

# Codes

April 18, 2024

## Import libraries

```
[112]: import torch
import torch.nn as nn
import torch.nn.functional as F

from torch.utils.data import TensorDataset
import torch.optim as optim
from torch.optim.lr_scheduler import StepLR, ReduceLROnPlateau
import pandas as pd
import os
import numpy as np
import datetime
import scipy
import seaborn as sns
import sys
from collections import Counter
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

from sklearn.utils import shuffle
from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTETomek, SMOTEENN
from sklearn.utils import resample
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder, \
    OneHotEncoder, OrdinalEncoder

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import multilabel_confusion_matrix
from sklearn.metrics import f1_score, accuracy_score

from sklearn.svm import SVC
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

```

import joblib
from sklearn.utils.class_weight import compute_class_weight
from skorch import NeuralNetClassifier
from skorch.callbacks import EarlyStopping, LRScheduler, Checkpoint
from skorch.helper import predefined_split
from skorch.dataset import Dataset
from skorch.callbacks import EpochScoring
from sklearn.metrics import RocCurveDisplay
from itertools import cycle
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import auc, roc_curve

%load_ext autotime

```

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```

[ ]: # Set random seed
np.random.seed(42)
torch.manual_seed(42)

```

```

[ ]: if torch.cuda.is_available():
    device = torch.device("cuda")

else:
    device = torch.device("cpu")
print(device)

```

## Functions and Tools

```

[ ]: def get_timestamp():
    """
        Get current timestamp
    """

    return datetime.datetime.now().strftime("%Y%m%dT%H%M%S")

```

```

[116]: def _import_data(path, validation_size=None):
    """
        Import source data
    """

    # Read source files
    df = pd.read_csv(f'source/mitbih_{path}.csv', header=None)

    # Extract data, and labels
    X = df.iloc[:, :-1].values
    y = df.iloc[:, -1].values.astype('int64')

```

```

    # Split into validation set, if needed
    if validation_size:
        X1, X2, y1, y2 = train_test_split(X, y, test_size=validation_size,
        ↪ random_state=42)

        return X1, y1, X2, y2

    else:
        return X, y

```

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```

[117]: def _gaussian_noise(X_train):
        """
        Add noise to dataset
        """

        noise = np.random.normal(loc=0, scale=0.03, size=X_train.shape)

        return X_train + noise

```

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```

[118]: def _balancing(X, y, num_sample):
        """
        Balancing data with specific number of records
        """

        # Get records count
        label, count = np.unique(y, return_counts=True)

        X_balanced = []
        y_balanced = []

        for lbl, cnt in zip(label, count):
            X_filter = X[y==lbl]
            y_filter = y[y==lbl]

            # Downsampling if data exceeds desire number
            if cnt > num_sample:
                X_filter, y_filter = resample(X_filter, y_filter,
                                                replace=False,
                                                n_samples=num_sample,
                                                random_state=42)

            # Otherwise, upsampling with bootstrap
            elif cnt < num_sample:
                X_filter, y_filter = resample(X_filter, y_filter,

```

```

        replace=True,
        n_samples=num_sample,
        random_state=42)

    X_balanced.append(X_filter)
    y_balanced.append(y_filter)

X_balanced = np.concatenate(X_balanced, axis=0)
y_balanced = np.concatenate(y_balanced, axis=0)

return X_balanced, y_balanced

```

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```

[119]: def _get_report(y_true, y_pred):
        """
        Generate classification report
        """

        report = classification_report(y_true, y_pred)

        print(report)

```

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```

[2]: def _roc_curve(y_true, y_pred):
        """
        Generate ROC curve
        Code for generating ROC curve obtained from documentation :
        https://scikit-learn.org/stable/auto_examples/model_selection/plot_roc.html
        """

        # Convert true labels to one-hot encoding
        y_true = LabelBinarizer().fit_transform(y_true)

        # Define the number of classes
        n_classes = 5
        class_labels = {0: 'N', 1: 'S', 2: 'V', 3: 'F', 4: 'Q'}

        # Define colors for each class
        colors = cycle(["aqua", "darkorange", "cornflowerblue", "olive", "maroon"])

        # Initialize dictionaries to store fpr, tpr, and roc_auc for each class
        fpr, tpr, roc_auc = dict(), dict(), dict()

        # Compute micro-average ROC
        fpr["micro"], tpr["micro"], _ = roc_curve(y_true.ravel(), y_pred.ravel())
        roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

```

```

# Compute macro-average ROC
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_true[:, i], y_pred[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

fpr_grid = np.linspace(0.0, 1.0, 1000)

# Interpolate all ROC curves at these points
mean_tpr = np.zeros_like(fpr_grid)
for i in range(n_classes):
    mean_tpr += np.interp(fpr_grid, fpr[i], tpr[i]) # linear interpolation

# Average interpolated TPRs and compute macro AUC
mean_tpr /= n_classes

fpr["macro"] = fpr_grid
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

fig, ax = plt.subplots()

# Set the figure size
fig.set_size_inches(8, 6)

# Plot micro-average ROC curve
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label=f"micro-average ROC curve (AUC = {roc_auc['micro']:.2f})",
    color="deeppink",
    linestyle=":",
    linewidth=4,
)

# Plot macro-average ROC curve
plt.plot(
    fpr["macro"],
    tpr["macro"],
    label=f"macro-average ROC curve (AUC = {roc_auc['macro']:.2f})",
    color="navy",
    linestyle=":",
    linewidth=4,
)

# Plot individual ROC curves for each class
for class_id, color in zip(range(n_classes), colors):
    RocCurveDisplay.from_predictions(

```

```

        y_true[:, class_id],
        y_pred[:, class_id],
        name=f"ROC curve for Class {class_labels[class_id]}",
        color=color,
        ax=ax,
    )

    # Set plot labels and title
    ax.set(
        xlabel="False Positive Rate",
        ylabel="True Positive Rate",
        title=" Receiver Operation Curve",
    )

    plt.legend()
    plt.show()

```

```

[ ]: def _get_confusion_matrix(y_true, y_pred, title=None):
    """
        Generate confusion matrix
    """

    cm = confusion_matrix(y_true, y_pred)

    class_labels = ['N', 'S', 'V', 'F', 'Q']

    # Calculate counts for each class
    class_totals = cm.sum(axis=1)

    # Calculate percentage for each class
    cm_percent = (cm.T / class_totals).T * 100

    plt.figure(figsize=(6, 6))

    # Plot confusion matrix with heatmap
    sns.heatmap(cm_percent, annot=False, cmap="Blues", fmt='d',
    ↪xticklabels=class_labels, yticklabels=class_labels, cbar=False,
    ↪linewidths=1, linecolor='white')

    # Annotate with total predictions
    for i in range(len(class_labels)):
        for j in range(len(class_labels)):
            # Annotations for count
            plt.text(j + 0.5, i + 0.6, f'{cm[i, j]}', ha='center', va='center',
            ↪color='black', fontsize=8)
            # Annotations for percentage

```

```

        plt.text(j + 0.5, i + 0.4, f'{cm_percent[i, j]:.2f}%', ha='center', va='center', color='black', fontsize=8)

plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title(title)
plt.grid(False)
plt.show()

```

## Models and Pipelines

### CNN

```

[131]: def _convert_to_tensor(X, y):
        """
        Convert data to tensor dataset
        """

        X = X.reshape(-1, 1, X.shape[-1])

        X = torch.from_numpy(X).float()
        y = torch.from_numpy(y).long()

        return X, y

```

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```

[133]: def _load_cnn_model(cnn, fn):
        """
        Load model for evaluation
        """

        # Load checkpoint
        checkpoint = torch.load(f"models/cnn/{fn}.pth", map_location=device)

        # Initialize model
        model = cnn()
        model_dict = model.state_dict()

        # Update model parameters with checkpoint values
        for key in checkpoint.keys():
            if key in model_dict:
                model_dict[key] = checkpoint[key]

        # Load updated parameters into the model
        model.load_state_dict(model_dict)

        # Move model to cuda (if available)

```

```

model.to(device)

# Set model to evaluation mode
model.eval()

return model

```

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```

[134]: def _evaluate_cnn(cnn, fn, subset='test', roc_curve=True):
        """
        Evaluate CNN model

        Params:
        -----
        cnn - Model Class (CNN or ResCNN)
        fn - Filename of model to be evaluated
        subset - Subset of source data to be evaluated (train, validation,
        test)
        roc_curve - Whether to show ROC curve

        """

        # Load model
        model = _load_cnn_model(cnn, fn)

        if subset == 'test':
            # Load data
            X_test, y_test = _import_data('test')

            # Preprocess data
            X, y = _preprocess(X_test, y_test)

        else:
            # Load data
            X_train, y_train, X_val, y_val = _import_data('train',
            validation_size=0.2)

            if subset == 'train':
                X, y = _preprocess(X_train, y_train)

            else:
                X, y = _preprocess(X_val, y_val)

        start = datetime.datetime.now()

```



```

# Evaluate, and predict with probability
with torch.no_grad():
    outputs = model(X)

end = datetime.datetime.now()
print(f"Predicting time: {end-start}")

# Get predicted labels with highest probability
_, y_pred = torch.max(outputs, 1)

# Get classification report
_get_report(y.cpu(), y_pred.cpu())

# Generate confusion matrix
_get_confusion_matrix(y.cpu(), y_pred.cpu())

if roc_curve:
    # Plot ROC curve
    _roc_curve(y.detach().cpu().numpy(), outputs.detach().cpu().numpy())

```

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```

[136]: def _initilise_cnn(model, **kwargs):
    """
        Initialise CNN model using skorch, NeuralNetClassifier
    """

    # Define batchsize, epoch, and loss function
    return NeuralNetClassifier(
        model,
        criterion=nn.CrossEntropyLoss,
        device=device,
        verbose=True,
        max_epochs=100,
        batch_size=128,
        **kwargs
    )

```

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```

[137]: def _callbacks(earlystop_patience=10, lr_scheduler=None, checkpoint=True):
    """
        Define callbacks for model training
    """

    # Earlystopping to prevent overfitting, by stop training when validation
    ↪ loss does not improve more than threshold

```

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    early_stop = EarlyStopping(monitor='valid_loss',
    ↪patience=earlystop_patience)

    # Model checkpoint to continuously save best model, with the focus on best
    ↪validation loss
    model_path = f'models/cnn/{get_timestamp()}.pth'
    checkpoint = Checkpoint(
        f_params=model_path,
        monitor='valid_loss_best',
        f_optimizer=None,
        f_history=None,
        f_criterion=None
    )

    # Define callback to compute and log training accuracy
    train_acc = EpochScoring(scoring='accuracy', name='train_acc',
    ↪on_train=True)

    if checkpoint:
        return [early_stop, lr_scheduler, checkpoint, train_acc]

    else:
        return [early_stop, lr_scheduler, train_acc]

```

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```

[1]: def _gridsearchcv(X_train, y_train, model, param_grid, cv=5,
    ↪scoring='f1_macro'):
    """
        Perform parameter tuning with stratify k-fold cross validation
    """

    skf = StratifiedKFold(n_splits=cv, shuffle=True, random_state=42)
    grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=skf,
    ↪scoring=scoring, n_jobs=-1, verbose=0)
    grid_result = grid.fit(X_train.cpu(), y_train.cpu())

    return grid_result

```

```

[141]: def _plot_history(history):
    """
        Plot training and validation loss/accuracy over epochs
    """

    fig, axs = plt.subplots(1, 2, figsize=(10, 4))

    axs[0].plot(history[:, 'train_loss'], label='Training')

```

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    axs[0].plot(history[:, 'valid_loss'], label='Validation')
    axs[0].set_xlabel('Epoch')
    axs[0].set_ylabel('Loss')
    axs[0].legend()

    axs[1].plot(history[:, 'train_acc'], label='Training')
    axs[1].plot(history[:, 'valid_acc'], label='Validation')
    axs[1].set_xlabel('Epoch')
    axs[1].set_ylabel('Accuracy')
    axs[1].legend()

    plt.tight_layout()
    plt.show()

```

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```

[142]: def _preprocess(X, y, balance=False, noise=False):
        """
        Preprocess data with optional balancing and augmentation,
        then convert to tensor dataset and move to CUDA (if available)
        """

        # Balance data if specified
        if balance:
            X, y = _balancing(X, y, balance)

        # Add noise for augmentation if specified
        if noise:
            X = _gaussian_noise(X)

        # Convert data to tensor dataset
        X, y = _convert_to_tensor(X, y)

        # Move data to CUDA device if available
        X, y = X.to(device), y.to(device)

        return X, y

```

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```

[139]: def _cnn_pipeline_with_gridsearch(cnn, param_grid, earllystop_patience=10,
                                         checkpoint=False, balance=False, noise=False,
                                         **kwargs):
        """
        Encapsulated CNN pipeline for importing training data,
        preprocessing, hyperparameter tuning,
        and returning the best parameters

```

*Params:*

```

    □
↪ -----
    cnn - Model Class (CNN or ResCNN)
    param_grid - Dictionary of parameters to be selected through
↪ gridsearch process
    earllystop_patience - Early stopping threshold
    checkpoint - Whether to enable checkpoint to continuously save best
↪ model during training
    balance - Whether to balance dataset or not
    noise - Whether to add noise to dataset or not

    """

    # Import training data, and filter out validation set
    X_train, y_train, X_val, y_val = _import_data('train', validation_size=0.2)

    # Preprocess train and validation set
    X_train, y_train = _preprocess(X_train, y_train, balance=balance,
↪ noise=noise)

    # Define scheduler to adjust learning rate during training
    lr_scheduler = LRScheduler(policy='ReduceLROnPlateau', mode='min',
↪ patience=5, factor=0.5, verbose=True)

    # Define callbacks for earlystopping and learning rate scheduler
    callbacks = _callbacks(earllystop_patience=earllystop_patience,
↪ lr_scheduler=lr_scheduler)

    # Initialize CNN model
    model = _initilise_cnn(cnn, callbacks=callbacks, optimizer=optim.SGD,
↪ optimizer__momentum=0.9,
                                optimizer__weight_decay=0.0001, lr=0.05, **kwargs)
    model.initialize()

    # Move to cuda (if available)
    model.module_.to(device)

    # Perform gridsearch cross-validation
    grid_result = _gridsearchcv(X_train, y_train, model, param_grid, cv=5)

    # Get best params and scores
    best_params = grid_result.best_params_
    best_score = grid_result.best_score_
    print("Best score: %f with %s" % (best_score, best_params))
```

```
return best_params
```

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```
[140]: def _cnn_pipeline_with_best_param(cnn, params, earlystop_patience=10,
                                         checkpoint=True, class_weight=False,
                                         ↪balance=False,
                                         noise=False, fn=None, optimizer=None,
                                         ↪lr_scheduler=None):
    """
        Encapsulated CNN pipeline for training model with best parameters

        Params:
        ↪-----
            cnn - Model Class (CNN or ResCNN)
            params - Dictionary of best parameters obtained from parameter_
            ↪selection process
                earlystop_patience - Early stopping threshold
                checkpoint - Whether to enable checkpoint to continuously save best_
            ↪model during training
                balance - Whether to balance dataset or not
                noise - Whether to add noise to dataset or not
                fn - Customized filename of final model will be saved to
                optimizer - Whether to use default optimizer settings, or manually_
            ↪passes
                lr_scheduler - Learning rate scheduler

    """

    # Import train and validation set
    X_train, y_train, X_val, y_val = _import_data('train', validation_size=0.2)

    # Compute class weight with class frequency to handle class imbalanced
    weights = torch.tensor(compute_class_weight('balanced',
                                                classes=np.unique(y_train),
                                                y=y_train.flatten()), dtype=torch.float)

    # Preprocess train and validation set
    X_train, y_train = _preprocess(X_train, y_train, balance=balance,
    ↪noise=noise)
    X_val, y_val = _preprocess(X_val, y_val, balance=balance, noise=noise)

    # Define scheduler to adjust learning rate during training
    if lr_scheduler is None:
```

```

lr_scheduler = LRScheduler(policy='ReduceLROnPlateau', mode='min',
↪patience=5, factor=0.5, verbose=True)

# Define callbacks
callbacks = _callbacks(earlystop_patience=earlystop_patience,
↪lr_scheduler=lr_scheduler, checkpoint=checkpoint)

# Initialize CNN model
if optimizer is None:
    if class_weight:
        model = _initilise_cnn(cnn, callbacks=callbacks,
↪train_split=predefined_split(Dataset(X_val, y_val)),
                                criterion__weight=weights, optimizer=optim.
↪SGD, optimizer__momentum=0.9, optimizer__weight_decay=0.0001, lr=0.
↪05,**params)

    else:
        model = _initilise_cnn(cnn, callbacks=callbacks,
↪train_split=predefined_split(Dataset(X_val, y_val)),
                                optimizer=optim.SGD, optimizer__momentum= 0.
↪9, optimizer__weight_decay=0.0001, lr=0.05,**params)

# To train model with replicate structure from reference paper
else:
    model = _initilise_cnn(cnn, callbacks=callbacks,
↪criterion__weight=weights, train_split=predefined_split(Dataset(X_val,
↪y_val)), **params)

model.initialize()

# Move model to cuda if available
model.module_.to(device)

# Train model
model.fit(X_train, y_train)

# Get model prediction on train set
y_pred = model.predict(X_train)

# Generate classification report for train set
_get_report(y_train.cpu().numpy(), y_pred)

# Get model prediction on validation set
y_pred = model.predict(X_val)

```

```

# Generate classification report for validation set
_get_report(y_val.cpu().numpy(), y_pred)

# Plot learning graph through epochs, with accuracy and loss of train and
validation set
_plot_history(model.history)

# Save final models
if not fn:
    fn = get_timestamp()

fp = f'models/cnn/{fn}.pth'
torch.save(model.module_.state_dict(), fp)

print(f"Best model saved to {fp}")

return model

```

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```

[ ]: class ConvBlock(nn.Module):
    """
    Convolutional block for a layer of convolution followed by batch
normalization, activation, and max pooling
    """

    def __init__(self, inputs, outputs, activation=nn.GELU, kernel_size=3,
padding='same', pool_kernel=3, pool_stride=2):

        super().__init__()

        # Define convolutional layer
        self.conv = nn.Conv1d(inputs, outputs, kernel_size=kernel_size,
padding=padding)

        # Batch normalization
        self.bn = nn.BatchNorm1d(outputs)

        # Activation function
        self.activation = activation()

        # Max pooling
        self.maxpool = nn.MaxPool1d(kernel_size=pool_kernel, stride=pool_stride)

    def forward(self, x):

```

```

        # Forward through convolution, batch normalization, activation, and max
        →pooling
        x = self.activation(self.bn(self.conv(x)))
        x = self.maxpool(x)
        return x

class CNN(nn.Module):
    """
        Convolutional Neural Network model with multiple ConvBlocks followed by
        →fully connected layers
    """

    def __init__(self, neurons=128, activation=nn.GELU, dropout=0.3):
        super().__init__()

        # Convolutional layers
        self.conv1 = ConvBlock(1, 32, activation=activation)
        self.conv2 = ConvBlock(32, 64, activation=activation)
        self.conv3 = ConvBlock(64, 128, activation=activation)
        self.conv4 = ConvBlock(128, 256, activation=activation)
        self.conv5 = ConvBlock(256, 512, activation=activation)

        # Adaptive max pooling
        self.pool = nn.AdaptiveMaxPool1d(1)

        # Activation function
        self.activation = activation()

        # Fully connected layer
        self.fc1 = nn.Linear(512, neurons)

        # Batch normalization
        self.bn = nn.BatchNorm1d(neurons)

        # Dropout layer
        self.dropout = nn.Dropout(dropout)

        # Output layer with 5 classes
        self.fc2 = nn.Linear(neurons, 5)

        self.softmax = nn.Softmax(dim=1)

    def forward(self, x):

        # Forward through convolutional layers
        x = self.conv1(x)

```



```

x = self.conv2(x)
x = self.conv3(x)
x = self.conv4(x)
x = self.conv5(x)

# Adaptive max pooling
x = self.pool(x)

# Flatten before passing to fully connected layers
x = torch.flatten(x, 1)

# Fully connected layers
x = self.activation(self.bn(self.fc1(x)))
x = self.dropout(x)
x = self.fc2(x)
x = self.softmax(x)

return x

```

```

[ ]: class ResidualBlock(nn.Module):
    """
        Residual block for a layer of convolution followed by activation and
        ↪max pooling.
        This structure is aimed to replicate the models done by M. Kachuee et
        ↪al.
        Further details will be described in glossary.
    """

    def __init__(self, in_channels, out_channels, kernel_size=5, stride=1,
        ↪padding='same', activation=nn.ReLU):
        super().__init__()

        # Define convolutional layers
        self.conv1 = nn.Conv1d(in_channels, out_channels, kernel_size, stride,
        ↪padding)
        self.conv2 = nn.Conv1d(out_channels, out_channels, kernel_size, stride,
        ↪padding)

        # Activation function
        self.activation = activation()

        # Max pooling layer
        self.maxpool = nn.MaxPool1d(kernel_size=5, stride=2)

    def forward(self, x):

        # Store the residual

```

```

        residual = x

        # Forward through the first convolutional layer and activation
        out = self.conv1(x)
        out = self.activation(out)

        # Forward through the second convolutional layer
        out = self.conv2(out)

        # Add residual to output
        out += residual

        # Apply activation to output
        out = self.activation(out)

        # Apply max pooling
        out = self.maxpool(out)

        return out

class ResCNN(nn.Module):
    """
        Residual Convolutional Neural Network model with multiple
        ↪ResidualBlocks followed by fully connected layers
    """

    def __init__(self, activation=nn.ReLU):
        super().__init__()

        # Define the initial convolutional layer
        self.conv1 = nn.Conv1d(1, 32, kernel_size=5, stride=1)

        # Define the sequence of residual blocks
        self.res_blocks = nn.Sequential(
            ResidualBlock(32, 32, activation=activation),
            ResidualBlock(32, 32, activation=activation),
            ResidualBlock(32, 32, activation=activation),
            ResidualBlock(32, 32, activation=activation),
            ResidualBlock(32, 32, activation=activation)
        )

        # Flatten layer
        self.flatten = nn.Flatten()

        # Activation function
        self.activation = activation()

```

```

    # Fully connected layers
    self.fc1 = nn.Linear(64, 32)
    self.fc2 = nn.Linear(32, 32)
    self.fc3 = nn.Linear(32, 5)

    def forward(self, x):

        # Forward through the initial convolutional layer
        x = self.conv1(x)

        # Forward through the sequence of residual blocks
        x = self.res_blocks(x)

        # Flatten the output
        x = self.flatten(x)

        # Fully connected layers
        x = self.fc1(x)
        x = self.activation(x)
        x = self.fc2(x)

        # Softmax activation for multiclass classification
        x = F.softmax(self.fc3(x), dim=1)

    return x

```

## SVM

```

[17]: def _svm_pipeline(balanced_sample=None, dimredc=None,
                        n_components=None, n_folds=5, class_weight=None,
                        decision_function_shape='ovr', model_fn=None,
                        max_iter=-1):

    """
    Encapsulated SVM pipeline to import data, preprocess,
    hyper parameter tuning, and training model

    Params:
    □
    ↪ -----
        balanced_sample - Number of records after balancing
        dimredc - Feature reduction type (PCA, LDA)
        n_components - Number of components will be retained after □
    ↪ transformation
        n_folds - Number of subsets that the dataset will be divided for □
    ↪ cross-validation
        class_weight - Whether to apply class weights or not
        decision_function_shape - Shape of the decision function (ovo, ovr)
        model_fn - Filename of final model
    """

```

```

        max_iter - Maximum number of iteration

"""

# Import train data
X_train, y_train = _import_data('train')

# Balance data if specific
if balanced_sample:
    X_train, y_train = _balancing(X_train, y_train, balanced_sample)
print(np.unique(y_train, return_counts=True))

# Feature reduction if specific
steps = []
if dimredc == 'pca':
    steps.append(('pca', PCA(n_components=n_components)))
elif dimredc == 'lda':
    steps.append(('lda',
↳LinearDiscriminantAnalysis(n_components=n_components)))

# Initialize SVM model
steps.append(('svm', SVC(decision_function_shape=decision_function_shape,
                        max_iter=max_iter,
                        verbose=1,
                        class_weight=class_weight)))
pipeline = Pipeline(steps)

# Perform stratified gridsearch cross validation
grid_search = GridSearchCV(pipeline, params,
↳cv=StratifiedKFold(n_splits=n_folds), n_jobs=-1, scoring='f1_macro')
grid_search.fit(X_train, y_train)

# Get best parameters
print("Best Parameters:", grid_search.best_params_)

# Define final model with best paramaters
best_model = grid_search.best_estimator_

# Save best model for further evaluation
if model_fn:
    model_fp = f'models/svm/{model_fn}.pkl'
else:
    model_fp = f'models/svm/{get_timestamp()}.pkl'

joblib.dump(best_model, model_fp)
print(f"Model saved to {model_fp}")

```

```

# Predict on train set, with classification report
y_pred = best_model.predict(X_train)
_get_report(y_train, y_pred)

```

time: 0 ns (started: 2024-03-27 13:59:12 +00:00)

```

[ ]: def _evaluate_svm(fn, subset='test', roc_curve=True):
    """
        Evaluate SVM model

        Params:
        -----
        fn - Filename of model to be evaluated
        subset - Subset of source data to be evaluated (train, validation,
        test)
        roc_curve - Whether to show ROC curve

    """
    if subset == 'test':
        # Load data
        X, y = _import_data('test')

    else:
        X, y = _import_data('train')

    # Load best model
    model = joblib.load(f"models/svm/{fn}.pkl")

    start = datetime.datetime.now()

    # Evaluate, and predict
    y_pred = model.predict(X)

    end = datetime.datetime.now()
    print(f"Predicting time: {end-start}")

    # Get classification report
    _get_report(y, y_pred)

    # Generate confusion matrix
    _get_confusion_matrix(y, y_pred)

    if roc_curve:

```

```

# Evaluate, and predict with probability
y_prob_test = model.predict_proba(X)

# Plot ROC curve
_roc_curve(y, y_prob_test)

```

## 1 Set up

```
[ ]: %run "tools.ipynb"
```

```

cuda
time: 109 ms (started: 2024-04-16 12:11:18 +01:00)

```

## 2 EDA

```

[ ]: train_df = pd.read_csv('source/mitbih_train.csv', header=None)
test_df = pd.read_csv('source/mitbih_test.csv', header=None)

if (train_df.isnull().sum().sum()) == 0 :
    print('No missing value in training set!')

if (test_df.isnull().sum().sum()) == 0 :
    print('No missing value in test set!')

```

```

No missing value in training set!
No missing value in test set!
time: 6.3 s (started: 2024-04-12 20:31:13 +01:00)

```

```
[ ]: train_df.describe()
```

	0	1	2	3	4 \
count	87554.000000	87554.000000	87554.000000	87554.000000	87554.000000
mean	0.890360	0.758160	0.423972	0.219104	0.201127
std	0.240909	0.221813	0.227305	0.206878	0.177058
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.921922	0.682486	0.250969	0.048458	0.082329
50%	0.991342	0.826013	0.429472	0.166000	0.147878
75%	1.000000	0.910506	0.578767	0.341727	0.258993
max	1.000000	1.000000	1.000000	1.000000	1.000000

	5	6	7	8	9 \
count	87554.000000	87554.000000	87554.000000	87554.000000	87554.000000
mean	0.210399	0.205808	0.201773	0.198691	0.196757
std	0.171909	0.178481	0.177240	0.171778	0.168357
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.088416	0.073333	0.066116	0.065000	0.068639
50%	0.158798	0.145324	0.144424	0.150000	0.148734

75%	0.287628	0.298237	0.295391	0.290832	0.283636
max	1.000000	1.000000	1.000000	1.000000	1.000000

	...	178	179	180	181 \
count	...	87554.000000	87554.000000	87554.000000	87554.000000
mean	...	0.005025	0.004628	0.004291	0.003945
std	...	0.044154	0.042089	0.040525	0.038651
min	...	0.000000	0.000000	0.000000	0.000000
25%	...	0.000000	0.000000	0.000000	0.000000
50%	...	0.000000	0.000000	0.000000	0.000000
75%	...	0.000000	0.000000	0.000000	0.000000
max	...	1.000000	1.000000	1.000000	1.000000

		182	183	184	185	186 \
count	87554.000000	87554.000000	87554.000000	87554.000000	87554.000000	
mean	0.003681	0.003471	0.003221	0.002945	0.002807	
std	0.037193	0.036255	0.034789	0.032865	0.031924	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	

	187
count	87554.000000
mean	0.473376
std	1.143184
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	4.000000

[8 rows x 188 columns]

time: 1.16 s (started: 2024-04-12 20:31:19 +01:00)

```
[ ]: X_train, y_train = _import_data('train')
      X_test, y_test = _import_data('test')
```

time: 5.89 s (started: 2024-04-16 12:11:18 +01:00)

```
[ ]: y_train.shape
```

(87554,)

time: 16 ms (started: 2024-04-16 12:11:24 +01:00)

```
[ ]: y_test.shape
```

(21892,)

time: 15 ms (started: 2024-04-16 12:11:29 +01:00)

```
[ ]: # Create subplot
fig, ax = plt.subplots(figsize=(8, 5))

# Get class counts for training and test sets
classes, train_counts = np.unique(y_train, return_counts=True)
test_counts = [np.sum(y_test == cls) for cls in classes]

# Calculate total counts for each class
total_counts = train_counts + test_counts

# Set the width of the bars
bar_width = 0.35

# Plot the training set counts
trainBars = ax.bar(classes - bar_width/2, train_counts, width=bar_width,
    color='steelblue', label='Training set')

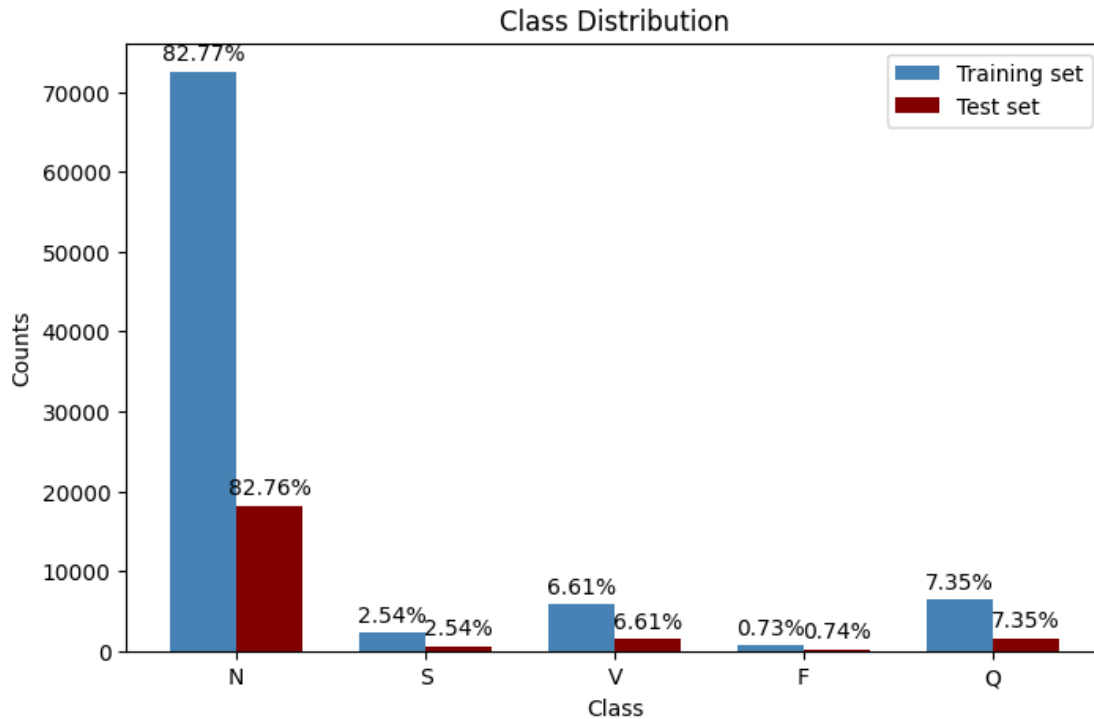
# Plot the test set counts
testBars = ax.bar(classes + bar_width/2, test_counts, width=bar_width,
    color='maroon', label='Test set')

# Set labels and title
ax.set_xlabel('Class')
ax.set_ylabel('Counts')
ax.set_title('Class Distribution')
label_mapping = {'N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4}
ax.set_xticks(list(label_mapping.values()), list(label_mapping.keys()))
ax.legend()

# Annotate the bars with percentage
for bars, counts in zip([trainBars, testBars], [train_counts, test_counts]):
    for bar, count in zip(bars, counts):
        height = bar.get_height()
        percentage = (count / len(y_train)) * 100 if bars == trainBars else
        (count / len(y_test)) * 100
        ax.annotate(f'{percentage:.2f}%', xy=(bar.get_x() + bar.get_width() /
        2, height), xytext=(0, 3),
            textcoords="offset points", ha='center', va='bottom')

plt.show()
```





time: 312 ms (started: 2024-04-15 22:52:44 +01:00)

Dataset contains highly imbalanced class, with over 82% belong to majority class N, and less than 10% of other classes each. Also, train and test set have the same class distribution.

```
[ ]: # Create subplots
fig, axs = plt.subplots(5, 1, figsize=(10, 8), sharex=True)
axs = axs.flatten()

# Define colors for each class
label_colors = ['blue', 'orange', 'green', 'red', 'purple']

# Define label mapping
label_mapping = {0: "N", 1: "S", 2: "V", 3: "F", 4: "Q"}

# Store 1 sample per class
samples_per_class = []
for label in np.unique(y_train):
    X_lbl = X_train[y_train == label][10:]
    samples_per_class.append(X_lbl)

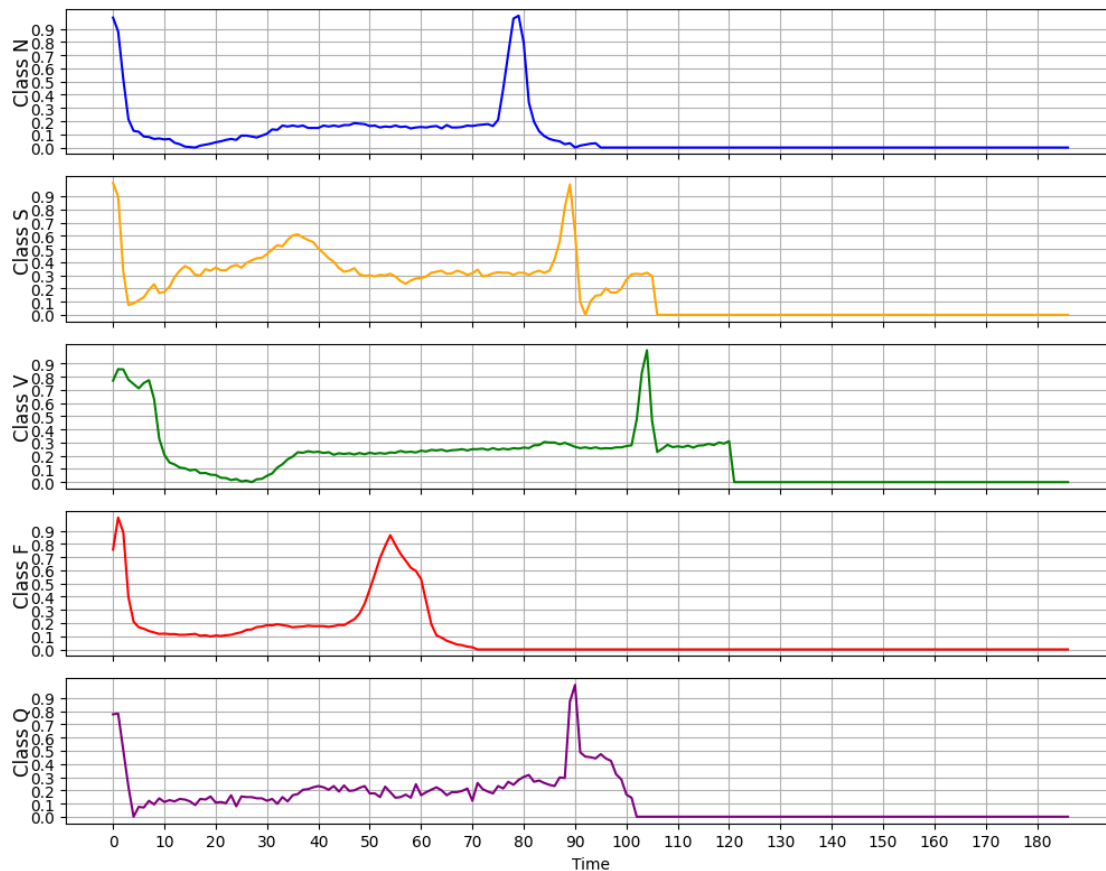
# Plot ECG signal for each class
for i, ax in enumerate(axs):
    sample = samples_per_class[i][0]
```

```

ax.plot(sample, color=label_colors[i])
ax.set_title(f"Class {label_mapping[i]}", rotation='vertical', x=-0.04, y=0.
↪3)
ax.set_xticks(np.arange(0, len(sample), 10))
ax.set_yticks(np.arange(0, 1, 0.1))
ax.grid(True)

plt.xlabel('Time')
plt.tight_layout()
plt.show()

```



time: 1.03 s (started: 2024-04-15 22:55:52 +01:00)

Time series plot shows the different pattern in ECG signal among 5 distinct classes.

```

[ ]: # Extract each class
X_train_0 = X_train[y_train == 0]
X_train_1 = X_train[y_train == 1]
X_train_2 = X_train[y_train == 2]
X_train_3 = X_train[y_train == 3]

```

```

X_train_4 = X_train[y_train == 4]

# Filter out zero-padding
X_train_0 = X_train_0[X_train_0 > 0]
X_train_1 = X_train_1[X_train_1 > 0]
X_train_2 = X_train_2[X_train_2 > 0]
X_train_3 = X_train_3[X_train_3 > 0]
X_train_4 = X_train_4[X_train_4 > 0]

plt.figure(figsize=(12, 8))

# Plot histogram for each class to see data characteristics
plt.subplot(2, 3, 1)
plt.hist(X_train_0.flatten(), bins=50, color='blue', alpha=0.7)
plt.title('Class N')
plt.xlabel('ECG Signal Value')
plt.ylabel('Frequency')

plt.subplot(2, 3, 2)
plt.hist(X_train_1.flatten(), bins=50, color='orange', alpha=0.7)
plt.title('Class S')
plt.xlabel('ECG Signal Value')
plt.ylabel('Frequency')

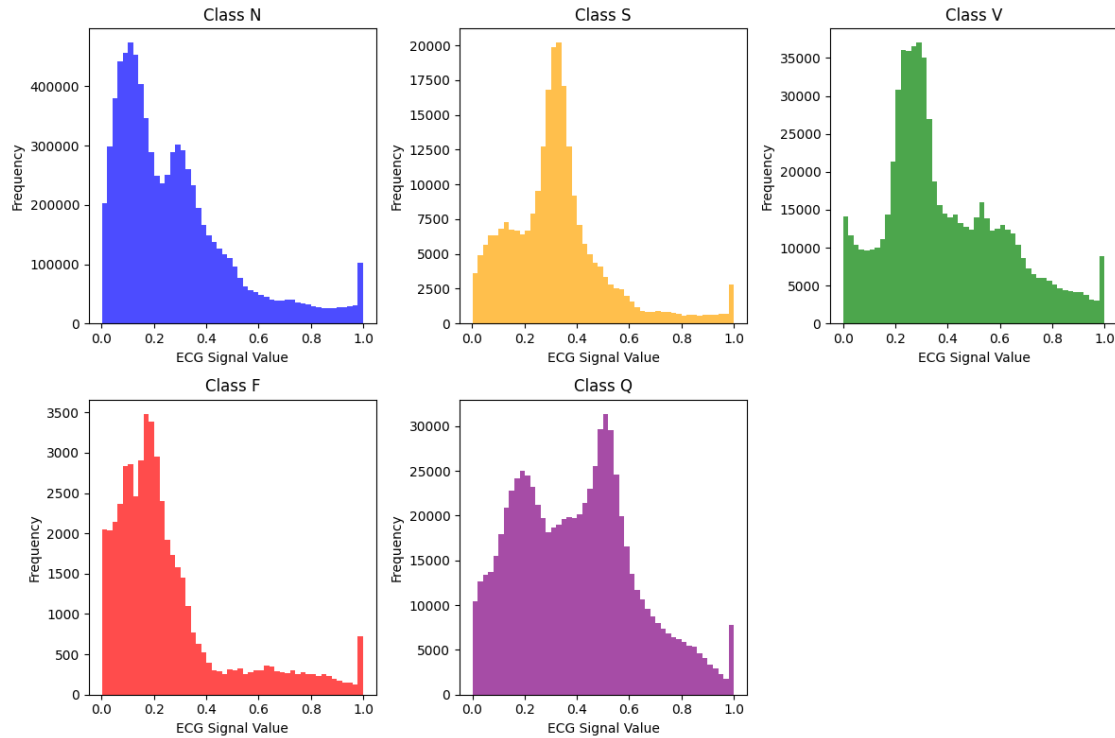
plt.subplot(2, 3, 3)
plt.hist(X_train_2.flatten(), bins=50, color='green', alpha=0.7)
plt.title('Class V')
plt.xlabel('ECG Signal Value')
plt.ylabel('Frequency')

plt.subplot(2, 3, 4)
plt.hist(X_train_3.flatten(), bins=50, color='red', alpha=0.7)
plt.title('Class F')
plt.xlabel('ECG Signal Value')
plt.ylabel('Frequency')

plt.subplot(2, 3, 5)
plt.hist(X_train_4.flatten(), bins=50, color='purple', alpha=0.7)
plt.title('Class Q')
plt.xlabel('ECG Signal Value')
plt.ylabel('Frequency')

plt.tight_layout()
plt.show()

```



time: 2.49 s (started: 2024-04-15 23:11:09 +01:00)

Histograms show the differences in data distribution among 5 classes

```
[ ]: # Create subplots
fig, ax = plt.subplots(figsize=(10, 5))

# Define label mapping
label_mapping = {0: "N", 1: "S", 2: "V", 3: "F", 4: "Q"}

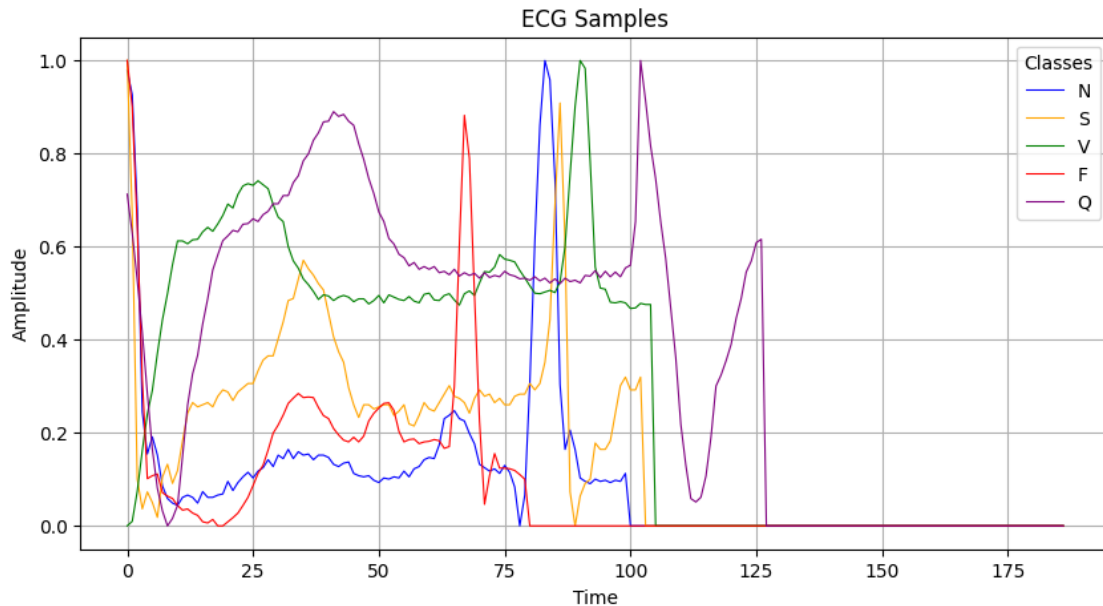
# Define color for each class
colors = ["blue", "orange", "green", "red", "purple"]

# Plot signal of each class
for label in np.unique(y_train):
    # Filter by each class
    X_lbl = X_train[y_train == label][:1]
    for sample in X_lbl:
        ax.plot(sample, color=colors[label], label=label_mapping[label], lw=0.8)

# Define title and label
ax.legend(title="Classes")
ax.set_title("ECG Samples")
ax.set_xlabel("Time")
```

```
ax.set_ylabel("Amplitude")
ax.grid(True)

plt.show()
```



time: 438 ms (started: 2024-04-15 23:14:09 +01:00)

```
[ ]: # Create subplots
fig, ax = plt.subplots(figsize=(10, 5))

# Define label mapping
label_mapping = {0: "N", 1: "S", 2: "V", 3: "F", 4: "Q"}

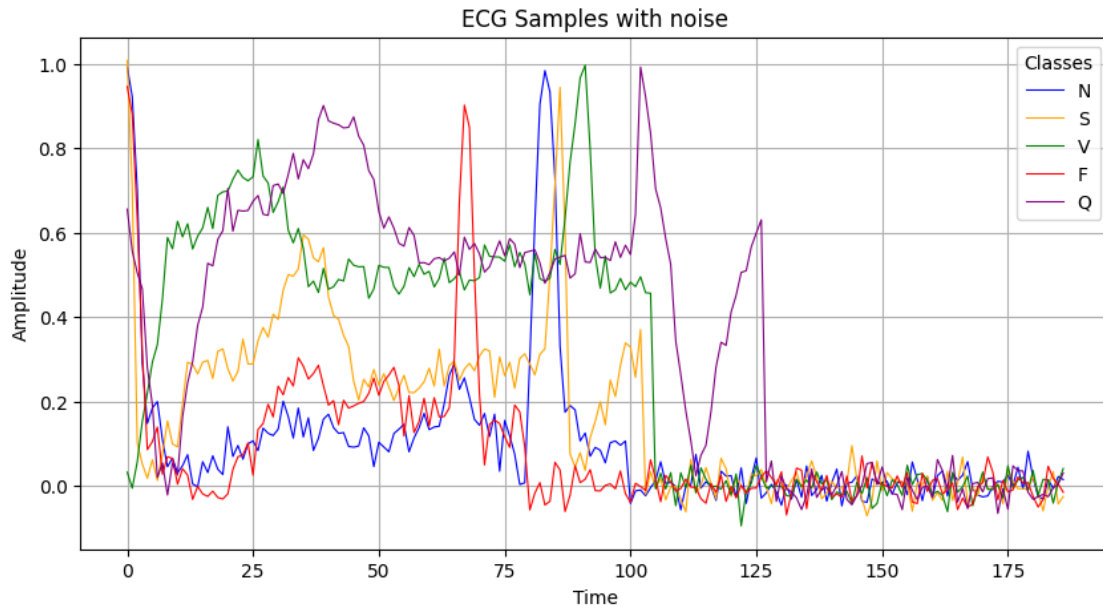
# Define color for each class
colors = ["blue", "orange", "green", "red", "purple"]

# Plot signal of each class
for label in np.unique(y_train):
    # Filter by each class
    X_lbl = _gaussian_noise(X_train)[y_train == label][:1]
    for sample in X_lbl:
        ax.plot(sample, color=colors[label], label=label_mapping[label], lw=0.8)

# Define title and label
ax.legend(title="Classes")
ax.set_title("ECG Samples with noise")
ax.set_xlabel("Time")
```

```
ax.set_ylabel("Amplitude")
ax.grid(True)

plt.show()
```



time: 5.11 s (started: 2024-04-15 23:15:22 +01:00)

ECG signals before and after applied gaussian noise for augmentation to make model more generalized to unseen data

## 3 CNN

### 3.0.1 Custom CNN

Parameters to be tuned through Gridserch on 5 folds cross validation

- Dropout rate
- Number of hidden neurons

```
[ ]: param_grid = {
    'module__dropout': [0.1, 0.2, 0.3, 0.4, 0.5],
    'module__neurons': [64, 128, 256]
}
```

time: 0 ns (started: 2024-04-15 23:27:54 +01:00)

```
[ ]: # Perform parameters tuning
best_params = _cnn_pipeline_with_gridsearch(CNN, param_grid,
                                             checkpoint=False,
```

balance=False, noise=False)						
epoch dur	train_acc	train_loss	valid_acc	valid_loss	cp	lr
-----						
-----						
1	0.8539	1.1332	0.9439			
0.9902	+ 0.0100	10.7654				
2	0.9495	0.9751	0.9569			
0.9620	+ 0.0100	9.0220				
3	0.9601	0.9586	0.9622			
0.9516	+ 0.0100	9.0153				
4	0.9648	0.9504	0.9655			
0.9459	+ 0.0100	8.7229				
5	0.9674	0.9453	0.9676			
0.9424	+ 0.0100	8.8085				
6	0.9693	0.9420	0.9694			
0.9401	+ 0.0100	8.5856				
7	0.9713	0.9393	0.9709			
0.9381	+ 0.0100	9.1406				
8	0.9731	0.9370	0.9720			
0.9364	+ 0.0100	8.8585				
9	0.9747	0.9349	0.9737			
0.9349	+ 0.0100	8.4018				
10	0.9761	0.9331	0.9742			
0.9336	+ 0.0100	9.4343				
11	0.9773	0.9315	0.9746			
0.9335	+ 0.0030	9.0732				
12	0.9779	0.9310	0.9749			
0.9332	+ 0.0030	9.2522				
13	0.9783	0.9306	0.9752			
0.9329	+ 0.0030	8.8847				
14	0.9786	0.9303	0.9754			
0.9326	+ 0.0030	8.6738				
15	0.9789	0.9299	0.9758			
0.9324	+ 0.0030	8.9361				
16	0.9793	0.9296	0.9758	0.9320		
+ 0.0030	9.3220					
17	0.9795	0.9292	0.9760			
0.9318	+ 0.0030	9.5151				
18	0.9797	0.9289	0.9764			
0.9316	+ 0.0030	9.5317				
19	0.9803	0.9285	0.9768			
0.9314	+ 0.0030	9.7765				
20	0.9805	0.9282	0.9772			
0.9311	+ 0.0030	9.3587				
21	0.9808	0.9278	0.9768	0.9311		
+ 0.0009	8.9586					

22	0.9809	0.9278	0.9769	0.9310	
+ 0.0009	9.3320				
23	0.9811	0.9277	0.9770	0.9310	
+ 0.0009	9.2943				
24	0.9812	0.9276	0.9771	0.9309	
+ 0.0009	8.8890				
25	0.9813	0.9274	0.9770	0.9308	
+ 0.0009	8.9451				
26	0.9813	0.9273	0.9772	0.9308	
+ 0.0009	8.7363				
27	0.9814	0.9273	0.9772	0.9307	+
0.0009	8.9048				
28	0.9815	0.9272	0.9772		
0.9306	+ 0.0009	9.0423			
29	0.9816	0.9271	0.9774		
0.9305	+ 0.0009	9.2815			
30	0.9816	0.9271	0.9775		
0.9305	+ 0.0009	9.2394			
31	0.9819	0.9269	0.9774	0.9304	
+ 0.0003	9.6172				
32	0.9819	0.9268	0.9775	0.9304	
+ 0.0003	9.4173				
33	0.9819	0.9268	0.9777		
0.9304	+ 0.0003	7.4128			
34	0.9820	0.9268	0.9777	0.9304	
+ 0.0003	7.2125				
35	0.9821	0.9268	0.9777	0.9304	
+ 0.0003	7.1140				
36	0.9822	0.9267	0.9778		
0.9304	+ 0.0003	7.3040			
37	0.9820	0.9267	0.9775	0.9303	+
0.0003	7.2956				
38	0.9821	0.9267	0.9777	0.9303	
+ 0.0003	7.7008				
39	0.9820	0.9267	0.9777	0.9303	+
0.0003	7.0570				
40	0.9822	0.9266	0.9777	0.9303	
+ 0.0003	7.3041				
41	0.9822	0.9265	0.9778	0.9303	
+ 0.0001	7.1863				
42	0.9822	0.9266	0.9778	0.9303	+
0.0001	7.3058				
43	0.9822	0.9266	0.9779	0.9303	
+ 0.0001	7.2984				
44	0.9822	0.9266	0.9778	0.9303	0.0001
7.2452					
45	0.9824	0.9265	0.9779	0.9302	+
0.0001	7.2556				



epoch	train_acc	train_loss	valid_acc	valid_loss	cp	dur
46	0.9823	0.9265	0.9779	0.9302		
+ 0.0001	7.3535					
47	0.9822	0.9265	0.9779			
0.9302	+ 0.0001	7.5370				
48	0.9822	0.9265	0.9780	0.9302		
+ 0.0001	7.2751					
49	0.9821	0.9265	0.9779	0.9302	+	
0.0001	7.4848					
50	0.9823	0.9266	0.9780	0.9302	+	
0.0001	7.0033					
51	0.9823	0.9265	0.9781	0.9302		
+ 0.0000	7.0686					
52	0.9822	0.9265	0.9781	0.9302		
+ 0.0000	7.2410					
53	0.9823	0.9265	0.9781	0.9302	+	
0.0000	7.1883					
54	0.9824	0.9265	0.9781	0.9302	+	
0.0000	7.3135					
55	0.9824	0.9265	0.9781	0.9302		
0.0000	7.2605					
56	0.9822	0.9265	0.9781	0.9302	+	
0.0000	7.4943					

Stopping since valid\_loss has not improved in the last 10 epochs.  
Best score: 0.977442 with {'module\_\_dropout': 0.1, 'module\_\_neurons': 128}  
time: 1d 9h 28min 15s (started: 2024-04-13 17:14:17 +01:00)

```
[ ]: print(best_params)
```

```
{'module__dropout': 0.1, 'module__neurons': 128}
time: 0 ns (started: 2024-04-15 10:35:15 +01:00)
```

### Train model

```
[ ]: # Create final model with best parameter gained from grid search
model = _cnn_pipeline_with_best_param(CNN, best_params,
                                       earlystop_patience=15, checkpoint=True,
                                       class_weight=False, balance=False,
                                       noise=False)
```

Re-initializing module because the following parameters were re-set: dropout, neurons.

Re-initializing criterion.

Re-initializing optimizer.

C:\Users\kornk\anaconda3\envs\mn\lib\site-

packages\torch\optim\lr\_scheduler.py:28: UserWarning: The verbose parameter is deprecated. Please use get\_last\_lr() to access the learning rate.

warnings.warn("The verbose parameter is deprecated. Please use get\_last\_lr() "

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	dur
-----	-----	-----	-----	-----	----	-----

1	0.9397	0.9689	0.9568		
0.9489	+ 9.4336				
2	0.9567	0.9489	0.9588		
0.9469	+ 9.1213				
3	0.9591	0.9462	0.9611		
0.9438	+ 9.0853				
4	0.9705	0.9361	0.9716		
0.9338	+ 9.3393				
5	0.9736	0.9320	0.9701	0.9345	
9.3094					
6	0.9751	0.9304	0.9733		
0.9315	+ 10.3064				
7	0.9781	0.9278	0.9785		
0.9268	+ 7.9249				
8	0.9807	0.9253	0.9788		
0.9265	+ 9.5960				
9	0.9815	0.9243	0.9794		
0.9258	+ 9.2702				
10	0.9826	0.9232	0.9816		
0.9235	+ 9.0372				
11	0.9855	0.9202	0.9830		
0.9226	+ 9.2424				
12	0.9862	0.9195	0.9818	0.9233	
9.4364					
13	0.9871	0.9185	0.9836		
0.9215	+ 9.2527				
14	0.9877	0.9179	0.9844		
0.9208	+ 9.5733				
15	0.9882	0.9175	0.9857		
0.9195	+ 9.7071				
16	0.9880	0.9175	0.9853	0.9200	9.0425
17	0.9886	0.9172	0.9846	0.9209	
9.1401					
18	0.9884	0.9172	0.9813	0.9242	
9.2926					
19	0.9891	0.9164	0.9855	0.9199	
8.7236					
20	0.9898	0.9158	0.9859		
0.9194	+ 9.3346				
21	0.9901	0.9156	0.9854	0.9198	
9.5157					
22	0.9901	0.9155	0.9864		
0.9188	+ 9.3885				
23	0.9901	0.9155	0.9862	0.9193	
9.5768					
24	0.9902	0.9153	0.9849	0.9203	
9.2868					
25	0.9906	0.9151	0.9857	0.9198	

9.3491					
26	0.9905	0.9151	0.9857	0.9201	
9.2264					
27	0.9912	0.9145	0.9866		
0.9186	+	9.5265			
28	0.9918	0.9139	0.9874	0.9188	
9.5518					
29	0.9917	0.9139	0.9867	0.9186	+
9.3035					
30	0.9919	0.9137	0.9853	0.9200	
9.2138					
31	0.9918	0.9137	0.9866	0.9188	
9.4149					
32	0.9915	0.9140	0.9882	0.9175	
+ 9.2845					
33	0.9927	0.9129	0.9873	0.9187	
9.1830					
34	0.9927	0.9129	0.9875	0.9175	9.0731
35	0.9930	0.9126	0.9862	0.9190	
9.1072					
36	0.9928	0.9129	0.9872	0.9187	9.0756
37	0.9923	0.9132	0.9874	0.9180	9.3046
38	0.9927	0.9129	0.9868	0.9183	9.3763
39	0.9932	0.9123	0.9852	0.9194	
9.6227					
40	0.9933	0.9124	0.9863	0.9196	9.6892
41	0.9931	0.9124	0.9838	0.9213	9.4488
42	0.9935	0.9121	0.9879	0.9184	
9.3823					
43	0.9938	0.9117	0.9873	0.9181	
9.5229					
44	0.9938	0.9118	0.9872	0.9184	9.4323
45	0.9942	0.9115	0.9858	0.9196	
9.2577					
46	0.9938	0.9119	0.9879	0.9173	+
9.4048					
47	0.9939	0.9117	0.9876	0.9182	9.6746
48	0.9943	0.9112	0.9886		
0.9168	+	9.7949			
49	0.9942	0.9114	0.9871	0.9180	9.3420
50	0.9942	0.9114	0.9882	0.9173	9.3905
51	0.9943	0.9113	0.9874	0.9181	9.2120
52	0.9943	0.9113	0.9871	0.9183	9.0525
53	0.9943	0.9114	0.9867	0.9180	9.0384
54	0.9942	0.9113	0.9876	0.9178	9.2766
55	0.9954	0.9099	0.9891		
0.9161	+	9.4243			
56	0.9957	0.9095	0.9890	0.9159	

+ 9.5320					
57	0.9961	0.9090	0.9893		
0.9159 + 9.1651					
58	0.9960	0.9090	0.9895	0.9155	
+ 9.5528					
59	0.9963	0.9087	0.9893	0.9159	
9.4884					
60	0.9964	0.9087	0.9897	0.9156	
9.5678					
61	0.9965	0.9086	0.9891	0.9159	
9.3629					
62	0.9966	0.9085	0.9897	0.9157	
9.4445					
63	0.9966	0.9085	0.9895	0.9155	9.3120
64	0.9968	0.9083	0.9895	0.9157	
9.5840					
65	0.9969	0.9083	0.9896	0.9157	
9.5502					
66	0.9971	0.9081	0.9893	0.9157	
9.1607					
67	0.9969	0.9083	0.9890	0.9164	9.5691
68	0.9970	0.9082	0.9902	0.9153	
+ 9.7085					
69	0.9971	0.9081	0.9898	0.9155	
9.4443					
70	0.9972	0.9081	0.9891	0.9158	9.4413
71	0.9973	0.9080	0.9897	0.9157	
9.5149					
72	0.9973	0.9081	0.9894	0.9162	9.3699
73	0.9973	0.9079	0.9891	0.9162	
9.7471					
74	0.9975	0.9077	0.9892	0.9159	
9.6346					
75	0.9973	0.9078	0.9886	0.9167	8.9931
76	0.9972	0.9082	0.9891	0.9178	8.4420
77	0.9972	0.9083	0.9890	0.9166	9.3346
78	0.9973	0.9081	0.9897	0.9154	9.1190
79	0.9972	0.9082	0.9897	0.9156	9.2462
80	0.9973	0.9082	0.9894	0.9161	9.2093
81	0.9976	0.9075	0.9899	0.9153	
9.1218					
82	0.9977	0.9073	0.9899	0.9151	
+ 9.1884					
83	0.9977	0.9073	0.9897	0.9155	
9.2774					
84	0.9977	0.9073	0.9903		
0.9150 + 8.4976					
85	0.9978	0.9072	0.9905		

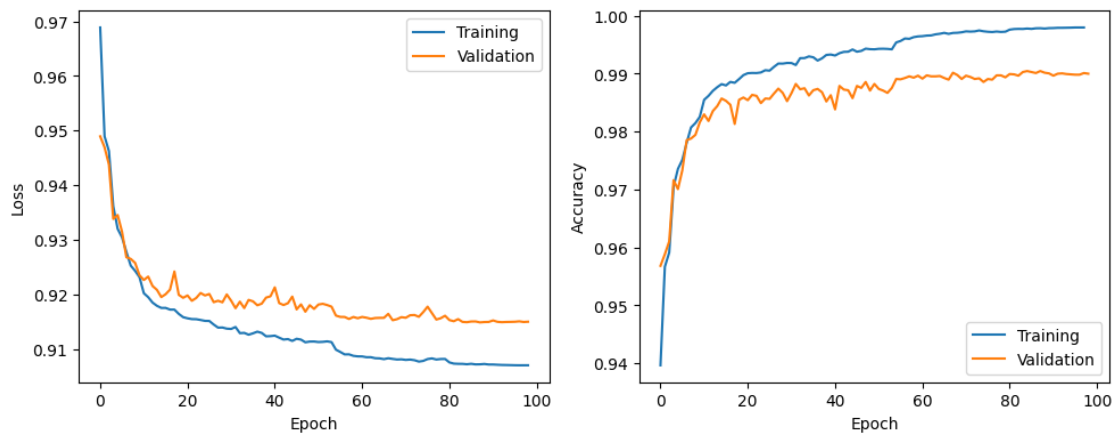
0.9149	+	8.8975				
86		0.9977	0.9073	0.9903	0.9150	9.7051
87		0.9978	0.9072	0.9901	0.9150	
9.1389						
88		0.9979	0.9072	0.9905	0.9149	+
9.2376						
89		0.9978	0.9073	0.9902	0.9149	8.9907
90		0.9979	0.9072	0.9901	0.9150	
9.6113						
91		0.9979	0.9072	0.9897	0.9152	
9.1120						
92		0.9979	0.9071	0.9900	0.9150	
9.2032						
93		0.9979	0.9071	0.9901	0.9149	
9.0313						
94		0.9979	0.9071	0.9899	0.9149	
9.2120						
95		0.9980	0.9070	0.9899	0.9150	
9.6548						
96		0.9980	0.9070	0.9898	0.9150	
9.0758						
97		0.9980	0.9070	0.9898	0.9151	
9.3722						
98		0.9980	0.9070	0.9901	0.9149	9.0986

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	57892
1	1.00	0.96	0.98	1797
2	1.00	1.00	1.00	4676
3	0.99	0.93	0.96	496
4	1.00	1.00	1.00	5182
accuracy			1.00	70043
macro avg	1.00	0.98	0.99	70043
weighted avg	1.00	1.00	1.00	70043

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.94	0.84	0.89	426
2	0.98	0.97	0.97	1112
3	0.89	0.81	0.84	145
4	1.00	0.99	1.00	1249
accuracy			0.99	17511
macro avg	0.96	0.92	0.94	17511
weighted avg	0.99	0.99	0.99	17511



Best model saved to models/cnn/20240415T112137.pth  
time: 15min 51s (started: 2024-04-15 11:05:46 +01:00)

### Additional approaches for comparison

```
[ ]: # ReLU

best_params = {'module__dropout': 0.1,
               'module__activation': nn.ReLU,
               'module__neurons': 128}

model = _cnn_pipeline_with_best_param(CNN, best_params,
                                     earlystop_patience=15, checkpoint=True,
                                     class_weight=False, balance=False,
                                     noise=False)
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
```

Re-initializing module because the following parameters were re-set: activation, dropout, neurons.

Re-initializing criterion.

Re-initializing optimizer.

C:\Users\kornk\anaconda3\envs\nn\lib\site-

packages\torch\optim\lr\_scheduler.py:28: UserWarning: The verbose parameter is deprecated. Please use get\_last\_lr() to access the learning rate.

warnings.warn("The verbose parameter is deprecated. Please use get\_last\_lr() "

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	dur
1	0.9412	0.9663	0.9555			
0.9511	+ 9.4769					
2	0.9567	0.9486	0.9591			

0.9459	+	9.0507			
3		0.9593	0.9460	0.9595	
0.9455	+	8.9376			
4		0.9605	0.9445	0.9596	
0.9454	+	9.0370			
5		0.9615	0.9435	0.9612	
0.9440	+	9.2897			
6		0.9623	0.9427	0.9600	0.9446
8.9918					
7		0.9628	0.9421	0.9591	0.9460
8.9469					
8		0.9632	0.9418	0.9614	
0.9434	+	9.2820			
9		0.9635	0.9415	0.9608	0.9434
+ 8.8828					
10		0.9658	0.9376	0.9725	
0.9323	+	9.1782			
11		0.9771	0.9281	0.9775	
0.9277	+	9.2035			
12		0.9797	0.9256	0.9784	
0.9266	+	9.0920			
13		0.9805	0.9247	0.9776	0.9276
9.1793					
14		0.9809	0.9242	0.9802	
0.9249	+	9.2926			
15		0.9816	0.9236	0.9795	0.9252
9.1915					
16		0.9827	0.9225	0.9806	
0.9246	+	9.0351			
17		0.9827	0.9225	0.9772	0.9282
9.1965					
18		0.9830	0.9221	0.9806	0.9246
+ 9.1886					
19		0.9836	0.9214	0.9806	0.9244
+ 9.1207					
20		0.9843	0.9209	0.9810	
0.9241	+	9.1066			
21		0.9844	0.9207	0.9809	0.9239
+ 9.1089					
22		0.9848	0.9203	0.9821	
0.9229	+	9.3463			
23		0.9857	0.9194	0.9820	0.9227
+ 9.3201					
24		0.9863	0.9189	0.9837	
0.9212	+	9.1017			
25		0.9869	0.9181	0.9854	
0.9194	+	9.0263			
26		0.9891	0.9160	0.9861	

0.9189	+	8.9709			
27		0.9896	0.9155	0.9854	0.9194
9.0150					
28		0.9901	0.9151	0.9856	0.9193
9.1316					
29		0.9902	0.9148	0.9863	0.9190
8.9114					
30		0.9903	0.9147	0.9864	
0.9185	+	9.1689			
31		0.9903	0.9146	0.9863	0.9186
9.0649					
32		0.9912	0.9139	0.9860	0.9189
9.1915					
33		0.9914	0.9137	0.9870	
0.9178	+	9.0381			
34		0.9916	0.9135	0.9866	0.9184
9.0842					
35		0.9920	0.9131	0.9873	
0.9178	+	9.0380			
36		0.9922	0.9129	0.9876	
0.9173	+	9.0866			
37		0.9924	0.9126	0.9870	0.9179
9.0543					
38		0.9925	0.9124	0.9866	0.9181
9.1183					
39		0.9924	0.9124	0.9872	0.9178
40		0.9929	0.9122	0.9873	0.9174
9.0708					
41		0.9931	0.9120	0.9883	
0.9167	+	8.8861			
42		0.9933	0.9117	0.9868	0.9181
9.0306					
43		0.9934	0.9116	0.9881	0.9170
9.2468					
44		0.9933	0.9117	0.9880	0.9170
45		0.9938	0.9112	0.9885	8.9612
0.9162	+	9.0153			
46		0.9939	0.9112	0.9881	0.9167
9.1338					
47		0.9937	0.9112	0.9863	0.9186
48		0.9938	0.9112	0.9874	0.9173
49		0.9943	0.9107	0.9872	0.9176
9.0486					
50		0.9944	0.9106	0.9876	0.9171
9.1488					
51		0.9943	0.9107	0.9870	0.9179
52		0.9947	0.9103	0.9876	0.9171
9.2848					

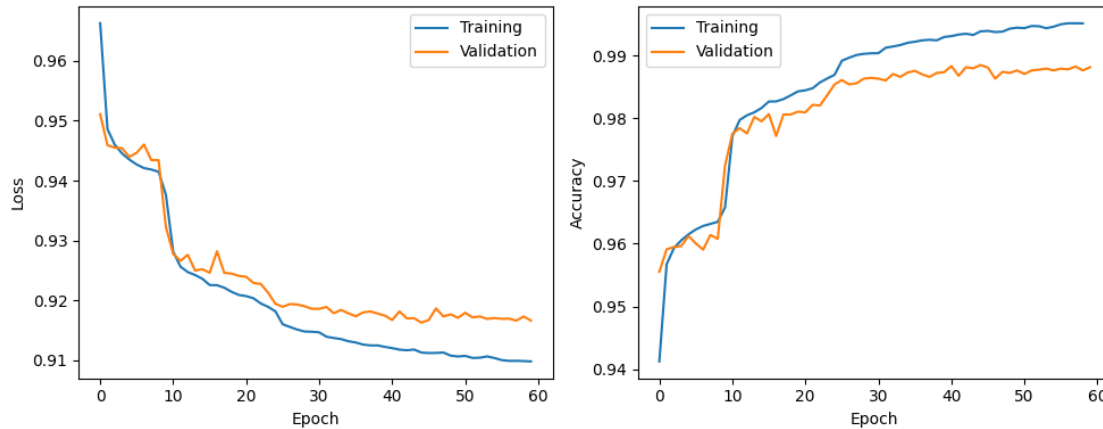


53	0.9946	0.9104	0.9877	0.9173	9.0446
54	0.9943	0.9106	0.9879	0.9169	9.1593
55	0.9946	0.9103	0.9876	0.9170	
8.9580					
56	0.9950	0.9100	0.9879	0.9169	
9.1170					
57	0.9951	0.9098	0.9878	0.9169	
9.0373					
58	0.9951	0.9099	0.9882	0.9166	9.2081
59	0.9951	0.9098	0.9876	0.9173	
9.0646					

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	57892
1	0.99	0.90	0.94	1797
2	0.99	0.99	0.99	4676
3	0.95	0.85	0.89	496
4	1.00	1.00	1.00	5182
accuracy			1.00	70043
macro avg	0.99	0.95	0.96	70043
weighted avg	1.00	1.00	1.00	70043

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.93	0.81	0.87	426
2	0.98	0.96	0.97	1112
3	0.90	0.79	0.84	145
4	1.00	0.99	0.99	1249
accuracy			0.99	17511
macro avg	0.96	0.91	0.93	17511
weighted avg	0.99	0.99	0.99	17511



Best model saved to models/cnn/20240413T150503.pth  
time: 9min 28s (started: 2024-04-13 14:55:34 +01:00)

```
[ ]: # With LeakyReLU

best_params = {'module__dropout': 0.1,
               'module__activation': nn.LeakyReLU,
               'module__neurons': 128}

%run "Tools.ipynb"
model = _cnn_pipeline_with_best_param(CNN, best_params,
                                     earlystop_patience=15, checkpoint=True,
                                     class_weight=None, balance=False,
                                     noise=False)
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
```

Re-initializing module because the following parameters were re-set: activation, dropout, neurons.

Re-initializing criterion.

Re-initializing optimizer.

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	lr
1	0.9425	0.9650	0.9575			
2	0.9567	0.9485	0.9573	0.9482		
3	0.9593	0.9461	0.9593			
4	0.9601	0.9450	0.9605			

5	0.9612	0.9440	0.9584	0.9467
0.0500	6.3879			
6	0.9620	0.9430	0.9611	
0.9436	+ 0.0500	6.2798		
7	0.9627	0.9417	0.9625	
0.9411	+ 0.0500	6.2113		
8	0.9739	0.9319	0.9726	
0.9322	+ 0.0500	6.2545		
9	0.9763	0.9290	0.9741	
0.9307	+ 0.0500	6.2490		
10	0.9770	0.9280	0.9745	
0.9303	+ 0.0500	6.5303		
11	0.9784	0.9266	0.9758	
0.9290	+ 0.0150	6.3700		
12	0.9793	0.9257	0.9764	
0.9283	+ 0.0150	6.2050		
13	0.9799	0.9251	0.9768	
0.9279	+ 0.0150	6.4005		
14	0.9803	0.9246	0.9770	
0.9275	+ 0.0150	6.6155		
15	0.9808	0.9241	0.9768	0.9275
0.0150	6.2211			
16	0.9810	0.9237	0.9766	0.9274
+ 0.0150	6.0781			
17	0.9812	0.9234	0.9771	
0.9270	+ 0.0150	6.1254		
18	0.9815	0.9230	0.9793	
0.9249	+ 0.0150	6.2195		
19	0.9839	0.9207	0.9794	
0.9247	+ 0.0150	6.6632		
20	0.9848	0.9203	0.9806	0.9247
0.0150	6.7984			
21	0.9859	0.9196	0.9826	
0.9234	+ 0.0045	6.3415		
22	0.9867	0.9190	0.9829	
0.9228	+ 0.0045	6.5141		
23	0.9868	0.9186	0.9831	
0.9222	+ 0.0045	6.6634		
24	0.9869	0.9184	0.9832	
0.9220	+ 0.0045	6.2202		
25	0.9871	0.9181	0.9833	
0.9218	+ 0.0045	6.0442		
26	0.9872	0.9179	0.9831	0.9217
+ 0.0045	6.2188			
27	0.9876	0.9176	0.9836	
0.9215	+ 0.0045	6.3302		
28	0.9878	0.9174	0.9836	0.9214
+ 0.0045	6.2968			

29	0.9880	0.9172	0.9836	0.9213	
+ 0.0045	6.2819				
30	0.9881	0.9171	0.9837		
0.9212	+ 0.0045	6.1148			
31	0.9883	0.9169	0.9836	0.9213	
0.0013	6.2650				
32	0.9884	0.9168	0.9834	0.9213	
0.0013	6.4477				
33	0.9884	0.9167	0.9834	0.9213	
0.0013	5.9978				
34	0.9885	0.9167	0.9836	0.9212	
+ 0.0013	6.1424				
35	0.9885	0.9166	0.9836	0.9212	
0.0013	6.2621				
36	0.9886	0.9165	0.9834	0.9212	
0.0013	6.3442				
37	0.9887	0.9164	0.9832	0.9212	
+ 0.0013	6.3761				
38	0.9890	0.9162	0.9836	0.9208	
+ 0.0013	6.4961				
39	0.9897	0.9158	0.9854		
0.9198	+ 0.0013	6.4411			
40	0.9903	0.9152	0.9859		
0.9193	+ 0.0013	6.4088			
41	0.9905	0.9149	0.9858	0.9192	
+ 0.0004	6.4701				
42	0.9909	0.9147	0.9858	0.9191	
+ 0.0004	6.5533				
43	0.9909	0.9147	0.9857	0.9191	+
0.0004	6.4603				
44	0.9911	0.9146	0.9858	0.9190	
+ 0.0004	6.4932				
45	0.9910	0.9147	0.9859	0.9190	+
0.0004	6.3853				
46	0.9912	0.9146	0.9860		
0.9189	+ 0.0004	6.4278			
47	0.9911	0.9146	0.9860	0.9189	
+ 0.0004	6.4227				
48	0.9913	0.9144	0.9861		
0.9189	+ 0.0004	6.4535			
49	0.9912	0.9144	0.9861		
0.9188	+ 0.0004	6.6075			
50	0.9912	0.9144	0.9861	0.9188	
+ 0.0004	6.3223				
51	0.9912	0.9142	0.9862		
0.9187	+ 0.0001	6.3359			
52	0.9913	0.9143	0.9862	0.9188	0.0001
6.6168					

53	0.9915	0.9141	0.9862	0.9187	
+ 0.0001 6.3620					
54	0.9913	0.9143	0.9861	0.9187	0.0001
6.4619					
55	0.9913	0.9142	0.9862	0.9187	+
0.0001 6.4021					
56	0.9915	0.9141	0.9862	0.9187	
+ 0.0001 6.5470					
57	0.9914	0.9142	0.9861	0.9187	+
0.0001 6.2971					
58	0.9915	0.9141	0.9862	0.9187	0.0001
6.2987					
59	0.9914	0.9142	0.9862	0.9187	0.0001
6.2600					
60	0.9915	0.9141	0.9862	0.9187	+
0.0001 6.3117					
61	0.9915	0.9141	0.9862	0.9187	+
0.0000 6.3127					
62	0.9914	0.9140	0.9862	0.9187	
+ 0.0000 6.1781					
63	0.9914	0.9142	0.9862	0.9187	+
0.0000 6.2346					
64	0.9915	0.9142	0.9862	0.9187	0.0000
6.4051					
65	0.9915	0.9141	0.9862	0.9187	0.0000
6.1205					

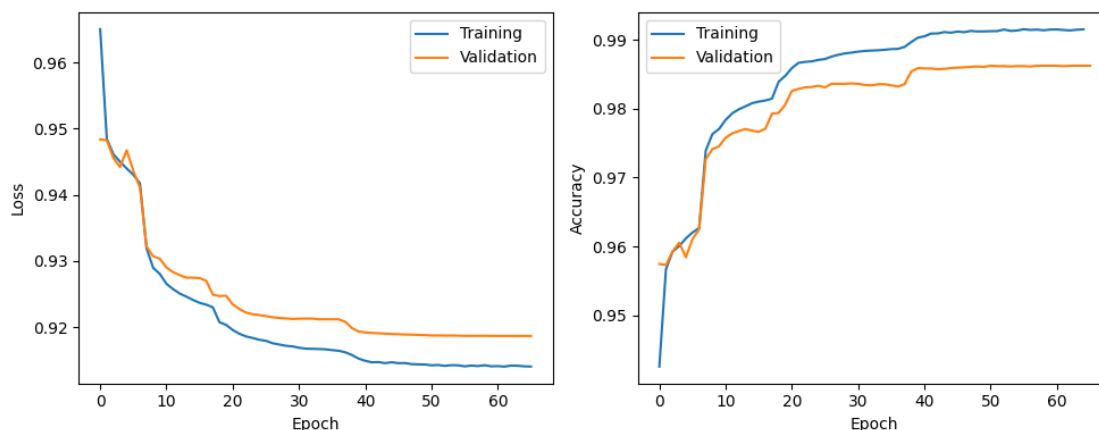
Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	0.99	1.00	1.00	57892
1	0.99	0.80	0.89	1797
2	0.99	0.99	0.99	4676
3	0.96	0.73	0.83	496
4	1.00	1.00	1.00	5182
accuracy			0.99	70043
macro avg	0.99	0.90	0.94	70043
weighted avg	0.99	0.99	0.99	70043

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.93	0.74	0.82	426
2	0.97	0.96	0.97	1112
3	0.92	0.73	0.82	145
4	0.99	0.99	0.99	1249
accuracy			0.99	17511

macro avg	0.96	0.88	0.92	17511
weighted avg	0.99	0.99	0.99	17511



Best model saved to models/cnn/20240413T004512.pth  
time: 7min 16s (started: 2024-04-13 00:37:55 +01:00)

```
[ ]: # With class weights

best_params = {'module__dropout': 0.1,
               'module__neurons': 128}

model = _cnn_pipeline_with_best_param(CNN, best_params,
                                       earlystop_patience=15, checkpoint=True,
                                       class_weight=True, balance=False,
                                       noise=False)
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
```

Re-initializing module because the following parameters were re-set: activation, dropout, neurons.

Re-initializing criterion because the following parameters were re-set: weight.

Re-initializing optimizer.

C:\Users\kornk\anaconda3\envs\nn\lib\site-

packages\torch\optim\lr\_scheduler.py:28: UserWarning: The verbose parameter is deprecated. Please use get\_last\_lr() to access the learning rate.

```
warnings.warn("The verbose parameter is deprecated. Please use get_last_lr() "
```

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	dur
1	0.7290	1.0989	0.8646			
1.0405	+	9.3654				
2	0.8500	1.0405	0.8198	1.0259		

+ 9.1883					
3	0.8758	1.0237	0.9018		
1.0208	+ 9.1671				
4	0.8792	1.0157	0.8857	1.0015	
+ 9.1999					
5	0.8969	1.0021	0.8985	0.9975	
+ 9.0275					
6	0.9053	0.9975	0.9162	0.9984	
9.1147					
7	0.9067	0.9950	0.9148	0.9869	
+ 9.0160					
8	0.9093	0.9906	0.8907	0.9937	
9.1138					
9	0.9169	0.9850	0.9027	0.9894	
9.5245					
10	0.9215	0.9812	0.9103	0.9867	
+ 9.4169					
11	0.9209	0.9745	0.9116	0.9781	
+ 9.7799					
12	0.9284	0.9695	0.9476		
0.9746	+ 9.4232				
13	0.9299	0.9681	0.9361	0.9764	
9.3713					
14	0.9371	0.9660	0.9447	0.9713	
+ 9.3350					
15	0.9375	0.9642	0.9211	0.9856	
9.1023					
16	0.9385	0.9617	0.9372	0.9801	
9.3777					
17	0.9407	0.9649	0.9393	0.9791	9.3136
18	0.9460	0.9633	0.9547	0.9723	
9.2096					
19	0.9537	0.9571	0.9600	0.9731	
9.1114					
20	0.9404	0.9617	0.9307	0.9828	9.2274
21	0.9335	0.9617	0.9464	0.9712	+
9.0888					
22	0.9508	0.9592	0.9372	0.9730	9.1070
23	0.9504	0.9556	0.9305	0.9764	
9.1922					
24	0.9383	0.9610	0.9531	0.9672	+
9.1775					
25	0.9465	0.9564	0.9521	0.9656	+
9.0899					
26	0.9406	0.9577	0.9329	0.9655	+
9.4965					
27	0.9430	0.9532	0.9461	0.9668	
9.3117					

28	0.9496	0.9521	0.9589	0.9698	
9.0634					
29	0.9537	0.9496	0.9539	0.9633	
+ 9.3468					
30	0.9501	0.9507	0.9638	0.9686	
9.1610					
31	0.9569	0.9496	0.9512	0.9643	
9.5245					
32	0.9447	0.9537	0.9584	0.9602	+
9.0295					
33	0.9615	0.9477	0.9657	0.9710	
9.1164					
34	0.9493	0.9510	0.9356	0.9669	9.1024
35	0.9518	0.9508	0.9608	0.9771	9.0464
36	0.9604	0.9471	0.9571	0.9644	
9.0611					
37	0.9672	0.9472	0.9666	0.9712	
9.3670					
38	0.9677	0.9464	0.9659	0.9618	
9.1247					
39	0.9717	0.9415	0.9756	0.9664	
9.3451					
40	0.9730	0.9440	0.9552	0.9705	9.1744
41	0.9539	0.9471	0.9478	0.9664	9.1196
42	0.9527	0.9481	0.9532	0.9689	9.2367
43	0.9560	0.9461	0.9627	0.9719	9.2175
44	0.9664	0.9451	0.9551	0.9635	9.3446
45	0.9648	0.9440	0.9715	0.9648	9.3201
46	0.9796	0.9388	0.9753	0.9657	
9.3749					

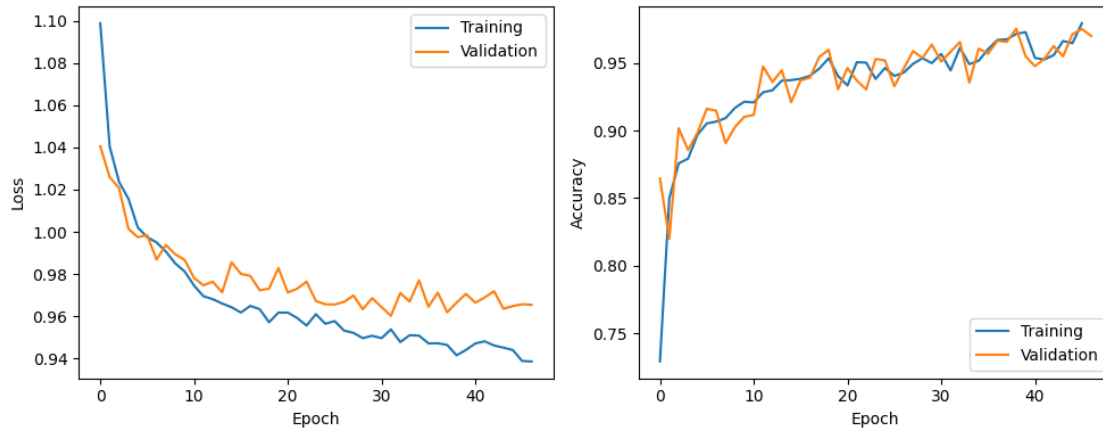
Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	1.00	0.97	0.98	57892
1	0.84	0.94	0.89	1797
2	0.95	0.98	0.97	4676
3	0.29	0.93	0.44	496
4	0.99	1.00	0.99	5182
accuracy			0.97	70043
macro avg	0.81	0.96	0.85	70043
weighted avg	0.99	0.97	0.98	70043

	precision	recall	f1-score	support
0	0.99	0.97	0.98	14579
1	0.80	0.86	0.83	426
2	0.94	0.96	0.95	1112



3	0.33	0.91	0.49	145
4	0.99	0.99	0.99	1249
accuracy			0.97	17511
macro avg	0.81	0.94	0.85	17511
weighted avg	0.98	0.97	0.97	17511



Best model saved to models/cnn/20240413T125808.pth  
time: 7min 34s (started: 2024-04-13 12:50:33 +01:00)

```
[ ]: # With noise

best_params = {'module__dropout': 0.1,
               'module__neurons': 128}

model = _cnn_pipeline_with_best_param(CNN, best_params,
                                     earlystop_patience=15, checkpoint=True,
                                     class_weight=False, balance=False,
                                     noise=True)
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
Re-initializing module because the following parameters were re-set: activation,
dropout, neurons.
Re-initializing criterion.
Re-initializing optimizer.
```

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	lr
1	0.9499	0.9594	0.9657			
0.9395	+ 0.0500	7.5531				

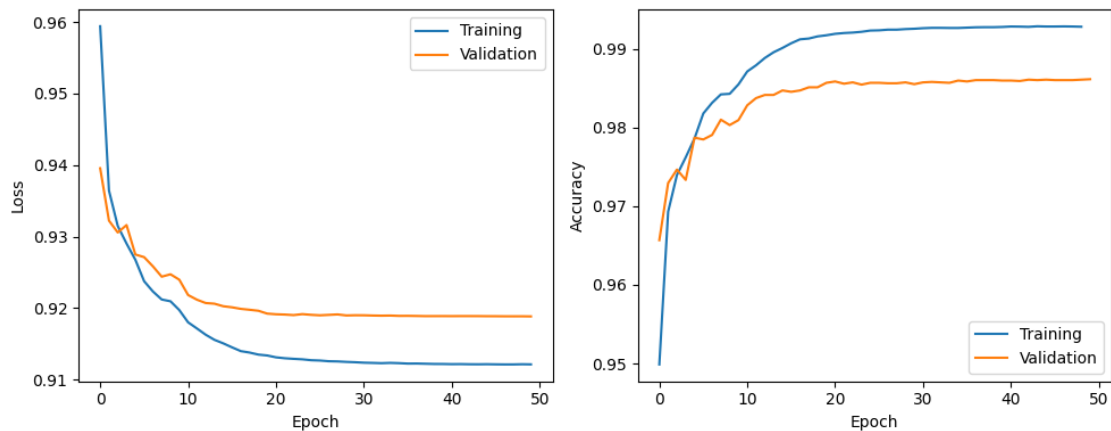
2	0.9693	0.9364	0.9729	
0.9322	+ 0.0500	7.4975		
3	0.9739	0.9315	0.9746	
0.9306	+ 0.0500	7.5624		
4	0.9762	0.9290	0.9733	0.9316
0.0500	7.5365			
5	0.9786	0.9268	0.9787	
0.9275	+ 0.0500	7.6423		
6	0.9818	0.9238	0.9785	0.9271
+ 0.0500	7.7520			
7	0.9831	0.9223	0.9790	
0.9258	+ 0.0500	7.4463		
8	0.9842	0.9212	0.9810	
0.9244	+ 0.0500	7.6275		
9	0.9843	0.9209	0.9803	0.9247
0.0500	7.4080			
10	0.9855	0.9197	0.9809	0.9240
+ 0.0500	7.4302			
11	0.9871	0.9180	0.9828	
0.9218	+ 0.0150	7.6209		
12	0.9879	0.9172	0.9837	
0.9212	+ 0.0150	7.7226		
13	0.9888	0.9163	0.9841	
0.9207	+ 0.0150	7.3813		
14	0.9895	0.9156	0.9841	0.9206
+ 0.0150	7.4572			
15	0.9901	0.9151	0.9847	
0.9203	+ 0.0150	7.4060		
16	0.9907	0.9145	0.9845	0.9201
+ 0.0150	7.3525			
17	0.9912	0.9140	0.9847	0.9199
+ 0.0150	7.6057			
18	0.9913	0.9138	0.9851	
0.9198	+ 0.0150	7.6922		
19	0.9916	0.9135	0.9851	0.9196
+ 0.0150	7.3478			
20	0.9917	0.9134	0.9857	
0.9192	+ 0.0150	7.4078		
21	0.9919	0.9131	0.9858	
0.9191	+ 0.0045	7.4719		
22	0.9920	0.9130	0.9856	0.9191
+ 0.0045	7.4126			
23	0.9920	0.9129	0.9857	0.9190
+ 0.0045	7.6099			
24	0.9921	0.9128	0.9854	0.9191
0.0045	7.5896			
25	0.9923	0.9127	0.9857	0.9191
0.0045	7.4342			

26	0.9923	0.9127	0.9857	0.9190	
+ 0.0045	7.4891				
27	0.9924	0.9126	0.9856	0.9190	
0.0045	7.4701				
28	0.9924	0.9125	0.9856	0.9191	
0.0045	7.4539				
29	0.9925	0.9125	0.9857	0.9190	
+ 0.0045	7.4661				
30	0.9925	0.9124	0.9855	0.9190	
0.0045	7.6559				
31	0.9926	0.9124	0.9857	0.9190	
0.0013	7.4272				
32	0.9926	0.9123	0.9858	0.9190	
+ 0.0013	7.6714				
33	0.9926	0.9123	0.9857	0.9189	
+ 0.0013	7.5241				
34	0.9926	0.9123	0.9857	0.9189	0.0013
7.5424					
35	0.9926	0.9123	0.9860	0.9189	
+ 0.0013	7.5592				
36	0.9927	0.9122	0.9858	0.9189	
0.0013	7.5898				
37	0.9927	0.9122	0.9860	0.9189	
+ 0.0013	7.5598				
38	0.9927	0.9122	0.9860	0.9189	
+ 0.0013	7.4851				
39	0.9927	0.9122	0.9860	0.9189	
0.0013	7.6400				
40	0.9928	0.9122	0.9860	0.9189	
0.0013	7.5404				
41	0.9928	0.9122	0.9860	0.9189	
0.0004	7.6700				
42	0.9928	0.9122	0.9859	0.9189	0.0004
7.7998					
43	0.9928	0.9121	0.9861	0.9189	
0.0004	7.5054				
44	0.9928	0.9121	0.9860	0.9189	
0.0004	7.3961				
45	0.9928	0.9121	0.9861	0.9189	+
0.0004	7.4161				
46	0.9928	0.9121	0.9860	0.9189	
+ 0.0004	7.4564				
47	0.9928	0.9121	0.9860	0.9188	
+ 0.0004	7.3999				
48	0.9928	0.9121	0.9860	0.9188	+
0.0004	7.5602				
49	0.9928	0.9121	0.9861	0.9188	0.0004
7.9389					

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	0.99	1.00	1.00	57892
1	0.99	0.82	0.90	1797
2	0.99	0.99	0.99	4676
3	0.99	0.82	0.90	496
4	1.00	1.00	1.00	5182
accuracy			0.99	70043
macro avg	0.99	0.92	0.96	70043
weighted avg	0.99	0.99	0.99	70043

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.94	0.75	0.84	426
2	0.96	0.95	0.96	1112
3	0.90	0.73	0.81	145
4	1.00	0.99	0.99	1249
accuracy			0.99	17511
macro avg	0.96	0.89	0.92	17511
weighted avg	0.99	0.99	0.99	17511



Best model saved to models/cnn/20240413T110602.pth  
time: 6min 34s (started: 2024-04-13 10:59:28 +01:00)

```
[ ]: # With Step learning rate scheduler
```

```
lr_scheduler = LRScheduler(policy='StepLR', step_size=10, gamma=0.3)
```

```

best_params = {'module__dropout': 0.1,
               'module__neurons': 128}

model = _cnn_pipeline_with_best_param(CNN, best_params, lrschedule=lr_scheduler,
                                     earlystop_patience=15, checkpoint=True,
                                     class_weight=None, balance=False,
                                     noise=False)

```

Re-initializing module because the following parameters were re-set: activation, dropout, neurons.

Re-initializing criterion.

Re-initializing optimizer.

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	lr
dur						
-----	-----	-----	-----	-----	----	-----
-----						
1	0.9550	0.1662	0.9643			
0.1320	+ 0.0100	7.5059				
2	0.9755	0.0916	0.9714			
0.1050	+ 0.0100	6.5200				
3	0.9799	0.0726	0.9819			
0.0722	+ 0.0100	6.4677				
4	0.9818	0.0616	0.9790	0.0727		
0.0100	6.3224					
5	0.9838	0.0542	0.9797	0.0728		
0.0100	6.2651					
6	0.9855	0.0478	0.9830			
0.0656	+ 0.0100	6.3778				
7	0.9864	0.0433	0.9849			
0.0597	+ 0.0100	6.3579				
8	0.9870	0.0405	0.9853			
0.0583	+ 0.0100	6.4560				
9	0.9884	0.0359	0.9850	0.0599		
0.0100	6.4587					
10	0.9894	0.0342	0.9857			
0.0541	+ 0.0100	6.3375				
11	0.9929	0.0202	0.9887			
0.0536	+ 0.0030	6.4054				
12	0.9948	0.0150	0.9882	0.0571		
0.0030	6.4361					
13	0.9954	0.0134	0.9887	0.0617		
0.0030	6.3275					
14	0.9959	0.0113	0.9885	0.0598		
0.0030	6.4277					
15	0.9964	0.0099	0.9879	0.0727		
0.0030	6.4376					
16	0.9969	0.0090	0.9884	0.0792		
0.0030	7.2261					

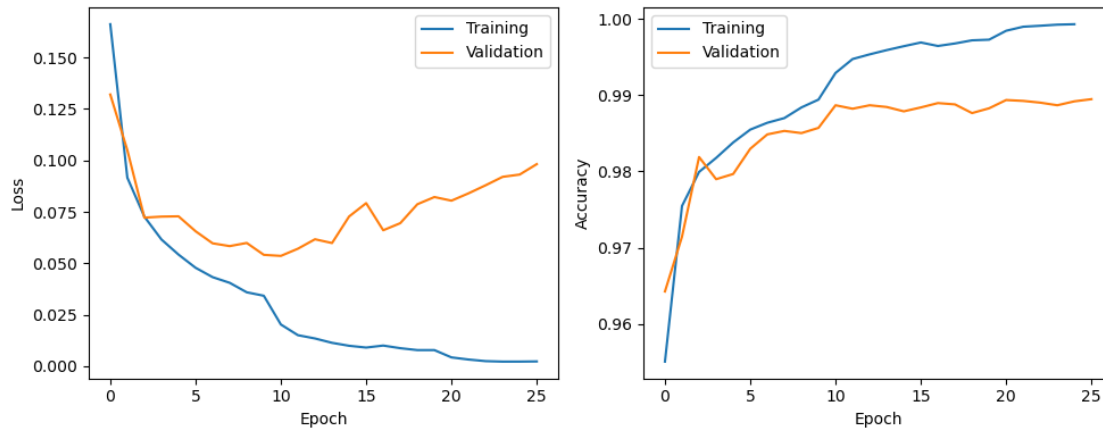
17	0.9965	0.0100	0.9890	0.0660
0.0030 6.4022				
18	0.9968	0.0087	0.9888	0.0695
0.0030 6.3624				
19	0.9972	0.0078	0.9877	0.0787
0.0030 7.1420				
20	0.9973	0.0078	0.9883	0.0822
0.0030 9.3075				
21	0.9985	0.0042	0.9894	0.0804
0.0009 7.3965				
22	0.9990	0.0032	0.9893	0.0840
0.0009 8.2413				
23	0.9991	0.0024	0.9890	0.0879
0.0009 7.9417				
24	0.9993	0.0022	0.9887	0.0920
0.0009 8.9985				
25	0.9993	0.0022	0.9892	0.0931
6.9576				0.0009

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	57892
1	1.00	0.99	1.00	1797
2	1.00	1.00	1.00	4676
3	0.96	0.95	0.95	496
4	1.00	1.00	1.00	5182
accuracy			1.00	70043
macro avg	0.99	0.99	0.99	70043
weighted avg	1.00	1.00	1.00	70043

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.92	0.85	0.88	426
2	0.98	0.97	0.97	1112
3	0.90	0.79	0.84	145
4	1.00	0.99	0.99	1249
accuracy			0.99	17511
macro avg	0.96	0.92	0.94	17511
weighted avg	0.99	0.99	0.99	17511



Best model saved to models/cnn/20240403T184404.pth  
time: 3min 15s (started: 2024-04-03 18:40:48 +01:00)

```
[ ]: # With data balancing

best_params = {'module__dropout': 0.1,
               'module__neurons': 128}

model = _cnn_pipeline_with_best_param(CNN, best_params,
                                     earllystop_patience=15, checkpoint=True,
                                     class_weight=False, balance=20000,
                                     noise=False)
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
```

Re-initializing module because the following parameters were re-set: activation, dropout, neurons.

Re-initializing criterion.

Re-initializing optimizer.

/usr/local/lib/python3.10/dist-packages/torch/optim/lr\_scheduler.py:28:

UserWarning: The verbose parameter is deprecated. Please use get\_last\_lr() to access the learning rate.

```
warnings.warn("The verbose parameter is deprecated. Please use get_last_lr() ")
```

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	dur
1	0.6758	1.2347	0.2000			
1.7047	+ 8.8092					
2	0.6672	1.2391	0.1824	1.7201		
8.0163						
3	0.7307	1.1765	0.2256			
1.6780	+ 8.5924					
4	0.7067	1.1961	0.1801	1.7059		8.8382

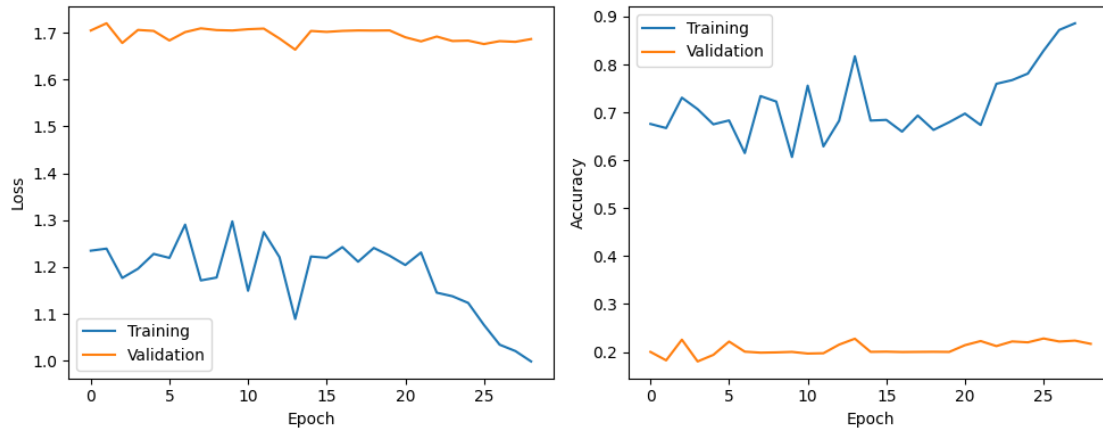
5	0.6751	1.2279	0.1938	1.7038	7.9770
6	0.6832	1.2193	0.2217	1.6834	8.5457
7	0.6150	1.2903	0.2005	1.7013	
8.7747					
8	0.7340	1.1712	0.1984	1.7093	
7.9737					
9	0.7226	1.1774	0.1990	1.7056	8.4941
10	0.6068	1.2973	0.2000	1.7047	
8.8832					
11	0.7558	1.1492	0.1966	1.7074	
8.0631					
12	0.6289	1.2745	0.1972	1.7088	8.5041
13	0.6826	1.2209	0.2152	1.6876	8.8821
14	0.8171	1.0890	0.2276		
1.6638	+	8.0340			
15	0.6829	1.2223	0.2001	1.7037	8.6226
16	0.6843	1.2195	0.2005	1.7017	8.8141
17	0.6598	1.2424	0.1997	1.7038	8.0918
18	0.6934	1.2112	0.2000	1.7048	8.5498
19	0.6634	1.2406	0.2002	1.7046	8.6406
20	0.6795	1.2240	0.2000	1.7048	8.1519
21	0.6974	1.2041	0.2140	1.6903	8.5743
22	0.6735	1.2308	0.2227	1.6814	8.5315
23	0.7596	1.1451	0.2121	1.6918	8.3079
24	0.7673	1.1374	0.2218	1.6822	8.5838
25	0.7809	1.1232	0.2200	1.6831	8.2319
26	0.8286	1.0764	0.2280	1.6758	
8.5398					
27	0.8721	1.0341	0.2217	1.6820	
8.7515					
28	0.8859	1.0205	0.2235	1.6805	
8.0470					

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	0.40	0.02	0.04	20000
1	0.00	0.00	0.00	20000
2	0.71	0.06	0.11	20000
3	0.00	0.00	0.00	20000
4	0.21	1.00	0.34	20000
accuracy			0.22	100000
macro avg	0.26	0.22	0.10	100000
weighted avg	0.26	0.22	0.10	100000
	precision	recall	f1-score	support
0	0.46	0.02	0.04	20000



	1	0.00	0.00	0.00	20000
	2	0.82	0.06	0.12	20000
	3	0.00	0.00	0.00	20000
	4	0.21	1.00	0.34	20000
accuracy				0.22	100000
macro avg	0.30	0.22	0.10		100000
weighted avg	0.30	0.22	0.10		100000



Best model saved to drive/MyDrive/Colab  
 Notebooks/Project/models/cnn/20240415T100929.pth  
 time: 4min 22s (started: 2024-04-15 10:05:07 +00:00)

### 3.0.2 Residual neural network (based on M. Kachuee et al.)

```
[ ]: params = {'module__activation': nn.ReLU,
               'optimizer': optim.Adam,
               'lr': 0.001}

scheduler = LRScheduler(policy='ExponentialLR', gamma=0.75)

model = _cnn_pipeline_with_best_param(ResCNN, params, lr_scheduler=scheduler,
                                     earlystop_patience=15, checkpoint=True,
                                     optimizer=True)
```

Re-initializing module because the following parameters were re-set: activation.  
 Re-initializing criterion because the following parameters were re-set: weight.  
 Re-initializing optimizer.

epoch	train_acc	train_loss	valid_acc	valid_loss	cp	lr
dur						
-----	-----	-----	-----	-----	----	-----
-----						

1	0.6076	1.2688	0.7967		
1.1120	+ 0.0010	45.0406			
2	0.7822	1.1074	0.8654		
1.0803	+ 0.0010	22.6163			
3	0.8060	1.0926	0.8294	1.0798	
+ 0.0010	22.2166				
4	0.8224	1.0680	0.7668	1.0705	
+ 0.0010	22.8190				
5	0.8533	1.0562	0.9143		
1.0421	+ 0.0010	22.6351			
6	0.8401	1.0507	0.8675	1.0206	
+ 0.0010	22.0015				
7	0.8285	1.0527	0.8280	1.0464	0.0010
22.0334					
8	0.8589	1.0421	0.9021	1.0302	
0.0010	22.3899				
9	0.8552	1.0453	0.8959	1.0246	0.0010
22.9173					
10	0.8529	1.0501	0.8682	1.0581	0.0010
23.6895					
11	0.8551	1.0406	0.8933	1.0207	
0.0003	23.4467				
12	0.8833	1.0200	0.9187		
1.0187	+ 0.0003	23.2027			
13	0.8845	1.0118	0.8825	1.0095	
+ 0.0003	23.2078				
14	0.9107	1.0040	0.9122	1.0076	
+ 0.0003	22.7886				
15	0.9018	1.0030	0.7951	1.0356	
0.0003	22.4892				
16	0.9049	1.0111	0.9114	1.0045	+
0.0003	21.9644				
17	0.9188	0.9998	0.9350	1.0062	
0.0003	21.9745				
18	0.9092	0.9973	0.9016	1.0049	
0.0003	20.1796				
19	0.9196	0.9936	0.9157	1.0068	
0.0003	19.8418				
20	0.9084	0.9982	0.8769	1.0029	+
0.0003	19.3045				
21	0.9070	0.9922	0.9141	0.9962	
+ 0.0001	18.4385				
22	0.9233	0.9865	0.9150	0.9963	
0.0001	17.5530				
23	0.9211	0.9840	0.9281	0.9932	
+ 0.0001	16.9179				
24	0.9258	0.9820	0.9301	0.9920	
+ 0.0001	17.1739				

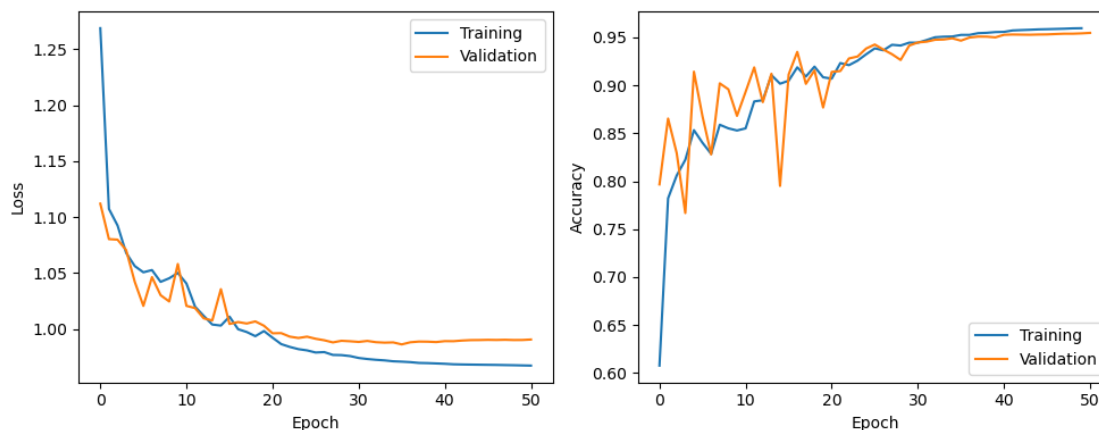
25	0.9325	0.9809	0.9384	0.9931
0.0001	16.9192			
26	0.9386	0.9790	0.9426	
0.9913	+ 0.0001	17.2744		
27	0.9366	0.9794	0.9374	0.9899
0.0001	16.6498			+
28	0.9423	0.9768	0.9325	0.9880
+ 0.0001	16.7674			
29	0.9416	0.9767	0.9265	0.9894
0.0001	16.7618			
30	0.9446	0.9758	0.9415	0.9890
0.0001	14.3881			
31	0.9445	0.9741	0.9448	0.9884
0.0000	15.6936			
32	0.9472	0.9732	0.9456	0.9893
0.0000	15.0261			
33	0.9502	0.9725	0.9476	0.9882
0.0000	14.2160			
34	0.9508	0.9719	0.9479	
0.9878	+ 0.0000	14.1285		
35	0.9510	0.9711	0.9491	0.9880
0.0000	12.4536			
36	0.9527	0.9708	0.9467	0.9862
+ 0.0000	13.0646			
37	0.9527	0.9704	0.9499	0.9881
0.0000	12.3366			
38	0.9545	0.9697	0.9509	0.9888
0.0000	12.0045			
39	0.9548	0.9695	0.9508	0.9887
0.0000	11.4171			
40	0.9556	0.9692	0.9501	0.9883
0.0000	11.7081			
41	0.9558	0.9689	0.9528	0.9891
0.0000	11.3872			
42	0.9573	0.9685	0.9531	0.9891
0.0000	11.4429			
43	0.9577	0.9683	0.9529	0.9897
0.0000	9.0214			
44	0.9580	0.9682	0.9528	0.9901
0.0000	9.6019			
45	0.9584	0.9681	0.9531	0.9901
0.0000	9.5109			
46	0.9586	0.9680	0.9532	0.9903
0.0000	8.8917			
47	0.9589	0.9679	0.9536	0.9902
0.0000	8.4810			
48	0.9591	0.9677	0.9539	0.9904
0.0000	8.7160			

49	0.9595	0.9676	0.9539	0.9901
0.0000	8.4946			
50	0.9596	0.9674	0.9543	0.9902
0.0000	8.7672			

Stopping since valid\_loss has not improved in the last 15 epochs.

	precision	recall	f1-score	support
0	0.99	0.96	0.98	57892
1	0.64	0.88	0.74	1797
2	0.88	0.96	0.92	4676
3	0.39	0.90	0.54	496
4	0.97	0.98	0.97	5182
accuracy			0.96	70043
macro avg	0.77	0.94	0.83	70043
weighted avg	0.97	0.96	0.96	70043

	precision	recall	f1-score	support
0	0.99	0.96	0.97	14579
1	0.59	0.81	0.68	426
2	0.85	0.92	0.88	1112
3	0.41	0.90	0.57	145
4	0.97	0.97	0.97	1249
accuracy			0.95	17511
macro avg	0.76	0.91	0.82	17511
weighted avg	0.96	0.95	0.96	17511



Best model saved to models/cnn/20240403T190703.pth  
time: 15min 21s (started: 2024-04-03 18:51:41 +01:00)

## 4 SVM

Evaluate number of components for PCA and LDA by examining explained variance plot

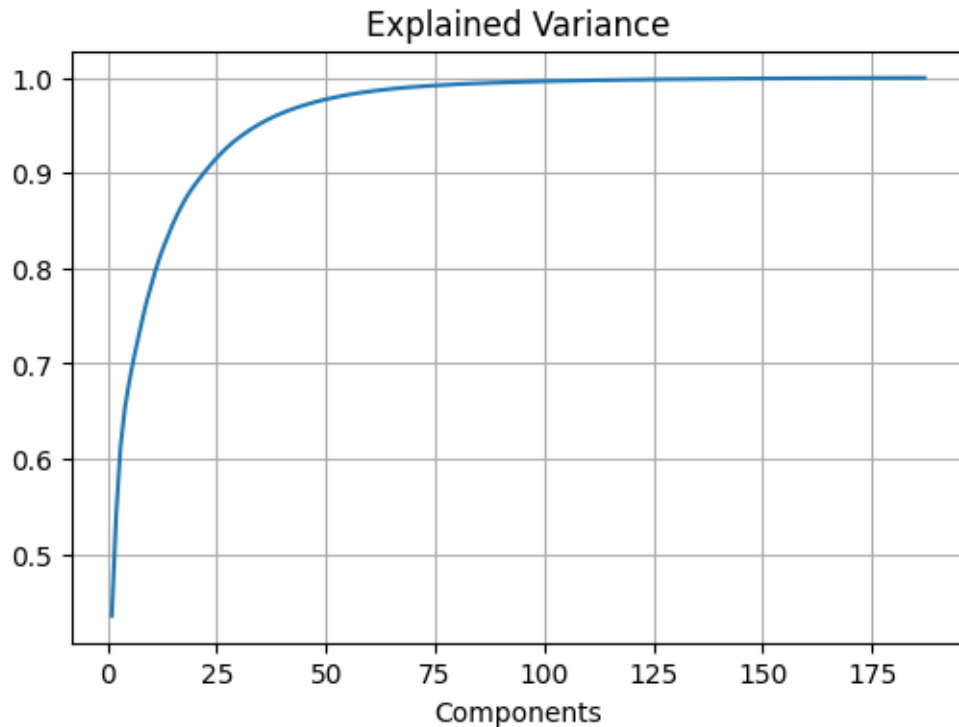
```
[ ]: X_train, y_train = _import_data('train')
```

time: 5.12 s (started: 2024-04-03 19:09:46 +01:00)

```
[ ]: # Perform PCA on training set
pca = PCA()
pca.fit(X_train)

# Calculate the explained variance ratio
ev_pca = pca.explained_variance_ratio_.cumsum()

# Plot the explained variance
plt.figure(figsize=(6, 4))
plt.plot(range(1, len(ev_pca) + 1), ev_pca)
plt.title('Explained Variance')
plt.xlabel('Components')
plt.grid(True)
plt.show()
```



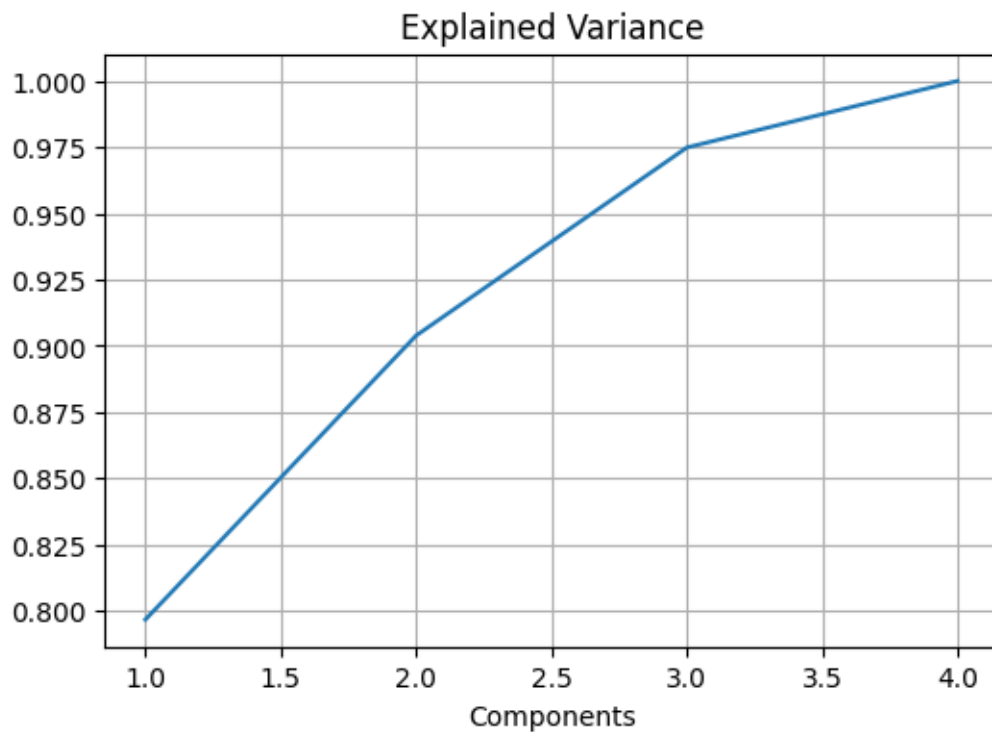
time: 2.36 s (started: 2024-04-16 00:09:09 +01:00)

From the explained variance plot, 100 components will be used as PCA captures nearly 100% of the variance

```
[ ]: # Perform LDA on training set
lda = LinearDiscriminantAnalysis()
lda.fit(X_train, y_train)

# Calculate the explained variance ratio
ev_lda = lda.explained_variance_ratio_.cumsum()

# Plot the explained variance
plt.figure(figsize=(6, 4))
plt.plot(range(1, len(ev_lda) + 1), ev_lda)
plt.title('Explained Variance')
plt.xlabel('Components')
plt.grid(True)
plt.show()
```



time: 2.48 s (started: 2024-04-16 00:09:14 +01:00)

From the explained variance plot, 4 components will be used as LDA captures 100% of the variance

**Parameter Tuning and Model Training** Parameters to be tuned through Gridsearch on 5 folds cross validation - C (Regularization parameter) - Gamma - Kernel

```
[ ]: params = {
    'svm__C': [0.1, 1, 10, 100, 1000],
    'svm__gamma': [0.001, 0.01, 0.1, 1],
    'svm__kernel': ['linear', 'rbf'],
}
```

time: 0 ns (started: 2024-04-03 19:09:20 +01:00)

```
[ ]: # With class weight
_svm_pipeline(balanced_sample=None, dimredc=None,
               n_components=None, n_folds=5, class_weight='balanced',
               ↪model_fn=None,
               max_iter=1500)
```

(array([0, 1, 2, 3, 4], dtype=int64), array([72471, 2223, 5788, 641, 6431], dtype=int64))

[LibSVM]

C:\Users\kornk\anaconda3\lib\site-packages\sklearn\svm\\_base.py:297:

ConvergenceWarning: Solver terminated early (max\_iter=1500). Consider pre-processing your data with StandardScaler or MinMaxScaler.

warnings.warn(

Best Parameters: {'svm\_\_C': 100, 'svm\_\_gamma': 1, 'svm\_\_kernel': 'rbf'}

Model saved to models/svm/20240327T164911.pkl

	precision	recall	f1-score	support
0	1.00	1.00	1.00	72471
1	1.00	1.00	1.00	2223
2	1.00	1.00	1.00	5788
3	0.98	1.00	0.99	641
4	1.00	1.00	1.00	6431
accuracy			1.00	87554
macro avg	1.00	1.00	1.00	87554
weighted avg	1.00	1.00	1.00	87554

	precision	recall	f1-score	support
0	0.98	0.99	0.99	18118
1	0.84	0.75	0.79	556
2	0.96	0.93	0.94	1448
3	0.85	0.75	0.80	162
4	1.00	0.97	0.98	1608
accuracy			0.98	21892
macro avg	0.93	0.88	0.90	21892
weighted avg	0.98	0.98	0.98	21892

time: 1h 22min 13s (started: 2024-03-27 15:31:30 +00:00)

### Additional approaches for comparison

```
[ ]: # Downsampling majority to 20000, and upsampling using bootstrapping method to
      ↪ all minority classes to 20000 each
      _svm_pipeline(balanced_sample=20000, dimredc=None,
                    n_components=None, n_folds=5, model_fn=None,
                    max_iter=1500)
```

```
(array([0, 1, 2, 3, 4], dtype=int64), array([20000, 20000, 20000, 20000, 20000],
dtype=int64))
```

[LibSVM]

C:\Users\kornk\anaconda3\lib\site-packages\sklearn\svm\\_base.py:297:

ConvergenceWarning: Solver terminated early (max\_iter=1500). Consider pre-processing your data with StandardScaler or MinMaxScaler.

warnings.warn(

Best Parameters: {'svm\_C': 1000, 'svm\_gamma': 1, 'svm\_kernel': 'rbf'}

Model saved to models/svm/20240327T195247.pkl

	precision	recall	f1-score	support
0	1.00	0.99	0.99	72471
1	0.83	1.00	0.91	2223
2	0.96	1.00	0.98	5788
3	0.87	1.00	0.93	641
4	0.99	1.00	0.99	6431

accuracy			0.99	87554
macro avg	0.93	1.00	0.96	87554
weighted avg	0.99	0.99	0.99	87554

	precision	recall	f1-score	support
0	0.99	0.98	0.99	18118
1	0.72	0.78	0.75	556
2	0.92	0.94	0.93	1448
3	0.74	0.79	0.76	162
4	0.99	0.97	0.98	1608

accuracy			0.97	21892
macro avg	0.87	0.89	0.88	21892
weighted avg	0.97	0.97	0.97	21892

time: 1h 50min 40s (started: 2024-03-27 18:06:42 +00:00)

```
[ ]: # With LDA, feature reduction
      _svm_pipeline(balanced_sample=None, scaler=None, dimredc='lda',
                    n_components=4, n_folds=5, class_weight='balanced', model_fn=None,
```



```
max_iter=1500)
```

```
(array([0, 1, 2, 3, 4], dtype=int64), array([72471, 2223, 5788, 641, 6431],
dtype=int64))
```

```
[LibSVM]
```

```
C:\Users\kornk\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
```

```
ConvergenceWarning: Solver terminated early (max_iter=1500). Consider pre-
processing your data with StandardScaler or MinMaxScaler.
```

```
warnings.warn(
```

```
Best Parameters: {'svm__C': 1000, 'svm__gamma': 1, 'svm__kernel': 'rbf'}
```

```
Model saved to models/svm/20240403T194254.pkl
```

	precision	recall	f1-score	support
0	0.90	0.49	0.64	72471
1	0.01	0.10	0.02	2223
2	0.15	0.73	0.25	5788
3	0.27	0.26	0.26	641
4	0.13	0.03	0.05	6431
accuracy			0.46	87554
macro avg	0.29	0.32	0.24	87554
weighted avg	0.77	0.46	0.55	87554

```
time: 15min 5s (started: 2024-04-03 19:29:23 +01:00)
```

```
[ ]: # With PCA, feature reduction
_svm_pipeline(balanced_sample=None, scaler=None, dimredc='pca',
               n_components=100, n_folds=5, class_weight='balanced',
               ↪model_fn=None,
               max_iter=1500)
```

```
(array([0, 1, 2, 3, 4], dtype=int64), array([72471, 2223, 5788, 641, 6431],
dtype=int64))
```

```
[LibSVM]
```

```
C:\Users\kornk\anaconda3\lib\site-packages\sklearn\svm\_base.py:297:
```

```
ConvergenceWarning: Solver terminated early (max_iter=1500). Consider pre-
processing your data with StandardScaler or MinMaxScaler.
```

```
warnings.warn(
```

```
Best Parameters: {'svm__C': 100, 'svm__gamma': 1, 'svm__kernel': 'rbf'}
```

```
Model saved to models/svm/20240327T180008.pkl
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	72471
1	1.00	1.00	1.00	2223
2	1.00	1.00	1.00	5788
3	0.98	1.00	0.99	641

	4	1.00	1.00	1.00	6431
accuracy				1.00	87554
macro avg	0.99	1.00	1.00		87554
weighted avg	1.00	1.00	1.00		87554

		precision	recall	f1-score	support
0	0.98	0.99	0.99	0.98	18118
1	0.83	0.74	0.79	0.79	556
2	0.96	0.93	0.94	0.94	1448
3	0.83	0.74	0.78	0.78	162
4	1.00	0.97	0.98	0.98	1608

accuracy				0.98	21892
macro avg	0.92	0.88	0.90		21892
weighted avg	0.98	0.98	0.98		21892

time: 47min 58s (started: 2024-03-27 17:15:18 +00:00)

## 5 Set up

```
[ ]: %run "tools.ipynb"
```

The autotime extension is already loaded. To reload it, use:

```
%reload_ext autotime
```

```
cpu
```

time: 94 ms (started: 2024-04-17 22:34:31 +01:00)

## 6 CNN

### 6.0.1 CNN

```
[ ]: # Evaluate on Test set
```

```
_evaluate_cnn(CNN, '20240415T112137', subset='test')
```

Predicting time: 0:00:04.909453

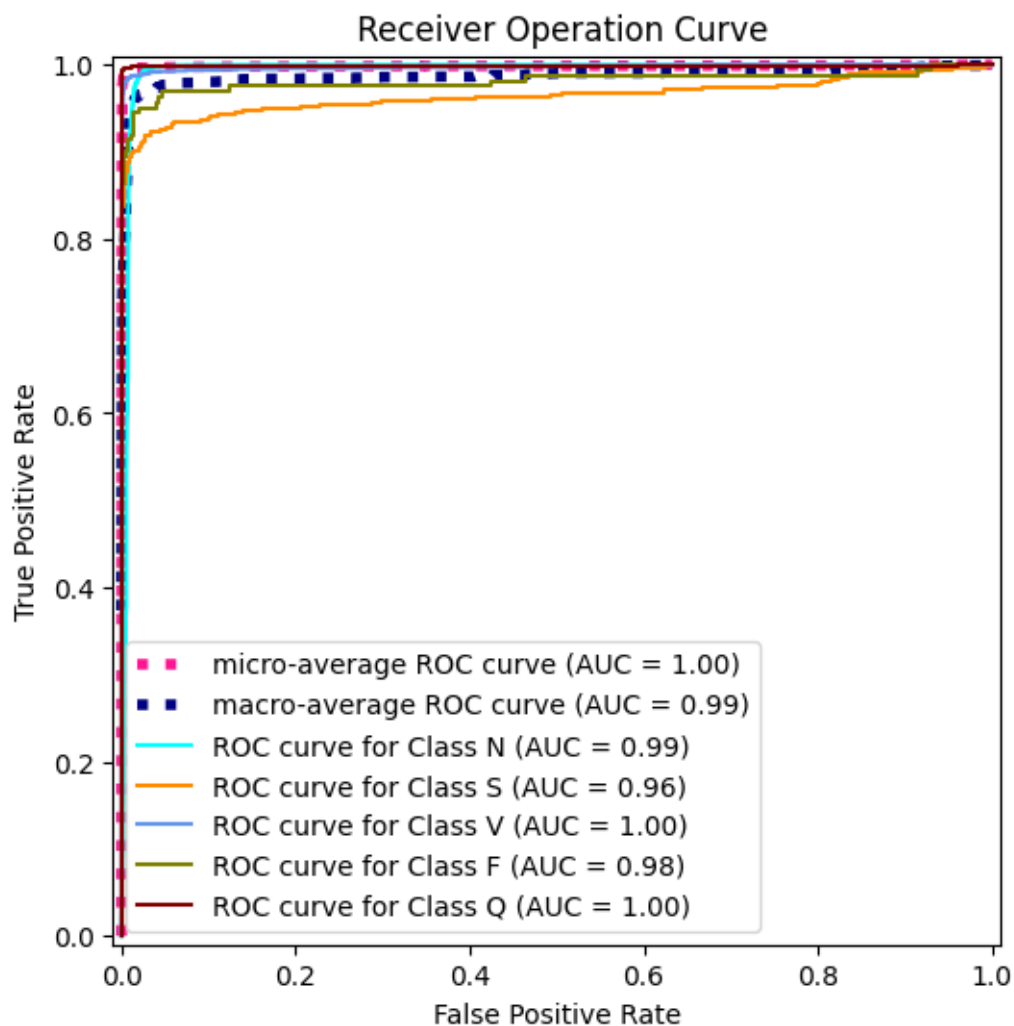
		precision	recall	f1-score	support
0	0.99	1.00	0.99	0.99	18118
1	0.95	0.82	0.88	0.88	556
2	0.97	0.97	0.97	0.97	1448
3	0.87	0.81	0.84	0.84	162
4	1.00	0.99	0.99	0.99	1608

accuracy				0.99	21892
macro avg	0.96	0.92	0.94		21892

weighted avg      0.99      0.99      0.99      21892

True Label	N	99.76% 18074	0.11% 20	0.09% 17	0.03% 5	0.01% 2
	S	16.73% 93	82.01% 456	1.26% 7	0.00% 0	0.00% 0
	V	1.86% 27	0.21% 3	96.82% 1402	0.97% 14	0.14% 2
	F	11.11% 18	0.00% 0	8.02% 13	80.86% 131	0.00% 0
	Q	0.93% 15	0.00% 0	0.25% 4	0.00% 0	98.82% 1589
		N	S	V	F	Q
		Predicted Label				



time: 6.72 s (started: 2024-04-17 23:31:04 +01:00)

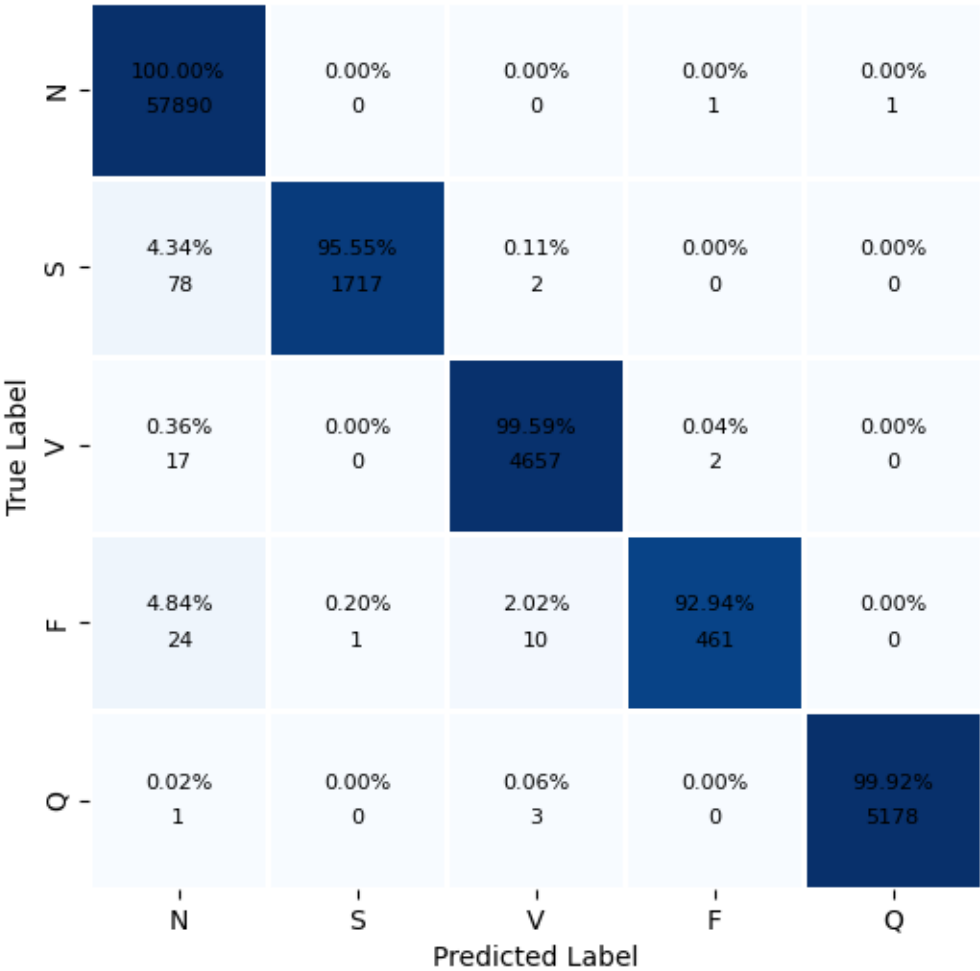
### Results on Train and Validation Set

[ ]: *# Evaluate on Train set*

```
# _evaluate_cnn(CNN, '20240415T112137', subset='train', roc_curve=False)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	57892
1	1.00	0.96	0.98	1797
2	1.00	1.00	1.00	4676
3	0.99	0.93	0.96	496
4	1.00	1.00	1.00	5182
accuracy			1.00	70043

macro avg	1.00	0.98	0.99	70043
weighted avg	1.00	1.00	1.00	70043



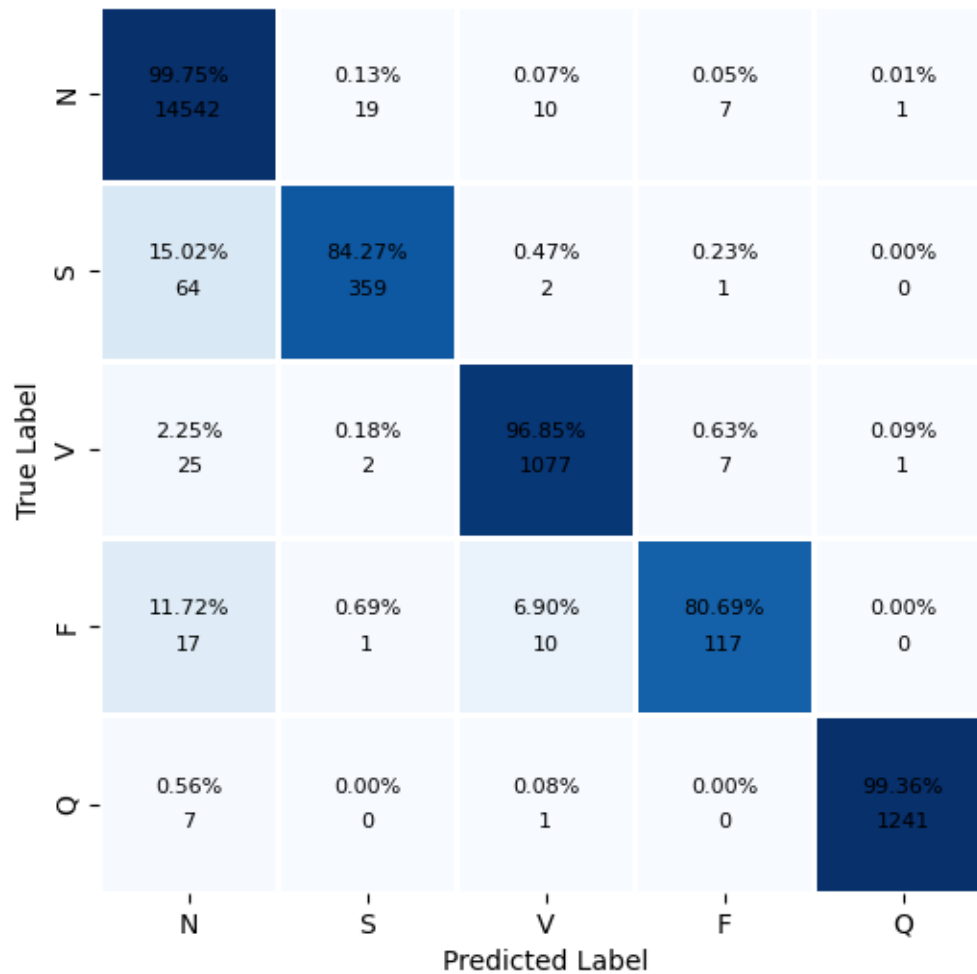
time: 23.5 s (started: 2024-04-16 00:38:20 +01:00)

```
[ ]: # Evaluate on Validation set

# _evaluate_cnn(CNN, '20240415T112137', subset='validation', roc_curve=False)
```

	precision	recall	f1-score	support
0	0.99	1.00	0.99	14579
1	0.94	0.84	0.89	426
2	0.98	0.97	0.97	1112
3	0.89	0.81	0.84	145
4	1.00	0.99	1.00	1249

accuracy			0.99	17511
macro avg	0.96	0.92	0.94	17511
weighted avg	0.99	0.99	0.99	17511



time: 9.42 s (started: 2024-04-16 00:39:08 +01:00)

### 6.0.2 Residual neural network (replicate structure and parameters obtained from M. Kachuee et al.)

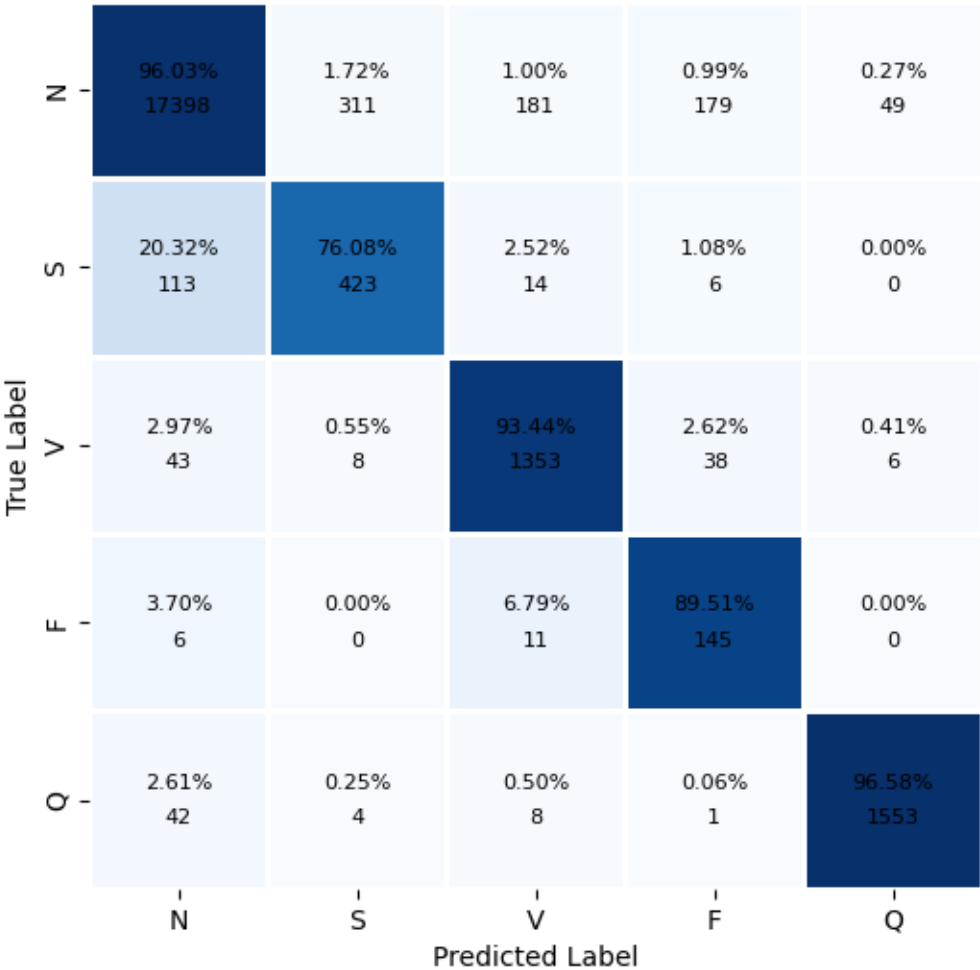
M. Kachuee, S. Fazeli and M. Sarrafzadeh, "ECG Heartbeat Classification: A Deep Transferable Representation," 2018 IEEE International Conference on Healthcare Informatics (ICHI), New York, NY, USA, 2018, pp. 443-444, doi: 10.1109/ICHI.2018.0009

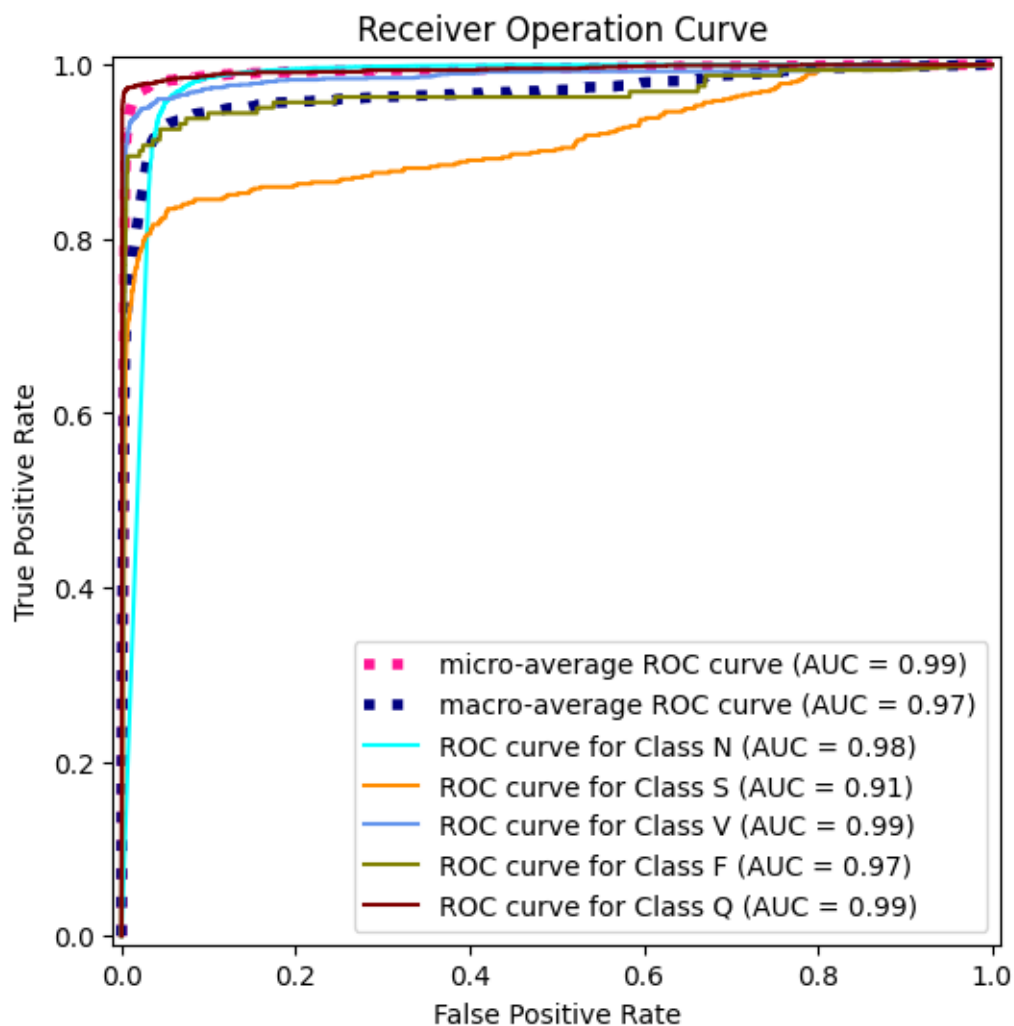
```
[ ]: # Evaluate on Test set
```

```
_evaluate_cnn(ResCNN, '20240403T190703', subset='test')
```

Predicting time: 0:00:03.349093

	precision	recall	f1-score	support
0	0.99	0.96	0.97	18118
1	0.57	0.76	0.65	556
2	0.86	0.93	0.90	1448
3	0.39	0.90	0.55	162
4	0.97	0.97	0.97	1608
accuracy			0.95	21892
macro avg	0.76	0.90	0.81	21892
weighted avg	0.96	0.95	0.96	21892





time: 5.5 s (started: 2024-04-17 20:46:02 +01:00)

## 7 SVM

```
[ ]: # Evaluate on Test set without ROC curve
# Takes around 1.30 mins for loading model, and predicting labels

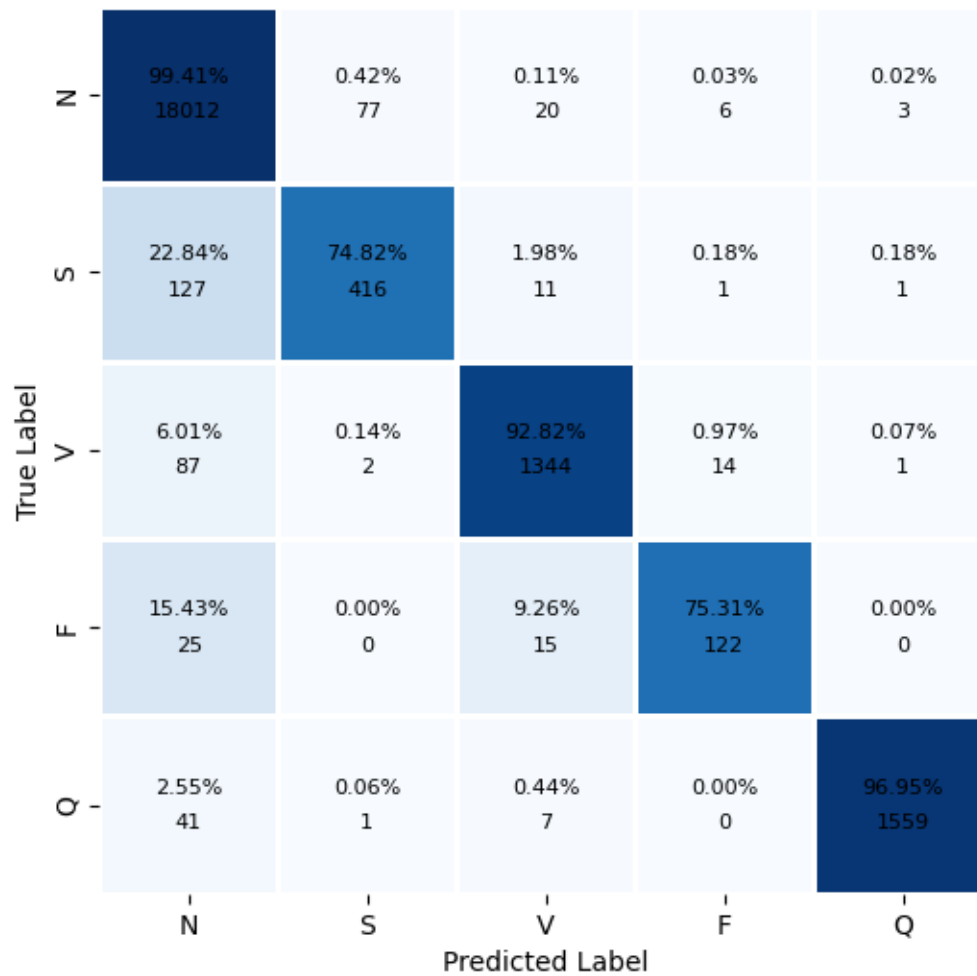
_evaluate_svm('20240415T231637', subset='test', roc_curve=False)
```

Predicting time: 0:00:57.763997

	precision	recall	f1-score	support
0	0.98	0.99	0.99	18118
1	0.84	0.75	0.79	556
2	0.96	0.93	0.94	1448



	3	0.85	0.75	0.80	162
	4	1.00	0.97	0.98	1608
accuracy				0.98	21892
macro avg	0.93	0.88	0.90		21892
weighted avg	0.98	0.98	0.98		21892



time: 58.7 s (started: 2024-04-17 22:32:04 +01:00)

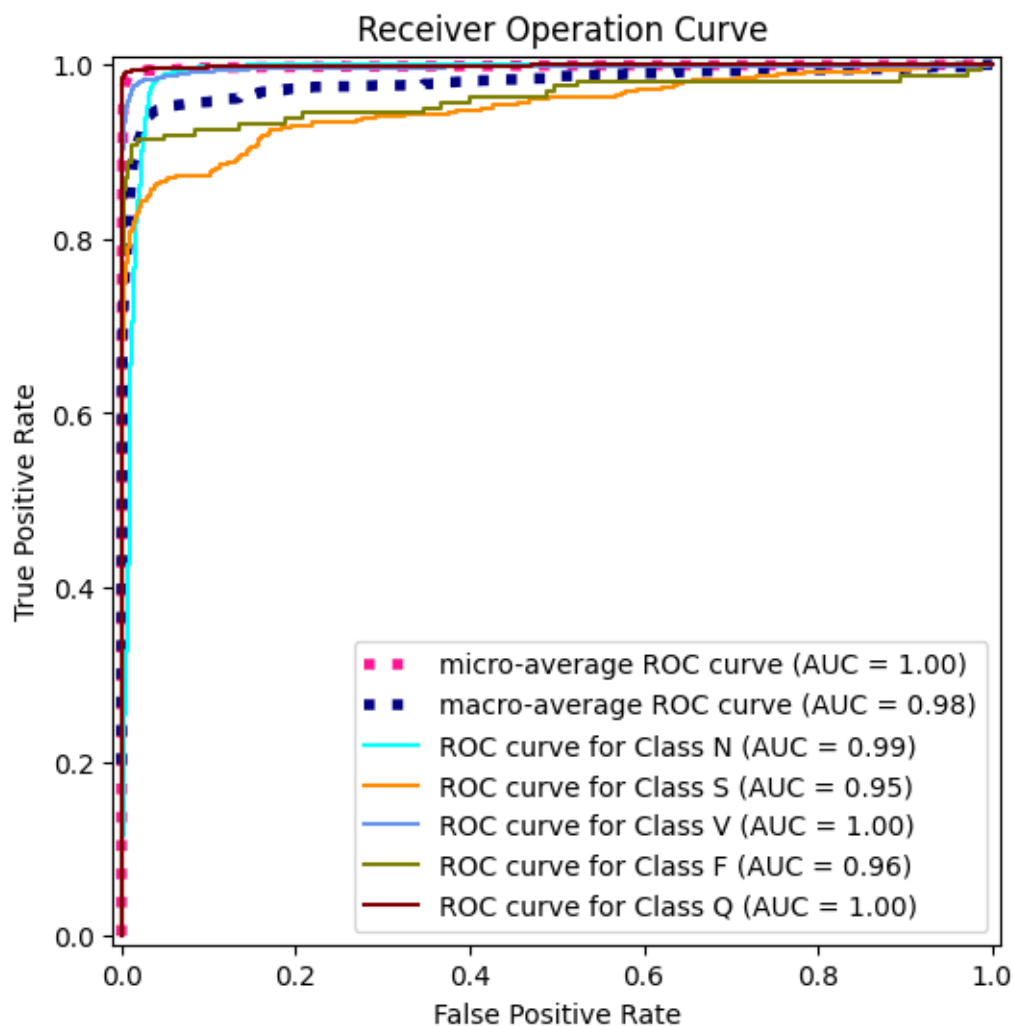
```
[ ]: # Evaluate on Test set with ROC curve
# Takes around 4 mins for loading model, predicting labels, and generate ROC
↳ curve

_evaluate_svm('20240415T231637', subset='test')
```

Predicting time: 0:00:59.283368

	precision	recall	f1-score	support
0	0.98	0.99	0.99	18118
1	0.84	0.75	0.79	556
2	0.96	0.93	0.94	1448
3	0.85	0.75	0.80	162
4	1.00	0.97	0.98	1608
accuracy			0.98	21892
macro avg	0.93	0.88	0.90	21892
weighted avg	0.98	0.98	0.98	21892

True Label	N	99.41% 18012	0.42% 77	0.11% 20	0.03% 6	0.02% 3
	S	22.84% 127	74.82% 416	1.98% 11	0.18% 1	0.18% 1
	V	6.01% 87	0.14% 2	92.82% 1344	0.97% 14	0.07% 1
	F	15.43% 25	0.00% 0	9.26% 15	75.31% 122	0.00% 0
	Q	2.55% 41	0.06% 1	0.44% 7	0.00% 0	96.95% 1559
		N	S	V	F	Q
		Predicted Label				



time: 2min (started: 2024-04-17 22:34:35 +01:00)

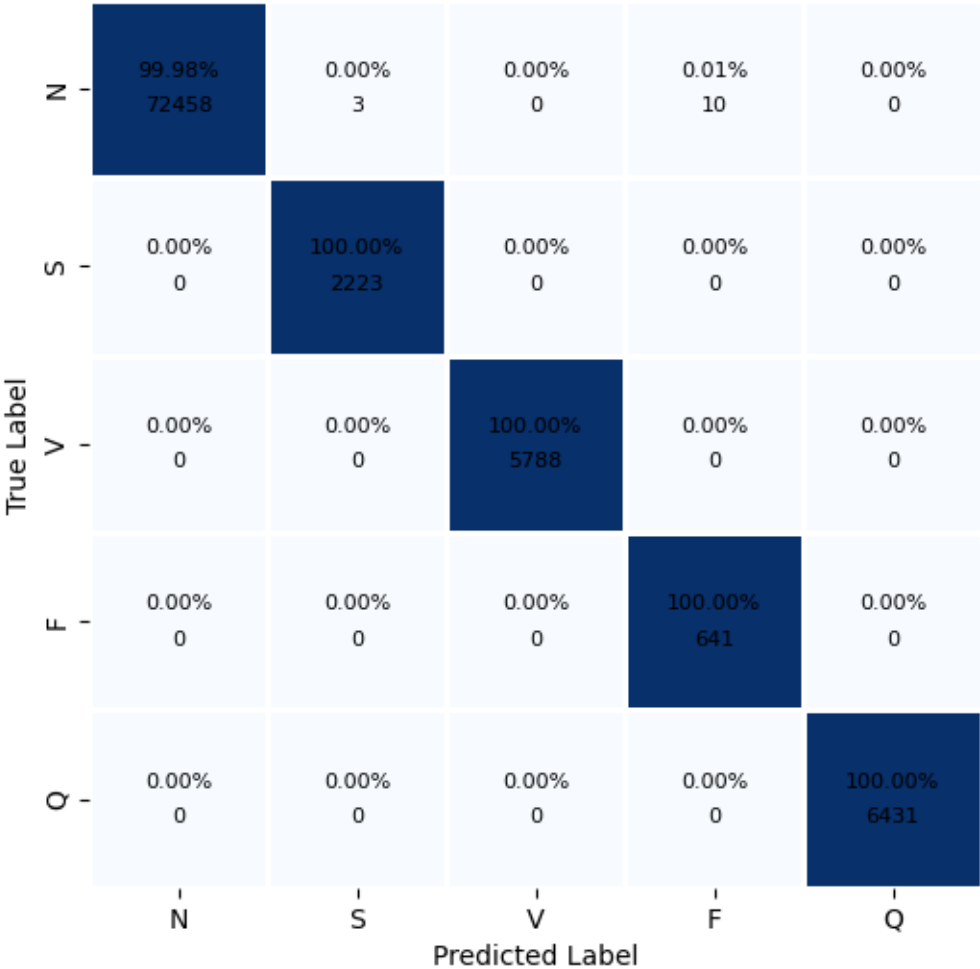
### Results on Train Set

```
[ ]: # Evaluate on Train set with ROC curve
# Takes around 6 mins for loading model, predicting labels

# _evaluate_sum('20240415T231637', subset='train', roc_curve=False)
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	72471
1	1.00	1.00	1.00	2223
2	1.00	1.00	1.00	5788
3	0.98	1.00	0.99	641
4	1.00	1.00	1.00	6431

accuracy			1.00	87554
macro avg	1.00	1.00	1.00	87554
weighted avg	1.00	1.00	1.00	87554



time: 5min 58s (started: 2024-04-16 00:45:33 +01:00)