Malware Detection Using Ember features and Feed Forward Neural Network

used a simple 3-layer feed-forward network with dropout and batch-norm.

At the end it can be seen that the training accuracy is 100% and validation accuracy is 96.6% , and testing accuracy is 97% The model is converging in the inital few epochs itself.

the corressponding confusion matrix and classification reports and plots can be seen at the end.

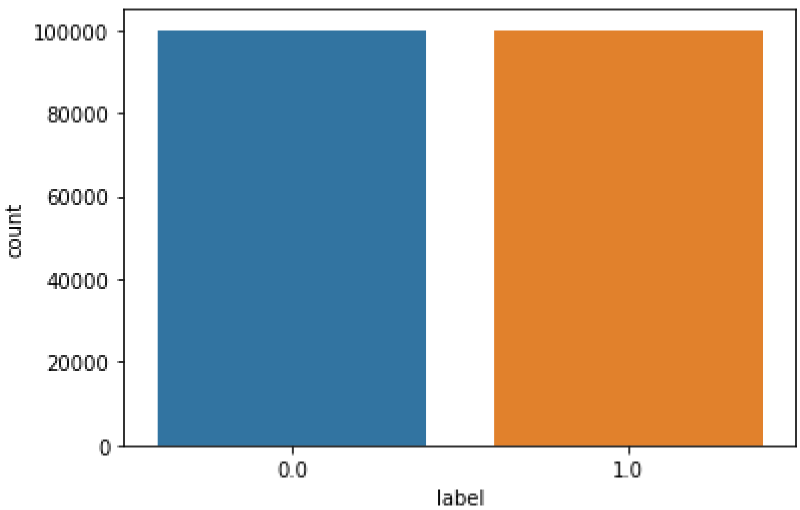
the architecure implemented here is very simple and more similar to the one in this link: https://towardsdatascience.com/pytorch-tabular-multiclass-classification-9f8211a123ab

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, WeightedRandomSampler

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report,accuracy_score
```

In [2]:
```
ember2018 = '../Dataset/ember_zip/ember2018'
test_dataset = np.load(os.path.join(ember2018,'ember2018_test_data.npz'),allow_pickl
X_train,y_train = test_dataset['arr_0'],test_dataset['arr_1']
EPOCHS = 50
BATCH_SIZE = 16
LEARNING_RATE = 0.0007
NUM_FEATURES = 2381
NUM_CLASSES =  2
```

In [4]:
```
df = pd.DataFrame(data=y_train, columns=["label"])
sns.countplot(x = 'label', data=df);
```



In [5]:
```
# Split into train+val and test
X_trainval, X_test, y_trainval, y_test = train_test_split(X_train, y_train, test_siz
```

```
# Split train into train-val
X_train, X_val, y_train, y_val = train_test_split(X_trainval, y_trainval, test_size=
```

In [6]:

```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)
X_train, y_train = np.array(X_train), np.array(y_train)
X_val, y_val = np.array(X_val), np.array(y_val)
X_test, y_test = np.array(X_test), np.array(y_test)
```

In [7]:

```
class ClassifierDataset(Dataset):
    def __init__(self, X_data, y_data):
        self.X_data = X_data
        self.y_data = y_data
    def __getitem__(self, index):
        return self.X_data[index], self.y_data[index]
    def __len__ (self):
        return len(self.X_data)

class MulticlassClassification(nn.Module):
    def __init__(self, num_feature, num_class):
        super(MulticlassClassification, self).__init__()

        self.layer_1 = nn.Linear(num_feature, 512)
        self.layer_2 = nn.Linear(512, 128)
        self.layer_3 = nn.Linear(128, 64)
        self.layer_out = nn.Linear(64, num_class)

        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(p=0.2)
        self.batchnorm1 = nn.BatchNorm1d(512)
        self.batchnorm2 = nn.BatchNorm1d(128)
        self.batchnorm3 = nn.BatchNorm1d(64)

    def forward(self, x):
        x = self.layer_1(x)
        x = self.batchnorm1(x)
        x = self.relu(x)

        x = self.layer_2(x)
        x = self.batchnorm2(x)
        x = self.relu(x)
        x = self.dropout(x)

        x = self.layer_3(x)
        x = self.batchnorm3(x)
        x = self.relu(x)
        x = self.dropout(x)

        x = self.layer_out(x)

        return x
```

In [8]:

```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
values,counts = np.unique(y_train,return_counts=True)
class_weights = 1./torch.tensor(counts, dtype=torch.float)
print(class_weights)
```

```
tensor([1.3889e-05, 1.3889e-05])
```

In [9]:

```
train_dataset = ClassifierDataset(torch.from_numpy(X_train).float(), torch.from_nump
val_dataset = ClassifierDataset(torch.from_numpy(X_val).float(), torch.from_numpy(y_
test_dataset = ClassifierDataset(torch.from_numpy(X_test).float(), torch.from_numpy(
```

```
train_loader = DataLoader(dataset=train_dataset,
                          batch_size=BATCH_SIZE,
)
val_loader = DataLoader(dataset=val_dataset, batch_size=1)
test_loader = DataLoader(dataset=test_dataset, batch_size=1)
```

In [12]:

```
model = MulticlassClassification(num_feature = NUM_FEATURES, num_class=NUM_CLASSES)
model.load_state_dict(torch.load(os.path.join(ember2018,'detection.pth')))
model.eval()
model.to(device)
```

Out[12]:

```
MulticlassClassification(
  (layer_1): Linear(in_features=2381, out_features=512, bias=True)
  (layer_2): Linear(in_features=512, out_features=128, bias=True)
  (layer_3): Linear(in_features=128, out_features=64, bias=True)
  (layer_out): Linear(in_features=64, out_features=2, bias=True)
  (relu): ReLU()
  (dropout): Dropout(p=0.2)
  (batchnorm1): BatchNorm1d(512, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
  (batchnorm2): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
  (batchnorm3): BatchNorm1d(64, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
)
```

In [14]:

```
model = MulticlassClassification(num_feature = NUM_FEATURES, num_class=NUM_CLASSES)
model.to(device)

criterion = nn.CrossEntropyLoss(weight=class_weights.to(device))
optimizer = optim.Adam(model.parameters(), lr=LEARNING_RATE)
print(model)
```

```
MulticlassClassification(
  (layer_1): Linear(in_features=2381, out_features=512, bias=True)
  (layer_2): Linear(in_features=512, out_features=128, bias=True)
  (layer_3): Linear(in_features=128, out_features=64, bias=True)
  (layer_out): Linear(in_features=64, out_features=2, bias=True)
  (relu): ReLU()
  (dropout): Dropout(p=0.2)
  (batchnorm1): BatchNorm1d(512, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
  (batchnorm2): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True, track_running
_stats=True)
  (batchnorm3): BatchNorm1d(64, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
)
```

In [15]:

```
def multi_acc(y_pred, y_test):
    y_pred_softmax = torch.log_softmax(y_pred, dim = 1)
    _, y_pred_tags = torch.max(y_pred_softmax, dim = 1)

    correct_pred = (y_pred_tags == y_test).float()
    acc = correct_pred.sum() / len(correct_pred)

    acc = torch.round(acc * 100)

    return (acc)
```

In [16]:

```
accuracy_stats = {
    'train': [],
    "val": []
}
loss_stats = {
    'train': [],
```

```
    "val": []
}
```

In [17]:

```
for e in tqdm(range(1, EPOCHS+1)):

    # TRAINING
    train_epoch_loss = 0
    train_epoch_acc = 0
    model.train()
    for X_train_batch, y_train_batch in train_loader:
        X_train_batch, y_train_batch = X_train_batch.to(device), y_train_batch.to(de
        optimizer.zero_grad()

        y_train_pred = model(X_train_batch)

        train_loss = criterion(y_train_pred, y_train_batch)
        train_acc =  multi_acc(y_train_pred, y_train_batch)

        train_loss.backward()
        optimizer.step()

        train_epoch_loss += train_loss.item()
        train_epoch_acc += train_acc.item()


    # VALIDATION
    with torch.no_grad():

        val_epoch_loss = 0
        val_epoch_acc = 0

        model.eval()
        for X_val_batch, y_val_batch in val_loader:
            X_val_batch, y_val_batch = X_val_batch.to(device), y_val_batch.to(device

            y_val_pred = model(X_val_batch)

            val_loss = criterion(y_val_pred, y_val_batch)
            val_acc = multi_acc(y_val_pred, y_val_batch)

            val_epoch_loss += val_loss.item()
            val_epoch_acc += val_acc.item()
    loss_stats['train'].append(train_epoch_loss/len(train_loader))
    loss_stats['val'].append(val_epoch_loss/len(val_loader))
    accuracy_stats['train'].append(train_epoch_acc/len(train_loader))
    accuracy_stats['val'].append(val_epoch_acc/len(val_loader))


    print(f'Epoch {e+0:03}: | Train Loss: {train_epoch_loss/len(train_loader):.5f} |
```

```
Epoch 001: | Train Loss: 0.20881 | Val Loss: 0.69888 | Train Acc: 91.810| Val Acc: 9
4.388
Epoch 002: | Train Loss: 0.12978 | Val Loss: 0.99220 | Train Acc: 95.153| Val Acc: 9
5.162
Epoch 003: | Train Loss: 0.09693 | Val Loss: 0.43272 | Train Acc: 96.453| Val Acc: 9
5.650
Epoch 004: | Train Loss: 0.07583 | Val Loss: 0.44156 | Train Acc: 97.247| Val Acc: 9
4.781
Epoch 005: | Train Loss: 0.06221 | Val Loss: 0.96631 | Train Acc: 97.780| Val Acc: 9
5.312
Epoch 006: | Train Loss: 0.05200 | Val Loss: 1.31929 | Train Acc: 98.152| Val Acc: 9
5.888
Epoch 007: | Train Loss: 0.04470 | Val Loss: 1.15506 | Train Acc: 98.432| Val Acc: 9
5.856
Epoch 008: | Train Loss: 0.03699 | Val Loss: 1.33602 | Train Acc: 98.701| Val Acc: 9
```

```
6.250
Epoch 009: | Train Loss: 0.03446 | Val Loss: 0.97687 | Train Acc: 98.802| Val Acc: 9
6.381
Epoch 010: | Train Loss: 0.03075 | Val Loss: 1.55790 | Train Acc: 98.916| Val Acc: 9
6.306
Epoch 011: | Train Loss: 0.02611 | Val Loss: 1.00609 | Train Acc: 99.106| Val Acc: 9
3.875
Epoch 012: | Train Loss: 0.02416 | Val Loss: 1.02547 | Train Acc: 99.162| Val Acc: 9
6.056
Epoch 013: | Train Loss: 0.02099 | Val Loss: 1.01989 | Train Acc: 99.268| Val Acc: 9
6.412
Epoch 014: | Train Loss: 0.02016 | Val Loss: 1.70420 | Train Acc: 99.319| Val Acc: 9
6.506
Epoch 015: | Train Loss: 0.01783 | Val Loss: 1.02502 | Train Acc: 99.404| Val Acc: 9
6.519
Epoch 016: | Train Loss: 0.01730 | Val Loss: 1.10259 | Train Acc: 99.416| Val Acc: 9
6.369
Epoch 017: | Train Loss: 0.01557 | Val Loss: 1.08580 | Train Acc: 99.456| Val Acc: 9
6.581
Epoch 018: | Train Loss: 0.01469 | Val Loss: 0.71794 | Train Acc: 99.499| Val Acc: 9
6.381
Epoch 019: | Train Loss: 0.01353 | Val Loss: 0.90592 | Train Acc: 99.550| Val Acc: 9
6.406
Epoch 020: | Train Loss: 0.01233 | Val Loss: 0.99587 | Train Acc: 99.583| Val Acc: 9
6.338
Epoch 021: | Train Loss: 0.01202 | Val Loss: 0.97118 | Train Acc: 99.598| Val Acc: 9
6.506
Epoch 022: | Train Loss: 0.01200 | Val Loss: 0.96579 | Train Acc: 99.632| Val Acc: 9
6.444
Epoch 023: | Train Loss: 0.01046 | Val Loss: 0.81176 | Train Acc: 99.657| Val Acc: 9
6.300
Epoch 024: | Train Loss: 0.01027 | Val Loss: 0.80426 | Train Acc: 99.673| Val Acc: 9
6.444
Epoch 025: | Train Loss: 0.00950 | Val Loss: 0.73155 | Train Acc: 99.692| Val Acc: 9
6.475
Epoch 026: | Train Loss: 0.00941 | Val Loss: 1.84765 | Train Acc: 99.714| Val Acc: 9
6.438
Epoch 027: | Train Loss: 0.00864 | Val Loss: 0.83684 | Train Acc: 99.721| Val Acc: 9
6.225
Epoch 028: | Train Loss: 0.00808 | Val Loss: 0.87738 | Train Acc: 99.743| Val Acc: 9
5.838
Epoch 029: | Train Loss: 0.00754 | Val Loss: 0.71148 | Train Acc: 99.741| Val Acc: 9
6.594
Epoch 030: | Train Loss: 0.00764 | Val Loss: 0.74604 | Train Acc: 99.757| Val Acc: 9
6.219
Epoch 031: | Train Loss: 0.00744 | Val Loss: 0.82273 | Train Acc: 99.749| Val Acc: 9
6.662
Epoch 032: | Train Loss: 0.00657 | Val Loss: 0.81865 | Train Acc: 99.790| Val Acc: 9
6.694
Epoch 033: | Train Loss: 0.00654 | Val Loss: 0.88643 | Train Acc: 99.779| Val Acc: 9
6.550
Epoch 034: | Train Loss: 0.00648 | Val Loss: 0.80547 | Train Acc: 99.787| Val Acc: 9
6.656
Epoch 035: | Train Loss: 0.00654 | Val Loss: 0.74443 | Train Acc: 99.798| Val Acc: 9
6.569
Epoch 036: | Train Loss: 0.00569 | Val Loss: 0.81156 | Train Acc: 99.830| Val Acc: 9
6.706
Epoch 037: | Train Loss: 0.00623 | Val Loss: 1.00325 | Train Acc: 99.800| Val Acc: 9
6.325
Epoch 038: | Train Loss: 0.00603 | Val Loss: 0.93067 | Train Acc: 99.815| Val Acc: 9
6.537
Epoch 039: | Train Loss: 0.00531 | Val Loss: 1.03104 | Train Acc: 99.836| Val Acc: 9
6.581
Epoch 040: | Train Loss: 0.00540 | Val Loss: 1.06213 | Train Acc: 99.821| Val Acc: 9
6.138
Epoch 041: | Train Loss: 0.00513 | Val Loss: 0.90087 | Train Acc: 99.849| Val Acc: 9
6.550
Epoch 042: | Train Loss: 0.00479 | Val Loss: 1.00851 | Train Acc: 99.842| Val Acc: 9
6.769
```

```
Epoch 043: | Train Loss: 0.00518 | Val Loss: 0.99220 | Train Acc: 99.852| Val Acc: 9
6.481
Epoch 044: | Train Loss: 0.00467 | Val Loss: 0.70061 | Train Acc: 99.850| Val Acc: 9
6.506
Epoch 045: | Train Loss: 0.00489 | Val Loss: 0.76383 | Train Acc: 99.850| Val Acc: 9
6.719
Epoch 046: | Train Loss: 0.00476 | Val Loss: 0.97113 | Train Acc: 99.855| Val Acc: 9
6.675
Epoch 047: | Train Loss: 0.00477 | Val Loss: 0.71315 | Train Acc: 99.851| Val Acc: 9
6.825
Epoch 048: | Train Loss: 0.00514 | Val Loss: 0.78307 | Train Acc: 99.871| Val Acc: 9
6.425
Epoch 049: | Train Loss: 0.00413 | Val Loss: 0.91424 | Train Acc: 99.879| Val Acc: 9
6.713
Epoch 050: | Train Loss: 0.00415 | Val Loss: 0.84226 | Train Acc: 99.877| Val Acc: 9
6.669
```

In [19]:

```
torch.save(model.state_dict(), os.path.join(ember2018,'detection.pth'))
```

In [18]:

```
os.path.join(ember2018,'detection.pth')
```

Out[18]:

```
'../Dataset/ember_zip/ember2018/detection.pth'
```

In [30]:

```
!ls ../Dataset/sorel/
```

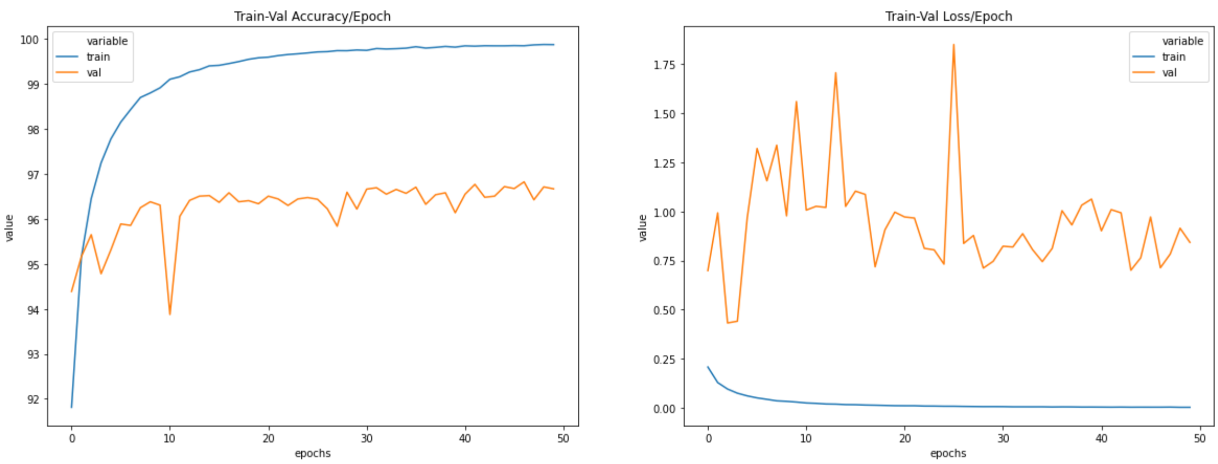
```
classification.pth  sorel_label.csv        test-features.npz
db                  sorel_label_sum25.csv  validation-features.npz
meta.db             sorel_malware1.csv
sorel_data.npz      sorel_malware.csv
```

In [20]:

```
# Create dataframes
train_val_acc_df = pd.DataFrame.from_dict(accuracy_stats).reset_index().melt(id_vars
train_val_loss_df = pd.DataFrame.from_dict(loss_stats).reset_index().melt(id_vars=['
# Plot the dataframes
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20,7))
sns.lineplot(data=train_val_acc_df, x = "epochs", y="value", hue="variable",  ax=axe
sns.lineplot(data=train_val_loss_df, x = "epochs", y="value", hue="variable", ax=axe
```

Out[20]:

```
Text(0.5, 1.0, 'Train-Val Loss/Epoch')
```



In [21]:

```
y_pred_list = []
y_prob_list = []
with torch.no_grad():
    model.eval()
    for X_batch, _ in test_loader:
        X_batch = X_batch.to(device)
        y_test_pred = model(X_batch)
        _, y_pred_tags = torch.max(y_test_pred, dim = 1)
```

```
        y_pred_list.append(y_pred_tags.cpu().numpy())
        y_prob_list.append(y_test_pred)


y_pred_list = [a.squeeze().tolist() for a in y_pred_list]
```

In [33]:
```
y_prob_list[0],y_pred_list[0]
```

Out[33]:
```
(tensor([[-15.1259, -23.0870, -25.0988, -23.7968, -21.3749, -21.3992, -19.6963,
          -17.8799,   5.0449, -22.6265, -18.0614]], device='cuda:0'),
 8)
```

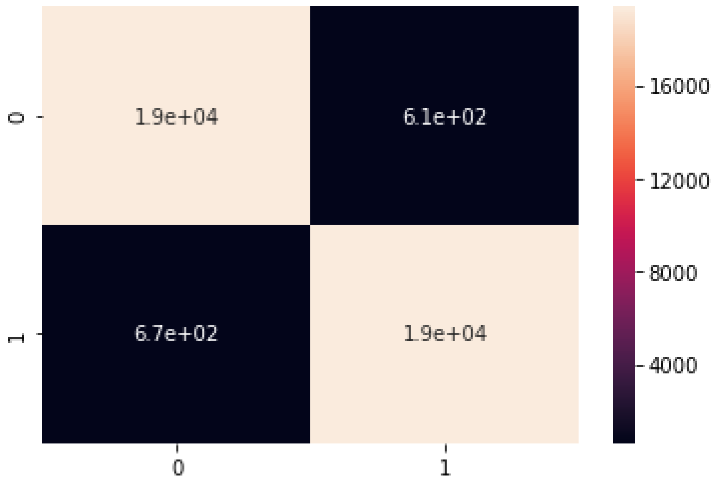
In [22]:
```
y_test.astype('long')
```

Out[22]:
```
array([0, 1, 1, ..., 0, 0, 1])
```

In [23]:
```
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_test.astype('long'), y_pred_li

sns.heatmap(confusion_matrix_df, annot=True)
```

Out[23]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b055b096b70>
```



In [24]:
```
confusion_matrix_df
```

Out[24]:

	0	1
0	19391	609
1	669	19331

In [25]:
```
print(classification_report(y_test.astype('long'), y_pred_list))
```

```
              precision    recall  f1-score   support

           0       0.97      0.97      0.97     20000
           1       0.97      0.97      0.97     20000

    accuracy                           0.97     40000
   macro avg       0.97      0.97      0.97     40000
weighted avg       0.97      0.97      0.97     40000
```