Notebook

November 9, 2025

1 Multiclass classification

1.1 Import libraries

[1]:
```
import torch
import torch.nn as nn
import torchmetrics
from torch.utils.data import Dataset
import pandas as pd
import wandb
```

1.2 Config

[2]:
```
import torch.nn as nn
import numpy as np

torch.manual_seed(42)

np.random.seed(42)

BATCH_SIZE = 32
LR = 0.001
CLASSES = 6

TRAIN_VAL_TEST_SPLIT = [0.7, 0.15, 0.15]

MAX_EPOCHS = 100

LOSS_WEIGHTS = [4.0,4.0,2.0,3.0,5.0,5.0]
LOSS_FUNCTION =nn.CrossEntropyLoss(weight=torch.
 ↪tensor(LOSS_WEIGHTS))#weight=torch.tensor([2.0, 1.0,3.0,4.0,8.0,4.0]

DROPOUT_COEF = 0.35


SAVE_BEST_MODEL = True
IS_MULTICLASS = True if CLASSES > 2 else False
NUM_OF_WORKERS = 0
```

```
REDUCE_LR_PATIENCE = 10
EARLY_STOPPING_PATIENCE = 20
```

1.3 WANDB Init

[3]:
```
wandb.init(project="zneus-project-1-multiclass", name="Basic model with higher␣
 ↪amount of neurons")

# Config hyperparameters
config = wandb.config

config.batch_size = BATCH_SIZE
config.learning_rate = LR
config.max_epochs = MAX_EPOCHS
config.dropout_coef = DROPOUT_COEF
config.desc = "MLP: (1024, BatchNorm,ReLU,Dropout) (512,BatchNorm,␣
 ↪ReLU,Dropout) (256,BatchNorm, ReLU, Dropout) (1)"
config.loss_function = "BinaryCrossentropy with logits"
config.reduce_lr_patience = REDUCE_LR_PATIENCE
config.early_stopping_patience = EARLY_STOPPING_PATIENCE
config.loss_weights = LOSS_WEIGHTS
```

```
wandb: Currently logged in as: amal-akhmadinurov
(amal-akhmadinurov-stu) to https://api.wandb.ai. Use
`wandb login --relogin` to force relogin

wandb: Tracking run with wandb version 0.22.3

wandb: Run data is saved locally in
/Users/amalahmadinurov/Desktop/Subjects_ZS_2025/ZNEUS/zneus-

project-1/wandb/run-20251109_195710-m2pgb3xo
wandb: Run `wandb offline` to turn off syncing.

wandb: Syncing run Basic model with higher amount of

neurons

wandb:  View project at␣
 ↪https://wandb.ai/amal-akhmadinurov-stu/zneus-project-1-multiclass

wandb:  View run at␣
 ↪https://wandb.ai/amal-akhmadinurov-stu/zneus-project-1-multiclass/runs/m2pgb3xo
```

1.4 Define Dataset

[4]:
```
class SteelPlateDataset(Dataset):

    def __init__(self, dataset_path):
        super().__init__()
```

```
        self.path = dataset_path
        self.df = pd.read_csv(self.path)

        self.features = self.df.drop(["Class", *("Pastry Z_Scratch K_Scratch␣
↪Stains Dirtiness Bumps".split(" "))] ,axis= 1).values.tolist() # V28 V29 V30␣
↪V31 V32 V33
        self.labels =  self.df[[*"Pastry Z_Scratch K_Scratch Stains Dirtiness␣
↪Bumps".split(" ")]].dot([i for i in range(6)]).values.tolist() # V28 V29 V30␣
↪V31 V32 V33

    def __getitem__(self, index):

        return torch.tensor(self.features[index]), torch.tensor(self.
↪labels[index]).float()

    def __len__(self):
        return len(self.labels)
```

1.5 Create datasets

[5]:
```
from sklearn.model_selection import train_test_split
from torch.utils.data import DataLoader, Subset

dataset = SteelPlateDataset("data/norm_multiclass_data.csv")

labels = np.array(dataset.labels)
print(labels)
train_size, val_size, test_size = TRAIN_VAL_TEST_SPLIT

train_val_indices, test_indices = train_test_split(
    range(len(dataset)),
    test_size=TRAIN_VAL_TEST_SPLIT[1],
    stratify=dataset.labels,
    random_state=42
)

# Update labels for train+val indices
train_val_labels = labels[train_val_indices]

# Second split: train vs val
train_indices, val_indices = train_test_split(
    train_val_indices,
    test_size=val_size / (train_size + val_size),  # Adjust proportion for␣
↪train+val
    stratify=train_val_labels,
    random_state=42
```

```
)



train_dataset = Subset(dataset, train_indices)
val_dataset = Subset(dataset, val_indices)
test_dataset = Subset(dataset, test_indices)
```

```
[0 0 0 … 0 0 0]
```

1.6 Define device

[6]:
```
if torch.cuda.is_available():
    device_name = "cuda"
elif torch.backends.mps.is_available():
    device_name = "mps"
else:
    device_name = "cpu"
```

1.7 Create dataloaders

[7]:
```
from torch.utils.data import DataLoader



train_dataloader = DataLoader(
    train_dataset,
    batch_size=BATCH_SIZE,

    shuffle=True,  # Default shuffling for training
    num_workers=NUM_OF_WORKERS
)
val_dataloader = DataLoader(
    val_dataset,
    batch_size=BATCH_SIZE,
    shuffle=False,  # No shuffling for validation
    num_workers=NUM_OF_WORKERS
)
test_dataloader = DataLoader(
    test_dataset,
    batch_size=BATCH_SIZE,
    shuffle=False,  # No shuffling for test
    num_workers=NUM_OF_WORKERS
)

# Print dataset sizes
print(f"Train dataset size: {len(train_dataset)}")
print(f"Validation dataset size: {len(val_dataset)}")
```

```
print(f"Test dataset size: {len(test_dataset)}")
```

```
Train dataset size: 1129
Validation dataset size: 242
Test dataset size: 242
```

1.8 Define EarlyStopping class

[8]:
```
import torch

class EarlyStopping:
    def __init__(self, patience=5, min_delta=0.0):
        """
        Args:
            patience (int): How many epochs to wait after last improvement.
            min_delta (float): Minimum change to qualify as an improvement.
        """
        self.patience = patience
        self.min_delta = min_delta
        self.counter = 0
        self.best_loss = None
        self.early_stop = False

    def __call__(self, val_loss):
        if self.best_loss is None:
            self.best_loss = val_loss
        elif val_loss > self.best_loss - self.min_delta:
            self.counter += 1
            if self.counter >= self.patience:
                self.early_stop = True
        else:
            self.best_loss = val_loss
            self.counter = 0
```

1.9 Define model

[9]:
```
from torchmetrics.classification import Accuracy, Precision
from torch.optim.lr_scheduler import ReduceLROnPlateau


class MyModel(nn.Module):
    def __init__(self, input_size,lr=0.001, loss_fn=nn.BCELoss(),␣
 ↪num_classes=2,reduce_lr_patience=10, early_stopping_patience=10):
        super().__init__()
        self.accuracy = Accuracy(task="multiclass",␣
 ↪num_classes=num_classes,average="macro")
```

```
        self.precision = Precision(task="multiclass", num_classes=num_classes,␣
↪average="macro")
        self.loss_fn = loss_fn


        self.model = nn.Sequential(
            nn.Linear(input_size, 512),
            nn.BatchNorm1d(512),
            nn.ReLU(),
            nn.Dropout(DROPOUT_COEF),

            nn.Linear(512, 256),
            nn.BatchNorm1d(256),
            nn.ReLU(),
            nn.Dropout(DROPOUT_COEF),

            nn.Linear(256, 128),
            nn.BatchNorm1d(128),
            nn.ReLU(),
            nn.Dropout(DROPOUT_COEF),



            nn.Linear(128, num_classes)
        )
        self.to(device_name)

        self.optimizer = torch.optim.Adam(self.parameters(), lr=lr)

        self.early_stopping = EarlyStopping(patience=early_stopping_patience,␣
↪min_delta=0.01)

        self.scheduler = ReduceLROnPlateau(
            self.optimizer, mode='min', factor=0.5, patience=reduce_lr_patience
        )

    def forward(self, x):
        return self.model(x)


    def evaluate(self, dataloader):
        self.eval()
        eval_loss = 0

        self.precision.reset()
        self.accuracy.reset()
```

```
        with torch.no_grad():
            for batch in dataloader:

                x = batch[0].to(device_name)
                y = batch[1].to(device_name)

                output = self.forward(x)
                output = torch.sigmoid(output).squeeze(1)
                y = y.float()



                loss = self.loss_fn(output, y)

                self.accuracy(output, y)
                self.precision(output, y)


                eval_loss += loss.item()

        self.train()
        return (eval_loss/len(dataloader), self.accuracy.compute(), self.
↪precision.compute())


    def fit(self, train_dataloader, val_dataloader, epochs=10):
        self.train()
        best_val_loss = 9999



        for i in range(0,epochs):

            self.accuracy.reset()
            epoch_loss = 0
            for batch in train_dataloader:

                x = batch[0].to(device_name)
                y = batch[1].to(device_name)


                output = self.forward(x)
                output = torch.sigmoid(output).squeeze(1)
                y = y.float()
```

```
            loss = self.loss_fn(output, y)


            self.accuracy(output, y)
            self.precision(output, y)

            epoch_loss += loss.item()

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


        epoch_loss/=len(train_dataloader)

        epoch_acc = self.accuracy.compute()
        epoch_precision = self.precision.compute()



        val_loss, val_acc, val_precision = self.evaluate(val_dataloader)
        if best_val_loss > val_loss:
            best_val_loss = val_loss
            torch.save(self.state_dict(), "best-model-multiclass.pth")


        self.scheduler.step(val_loss)
        wandb.log({"epoch": i, "Train Loss": epoch_loss, "Train Acc":
↪epoch_acc,"Train Precision":epoch_precision, "Val Loss":val_loss, "Val Acc":
↪val_acc,"Val Precision":val_precision, "LR":self.optimizer.
↪param_groups[0]['lr']})
        print(f"Epoch {i+1} Loss:{epoch_loss:.4f} Accuracy:{epoch_acc:.4f}␣
↪Precision:{epoch_precision:.4f} Val Loss:{val_loss:.4f} Val Accuracy:
↪{val_acc:.4f} Val Precision:{val_precision:.4f} LR = {self.optimizer.
↪param_groups[0]['lr']}")
        self.early_stopping(val_loss)
        if self.early_stopping.early_stop:
            print("Early stopping")
            break
    wandb.finish()
```

1.10 Create model

[10]:
```
model = MyModel(
    input_size=len(dataset.features[0]),
    num_classes=CLASSES,
    loss_fn=LOSS_FUNCTION, lr=LR,
    reduce_lr_patience=REDUCE_LR_PATIENCE,
    early_stopping_patience=EARLY_STOPPING_PATIENCE
)
```

1.11 Train model

[11]:
```
model.fit(train_dataloader, val_dataloader, epochs=MAX_EPOCHS)
```

```
Epoch 1 Loss:1.5967 Accuracy:0.4945 Precision:0.4459 Val Loss:1.4830 Val
Accuracy:0.5605 Val Precision:0.5862 LR = 0.001

Epoch 2 Loss:1.4091 Accuracy:0.4851 Precision:0.6044 Val Loss:1.3765 Val
Accuracy:0.5742 Val Precision:0.6283 LR = 0.001

Epoch 3 Loss:1.3436 Accuracy:0.5435 Precision:0.6493 Val Loss:1.3308 Val
Accuracy:0.6310 Val Precision:0.6404 LR = 0.001

Epoch 4 Loss:1.3092 Accuracy:0.6271 Precision:0.6611 Val Loss:1.3044 Val
Accuracy:0.6447 Val Precision:0.6282 LR = 0.001

Epoch 5 Loss:1.2875 Accuracy:0.6594 Precision:0.6708 Val Loss:1.2955 Val
Accuracy:0.6652 Val Precision:0.6433 LR = 0.001

Epoch 6 Loss:1.2728 Accuracy:0.6776 Precision:0.6771 Val Loss:1.2829 Val
Accuracy:0.6570 Val Precision:0.6536 LR = 0.001

Epoch 7 Loss:1.2632 Accuracy:0.6880 Precision:0.6814 Val Loss:1.2806 Val
Accuracy:0.6638 Val Precision:0.6599 LR = 0.001

Epoch 8 Loss:1.2529 Accuracy:0.6909 Precision:0.6810 Val Loss:1.2727 Val
Accuracy:0.6650 Val Precision:0.6529 LR = 0.001

Epoch 9 Loss:1.2445 Accuracy:0.6867 Precision:0.6825 Val Loss:1.2721 Val
Accuracy:0.6475 Val Precision:0.6511 LR = 0.001

Epoch 10 Loss:1.2411 Accuracy:0.6932 Precision:0.7644 Val Loss:1.2682 Val
Accuracy:0.6387 Val Precision:0.6349 LR = 0.001

Epoch 11 Loss:1.2432 Accuracy:0.7050 Precision:0.8470 Val Loss:1.2677 Val
Accuracy:0.6464 Val Precision:0.6393 LR = 0.001

Epoch 12 Loss:1.2281 Accuracy:0.7138 Precision:0.8416 Val Loss:1.2728 Val
Accuracy:0.6675 Val Precision:0.6570 LR = 0.001

Epoch 13 Loss:1.2281 Accuracy:0.7204 Precision:0.8631 Val Loss:1.2726 Val
Accuracy:0.6750 Val Precision:0.8230 LR = 0.001

Epoch 14 Loss:1.2262 Accuracy:0.7304 Precision:0.8600 Val Loss:1.2767 Val
Accuracy:0.6810 Val Precision:0.8052 LR = 0.001
```

```
Epoch 15 Loss:1.2239 Accuracy:0.7209 Precision:0.8492 Val Loss:1.2651 Val
Accuracy:0.6898 Val Precision:0.8072 LR = 0.001

Epoch 16 Loss:1.2124 Accuracy:0.7318 Precision:0.8419 Val Loss:1.2678 Val
Accuracy:0.6825 Val Precision:0.8139 LR = 0.001

Epoch 17 Loss:1.2113 Accuracy:0.7222 Precision:0.8363 Val Loss:1.2784 Val
Accuracy:0.6896 Val Precision:0.8084 LR = 0.001

Epoch 18 Loss:1.2156 Accuracy:0.7417 Precision:0.8336 Val Loss:1.2624 Val
Accuracy:0.6930 Val Precision:0.8212 LR = 0.001

Epoch 19 Loss:1.2028 Accuracy:0.7387 Precision:0.8302 Val Loss:1.2583 Val
Accuracy:0.6989 Val Precision:0.8269 LR = 0.001

Epoch 20 Loss:1.2081 Accuracy:0.7763 Precision:0.8451 Val Loss:1.2606 Val
Accuracy:0.7193 Val Precision:0.8251 LR = 0.001

Epoch 21 Loss:1.2037 Accuracy:0.7720 Precision:0.8606 Val Loss:1.2669 Val
Accuracy:0.6850 Val Precision:0.8255 LR = 0.001

Epoch 22 Loss:1.2017 Accuracy:0.7716 Precision:0.8289 Val Loss:1.2621 Val
Accuracy:0.7254 Val Precision:0.8451 LR = 0.001

Epoch 23 Loss:1.1990 Accuracy:0.8151 Precision:0.8613 Val Loss:1.2576 Val
Accuracy:0.7670 Val Precision:0.8456 LR = 0.001

Epoch 24 Loss:1.2040 Accuracy:0.7917 Precision:0.8477 Val Loss:1.2632 Val
Accuracy:0.7864 Val Precision:0.8118 LR = 0.001

Epoch 25 Loss:1.2058 Accuracy:0.8112 Precision:0.8367 Val Loss:1.2529 Val
Accuracy:0.7491 Val Precision:0.8243 LR = 0.001

Epoch 26 Loss:1.2009 Accuracy:0.8179 Precision:0.8109 Val Loss:1.2601 Val
Accuracy:0.7529 Val Precision:0.8369 LR = 0.001

Epoch 27 Loss:1.2057 Accuracy:0.8429 Precision:0.8458 Val Loss:1.2524 Val
Accuracy:0.7988 Val Precision:0.7985 LR = 0.001

Epoch 28 Loss:1.1994 Accuracy:0.8106 Precision:0.8230 Val Loss:1.2664 Val
Accuracy:0.7480 Val Precision:0.8360 LR = 0.001

Epoch 29 Loss:1.1880 Accuracy:0.8508 Precision:0.8526 Val Loss:1.2606 Val
Accuracy:0.7356 Val Precision:0.7688 LR = 0.001

Epoch 30 Loss:1.1903 Accuracy:0.8243 Precision:0.8406 Val Loss:1.2547 Val
Accuracy:0.7727 Val Precision:0.8301 LR = 0.001

Epoch 31 Loss:1.1964 Accuracy:0.8203 Precision:0.8360 Val Loss:1.2633 Val
Accuracy:0.7699 Val Precision:0.8279 LR = 0.001

Epoch 32 Loss:1.1913 Accuracy:0.8472 Precision:0.8468 Val Loss:1.2653 Val
Accuracy:0.7143 Val Precision:0.8346 LR = 0.001

Epoch 33 Loss:1.1890 Accuracy:0.8411 Precision:0.8513 Val Loss:1.2627 Val
Accuracy:0.7730 Val Precision:0.8036 LR = 0.001
```

```
Epoch 34 Loss:1.1948 Accuracy:0.8212 Precision:0.8356 Val Loss:1.2652 Val
Accuracy:0.7666 Val Precision:0.7875 LR = 0.001

Epoch 35 Loss:1.1917 Accuracy:0.8089 Precision:0.8323 Val Loss:1.2637 Val
Accuracy:0.7496 Val Precision:0.8006 LR = 0.001

Epoch 36 Loss:1.1959 Accuracy:0.8396 Precision:0.8513 Val Loss:1.2626 Val
Accuracy:0.7822 Val Precision:0.8002 LR = 0.001

Epoch 37 Loss:1.1887 Accuracy:0.8371 Precision:0.8442 Val Loss:1.2685 Val
Accuracy:0.7643 Val Precision:0.8068 LR = 0.001

Epoch 38 Loss:1.1840 Accuracy:0.8446 Precision:0.8480 Val Loss:1.2667 Val
Accuracy:0.7740 Val Precision:0.8098 LR = 0.0005

Epoch 39 Loss:1.1901 Accuracy:0.8412 Precision:0.8422 Val Loss:1.2563 Val
Accuracy:0.7826 Val Precision:0.7942 LR = 0.0005

Epoch 40 Loss:1.1943 Accuracy:0.8164 Precision:0.8340 Val Loss:1.2598 Val
Accuracy:0.7715 Val Precision:0.8019 LR = 0.0005

Epoch 41 Loss:1.1821 Accuracy:0.8695 Precision:0.8442 Val Loss:1.2625 Val
Accuracy:0.7709 Val Precision:0.8096 LR = 0.0005

Epoch 42 Loss:1.1841 Accuracy:0.8606 Precision:0.8344 Val Loss:1.2610 Val
Accuracy:0.7722 Val Precision:0.8101 LR = 0.0005

Epoch 43 Loss:1.1728 Accuracy:0.8629 Precision:0.8666 Val Loss:1.2548 Val
Accuracy:0.7792 Val Precision:0.8061 LR = 0.0005

Epoch 44 Loss:1.1853 Accuracy:0.8460 Precision:0.8544 Val Loss:1.2544 Val
Accuracy:0.7807 Val Precision:0.8077 LR = 0.0005

Epoch 45 Loss:1.1792 Accuracy:0.8442 Precision:0.8599 Val Loss:1.2553 Val
Accuracy:0.7822 Val Precision:0.8050 LR = 0.0005

Epoch 46 Loss:1.1866 Accuracy:0.8580 Precision:0.8468 Val Loss:1.2546 Val
Accuracy:0.7730 Val Precision:0.8036 LR = 0.0005

wandb: updating run metadata

Epoch 47 Loss:1.1764 Accuracy:0.8481 Precision:0.8453 Val Loss:1.2534 Val
Accuracy:0.7838 Val Precision:0.8431 LR = 0.0005
Early stopping

wandb: uploading config.yaml

wandb:
wandb: Run history:
wandb:              LR
wandb:       Train Acc
wandb:      Train Loss
wandb: Train Precision
wandb:         Val Acc
wandb:        Val Loss
wandb:   Val Precision
```

```
wandb:           epoch
wandb:
wandb: Run summary:
wandb:               LR 0.0005
wandb:       Train Acc 0.84809
wandb:      Train Loss 1.17642
wandb: Train Precision 0.84532
wandb:         Val Acc 0.78377
wandb:        Val Loss 1.25344
wandb:   Val Precision 0.84305
wandb:           epoch 46
wandb:
wandb:   View run Basic model with higher amount of
neurons at:␣
↪https://wandb.ai/amal-akhmadinurov-stu/zneus-project-1-multiclass/runs/m2pgb3xo
wandb:   View project at:␣
↪https://wandb.ai/amal-akhmadinurov-stu/zneus-project-1-multiclass
wandb: Synced 4 W&B file(s), 0 media file(s), 0 artifact file(s)
and 0 other file(s)
wandb: Find logs at:
./wandb/run-20251109_195710-m2pgb3xo/logs
```

[12]:
```
val_loss, val_acc, val_precision = model.evaluate(val_dataloader)
print(f"Test Loss:{val_loss} Test Accuracy:{val_acc.item()} Test Precision:
↪{val_precision.item()}")
```

```
Test Loss:1.253436490893364 Test Accuracy:0.7837744951248169 Test
Precision:0.8430511355400085
```

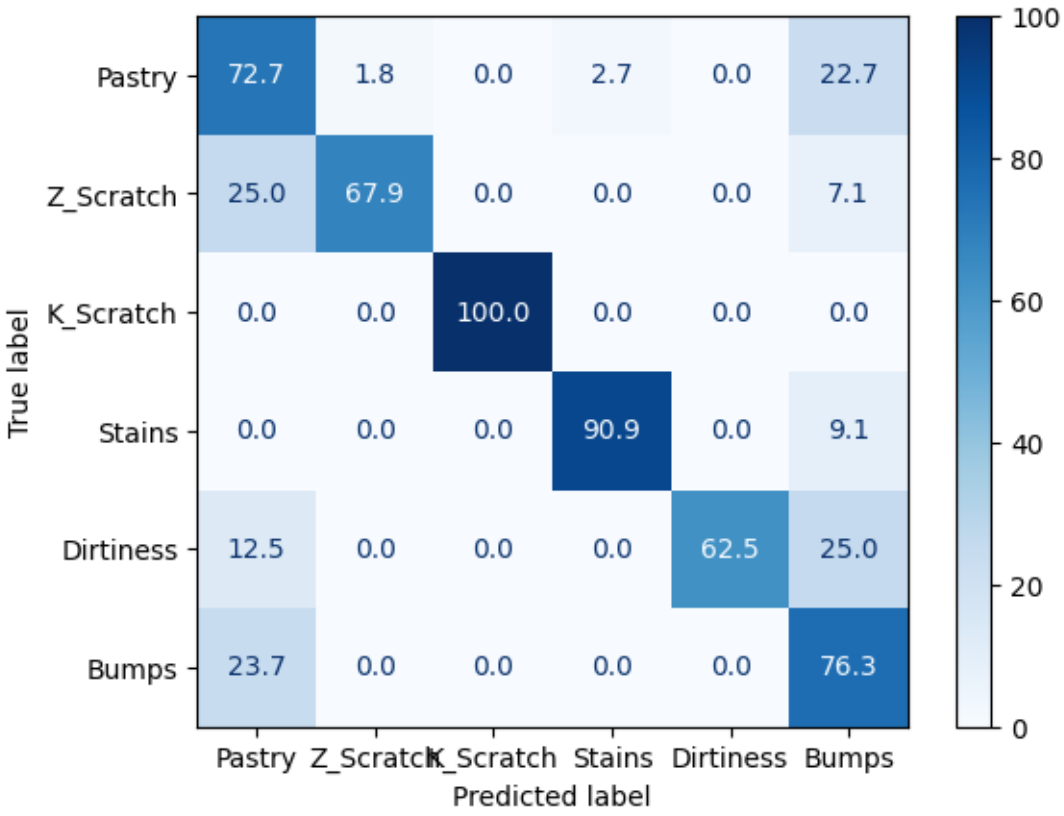
1.12 Confusion Matrix on validation set

[13]:
```
import numpy as np
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Example data (each pixel has an integer class label)
val_dataloader = DataLoader(
    val_dataset,
    batch_size=len(val_dataset),
    shuffle=False,  # Use sampler instead of shuffle
    num_workers=NUM_OF_WORKERS
)

features, ground_truth = next(iter(val_dataloader))
```

```
images = features.to(device_name)
model.eval()
predictions = model(images)

predictions =  torch.argmax(predictions, dim=1).float()
y_true = ground_truth.numpy()
y_pred = predictions.detach().cpu().int().numpy()

y_true_flat = y_true.flatten()
y_pred_flat = y_pred.flatten()

cm = confusion_matrix(y_true_flat, y_pred_flat, labels=[0, 1, 2,3,4,5])
print(cm)
# Convert to percentage (%)
cm_percent = cm.astype('float') / cm.sum(axis=1, keepdims=True) * 100
disp = ConfusionMatrixDisplay(confusion_matrix=cm_percent,
                              display_labels=["Pastry",␣
 ↪"Z_Scratch","K_Scratch"        ,"Stains"        ,"Dirtiness"        ,"Bumps"])

disp.plot(cmap='Blues', values_format='.1f')
```

```
[[80  2  0  3  0 25]
 [ 7 19  0  0  0  2]
 [ 0  0 26  0  0  0]
 [ 0  0  0 10  0  1]
 [ 1  0  0  0  5  2]
 [14  0  0  0  0 45]]
```

[13]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x120647230>



1.13 Load the best model by loss

[14]:
```
model.load_state_dict(torch.load("best-model-multiclass.pth",␣
↪map_location=device_name))
```

[14]:
```
<All keys matched successfully>
```

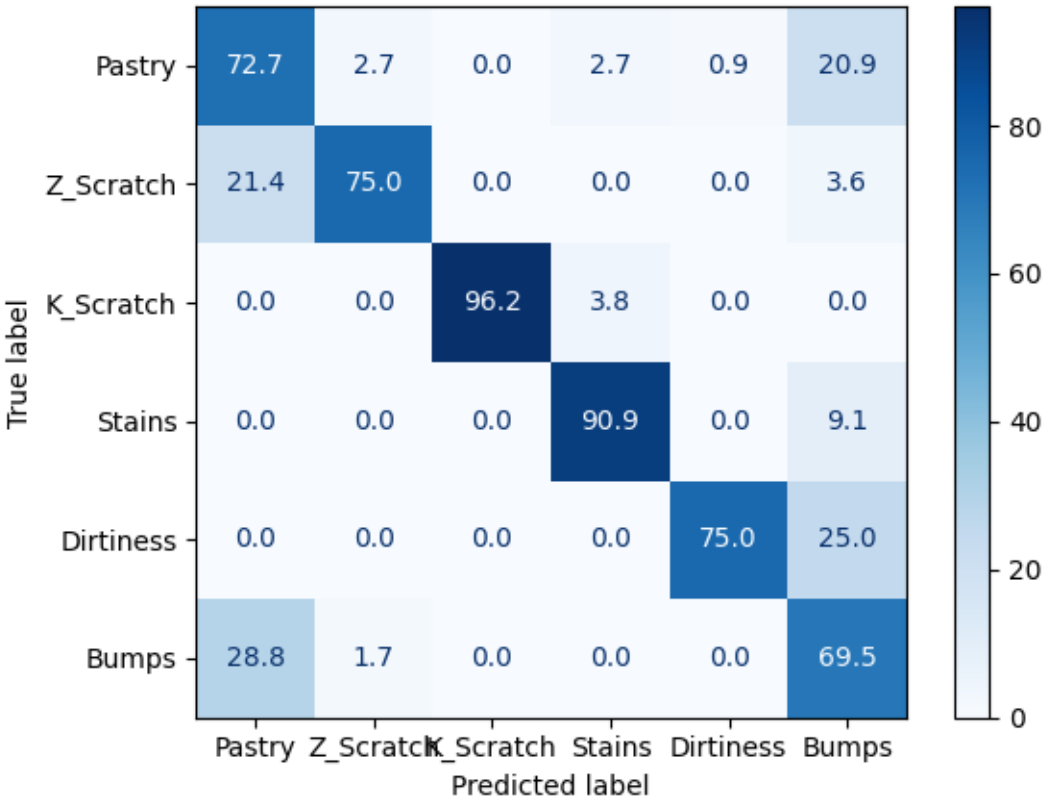
1.14 Confusion Matrix on validation set

[15]:
```
import numpy as np
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Example data (each pixel has an integer class label)
val_dataloader = DataLoader(
    val_dataset,
    batch_size=len(val_dataset),
    shuffle=False,  # Use sampler instead of shuffle
    num_workers=NUM_OF_WORKERS
)
```

```
features, ground_truth = next(iter(val_dataloader))

images = features.to(device_name)
model.eval()
predictions = model(images)

predictions =  torch.argmax(predictions, dim=1).float()
y_true = ground_truth.numpy()
y_pred = predictions.detach().cpu().int().numpy()

y_true_flat = y_true.flatten()
y_pred_flat = y_pred.flatten()

cm = confusion_matrix(y_true_flat, y_pred_flat, labels=[0, 1, 2,3,4,5])
print(cm)
# Convert to percentage (%)
cm_percent = cm.astype('float') / cm.sum(axis=1, keepdims=True) * 100
disp = ConfusionMatrixDisplay(confusion_matrix=cm_percent,
                              display_labels=["Pastry",␣
 ↪"Z_Scratch","K_Scratch"        ,"Stains"        ,"Dirtiness"        ,"Bumps"])



disp.plot(cmap='Blues', values_format='.1f')
```

```
[[80  3  0  3  1 23]
 [ 6 21  0  0  0  1]
 [ 0  0 25  1  0  0]
 [ 0  0  0 10  0  1]
 [ 0  0  0  0  6  2]
 [17  1  0  0  0 41]]
```

[15]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1357accd0>



1.15 Test on the test set (only for final evaluation)

1.15.1 Test set class distribution

[16]:
```
from collections import Counter

labels = [label.item() for _, label in test_dataset]
class_counts = Counter(labels)

print("\nClass Distribution:")
print("-" * 30)
class_names = ["Pastry",␣
 ↪"Z_Scratch","K_Scratch"        ,"Stains"        ,"Dirtiness"        ,"Bumps"]
for cls, count in sorted(class_counts.items()):
    print(f"Class {class_names[int(cls)]} | Count: {count}")
print("-" * 30)
```

```
Class Distribution:
------------------------------
Class Pastry | Count: 110
Class Z_Scratch | Count: 28
```

```
Class K_Scratch | Count: 26
Class Stains | Count: 11
Class Dirtiness | Count: 8
Class Bumps | Count: 59
------------------------------
```

[17]:
```
test_loss, test_acc, test_precision = model.evaluate(test_dataloader)
print(f"Test Loss:{test_loss} Test Accuracy:{test_acc.item()} Test Precision:
 ↪{test_precision.item()}")
```

```
Test Loss:1.24232979118824 Test Accuracy:0.8337084650993347 Test
Precision:0.7915846705436707
```

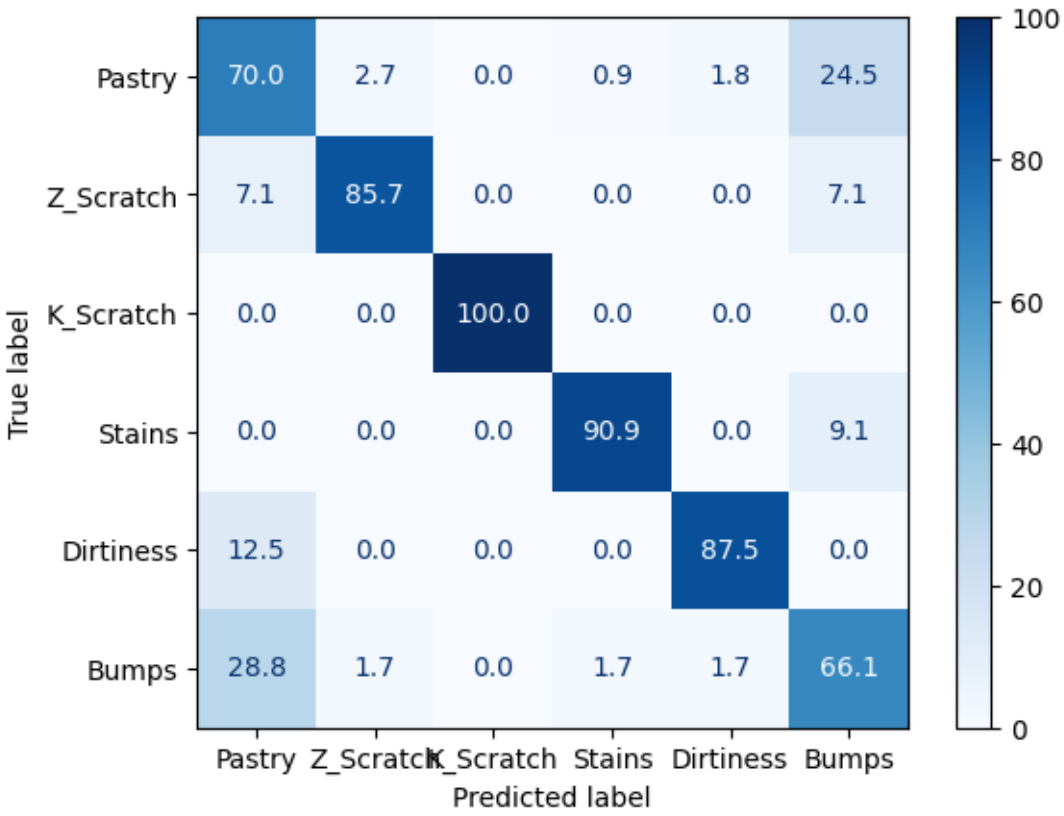
1.15.2 Confusion Matrix

[18]:
```
import numpy as np
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Example data (each pixel has an integer class label)
test_dataloader = DataLoader(
    test_dataset,
    batch_size=len(test_dataset),
    shuffle=False,  # Use sampler instead of shuffle
    num_workers=NUM_OF_WORKERS
)

features, ground_truth = next(iter(test_dataloader))

images = features.to(device_name)
model.eval()
predictions = model(images)

predictions =  torch.argmax(predictions, dim=1).float()
y_true = ground_truth.numpy()
y_pred = predictions.detach().cpu().int().numpy()

y_true_flat = y_true.flatten()
y_pred_flat = y_pred.flatten()

cm = confusion_matrix(y_true_flat, y_pred_flat, labels=[0, 1, 2,3,4,5])
print(cm)
# Convert to percentage (%)
cm_percent = cm.astype('float') / cm.sum(axis=1, keepdims=True) * 100
disp = ConfusionMatrixDisplay(confusion_matrix=cm_percent,
                              display_labels=["Pastry",␣
 ↪"Z_Scratch",        "K_Scratch"        ,"Stains"        ,"Dirtiness"        ,"Bumps"])
```

```
disp.plot(cmap='Blues', values_format='.1f')
```

```
[[77  3  0  1  2 27]
 [ 2 24  0  0  0  2]
 [ 0  0 26  0  0  0]
 [ 0  0  0 10  0  1]
 [ 1  0  0  0  7  0]
 [17  1  0  1  1 39]]
```

[18]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x12069b9d0>



[ ]: