	Changes	Time	Difficulty
	resize images to be 128 by 128 and convert it to tensor	10 mins	1
	Create dataloaders and setting the batch size to 32. Shuffle training data but left testing data unshuffle	10 mins	1
	Initialise the model with 2 conv layers and 1 pooling in between them. After running the training with 15 epocs , the loss is 0.0035 but the accuracy is 51.9%	30 mins	3
	Try changing the number of layer but was met with error for number of output and input were different	1 hour	6
	use 3 conv layer and pooling after every conv layer but accuracy was lower. I think is because it has too many pooling layer	30 mins	3
	Try different epocs value but loss reduce less at around 15 epocs	20 mins	2
	Change the learning rate to 0.0005 instead of 0.001 but similar result	5 mins	1
	Add another conv layer to make it to 3 layer and do pooling at the end of conv layer instead of in between and increase the accuracy to 52.2%	30 mins	3
	The loss is very low, it could be the neural network was memorizing the training set so include drop out to drop a neuron for better generalisation. The loss is now 0.3859 but accuracy increase to 55%	45 mins	5
In [2]:	<pre>import torch import torchvision import torchvision.transforms as transforms from torch.utils.data import DataLoader, Dataset from torchvision.datasets import ImageFolder import matplotlib.pyplot as plt import numpy as np from tqdm import tqdm import torch.nn as nn import torch.nn.functional as F import os os.environ["CUDA_LAUNCH_BLOCKING"] = "1"</pre>		
In [174	<pre>transform = transforms.Compose([transforms.Resize((128, 128)), # Resize images transforms.ToTensor(), # Convert to tensor transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5])</pre>	, 0.5])	# Normali

```
# Load training dataset
   In [176...
                       train_dataset = ImageFolder(root="fruit_data/train", transform=transform)
                        # Load validation dataset
                       val_dataset = ImageFolder(root="fruit_data/test", transform=transform)
                       # Create DataLoaders
                        train loader = DataLoader(train dataset, batch size=32, shuffle=True)
                       val loader = DataLoader(val dataset, batch size=32, shuffle=False)
   In [178...
                      print(train dataset.classes) # Check labels
                     ['Apple', 'Banana', 'avocado', 'cherry', 'kiwi', 'mango', 'orange', 'pinenapple',
                      'strawberries', 'watermelon']
class FruitCNN(nn.Module): def __init__(self, num_classes=10): # 10 classes of label super(FruitCNN, self). __init__()
self.conv1 = nn.Conv2d(3, 32, kernel size=3, stride=1, padding=1) self.pool = nn.MaxPool2d(kernel size=2, stride=2,
padding=0) self.conv2 = nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1) self.fc1 = nn.Linear(64 * 32 * 32, 128)
self.fc2 = nn.Linear(128, num\_classes) def forward(self, x): x = self.pool(F.relu(self.conv1(x))) x = self.pool(F.relu(s
self.pool(F.relu(self.conv2(x))) x = x.view(x.size(0), -1) # Flatten x = F.relu(self.fc1(x)) x = self.fc2(x) return x
   In [180...
                      class FruitCNN(nn.Module):
                               def init (self, num classes=10):
                                       super(FruitCNN, self).__init__()
                                       # Convolutional Layers
                                       self.conv1 = nn.Conv2d(3, 32, kernel_size=3, stride=1, padding=1)
                                       self.conv2 = nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1)
                                       self.conv3 = nn.Conv2d(64, 128, kernel size=3, stride=1, padding=1)
                                       # Pooling Layer
                                       self.pool = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)
                                       # Fully Connected Layers
                                       self.fc1 = nn.Sequential(nn.Linear(128 * 16 * 16, 256), nn.ReLU(), nn.Dr
                                       self.fc2 = nn.Linear(256, 128)
                                       self.fc3 = nn.Linear(128, num_classes) # Final output layer
                               def forward(self, x):
                                       x = self.pool(F.relu(self.conv1(x))) # (B, 32, 64, 64) \rightarrow (B, 32, 32, 32)
                                       x = self.pool(F.relu(self.conv2(x))) # (B, 64, 32, 32) \rightarrow (B, 64, 16, 16)
                                       x = self.pool(F.relu(self.conv3(x))) # (B, 128, 16, 16) \rightarrow (B, 128, 8, 8)
                                       x = x.view(x.size(0), -1) # Flatten (B, 128*8*8)
                                       x = F.relu(self.fc1(x))
                                       x = F.relu(self.fc2(x))
                                       x = self.fc3(x)
                                       return x
                       device = torch.device("cuda" if torch.cuda.is available() else "cpu")
   In [182...
                       print("Using device:", device)
                       model = FruitCNN(num classes=10).to(device)
                     Using device: cuda
   In [184...
                      criterion = nn.CrossEntropyLoss() # For classification tasks
                       optimizer = torch.optim.Adam(model.parameters(), 1r=0.0005)
```

```
In [186...
          num_epochs = 15
          for epoch in range(num_epochs):
              model.train()
              running_loss = 0.0
              # Show progress bar
              progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{num_epochs}", leav
              for images, labels in progress_bar:
                  images = images.to(device)
                  labels = labels.to(device).long()
                  optimizer.zero_grad()
                  outputs = model(images)
                  loss = criterion(outputs, labels)
                  loss.backward()
                  optimizer.step()
                  running_loss += loss.item()
                  progress_bar.set_postfix(loss=f"{loss.item():.4f}")
              print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {running_loss/len(train_loader
          print("Training complete.")
         Epoch [1/15], Loss: 1.9787
         Epoch [2/15], Loss: 1.5860
         Epoch [3/15], Loss: 1.4432
         Epoch [4/15], Loss: 1.3581
         Epoch [5/15], Loss: 1.1981
         Epoch [6/15], Loss: 1.1433
         Epoch [7/15], Loss: 1.0319
         Epoch [8/15], Loss: 0.9079
         Epoch [9/15], Loss: 0.8144
         Epoch [10/15], Loss: 0.7014
         Epoch [11/15], Loss: 0.5907
         Epoch [12/15], Loss: 0.4919
         Epoch [13/15], Loss: 0.4201
         Epoch [14/15], Loss: 0.3389
```

Epoch [15/15], Loss: 0.2640 Training complete.

```
In [187...
          model.eval()
          correct = 0
          total = 0
          with torch.no grad():
              for images, labels in val_loader:
                  images, labels = images.to(device), labels.to(device)
                  outputs = model(images)
                   _, predicted = torch.max(outputs, 1)
                  total += labels.size(0)
                  correct += (predicted == labels).sum().item()
          print(f"Validation Accuracy: {100 * correct / total:.2f}%")
         Validation Accuracy: 54.44%
In [188...
          correct = torch.zeros(10).to(device)
          total = torch.zeros(10).to(device)
          model.eval()
          with torch.no_grad():
              for images, labels in val_loader:
                  images, labels = images.to(device), labels.to(device)
                  outputs = model(images)
                  preds = torch.argmax(outputs, dim=1)
                  for label in range(10):
                      correct[label] += (preds[labels == label] == label).sum()
                      total[label] += (labels == label).sum()
          accuracy_per_class = correct / total
          print(accuracy_per_class.cpu().numpy()) # See per-class accuracy
         [0.76404494 0.10476191 0.04716981 0.72380954 0.6952381 0.31428573
          0.82474226 0.83809525 0.61165047 0.5809524 ]
 In [ ]:
```