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In [1]:
```
#Importing the required Python Libraries
import numpy as npy
import scipy as spy
import pandas as pds
import matplotlib as mpl
import seaborn as sbn
from IPython.display import display, HTML

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Importing the Malware_Multiclass Dataset
DataFrame = pds.read_csv('C:/Users/ishan/Downloads/malware_MultiClass.csv')

# Printing and Display the Dataframe in HTML
display(HTML(DataFrame.head(10).to_html()))
```

	hash	millisecond	classi
0	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	0	r
1	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	1	r
2	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	2	r
3	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	3	r
4	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	4	r
5	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	5	r
6	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	6	r
7	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	7	r
8	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	8	r
9	42fb5e2ec009a05ff5143227297074f1e9c6c3ebb9c914e223349672eca79ad0	9	r

In [3]:
```
# Printing the Shape of the dataframe
print(DataFrame.shape)

# Selected required columns
SelectedColumns = ['classification','os','usage_counter','prio','static_prio','n

# Extracting the required selected columns
DataFrame = DataFrame[SelectedColumns]

# Displaying the selected data
DataFrame.head(5)
```

```
(100000, 36)
```

Out[3]:

	classification	os	usage_counter	prio	static_prio	normal_prio	vm_pg
0	malware	CentOS	0	3069378560	14274	0	
1	malware	Windows	0	3069378560	14274	0	
2	malware	Mac	0	3069378560	14274	0	
3	malware	Ubuntu	0	3069378560	14274	0	
4	malware	Mac	0	3069378560	14274	0	

In [4]:
```
# Striping the column names
DataFrame=DataFrame.rename(columns=lambda x: x.strip())
cols=DataFrame.columns

# Displaying rows of the DataFrame
DataFrame.head(5)
```

Out[4]:

	classification	os	usage_counter	prio	static_prio	normal_prio	vm_pg
0	malware	CentOS	0	3069378560	14274	0	
1	malware	Windows	0	3069378560	14274	0	
2	malware	Mac	0	3069378560	14274	0	
3	malware	Ubuntu	0	3069378560	14274	0	
4	malware	Mac	0	3069378560	14274	0	

In [5]:
```
# Checking for missing values in DataFrame
print('ColumnName, DataType, MissingValues')
for i in cols:
    print(i, ',', DataFrame[i].dtype,',', DataFrame[i].isnull().any())
```

```
ColumnName, DataType, MissingValues
classification , object , False
os , object , False
usage_counter , int64 , False
prio , int64 , False
static_prio , int64 , False
normal_prio , int64 , False
vm_pgoff , int64 , False
vm_truncate_count , int64 , False
task_size , int64 , False
map_count , int64 , False
hiwater_rss , int64 , False
total_vm , int64 , False
shared_vm , int64 , False
exec_vm , int64 , False
reserved_vm , int64 , False
nr_ptes , int64 , False
nvcsw , int64 , False
nivcsw , int64 , False
signal_nvcsw , int64 , False
```

In [6]:
```
# Encoding the labels

from sklearn import preprocessing
from IPython.display import display, HTML

# defining label as nominal values
y = DataFrame['classification']
le = preprocessing.LabelEncoder()
le.fit(y)

# Encoding the nominal labels to integers
y_encoded = le.transform(y)
DataFrame['classification'] = y_encoded

# Printing and displaying dataframe as tables in HTML
display(HTML(DataFrame.head(10).to_html()))
```

	classification	os	usage_counter	prio	static_prio	normal_prio	vm_pgoff
0	1	CentOS	0	3069378560	14274	0	C
1	1	Windows	0	3069378560	14274	0	C
2	1	Mac	0	3069378560	14274	0	C
3	1	Ubuntu	0	3069378560	14274	0	C
4	1	Mac	0	3069378560	14274	0	C
5	1	Windows	0	3069378560	14274	0	C
6	1	Ubuntu	0	3069378560	14274	0	C
7	1	Mac	0	3069378560	14274	0	C
8	1	CentOS	0	3069378560	14274	0	C
9	1	Mac	0	3069378560	14274	0	C

In [7]:
```
# Data preprocessing

print('Column Datatypes:\n',DataFrame.dtypes)

# Converting all the nominal variables to binary variables
DataFrame_num=DataFrame.copy(deep=True)

# Creating the new binary columns
DataFrame_dummies=pds.get_dummies(DataFrame_num[['os']])

# Adding them to the dataframe
DataFrame_num=DataFrame_num.join(DataFrame_dummies)

# Droping the original columns
DataFrame_num=DataFrame_num.drop('os',axis=1)

display('DataFrame_num:',HTML(DataFrame_num.head(5).to_html()))
```

```
Column Datatypes:
 classification        int32
os                    object
usage_counter          int64
prio                   int64
static_prio            int64
normal_prio            int64
vm_pgoff               int64
vm_truncate_count      int64
task_size              int64
map_count              int64
hiwater_rss            int64
total_vm               int64
shared_vm              int64
exec_vm                int64
reserved_vm            int64
nr_ptes                int64
nvcsw                  int64
nivcsw                 int64
signal_nvcsw           int64
dtype: object
'DataFrame_num:'
```

	classification	usage_counter	prio	static_prio	normal_prio	vm_pgoff	vm_trun
0	1	0	3069378560	14274	0	0	
1	1	0	3069378560	14274	0	0	
2	1	0	3069378560	14274	0	0	
3	1	0	3069378560	14274	0	0	
4	1	0	3069378560	14274	0	0	

In [8]:

```
# N-1 dummy variable is encoded to avoid the multicollinearity issues

DataFrame_num=DataFrame_num.drop('os_Windows', axis=1)
DataFrame_num.head(10)
```

Out[8]:

	classification	usage_counter	prio	static_prio	normal_prio	vm_pgoff	vm_tru
0	1	0	3069378560	14274	0	0	
1	1	0	3069378560	14274	0	0	
2	1	0	3069378560	14274	0	0	
3	1	0	3069378560	14274	0	0	
4	1	0	3069378560	14274	0	0	
5	1	0	3069378560	14274	0	0	
6	1	0	3069378560	14274	0	0	
7	1	0	3069378560	14274	0	0	
8	1	0	3069378560	14274	0	0	
9	1	0	3069378560	14274	0	0	

10 rows × 22 columns

In [9]:

```
# Visualizing the best Tree model

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_validate, cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall
from sklearn.utils import shuffle

y = DataFrame_num['classification']
x = DataFrame_num.drop('classification', axis=1)

# Using N-fold cross validation method
clfn=DecisionTreeClassifier(criterion='log_loss', max_depth=3, max_leaf_nodes =

precision = make_scorer(precision_score, average='macro')
recall = make_scorer(recall_score, average='macro')
auc = make_scorer(roc_auc_score, average='macro', multi_class='ovr', needs_proba

x, y = shuffle(x, y)
acc=cross_val_score(clfn, x, y, cv=5, scoring='accuracy').mean()
pre=cross_val_score(clfn, x, y, cv=5, scoring=precision).mean()
rec=cross_val_score(clfn, x, y, cv=5, scoring=recall).mean()
auc=cross_val_score(clfn, x, y, cv=5, scoring=auc).mean()
print('By N-fold Cross Validation: Accuracy = ',acc, ', Precison = ', pre, ', Re
```

```
By N-fold Cross Validation: Accuracy =  0.9175599999999999 , Precison =  0.613564
8925406842 , Recall =  0.6133668967089759 , Auc =  0.848447077134497
```

In [10]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_validate, cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall
from sklearn.utils import shuffle

y = DataFrame_num['classification']
x = DataFrame_num.drop('classification', axis=1)
```

```
# Performing the cross fold validation
clfn=DecisionTreeClassifier(criterion='entropy', max_depth=4, max_leaf_nodes = 5
                            min_samples_split=2,min_impurity_decrease=0.02)


precision = make_scorer(precision_score, average='macro')
recall = make_scorer(recall_score, average='macro')
auc = make_scorer(roc_auc_score, average='macro', multi_class='ovr', needs_proba

x, y = shuffle(x, y)
acc=cross_val_score(clfn, x, y, cv=5, scoring='accuracy').mean()
pre=cross_val_score(clfn, x, y, cv=5, scoring=precision).mean()
rec=cross_val_score(clfn, x, y, cv=5, scoring=recall).mean()
auc=cross_val_score(clfn, x, y, cv=5, scoring=auc).mean()
print('By N-fold Cross Validation after changing scoring factor and hyperparamet
```

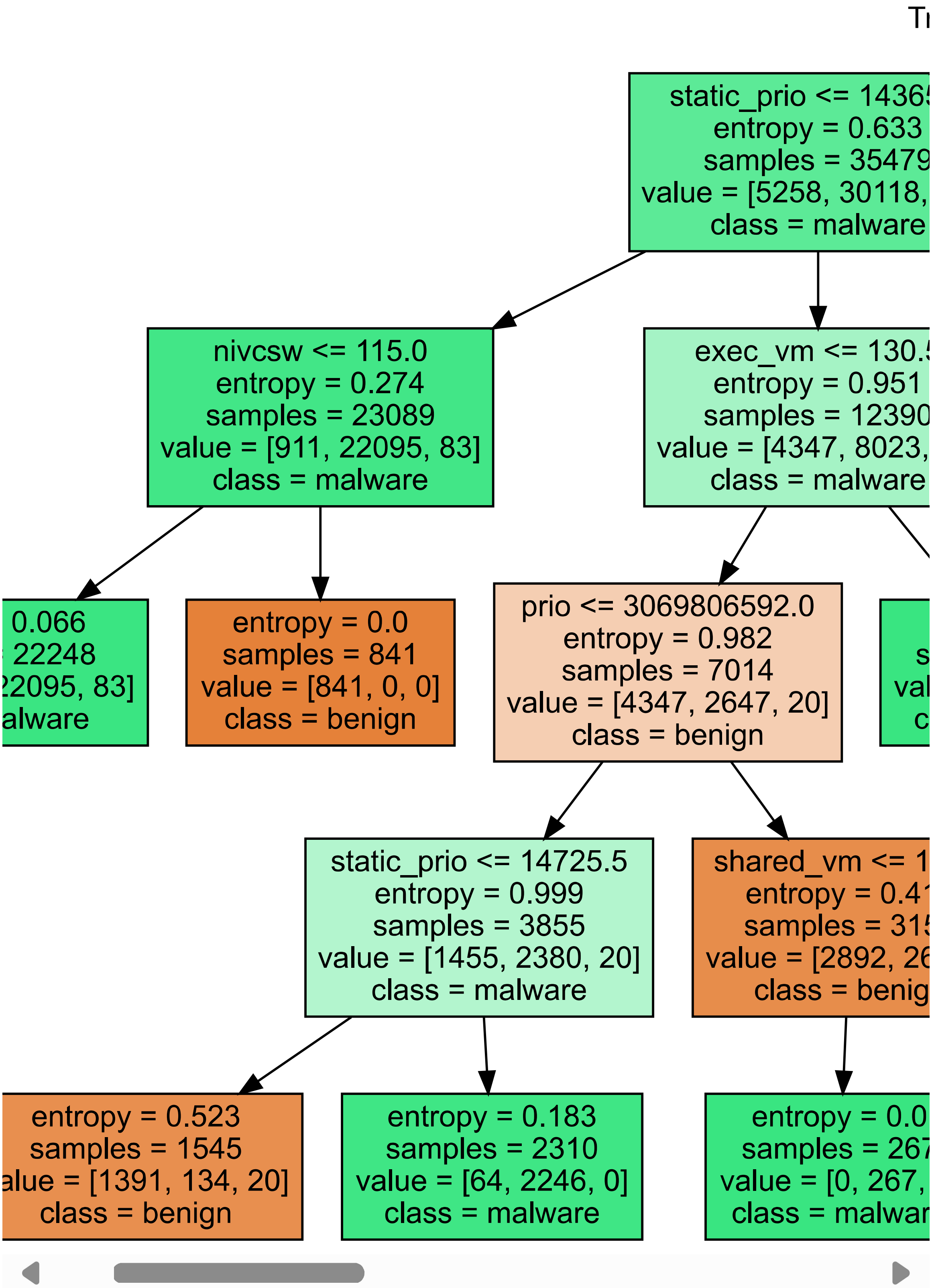
```
By N-fold Cross Validation after changing scoring factor and hyperparameters: Acc
uracy =  0.9195399999999999 , Precison =  0.615105261410666 , Recall =  0.6146923
453405456 , Auc =  0.8539552922910012
```

In [12]:

```
from sklearn import tree
import graphviz

clfn=DecisionTreeClassifier(criterion='entropy', max_depth=10, ccp_alpha = 0.01)
rst = cross_validate(clfn, x, y, cv=10, scoring='roc_auc', return_estimator=True

# Fitting the trees for each fold
trees = rst['estimator']

# Printing the accuracy scores for each fold
scores = rst['test_score']

# Printing the details for debugging
print("Fold AUC Scores: ", [trees[i].score(x, y) for i in range(len(trees))])
print("Best AUC Fold Index: ", scores.argmax())

best_fold_index = scores.argmax()
best_clfn = trees[best_fold_index]
best_clfn

labels = le.inverse_transform(best_clfn.classes_)
print('features: ', x.columns.to_list())
print('labels: ', labels)

# DOT data
dot_data = tree.export_graphviz(best_clfn, out_file=None, feature_names=x.column

# Drawing the graph
graph = graphviz.Source(dot_data, format="png")

# Saving the graph to DecisionTree_HW4.png
graph.render("DecisionTree_HW4")
graph
```

```
Fold AUC Scores:  [0.98912, 0.98911, 0.98912, 0.98912, 0.98912, 0.98912, 0.98912,
0.98912, 0.98912, 0.9893]
Best AUC Fold Index:  0
features:  ['usage_counter', 'prio', 'static_prio', 'normal_prio', 'vm_pgoff', 'v
m_truncate_count', 'task_size', 'map_count', 'hiwater_rss', 'total_vm', 'shared_v
m', 'exec_vm', 'reserved_vm', 'nr_ptes', 'nvcsw', 'nivcsw', 'signal_nvcsw', 'os_C
entOS', 'os_Debian', 'os_Mac', 'os_Ubuntu']
labels:  ['benign' 'malware' 'unknown']
```

Out[12]:



Conclusion

The decision tree is built

For the criterion log_loss

The decision tree model achieves 91.75% accuracy, with 61.35% precision and 61.33% recall.

AUC stands at 84.84%, indicating good class distinction capabilities overall. Further optimization may enhance performance.

For the criterion entropy

The decision tree model with adjusted scoring and hyperparameters, the model achieves high consistency across metrics:

Accuracy 91.95%, Precision 61.51% and Recall 61.46%, along with a notably improved AUC of 85.39%.

The criterion entropy has improved consistency and significantly higher AUC (85.39%)

with adjusted scoring and hyperparameters; overall better performance.

In [ ]: