_test)
```

In [8]:

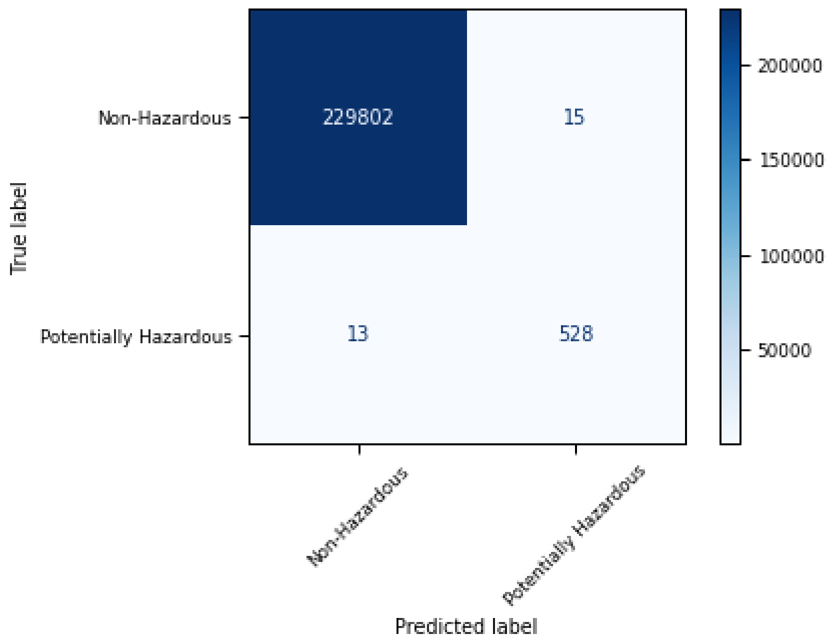
```
print('Train Report')
print(classification_report(y_train, tree_pipe.predict(X_train)))
print('\n')
print('Test Report')
print(classification_report(y_test, y_pred))
```

```
Train Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    689548
           1       1.00      1.00      1.00      1524

    accuracy                           1.00    691072
   macro avg       1.00      1.00      1.00    691072
weighted avg       1.00      1.00      1.00    691072
```

```
Test Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    229817
           1       0.97      0.98      0.97       541

    accuracy                           1.00    230358
   macro avg       0.99      0.99      0.99    230358
weighted avg       1.00      1.00      1.00    230358
```

The testing metrics look promising, but the model is overfit to the training data. The baseline model performs better than Iteration 3 of logistic regression. The macro avg for recall is 1% lower than it was in logistic regression: Iteration 3, and recall for the positive class is 2% lower, but these values will likely go up with enough model tuning.

In [58]:
```
sns.set_context('paper')

plot_confusion_matrix(tree_pipe, X_test, y_test, cmap=plt.cm.Blues,
                      display_labels=['Non-Hazardous', 'Potentially Hazardous'],
```



This model has fewer false positives than logistic regression, and I expect the number of false negatives to decrease as the model is tuned while prioritizing recall.

In [10]:
```
tree_pipe.steps[1][1].get_params()
```

Out[10]:
```
{'ccp_alpha': 0.0,
 'class_weight': {0: 1, 1: 200},
 'criterion': 'gini',
 'max_depth': None,
 'max_features': None,
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'presort': 'deprecated',
 'random_state': 123,
 'splitter': 'best'}
```

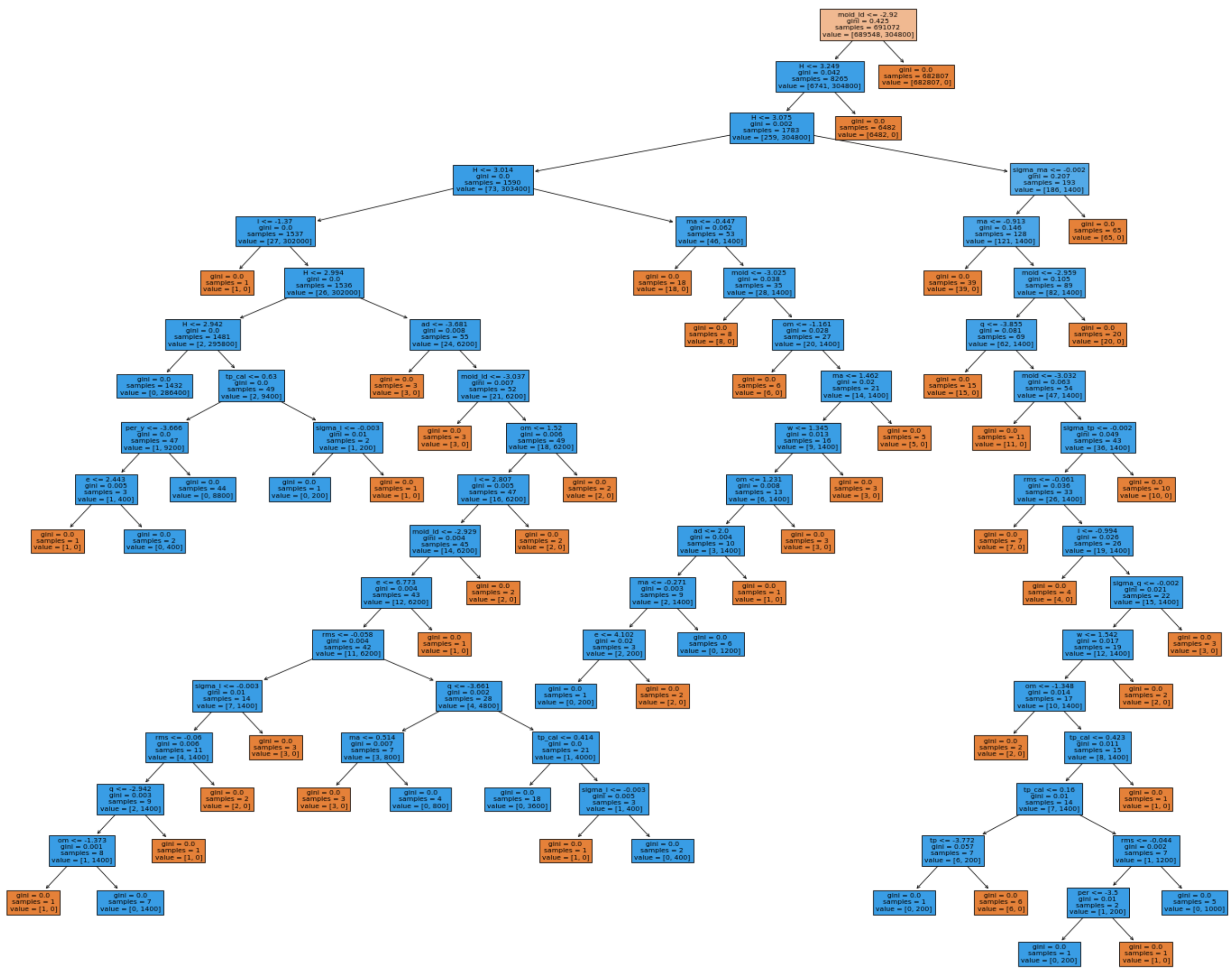
In [11]:
```
tree_pipe.steps[1][1].get_depth()
```

Out[11]:
```
18
```

The initial tree has a max depth of 18. Will try some lower values in the next iteration in order to address overfitting.

In [12]:
```
from sklearn.tree import plot_tree
```

In [59]:
```
fig= plt.figure(figsize=(25, 20))
_ = plot_tree(tree_pipe.steps[1][1],
              feature_names=X.columns,
              filled=True)
```



Iteration 2

This iteration attempts some initial pruning with values < 18 for `max_depth` and some higher values for `min_samples_leaf` and `min_samples_split` .

In [28]:
```
tree_pipe2 = Pipeline([('ss', StandardScaler()),
                       ('clf', DecisionTreeClassifier(random_state=123))])

param_grid = {
    'clf__class_weight': ['balanced', {0:1, 1:200}],
    'clf__max_depth': [8, 16],
    'clf__min_samples_leaf': [1, 3, 6, 9],
```

```
    'clf__min_samples_split': [2, 4, 6, 8]
}
```

In [29]:
```
tree_grid2 = GridSearchCV(tree_pipe2, param_grid=param_grid, cv=3, scoring='reca
```

In [30]:
```
tree_grid2.fit(X_train, y_train)
```

Out[30]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('clf',
                                        DecisionTreeClassifier(random_state=12
3))]),
             param_grid={'clf__class_weight': ['balanced', {0: 1, 1: 200}],
                         'clf__max_depth': [8, 16],
                         'clf__min_samples_leaf': [1, 3, 6, 9],
                         'clf__min_samples_split': [2, 4, 6, 8]},
             scoring='recall')
```

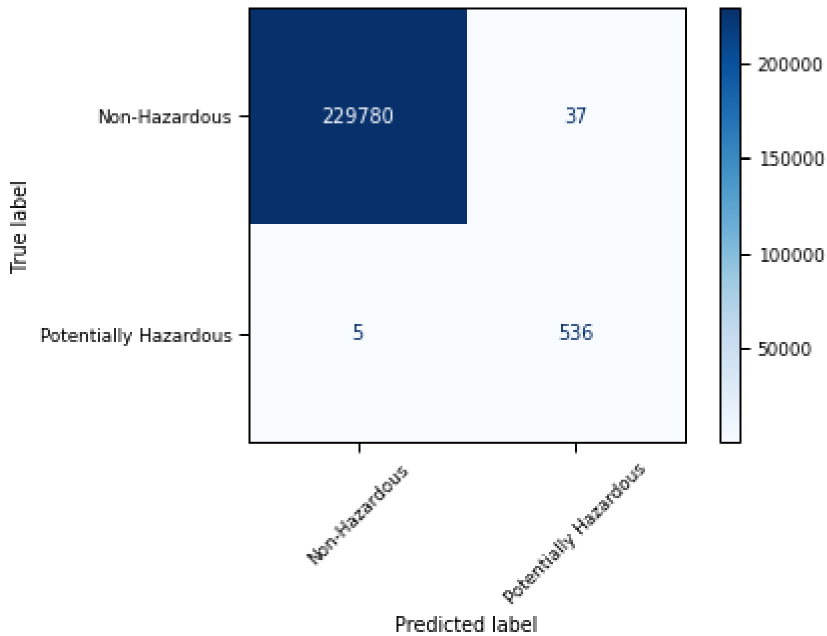
In [31]:
```
tree_grid2.best_estimator_
```

Out[31]:
```
Pipeline(steps=[('ss', StandardScaler()),
                ('clf',
                 DecisionTreeClassifier(class_weight='balanced', max_depth=8,
                                        min_samples_leaf=9,
                                        random_state=123))])
```

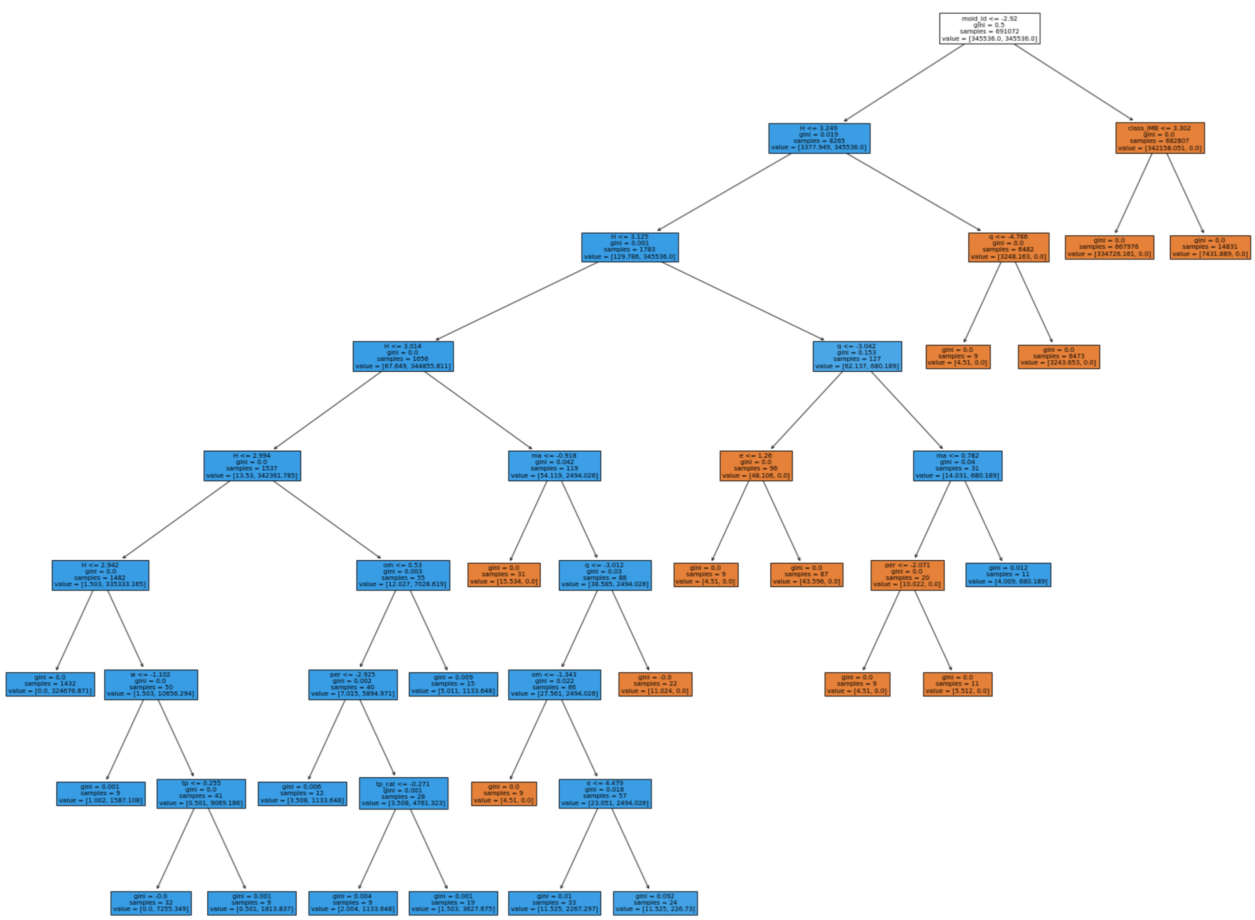
In [32]:
```
y_pred = tree_grid2.predict(X_test)

print('Train Report')
print(classification_report(y_train, tree_grid2.predict(X_train)))
print('\n')
print('Test Report')
print(classification_report(y_test, y_pred))
```

```
Train Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    689548
           1       0.95      1.00      0.97      1524

    accuracy                           1.00    691072
   macro avg       0.97      1.00      0.99    691072
weighted avg       1.00      1.00      1.00    691072



Test Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    229817
           1       0.94      0.99      0.96       541

    accuracy                           1.00    230358
   macro avg       0.97      1.00      0.98    230358
weighted avg       1.00      1.00      1.00    230358
```

In [60]:
```
plot_confusion_matrix(tree_grid2, X_test, y_test, cmap=plt.cm.Blues,
                      display_labels=['Non-Hazardous', 'Potentially Hazardous'],
```

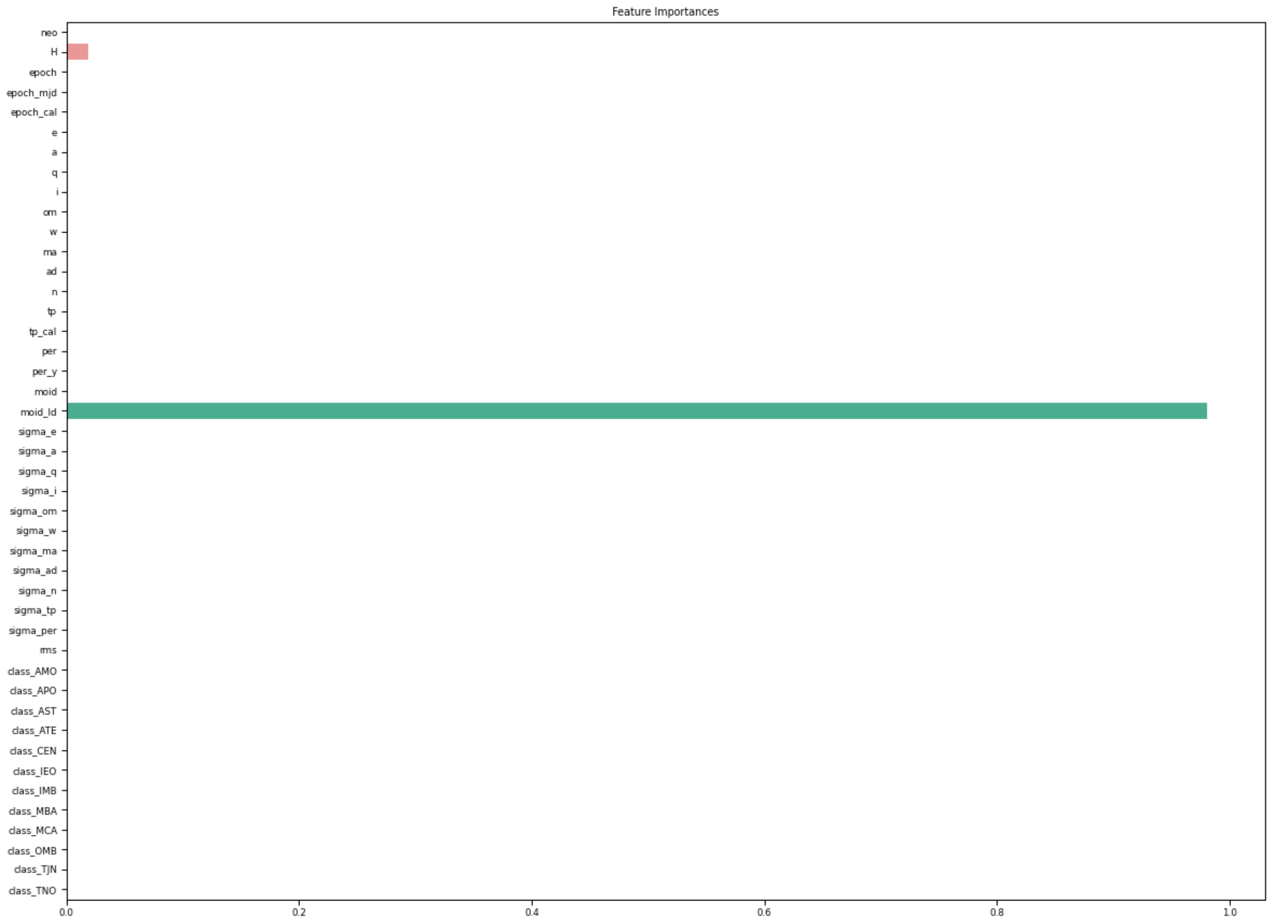


In [61]:
```
fig = plt.figure(figsize=(25, 20))
_ = plot_tree(tree_grid2.best_estimator_.steps[1][1],
              feature_names=X.columns,
              filled=True)
```



In [62]:
```
plt.figure(figsize=(20, 15))
sns.barplot(x = tree_grid2.best_estimator_.steps[1][1].feature_importances_,
```

```
                y = X.columns)
plt.title('Feature Importances');
```



`moid_ld` (closeness of orbit to orbit of Earth) is the most significant feature by far, followed by `H` (visual magnitude). Other features do not seem to have a signal in the feature importances plot, which is concerning.

In [36]:
```
tree_grid2.best_params_
```

Out[36]:
```
{'clf__class_weight': 'balanced',
 'clf__max_depth': 8,
 'clf__min_samples_leaf': 9,
 'clf__min_samples_split': 2}
```

The model chose the lower end of `max_depth`, the higher end of `min_samples_leaf`, and the default `min_samples_split`.

Iteration 3

This iteration searches around the best parameters of the previous iteration.

In [6]:
```
tree_pipe3 = Pipeline([('ss', StandardScaler()),
                       ('clf', DecisionTreeClassifier(random_state=123))])

param_grid = {
    'clf__class_weight': ['balanced', {0:1, 1:200}],
    'clf__max_depth': [4, 6, 8, 12],
    'clf__min_samples_leaf': [7, 8, 9, 10, 11],
    'clf__min_samples_split': [2, 3, 4]
}
```

In [7]:
```
tree_grid3 = GridSearchCV(tree_pipe3, param_grid=param_grid, cv=3, scoring='reca
```

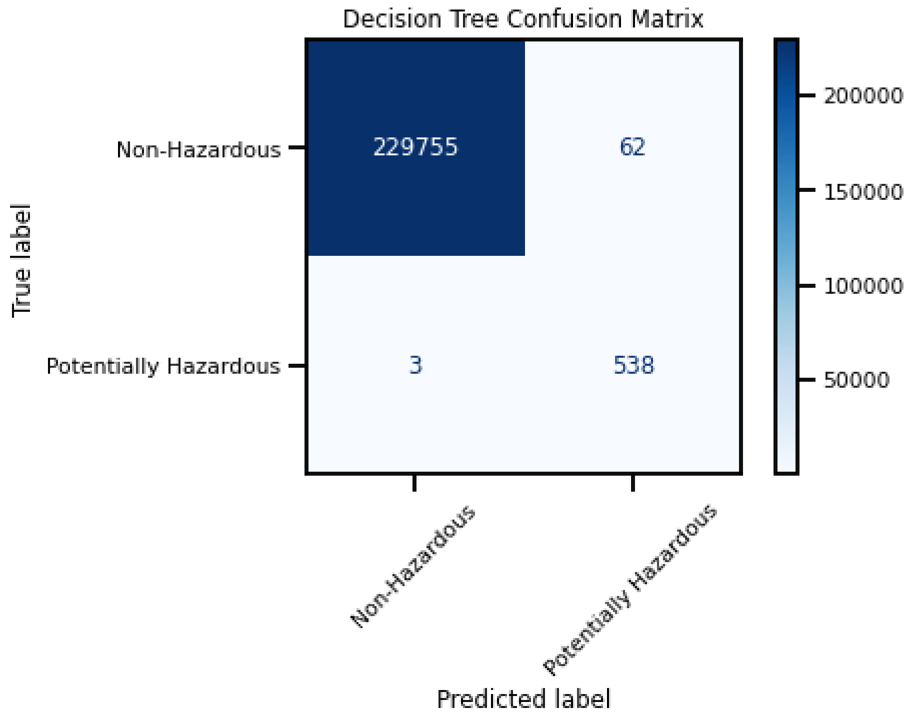
In [8]:
```
tree_grid3.fit(X_train, y_train)
```

Out[8]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('clf',
                                        DecisionTreeClassifier(random_state=12
3))]),
             param_grid={'clf__class_weight': ['balanced', {0: 1, 1: 200}],
                         'clf__max_depth': [4, 6, 8, 12],
                         'clf__min_samples_leaf': [7, 8, 9, 10, 11],
                         'clf__min_samples_split': [2, 3, 4]},
             scoring='recall')
```

In [9]:
```
y_pred = tree_grid3.predict(X_test)

print('Train Report')
print(classification_report(y_train, tree_grid3.predict(X_train)))
print('\n')
print('Test Report')
print(classification_report(y_test, y_pred))
```

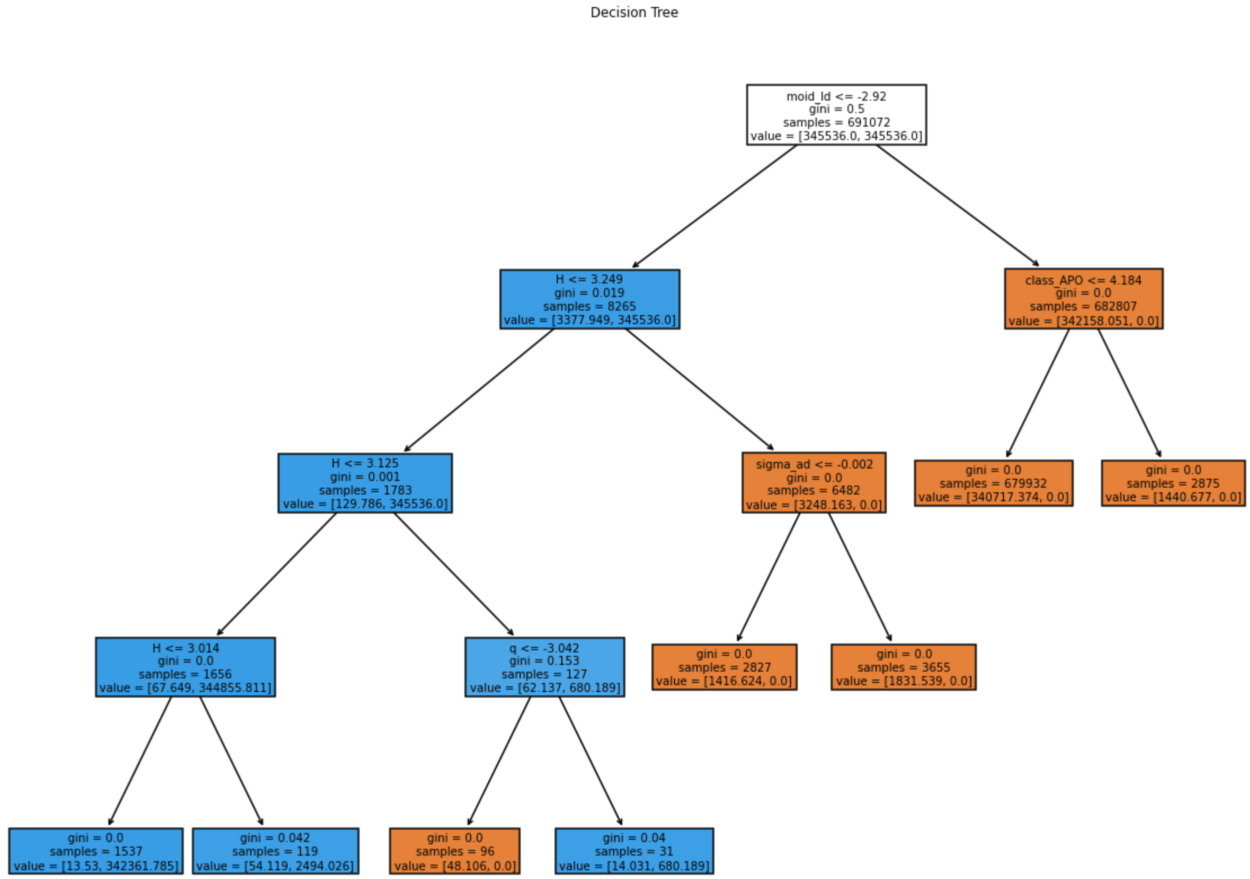
```
Train Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    689548
           1       0.90      1.00      0.95      1524

    accuracy                           1.00    691072
   macro avg       0.95      1.00      0.97    691072
weighted avg       1.00      1.00      1.00    691072



Test Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    229817
           1       0.90      0.99      0.94       541

    accuracy                           1.00    230358
   macro avg       0.95      1.00      0.97    230358
weighted avg       1.00      1.00      1.00    230358
```

In [10]:
```
sns.set_context('talk', font_scale=0.65)

plot_confusion_matrix(tree_grid3, X_test, y_test, cmap=plt.cm.Blues,
                      display_labels=['Non-Hazardous', 'Potentially Hazardous'],
plt.title('Decision Tree Confusion Matrix')
plt.savefig('Images/DT-matrix.png', bbox_inches='tight');
```



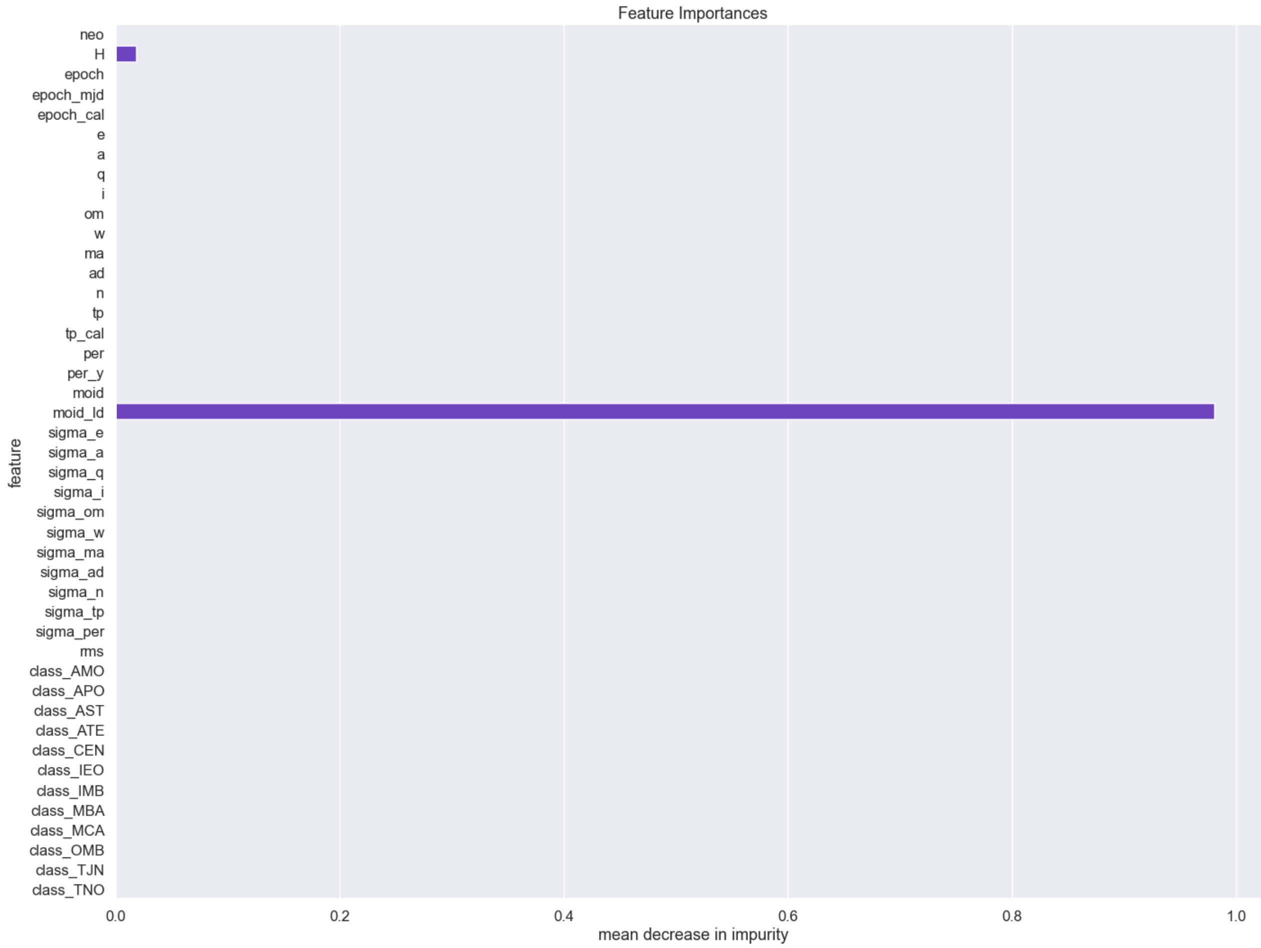
We have sacrificed some precision in order to identify more potentially hazardous asteroids correctly.

In [15]:
```
fig = plt.figure(figsize=(20, 15))
_ = plot_tree(tree_grid3.best_estimator_.steps[1][1],
              feature_names=X.columns,
              filled=True)
plt.title('Decision Tree')
plt.savefig('Images/decision-tree.png');
```



In [18]:

```
sns.set_context('talk')
sns.set_style('darkgrid')

plt.figure(figsize=(20, 15))
sns.barplot(x = tree_grid3.best_estimator_.steps[1][1].feature_importances_,
            y = X.columns, color='#682dd3')
plt.title('Feature Importances')
plt.xlabel('mean decrease in impurity')
plt.ylabel('feature')
plt.tight_layout()
plt.savefig('Images/DT-importances.png');
```



Only `H` and `moid_ld` have a signal on the feature importances plot.

In [43]:
```
tree_grid3.best_params_
```

Out[43]:
```
{'clf__class_weight': 'balanced',
 'clf__max_depth': 4,
 'clf__min_samples_leaf': 7,
 'clf__min_samples_split': 2}
```

Iteration 4

In [45]:
```
tree_pipe4 = Pipeline([('ss', StandardScaler()),
                       ('clf', DecisionTreeClassifier(random_state=123,
                                                      min_samples_split=2))])

param_grid = {
    'clf__class_weight': ['balanced', {0:1, 1:200}],
    'clf__max_depth': [3, 4, 5],
    'clf__min_samples_leaf': [6, 7, 8]
}

tree_grid4 = GridSearchCV(tree_pipe4, param_grid=param_grid, cv=3, scoring='reca
```

In [46]:
```
tree_grid4.fit(X_train, y_train)
```

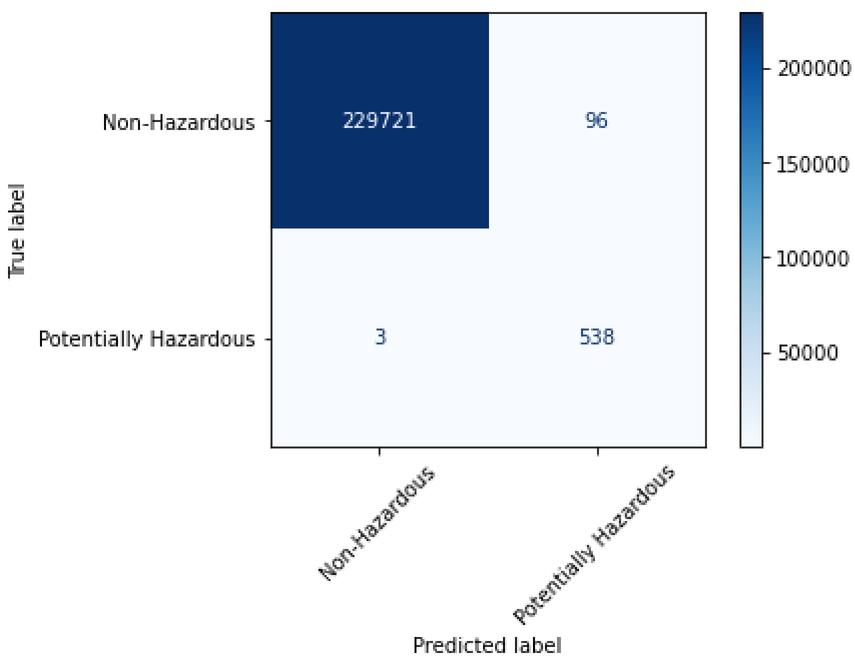
Out[46]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('ss', StandardScaler()),
                                       ('clf',
                                        DecisionTreeClassifier(random_state=12
3))]),
```

```
                    param_grid={'clf__class_weight': ['balanced', {0: 1, 1: 200}],
                                'clf__max_depth': [3, 4, 5],
                                'clf__min_samples_leaf': [6, 7, 8]},
                    scoring='recall')
```

In [47]:
```
y_pred = tree_grid4.predict(X_test)

print('Train Report')
print(classification_report(y_train, tree_grid4.predict(X_train)))
print('\n')
print('Test Report')
print(classification_report(y_test, y_pred))
```

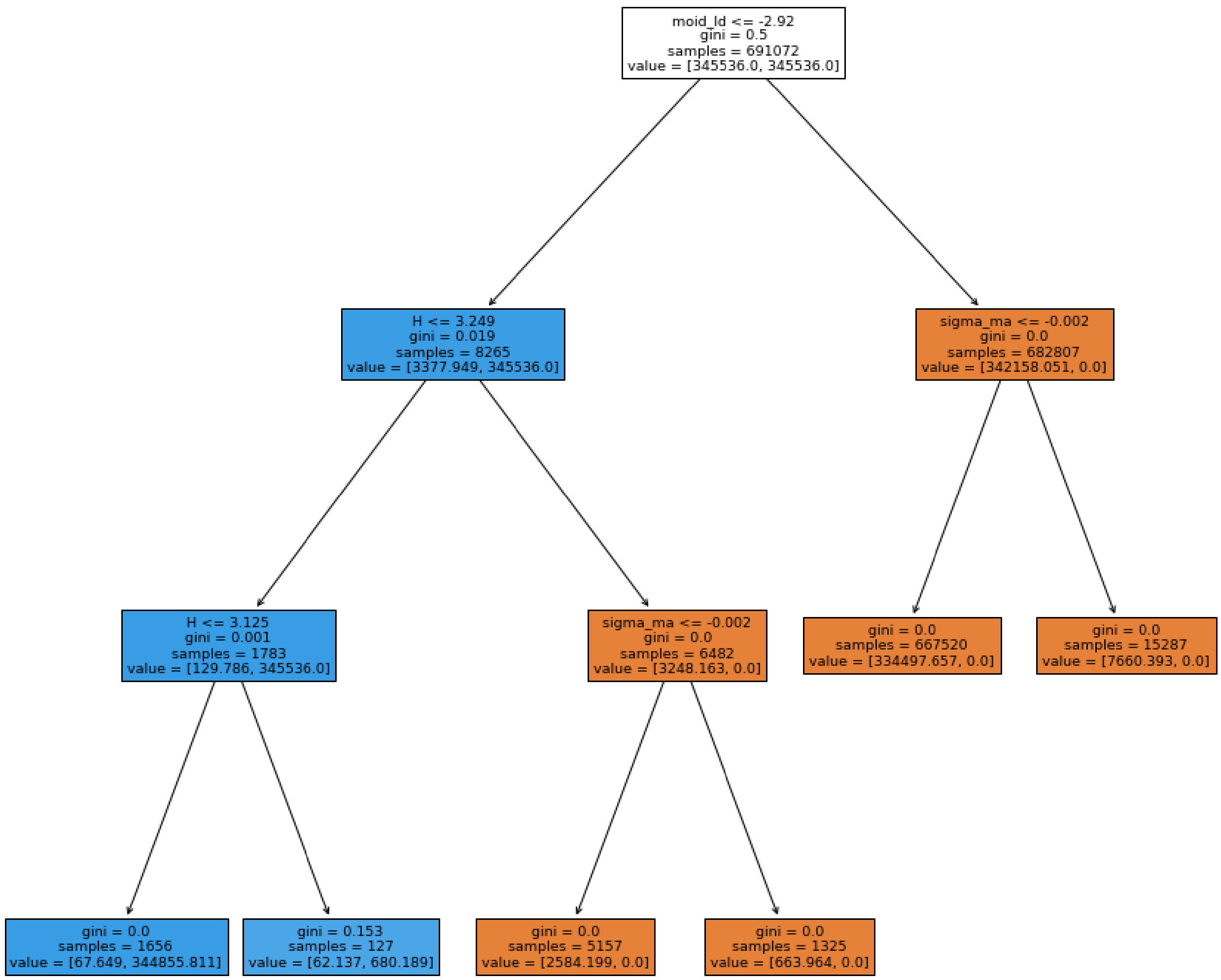
```
Train Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    689548
           1       0.85      1.00      0.92      1524

    accuracy                           1.00    691072
   macro avg       0.93      1.00      0.96    691072
weighted avg       1.00      1.00      1.00    691072



Test Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    229817
           1       0.85      0.99      0.92       541

    accuracy                           1.00    230358
   macro avg       0.92      1.00      0.96    230358
weighted avg       1.00      1.00      1.00    230358
```

In [48]:
```
plot_confusion_matrix(tree_grid4, X_test, y_test, cmap=plt.cm.Blues,
                      display_labels=['Non-Hazardous', 'Potentially Hazardous'],
```



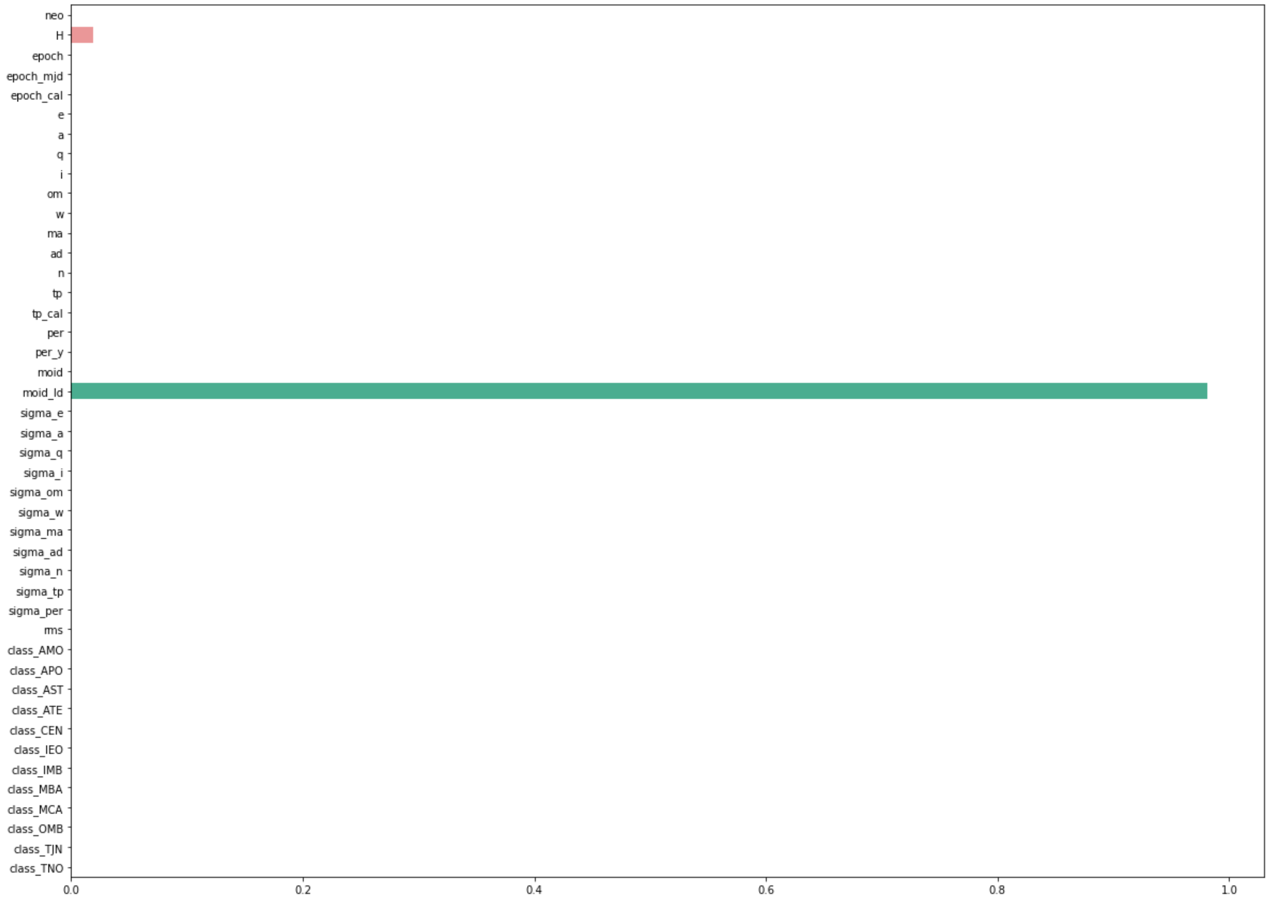
Continuing to prioritize recall while gridsearching parameters does not seem to increase recall for the positive class (model has still only missed 3 potentially hazardous asteroids), but now there are more false positives than the previous run (96 as opposed to 62, from the previous iteration).

In [49]:
```
fig= plt.figure(figsize=(15, 15))
_ = plot_tree(tree_grid4.best_estimator_.steps[1][1],
              feature_names=X.columns,
              filled=True)
```



In [50]:
```
plt.figure(figsize=(20, 15))
sns.barplot(x = tree_grid4.best_estimator_.steps[1][1].feature_importances_,
            y = X.columns)
```

Out[50]: <AxesSubplot:>



In [51]:
```
tree_grid4.best_params_
```

Out[51]:
```
{'clf__class_weight': 'balanced',
 'clf__max_depth': 3,
 'clf__min_samples_leaf': 6}
```