In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, random_split
from torchvision import transforms, models
import h5py
import numpy as np
import random
import time
import matplotlib.pyplot as plt
from tqdm import tqdm
import os

DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", DEVICE)
```

```
Using device: cuda
```

I'm including random horizontal/vertical flips and random cropping. These augmentations are critical according to the SimCLR paper to generate different views of the same image for contrastive learning. The same transformation pipeline is used for both pretraining and fine-tuning.

In [2]:
```
class RandomHorizontalFlipTensor(object):
    def __init__(self, p=0.5):
        self.p = p
    def __call__(self, x):
        if random.random() < self.p:
            return torch.flip(x, dims=[2])
        return x

class RandomVerticalFlipTensor(object):
    def __init__(self, p=0.5):
        self.p = p
    def __call__(self, x):
        if random.random() < self.p:
            return torch.flip(x, dims=[1])
        return x

class RandomCropTensor(object):
    def __init__(self, output_size):
        self.output_size = output_size
    def __call__(self, x):
        _, h, w = x.shape
        new_h, new_w = self.output_size
        if h == new_h and w == new_w:
            return x
        top = random.randint(0, h - new_h)
        left = random.randint(0, w - new_w)
        return x[:, top: top + new_h, left: left + new_w]

simclr_transform = transforms.Compose([
    RandomHorizontalFlipTensor(p=0.5),
    RandomVerticalFlipTensor(p=0.5),
    RandomCropTensor((112, 112)),
    transforms.Normalize(mean=[0.5]*8, std=[0.5]*8)
```

```
])
labelled_transform = simclr_transform
```

In [3]:
```
class UnlabelledDataset(Dataset):
    def __init__(self, h5_path, transform=None):
        self.h5_path = h5_path
        self.transform = transform
        self.h5_file = None
        with h5py.File(self.h5_path, 'r') as f:
            self.length = f['jet'].shape[0]

    def __len__(self):
        return self.length

    def __getitem__(self, idx):
        if self.h5_file is None:
            self.h5_file = h5py.File(self.h5_path, 'r')
        image = self.h5_file['jet'][idx]
        image = torch.tensor(image, dtype=torch.float32).permute(2, 0, 1)
        # Generate two augmented views.
        view1 = self.transform(image) if self.transform else image
        view2 = self.transform(image) if self.transform else image
        return view1, view2

    def __del__(self):
        if self.h5_file is not None:
            self.h5_file.close()

unlabelled_h5_path = "/kaggle/input/data2-st/unlabelled2/content/Dataset_Specifi
unlabelled_dataset = UnlabelledDataset(h5_path=unlabelled_h5_path, transform=sim
print("Unlabelled dataset size:", len(unlabelled_dataset))

BATCH_SZ_UNLABELLED = 8
unlabelled_loader = DataLoader(unlabelled_dataset, batch_size=BATCH_SZ_UNLABELLE
                               shuffle=True, drop_last=True, pin_memory=True)
```

```
Unlabelled dataset size: 60000
```

In this cell, I have defined a custom ResNet15 backbone by modifying a ResNet18 model. The first convolution layer is adapted for 8-channel images, and I remove part of the last layer to create a smaller network (approximating ResNet15).The SimCLR model wraps this backbone with a projection head. The projection head maps the encoder's 512-dimensional features to a 256-dimensional latent space. This projection is necessary in contrastive learning, as it helps the network focus on useful representations. The NT-Xent loss is later used to train this model by comparing the similarity between augmented views.

In [4]:
```
class Identity(nn.Module):
    def __init__(self):
        super(Identity, self).__init__()
    def forward(self, x):
        return x

def get_resnet15():
    resnet15 = models.resnet18(pretrained=False)
    resnet15.conv1 = nn.Conv2d(8, 64, kernel_size=7, stride=2, padding=3, bias=F
    resnet15.layer4 = nn.Sequential(*list(resnet15.layer4.children())[:1])
```

```
    resnet15.fc = Identity()
    return resnet15

class SimCLR(nn.Module):
    def __init__(self, linear_eval=False):
        super(SimCLR, self).__init__()
        self.linear_eval = linear_eval
        self.encoder = get_resnet15().to(DEVICE)
        self.projection = nn.Sequential(
            nn.Linear(512, 512),
            nn.ReLU(),
            nn.Linear(512, 256)
        ).to(DEVICE)

    def forward(self, x):
        if not self.linear_eval:
            x = torch.cat(x, dim=0)
        encoding = self.encoder(x)
        projection = self.projection(encoding)
        return projection

simclr_model = SimCLR().to(DEVICE)
```

```
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:208: UserWar
ning: The parameter 'pretrained' is deprecated since 0.13 and may be removed in t
he future, please use 'weights' instead.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torchvision/models/_utils.py:223: UserWar
ning: Arguments other than a weight enum or `None` for 'weights' are deprecated s
ince 0.13 and may be removed in the future. The current behavior is equivalent to
passing `weights=None`.
  warnings.warn(msg)
```

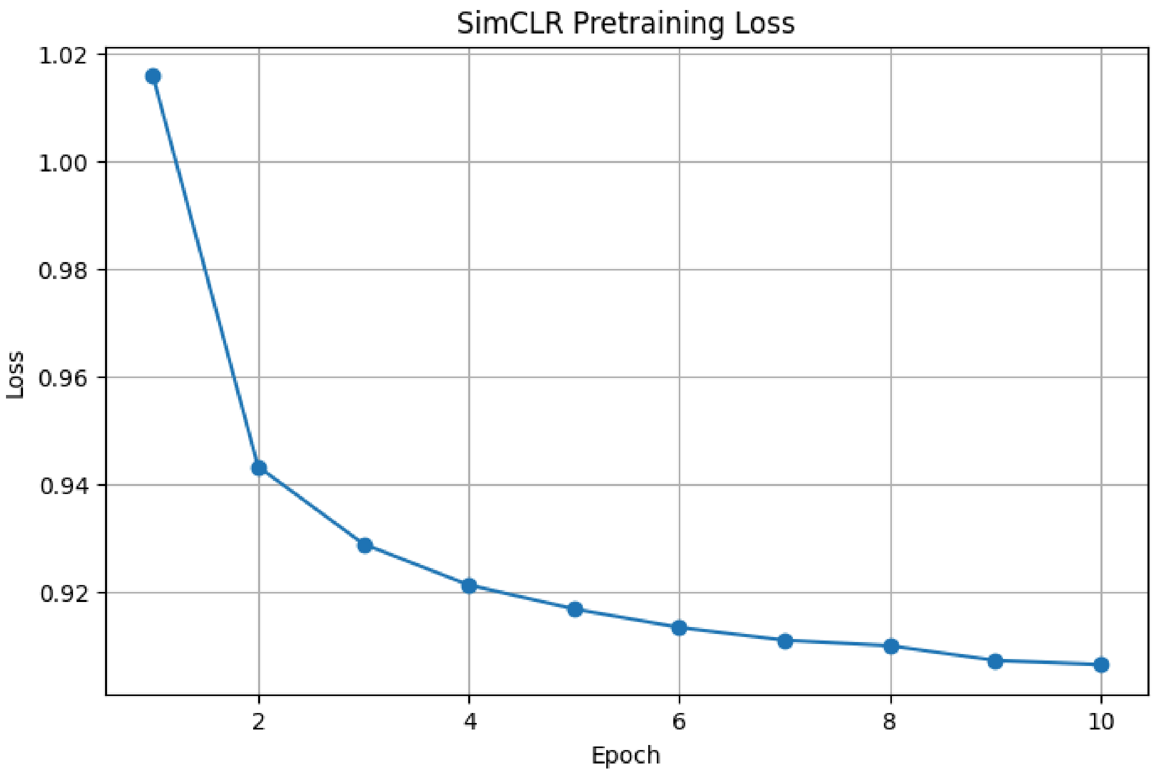
here I'm pretraining the SimCLR model using the unlabelled dataset. The NT-Xent loss is used to train the model to bring augmented views of the same image closer in the latent space while pushing away representations of different images. The key idea is to learn representations that are invariant to augmentations. Two views of the same image (generated via the transformations) are processed through the encoder and projection head. Their similarity is measured and optimized with a contrastive loss.

In [5]:
```
def simclr_loss(features, temperature=0.5):
    device = features.device
    batch_size = features.shape[0] // 2
    features = F.normalize(features, dim=1)
    similarity_matrix = torch.matmul(features, features.T)
    mask = torch.eye(2 * batch_size, dtype=torch.bool, device=device)
    similarity_matrix = similarity_matrix.masked_fill(mask, -float('inf'))

    similarity_matrix /= temperature

    targets = torch.cat([torch.arange(batch_size, device=device) + batch_size,
                         torch.arange(batch_size, device=device)])
    loss = F.cross_entropy(similarity_matrix, targets)
    return loss


optimizer = optim.Adam(simclr_model.parameters(), lr=1e-3)
```

```
scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='min', fa

pretrain_epochs = 10
temperature = 0.5

pretrain_losses = []

simclr_model.train()
for epoch in range(pretrain_epochs):
    t0 = time.time()
    running_loss = 0.0
    num_batches = 0
    for view1, view2 in tqdm(unlabelled_loader, desc=f"SimCLR Pretraining Epoch
        view1, view2 = view1.to(DEVICE), view2.to(DEVICE)
        # Pass list of two views.
        projections = simclr_model([view1, view2])
        loss = simclr_loss(projections, temperature=temperature)

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

        running_loss += loss.item()
        num_batches += 1

    avg_loss = running_loss / num_batches
    pretrain_losses.append(avg_loss)
    print(f"Epoch {epoch+1} completed in {(time.time()-t0)/60:.3f} mins, Avg Los
    scheduler.step(avg_loss)
    torch.cuda.empty_cache()

torch.save(simclr_model.state_dict(), "simclr_pretrained_resnet15.pth")
print("SimCLR Pretraining completed and weights saved as simclr_pretrained_resne

import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.plot(range(1, pretrain_epochs+1), pretrain_losses, marker='o')
plt.title("SimCLR Pretraining Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.grid(True)
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/torch/optim/lr_scheduler.py:62: UserWarni
ng: The verbose parameter is deprecated. Please use get_last_lr() to access the l
earning rate.
  warnings.warn(
SimCLR Pretraining Epoch 1/10: 100%|██████████| 7500/7500 [09:53<00:00, 12.63it/
s]
Epoch 1 completed in 9.896 mins, Avg Loss: 1.0157
SimCLR Pretraining Epoch 2/10: 100%|██████████| 7500/7500 [05:30<00:00, 22.71it/
s]
Epoch 2 completed in 5.504 mins, Avg Loss: 0.9431
SimCLR Pretraining Epoch 3/10: 100%|██████████| 7500/7500 [04:14<00:00, 29.45it/
s]
Epoch 3 completed in 4.244 mins, Avg Loss: 0.9288
SimCLR Pretraining Epoch 4/10: 100%|██████████| 7500/7500 [04:09<00:00, 30.04it/
s]
Epoch 4 completed in 4.162 mins, Avg Loss: 0.9212
```

```
SimCLR Pretraining Epoch 6/10: 100%|██████████| 7500/7500 [03:43<00:00, 33.49it/s]
Epoch 6 completed in 3.732 mins, Avg Loss: 0.9133
SimCLR Pretraining Epoch 7/10: 100%|██████████| 7500/7500 [03:37<00:00, 34.44it/s]
Epoch 7 completed in 3.629 mins, Avg Loss: 0.9109
SimCLR Pretraining Epoch 8/10: 100%|██████████| 7500/7500 [03:35<00:00, 34.77it/s]
Epoch 8 completed in 3.595 mins, Avg Loss: 0.9099
SimCLR Pretraining Epoch 9/10: 100%|██████████| 7500/7500 [03:33<00:00, 35.07it/s]
Epoch 9 completed in 3.565 mins, Avg Loss: 0.9071
SimCLR Pretraining Epoch 10/10: 100%|██████████| 7500/7500 [03:33<00:00, 35.12it/s]
Epoch 10 completed in 3.559 mins, Avg Loss: 0.9064
SimCLR Pretraining completed and weights saved as simclr_pretrained_resnet15.pth.
```



In [6]:
```python
class H5LabelledDataset(Dataset):
    def __init__(self, h5_path, transform=None):
        self.h5_path = h5_path
        self.transform = transform
        self.h5_file = None
        with h5py.File(self.h5_path, 'r') as f:
            self.length = f['jet'].shape[0]

    def __len__(self):
        return self.length

    def __getitem__(self, idx):
        if self.h5_file is None:
            self.h5_file = h5py.File(self.h5_path, 'r')
        image = self.h5_file['jet'][idx]
        image = torch.tensor(image, dtype=torch.float32).permute(2, 0, 1)
        if self.transform is not None:
            image = self.transform(image)
```

```
        y = int(self.h5_file['Y'][idx][0])
        m = self.h5_file['m'][idx]
        pt = self.h5_file['pT'][idx]
        reg_target = torch.tensor(np.concatenate([m, pt], axis=0), dtype=torch.f
        return image, y, reg_target

    def __del__(self):
        if self.h5_file is not None:
            self.h5_file.close()
labelled_h5_path = "/kaggle/input/data2-st/specific-labelled2/content/Dataset_Sp
full_labelled_dataset = H5LabelledDataset(h5_path=labelled_h5_path, transform=la
print("Total labelled dataset size:", len(full_labelled_dataset))
total_len = len(full_labelled_dataset)
train_len = int(0.8 * total_len)
test_len = total_len - train_len
train_dataset, test_dataset = random_split(full_labelled_dataset, [train_len, te
print("Train samples:", len(train_dataset), "Test samples:", len(test_dataset))

BATCH_SZ_LABELLED = 64
train_loader_labelled = DataLoader(train_dataset, batch_size=BATCH_SZ_LABELLED,
test_loader_labelled = DataLoader(test_dataset, batch_size=BATCH_SZ_LABELLED, sh
```

```
Total labelled dataset size: 10000
Train samples: 8000 Test samples: 2000
```

In [7]:

```
class FineTuneClassifier(nn.Module):
    def __init__(self, simclr_model, num_classes=2):
        super().__init__()
        # Load pretrained encoder and remove projection head
        self.encoder = simclr_model.encoder
        self.linear = nn.Linear(512, num_classes)

    def forward(self, x):
        features = self.encoder(x)
        return self.linear(features)

class FineTuneRegressor(nn.Module):
    def __init__(self, simclr_model, out_dim=2):
        super().__init__()
        self.encoder = simclr_model.encoder
        self.regressor = nn.Linear(512, out_dim)

    def forward(self, x):
        features = self.encoder(x)
        return self.regressor(features)
```

Two learning rates are used: a lower learning rate for the encoder (to avoid large updates) and a higher rate for the new classification head.

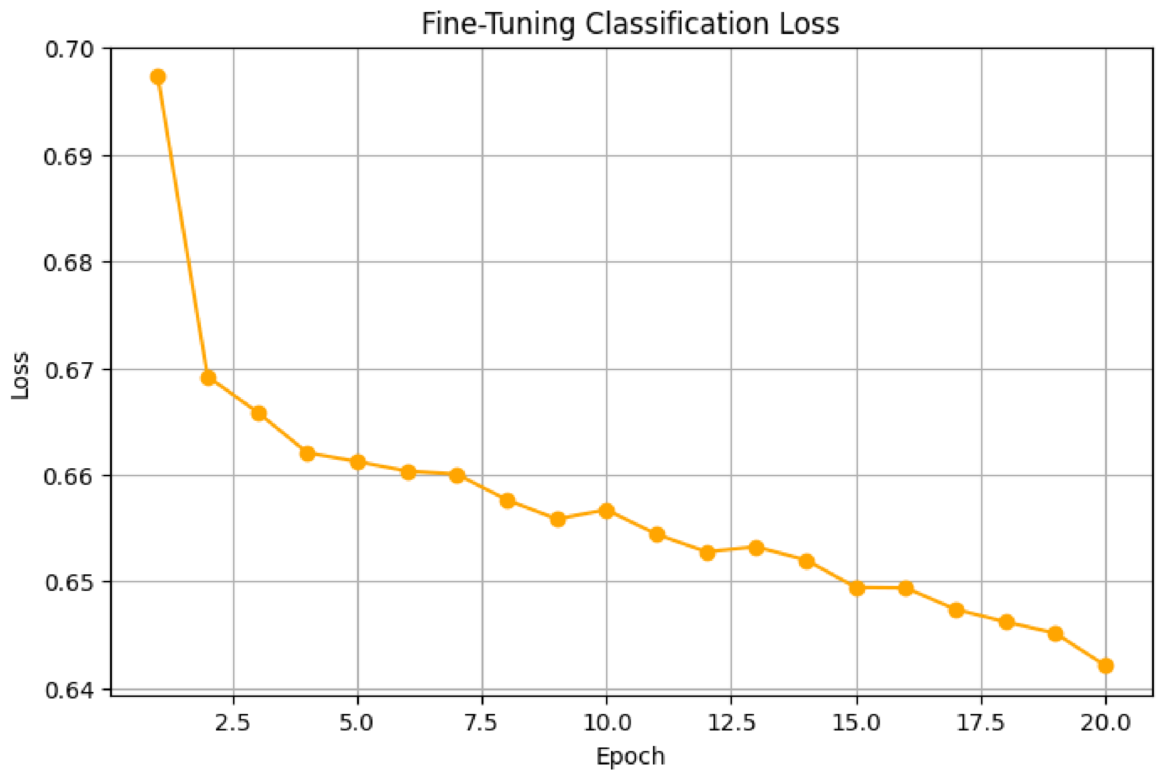
In [8]:

```
pretrained_weights = torch.load("simclr_pretrained_resnet15.pth", map_location=D
simclr_model.load_state_dict(pretrained_weights)

clf_model = FineTuneClassifier(simclr_model).to(DEVICE)
criterion_clf = nn.CrossEntropyLoss()

optimizer_clf = optim.Adam([
    {'params': clf_model.encoder.parameters(), 'lr': 1e-5},
    {'params': clf_model.linear.parameters(), 'lr': 1e-4}
])
```

```python
scheduler_clf = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer_clf, mode='

num_epochs_cls = 20

cls_losses = []
clf_model.train()
for epoch in range(num_epochs_cls):
    running_loss = 0.0
    for images, y, _ in tqdm(train_loader_labelled, desc=f"Classification Epoch
        images = images.to(DEVICE)
        labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
        outputs = clf_model(images)
        loss = criterion_clf(outputs, labels)
        optimizer_clf.zero_grad()
        loss.backward()
        optimizer_clf.step()
        running_loss += loss.item()
    avg_loss = running_loss / len(train_loader_labelled)
    cls_losses.append(avg_loss)
    scheduler_clf.step(avg_loss)
    print(f"Epoch {epoch+1} Classification Loss: {avg_loss:.4f}")

clf_model.eval()
correct, total = 0, 0
with torch.no_grad():
    for images, y, _ in test_loader_labelled:
        images = images.to(DEVICE)
        labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
        outputs = clf_model(images)
        preds = outputs.argmax(dim=1)
        total += labels.size(0)
        correct += (preds == labels).sum().item()
clf_acc = 100 * correct / total
print(f"Fine-tuned (Pretrained) Classification Accuracy: {clf_acc:.2f}%")

import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.plot(range(1, num_epochs_cls+1), cls_losses, marker='o', color='orange')
plt.title("Fine-Tuning Classification Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.grid(True)
plt.show()
```

```
<ipython-input-8-7b9dfd4b6642>:1: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only` will be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.
  pretrained_weights = torch.load("simclr_pretrained_resnet15.pth", map_location=DEVICE)
Classification Epoch 1/20:   0%|          | 0/125 [00:00<?, ?it/s]<ipython-input-8-7b9dfd4b6642>:22: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
Classification Epoch 1/20: 100%|██████████| 125/125 [01:04<00:00,  1.93it/s]
Epoch 1 Classification Loss: 0.6973
Classification Epoch 2/20: 100%|██████████| 125/125 [00:50<00:00,  2.46it/s]
Epoch 2 Classification Loss: 0.6692
Classification Epoch 3/20: 100%|██████████| 125/125 [00:17<00:00,  7.20it/s]
Epoch 3 Classification Loss: 0.6659
Classification Epoch 4/20: 100%|██████████| 125/125 [00:17<00:00,  7.25it/s]
Epoch 4 Classification Loss: 0.6621
Classification Epoch 5/20: 100%|██████████| 125/125 [00:17<00:00,  7.35it/s]
Epoch 5 Classification Loss: 0.6612
Classification Epoch 6/20: 100%|██████████| 125/125 [00:17<00:00,  7.30it/s]
Epoch 6 Classification Loss: 0.6603
Classification Epoch 7/20: 100%|██████████| 125/125 [00:17<00:00,  7.33it/s]
Epoch 7 Classification Loss: 0.6601
Classification Epoch 8/20: 100%|██████████| 125/125 [00:17<00:00,  7.25it/s]
Epoch 8 Classification Loss: 0.6577
Classification Epoch 9/20: 100%|██████████| 125/125 [00:16<00:00,  7.37it/s]
Epoch 9 Classification Loss: 0.6559
Classification Epoch 10/20: 100%|██████████| 125/125 [00:17<00:00,  7.30it/s]
Epoch 10 Classification Loss: 0.6567
Classification Epoch 11/20: 100%|██████████| 125/125 [00:17<00:00,  7.35it/s]
Epoch 11 Classification Loss: 0.6544
Classification Epoch 12/20: 100%|██████████| 125/125 [00:17<00:00,  7.25it/s]
Epoch 12 Classification Loss: 0.6528
Classification Epoch 13/20: 100%|██████████| 125/125 [00:16<00:00,  7.39it/s]
Epoch 13 Classification Loss: 0.6532
Classification Epoch 14/20: 100%|██████████| 125/125 [00:17<00:00,  7.29it/s]
Epoch 14 Classification Loss: 0.6520
Classification Epoch 15/20: 100%|██████████| 125/125 [00:17<00:00,  7.31it/s]
Epoch 15 Classification Loss: 0.6495
Classification Epoch 16/20: 100%|██████████| 125/125 [00:17<00:00,  7.30it/s]
Epoch 16 Classification Loss: 0.6494
Classification Epoch 17/20: 100%|██████████| 125/125 [00:17<00:00,  7.31it/s]
Epoch 17 Classification Loss: 0.6474
Classification Epoch 18/20: 100%|██████████| 125/125 [00:17<00:00,  7.29it/s]
Epoch 18 Classification Loss: 0.6462
```

```
Classification Epoch 19/20: 100%|██████████| 125/125 [00:17<00:00,  7.25it/s]
Epoch 19 Classification Loss: 0.6452
Classification Epoch 20/20: 100%|██████████| 125/125 [00:17<00:00,  7.35it/s]
Epoch 20 Classification Loss: 0.6421
<ipython-input-8-7b9dfd4b6642>:39: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
Fine-tuned (Pretrained) Classification Accuracy: 64.65%
```



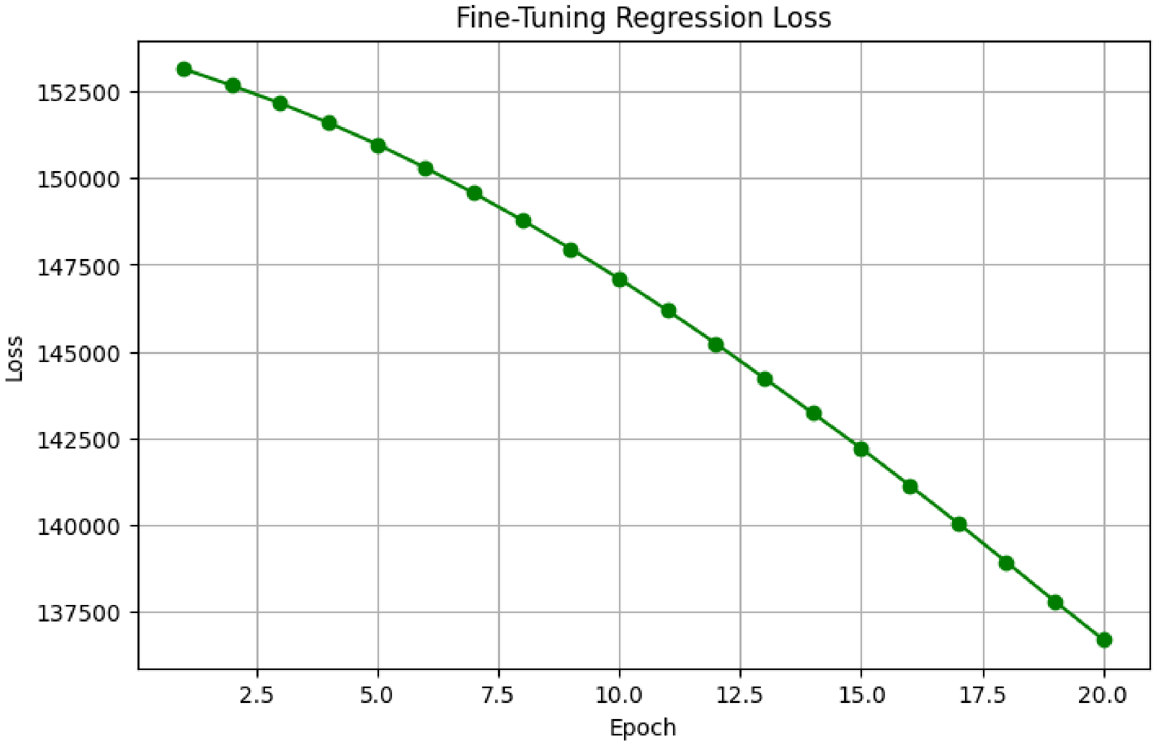
In [9]:

```
reg_model = FineTuneRegressor(simclr_model).to(DEVICE)
criterion_reg = nn.MSELoss()
optimizer_reg = optim.Adam([
    {'params': reg_model.encoder.parameters(), 'lr': 1e-5},
    {'params': reg_model.regressor.parameters(), 'lr': 1e-4}
])

scheduler_reg = torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer_reg, mode='

num_epochs_reg = 20

reg_losses = []
reg_model.train()
for epoch in range(num_epochs_reg):
    running_loss = 0.0
    for images, _, reg_targets in tqdm(train_loader_labelled, desc=f"Regression
        images = images.to(DEVICE)
        reg_targets = reg_targets.to(DEVICE)
        outputs = reg_model(images)
        loss = criterion_reg(outputs, reg_targets)
        optimizer_reg.zero_grad()
        loss.backward()
        optimizer_reg.step()
        running_loss += loss.item()
    avg_loss = running_loss / len(train_loader_labelled)
    reg_losses.append(avg_loss)
```

```
    scheduler_reg.step(avg_loss)
    print(f"Epoch {epoch+1} Regression Loss: {avg_loss:.4f}")

reg_model.eval()
total_loss = 0.0
with torch.no_grad():
    for images, _, reg_targets in test_loader_labelled:
        images = images.to(DEVICE)
        reg_targets = reg_targets.to(DEVICE)
        outputs = reg_model(images)
        loss = criterion_reg(outputs, reg_targets)
        total_loss += loss.item() * images.size(0)
avg_mse = total_loss / len(test_dataset)
print(f"Fine-tuned (Pretrained) Regression MSE: {avg_mse:.4f}")

import matplotlib.pyplot as plt
plt.figure(figsize=(8,5))
plt.plot(range(1, num_epochs_reg+1), reg_losses, marker='o', color='green')
plt.title("Fine-Tuning Regression Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.grid(True)
plt.show()
```

```
Regression Epoch 5/20: 100%|██████████| 125/125 [00:17<00:00,  7.18it/s]
Epoch 5 Regression Loss: 150978.7370
Regression Epoch 6/20: 100%|██████████| 125/125 [00:17<00:00,  7.11it/s]
Epoch 6 Regression Loss: 150299.1296
Regression Epoch 7/20: 100%|██████████| 125/125 [00:17<00:00,  7.08it/s]
Epoch 7 Regression Loss: 149567.9655
Regression Epoch 8/20: 100%|██████████| 125/125 [00:17<00:00,  7.19it/s]
Epoch 8 Regression Loss: 148790.4956
Regression Epoch 9/20: 100%|██████████| 125/125 [00:17<00:00,  7.09it/s]
Epoch 9 Regression Loss: 147963.2714
Regression Epoch 10/20: 100%|██████████| 125/125 [00:17<00:00,  7.26it/s]
Epoch 10 Regression Loss: 147101.4756
Regression Epoch 11/20: 100%|██████████| 125/125 [00:17<00:00,  7.09it/s]
Epoch 11 Regression Loss: 146185.5391
Regression Epoch 12/20: 100%|██████████| 125/125 [00:17<00:00,  7.11it/s]
Epoch 12 Regression Loss: 145230.5359
Regression Epoch 13/20: 100%|██████████| 125/125 [00:17<00:00,  7.06it/s]
Epoch 13 Regression Loss: 144231.4893
Regression Epoch 14/20: 100%|██████████| 125/125 [00:17<00:00,  7.13it/s]
Epoch 14 Regression Loss: 143226.9588
Regression Epoch 15/20: 100%|██████████| 125/125 [00:17<00:00,  7.03it/s]
Epoch 15 Regression Loss: 142210.0816
Regression Epoch 16/20: 100%|██████████| 125/125 [00:17<00:00,  7.14it/s]
Epoch 16 Regression Loss: 141139.7742
Regression Epoch 17/20: 100%|██████████| 125/125 [00:17<00:00,  7.22it/s]
Epoch 17 Regression Loss: 140052.5574
Regression Epoch 18/20: 100%|██████████| 125/125 [00:17<00:00,  7.04it/s]
Epoch 18 Regression Loss: 138928.8890
Regression Epoch 19/20: 100%|██████████| 125/125 [00:17<00:00,  7.19it/s]
Epoch 19 Regression Loss: 137797.1689
Regression Epoch 20/20: 100%|██████████| 125/125 [00:17<00:00,  7.01it/s]
```

```
Epoch 20 Regression Loss: 136691.5895
Fine-tuned (Pretrained) Regression MSE: 135212.7487
```



i have implemented a vgg 11 model for comparison.

In [10]:
```
class VGG(nn.Module):
    def __init__(self, num_classes=2, regression_out=2, mode='classification'):
        super(VGG, self).__init__()
        self.features = nn.Sequential(
            nn.Conv2d(8, 64, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),

            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )
        self.avgpool = nn.AdaptiveAvgPool2d((3,3))
        self.mode = mode
        if mode == 'classification':
            self.classifier = nn.Sequential(
```

```
                nn.Linear(512 * 3 * 3, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(),
                nn.Linear(4096, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(),
                nn.Linear(4096, num_classes)
            )
        else:
            self.regressor = nn.Sequential(
                nn.Linear(512 * 3 * 3, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(),
                nn.Linear(4096, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(),
                nn.Linear(4096, regression_out)
            )
    def forward(self, x):
        x = self.features(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        if self.mode == 'classification':
            x = self.classifier(x)
        else:
            x = self.regressor(x)
        return x
```

In [11]:

```
vgg_classifier = VGG(num_classes=2, mode='classification').to(DEVICE)
criterion_vgg_clf = nn.CrossEntropyLoss()
optimizer_vgg_clf = optim.Adam(vgg_classifier.parameters(), lr=1e-3)
num_epochs_vgg_cls = 10

vgg_cls_losses = []
vgg_classifier.train()
for epoch in range(num_epochs_vgg_cls):
    running_loss = 0.0
    for images, y, _ in tqdm(train_loader_labelled, desc=f"VGG Classification Ep
        images = images.to(DEVICE)
        labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
        outputs = vgg_classifier(images)
        loss = criterion_vgg_clf(outputs, labels)
        optimizer_vgg_clf.zero_grad()
        loss.backward()
        optimizer_vgg_clf.step()
        running_loss += loss.item()
    avg_loss = running_loss / len(train_loader_labelled)
    vgg_cls_losses.append(avg_loss)
    print(f"Epoch {epoch+1} VGG Classification Loss: {avg_loss:.4f}")

vgg_classifier.eval()
correct, total = 0, 0
with torch.no_grad():
    for images, y, _ in test_loader_labelled:
        images = images.to(DEVICE)
        labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
        outputs = vgg_classifier(images)
        preds = outputs.argmax(dim=1)
        total += labels.size(0)
        correct += (preds == labels).sum().item()
```

```
vgg_cls_acc = 100 * correct / total
print(f"Scratch VGG Classification Accuracy: {vgg_cls_acc:.2f}%")
torch.save(vgg_classifier.state_dict(), "scratch_vgg_classifier.pth")
```

```
VGG Classification Epoch 1/10:   0%|          | 0/125 [00:00<?, ?it/s]<ipython-in
put-11-822824c94d8f>:12: UserWarning: To copy construct from a tensor, it is reco
mmended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().req
uires_grad_(True), rather than torch.tensor(sourceTensor).
  labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
VGG Classification Epoch 1/10: 100%|██████████| 125/125 [00:27<00:00,  4.47it/s]
Epoch 1 VGG Classification Loss: 1.5522
VGG Classification Epoch 2/10: 100%|██████████| 125/125 [00:27<00:00,  4.54it/s]
Epoch 2 VGG Classification Loss: 0.6955
VGG Classification Epoch 3/10: 100%|██████████| 125/125 [00:27<00:00,  4.57it/s]
Epoch 3 VGG Classification Loss: 0.6930
VGG Classification Epoch 4/10: 100%|██████████| 125/125 [00:27<00:00,  4.60it/s]
Epoch 4 VGG Classification Loss: 0.6936
VGG Classification Epoch 5/10: 100%|██████████| 125/125 [00:27<00:00,  4.56it/s]
Epoch 5 VGG Classification Loss: 0.6932
VGG Classification Epoch 6/10: 100%|██████████| 125/125 [00:27<00:00,  4.56it/s]
Epoch 6 VGG Classification Loss: 0.6933
VGG Classification Epoch 7/10: 100%|██████████| 125/125 [00:27<00:00,  4.56it/s]
Epoch 7 VGG Classification Loss: 0.6934
VGG Classification Epoch 8/10: 100%|██████████| 125/125 [00:27<00:00,  4.53it/s]
Epoch 8 VGG Classification Loss: 0.6931
VGG Classification Epoch 9/10: 100%|██████████| 125/125 [00:27<00:00,  4.54it/s]
Epoch 9 VGG Classification Loss: 0.6932
VGG Classification Epoch 10/10: 100%|██████████| 125/125 [00:27<00:00,  4.56it/s]
<ipython-input-11-822824c94d8f>:28: UserWarning: To copy construct from a tensor,
it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().de
tach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  labels = torch.tensor(y, dtype=torch.long).to(DEVICE)
Epoch 10 VGG Classification Loss: 0.6931
Scratch VGG Classification Accuracy: 52.85%
```

In [16]:

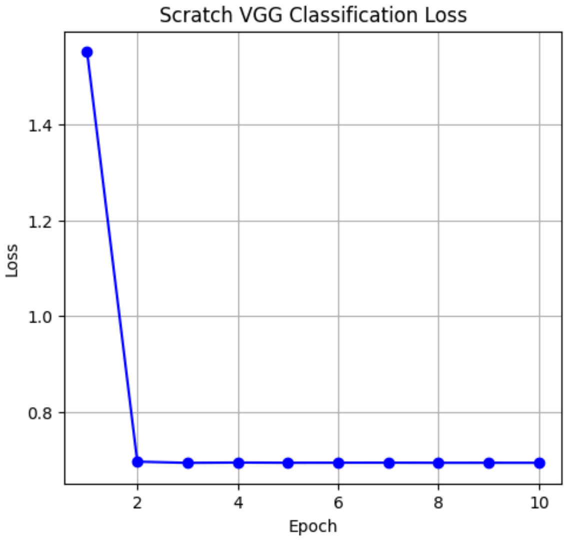
```
vgg_regressor = VGG(regression_out=2, mode='regression').to(DEVICE)
criterion_vgg_reg = nn.MSELoss()
optimizer_vgg_reg = optim.Adam(vgg_regressor.parameters(), lr=1e-3)
num_epochs_vgg_reg = 10

vgg_reg_losses = []
vgg_regressor.train()
for epoch in range(num_epochs_vgg_reg):
    running_loss = 0.0
    for images, _, reg_targets in tqdm(train_loader_labelled, desc=f"VGG Regress
        images = images.to(DEVICE)
        reg_targets = reg_targets.to(DEVICE)
        outputs = vgg_regressor(images)
        loss = criterion_vgg_reg(outputs, reg_targets)
        optimizer_vgg_reg.zero_grad()
        loss.backward()
        optimizer_vgg_reg.step()
        running_loss += loss.item()
    avg_loss = running_loss / len(train_loader_labelled)
    vgg_reg_losses.append(avg_loss)
    print(f"Epoch {epoch+1} VGG Regression Loss: {avg_loss:.4f}")
```

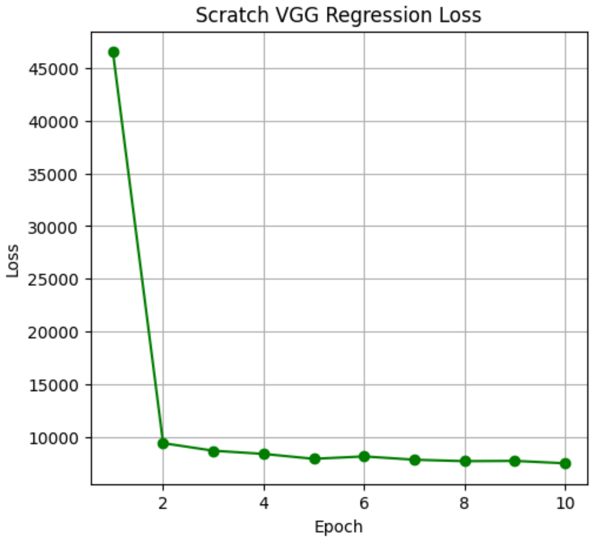
```
vgg_regressor.eval()
total_loss = 0.0
with torch.no_grad():
    for images, _, reg_targets in test_loader_labelled:
        images = images.to(DEVICE)
        reg_targets = reg_targets.to(DEVICE)
        outputs = vgg_regressor(images)
        loss = criterion_vgg_reg(outputs, reg_targets)
        total_loss += loss.item() * images.size(0)
vgg_avg_mse = total_loss / len(test_dataset)
print(f"Scratch VGG Regression MSE: {vgg_avg_mse:.4f}")
torch.save(vgg_regressor.state_dict(), "scratch_vgg_regressor.pth")
```

```
VGG Regression Epoch 1/10: 100%|██████████| 125/125 [00:27<00:00,  4.50it/s]
Epoch 1 VGG Regression Loss: 46530.4767
VGG Regression Epoch 2/10: 100%|██████████| 125/125 [00:28<00:00,  4.44it/s]
Epoch 2 VGG Regression Loss: 9406.1688
VGG Regression Epoch 3/10: 100%|██████████| 125/125 [00:27<00:00,  4.53it/s]
Epoch 3 VGG Regression Loss: 8690.0128
VGG Regression Epoch 4/10: 100%|██████████| 125/125 [00:27<00:00,  4.51it/s]
Epoch 4 VGG Regression Loss: 8385.3887
VGG Regression Epoch 5/10: 100%|██████████| 125/125 [00:27<00:00,  4.48it/s]
Epoch 5 VGG Regression Loss: 7920.7742
VGG Regression Epoch 6/10: 100%|██████████| 125/125 [00:27<00:00,  4.52it/s]
Epoch 6 VGG Regression Loss: 8148.6947
VGG Regression Epoch 7/10: 100%|██████████| 125/125 [00:27<00:00,  4.50it/s]
Epoch 7 VGG Regression Loss: 7836.9689
VGG Regression Epoch 8/10: 100%|██████████| 125/125 [00:27<00:00,  4.51it/s]
Epoch 8 VGG Regression Loss: 7697.7678
VGG Regression Epoch 9/10: 100%|██████████| 125/125 [00:27<00:00,  4.49it/s]
Epoch 9 VGG Regression Loss: 7724.3109
VGG Regression Epoch 10/10: 100%|██████████| 125/125 [00:27<00:00,  4.48it/s]
Epoch 10 VGG Regression Loss: 7495.5629
Scratch VGG Regression MSE: 6104.1699
```

In [17]:

```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(range(1, num_epochs_vgg_cls+1), vgg_cls_losses, marker='o', color='blue
plt.title("Scratch VGG Classification Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.grid(True)

plt.subplot(1,2,2)
plt.plot(range(1, num_epochs_vgg_reg+1), vgg_reg_losses, marker='o', color='gree
plt.title("Scratch VGG Regression Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.grid(True)
plt.show()

print(f"Scratch VGG Classification Accuracy: {vgg_cls_acc:.2f}%")
print(f"Scratch VGG Regression MSE: {vgg_avg_mse:.4f}")
```






```
Scratch VGG Classification Accuracy: 52.85%
Scratch VGG Regression MSE: 6104.1699
```

In [18]:
```
torch.save(clf_model.state_dict(), "finetuned_classifier.pth")
torch.save(reg_model.state_dict(), "finetuned_regressor.pth")

torch.save(vgg_classifier.state_dict(), "scratch_vgg_classifier.pth")
torch.save(vgg_regressor.state_dict(), "scratch_vgg_regressor.pth")

print(f"Fine-tuned Classification Accuracy: {clf_acc:.2f}%")
print(f"Fine-tuned Regression MSE: {avg_mse:.4f}")
print(f"Scratch VGG Classification Accuracy: {vgg_cls_acc:.2f}%")
print(f"Scratch VGG Regression MSE: {vgg_avg_mse:.4f}")
```

```
Fine-tuned Classification Accuracy: 64.65%
Fine-tuned Regression MSE: 135212.7487
Scratch VGG Classification Accuracy: 52.85%
Scratch VGG Regression MSE: 6104.1699
```

In [20]:
```
!zip -r models.zip simclr_pretrained_resnet15.pth finetuned_classifier.pth finet
```

```
updating: finetuned_classifier.pth (deflated 7%)
updating: finetuned_regressor.pth (deflated 7%)
updating: scratch_vgg_classifier.pth (deflated 8%)
updating: scratch_vgg_regressor.pth (deflated 8%)
  adding: simclr_pretrained_resnet15.pth (deflated 7%)
```

In [ ]: