FA24-CS634853 Data Mining Final Project Binary Classification

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Course: CS634 Data Mining
Dataset Link: https://archive.ics.uci.edu/dataset/379/website+phishing
Github Link: https://github.com/adonispujols-njit/cs634-final-project

Outline

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1. Discussion

1.a Introduction

This project implements the required and optional algorithms for the binary classification of website phising. The dataset consists of over a thousand websites divided into legitimate, phishing, and suspicious. The features consists of whether it has a popup window, the age of the domain, the url length, etc.

1.b Setup

Requirements

Packages:

* refer to requirements.txt

Install

Conda setup steps: You may skip if you already have a compatible conda enviroment running. But make sure to install the requirements as noted below
conda init # unless conda is already running
conda create -n cs634 python # create enviroment, but any existing python3 enviroment will do
conda activate cs634

Extract pujols_adonis_finalproj.zip using any tool of your choice. Assuming you already have conda/pip installed, run the following command to install all required packages:
pip install -r requirements.txt

1.c Analysis/Conclusion (final results at bottom)

Surprisingly, SVM was the highest performing model compared to all of them, with RandomForest scoring the lowest. However all models including KNN and Conv1D were able to achieve both 97%+ accuracy and a F1 Score >= 0.97. Conv1D was second best at precision, however. The slight gap between SVM and the neural network could be explained by the necessary padding done to the data. As I was running this on my local machine, I forced a matrix size for torch that would be optimized to my hardware. This involved slight padding with null values that may have reduced the accuracy somewhat for the benefit of speed. The high coorelation between the labels and attributes atttributed to the sucess of all of these models. Moving forward, one should apply this technique on a dataset with more over a hundred or a thousand features to see the true benefits gained from the Conv1D neural network.

2. Preprocessing:

2.a Loading Data

In [62]:
```
from scipy import stats
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import (
    train_test_split,
    StratifiedShuffleSplit,
    GridSearchCV
)
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
import torch
from torch import nn
from torch.utils.data import DataLoader, TensorDataset
```

```python
from torchinfo import summary
import warnings


# useful functions for later
class KFoldCrossValidateInTorch:
    def __init__(
        self,
        model_class,
        loss_fn,
        learning_rate,
        epochs,
        batch_size,
        cv: StratifiedShuffleSplit,
        device,
    ) -> None:
        self.model_class = model_class
        self.loss_fn = loss_fn
        self.learning_rate = learning_rate
        self.epochs = epochs
        self.batch_size = batch_size
        self.cv = cv
        self.device = device
        self.models = []

    def training_loop(self, train_loader, model, optimizer):
        model.train()
        for X_batch, y_batch in train_loader:
            pred = model(X_batch)
            loss = self.loss_fn(pred, y_batch)

            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

        model.eval()
        with torch.no_grad():
            pred = model(train_loader.dataset.tensors[0])
            y_train = train_loader.dataset.tensors[1]

            matrix = confusion_matrix( torch.argmax(y_train, dim=1).cpu().numpy(), tor
            TP = matrix[0][0]
            FP = matrix[1][0]
            FN = matrix[0][1]
            P = TP + FN
            recall = TP / P
            precision = TP / (TP + FP)
            f1_score = 2 * (precision * recall) / (precision + recall)

    def val_nn_model(self, val_dataset: TensorDataset, model):
        model.eval()
        with torch.no_grad():
            X_val, y_val = val_dataset.tensors
            pred = model(X_val)
            loss = self.loss_fn(pred, y_val)

            matrix = confusion_matrix( torch.argmax(y_val, dim=1).cpu().numpy(), torch
            TP = matrix[0][0]
            FP = matrix[1][0]
            FN = matrix[0][1]
            P = TP + FN
            recall = TP / P
```

```python
        precision = TP / (TP + FP)
        f1_score = 2 * (precision * recall) / (precision + recall)

        return loss, pred, f1_score

    def fit(self, X, y):
        val_cv = {}
        for cv_step, (train_index, val_index) in enumerate(self.cv.split(X, y)):
            best_f1_score = -1
            print(f"Cross validation step {cv_step+1}\n")

            model = self.model_class()
            optimizer = torch.optim.Adamax(model.parameters(), lr=self.learning_rate)
            lr_scheduler = torch.optim.lr_scheduler.StepLR(
                optimizer, step_size=5, gamma=0.45
            )

            X_train = torch.tensor(
                X[train_index], dtype=torch.float32
            )
            y_train = torch.tensor(
                y[train_index], dtype=torch.float32
            )

            X_val = torch.tensor(X[val_index], dtype=torch.float32)
            y_val = torch.tensor(y[val_index], dtype=torch.float32)

            train_dataset = TensorDataset(X_train, y_train)
            train_loader = DataLoader(
                train_dataset, batch_size=self.batch_size, shuffle=True
            )
            val_dataset = TensorDataset(X_val, y_val)

            for epoch in range(self.epochs):
                print(f"Epoch {epoch + 1}\n-------------------------------")
                self.training_loop(train_loader, model, optimizer)
                lr_scheduler.step()

                _, _, val_f1_score = self.val_nn_model(val_dataset, model)

                print(f"Epoch {epoch + 1} completed\n")

            _, y_pred, _ = self.val_nn_model(val_dataset, model)
            val_cv[cv_step + 1] = print_data_matrix(
                y_val.argmax(dim=1), y_pred.argmax(dim=1)
            )
            val_cv[cv_step + 1]["Brier Score"] = (
                torch.mean((y_pred[:, 1] - y_val.argmax(dim=1)) ** 2).cpu().numpy()
            )
            val_cv[cv_step + 1]["Brier Skill Score"] = (
                (
                    val_cv[cv_step + 1]["Brier Score"]
                    / (
                        torch.mean(
                            (y_val.argmax(dim=1) - torch.mean(y_pred[:, 1])) ** 2
                        )
                    )
                )
                .cpu()
                .numpy()
            )
            self.models.append(model)
```

```
        val_cv["mean"] = pd.DataFrame(val_cv).mean(axis=1)
        return pd.DataFrame(val_cv).round(4)


    def predict(self, X):
        preds = []
        for cv_model in self.models:
            cv_model.eval()
            with torch.no_grad():
                preds.append(cv_model(X).cpu())
        preds = np.array(preds)
        return np.mean(preds, axis=0)

def print_data_matrix(y_test, y_pred):
    matrix = confusion_matrix(y_test, y_pred)
    FN = matrix[0][1]
    TP = matrix[0][0]
    FP = matrix[1][0]
    TN = matrix[1][1]
    P = TP + FN
    N = TN + FP
    TPR = TP / P
    TNR = TN / N
    FPR = FP / N
    FNR = FN / P
    recall = TPR
    precision = TP / (TP + FP)
    f1_score = 2 * (precision * recall) / (precision + recall)
    error_rate = (FP + FN) / (P + N)
    accuracy = (TP + TN) / (P + N)
    heidke_skill_score = (TP) / (TP + FN) - (FP) / (FP + TN)
    true_skill_statistics = TPR - FPR

    balanced_accuracy = (TPR + TNR) / 2

    return {
        "TP": TP,
        "TN": TN,
        "FP": FP,
        "FN": FN,
        "P": P,
        "N": N,
        "TPR": TPR,
        "TNR": TNR,
        "FPR": FPR,
        "FNR": FNR,
        "Recall": recall,
        "Precision": precision,
        "F1 Score": f1_score,
        "Accuracy": accuracy,
        "Error Rate": error_rate,
        "Accuracy (balanced)": balanced_accuracy,
        "(True) Skill Difference": true_skill_statistics,
        "Heidke Skill Score": heidke_skill_score,
    }
```

In [63]:

```
df = pd.read_csv('./data/PhishingData.csv')
df.head()
```

Out[63]:

	sfh	popupwidnow	sslfinal_state	request_url	url_of_anchor	web_traffic	url_length	age_of_do
0	1	-1	1	-1	-1	1	1	
1	-1	-1	-1	-1	-1	0	1	
2	1	-1	0	0	-1	0	-1	
3	1	0	1	-1	-1	0	1	
4	-1	-1	1	-1	0	0	-1	

2.b Dataset Analysis

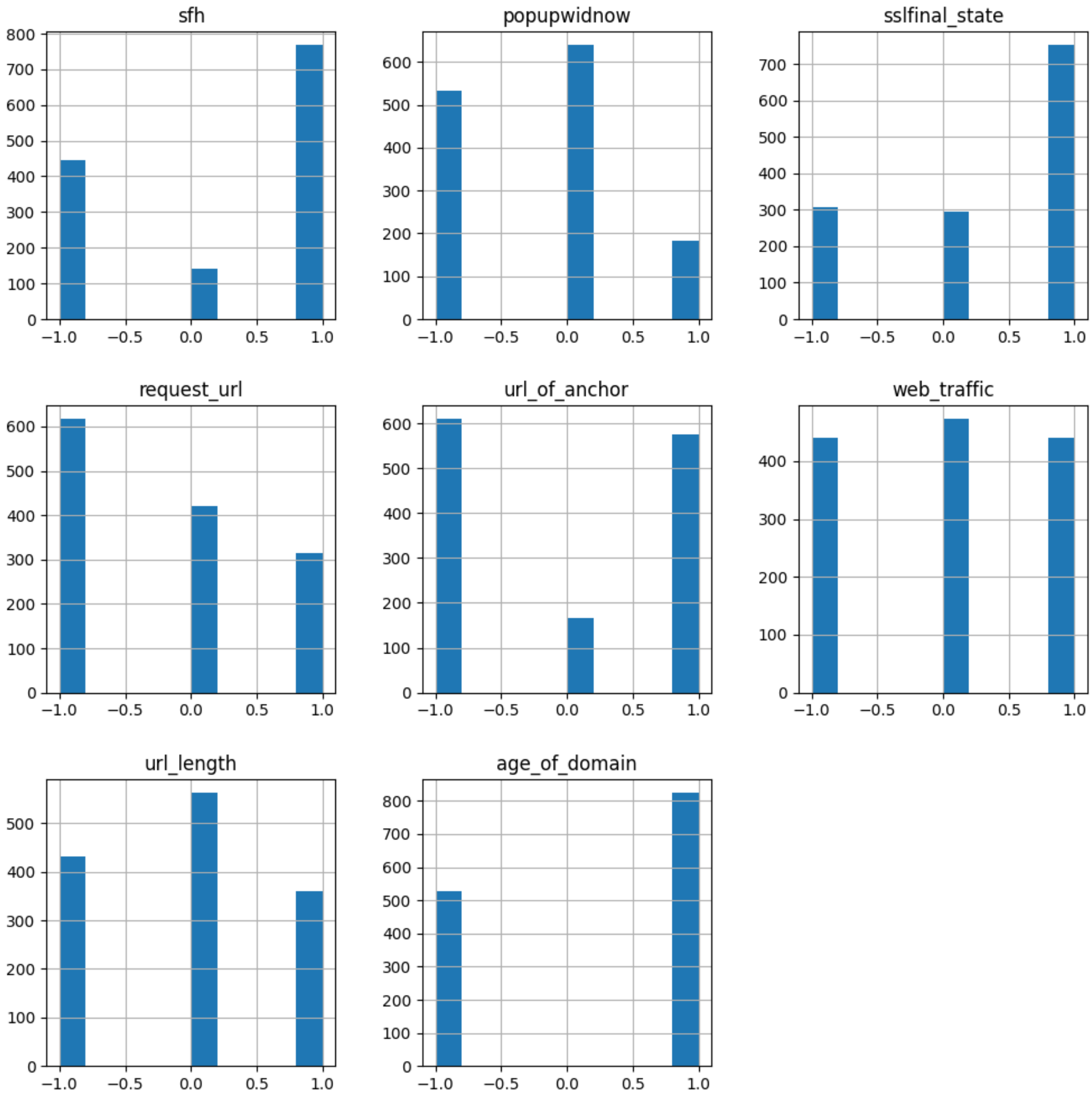
Verify there are no null values (dataset also reported this but it is important to verify)

In [64]:
```
df.isna().any()
```

Out[64]:
```
sfh                  False
popupwidnow          False
sslfinal_state       False
request_url          False
url_of_anchor        False
web_traffic          False
url_length           False
age_of_domain        False
having_ip_address    False
result               False
dtype: bool
```

Feature Distribution

In [65]:
```
_ = df.iloc[:, :-2].hist(figsize=(12, 12))
```



Correlations

The heatmap here for correlations confirms that there is high correlation between a few of our features.

In [66]:
```
heatmap = pd.concat([df.iloc[:, :-1], pd.Series(df['result'].factorize()[0], name='resu
heatmap.corr().style.background_gradient(cmap='coolwarm')
```

Out[66]:

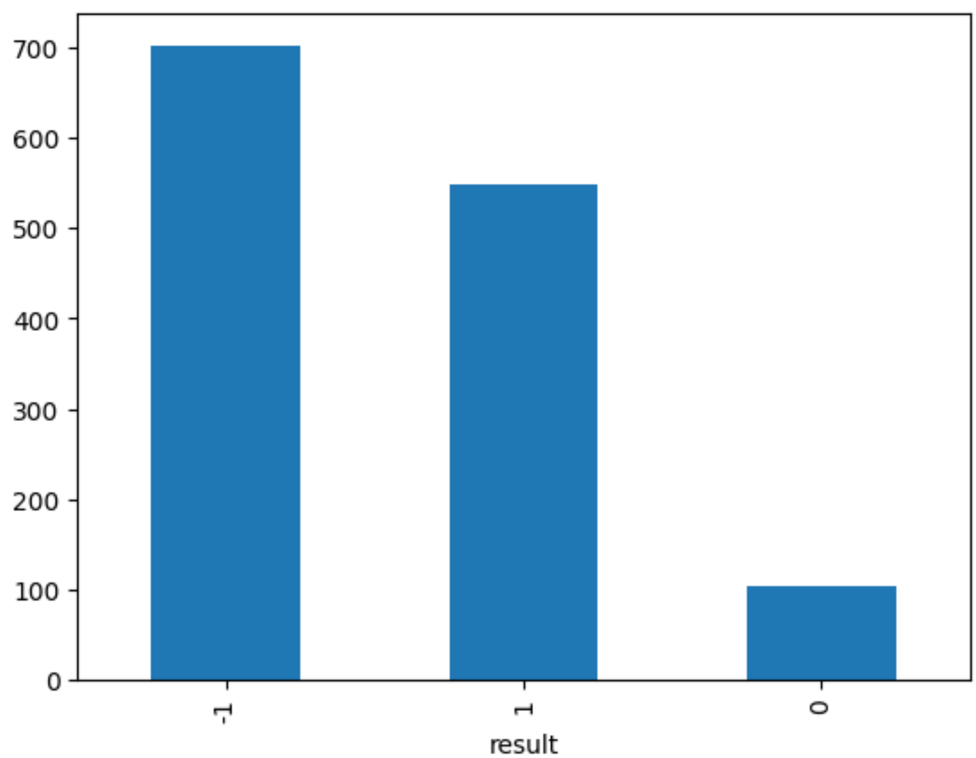
	sfh	popupwidnow	sslfinal_state	request_url	url_of_anchor	web_traffic
sfh	1.000000	0.375943	0.368690	0.257247	0.333703	-0.187082
popupwidnow	0.375943	1.000000	0.218050	0.111520	0.167760	-0.140407
sslfinal_state	0.368690	0.218050	1.000000	0.057239	0.088525	-0.171719
request_url	0.257247	0.111520	0.057239	1.000000	0.337277	-0.045858
url_of_anchor	0.333703	0.167760	0.088525	0.337277	1.000000	-0.092045
web_traffic	-0.187082	-0.140407	-0.171719	-0.045858	-0.092045	1.000000
url_length	0.151503	0.136229	0.095055	0.048431	0.097581	-0.108204
age_of_domain	0.163182	0.076815	0.208091	0.053348	0.069178	-0.683857
having_ip_address	0.043349	0.123399	0.108000	0.013346	0.039412	-0.094957
result	0.565158	0.401551	0.352899	0.339158	0.270117	-0.145090

Target Output Distribution

Note that -1 means confirmed phising, 0 means suspicious, and 1 means a legitimate website.

In [67]:
```
df['result'].value_counts().plot(kind='bar')
```

Out[67]: <Axes: xlabel='result'>



2.c Normalization

In [68]:
```python
encoder = LabelEncoder()
df['Class_numerical'] = encoder.fit_transform(df['result'])
```

In [69]:
```python
encoder.inverse_transform([0, 1])
```

Out[69]:
```
array([-1,  0])
```

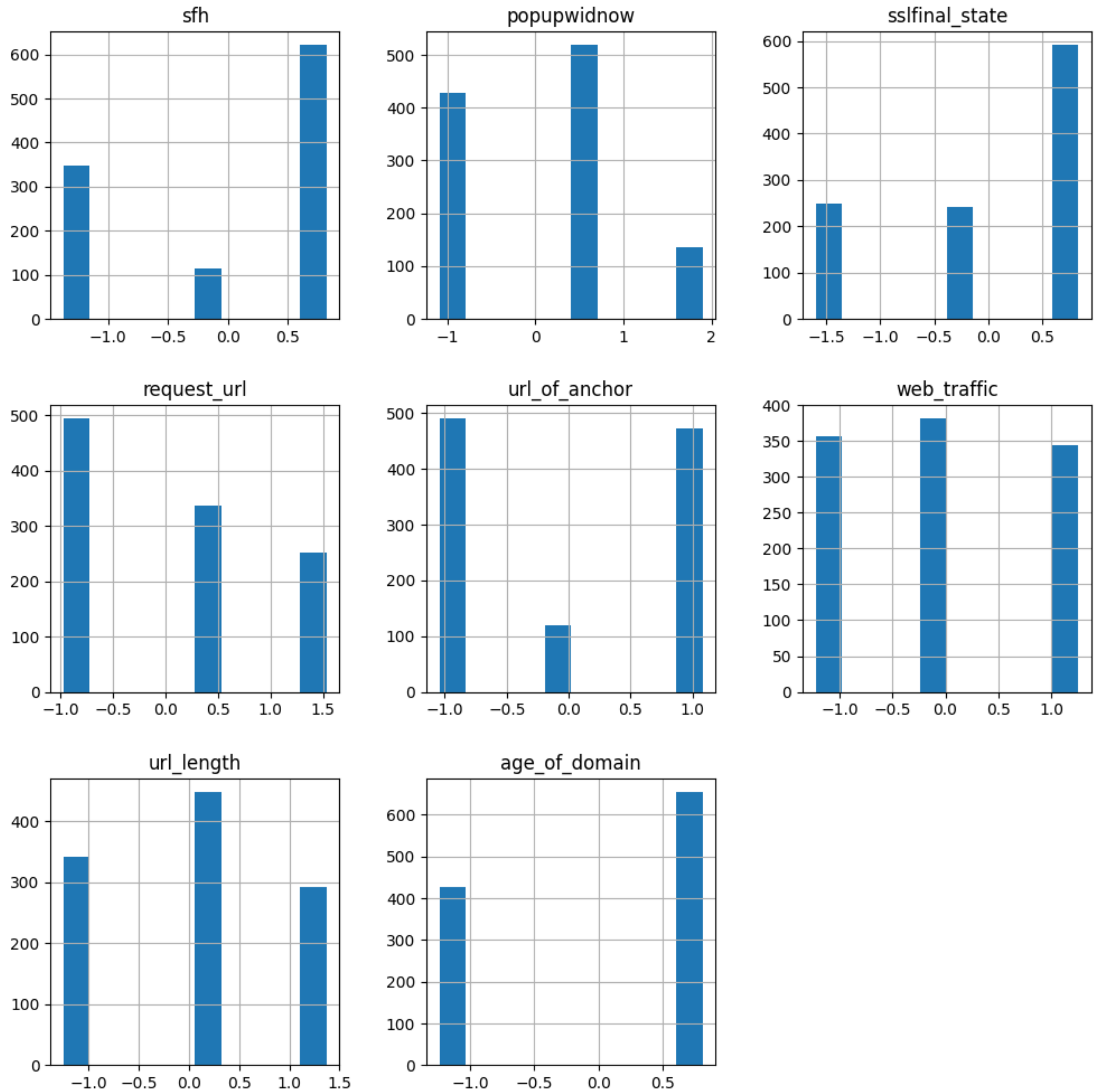
In [70]:
```python
X_train, X_test, y_train, y_test = train_test_split(
    df.iloc[:, :-2],
    df["Class_numerical"],
    test_size=0.2,
    random_state=42,
    shuffle=True,
    stratify=df["Class_numerical"],
)
```

In [71]:
```python
scaler = StandardScaler()
scaled_features = scaler.fit_transform(X_train)
X_train = pd.DataFrame(scaled_features, columns=df.columns[:-2])
X_test = pd.DataFrame(scaler.transform(X_test), columns=df.columns[:-2])
X_train.head()
```

Out[71]:

	sfh	popupwidnow	sslfinal_state	request_url	url_of_anchor	web_traffic	url_length	age_
0	-0.276630	-1.09032	-0.384314	0.281147	0.017646	-1.227590	0.060479	
1	-1.373016	-1.09032	-0.384314	-0.970711	-1.043057	1.257448	-1.248286	
2	-1.373016	-1.09032	0.831557	-0.970711	-1.043057	0.014929	0.060479	
3	-1.373016	-1.09032	0.831557	-0.970711	-1.043057	1.257448	-1.248286	
4	0.819757	-1.09032	0.831557	-0.970711	1.078348	1.257448	-1.248286	

In [72]:
```python
_ = X_train.iloc[:, :-1].hist(figsize=(12, 12))
```



3. Model Training:

```
In [73]: matrix_results = pd.DataFrame({'RandomForest': {}, 'SVM': {}, 'KNN': {}, 'Conv1D': {}}
```

3.a Random Forests

```
In [74]: stratified_split = StratifiedShuffleSplit(n_splits=10, test_size=0.1, random_state=42)
```

```
In [75]: random_forest_cv = {}
         random_forest_cv_models = []

         for i, (train_index, test_index) in enumerate(stratified_split.split(X_train, y_train)
             X_train_fold, X_val_fold = X_train.iloc[train_index], X_train.iloc[test_index]
             y_train_fold, y_val_fold = y_train.iloc[train_index], y_train.iloc[test_index]

             random_forest = RandomForestClassifier(n_estimators=300, max_depth=12, ccp_alpha=5e
```

```
    random_forest.fit(X_train_fold, y_train_fold)

    y_pred = random_forest.predict(X_val_fold)
    y_pred_proba = random_forest.predict_proba(X_val_fold)[:, 1]
    random_forest_cv[i+1] = print_data_matrix(y_val_fold, y_pred)
    random_forest_cv[i+1]['Brier Score'] = np.mean((y_pred_proba - y_val_fold)**2)
    random_forest_cv[i+1]['Brier Skill Score'] = random_forest_cv[i+1]['Brier Score'] /
    random_forest_cv_models.append(random_forest)

random_forest_cv['mean'] = pd.DataFrame(random_forest_cv).mean(axis=1)
pd.DataFrame(random_forest_cv).round(4)
```

Out[75]:

	1	2	3	4	5	6	7	8	9	1
TP	52.0000	53.0000	53.0000	52.0000	54.0000	52.0000	49.0000	54.0000	52.0000	52.000
TN	6.0000	7.0000	5.0000	6.0000	6.0000	7.0000	6.0000	4.0000	7.0000	7.000
FP	1.0000	0.0000	1.0000	0.0000	2.0000	0.0000	0.0000	0.0000	1.0000	0.000
FN	0.0000	1.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	0.0000	1.000
P	52.0000	54.0000	54.0000	53.0000	54.0000	52.0000	50.0000	55.0000	52.0000	53.000
N	7.0000	7.0000	6.0000	6.0000	8.0000	7.0000	6.0000	4.0000	8.0000	7.000
TPR	1.0000	0.9815	0.9815	0.9811	1.0000	1.0000	0.9800	0.9818	1.0000	0.981
TNR	0.8571	1.0000	0.8333	1.0000	0.7500	1.0000	1.0000	1.0000	0.8750	1.000
FPR	0.1429	0.0000	0.1667	0.0000	0.2500	0.0000	0.0000	0.0000	0.1250	0.000
FNR	0.0000	0.0185	0.0185	0.0189	0.0000	0.0000	0.0200	0.0182	0.0000	0.018
Recall	1.0000	0.9815	0.9815	0.9811	1.0000	1.0000	0.9800	0.9818	1.0000	0.981
Precision	0.9811	1.0000	0.9815	1.0000	0.9643	1.0000	1.0000	1.0000	0.9811	1.000
F1 Score	0.9905	0.9907	0.9815	0.9905	0.9818	1.0000	0.9899	0.9908	0.9905	0.990
Accuracy	0.9831	0.9836	0.9667	0.9831	0.9677	1.0000	0.9821	0.9831	0.9833	0.983
Error Rate	0.0169	0.0164	0.0333	0.0169	0.0323	0.0000	0.0179	0.0169	0.0167	0.016
Accuracy (balanced)	0.9286	0.9907	0.9074	0.9906	0.8750	1.0000	0.9900	0.9909	0.9375	0.990
(True) Skill Difference	0.8571	0.9815	0.8148	0.9811	0.7500	1.0000	0.9800	0.9818	0.8750	0.981
Heidke Skill Score	0.8571	0.9815	0.8148	0.9811	0.7500	1.0000	0.9800	0.9818	0.8750	0.981
Brier Score	1.5942	1.5929	1.5587	1.5948	1.5840	1.5969	1.5816	1.6163	1.5746	1.586
Brier Skill Score	1.0024	1.0242	1.0115	1.0176	1.0113	1.0181	1.0112	1.0202	1.0024	1.019

In [76]:

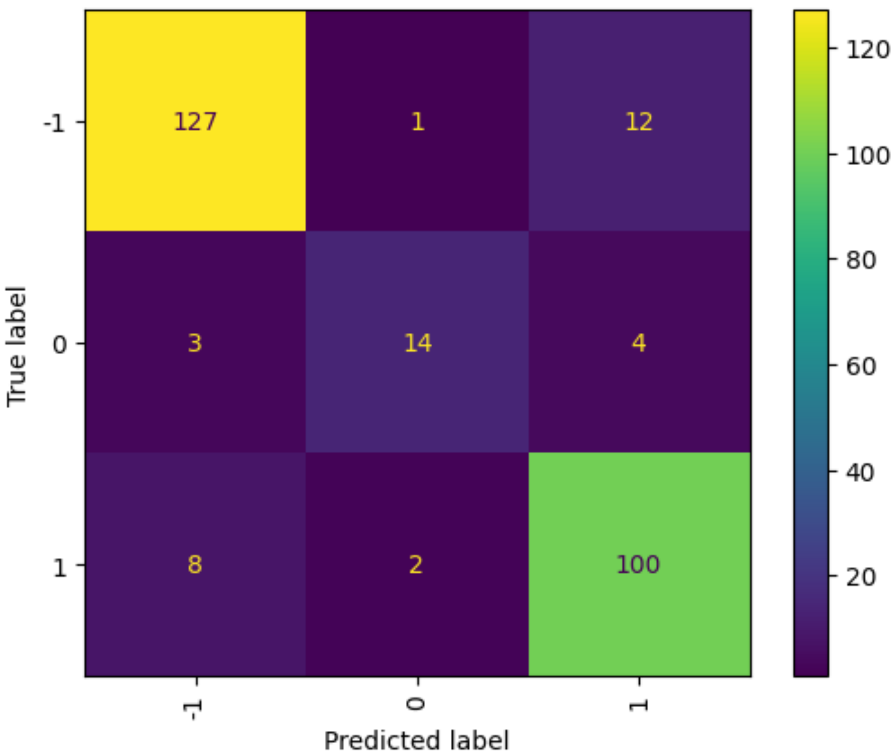
```
y_pred = stats.mode([model.predict(X_test) for model in random_forest_cv_models]).mode


matrix_results['RandomForest'] = print_data_matrix(y_test, y_pred)
```

```
matrix_results.loc["Brier Score", "RandomForest"] = np.mean((y_pred - y_test) ** 2)
matrix_results.loc["Brier Skill Score", "RandomForest"] = matrix_results["RandomForest"][
    "Brier Score"
] / (np.mean((y_test - np.mean(y_pred)) ** 2))

warnings.filterwarnings("ignore", message="The number of FixedLocator locations")
try:
    ConfusionMatrixDisplay.from_predictions(
        y_test,
        y_pred,
        display_labels=[-1,0,1],
        xticks_rotation="vertical",
    )

    RocCurveDisplay.from_predictions(y_test, y_pred)
except ValueError:
    pass
```



3.b SVM

In [77]:
```
stratified_split = StratifiedShuffleSplit(n_splits=10, test_size=0.1, random_state=42)
```

In [78]:
```
svc_cv = {}
svc_cv_models = []

for i, (train_index, test_index) in enumerate(stratified_split.split(X_train, y_train)
    X_train_fold, X_val_fold = X_train.iloc[train_index], X_train.iloc[test_index]
    y_train_fold, y_val_fold = y_train.iloc[train_index], y_train.iloc[test_index]

    svc = SVC(C= 100, degree= 2, kernel= 'rbf', probability=True, random_state=42)
    svc.fit(X_train_fold, y_train_fold)

    y_pred = svc.predict(X_val_fold)
    y_pred_proba = svc.predict_proba(X_val_fold)[:, 1]
```

```
    svc_cv[i+1] = print_data_matrix(y_val_fold, y_pred)
    svc_cv[i+1]['Brier Score'] = np.mean((y_pred_proba - y_val_fold)**2)
    svc_cv[i+1]['Brier Skill Score'] = svc_cv[i+1]['Brier Score'] / (np.mean((y_val_fo
    svc_cv_models.append(svc)

svc_cv['mean'] = pd.DataFrame(svc_cv).mean(axis=1)
pd.DataFrame(svc_cv).round(4)
```

Out[78]:

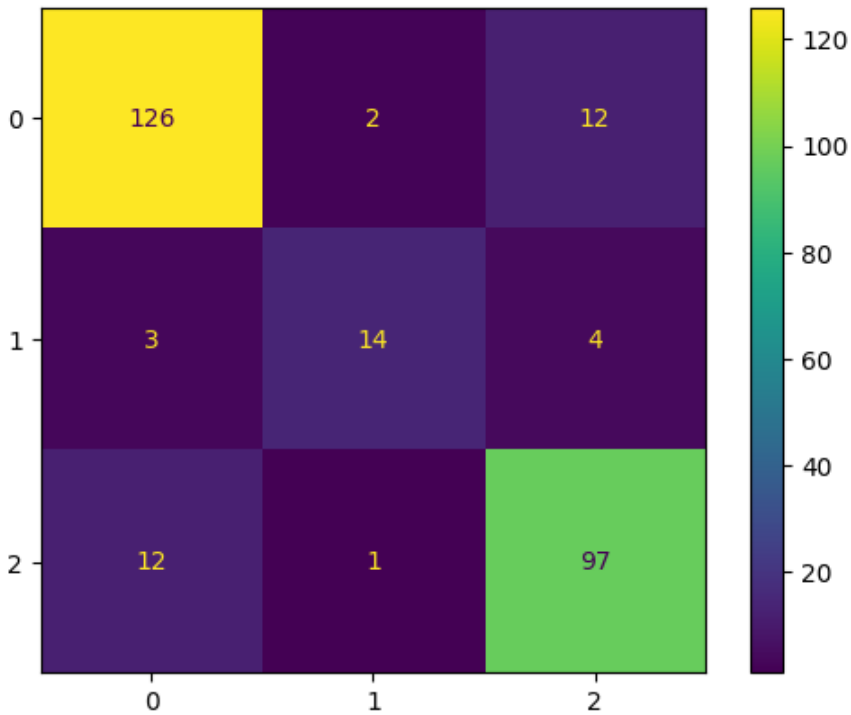
	1	2	3	4	5	6	7	8	9	10
TP	52.0000	52.0000	53.0000	52.0000	52.0000	50.0000	51.0000	53.0000	52.0000	50.000
TN	5.0000	7.0000	5.0000	5.0000	6.0000	7.0000	6.0000	5.0000	6.0000	6.000
FP	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	1.000
FN	0.0000	0.0000	1.0000	1.0000	1.0000	0.0000	1.0000	1.0000	0.0000	1.000
P	52.0000	52.0000	54.0000	53.0000	53.0000	50.0000	52.0000	54.0000	52.0000	51.000
N	6.0000	7.0000	6.0000	5.0000	7.0000	7.0000	7.0000	5.0000	7.0000	7.000
TPR	1.0000	1.0000	0.9815	0.9811	0.9811	1.0000	0.9808	0.9815	1.0000	0.980
TNR	0.8333	1.0000	0.8333	1.0000	0.8571	1.0000	0.8571	1.0000	0.8571	0.857
FPR	0.1667	0.0000	0.1667	0.0000	0.1429	0.0000	0.1429	0.0000	0.1429	0.142
FNR	0.0000	0.0000	0.0185	0.0189	0.0189	0.0000	0.0192	0.0185	0.0000	0.019
Recall	1.0000	1.0000	0.9815	0.9811	0.9811	1.0000	0.9808	0.9815	1.0000	0.980
Precision	0.9811	1.0000	0.9815	1.0000	0.9811	1.0000	0.9808	1.0000	0.9811	0.980
F1 Score	0.9905	1.0000	0.9815	0.9905	0.9811	1.0000	0.9808	0.9907	0.9905	0.980
Accuracy	0.9828	1.0000	0.9667	0.9828	0.9667	1.0000	0.9661	0.9831	0.9831	0.965
Error Rate	0.0172	0.0000	0.0333	0.0172	0.0333	0.0000	0.0339	0.0169	0.0169	0.034
Accuracy (balanced)	0.9167	1.0000	0.9074	0.9906	0.9191	1.0000	0.9190	0.9907	0.9286	0.918
(True) Skill Difference	0.8333	1.0000	0.8148	0.9811	0.8383	1.0000	0.8379	0.9815	0.8571	0.837
Heidke Skill Score	0.8333	1.0000	0.8148	0.9811	0.8383	1.0000	0.8379	0.9815	0.8571	0.837
Brier Score	1.5796	1.5402	1.5573	1.6170	1.5759	1.5606	1.5913	1.6150	1.5602	1.556
Brier Skill Score	1.0050	0.9957	1.0085	1.0274	1.0031	1.0042	1.0143	1.0170	0.9978	1.009

In [79]:

```
y_pred = stats.mode([model.predict(X_test) for model in svc_cv_models]).mode
matrix = confusion_matrix(y_test, y_pred)

matrix_results['SVM'] = print_data_matrix(y_test, y_pred)
matrix_results.loc["Brier Score", "SVM"] = np.mean((y_pred - y_test) ** 2)
matrix_results.loc["Brier Skill Score", "SVM"] = matrix_results["SVM"][
    "Brier Score"
] / (np.mean((y_test - np.mean(y_pred)) ** 2))
```

```python
try:
    ConfusionMatrixDisplay.from_predictions(
        y_test,
        y_pred,
        display_labels=encoder.inverse_transform([0, 1]),
        xticks_rotation="vertical",
    )
except ValueError:
    pass
```



3.c KNN

In [80]:
```python
stratified_split = StratifiedShuffleSplit(n_splits=6, test_size=0.1, random_state=42)
```

In [81]:
```python
knn_cv = {}
knn_cv_models = []

for i, (train_index, test_index) in enumerate(stratified_split.split(X_train, y_train))
    X_train_fold, X_val_fold = X_train.iloc[train_index], X_train.iloc[test_index]
    y_train_fold, y_val_fold = y_train.iloc[train_index], y_train.iloc[test_index]

    knn = KNeighborsClassifier(
        algorithm="ball_tree",
        leaf_size=10,
        n_neighbors=5,
        p=2,
        weights="distance",
        n_jobs=-1,
    )
    knn.fit(X_train_fold, y_train_fold)

    y_pred = knn.predict(X_val_fold)
    y_pred_proba = knn.predict_proba(X_val_fold)[:, 1]
    knn_cv[i + 1] = print_data_matrix(y_val_fold, y_pred)
```

```
    knn_cv[i+1]['Brier Score'] = np.mean((y_pred_proba - y_val_fold)**2)
    knn_cv[i+1]['Brier Skill Score'] = knn_cv[i+1]['Brier Score'] / (np.mean((y_val_fo
    knn_cv_models.append(knn)

knn_cv["mean"] = pd.DataFrame(knn_cv).mean(axis=1)
pd.DataFrame(knn_cv).round(4)
```

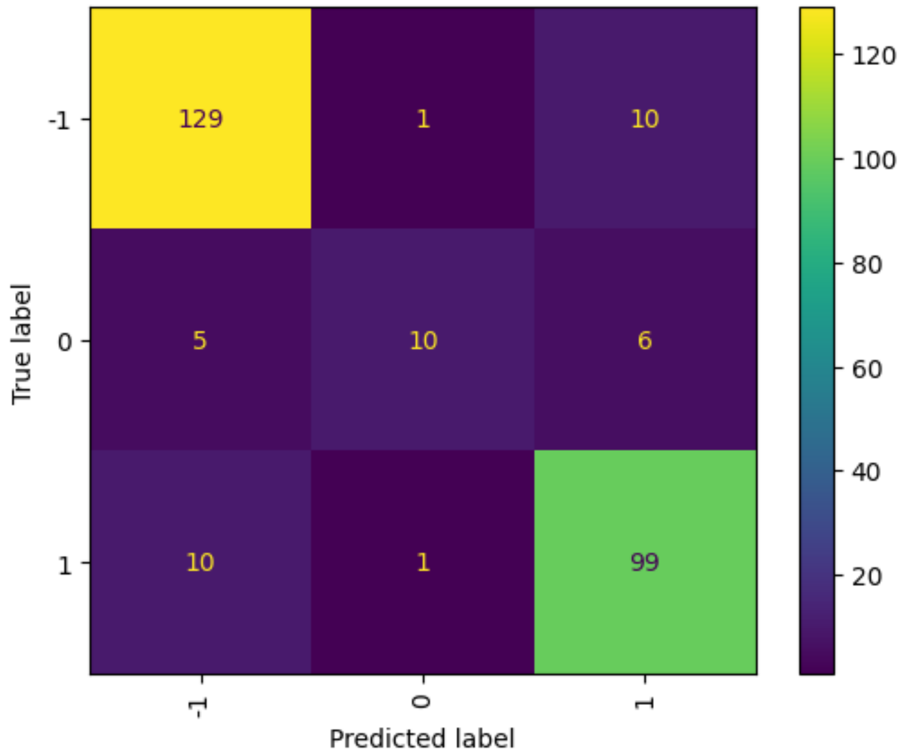
Out[81]:

	1	2	3	4	5	6	mean
TP	51.0000	50.0000	51.0000	50.0000	51.0000	51.0000	50.6667
TN	4.0000	7.0000	7.0000	4.0000	4.0000	6.0000	5.3333
FP	2.0000	0.0000	0.0000	1.0000	2.0000	0.0000	0.8333
FN	0.0000	1.0000	2.0000	2.0000	0.0000	0.0000	0.8333
P	51.0000	51.0000	53.0000	52.0000	51.0000	51.0000	51.5000
N	6.0000	7.0000	7.0000	5.0000	6.0000	6.0000	6.1667
TPR	1.0000	0.9804	0.9623	0.9615	1.0000	1.0000	0.9840
TNR	0.6667	1.0000	1.0000	0.8000	0.6667	1.0000	0.8556
FPR	0.3333	0.0000	0.0000	0.2000	0.3333	0.0000	0.1444
FNR	0.0000	0.0196	0.0377	0.0385	0.0000	0.0000	0.0160
Recall	1.0000	0.9804	0.9623	0.9615	1.0000	1.0000	0.9840
Precision	0.9623	1.0000	1.0000	0.9804	0.9623	1.0000	0.9842
F1 Score	0.9808	0.9901	0.9808	0.9709	0.9808	1.0000	0.9839
Accuracy	0.9649	0.9828	0.9667	0.9474	0.9649	1.0000	0.9711
Error Rate	0.0351	0.0172	0.0333	0.0526	0.0351	0.0000	0.0289
Accuracy (balanced)	0.8333	0.9902	0.9811	0.8808	0.8333	1.0000	0.9198
(True) Skill Difference	0.6667	0.9804	0.9623	0.7615	0.6667	1.0000	0.8396
Heidke Skill Score	0.6667	0.9804	0.9623	0.7615	0.6667	1.0000	0.8396
Brier Score	1.6182	1.6142	1.5848	1.6194	1.6072	1.5837	1.6046
Brier Skill Score	1.0069	1.0337	1.0308	1.0363	1.0132	1.0190	1.0233

In [82]:

```
y_pred = stats.mode([model.predict(X_test) for model in knn_cv_models]).mode
matrix = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay.from_predictions(
    y_test,
    y_pred,
    display_labels=[-1,0,1],
    xticks_rotation="vertical",
)

matrix_results['KNN'] = print_data_matrix(y_test, y_pred)
matrix_results.loc["Brier Score", "KNN"] = np.mean((y_pred - y_test) ** 2)
matrix_results.loc["Brier Skill Score", "KNN"] = matrix_results["KNN"][
    "Brier Score"
] / (np.mean((y_test - np.mean(y_pred)) ** 2))
```



3.d Conv1D

In [83]:

```python
device = (
    "cuda"
    if torch.cuda.is_available()
    else "mps" if torch.backends.mps.is_available() else "cpu"
)
print(f"Using {device} device for torch models")
```

```
Using cuda device for torch models
```

In [84]:

```python
class Conv1DNNModel(nn.Module):
    def __init__(self, *args, **kwargs) -> None:
        super().__init__(*args, **kwargs)
        self.conv1d_relu_stack = nn.Sequential(
           nn.Conv1d(in_channels=1, out_channels=128, kernel_size=3, padding=1),
                nn.ReLU(),
                nn.BatchNorm1d(128),
                nn.Conv1d(in_channels=128, out_channels=64, kernel_size=3, padding=1),
                nn.ReLU(),
                nn.BatchNorm1d(64),
                nn.Conv1d(in_channels=64, out_channels=32, kernel_size=3, padding=1),
                nn.ReLU(),
                nn.BatchNorm1d(32),
                nn.Flatten(),
                nn.Linear(32 * 16, 64),
                nn.ReLU(),
                nn.BatchNorm1d(64),
                nn.Linear(64, 3),  # outputting 3 values, one for each class
                nn.Softmax(dim=1))  # Use Softmax for multi-class probabilities

    def forward(self, x):
        return self.conv1d_relu_stack(x)
```

In [85]:
```python
learning_rate = 1e-2
batch_size = 64
epochs = 20

conv1d_model = Conv1DNNModel()
loss_fn = nn.BCEWithLogitsLoss()
summary(conv1d_model, input_size=(batch_size, 1, 16))
```

Out[85]:
```
=======================================================================================
====
Layer (type:depth-idx)                   Output Shape              Param #
=======================================================================================
====
Conv1DNNModel                            [64, 3]                   --
├─Sequential: 1-1                        [64, 3]                   --
│    └─Conv1d: 2-1                       [64, 128, 16]             512
│    └─ReLU: 2-2                         [64, 128, 16]             --
│    └─BatchNorm1d: 2-3                  [64, 128, 16]             256
│    └─Conv1d: 2-4                       [64, 64, 16]              24,640
│    └─ReLU: 2-5                         [64, 64, 16]              --
│    └─BatchNorm1d: 2-6                  [64, 64, 16]              128
│    └─Conv1d: 2-7                       [64, 32, 16]              6,176
│    └─ReLU: 2-8                         [64, 32, 16]              --
│    └─BatchNorm1d: 2-9                  [64, 32, 16]              64
│    └─Flatten: 2-10                     [64, 512]                 --
│    └─Linear: 2-11                      [64, 64]                  32,832
│    └─ReLU: 2-12                        [64, 64]                  --
│    └─BatchNorm1d: 2-13                 [64, 64]                  128
│    └─Linear: 2-14                      [64, 3]                   195
│    └─Softmax: 2-15                     [64, 3]                   --
=======================================================================================
====
Total params: 64,931
Trainable params: 64,931
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 34.23
=======================================================================================
====
Input size (MB): 0.00
Forward/backward pass size (MB): 3.74
Params size (MB): 0.26
Estimated Total Size (MB): 4.00
=======================================================================================
====
```

In [86]:
```python
y_train_one_hot = pd.get_dummies(y_train.values, dtype=np.float32)
y_test_one_hot = pd.get_dummies(y_test.values, dtype=np.float32)

import numpy as np
import pandas as pd

desired_length = 16

# pad our data to fit in network
def pad_or_truncate(data, desired_length, is_X = False):
    padded_data = []

    # Convert to NumPy array if it's a DataFrame
    if isinstance(data, pd.DataFrame):
        data = data.values
    elif isinstance(data, pd.Series):
        data = data.values
```

```
    if is_X:
        for seq in data:
            if len(seq) < desired_length:
                padding_length = desired_length - len(seq)
                padded_seq = np.pad(seq, (0, padding_length), 'constant')  # Pad with
            else:
                padded_seq = seq[:desired_length]  # Truncate if longer
            padded_data.append(padded_seq)
    else:
        padded_data = data
    return np.array(padded_data)


# Apply padding/truncation to our features (X)
padded_X_train = pad_or_truncate(X_train, desired_length, is_X = True)
padded_X_test = pad_or_truncate(X_test, desired_length, is_X = True)


train_dataset = TensorDataset(
    torch.tensor(padded_X_train.reshape((-1, 1, desired_length)), dtype=torch.float32)
    torch.tensor(y_train.values, dtype=torch.float32),
)
test_dataset = TensorDataset(
    torch.tensor(padded_X_test.reshape((-1, 1, desired_length)), dtype=torch.float32),
    torch.tensor(y_test.values, dtype=torch.float32),
)
```

In [87]:
```
stratified_cv_split = StratifiedShuffleSplit(n_splits=10, test_size=0.1, random_state=

conv1d_cv = KFoldCrossValidateInTorch(
    model_class=Conv1DNNModel,
    loss_fn=loss_fn,
    learning_rate=learning_rate,
    batch_size=batch_size,
    epochs=epochs,
    cv=stratified_cv_split,
    device=device
)
conv1d_cv.fit(padded_X_train.reshape((-1, 1, desired_length)), y_train_one_hot.values)
```

```
Cross validation step 1
(verbose output skipped)
```

Out[87]:

	1	2	3	4	5	6	7	8
TP	54	53	52	51	54	55	47	49
TN	3	2	1	4	4	3	3	4
FP	3	2	3	1	2	3	2	2
FN	0	0	0	4	0	0	2	1
P	54	53	52	55	54	55	49	50
N	6	4	4	5	6	6	5	6
TPR	1.0	1.0	1.0	0.927273	1.0	1.0	0.959184	0.98
TNR	0.5	0.5	0.25	0.8	0.666667	0.5	0.6	0.666667
FPR	0.5	0.5	0.75	0.2	0.333333	0.5	0.4	0.333333
FNR	0.0	0.0	0.0	0.072727	0.0	0.0	0.040816	0.02
Recall	1.0	1.0	1.0	0.927273	1.0	1.0	0.959184	0.98
Precision	0.947368	0.963636	0.945455	0.980769	0.964286	0.948276	0.959184	0.960784
F1 Score	0.972973	0.981481	0.971963	0.953271	0.981818	0.973451	0.959184	0.970297
Accuracy	0.95	0.964912	0.946429	0.916667	0.966667	0.95082	0.925926	0.946429
Error Rate	0.05	0.035088	0.053571	0.083333	0.033333	0.04918	0.074074	0.053571
Accuracy (balanced)	0.75	0.75	0.625	0.863636	0.833333	0.75	0.779592	0.823333
(True) Skill Difference	0.5	0.5	0.25	0.727273	0.666667	0.5	0.559184	0.646667
Heidke Skill Score	0.5	0.5	0.25	0.727273	0.666667	0.5	0.559184	0.646667
Brier Score	1.6358175	1.6354934	1.6651989	1.6536143	1.5986726	1.6321561	1.6694063	1.6100416
Brier Skill Score	1.0026135	1.003077	1.0086839	1.070279	0.9981287	1.0082306	1.0406904	1.0179701

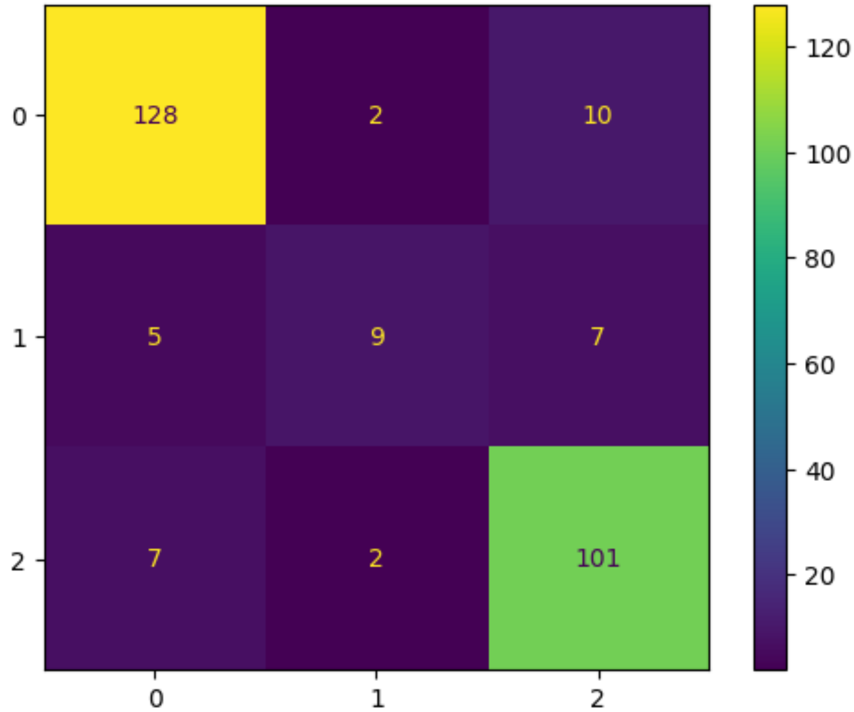
In [88]:

```
y_pred = conv1d_cv.predict(test_dataset.tensors[0]).argmax(axis=1)
matrix = confusion_matrix(y_test, y_pred)

matrix_results["Conv1D"] = print_data_matrix(y_test, y_pred)
matrix_results.loc["Brier Score", "Conv1D"] = np.mean((y_pred - y_test) ** 2)
matrix_results.loc["Brier Skill Score", "Conv1D"] = matrix_results["Conv1D"][
    "Brier Score"
] / (np.mean((y_test - np.mean(y_pred)) ** 2))

try:
    ConfusionMatrixDisplay.from_predictions(
        y_test,
        y_pred,
        display_labels=encoder.inverse_transform([0, 1]),
        xticks_rotation="vertical",
    )
```

```
except ValueError:
    pass
```



5. Results (analysis is above):

In [89]:
```
# comparing all the models
matrix_results.round(4)
```

Out[89]:

	RandomForest	SVM	KNN	Conv1D
TP	127.0000	126.0000	129.0000	128.0000
TN	14.0000	14.0000	10.0000	9.0000
FP	3.0000	3.0000	5.0000	5.0000
FN	1.0000	2.0000	1.0000	2.0000
P	128.0000	128.0000	130.0000	130.0000
N	17.0000	17.0000	15.0000	14.0000
TPR	0.9922	0.9844	0.9923	0.9846
TNR	0.8235	0.8235	0.6667	0.6429
FPR	0.1765	0.1765	0.3333	0.3571
FNR	0.0078	0.0156	0.0077	0.0154
Recall	0.9922	0.9844	0.9923	0.9846
Precision	0.9769	0.9767	0.9627	0.9624
F1 Score	0.9845	0.9805	0.9773	0.9734
Accuracy	0.9724	0.9655	0.9586	0.9514
Error Rate	0.0276	0.0345	0.0414	0.0486
Accuracy (balanced)	0.9079	0.9040	0.8295	0.8137
(True) Skill Difference	0.8157	0.8079	0.6590	0.6275
Heidke Skill Score	0.8157	0.8079	0.6590	0.6275
Brier Score	0.3321	0.3911	0.3432	0.3100
Brier Skill Score	0.3645	0.4297	0.3770	0.3402