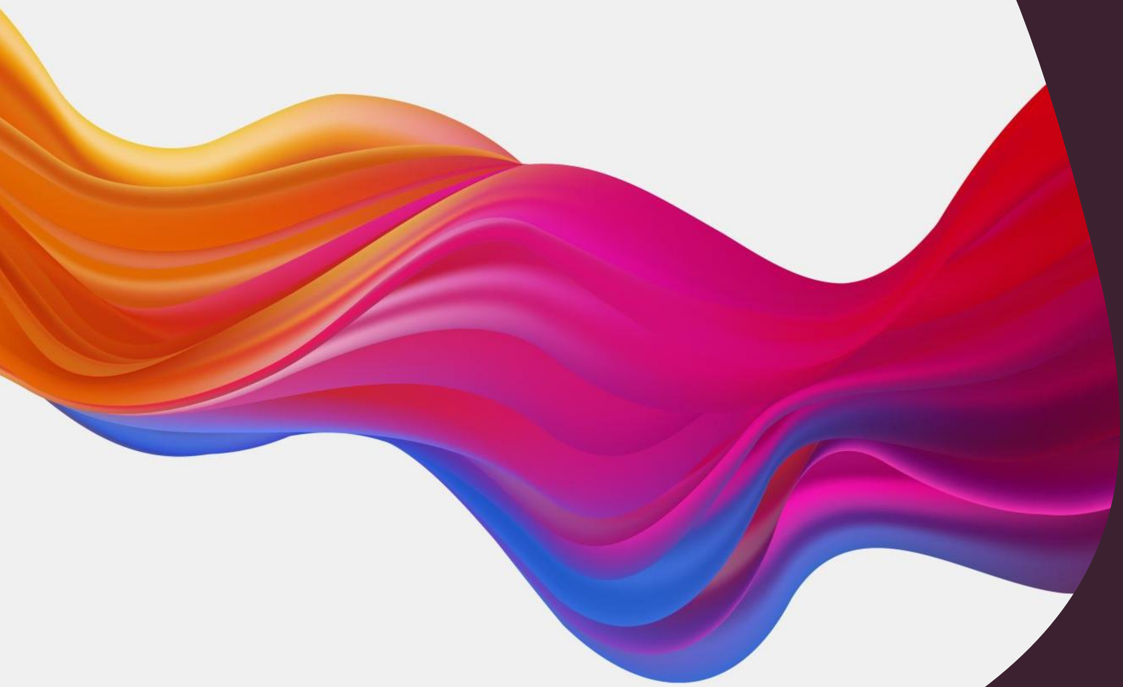

Microsoft-PE-malware-detection

Using machine learning and Deep Learning Methods

Submitters:

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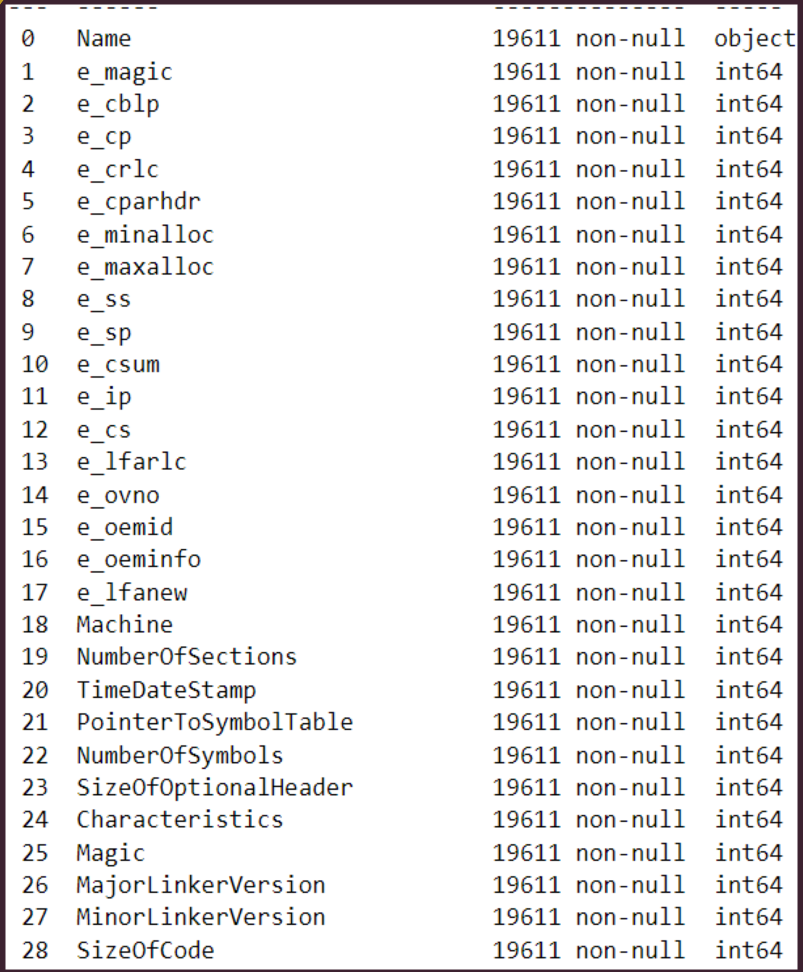
INTRODUCTION

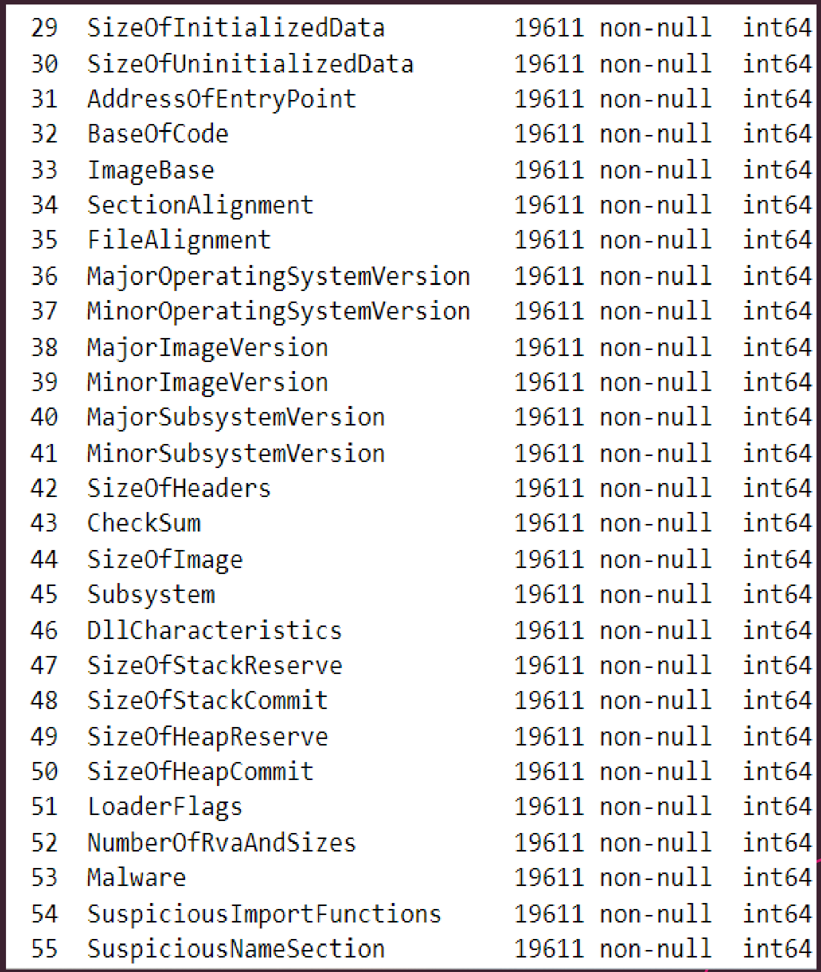
- Malware detection is the process of ascertaining the presence of malware on a system or determining whether a program is malicious or harmless so that the system can be protected or recovered from any effects caused by the malicious code
- As the number of legitimate users of the Internet increases, so do the opportunities for cybercriminals to gain from manufacturing malware
- This is the reason that prompted the authors of the article we investigated to develop a model for predicting whether a PE file is malicious or benign by methods of deep learning and group learning.
- We implemented the idea in the models and tried to slightly improve the results, which we did manage to do eventually.
- We used the dataset of the research from Kaggle.

GETTING KNOW THE DATA

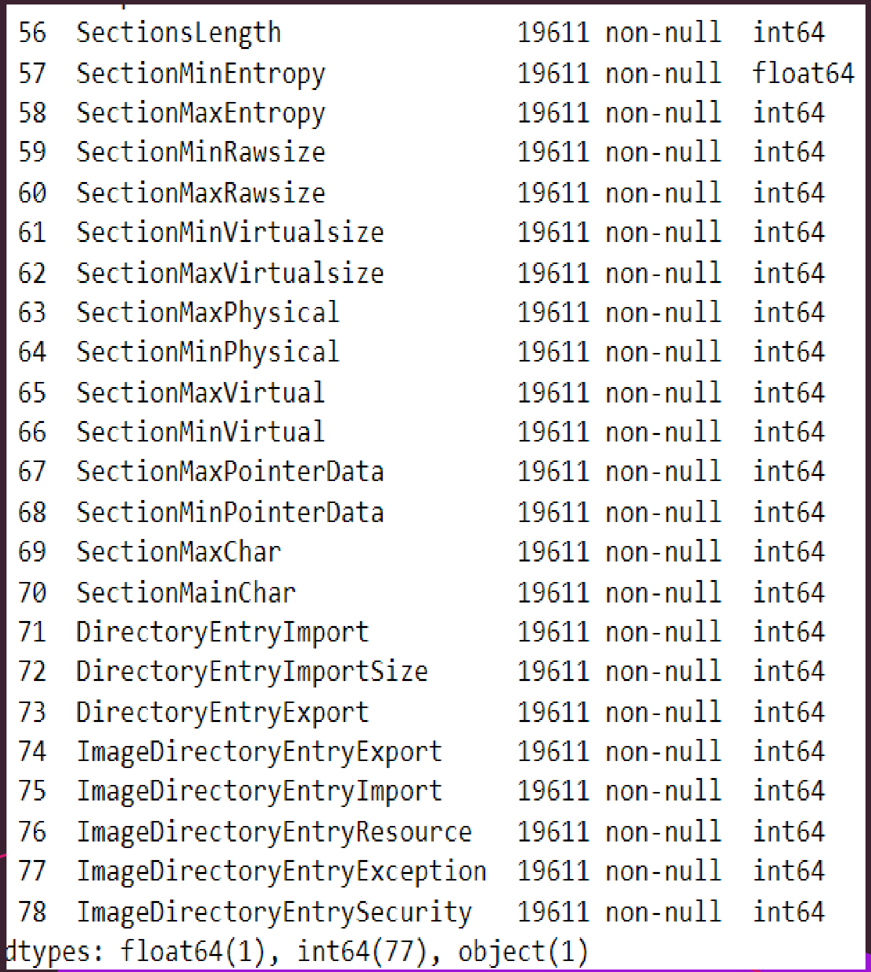
- The data contains 19611 rows, and 79 columns



```
---  ------                      --------------  ------
0    Name                        19611 non-null  object
1    e_magic                     19611 non-null  int64
2    e_cblp                      19611 non-null  int64
3    e_cp                        19611 non-null  int64
4    e_crlc                      19611 non-null  int64
5    e_cparhdr                   19611 non-null  int64
6    e_minalloc                  19611 non-null  int64
7    e_maxalloc                  19611 non-null  int64
8    e_ss                        19611 non-null  int64
9    e_sp                        19611 non-null  int64
10   e_csum                      19611 non-null  int64
11   e_ip                        19611 non-null  int64
12   e_cs                        19611 non-null  int64
13   e_lfarlc                    19611 non-null  int64
14   e_ovno                      19611 non-null  int64
15   e_oemid                     19611 non-null  int64
16   e_oeminfo                   19611 non-null  int64
17   e_lfanew                    19611 non-null  int64
18   Machine                     19611 non-null  int64
19   NumberOfSections            19611 non-null  int64
20   TimeDateStamp               19611 non-null  int64
21   PointerToSymbolTable        19611 non-null  int64
22   NumberOfSymbols             19611 non-null  int64
23   SizeOfOptionalHeader        19611 non-null  int64
24   Characteristics             19611 non-null  int64
25   Magic                       19611 non-null  int64
26   MajorLinkerVersion          19611 non-null  int64
27   MinorLinkerVersion          19611 non-null  int64
28   SizeOfCode                  19611 non-null  int64
```



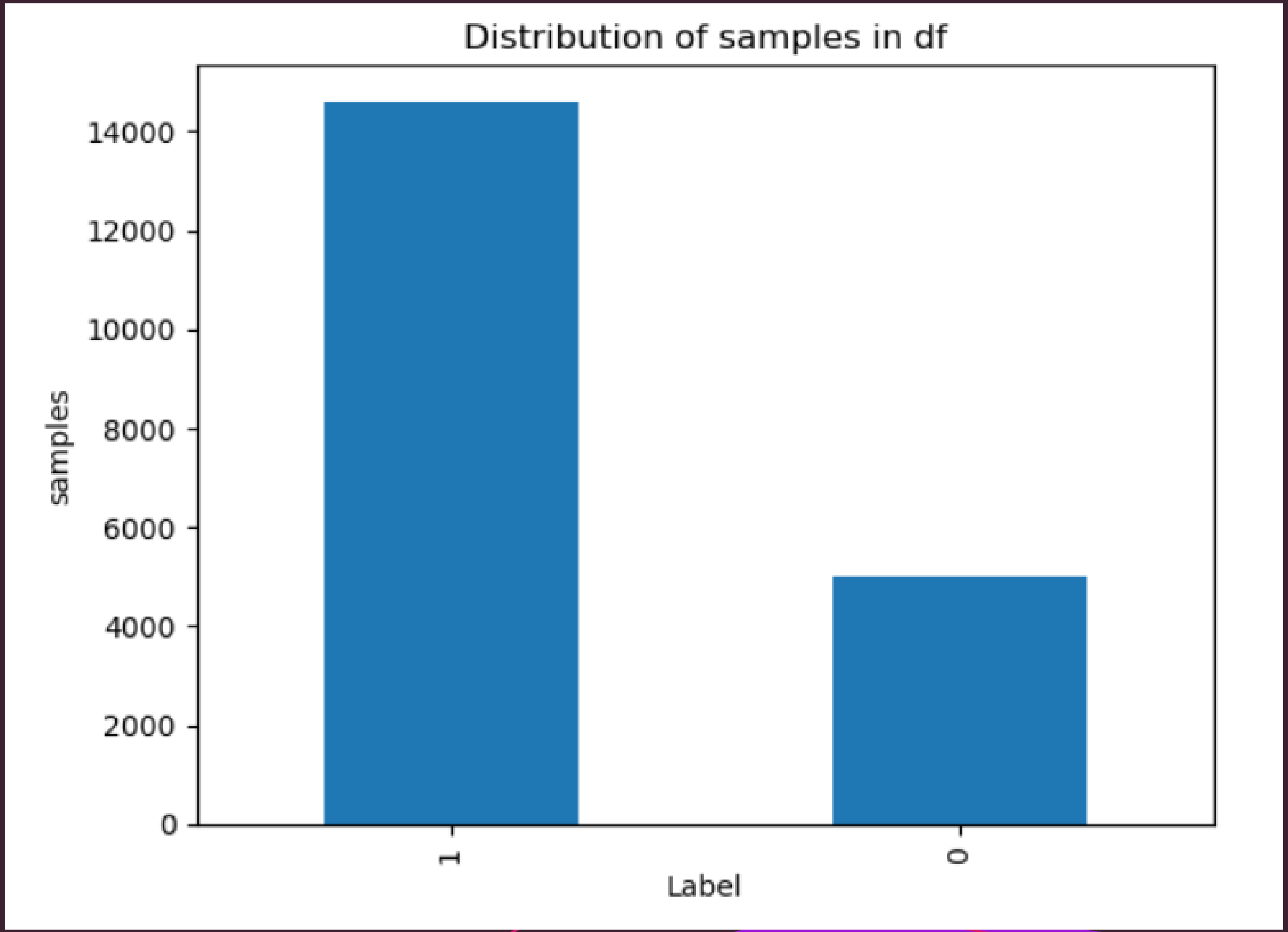
```
29   SizeOfInitializedData           19611 non-null  int64
30   SizeOfUninitializedData         19611 non-null  int64
31   AddressOfEntryPoint             19611 non-null  int64
32   BaseOfCode                      19611 non-null  int64
33   ImageBase                       19611 non-null  int64
34   SectionAlignment                19611 non-null  int64
35   FileAlignment                   19611 non-null  int64
36   MajorOperatingSystemVersion     19611 non-null  int64
37   MinorOperatingSystemVersion     19611 non-null  int64
38   MajorImageVersion               19611 non-null  int64
39   MinorImageVersion               19611 non-null  int64
40   MajorSubsystemVersion           19611 non-null  int64
41   MinorSubsystemVersion           19611 non-null  int64
42   SizeOfHeaders                   19611 non-null  int64
43   CheckSum                        19611 non-null  int64
44   SizeOfImage                     19611 non-null  int64
45   Subsystem                       19611 non-null  int64
46   DllCharacteristics              19611 non-null  int64
47   SizeOfStackReserve              19611 non-null  int64
48   SizeOfStackCommit               19611 non-null  int64
49   SizeOfHeapReserve               19611 non-null  int64
50   SizeOfHeapCommit                19611 non-null  int64
51   LoaderFlags                     19611 non-null  int64
52   NumberOfRvaAndSizes             19611 non-null  int64
53   Malware                         19611 non-null  int64
54   SuspiciousImportFunctions       19611 non-null  int64
55   SuspiciousNameSection           19611 non-null  int64
```



```
56   SectionsLength                  19611 non-null  int64
57   SectionMinEntropy               19611 non-null  float64
58   SectionMaxEntropy               19611 non-null  int64
59   SectionMinRawsize               19611 non-null  int64
60   SectionMaxRawsize               19611 non-null  int64
61   SectionMinVirtualsize           19611 non-null  int64
62   SectionMaxVirtualsize           19611 non-null  int64
63   SectionMaxPhysical              19611 non-null  int64
64   SectionMinPhysical              19611 non-null  int64
65   SectionMaxVirtual               19611 non-null  int64
66   SectionMinVirtual               19611 non-null  int64
67   SectionMaxPointerData           19611 non-null  int64
68   SectionMinPointerData           19611 non-null  int64
69   SectionMaxChar                  19611 non-null  int64
70   SectionMainChar                 19611 non-null  int64
71   DirectoryEntryImport            19611 non-null  int64
72   DirectoryEntryImportSize        19611 non-null  int64
73   DirectoryEntryExport            19611 non-null  int64
74   ImageDirectoryEntryExport       19611 non-null  int64
75   ImageDirectoryEntryImport       19611 non-null  int64
76   ImageDirectoryEntryResource     19611 non-null  int64
77   ImageDirectoryEntryException    19611 non-null  int64
78   ImageDirectoryEntrySecurity     19611 non-null  int64
dtypes: float64(1), int64(77), object(1)
```

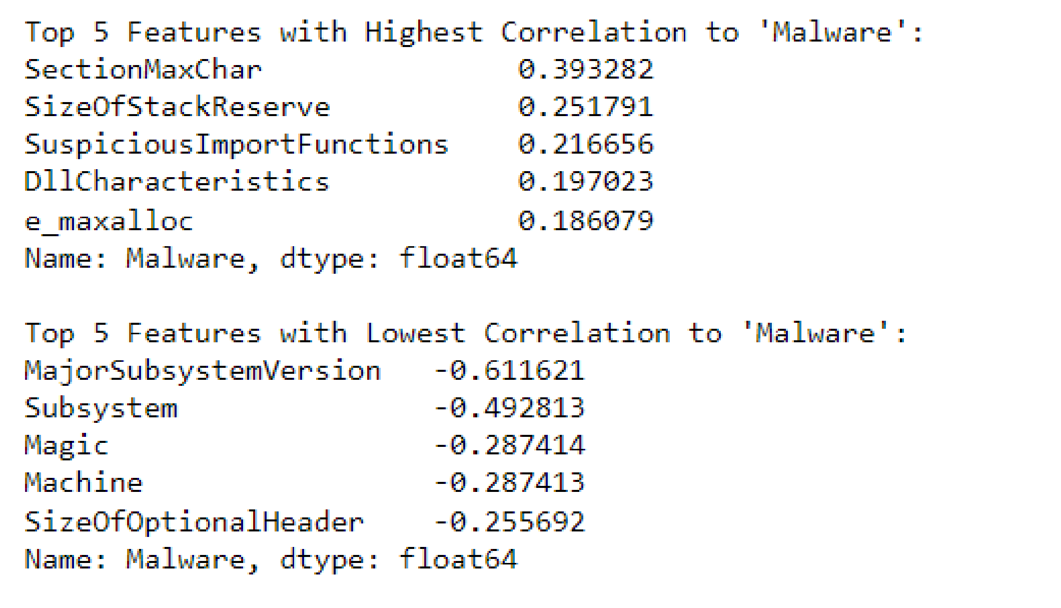
GETTING KNOW THE DATA

- Although The data is a bit biased to the “ Malware” cluster, we have enough data such that the model will be able to learn all the labels well



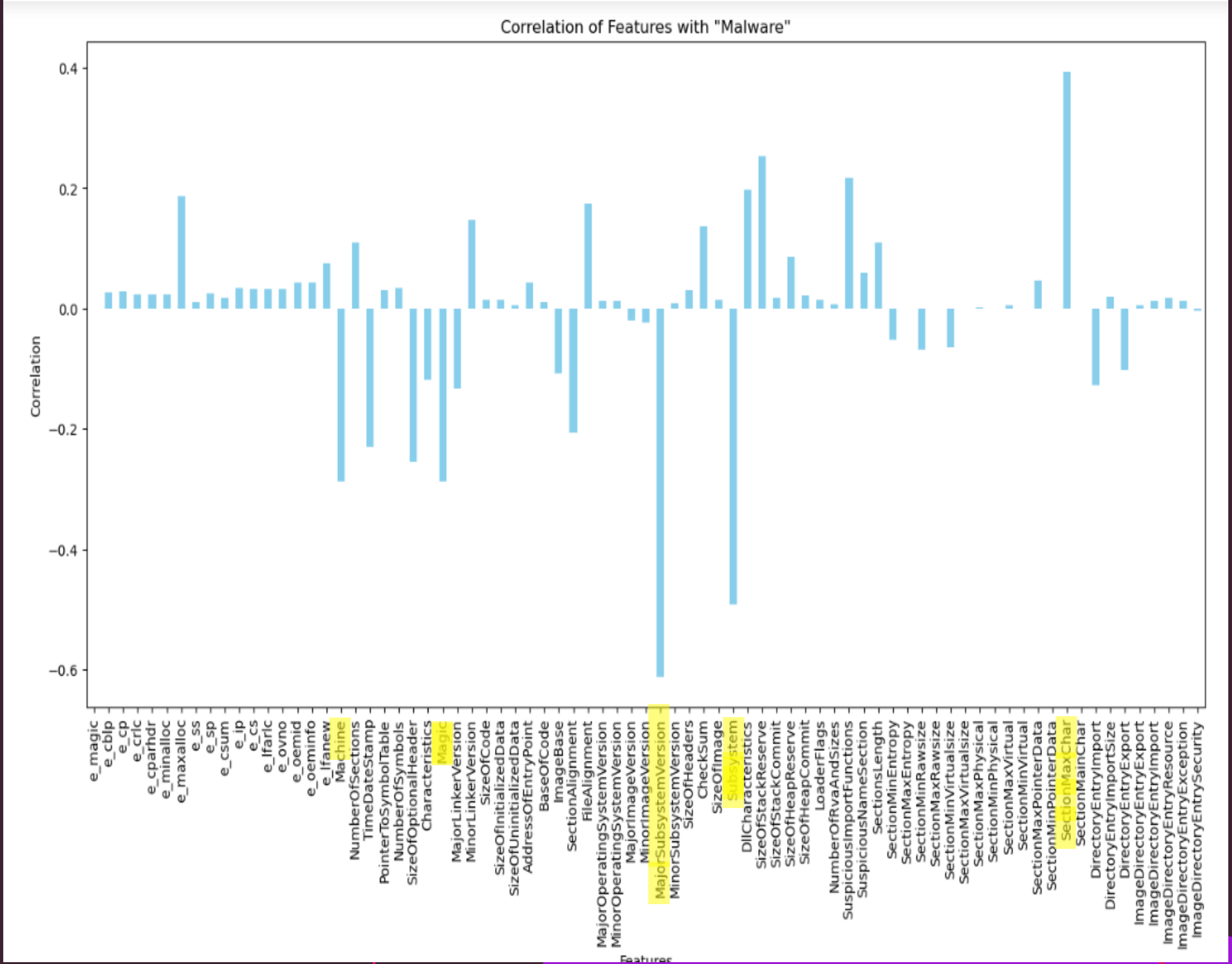
GETTING KNOW THE DATA

- We would like to check the correlation of the features to the label: " Malware", but still the correlations aren't compromising



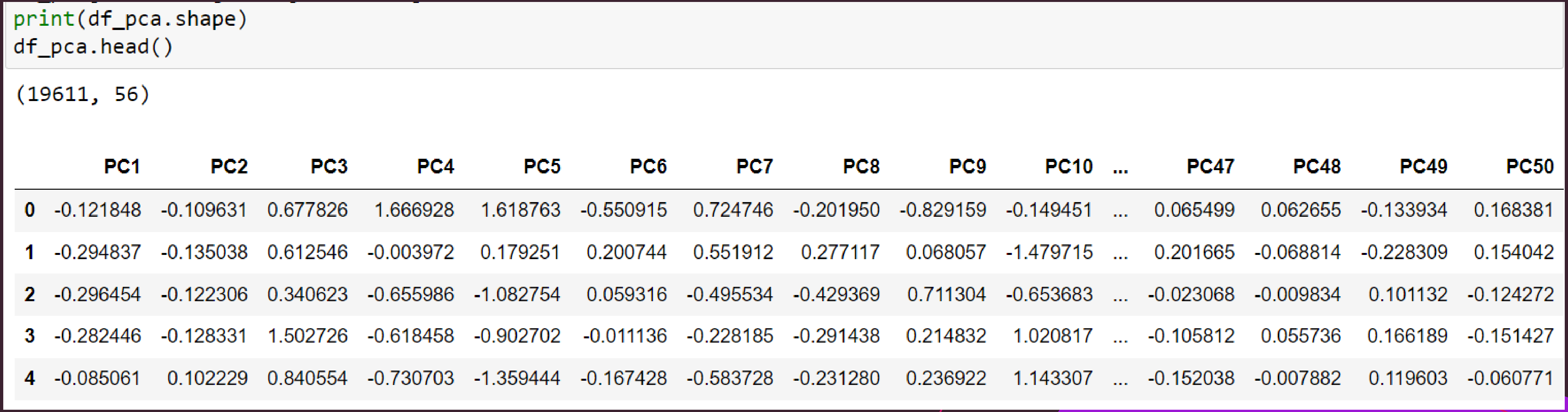
```
Top 5 Features with Highest Correlation to 'Malware':
SectionMaxChar                0.393282
SizeOfStackReserve            0.251791
SuspiciousImportFunctions     0.216656
DllCharacteristics            0.197023
e_maxalloc                    0.186079
Name: Malware, dtype: float64

Top 5 Features with Lowest Correlation to 'Malware':
MajorSubsystemVersion    -0.611621
Subsystem                -0.492813
Magic                    -0.287414
Machine                  -0.287413
SizeOfOptionalHeader     -0.255692
Name: Malware, dtype: float64
```



DIMENSIONALITY REDUCTION

- Following the research work - we used PCA to reduce the number of columns to 55, as determined by the researchers.
- Before that, we carried out our own research and found that in advance we could not refer to 4 columns ('Name', 'Machine’, 'TimeDateStamp', and the target label 'Malware’ that mustn’t be reduced) that represent general or not significant information so that it does not constitute an impact on the data



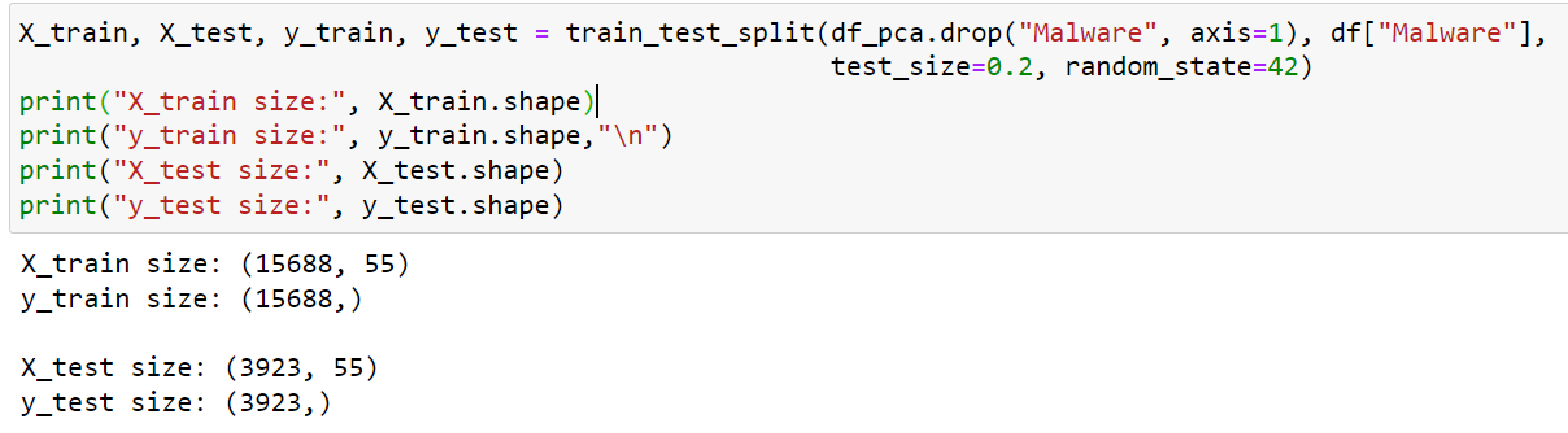
```
print(df_pca.shape)
df_pca.head()
```

```
(19611, 56)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	...	PC47	PC48	PC49	PC50
0	-0.121848	-0.109631	0.677826	1.666928	1.618763	-0.550915	0.724746	-0.201950	-0.829159	-0.149451	...	0.065499	0.062655	-0.133934	0.168381
1	-0.294837	-0.135038	0.612546	-0.003972	0.179251	0.200744	0.551912	0.277117	0.068057	-1.479715	...	0.201665	-0.068814	-0.228309	0.154042
2	-0.296454	-0.122306	0.340623	-0.655986	-1.082754	0.059316	-0.495534	-0.429369	0.711304	-0.653683	...	-0.023068	-0.009834	0.101132	-0.124272
3	-0.282446	-0.128331	1.502726	-0.618458	-0.902702	-0.011136	-0.228185	-0.291438	0.214832	1.020817	...	-0.105812	0.055736	0.166189	-0.151427
4	-0.085061	0.102229	0.840554	-0.730703	-1.359444	-0.167428	-0.583728	-0.231280	0.236922	1.143307	...	-0.152038	-0.007882	0.119603	-0.060771

PRE-PROCESSING

- In the last stage we split the data to trains and tests sets



```
X_train, X_test, y_train, y_test = train_test_split(df_pca.drop("Malware", axis=1), df["Malware"],
                                                    test_size=0.2, random_state=42)
print("X_train size:", X_train.shape)
print("y_train size:", y_train.shape,"\n")
print("X_test size:", X_test.shape)
print("y_test size:", y_test.shape)
```

```
X_train size: (15688, 55)
y_train size: (15688,)

X_test size: (3923, 55)
y_test size: (3923,)
```

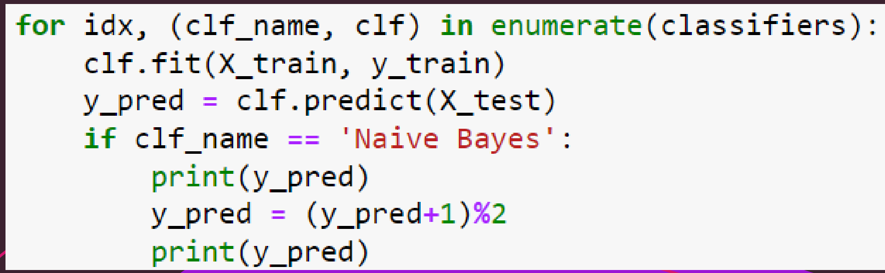
ML MODELS

- In the first stage the researchers implemented 5 machine-learning models:
  1. Naive Bayes
  2. Decision Tree
  3. Random Forest
  4. AdaBoost
  5. Gradient Boosting
- We ran these models on the new df (with the 55 new features after the PCA dimensional reduction)
- Since we want to detect malware, we decided to present the scores in a recall metric, which is more relevant in these cases.

ML MODELS – RECALL SCORES

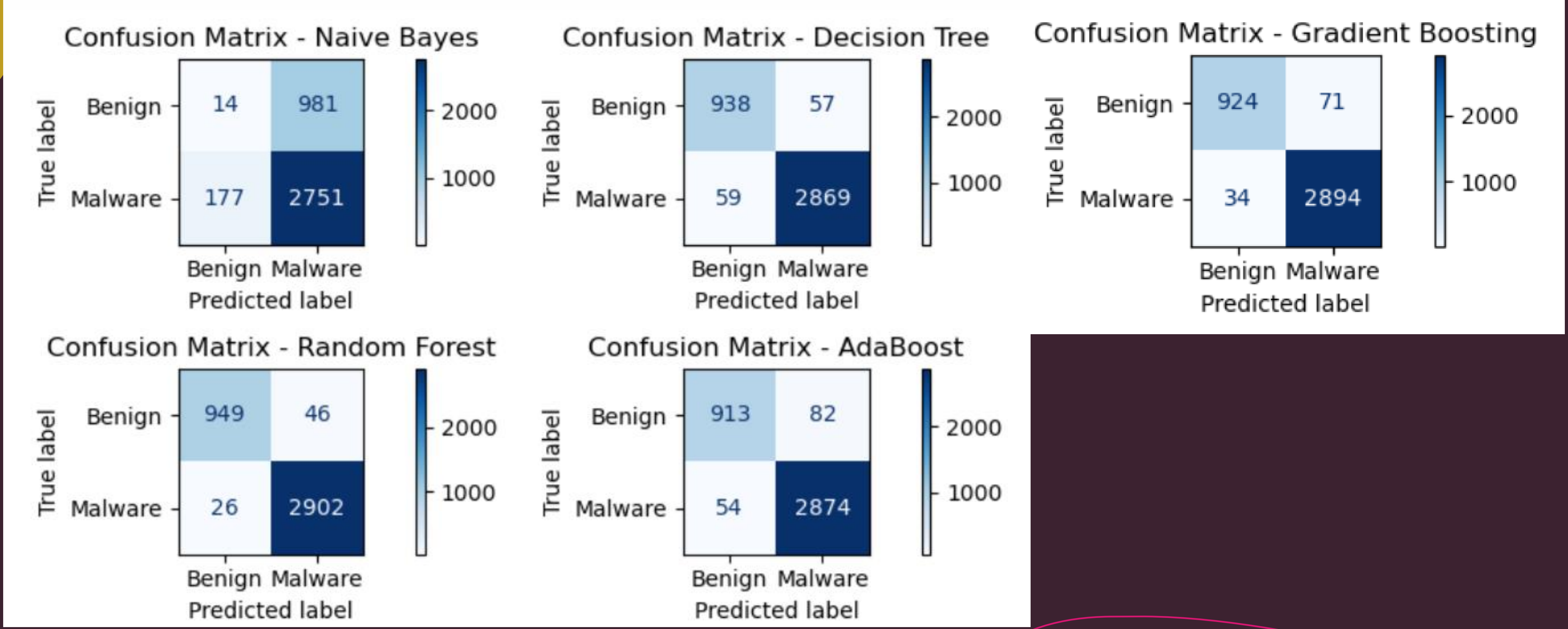
	Our scores	Researcher's scores
Naive Bayes	0.94	0.99
Decision Tree	0.98	0.95
Random Forest	0.991	0.98
AdaBoost	0.981	0.95
Gradient Boosting	0.988	0.93

- Note – we saw that Naïve bayes returns a recall score of 0.06045, which means almost always wrong, so we decided that whatever this model says – we will take the opposite. Which changed the recall score to 0.94



```
for idx, (clf_name, clf) in enumerate(classifiers):
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    if clf_name == 'Naive Bayes':
        print(y_pred)
        y_pred = (y_pred+1)%2
        print(y_pred)
```

ML MODELS – CONF-MATRIX



Confusion Matrix - Naive Bayes

True label \ Predicted label	Benign	Malware
Benign	14	981
Malware	177	2751

Confusion Matrix - Decision Tree

True label \ Predicted label	Benign	Malware
Benign	938	57
Malware	59	2869

Confusion Matrix - Gradient Boosting

True label \ Predicted label	Benign	Malware
Benign	924	71
Malware	34	2894

Confusion Matrix - Random Forest

True label \ Predicted label	Benign	Malware
Benign	949	46
Malware	26	2902

Confusion Matrix - AdaBoost

True label \ Predicted label	Benign	Malware
Benign	913	82
Malware	54	2874

DEEP LEARNING MODELS

- The next stage was implementing 3 DL models:
  1. MLP with 1 hidden layer with 50 neurons
  2. MLP with 2 hidden layers with (40,40) neurons
  3. 1D CNN model with 40 neurons and 60 filters

- in all experiments we used sparse categorical cross-entropy loss and Adam optimizer.
- 80% of the data was used for training and 20% for testing. The results are shown in Tables 4–6. We trained Dense-1 and Dense-2 models for 200 epochs, while the 1D-CNN model were trained for 50 epochs
- We checked with different learning rates but the changes were small.

'ADAM' OPTIMIZER

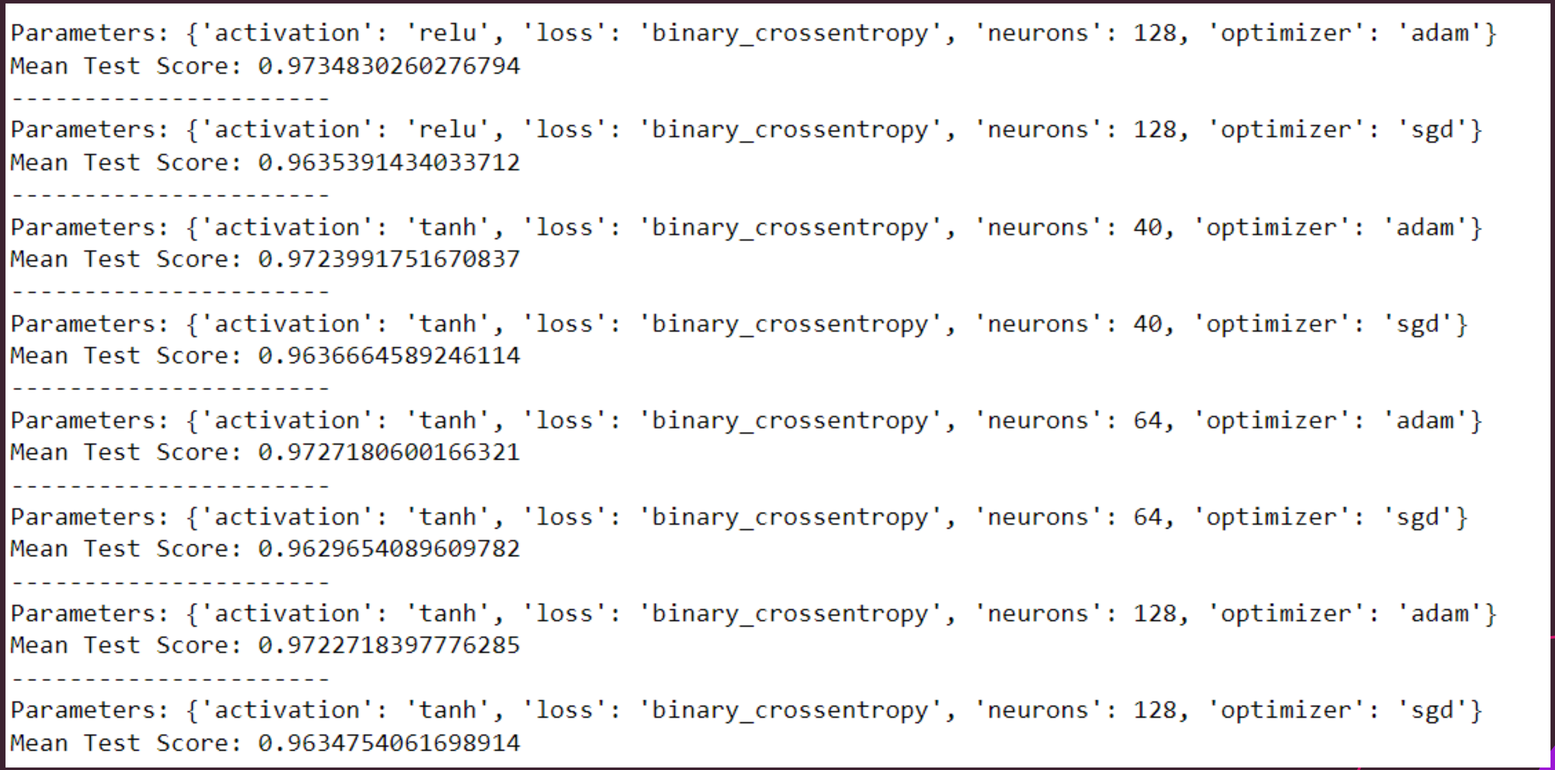
- Adam (Adaptive Moment Estimation) helps minimize the loss function by iteratively adjusting the learning rate for each parameter in the model based on past gradients by fast convergence (if the loss is high – the adjustment in the learning rate will be much more significant than if the loss is low)

DL MODELS - RESULTS

	Our scores	Researcher’s scores
Mlp- 1 hidden layer	0.978	0.983
Mlp- 2 hidden layers	0.978	0.988
1D CNN	0.979	0.978

DL MODELS - RESULTS

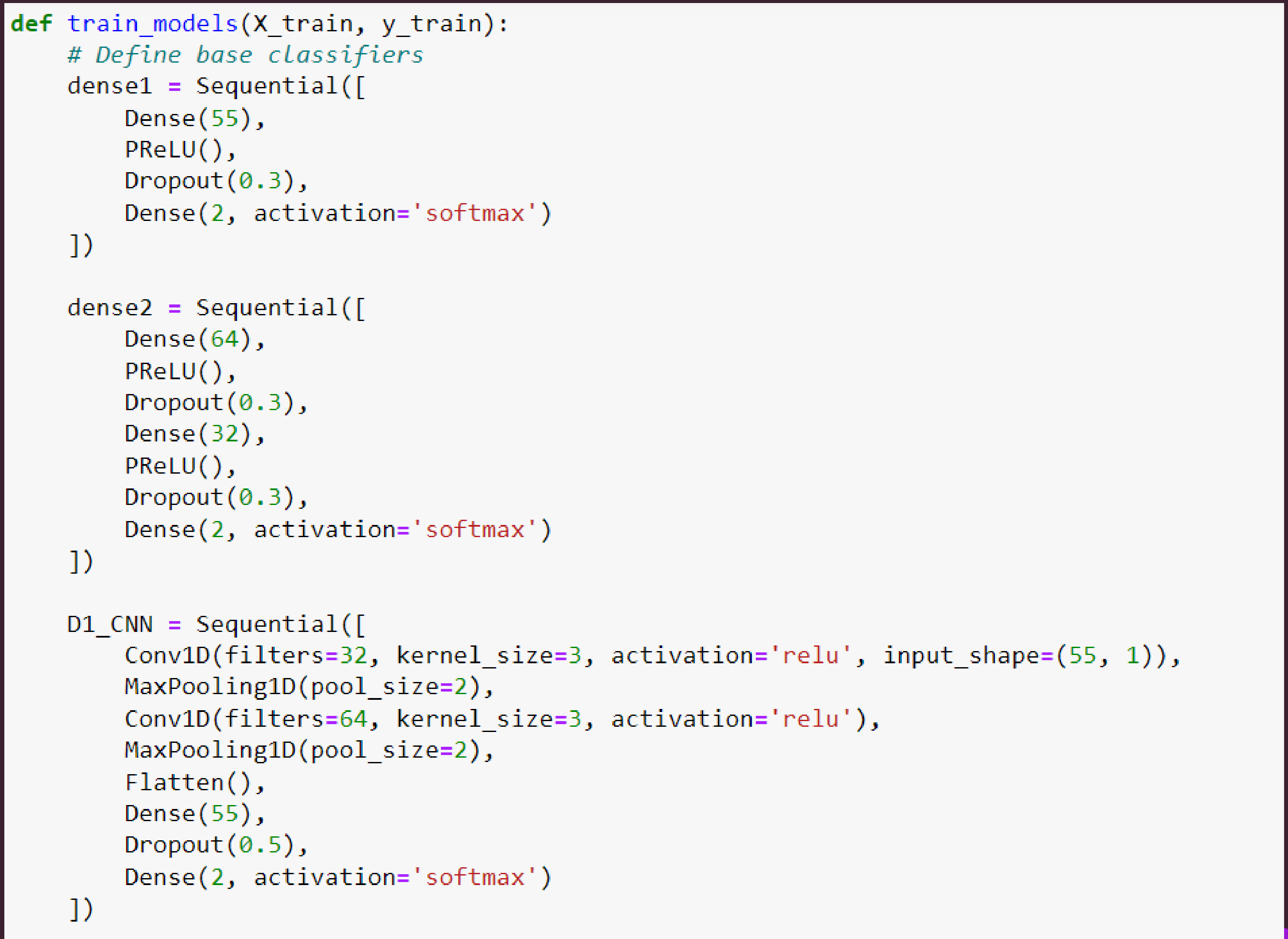
- We made a grid search to find the best parameters of 1D CNN model with different parameters and we achieved 98%
- We implemented only the 1D CNN model with different parameters(tanh activation function, 2 conv1D of 32 and 64, and 2 max pooling, and fully connected 128 neurons) and we achieved 98% (0.9798 if we want to be precise)



```
Parameters: {'activation': 'relu', 'loss': 'binary_crossentropy', 'neurons': 128, 'optimizer': 'adam'}
Mean Test Score: 0.9734830260276794
----------------------
Parameters: {'activation': 'relu', 'loss': 'binary_crossentropy', 'neurons': 128, 'optimizer': 'sgd'}
Mean Test Score: 0.9635391434033712
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 40, 'optimizer': 'adam'}
Mean Test Score: 0.9723991751670837
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 40, 'optimizer': 'sgd'}
Mean Test Score: 0.9636664589246114
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 64, 'optimizer': 'adam'}
Mean Test Score: 0.9727180600166321
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 64, 'optimizer': 'sgd'}
Mean Test Score: 0.9629654089609782
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 128, 'optimizer': 'adam'}
Mean Test Score: 0.9722718397776285
----------------------
Parameters: {'activation': 'tanh', 'loss': 'binary_crossentropy', 'neurons': 128, 'optimizer': 'sgd'}
Mean Test Score: 0.9634754061698914
```

ENSEMBLE LEARNING

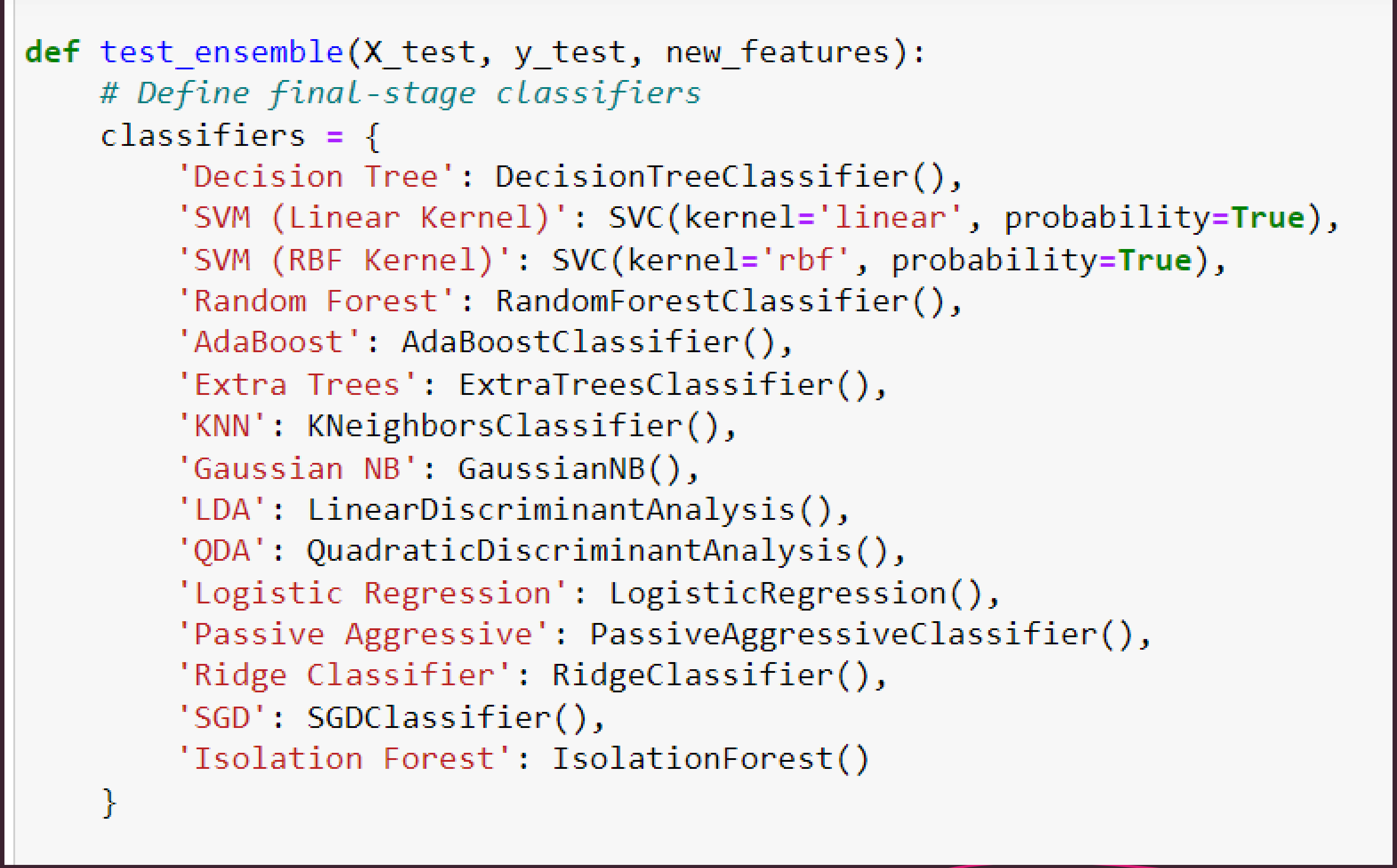
- In the last stage they implemented an ensemble learning model by implementing the previous 3 dl models as the first stage, and on top of these results – machine learning models were implemented as the final stage.



```python
def train_models(X_train, y_train):
    # Define base classifiers
    dense1 = Sequential([
        Dense(55),
        PReLU(),
        Dropout(0.3),
        Dense(2, activation='softmax')
    ])

    dense2 = Sequential([
        Dense(64),
        PReLU(),
        Dropout(0.3),
        Dense(32),
        PReLU(),
        Dropout(0.3),
        Dense(2, activation='softmax')
    ])

    D1_CNN = Sequential([
        Conv1D(filters=32, kernel_size=3, activation='relu', input_shape=(55, 1)),
        MaxPooling1D(pool_size=2),
        Conv1D(filters=64, kernel_size=3, activation='relu'),
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(55),
        Dropout(0.5),
        Dense(2, activation='softmax')
    ])
```



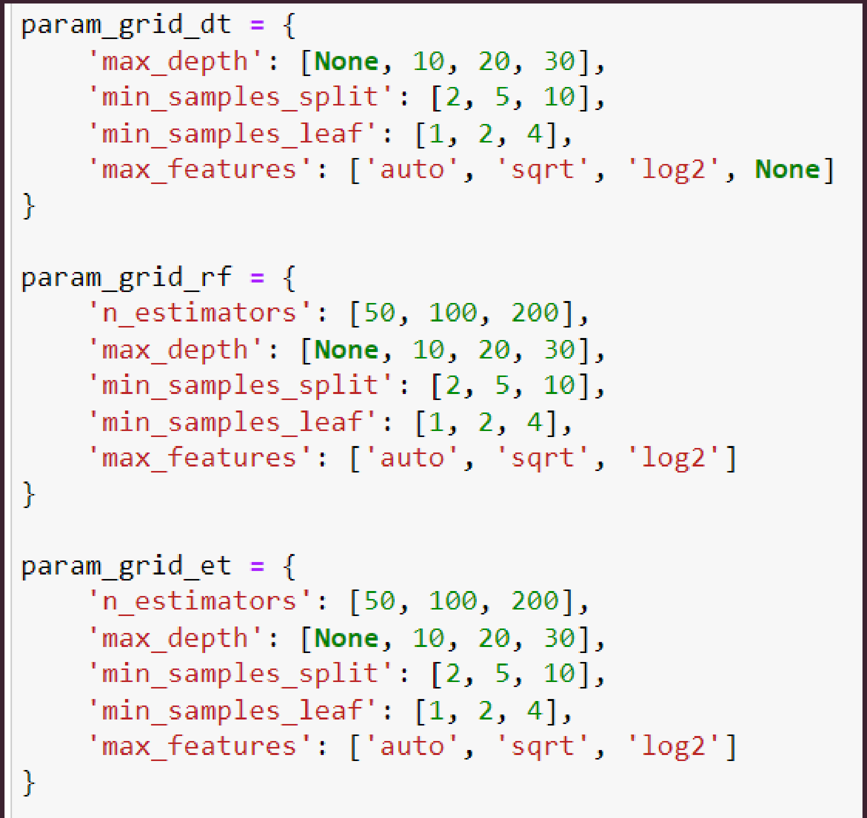
```python
def test_ensemble(X_test, y_test, new_features):
    # Define final-stage classifiers
    classifiers = {
        'Decision Tree': DecisionTreeClassifier(),
        'SVM (Linear Kernel)': SVC(kernel='linear', probability=True),
        'SVM (RBF Kernel)': SVC(kernel='rbf', probability=True),
        'Random Forest': RandomForestClassifier(),
        'AdaBoost': AdaBoostClassifier(),
        'Extra Trees': ExtraTreesClassifier(),
        'KNN': KNeighborsClassifier(),
        'Gaussian NB': GaussianNB(),
        'LDA': LinearDiscriminantAnalysis(),
        'QDA': QuadraticDiscriminantAnalysis(),
        'Logistic Regression': LogisticRegression(),
        'Passive Aggressive': PassiveAggressiveClassifier(),
        'Ridge Classifier': RidgeClassifier(),
        'SGD': SGDClassifier(),
        'Isolation Forest': IsolationForest()
    }
```

ML MODELS – RECALL SCORES

	Our scores	Researcher's scores
Decision Tree	0.99981	0.989
Random Forest	0.99981	0.984
Extra Trees	0.99981	1
KNN	0.98266	0.986
LDA	0.97705	0.98
AdaBoost	0.97673	0.982
SVM RBF	0.97654	0.982
Ridge Classifier	0.97654	0.981
SVM Linear	0.97642	0.979
Logistic Regression	0.97642	0.981
SGD	0.97508	0.979
Passive Aggressive	0.97444	0.978
Gaussian NB	0.97291	0.972
QDA	0.96577	0.973

ENSEMBLE LEARNING

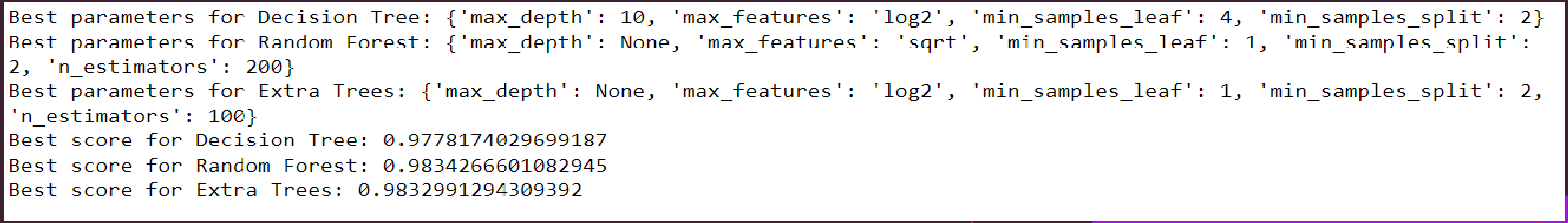
- On top of these data, we tried to flip the order of the stages, and use ml models, and send the output features to dl models but it didn’t beat our previous model.
- In addition we tried to run on the 3 models that achieved the best scores (Random forest, Extra trees, Decision tree) with grid search to find the best parameters. But again the scores didn’t improve



```python
param_grid_dt = {
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2', None]
}

param_grid_rf = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}

param_grid_et = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```



```
Best parameters for Decision Tree: {'max_depth': 10, 'max_features': 'log2', 'min_samples_leaf': 4, 'min_samples_split': 2}
Best parameters for Random Forest: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split':
2, 'n_estimators': 200}
Best parameters for Extra Trees: {'max_depth': None, 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split': 2,
'n_estimators': 100}
Best score for Decision Tree: 0.9778174029699187
Best score for Random Forest: 0.9834266601082945
Best score for Extra Trees: 0.9832991294309392
```

CONCLUSIONS

- We explored using machine learning and neural networks to improve malware detection possibilities. Our system achieved better accuracy than traditional methods by automatically learning from data but requires labeled data which may not always be available.
- Our scores do not beat the researchers' best model score, since according to the article the researchers stated that they reached an accuracy of 1.
- However we gained results which is almost certain identification – 99.98%.