Project 1 - Cat & Dog Classification

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DM873: Deep Learning
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1 Introduction

The objective of this project is to develop a deep learning model capable of distinguishing between images of cats and dogs. The task involves training a neural network using a dataset containing 3,600 images, equally divided between the two categories. The code and the notebook including all the results is available in the Appendix.

2 Explorative Analysis

The dataset contains a mix of different breeds of cats and dogs. The images are very diverse in terms of size, orientation, lighting, focus, and resolution. Also, the images are taken from different angles and distances. The images are mostly around 200-500 pixels width/height and are all in color, meaning they have 3 color channels. In Figure 1, examples of cats and dogs from the dataset are shown.

(a) Cats **(b)** Dogs

Fig. 1. Sample images of cats and dogs from the dataset.

From the images we see that cats and dogs have different features that can be used to distinguish between them. For example, cats have generally shorter faces often with triangular ears and pointed noses, while dogs generally have longer snouts and have more different ear shapes. Moreover, the eyes of cats are generally more sharp-shaped, while dogs have rounder eyes. The goal is therefore to create a model that can learn some of these features.

3 Base Model

First, we set out to develop a base model. However, first, we had to decide which image size to use. We choose an image size of 224x224, as this size seems to capture enough details, see page Appendix B - 0.5 Image Size. Also, many of the pretrained models uses the same image size, making our model more comparable to these. Resizing the images has the effect of making training of the model significantly faster and less focused on finer details.

Next, we had to decide how many layers our model should have. As the task is relatively simple, we decided to use 4 convolutional layers and 3 fully connected layers, including the binary output layer. Since the input images are in color and 224x224 pixels, inputting that image directly into the fully connected layers would result in a $224 \cdot 224 \cdot 3 = 150528$ input size into the model. We would like to reduce this further, so the fully connected layers does not get an input of 150528. The convolution layers extract features, which makes it possible for the neural network to recognise a specific feature no matter where it is in the image, instead of having to learn that feature for every possible position in an image.

For the loss function, we choose the cross-entropy since it is generally good and popular for classification tasks. For the optimizer, we choose Adam as it combines the strength of several other optimizers. Since we have

4/5 convolutional layers we choose to go with a pretty small kernel size of 3 by 3. A small kernel size is good for preserving details and since we have several convolutional layers it is still possible for us to capture broader features. We use max pooling after each convolutional layer for several reasons. First of all it improves generalization since it focuses on more prominent features. It reduces the dimensionality of the layer, which mean less computation and also reducing complexity so overfitting is less likely. For the activation function, we choose ReLU, as it is the most used activation function for convolutional neural networks.

Note that the architecture of the model is highly configurable making it easy to experiment with different configurations like different layers, kernels and regularization, see Appendix A - convolutionalNetwork.py.

The final base model is provided in Table 1.

	Output kernels/features	**Kernel**	**MaxPooling**	**Activation**
Conv2D w/	32	3x3	2x2	ReLU
Conv2D w/	64	3x3	2x2	ReLU
Conv2D w/	128	3x3	2x2	ReLU
Conv2D w/	256	3x3	2x2	ReLU
Linear w/	256	-	-	ReLU
Linear w/	128	-	-	ReLU
Linear w/	2	-	-	-

Table 1. Base Model.

The model was trained for 25 epochs as a start. The learning rate was set to 0.001 as this is a generally good choice. A learning rate that is too small could result in a very slow learning process that might get stuck, and a too big learning rate could result in a local minimum or an unstable learning process. Results of the base model after 25 epochs are shown in Figure 2.

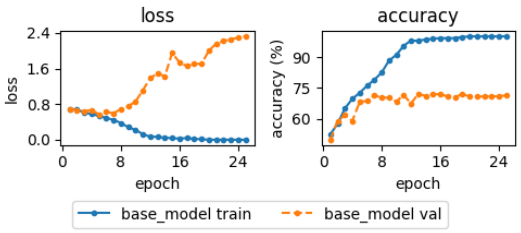


Fig. 2. Base Model Results.

Clearly, the base model is overfitting, therefore, we need to add some regularization to the model.

4 Regularization

4.1 Data Augmentation

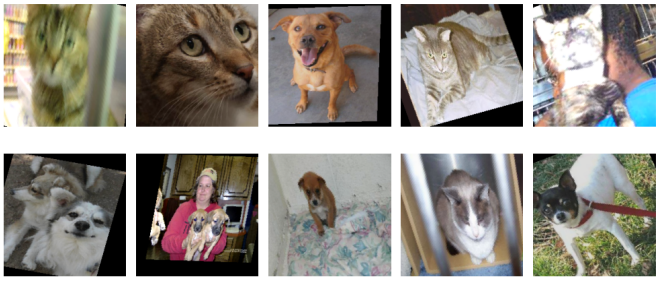
One way, especially for small datasets as in this case, to reduce overfitting is to use data augmentation, enabling the model to learn from 'more' data. We choose to augment the data in a few different ways since we want to generalize the data so the important features remain. Using augmentation ensures that it will get better accuracy when faced with new images. In other words, it reduces overfitting. By using one image we tested different techniques and found those which fits to this task, see Appendix B - 0.7 Data Augmentation.

The images are of varying quality and taken in different lighting, and this is also what we can expect from the final test set. For this reason we change the brightness, saturation, and contrast. Furthermore, the images are taken from different angles so we rotate the pictures slightly and flip them horizontally. Generally, images of animals are not vertically flipped, so we chose not to do this, but of course, some cases may exist. Also, the images are cropped differently to get finer details from the images, as well as the images becomes scale invariant. Moreover, we shear and translate the images to emulate images taken from different angles of the animal. Even though some of the images are more blurry than others, we chose not to blur the images, as it effectively just reduces the data of the image without reducing input to the model.

The final techniques used as well as augmented sample images using these techniques are shown in Figure 3.

Data Augmentation	Parameters
RandomHorizontalFlip	50%
ColorJitter	brightness=0.2 contrast=0.2 saturation=0.2 hue=0
RandomAffine	degrees=25 translate=(0.1, 0.1) scale=(0.7, 1.3) shear=(-10, 10)

(a) Data Augmentation Techniques.



(b) Sample images after augmentation.

Fig. 3. Data augmentation techniques.

The following Figure 4 shows the results of running the base model with data augmentation.

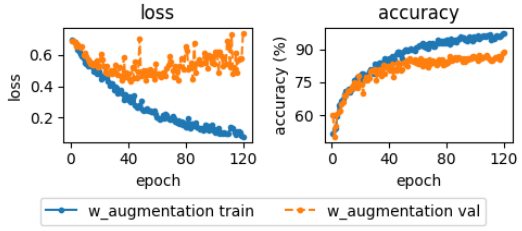


Fig. 4. Results using augmentation.

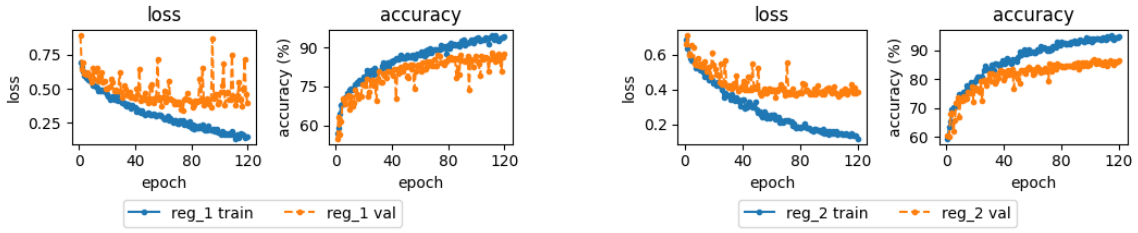
Clearly, the model performs better than without data augmentation and we are now able to train the model for more epochs without overfitting. The training accuracy of the model was 97% with validation accuracy of 88%, which indicates that improvements still can be made.

4.2 More Regularization Techniques

To achieve even better results, more regularization than just data augmentation is needed. Therefore, we change the base model a bit.

First of all, batch normalization was added to each convolutional layer for stabilizing training and improve convergence. Also, dropout is added to make the model more robust, so no single neurons predicts them all. The results using this model, called 'reg_1', is shown in Figure 6a.

We also experimented with adding weight decay (L2 regularization) to penalize large weights and encourage better generalization. Since it is recommended to use the AdamW optimizer for effective integration of weight decay, we opted for AdamW in this configuration. Also, we halve the learning rate every 25 epochs using 'StepLR'. The results using this model, called 'reg_2', is shown in Figure 6a.



(a) Regularized model 1.

(b) Regularized model 2.

Fig. 5. Results using regularization.

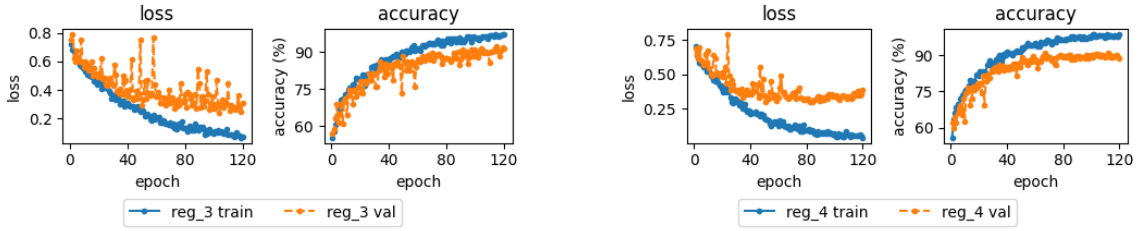
From the results, the end accuracy is very similar, however, as expected adding weight decay stabilize the training. The training accuracy of model 'reg_2' was 93% with validation accuracy of 85%. The training- and validation accuracy are now closer to each other, however, no real improvements in terms of validation accuracy is achieved compared to our base model with augmentation.

4.3 Adding one more convolutional layer

We wanted to try and improve the model even further, so we increased the number of kernels/features and added an extra convolutional layer, see Table 2. As before, we ran this model with and without weight decay. The results are shown in Figure 6.

	Output kernels/features	Kernel	BatchNorm	MaxPooling	Dropout	Activation
Conv2D w/	64	3x3	64	2x2	-	ReLU
Conv2D w/	128	3x3	128	2x2	-	ReLU
Conv2D w/	256	3x3	256	2x2	-	ReLU
Conv2D w/	512	3x3	512	2x2	-	ReLU
Conv2D w/	512	3x3	512	2x2	-	ReLU
Linear w/	512	-	512	-	40%	ReLU
Linear w/	256	-	128	-	20%	ReLU
Linear w/	2	-	-	-	-	-

Table 2. Reg4 Model.



(a) Regularized model 3. **(b)** Regularized model 4.

Fig. 6. Results using one more convolutional layer.

The training accuracy of model 'reg_4' was 99% with validation accuracy of 89%, indicating some overfitting on the training data. However, we chose to use this model as our final model, as it has the highest validation accuracy.

Based on the feature maps for a sample image of a cat, see Appendix B - 0.10 Predict, we can see that the first layer is mainly edge detection and colors. For the second layer, a lot of the feature maps captures the fur. In the third layer, the faces stands out from the rest of the picture. In the fourth layer there is focus on the head, the ears, and the whiskers.

5 Prediction

The reg_4 model is now applied to the test set to evaluate its performance. The test accuracy is summarized in Table 3.

Test Accuracy using Reg4 model
91.5%

Table 3. Test Accuracy using Reg4 Model.

Some of the misclassified and correctly classified images are given in Figure 7.

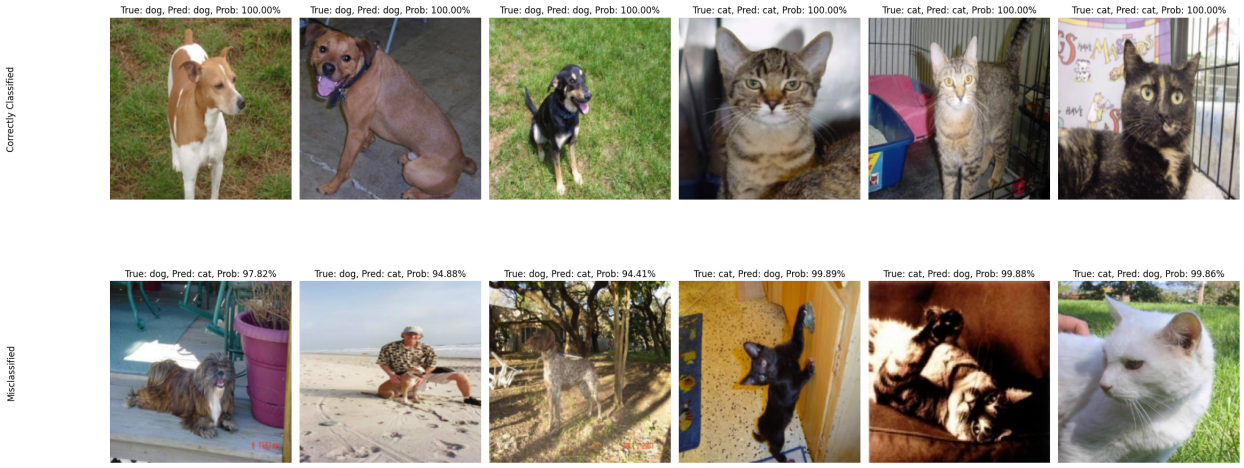
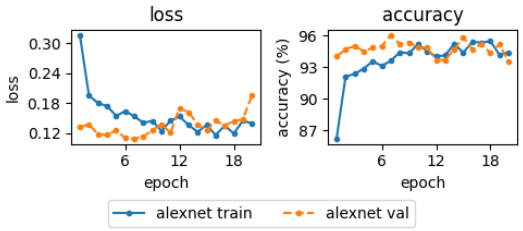


Fig. 7. Misclassified and correctly classified images.

From the misclassified images, we see that may some more data augmentation could be applied to improve the model's performance. For example, the cat that rotate its head by almost 90 degrees. Moreover, the model may be improved by adding more crop-scale augmentation.

6 Pretrained Model (AlexNet)

To see how good our model performs compared to a well-known model, we used the pretrained model 'AlexNet'. This model is pretrained on the ImageNet dataset, which contains 1.2 million images and 1000 classes, also including cats and dogs. However, to use the pretrained model for this binary classification task, the output layer is modified. The results of the pretrained model after 20 epochs are shown in Figure 8a. The test accuracy is summarized in Table 8b.



(a) Loss and Accuracy scores using AlexNet.

Test Accuracy using AlexNet
93.5%

(b) Test Accuracy using AlexNet.

Fig. 8. AlexNet results.

As expected the pretrained model performs sligtly better than our model. However, AlexNet also is trained on a much larger dataset and has a lot more parameters ($\sim$ 57 million) compared to our model ($\sim$ 21 million). The feature maps look pretty similar to our model, but is less interpretable, probably generalizing better to other objects.

7 Conclusion

The model we ended up with was a convolutional neural network with 5 convolutional layers that extracted 512 feature maps, and with 3 fully connected layers. We perform several different types of data augmentation on the pictures including horizontal flipping, color jitter, and rotation having in total $\sim 21 million$ parameters. We ended up with a model that has 91.5% test accuracy. The pretrained model AlexNet has a test accuracy of 93.5%. Our result is pretty good, especially since the pretrained model had a lot more training data than we did, but at the same time it recognises a lot more classes than just cats and dogs. It is worth noticing that some of the pictures are very hard to classify, like dog.1335 and dog.1395 in the test set.

Overall we are satisfied with our result but it could have been improved. First of all more training data would very likely improve the model a lot. In some of the pictures its very hard to see whether its a cat or a dog and its doubtful that the model would learn anything from the picture, so removing those pictures from the dataset would potentially help the model learn more meaningful features and also train faster. We could have run epochs until the model began overfitting and then stopped at that point. If time was not a factor this is probably what we would have done. We could have also experimented more with the different parameters like learning rate and weight decay. We could have tried even more data augmentations to see what works best. We only rotate the pictures up to 25 degrees, which means that the model as an example would have a hard time recognising pictures of animals upside down.

7.1 Individual Contributions

	Henrik Daniel Christensen	**Frode Engtoft Johansen**
Code	- Base model - Data Augmentation - Regularization - Pre-trained	- Base model
Report	- Introduction - Explorative Analysis - Base Model - Regularization - Prediction - Pretrained Model - Conclusion	- Base Model - Regularization - Conclusion

Table 4. Individual contributions.

A Code

Python Files

File: default_config.py

```
image_size = 224
batch_size = 64
num_workers = 8
pin_memory = True
normalize_mean = [0.485, 0.456, 0.406]
normalize_std = [0.229, 0.224, 0.225]
data_dir = "data"
train_dir = f"{data_dir}/train"
val_dir = f"{data_dir}/validation"
test_dir = f"{data_dir}/test"
label_map = {0: "cat", 1: "dog"}

default_transform_config = {
   "hflip": True,
   "brightness_jitter": 0.2,
   "contrast_jitter": 0.2,
   "saturation_jitter": 0.2,
   "hue_jitter": 0.0,
   "rotation": 25,  # rotation is in degrees
   "crop_scale": 0.3,  # crop_scale is like zooming in. 0.3 means zoom in by 30%
   "translate": 0.1,  # translate is like shifting the image. 0.1 means shift by 10%
   "shear": 10,  # shear is like skewing the image. 10 means shear by 10 degrees
}

no_transform_config = {
   "hflip": False,
   "brightness_jitter": 0,
   "contrast_jitter": 0,
   "saturation_jitter": 0,
   "hue_jitter": 0,
   "rotation": 0,
   "crop_scale": 1,
   "translate": 0,
   "shear": 0,
}

default_train_config = {
   "optimizer_type": "Adam",
   "learning_rate": 0.001,
   "weight_decay": 0,
   "momentum": None,
   "reg_type": "None",
   "reg_lambda": 0.001,
   "step_size": None,
   "gamma": None,
}

default_net_config = {
   "in_channels": 3,
   "num_classes": 2,
   "cv_layers": [
       {
           "out_channels": 16,
           "kernel_size": 3,
           "stride": 1,
           "padding": 1,
           "batch_norm": False,
           "max_pool": 0,
           "max_pool_stride": 1,
       },
       {
           "out_channels": 32,
           "kernel_size": 3,
           "stride": 1,
           "padding": 1,
           "batch_norm": False,
           "max_pool": 0,
           "max_pool_stride": 1,
       },
   ],
   "fc_layers": [{"out_features": 64, "batch_norm": False, "dropout_rate": 0}],
}
```

```
default_config = {
   "label": "Default Experiment",
   "n_epochs": 120,
   "transform_config": default_transform_config,
   "train_config": default_train_config,
   "net_config": default_net_config,
}
```

File: loaders.py

```
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
from default_config import (
   image_size,
   batch_size,
   num_workers,
   pin_memory,
   normalize_mean,
   normalize_std,
   default_transform_config,
   train_dir,
)


def get_train_loader(transform_config=default_transform_config):
   hflip = transform_config["hflip"]

   brightness_jitter = transform_config["brightness_jitter"]
   contrast_jitter = transform_config["contrast_jitter"]
   saturation_jitter = transform_config["saturation_jitter"]
   hue_jitter = transform_config["hue_jitter"]

   rotation = transform_config["rotation"]
   crop_scale = transform_config["crop_scale"]
   translate = transform_config["translate"]
   shear = transform_config["shear"]

   transform_list = [transforms.Resize((image_size, image_size))]  # always resizing

   # Add transformations
   if hflip:
       transform_list.append(transforms.RandomHorizontalFlip(p=0.5))

   color_jitter_params = {}
   if brightness_jitter > 0:
       color_jitter_params["brightness"] = brightness_jitter
   if contrast_jitter > 0:
       color_jitter_params["contrast"] = contrast_jitter
   if saturation_jitter > 0:
       color_jitter_params["saturation"] = saturation_jitter
   if hue_jitter > 0:
       color_jitter_params["hue"] = hue_jitter
   if brightness_jitter > 0 or contrast_jitter > 0 or saturation_jitter > 0 or hue_jitter > 0:
       transform_list.append(transforms.ColorJitter(**color_jitter_params))

   affine_params = {}
   if rotation > 0:
       affine_params["degrees"] = rotation
   if crop_scale < 1 and rotation > 0:
       affine_params["scale"] = (1 - crop_scale, 1 + crop_scale)
   if translate > 0 and rotation > 0:
       affine_params["translate"] = (translate, translate)
   if shear > 0 and rotation > 0:
       affine_params["shear"] = (-shear, shear)
   if rotation > 0:  # rotation must be set for RandomAffine to work
       transform_list.append(transforms.RandomAffine(**affine_params))

   # Convert to tensor
   transform_list.append(transforms.ToTensor())

   # Normalize
   transform_list.append(transforms.Normalize(mean=normalize_mean, std=normalize_std))

   # Compose all transformations into a single pipeline
   train_transform = transforms.Compose(transform_list)
```

```
    # Load data
    train_data = datasets.ImageFolder(train_dir, transform=train_transform)

    # Create data loader
    train_loader = DataLoader(
        train_data,
        batch_size=batch_size,
        shuffle=True,
        num_workers=num_workers,
        pin_memory=pin_memory,
    )
    return train_loader


def get_test_transform():
    return transforms.Compose(
        [
            transforms.Resize((image_size, image_size)),
            transforms.ToTensor(),
            transforms.Normalize(mean=normalize_mean, std=normalize_std),
        ]
    )


def get_test_loader(dir):
    test_transform = get_test_transform()

    test_data = datasets.ImageFolder(dir, transform=test_transform)

    test_loader = DataLoader(
        test_data,
        batch_size=batch_size,
        shuffle=False,
        num_workers=num_workers,
        pin_memory=pin_memory,
    )

    return test_loader
```

File: convolutionalNetwork.py

```
from default_config import default_net_config, image_size
import torch
import torch.nn as nn


class ConvolutionalNetwork(nn.Module):
    def __init__(self, net_config=default_net_config):
        super(ConvolutionalNetwork, self).__init__()

        in_channels = net_config["in_channels"]
        num_classes = net_config["num_classes"]

        layers = []
        self.relu = nn.ReLU()

        tmp_channels = in_channels
        for config in net_config["cv_layers"]:
            out_channels = config["out_channels"]
            kernel_size = config.get("kernel_size", 3)
            stride = config.get("stride", 1)
            padding = config.get("padding", 0)
            batch_norm = config.get("batch_norm", False)
            max_pool = config.get("max_pool", 0)

            # Convolutional layer
            # - Output channels are the number of filters in the convolutional layer
            # - Kernel size is the size of the filter
            # - Stride is the step size for the filter
            # - Padding is the number of pixels to add around the input image
            layers.append(
                nn.Conv2d(
                    tmp_channels,
                    out_channels,
                    kernel_size=kernel_size,
                    stride=stride,
```

```
                    padding=padding,
                )
            )

            # Batch Normalization
            # - Batch normalization is used to normalize the input layer by adjusting and scaling the activations.
            #   It is used to make the model faster and more stable.
            if batch_norm:
                layers.append(nn.BatchNorm2d(num_features=out_channels))

            # ReLU activation
            # - An activation function is used to introduce non-linearity to the output of a neuron
            layers.append(self.relu)

            # Maxpooling layer
            # - Max pooling is a downsampling operation that reduces the dimensionality of the input
            # - Kernel size is the size of the filter
            # - Stride is the step size for the filter
            if max_pool > 1:
                max_pool_stride = config.get("max_pool_stride", 1)
                layers.append(nn.MaxPool2d(kernel_size=max_pool, stride=max_pool_stride))

            # Update input channels for next iteration
            tmp_channels = out_channels

        # Sequential container for convolutional layers
        self.cv_layers = nn.Sequential(*layers)

        # Calculate input size of tensor after convolutional layers
        with torch.no_grad():
            sample_input = torch.randn(
                1, in_channels, image_size, image_size
            )  # create a random sample input tensor
            conv_output = self.cv_layers(sample_input)
            fc_input_features = (
                conv_output.numel()
            )  # calculate the number of elements in the tensor

        # Fully connected layers
        fc_layers_list = []
        for config in net_config["fc_layers"]:
            out_features = config["out_features"]
            dropout_rate = config.get("dropout_rate", 0)
            batch_norm = config.get("batch_norm", False)

            # Fully connected layer
            # - Input features are the number of neurons in previous layer
            # - Output features are the number of neurons to create in current layer
            fc_layers_list.append(
                nn.Linear(in_features=fc_input_features, out_features=out_features)
            )

            # Batch Normalization
            # - Batch normalization is used to normalize the input layer by adjusting and scaling the activations.
            #   It is used to make the model faster and more stable.
            if batch_norm:
                fc_layers_list.append(nn.BatchNorm1d(out_features))

            # ReLU activation
            # - An activation function is used to introduce non-linearity to the output of a neuron
            fc_layers_list.append(self.relu)

            # Dropout
            # - Dropout is a regularization technique to prevent overfitting by randomly setting some output features t
            if dropout_rate > 0:
                fc_layers_list.append(nn.Dropout(p=dropout_rate))

            # Update input features for next iteration
            fc_input_features = out_features

        # Output layer (no dropout or activation)
        fc_layers_list.append(nn.Linear(fc_input_features, num_classes))

        # Sequential container for fully connected layers
        self.fc_layers = nn.Sequential(*fc_layers_list)

    def forward(self, x):
        x = self.cv_layers(x)  # pass through convolutional layers
```

```
        x = x.flatten(
            start_dim=1, end_dim=-1
        )  # flatten tensor from convolutional layers for the linear fully connected layers
        x = self.fc_layers(x)  # pass through fully connected layers
        return x
```

File: train_model.py

```
from default_config import default_config, batch_size, image_size, val_dir
from loaders import get_train_loader, get_test_loader
import time
import torch
import torch.nn as nn
import torch.optim as optim
from torchinfo import summary


def train_model(model, device, config=default_config):
    label = config["label"]
    n_epochs = config["n_epochs"]

    train_config = config["train_config"]
    transform_config = config["transform_config"]

    model = model.to(device)  # move model to device

    criterion = nn.CrossEntropyLoss()  # loss function

    optimizer_type = train_config["optimizer_type"]
    learning_rate = train_config["learning_rate"]
    weight_decay = train_config.get("weight_decay", 0.0)
    momentum = train_config.get("momentum", 0.0)
    reg_type = train_config["reg_type"]
    reg_lambda = train_config["reg_lambda"]
    step_size = train_config["step_size"]
    gamma = train_config["gamma"]

    # Get transformations
    train_loader = get_train_loader(transform_config)
    val_loader = get_test_loader(val_dir)

    # Select optimizer
    if optimizer_type == "SGD":
        optimizer = optim.SGD(
            model.parameters(), lr=learning_rate, momentum=momentum, weight_decay=weight_decay
        )
    elif optimizer_type == "Adam":
        # If weight decay is specified, apply AdamW instead
        if weight_decay > 0:
            optimizer = optim.AdamW(model.parameters(), lr=learning_rate, weight_decay=weight_decay)
        else:
            optimizer = optim.Adam(model.parameters(), lr=learning_rate)

    # Scheduler
    if step_size is not None and gamma is not None:
        scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=step_size, gamma=gamma)

    train_losses = []
    train_accuracies = []
    val_losses = []
    val_accuracies = []

    print(f"\nExperiment: {label}")

    # Track total training time
    total_start_time = time.time()

    for epoch in range(n_epochs):

        start_time = time.time()

        model.train()  # set model to training mode

        train_loss = 0.0
        correct = 0
        total = 0
```

```
    # Progress bar for training batches
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)  # move data to device
        optimizer.zero_grad()  # zero the parameter gradients
        outputs = model(images)
        loss = criterion(outputs, labels)  # calculate loss

        # Apply regularization if specified
        if reg_type == "L1":
            l1_norm = sum(param.abs().sum() for param in model.parameters())
            loss += reg_lambda * l1_norm
        elif reg_type == "L2":
            l2_norm = sum(param.pow(2).sum() for param in model.parameters())
            loss += reg_lambda * l2_norm

        loss.backward()  # backpropagation
        optimizer.step()  # update weights
        train_loss += loss.item()  # add the loss to the training set loss

        # Calculate training accuracy
        _, predicted = torch.max(outputs, 1)  # get predicted class
        total += labels.size(0)
        correct += (predicted == labels).sum().item()  # count correct predictions

    if step_size is not None and gamma is not None:
        scheduler.step()  # update learning rate

    # Training set statistics
    train_losses.append(round(train_loss / len(train_loader), 4))
    train_accuracies.append(round(100 * correct / total, 2) if total > 0 else 0)

    # Evaluation on validation set
    model.eval()  # set model to evaluation mode

    val_loss = 0.0
    correct = 0
    total = 0

    with torch.no_grad():  # no need to calculate gradients for validation set
        for images, labels in val_loader:
            images, labels = images.to(device), labels.to(device)  # move data to device
            outputs = model(images)
            loss = criterion(outputs, labels)  # calculate loss
            val_loss += loss.item()  # add the loss to the validation set loss
            _, predicted = torch.max(outputs, 1)  # get predicted class
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    # Validation set statistics
    val_losses.append(round(val_loss / len(val_loader), 4))
    val_accuracies.append(round(100 * correct / total, 2) if total > 0 else 0)

    # Print epoch summary
    epoch_duration = round(time.time() - start_time)
    print(
        f"Epoch {epoch+1}/{n_epochs} | Train Loss: {train_losses[-1]:.4f} (acc. {train_accuracies[-1]:.2f}%) | "
        f"Val Loss: {val_losses[-1]:.4f} (acc. {val_accuracies[-1]:.2f}%) | Time: {epoch_duration}s"
    )

# Calculate and print total training time
total_training_time = round(time.time() - total_start_time)
print(f"Training Time: {total_training_time}s")

# Save model and metrics to file
with open(f"models/{label}.txt", "w") as f:
    model_summary = summary(
        model, input_size=(batch_size, 3, image_size, image_size), verbose=0
    )
    f.write(str(model_summary))
    f.write("\nTraining and Validation Metrics:\n")
    f.write(f"Train Losses: {train_losses}\n")
    f.write(f"Train Accuracies: {train_accuracies}\n")
    f.write(f"Val Losses: {val_losses}\n")
    f.write(f"Val Accuracies: {val_accuracies}\n")

# Save model to file
torch.save(model.state_dict(), f"models/{label}.pth")
```

```
    return {
        "n_epochs": n_epochs,
        "train_losses": train_losses,
        "val_losses": val_losses,
        "train_accuracies": train_accuracies,
        "val_accuracies": val_accuracies,
    }
```

File: result_handler.py

```
from convolutionalNetwork import ConvolutionalNetwork
from train_model import train_model


def result_handler(configs, device):
    results = {}
    for config in configs:
        model = ConvolutionalNetwork(config["net_config"])
        result = train_model(model, device, config)
        label = config["label"]
        results[label] = result
    return results
```

File: plot_scores.py

```
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator


def plot_scores(results):
    for label, data in results.items():
        fig, axes = plt.subplots(1, 2, figsize=(5, 2.5))

        epochs = range(1, data["n_epochs"] + 1)

        # Plot loss
        axes[0].plot(epochs, data["train_losses"], marker="o", markersize=3, label=f"{label} train")
        axes[0].plot(
            epochs,
            data["val_losses"],
            marker="o",
            markersize=3,
            linestyle="--",
            label=f"{label} val",
        )
        axes[0].set_title("loss")
        axes[0].set_xlabel("epoch")
        axes[0].set_ylabel("loss")

        # Plot accuracy
        axes[1].plot(
            epochs, data["train_accuracies"], marker="o", markersize=3, label=f"{label} train"
        )
        axes[1].plot(
            epochs,
            data["val_accuracies"],
            marker="o",
            markersize=3,
            linestyle="--",
            label=f"{label} val",
        )
        axes[1].set_title("accuracy")
        axes[1].set_xlabel("epoch")
        axes[1].set_ylabel("accuracy (%)")

        # Set 4 ticks on the x and y-axis
        axes[0].yaxis.set_major_locator(MaxNLocator(nbins=4))
        axes[1].yaxis.set_major_locator(MaxNLocator(nbins=4))
        axes[0].xaxis.set_major_locator(MaxNLocator(nbins=4))
        axes[1].xaxis.set_major_locator(MaxNLocator(nbins=4))

        # Create a single legend below the plots
        handles, labels = axes[0].get_legend_handles_labels()
        fig.legend(handles, labels, loc="lower center", bbox_to_anchor=(0.5, 0), ncol=2)
```

```
        plt.tight_layout(rect=[0, 0.1, 1, 0.9])
        plt.show()
```

File: predict.py

```python
import torch
import matplotlib.pyplot as plt
from collections import defaultdict
from loaders import get_test_loader
from denormalize_image import denormalize_image
from default_config import label_map, test_dir
import csv


def plot_classified_and_misclassified(correctly_classified, misclassified):
    num_images = 3

    # Sort by confidence
    correctly_classified.sort(key=lambda x: x[1], reverse=True)
    misclassified.sort(key=lambda x: x[1], reverse=True)

    # Get top `num_images` for each class
    top_correct = []
    top_incorrect = []
    for label in set(x[2] for x in correctly_classified):
        top_correct.extend([x for x in correctly_classified if x[2] == label][:num_images])
        top_incorrect.extend([x for x in misclassified if x[2] == label][:num_images])

    # Plot correctly and misclassified images
    fig, axs = plt.subplots(2, num_images * 2 + 1, figsize=(25, 10))

    # Add row labels
    axs[0, 0].text(
        0.5, 0.5, "Correctly Classified", fontsize=12, ha="center", va="center", rotation=90
    )
    axs[0, 0].axis("off")
    axs[1, 0].text(0.5, 0.5, "Misclassified", fontsize=12, ha="center", va="center", rotation=90)
    axs[1, 0].axis("off")

    # Show correctly classified images
    for i, (img, prob, true_label, pred_label) in enumerate(top_correct):
        img = denormalize_image(img)
        axs[0, i + 1].imshow(img.permute(1, 2, 0))
        axs[0, i + 1].set_title(f"True: {true_label}, Pred: {pred_label}, Prob: {prob*100:.2f}%")
        axs[0, i + 1].axis("off")

    # Show misclassified images
    for i, (img, prob, true_label, pred_label) in enumerate(top_incorrect):
        img = denormalize_image(img)
        axs[1, i + 1].imshow(img.permute(1, 2, 0))
        axs[1, i + 1].set_title(f"True: {true_label}, Pred: {pred_label}, Prob: {prob*100:.2f}%")
        axs[1, i + 1].axis("off")

    plt.tight_layout()
    plt.show()


def predict(model, device, model_path, results_file="image_probabilities.csv"):
    # Load model
    model.to(device)
    model.load_state_dict(torch.load(model_path, weights_only=True))
    model.eval()

    # Get loader
    test_loader = get_test_loader(test_dir)

    misclassified = []
    correctly_classified = []
    correct_class_counts = defaultdict(int)
    misclass_class_counts = defaultdict(int)

    # Access image paths directly from the dataset within the loader
    image_paths = [sample[0] for sample in test_loader.dataset.samples]

    # Open CSV file for writing
```

```
    with open(results_file, mode="w", newline="") as file:
        writer = csv.writer(file)
        writer.writerow(
            ["Image Name", "Correct Prediction", "True Label", "Predicted Label", "Probabilities"]
        )

        with torch.no_grad():
            for batch_idx, (images, labels) in enumerate(test_loader):
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)

                probs = torch.softmax(outputs, dim=1)
                predicted_labels = torch.argmax(probs, dim=1)

                for idx in range(images.size(0)):
                    image_index = batch_idx * test_loader.batch_size + idx
                    img = images[idx].cpu()
                    image_name = image_paths[image_index]

                    true_label_num = labels[idx].cpu().item()
                    pred_label_num = predicted_labels[idx].cpu().item()
                    true_label = label_map[true_label_num]
                    pred_label = label_map[pred_label_num]

                    prob_values = probs[idx].cpu().tolist()
                    correct_prediction = true_label == pred_label

                    if correct_prediction:
                        correctly_classified.append((img, max(prob_values), true_label, pred_label))
                        correct_class_counts[true_label] += 1
                    else:
                        misclassified.append((img, max(prob_values), true_label, pred_label))
                        misclass_class_counts[true_label] += 1

                    # Write to CSV
                    writer.writerow(
                        [
                            image_name,
                            correct_prediction,
                            true_label,
                            pred_label,
                            [f"{p*100:.2f}%" for p in prob_values],
                        ]
                    )

    # Print total counts and accuracy
    total_correct = len(correctly_classified)
    total_misclassified = len(misclassified)
    total = total_correct + total_misclassified
    accuracy = round((total_correct / total) * 100, 2)
    total_cats = correct_class_counts["cat"] + misclass_class_counts["cat"]
    total_dogs = correct_class_counts["dog"] + misclass_class_counts["dog"]
    cat_acc = round(correct_class_counts["cat"] / total_cats * 100, 2)
    dog_acc = round(correct_class_counts["dog"] / total_dogs * 100, 2)
    print(
        f"Total Correctly Classified: {total_correct} | Total Misclassified: {total_misclassified} | Accuracy: {accurac
    )

    # Print class-wise statistics
    print("Class-wise Correctly Classified Counts:")
    for label, count in correct_class_counts.items():
        print(f"- Class {label}: {count}")
    print("Class-wise Misclassified Counts:")
    for label, count in misclass_class_counts.items():
        print(f"- Class {label}: {count}")
    print(f"Cat Accuracy: {cat_acc}% | Dog Accuracy: {dog_acc}%")

    plot_classified_and_misclassified(correctly_classified, misclassified)
```

File: plot_individual_feature_maps.py

```
import matplotlib.pyplot as plt
import torch
from PIL import Image
from loaders import get_test_transform
```

```python
def plot_individual_feature_maps(
    model, device, img_path, output_file="individual_feature_maps.png"
):
    # Load and preprocess the image
    img = Image.open(img_path).convert("RGB")
    test_transform = get_test_transform()
    img_tensor = (
        test_transform(img).unsqueeze(0).to(device)
    )  # apply transforms and add batch dimension

    # Plot and save the original image
    _, ax = plt.subplots(figsize=(5, 5))
    ax.imshow(img)
    ax.axis("off")
    ax.set_title("Original Image", fontsize=14)
    original_image_file = f"{output_file}_original.png"
    plt.savefig(original_image_file)
    plt.show()

    # Set model to evaluation mode and move to correct device
    model.eval()
    model.to(device)

    # Collect all convolutional layers
    conv_layers = []
    model_children = list(model.children())

    for layer in model_children:
        if isinstance(layer, torch.nn.Conv2d):
            conv_layers.append(layer)
        elif isinstance(layer, torch.nn.Sequential):
            for child in layer.children():
                if isinstance(child, torch.nn.Conv2d):
                    conv_layers.append(child)

    # Forward pass through model and collect feature maps
    outputs = []
    for layer in conv_layers:
        img_tensor = layer(img_tensor)
        outputs.append(img_tensor)

    # Create the figure for feature maps
    for layer_idx, feature_map in enumerate(outputs):
        feature_map = feature_map.squeeze(0).cpu()  # remove batch dimension and move to CPU
        num_filters = feature_map.size(0)  # number of filters in this layer

        # Determine grid layout for plotting all filters
        col_size = 8  # number of columns
        row_size = (num_filters + col_size - 1) // col_size

        _, axes = plt.subplots(row_size, col_size, figsize=(col_size * 2, row_size * 2))
        axes = axes.flatten()

        # Plot each filter's feature map
        for filter_idx in range(num_filters):
            single_filter_map = feature_map[filter_idx].detach().numpy()
            axes[filter_idx].imshow(single_filter_map, cmap="gray")
            axes[filter_idx].axis("off")
            axes[filter_idx].set_title(f"Filter {filter_idx + 1}", fontsize=8)

        # Turn off any unused subplots
        for idx in range(num_filters, len(axes)):
            axes[idx].axis("off")

        # Save figure for each layer
        plt.tight_layout()
        layer_output_file = f"{output_file}_layer_{layer_idx + 1}.png"
        plt.savefig(layer_output_file)
        plt.show()
```

File: plot_transformations.py

```python
import matplotlib.pyplot as plt
import math
```

```
num_images_in_row = 3


def plot_transformations(transformed_images, transforms):
    num_images = len(transformed_images)
    rows = math.ceil(num_images / num_images_in_row)

    _, axes = plt.subplots(
        rows,
        min(num_images_in_row, num_images),
        figsize=(3 * min(num_images_in_row, num_images), 3 * rows),
    )

    if rows == 1:
        axes = [axes]
    elif num_images <= num_images_in_row:
        axes = [axes]

    # Plot each image in the corresponding subplot
    for i, img in enumerate(transformed_images):
        row, col = divmod(i, num_images_in_row)
        axes[row][col].imshow(img)
        axes[row][col].set_title(f"{transforms[i]}")

    # Turn off axis for all subplots
    for row in axes:
        for ax in row:
            ax.axis("off")

    plt.tight_layout()
    plt.show()
```

B Notebook

notebook

November 17, 2024

0.1 Libraries

[ ]:
```
import os
import random
import matplotlib.pyplot as plt
from PIL import Image

import torch
import torch.nn as nn
from torchvision import datasets, transforms
import torchvision.transforms.functional as TF
from torchvision.models import alexnet, AlexNet_Weights, AlexNet

from default_config import default_config, default_net_config, default_train_config, data_dir, train_dir,␣
↪no_transform_config
from convolutionalNetwork import ConvolutionalNetwork
from predict import predict
from plot_scores import plot_scores
from plot_transformations import plot_transformations
from plot_individual_feature_maps import plot_individual_feature_maps
from denormalize_image import denormalize_image
from loaders import get_train_loader
from result_handler import result_handler
from train_model import train_model
```

0.2 Check device

[2]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
torch.__version__
```

```
cuda
```

[2]:
```
'2.5.1+cu124'
```

0.3 Seed

[3]:
```
seed = 42

random.seed(seed)
torch.manual_seed(seed)
torch.cuda.manual_seed(seed)
```

0.4 Explorative Data Analysis

0.4.1 Dataset walking

[4]:
```
for dirpath, dirnames, filenames in os.walk(data_dir):
    if len(dirnames) == 0: # only innermost directories
        print(f"'{dirpath}' directory contains {len(filenames)} images")
```

```
'data\test\cats' directory contains 200 images
'data\test\dogs' directory contains 200 images
'data\train\cats' directory contains 1000 images
'data\train\dogs' directory contains 1000 images
'data\validation\cats' directory contains 300 images
'data\validation\dogs' directory contains 300 images
```

0.4.2 Labels

[5]:
```
print(datasets.ImageFolder(train_dir, transform=transforms.ToTensor()).class_to_idx)
```

```
{'cats': 0, 'dogs': 1}
```

0.4.3 Plot 10 random images of both cats and dogs

[6]:
```
train_cats_dir = f"{train_dir}/cats"
train_dogs_dir = f"{train_dir}/dogs"

cats_images = random.sample([f"{train_cats_dir}/{filename}" for filename in os.listdir(train_cats_dir)], 10)
dogs_images = random.sample([f"{train_dogs_dir}/{filename}" for filename in os.listdir(train_dogs_dir)], 10)

# Plot cat images
fig1, axes1 = plt.subplots(2, 5, figsize=(6, 3))
for i, img in enumerate(cats_images):
    axes1[i // 5, i % 5].imshow(plt.imread(img))
    axes1[i // 5, i % 5].axis("off")
plt.tight_layout()
plt.show()

# Plot dog images
fig2, axes2 = plt.subplots(2, 5, figsize=(6, 3))
for i, img in enumerate(dogs_images):
    axes2[i // 5, i % 5].imshow(plt.imread(img))
    axes2[i // 5, i % 5].axis("off")
plt.tight_layout()
plt.show()
```

0.5 Image Size

[7]:
```
image = Image.open(cats_images[1])

print(f"Image size: {image.size}")

# Plot image_resized
plt.figure(figsize=(4, 4))
plt.imshow(image)
plt.title("Original Image")
plt.axis("off")
plt.show()
```

```
Image size: (500, 374)
```

[8]:
```
factors = [125, 150, 175, 200, 225, 250]

transformed_images = []
for factor in factors:
```

```
    transformed_image = TF.resize(image, factor)
    transformed_images.append(transformed_image)

plot_transformations(transformed_images, factors)
```

An image size of 225 seems good, however, for compatibility with pre-trained models we choose 224.

[9]:
```
image_resized = TF.resize(image, 224)
```

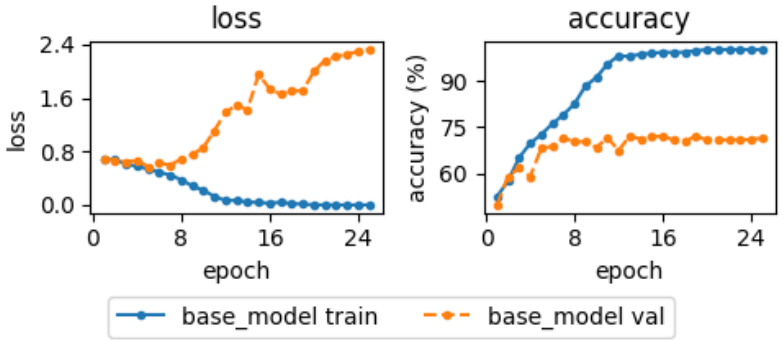
0.6 Base Model

[10]:
```
net_config0 = {**default_net_config,
    "cv_layers": [
        {"out_channels": 32, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": False},
        {"out_channels": 64, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": False},
        {"out_channels": 128, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": False},
        {"out_channels": 256, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": False},
    ],
    "fc_layers": [
        {"out_features": 256, "batch_norm": False, "dropout_rate": 0},
        {"out_features": 128, "batch_norm": False, "dropout_rate": 0},
    ]
}

config0 = [{**default_config, "label": "base_model", "n_epochs": 25, "net_config": net_config0,␣
↪"transform_config": no_transform_config}]
results = result_handler(config0, device)
plot_scores(results)
```

```
Experiment: base_model
Epoch 1/25 | Train Loss: 0.6952 (acc. 52.65%) | Val Loss: 0.6951 (acc. 50.00%) |
Time: 35s
```

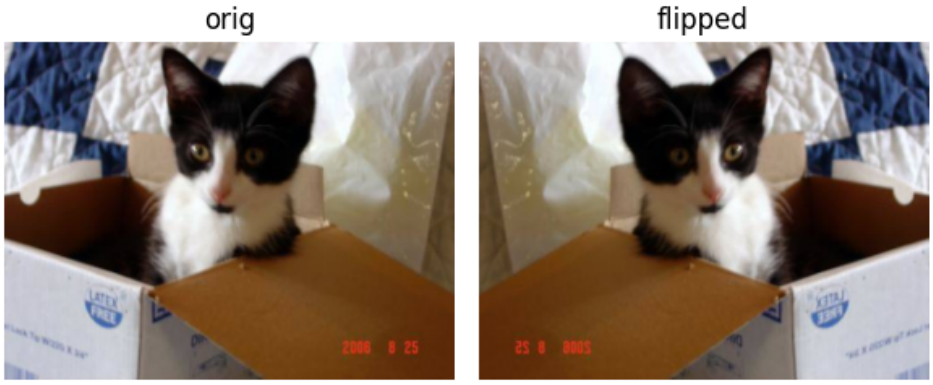
```
Epoch 2/25 | Train Loss: 0.6737 (acc. 57.75%) | Val Loss: 0.6627 (acc. 59.17%) |
Time: 35s
Epoch 3/25 | Train Loss: 0.6153 (acc. 65.20%) | Val Loss: 0.6417 (acc. 61.83%) |
Time: 34s
Epoch 4/25 | Train Loss: 0.5763 (acc. 69.80%) | Val Loss: 0.6698 (acc. 59.17%) |
Time: 34s
Epoch 5/25 | Train Loss: 0.5369 (acc. 72.65%) | Val Loss: 0.5722 (acc. 68.17%) |
Time: 33s
Epoch 6/25 | Train Loss: 0.4914 (acc. 76.10%) | Val Loss: 0.6250 (acc. 68.83%) |
Time: 34s
Epoch 7/25 | Train Loss: 0.4459 (acc. 79.00%) | Val Loss: 0.5959 (acc. 71.50%) |
Time: 34s
Epoch 8/25 | Train Loss: 0.3771 (acc. 82.50%) | Val Loss: 0.6838 (acc. 70.33%) |
Time: 34s
Epoch 9/25 | Train Loss: 0.2845 (acc. 88.25%) | Val Loss: 0.7522 (acc. 70.33%) |
Time: 34s
Epoch 10/25 | Train Loss: 0.2194 (acc. 91.05%) | Val Loss: 0.8570 (acc. 68.50%)
| Time: 33s
Epoch 11/25 | Train Loss: 0.1277 (acc. 95.40%) | Val Loss: 1.1103 (acc. 71.67%)
| Time: 34s
Epoch 12/25 | Train Loss: 0.0657 (acc. 98.00%) | Val Loss: 1.3821 (acc. 67.50%)
| Time: 33s
Epoch 13/25 | Train Loss: 0.0685 (acc. 97.80%) | Val Loss: 1.4903 (acc. 72.17%)
| Time: 33s
Epoch 14/25 | Train Loss: 0.0439 (acc. 98.55%) | Val Loss: 1.4245 (acc. 71.17%)
| Time: 33s
Epoch 15/25 | Train Loss: 0.0373 (acc. 98.80%) | Val Loss: 1.9494 (acc. 71.83%)
| Time: 34s
Epoch 16/25 | Train Loss: 0.0244 (acc. 99.20%) | Val Loss: 1.7371 (acc. 72.17%)
| Time: 34s
Epoch 17/25 | Train Loss: 0.0406 (acc. 99.05%) | Val Loss: 1.6526 (acc. 70.83%)
| Time: 33s
Epoch 18/25 | Train Loss: 0.0201 (acc. 99.20%) | Val Loss: 1.7009 (acc. 70.50%)
| Time: 33s
Epoch 19/25 | Train Loss: 0.0110 (acc. 99.65%) | Val Loss: 1.7072 (acc. 72.17%)
| Time: 33s
Epoch 20/25 | Train Loss: 0.0020 (acc. 100.00%) | Val Loss: 1.9952 (acc. 70.83%)
| Time: 34s
Epoch 21/25 | Train Loss: 0.0004 (acc. 100.00%) | Val Loss: 2.1588 (acc. 71.00%)
| Time: 33s
Epoch 22/25 | Train Loss: 0.0002 (acc. 100.00%) | Val Loss: 2.2134 (acc. 70.83%)
| Time: 33s
Epoch 23/25 | Train Loss: 0.0001 (acc. 100.00%) | Val Loss: 2.2571 (acc. 71.00%)
| Time: 34s
Epoch 24/25 | Train Loss: 0.0001 (acc. 100.00%) | Val Loss: 2.2897 (acc. 71.00%)
| Time: 33s
Epoch 25/25 | Train Loss: 0.0001 (acc. 100.00%) | Val Loss: 2.3216 (acc. 71.50%)
| Time: 33s
Training Time: 840s
```



0.7 Data Augmentation

0.7.1 Flip

[11]:
```
transformed_images = []
transformed_images.append(image_resized)
transformed_images.append(TF.hflip(image_resized))
plot_transformations(transformed_images, ["orig", "flipped"])
```



[12]:
```
transformed_images = []
transformed_images.append(image_resized)
transformed_images.append(TF.vflip(image_resized))
plot_transformations(transformed_images, ["orig", "flipped"])
```

Choose to only horizontal flip.

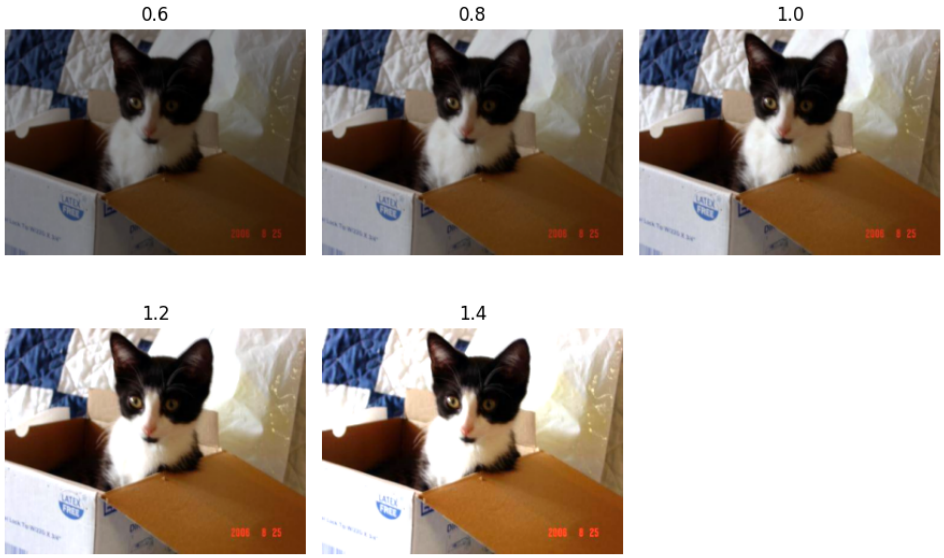
0.7.2 Image color

Brightness

[13]:
```
factors = [0.6, 0.8, 1.0, 1.2, 1.4]
```

```
transformed_images = []
for factor in factors:
    transformed_image = TF.adjust_brightness(image_resized, factor)
    transformed_images.append(transformed_image)

plot_transformations(transformed_images, factors)
```

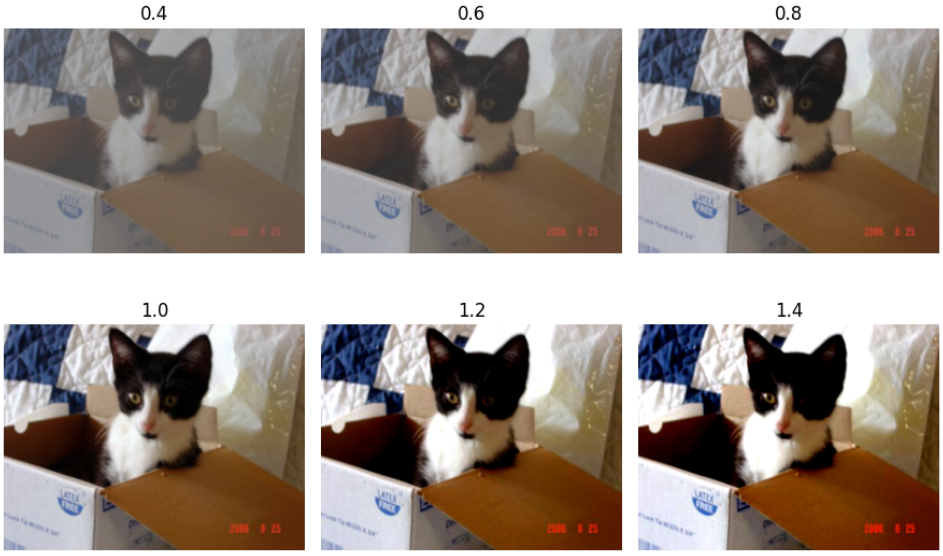


Contrast

[14]:
```
factors = [0.4, 0.6, 0.8, 1.0, 1.2, 1.4]

transformed_images = []
for factor in factors:
    transformed_image = TF.adjust_contrast(image_resized, factor)
    transformed_images.append(transformed_image)

plot_transformations(transformed_images, factors)
```

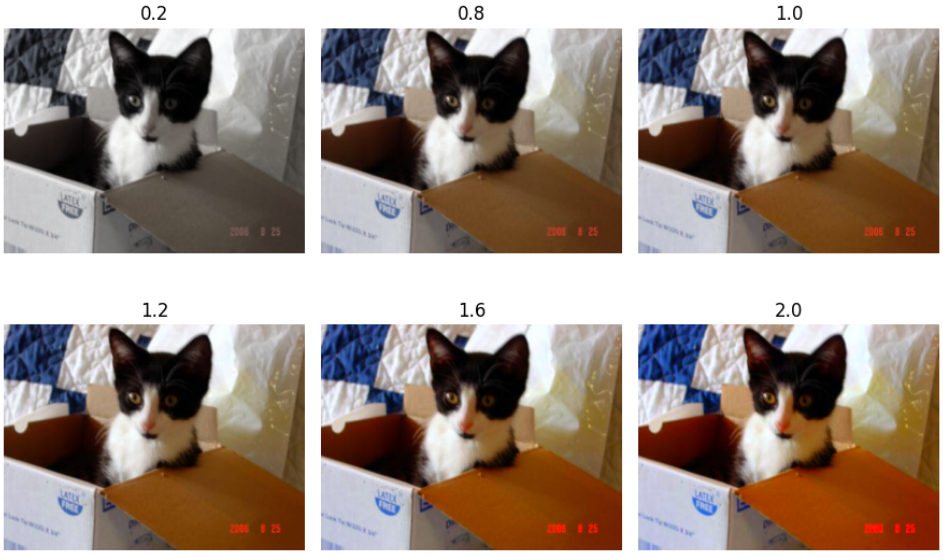


Saturation

[15]:
```
factors = [0.2, 0.8, 1.0, 1.2, 1.6, 2.0]

transformed_images = []
for factor in factors:
    transformed_image = TF.adjust_saturation(image_resized, factor)
    transformed_images.append(transformed_image)

plot_transformations(transformed_images, factors)
```



Hue

[16]:
```
factors = [0.2, 0.1, 0, -0.1, -0.2]

transformed_images = []
for factor in factors:
    transformed_image = TF.adjust_hue(image_resized, factor)
    transformed_images.append(transformed_image)

plot_transformations(transformed_images, factors)
```

0.7.3 Affine (rotation, scaling, translation, shearing)

[17]:
```
def apply_affine(image, angle, translate=(0, 0), scale=1.0, shear=0):
    return TF.affine(image, angle=angle, translate=translate, scale=scale, shear=shear)

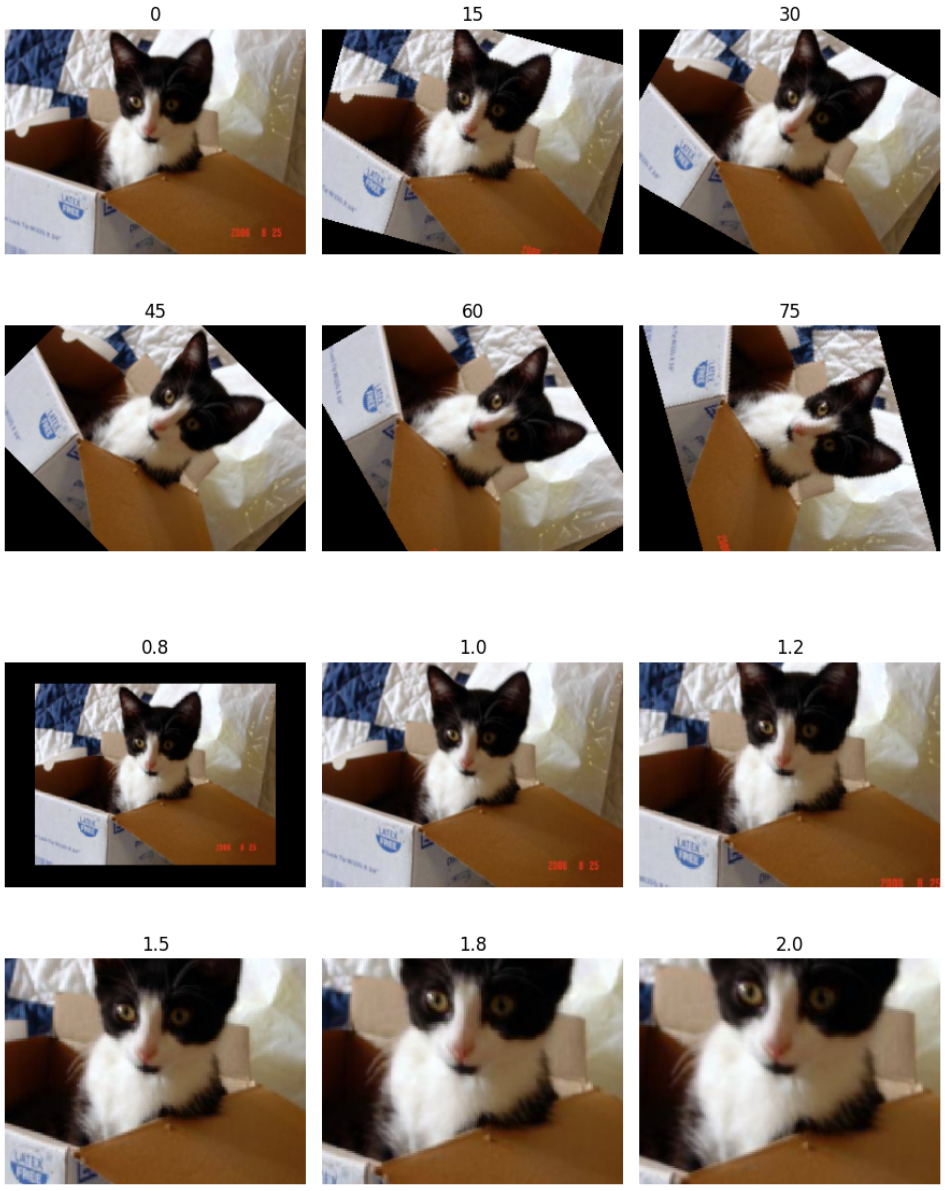
# Rotation
angles = [0, 15, 30, 45, 60, 75]
transformed_images = [apply_affine(image_resized, angle=angle) for angle in angles]
plot_transformations(transformed_images, angles)

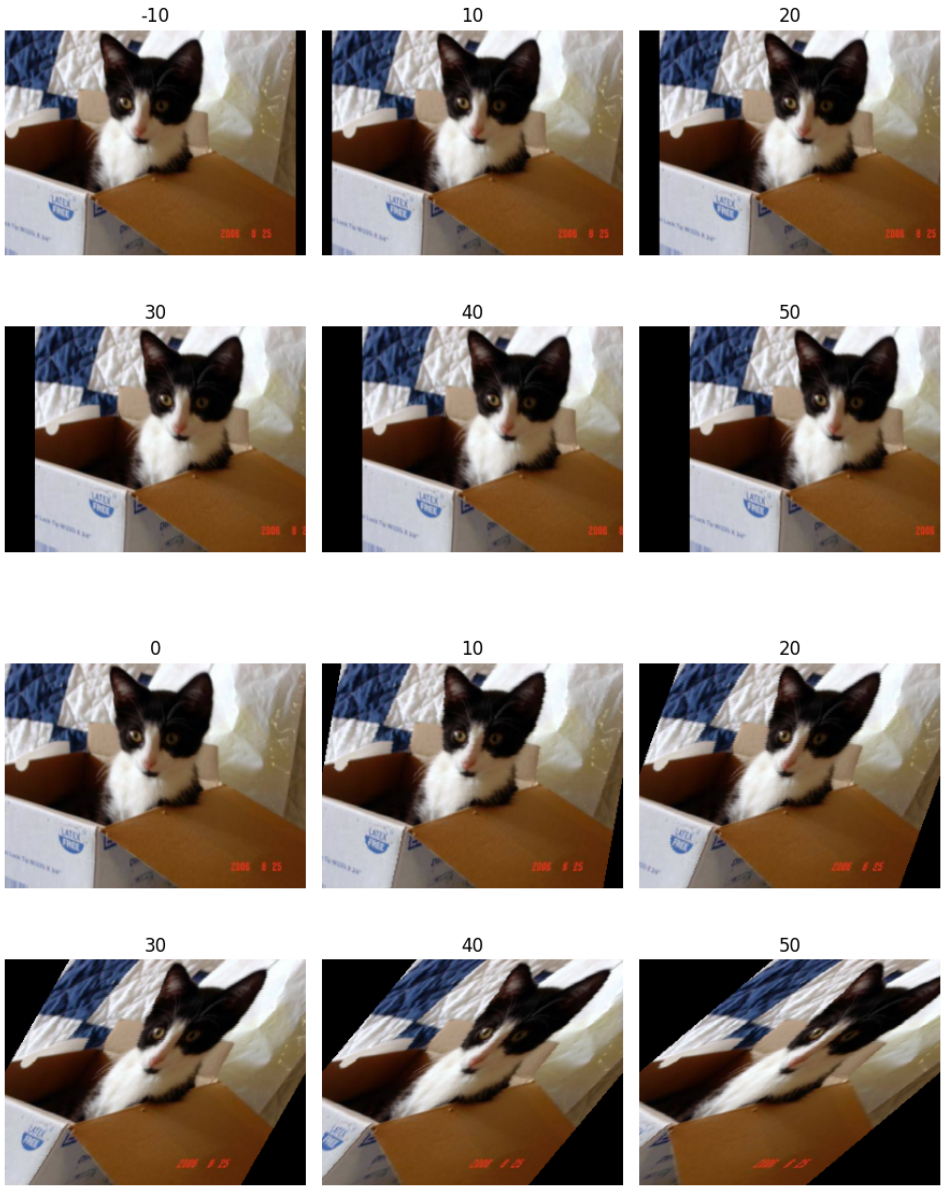
# Scales
scales = [0.8, 1.0, 1.2, 1.5, 1.8, 2.0]
transformed_images = [apply_affine(image_resized, angle=0, scale=scale) for scale in scales]
plot_transformations(transformed_images, scales)

# Translations
translations = [(-10, 0), (10, 0), (20, 0), (30, 0), (40, 0), (50, 0)]
transformed_images = [apply_affine(image_resized, angle=0, translate=translate) for translate in␣
↪translations]
plot_transformations(transformed_images, [t[0] for t in translations])

# Shear
shears = [0, 10, 20, 30, 40, 50]
```

```
transformed_images = [apply_affine(image_resized, angle=0, shear=shear) for shear in shears]
plot_transformations(transformed_images, shears)
```





0.7.4 Final loader

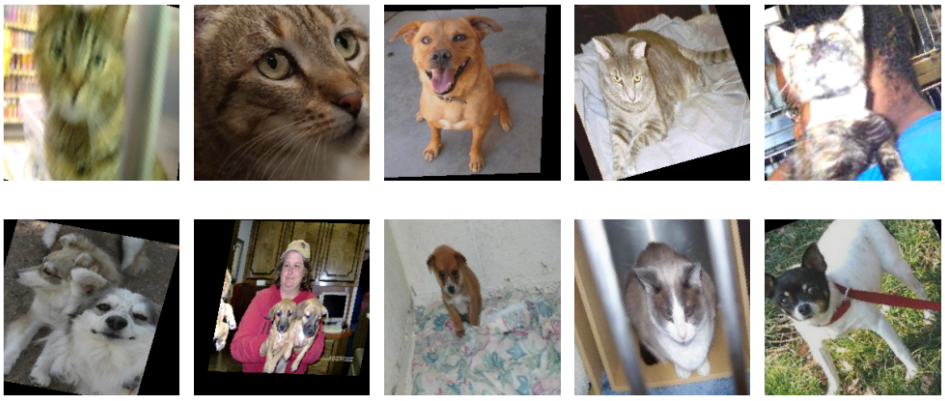
With normalization

[18]:
```
train_loader = get_train_loader()
images, _ = next(iter(train_loader))
fig, axes = plt.subplots(2, 5, figsize=(10, 5))
for i in range(10):
    img = images[i].permute(1, 2, 0).cpu().numpy() # convert to (H, W, C)
```

```
    img = img.clip(0, 1) # clip values to [0, 1]
    axes[i // 5, i % 5].imshow(img)
    axes[i // 5, i % 5].axis("off")
plt.tight_layout()
plt.show()
```

Without normalization

[19]:
```
train_loader = get_train_loader()
images, _ = next(iter(train_loader))
fig, axes = plt.subplots(2, 5, figsize=(10, 5))
for i in range(10):
    axes[i // 5, i % 5].imshow(denormalize_image(images[i]).permute(1, 2, 0)) # denormalize and convert to␣
↪(H, W, C)
    axes[i // 5, i % 5].axis("off")
plt.tight_layout()
plt.show()
```



0.8 With Data Augmentation

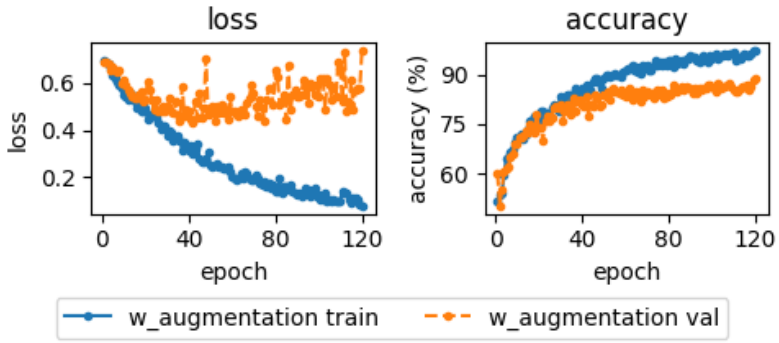
[20]:
```
config0 = [{**default_config, "label": "w_augmentation", "net_config": net_config0}]
results = result_handler(config0, device)
plot_scores(results)
```

```
Experiment: w_augmentation
Epoch 1/120 | Train Loss: 0.6994 (acc. 51.70%) | Val Loss: 0.6878 (acc. 60.17%)
| Time: 34s
Epoch 2/120 | Train Loss: 0.6895 (acc. 53.75%) | Val Loss: 0.6895 (acc. 50.33%)
| Time: 34s
Epoch 3/120 | Train Loss: 0.6801 (acc. 54.30%) | Val Loss: 0.6847 (acc. 55.33%)
| Time: 34s
Epoch 4/120 | Train Loss: 0.6598 (acc. 59.65%) | Val Loss: 0.6549 (acc. 60.83%)
| Time: 33s
Epoch 5/120 | Train Loss: 0.6371 (acc. 64.40%) | Val Loss: 0.6706 (acc. 61.67%)
| Time: 34s
Epoch 6/120 | Train Loss: 0.6208 (acc. 65.10%) | Val Loss: 0.6582 (acc. 62.33%)
| Time: 34s
Epoch 7/120 | Train Loss: 0.6096 (acc. 66.50%) | Val Loss: 0.6502 (acc. 65.00%)
| Time: 34s
Epoch 8/120 | Train Loss: 0.5936 (acc. 67.80%) | Val Loss: 0.6547 (acc. 66.00%)
| Time: 34s
Epoch 9/120 | Train Loss: 0.5776 (acc. 69.35%) | Val Loss: 0.5995 (acc. 68.83%)
| Time: 33s
Epoch 10/120 | Train Loss: 0.5514 (acc. 70.85%) | Val Loss: 0.6134 (acc. 68.83%)
| Time: 34s
Epoch 11/120 | Train Loss: 0.5418 (acc. 71.05%) | Val Loss: 0.5918 (acc. 71.00%)
| Time: 34s
Epoch 12/120 | Train Loss: 0.5302 (acc. 72.05%) | Val Loss: 0.5703 (acc. 71.17%)
| Time: 34s
Epoch 13/120 | Train Loss: 0.5586 (acc. 70.55%) | Val Loss: 0.5582 (acc. 71.33%)
| Time: 34s
Epoch 14/120 | Train Loss: 0.5514 (acc. 71.90%) | Val Loss: 0.5450 (acc. 73.17%)
| Time: 34s
Epoch 15/120 | Train Loss: 0.5221 (acc. 73.55%) | Val Loss: 0.5334 (acc. 72.33%)
| Time: 34s
Epoch 16/120 | Train Loss: 0.4971 (acc. 76.05%) | Val Loss: 0.5384 (acc. 75.00%)
| Time: 34s
Epoch 17/120 | Train Loss: 0.5000 (acc. 76.45%) | Val Loss: 0.5475 (acc. 72.83%)
| Time: 34s
Epoch 18/120 | Train Loss: 0.4822 (acc. 77.20%) | Val Loss: 0.5633 (acc. 72.33%)
| Time: 34s
Epoch 19/120 | Train Loss: 0.4796 (acc. 77.05%) | Val Loss: 0.5226 (acc. 77.83%)
| Time: 34s
Epoch 20/120 | Train Loss: 0.4964 (acc. 76.40%) | Val Loss: 0.5302 (acc. 74.00%)
| Time: 34s
Epoch 21/120 | Train Loss: 0.4484 (acc. 78.90%) | Val Loss: 0.6042 (acc. 74.00%)
| Time: 34s
Epoch 22/120 | Train Loss: 0.4650 (acc. 79.00%) | Val Loss: 0.5727 (acc. 70.17%)
| Time: 34s
Epoch 23/120 | Train Loss: 0.4698 (acc. 77.70%) | Val Loss: 0.5292 (acc. 75.83%)
| Time: 33s
Epoch 24/120 | Train Loss: 0.4604 (acc. 78.50%) | Val Loss: 0.4854 (acc. 77.67%)
| Time: 34s
Epoch 25/120 | Train Loss: 0.4516 (acc. 78.15%) | Val Loss: 0.5270 (acc. 76.00%)
| Time: 34s
Epoch 26/120 | Train Loss: 0.4324 (acc. 79.65%) | Val Loss: 0.4821 (acc. 77.17%)
| Time: 34s
Epoch 27/120 | Train Loss: 0.4048 (acc. 80.90%) | Val Loss: 0.4799 (acc. 79.83%)
| Time: 34s
Epoch 28/120 | Train Loss: 0.4169 (acc. 80.40%) | Val Loss: 0.5001 (acc. 80.50%)
| Time: 34s
Epoch 29/120 | Train Loss: 0.4174 (acc. 79.10%) | Val Loss: 0.4819 (acc. 80.00%)
| Time: 34s
Epoch 30/120 | Train Loss: 0.3744 (acc. 83.40%) | Val Loss: 0.5007 (acc. 80.67%)
| Time: 34s
```

```
Epoch 31/120 | Train Loss: 0.3946 (acc. 82.45%) | Val Loss: 0.5338 (acc. 75.83%)
| Time: 34s
Epoch 32/120 | Train Loss: 0.3896 (acc. 82.05%) | Val Loss: 0.4811 (acc. 79.00%)
| Time: 34s
Epoch 33/120 | Train Loss: 0.3570 (acc. 83.80%) | Val Loss: 0.4761 (acc. 80.67%)
| Time: 34s
Epoch 34/120 | Train Loss: 0.3720 (acc. 83.80%) | Val Loss: 0.5233 (acc. 81.00%)
| Time: 34s
Epoch 35/120 | Train Loss: 0.3777 (acc. 83.05%) | Val Loss: 0.4648 (acc. 78.00%)
| Time: 34s
Epoch 36/120 | Train Loss: 0.3590 (acc. 84.55%) | Val Loss: 0.4369 (acc. 82.83%)
| Time: 34s
Epoch 37/120 | Train Loss: 0.3132 (acc. 85.80%) | Val Loss: 0.5858 (acc. 78.67%)
| Time: 34s
Epoch 38/120 | Train Loss: 0.3517 (acc. 83.70%) | Val Loss: 0.4601 (acc. 81.67%)
| Time: 34s
Epoch 39/120 | Train Loss: 0.3332 (acc. 84.80%) | Val Loss: 0.4874 (acc. 82.33%)
| Time: 34s
Epoch 40/120 | Train Loss: 0.3167 (acc. 85.80%) | Val Loss: 0.4798 (acc. 80.83%)
| Time: 33s
Epoch 41/120 | Train Loss: 0.3366 (acc. 84.85%) | Val Loss: 0.4495 (acc. 80.50%)
| Time: 34s
Epoch 42/120 | Train Loss: 0.3023 (acc. 86.95%) | Val Loss: 0.4302 (acc. 83.50%)
| Time: 34s
Epoch 43/120 | Train Loss: 0.3226 (acc. 86.00%) | Val Loss: 0.5216 (acc. 77.67%)
| Time: 34s
Epoch 44/120 | Train Loss: 0.3410 (acc. 85.15%) | Val Loss: 0.4522 (acc. 81.00%)
| Time: 34s
Epoch 45/120 | Train Loss: 0.2803 (acc. 87.95%) | Val Loss: 0.5553 (acc. 80.50%)
| Time: 34s
Epoch 46/120 | Train Loss: 0.2632 (acc. 88.60%) | Val Loss: 0.4526 (acc. 83.83%)
| Time: 34s
Epoch 47/120 | Train Loss: 0.2690 (acc. 88.90%) | Val Loss: 0.4936 (acc. 83.00%)
| Time: 34s
Epoch 48/120 | Train Loss: 0.2800 (acc. 87.25%) | Val Loss: 0.7044 (acc. 80.50%)
| Time: 34s
Epoch 49/120 | Train Loss: 0.3054 (acc. 85.70%) | Val Loss: 0.4693 (acc. 80.83%)
| Time: 34s
Epoch 50/120 | Train Loss: 0.2540 (acc. 88.55%) | Val Loss: 0.4721 (acc. 83.67%)
| Time: 34s
Epoch 51/120 | Train Loss: 0.2448 (acc. 89.65%) | Val Loss: 0.5040 (acc. 83.17%)
| Time: 34s
Epoch 52/120 | Train Loss: 0.2511 (acc. 89.60%) | Val Loss: 0.4375 (acc. 84.83%)
| Time: 34s
Epoch 53/120 | Train Loss: 0.2566 (acc. 89.35%) | Val Loss: 0.5014 (acc. 82.17%)
| Time: 33s
Epoch 54/120 | Train Loss: 0.2481 (acc. 89.65%) | Val Loss: 0.4713 (acc. 85.67%)
| Time: 34s
Epoch 55/120 | Train Loss: 0.2428 (acc. 90.40%) | Val Loss: 0.5083 (acc. 84.83%)
| Time: 34s
Epoch 56/120 | Train Loss: 0.2408 (acc. 89.80%) | Val Loss: 0.4770 (acc. 84.83%)
| Time: 34s
Epoch 57/120 | Train Loss: 0.2381 (acc. 89.55%) | Val Loss: 0.4902 (acc. 84.33%)
| Time: 34s
Epoch 58/120 | Train Loss: 0.2443 (acc. 89.10%) | Val Loss: 0.4495 (acc. 85.17%)
| Time: 34s
Epoch 59/120 | Train Loss: 0.2241 (acc. 90.75%) | Val Loss: 0.5438 (acc. 83.83%)
| Time: 34s
Epoch 60/120 | Train Loss: 0.2040 (acc. 91.30%) | Val Loss: 0.4785 (acc. 83.17%)
| Time: 34s
Epoch 61/120 | Train Loss: 0.1963 (acc. 91.95%) | Val Loss: 0.4777 (acc. 84.67%)
| Time: 34s
Epoch 62/120 | Train Loss: 0.1884 (acc. 91.75%) | Val Loss: 0.4696 (acc. 85.67%)
| Time: 33s
Epoch 63/120 | Train Loss: 0.1929 (acc. 92.90%) | Val Loss: 0.4613 (acc. 82.33%)
| Time: 34s
Epoch 64/120 | Train Loss: 0.2146 (acc. 91.05%) | Val Loss: 0.4857 (acc. 83.50%)
| Time: 33s
```

```
Epoch 65/120 | Train Loss: 0.1977 (acc. 92.10%) | Val Loss: 0.4766 (acc. 84.67%)
| Time: 34s
Epoch 66/120 | Train Loss: 0.2258 (acc. 90.85%) | Val Loss: 0.4648 (acc. 82.67%)
| Time: 34s
Epoch 67/120 | Train Loss: 0.2171 (acc. 90.50%) | Val Loss: 0.5159 (acc. 82.00%)
| Time: 33s
Epoch 68/120 | Train Loss: 0.1954 (acc. 92.65%) | Val Loss: 0.5347 (acc. 85.33%)
| Time: 34s
Epoch 69/120 | Train Loss: 0.1857 (acc. 92.35%) | Val Loss: 0.5925 (acc. 83.33%)
| Time: 34s
Epoch 70/120 | Train Loss: 0.1920 (acc. 92.65%) | Val Loss: 0.5608 (acc. 85.00%)
| Time: 34s
Epoch 71/120 | Train Loss: 0.2130 (acc. 91.45%) | Val Loss: 0.5002 (acc. 84.33%)
| Time: 34s
Epoch 72/120 | Train Loss: 0.1979 (acc. 91.45%) | Val Loss: 0.4596 (acc. 84.00%)
| Time: 34s
Epoch 73/120 | Train Loss: 0.1767 (acc. 92.95%) | Val Loss: 0.5268 (acc. 83.00%)
| Time: 34s
Epoch 74/120 | Train Loss: 0.1656 (acc. 94.20%) | Val Loss: 0.4926 (acc. 84.83%)
| Time: 34s
Epoch 75/120 | Train Loss: 0.1819 (acc. 92.65%) | Val Loss: 0.4421 (acc. 85.17%)
| Time: 34s
Epoch 76/120 | Train Loss: 0.1640 (acc. 93.85%) | Val Loss: 0.5294 (acc. 83.67%)
| Time: 34s
Epoch 77/120 | Train Loss: 0.1723 (acc. 92.85%) | Val Loss: 0.5780 (acc. 85.17%)
| Time: 34s
Epoch 78/120 | Train Loss: 0.1559 (acc. 93.60%) | Val Loss: 0.5791 (acc. 82.83%)
| Time: 34s
Epoch 79/120 | Train Loss: 0.1657 (acc. 92.95%) | Val Loss: 0.5074 (acc. 83.50%)
| Time: 34s
Epoch 80/120 | Train Loss: 0.1373 (acc. 94.05%) | Val Loss: 0.6580 (acc. 84.17%)
| Time: 34s
Epoch 81/120 | Train Loss: 0.1428 (acc. 94.15%) | Val Loss: 0.6294 (acc. 83.67%)
| Time: 34s
Epoch 82/120 | Train Loss: 0.1931 (acc. 92.45%) | Val Loss: 0.5093 (acc. 86.67%)
| Time: 34s
Epoch 83/120 | Train Loss: 0.1341 (acc. 94.80%) | Val Loss: 0.5239 (acc. 85.33%)
| Time: 33s
Epoch 84/120 | Train Loss: 0.1632 (acc. 93.45%) | Val Loss: 0.5531 (acc. 85.00%)
| Time: 34s
Epoch 85/120 | Train Loss: 0.1598 (acc. 93.85%) | Val Loss: 0.4482 (acc. 85.67%)
| Time: 34s
Epoch 86/120 | Train Loss: 0.1448 (acc. 94.25%) | Val Loss: 0.6787 (acc. 86.33%)
| Time: 34s
Epoch 87/120 | Train Loss: 0.1676 (acc. 93.40%) | Val Loss: 0.4874 (acc. 85.17%)
| Time: 34s
Epoch 88/120 | Train Loss: 0.1412 (acc. 94.55%) | Val Loss: 0.5527 (acc. 86.17%)
| Time: 34s
Epoch 89/120 | Train Loss: 0.1353 (acc. 94.55%) | Val Loss: 0.5746 (acc. 85.67%)
| Time: 34s
Epoch 90/120 | Train Loss: 0.1245 (acc. 95.55%) | Val Loss: 0.5443 (acc. 85.67%)
| Time: 34s
Epoch 91/120 | Train Loss: 0.1351 (acc. 95.00%) | Val Loss: 0.5426 (acc. 84.17%)
| Time: 35s
Epoch 92/120 | Train Loss: 0.1204 (acc. 95.25%) | Val Loss: 0.5516 (acc. 86.00%)
| Time: 34s
Epoch 93/120 | Train Loss: 0.1281 (acc. 94.30%) | Val Loss: 0.6152 (acc. 84.17%)
| Time: 34s
Epoch 94/120 | Train Loss: 0.1511 (acc. 93.95%) | Val Loss: 0.5863 (acc. 86.00%)
| Time: 34s
Epoch 95/120 | Train Loss: 0.1466 (acc. 94.25%) | Val Loss: 0.5165 (acc. 85.17%)
| Time: 34s
Epoch 96/120 | Train Loss: 0.1164 (acc. 95.45%) | Val Loss: 0.5992 (acc. 86.00%)
| Time: 33s
Epoch 97/120 | Train Loss: 0.1358 (acc. 94.60%) | Val Loss: 0.5839 (acc. 85.67%)
| Time: 34s
Epoch 98/120 | Train Loss: 0.1526 (acc. 93.85%) | Val Loss: 0.5531 (acc. 86.67%)
| Time: 34s
```

```
Epoch 99/120 | Train Loss: 0.1201 (acc. 95.60%) | Val Loss: 0.5915 (acc. 86.67%)
| Time: 34s
Epoch 100/120 | Train Loss: 0.1278 (acc. 94.75%) | Val Loss: 0.5410 (acc.
86.50%) | Time: 34s
Epoch 101/120 | Train Loss: 0.1037 (acc. 95.50%) | Val Loss: 0.6229 (acc.
85.83%) | Time: 34s
Epoch 102/120 | Train Loss: 0.1052 (acc. 96.05%) | Val Loss: 0.6190 (acc.
84.67%) | Time: 34s
Epoch 103/120 | Train Loss: 0.1343 (acc. 94.55%) | Val Loss: 0.4870 (acc.
87.17%) | Time: 34s
Epoch 104/120 | Train Loss: 0.1016 (acc. 95.80%) | Val Loss: 0.6222 (acc.
85.67%) | Time: 34s
Epoch 105/120 | Train Loss: 0.1025 (acc. 95.90%) | Val Loss: 0.5933 (acc.
86.33%) | Time: 34s
Epoch 106/120 | Train Loss: 0.1005 (acc. 96.00%) | Val Loss: 0.5320 (acc.
86.50%) | Time: 34s
Epoch 107/120 | Train Loss: 0.1053 (acc. 95.80%) | Val Loss: 0.5832 (acc.
86.67%) | Time: 34s
Epoch 108/120 | Train Loss: 0.0956 (acc. 96.05%) | Val Loss: 0.5449 (acc.
87.33%) | Time: 34s
Epoch 109/120 | Train Loss: 0.0990 (acc. 96.30%) | Val Loss: 0.6869 (acc.
86.33%) | Time: 34s
Epoch 110/120 | Train Loss: 0.1009 (acc. 96.60%) | Val Loss: 0.6611 (acc.
85.50%) | Time: 34s
Epoch 111/120 | Train Loss: 0.1411 (acc. 94.25%) | Val Loss: 0.5240 (acc.
85.00%) | Time: 34s
Epoch 112/120 | Train Loss: 0.1319 (acc. 94.55%) | Val Loss: 0.7344 (acc.
84.67%) | Time: 34s
Epoch 113/120 | Train Loss: 0.1309 (acc. 94.85%) | Val Loss: 0.4805 (acc.
86.00%) | Time: 34s
Epoch 114/120 | Train Loss: 0.1069 (acc. 95.80%) | Val Loss: 0.5167 (acc.
86.50%) | Time: 34s
Epoch 115/120 | Train Loss: 0.0910 (acc. 96.20%) | Val Loss: 0.6112 (acc.
86.17%) | Time: 34s
Epoch 116/120 | Train Loss: 0.1115 (acc. 95.60%) | Val Loss: 0.4870 (acc.
87.00%) | Time: 34s
Epoch 117/120 | Train Loss: 0.1119 (acc. 95.45%) | Val Loss: 0.5688 (acc.
85.17%) | Time: 34s
Epoch 118/120 | Train Loss: 0.1028 (acc. 96.25%) | Val Loss: 0.5792 (acc.
86.50%) | Time: 34s
Epoch 119/120 | Train Loss: 0.0835 (acc. 96.95%) | Val Loss: 0.5764 (acc.
88.50%) | Time: 34s
Epoch 120/120 | Train Loss: 0.0785 (acc. 97.15%) | Val Loss: 0.7381 (acc.
88.83%) | Time: 34s
Training Time: 4035s
```



0.9 Regularization

[21]:
```
net_config1 = {**default_net_config,
    "cv_layers": [
        {"out_channels": 32, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": True},
        {"out_channels": 64, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": True},
        {"out_channels": 128, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 256, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
    ],
    "fc_layers": [
        {"out_features": 256, "batch_norm": True, "dropout_rate": 0.4},
        {"out_features": 128, "batch_norm": True, "dropout_rate": 0.2},
    ]
}

train_config1 = {**default_train_config, "step_size": 25, "gamma": 0.5, "weight_decay": 1e-4}

configs1 = [
    {**default_config, "label": "reg_1", "net_config": net_config1},
    {**default_config, "label": "reg_2", "net_config": net_config1, "train_config": train_config1},
]

results = result_handler(configs1, device)
plot_scores(results)
```

```
Experiment: reg_1
Epoch 1/120 | Train Loss: 0.6962 (acc. 56.95%) | Val Loss: 0.8926 (acc. 54.83%)
| Time: 34s
Epoch 2/120 | Train Loss: 0.6597 (acc. 58.95%) | Val Loss: 0.6464 (acc. 63.17%)
| Time: 34s
Epoch 3/120 | Train Loss: 0.6288 (acc. 64.65%) | Val Loss: 0.6925 (acc. 56.33%)
| Time: 34s
Epoch 4/120 | Train Loss: 0.5979 (acc. 67.80%) | Val Loss: 0.6143 (acc. 61.50%)
| Time: 34s
Epoch 5/120 | Train Loss: 0.5828 (acc. 68.55%) | Val Loss: 0.6010 (acc. 70.17%)
| Time: 34s
Epoch 6/120 | Train Loss: 0.5800 (acc. 68.15%) | Val Loss: 0.6204 (acc. 69.33%)
| Time: 34s
Epoch 7/120 | Train Loss: 0.5622 (acc. 70.75%) | Val Loss: 0.6065 (acc. 68.17%)
| Time: 34s
Epoch 8/120 | Train Loss: 0.5561 (acc. 72.35%) | Val Loss: 0.5784 (acc. 71.33%)
| Time: 34s
Epoch 9/120 | Train Loss: 0.5447 (acc. 72.15%) | Val Loss: 0.5474 (acc. 71.67%)
| Time: 34s
Epoch 10/120 | Train Loss: 0.5238 (acc. 73.80%) | Val Loss: 0.6497 (acc. 66.00%)
| Time: 34s
Epoch 11/120 | Train Loss: 0.5209 (acc. 74.15%) | Val Loss: 0.5724 (acc. 71.17%)
| Time: 34s
Epoch 12/120 | Train Loss: 0.5160 (acc. 73.65%) | Val Loss: 0.6286 (acc. 67.50%)
| Time: 34s
Epoch 13/120 | Train Loss: 0.5104 (acc. 74.75%) | Val Loss: 0.6504 (acc. 68.50%)
| Time: 34s
Epoch 14/120 | Train Loss: 0.4879 (acc. 75.85%) | Val Loss: 0.5559 (acc. 73.50%)
| Time: 34s
Epoch 15/120 | Train Loss: 0.4844 (acc. 76.60%) | Val Loss: 0.5910 (acc. 72.17%)
| Time: 34s
Epoch 16/120 | Train Loss: 0.4893 (acc. 76.20%) | Val Loss: 0.6220 (acc. 70.50%)
| Time: 34s
Epoch 17/120 | Train Loss: 0.4809 (acc. 77.30%) | Val Loss: 0.5460 (acc. 71.00%)
| Time: 34s
Epoch 18/120 | Train Loss: 0.4896 (acc. 76.25%) | Val Loss: 0.5584 (acc. 71.00%)
| Time: 34s
Epoch 19/120 | Train Loss: 0.4742 (acc. 77.50%) | Val Loss: 0.5032 (acc. 75.67%)
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| Time: 34s
Epoch 20/120 | Train Loss: 0.4576 (acc. 78.55%) | Val Loss: 0.4965 (acc. 75.83%)
| Time: 34s
Epoch 21/120 | Train Loss: 0.4478 (acc. 78.45%) | Val Loss: 0.5090 (acc. 75.33%)
| Time: 34s
Epoch 22/120 | Train Loss: 0.4220 (acc. 81.10%) | Val Loss: 0.5131 (acc. 77.83%)
| Time: 34s
Epoch 23/120 | Train Loss: 0.4385 (acc. 79.40%) | Val Loss: 0.5742 (acc. 71.17%)
| Time: 34s
Epoch 24/120 | Train Loss: 0.4452 (acc. 78.00%) | Val Loss: 0.5460 (acc. 72.67%)
| Time: 34s
Epoch 25/120 | Train Loss: 0.4184 (acc. 81.15%) | Val Loss: 0.4871 (acc. 77.00%)
| Time: 34s
Epoch 26/120 | Train Loss: 0.4355 (acc. 80.25%) | Val Loss: 0.4897 (acc. 77.67%)
| Time: 34s
Epoch 27/120 | Train Loss: 0.4517 (acc. 79.40%) | Val Loss: 0.4839 (acc. 75.33%)
| Time: 34s
Epoch 28/120 | Train Loss: 0.4137 (acc. 82.15%) | Val Loss: 0.4873 (acc. 76.67%)
| Time: 34s
Epoch 29/120 | Train Loss: 0.4234 (acc. 80.20%) | Val Loss: 0.6243 (acc. 69.50%)
| Time: 34s
Epoch 30/120 | Train Loss: 0.4175 (acc. 81.00%) | Val Loss: 0.4784 (acc. 78.00%)
| Time: 34s
Epoch 31/120 | Train Loss: 0.3980 (acc. 81.00%) | Val Loss: 0.4372 (acc. 80.67%)
| Time: 34s
Epoch 32/120 | Train Loss: 0.3954 (acc. 81.20%) | Val Loss: 0.5249 (acc. 76.83%)
| Time: 34s
Epoch 33/120 | Train Loss: 0.3764 (acc. 82.85%) | Val Loss: 0.4968 (acc. 76.67%)
| Time: 34s
Epoch 34/120 | Train Loss: 0.3727 (acc. 84.40%) | Val Loss: 0.4571 (acc. 80.17%)
| Time: 34s
Epoch 35/120 | Train Loss: 0.3894 (acc. 82.70%) | Val Loss: 0.4526 (acc. 79.33%)
| Time: 34s
Epoch 36/120 | Train Loss: 0.3736 (acc. 82.20%) | Val Loss: 0.4761 (acc. 78.33%)
| Time: 34s
Epoch 37/120 | Train Loss: 0.3521 (acc. 84.20%) | Val Loss: 0.4387 (acc. 81.00%)
| Time: 34s
Epoch 38/120 | Train Loss: 0.3841 (acc. 82.60%) | Val Loss: 0.4475 (acc. 80.83%)
| Time: 34s
Epoch 39/120 | Train Loss: 0.3636 (acc. 84.70%) | Val Loss: 0.4355 (acc. 80.50%)
| Time: 34s
Epoch 40/120 | Train Loss: 0.3646 (acc. 84.25%) | Val Loss: 0.4286 (acc. 80.67%)
| Time: 34s
Epoch 41/120 | Train Loss: 0.3341 (acc. 85.10%) | Val Loss: 0.4978 (acc. 79.33%)
| Time: 34s
Epoch 42/120 | Train Loss: 0.3456 (acc. 85.15%) | Val Loss: 0.4592 (acc. 81.50%)
| Time: 34s
Epoch 43/120 | Train Loss: 0.3361 (acc. 86.00%) | Val Loss: 0.6471 (acc. 70.50%)
| Time: 34s
Epoch 44/120 | Train Loss: 0.3250 (acc. 85.95%) | Val Loss: 0.4087 (acc. 81.50%)
| Time: 34s
Epoch 45/120 | Train Loss: 0.3379 (acc. 85.60%) | Val Loss: 0.4383 (acc. 79.83%)
| Time: 34s
Epoch 46/120 | Train Loss: 0.3135 (acc. 86.95%) | Val Loss: 0.4213 (acc. 82.33%)
| Time: 34s
Epoch 47/120 | Train Loss: 0.3069 (acc. 86.90%) | Val Loss: 0.4665 (acc. 80.67%)
| Time: 34s
Epoch 48/120 | Train Loss: 0.3151 (acc. 86.00%) | Val Loss: 0.4264 (acc. 80.67%)
| Time: 34s
Epoch 49/120 | Train Loss: 0.3276 (acc. 86.00%) | Val Loss: 0.3953 (acc. 83.17%)
| Time: 34s
Epoch 50/120 | Train Loss: 0.3132 (acc. 86.35%) | Val Loss: 0.4257 (acc. 82.50%)
| Time: 34s
Epoch 51/120 | Train Loss: 0.3066 (acc. 87.05%) | Val Loss: 0.5127 (acc. 78.83%)
| Time: 34s
Epoch 52/120 | Train Loss: 0.3112 (acc. 86.45%) | Val Loss: 0.5312 (acc. 78.50%)
| Time: 34s
Epoch 53/120 | Train Loss: 0.3156 (acc. 86.65%) | Val Loss: 0.3942 (acc. 83.50%)
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| Time: 34s
Epoch 54/120 | Train Loss: 0.3116 (acc. 86.35%) | Val Loss: 0.4176 (acc. 81.83%)
| Time: 34s
Epoch 55/120 | Train Loss: 0.2975 (acc. 87.35%) | Val Loss: 0.4386 (acc. 83.50%)
| Time: 34s
Epoch 56/120 | Train Loss: 0.3050 (acc. 86.00%) | Val Loss: 0.7170 (acc. 74.00%)
| Time: 34s
Epoch 57/120 | Train Loss: 0.3050 (acc. 87.30%) | Val Loss: 0.4180 (acc. 80.67%)
| Time: 34s
Epoch 58/120 | Train Loss: 0.3050 (acc. 87.45%) | Val Loss: 0.4370 (acc. 83.00%)
| Time: 34s
Epoch 59/120 | Train Loss: 0.3016 (acc. 87.30%) | Val Loss: 0.3755 (acc. 83.50%)
| Time: 34s
Epoch 60/120 | Train Loss: 0.2823 (acc. 87.10%) | Val Loss: 0.4339 (acc. 82.50%)
| Time: 34s
Epoch 61/120 | Train Loss: 0.2761 (acc. 88.35%) | Val Loss: 0.4827 (acc. 80.83%)
| Time: 34s
Epoch 62/120 | Train Loss: 0.2846 (acc. 87.85%) | Val Loss: 0.4043 (acc. 84.00%)
| Time: 34s
Epoch 63/120 | Train Loss: 0.3026 (acc. 86.60%) | Val Loss: 0.4255 (acc. 81.83%)
| Time: 34s
Epoch 64/120 | Train Loss: 0.2699 (acc. 88.85%) | Val Loss: 0.5582 (acc. 81.83%)
| Time: 34s
Epoch 65/120 | Train Loss: 0.2812 (acc. 87.60%) | Val Loss: 0.4267 (acc. 84.67%)
| Time: 34s
Epoch 66/120 | Train Loss: 0.2652 (acc. 89.10%) | Val Loss: 0.4230 (acc. 83.00%)
| Time: 34s
Epoch 67/120 | Train Loss: 0.2534 (acc. 89.50%) | Val Loss: 0.4107 (acc. 84.50%)
| Time: 34s
Epoch 68/120 | Train Loss: 0.2712 (acc. 88.05%) | Val Loss: 0.3898 (acc. 83.83%)
| Time: 34s
Epoch 69/120 | Train Loss: 0.2681 (acc. 88.85%) | Val Loss: 0.4008 (acc. 83.00%)
| Time: 34s
Epoch 70/120 | Train Loss: 0.2444 (acc. 89.45%) | Val Loss: 0.3871 (acc. 85.33%)
| Time: 34s
Epoch 71/120 | Train Loss: 0.2469 (acc. 89.15%) | Val Loss: 0.4005 (acc. 83.00%)
| Time: 34s
Epoch 72/120 | Train Loss: 0.2669 (acc. 89.15%) | Val Loss: 0.3852 (acc. 82.83%)
| Time: 34s
Epoch 73/120 | Train Loss: 0.2582 (acc. 88.95%) | Val Loss: 0.3484 (acc. 87.33%)
| Time: 34s
Epoch 74/120 | Train Loss: 0.2702 (acc. 89.15%) | Val Loss: 0.3432 (acc. 86.67%)
| Time: 34s
Epoch 75/120 | Train Loss: 0.2332 (acc. 90.90%) | Val Loss: 0.4229 (acc. 84.33%)
| Time: 34s
Epoch 76/120 | Train Loss: 0.2543 (acc. 89.50%) | Val Loss: 0.4300 (acc. 84.33%)
| Time: 34s
Epoch 77/120 | Train Loss: 0.2333 (acc. 90.00%) | Val Loss: 0.4691 (acc. 83.50%)
| Time: 34s
Epoch 78/120 | Train Loss: 0.2250 (acc. 90.50%) | Val Loss: 0.4165 (acc. 84.67%)
| Time: 34s
Epoch 79/120 | Train Loss: 0.2584 (acc. 87.75%) | Val Loss: 0.4136 (acc. 84.50%)
| Time: 34s
Epoch 80/120 | Train Loss: 0.2141 (acc. 90.85%) | Val Loss: 0.4059 (acc. 86.00%)
| Time: 34s
Epoch 81/120 | Train Loss: 0.2380 (acc. 89.85%) | Val Loss: 0.3663 (acc. 85.33%)
| Time: 34s
Epoch 82/120 | Train Loss: 0.2045 (acc. 91.65%) | Val Loss: 0.3784 (acc. 86.50%)
| Time: 34s
Epoch 83/120 | Train Loss: 0.2251 (acc. 90.80%) | Val Loss: 0.4138 (acc. 85.33%)
| Time: 34s
Epoch 84/120 | Train Loss: 0.2103 (acc. 91.55%) | Val Loss: 0.4051 (acc. 85.67%)
| Time: 34s
Epoch 85/120 | Train Loss: 0.2098 (acc. 90.80%) | Val Loss: 0.4096 (acc. 86.00%)
| Time: 34s
Epoch 86/120 | Train Loss: 0.2307 (acc. 90.75%) | Val Loss: 0.5740 (acc. 78.33%)
| Time: 34s
Epoch 87/120 | Train Loss: 0.2109 (acc. 91.40%) | Val Loss: 0.4140 (acc. 86.00%)
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| Time: 34s
Epoch 88/120 | Train Loss: 0.2360 (acc. 90.40%) | Val Loss: 0.6556 (acc. 79.67%)
| Time: 34s
Epoch 89/120 | Train Loss: 0.2013 (acc. 91.50%) | Val Loss: 0.3833 (acc. 87.17%)
| Time: 34s
Epoch 90/120 | Train Loss: 0.1938 (acc. 92.55%) | Val Loss: 0.3877 (acc. 85.00%)
| Time: 34s
Epoch 91/120 | Train Loss: 0.1927 (acc. 92.95%) | Val Loss: 0.4278 (acc. 85.17%)
| Time: 34s
Epoch 92/120 | Train Loss: 0.2265 (acc. 91.05%) | Val Loss: 0.4150 (acc. 84.83%)
| Time: 34s
Epoch 93/120 | Train Loss: 0.2065 (acc. 91.95%) | Val Loss: 0.3894 (acc. 85.17%)
| Time: 34s
Epoch 94/120 | Train Loss: 0.1946 (acc. 91.65%) | Val Loss: 0.3629 (acc. 86.83%)
| Time: 34s
Epoch 95/120 | Train Loss: 0.1932 (acc. 92.35%) | Val Loss: 0.8695 (acc. 73.67%)
| Time: 34s
Epoch 96/120 | Train Loss: 0.2053 (acc. 92.25%) | Val Loss: 0.4317 (acc. 85.50%)
| Time: 34s
Epoch 97/120 | Train Loss: 0.1840 (acc. 93.00%) | Val Loss: 0.4594 (acc. 85.00%)
| Time: 34s
Epoch 98/120 | Train Loss: 0.2060 (acc. 91.90%) | Val Loss: 0.4642 (acc. 82.50%)
| Time: 34s
Epoch 99/120 | Train Loss: 0.1801 (acc. 92.45%) | Val Loss: 0.3906 (acc. 85.50%)
| Time: 34s
Epoch 100/120 | Train Loss: 0.1802 (acc. 93.25%) | Val Loss: 0.4055 (acc.
86.67%) | Time: 34s
Epoch 101/120 | Train Loss: 0.1609 (acc. 93.85%) | Val Loss: 0.4797 (acc.
84.50%) | Time: 34s
Epoch 102/120 | Train Loss: 0.1848 (acc. 93.05%) | Val Loss: 0.5259 (acc.
83.67%) | Time: 34s
Epoch 103/120 | Train Loss: 0.1772 (acc. 92.55%) | Val Loss: 0.6819 (acc.
79.17%) | Time: 34s
Epoch 104/120 | Train Loss: 0.1614 (acc. 93.15%) | Val Loss: 0.3821 (acc.
86.83%) | Time: 34s
Epoch 105/120 | Train Loss: 0.1660 (acc. 93.20%) | Val Loss: 0.4707 (acc.
85.33%) | Time: 34s
Epoch 106/120 | Train Loss: 0.1755 (acc. 93.05%) | Val Loss: 0.4738 (acc.
86.00%) | Time: 34s
Epoch 107/120 | Train Loss: 0.1603 (acc. 93.75%) | Val Loss: 0.4198 (acc.
86.17%) | Time: 34s
Epoch 108/120 | Train Loss: 0.1622 (acc. 93.65%) | Val Loss: 0.4181 (acc.
85.83%) | Time: 34s
Epoch 109/120 | Train Loss: 0.1887 (acc. 91.50%) | Val Loss: 0.7485 (acc.
81.00%) | Time: 34s
Epoch 110/120 | Train Loss: 0.1603 (acc. 94.00%) | Val Loss: 0.4439 (acc.
85.50%) | Time: 34s
Epoch 111/120 | Train Loss: 0.1324 (acc. 94.55%) | Val Loss: 0.3805 (acc.
87.83%) | Time: 34s
Epoch 112/120 | Train Loss: 0.1569 (acc. 93.70%) | Val Loss: 0.4204 (acc.
87.00%) | Time: 34s
Epoch 113/120 | Train Loss: 0.1614 (acc. 92.95%) | Val Loss: 0.4518 (acc.
85.67%) | Time: 34s
Epoch 114/120 | Train Loss: 0.1423 (acc. 94.70%) | Val Loss: 0.5452 (acc.
84.83%) | Time: 34s
Epoch 115/120 | Train Loss: 0.1704 (acc. 93.15%) | Val Loss: 0.4222 (acc.
86.17%) | Time: 34s
Epoch 116/120 | Train Loss: 0.1626 (acc. 92.75%) | Val Loss: 0.3715 (acc.
87.50%) | Time: 34s
Epoch 117/120 | Train Loss: 0.1605 (acc. 93.40%) | Val Loss: 0.4975 (acc.
85.00%) | Time: 34s
Epoch 118/120 | Train Loss: 0.1431 (acc. 93.75%) | Val Loss: 0.7164 (acc.
81.00%) | Time: 34s
Epoch 119/120 | Train Loss: 0.1447 (acc. 93.85%) | Val Loss: 0.4568 (acc.
86.17%) | Time: 34s
Epoch 120/120 | Train Loss: 0.1490 (acc. 94.25%) | Val Loss: 0.3999 (acc.
87.67%) | Time: 34s
Training Time: 4112s
```

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Experiment: reg_2
Epoch 1/120 | Train Loss: 0.6836 (acc. 59.30%) | Val Loss: 0.6645 (acc. 60.33%)
| Time: 34s
Epoch 2/120 | Train Loss: 0.6343 (acc. 63.45%) | Val Loss: 0.7115 (acc. 60.00%)
| Time: 34s
Epoch 3/120 | Train Loss: 0.6051 (acc. 65.35%) | Val Loss: 0.6021 (acc. 67.83%)
| Time: 34s
Epoch 4/120 | Train Loss: 0.5782 (acc. 69.55%) | Val Loss: 0.6000 (acc. 68.50%)
| Time: 34s
Epoch 5/120 | Train Loss: 0.5681 (acc. 70.35%) | Val Loss: 0.6545 (acc. 61.83%)
| Time: 34s
Epoch 6/120 | Train Loss: 0.5626 (acc. 70.25%) | Val Loss: 0.6416 (acc. 65.83%)
| Time: 34s
Epoch 7/120 | Train Loss: 0.5540 (acc. 70.65%) | Val Loss: 0.5522 (acc. 71.83%)
| Time: 34s
Epoch 8/120 | Train Loss: 0.5263 (acc. 72.70%) | Val Loss: 0.5408 (acc. 73.67%)
| Time: 34s
Epoch 9/120 | Train Loss: 0.5294 (acc. 74.80%) | Val Loss: 0.5783 (acc. 66.67%)
| Time: 34s
Epoch 10/120 | Train Loss: 0.5449 (acc. 73.15%) | Val Loss: 0.5389 (acc. 72.67%)
| Time: 34s
Epoch 11/120 | Train Loss: 0.5085 (acc. 73.80%) | Val Loss: 0.5492 (acc. 72.50%)
| Time: 34s
Epoch 12/120 | Train Loss: 0.5174 (acc. 75.65%) | Val Loss: 0.5291 (acc. 74.17%)
| Time: 34s
Epoch 13/120 | Train Loss: 0.5021 (acc. 75.25%) | Val Loss: 0.5505 (acc. 72.83%)
| Time: 34s
Epoch 14/120 | Train Loss: 0.4755 (acc. 77.80%) | Val Loss: 0.5586 (acc. 73.17%)
| Time: 34s
Epoch 15/120 | Train Loss: 0.5140 (acc. 75.05%) | Val Loss: 0.5026 (acc. 75.67%)
| Time: 34s
Epoch 16/120 | Train Loss: 0.4761 (acc. 77.00%) | Val Loss: 0.5039 (acc. 75.33%)
| Time: 34s
Epoch 17/120 | Train Loss: 0.4528 (acc. 79.15%) | Val Loss: 0.5285 (acc. 75.00%)
| Time: 34s
Epoch 18/120 | Train Loss: 0.4641 (acc. 78.05%) | Val Loss: 0.4713 (acc. 77.33%)
| Time: 34s
Epoch 19/120 | Train Loss: 0.4549 (acc. 78.20%) | Val Loss: 0.6147 (acc. 72.17%)
| Time: 34s
Epoch 20/120 | Train Loss: 0.4364 (acc. 79.45%) | Val Loss: 0.5405 (acc. 77.00%)
| Time: 34s
Epoch 21/120 | Train Loss: 0.4396 (acc. 80.25%) | Val Loss: 0.5171 (acc. 76.33%)
| Time: 34s
Epoch 22/120 | Train Loss: 0.4259 (acc. 81.00%) | Val Loss: 0.4854 (acc. 76.17%)
| Time: 34s
Epoch 23/120 | Train Loss: 0.4458 (acc. 80.75%) | Val Loss: 0.4847 (acc. 75.67%)
| Time: 34s
Epoch 24/120 | Train Loss: 0.4250 (acc. 80.05%) | Val Loss: 0.4432 (acc. 79.17%)
| Time: 34s
Epoch 25/120 | Train Loss: 0.4174 (acc. 80.80%) | Val Loss: 0.5482 (acc. 72.50%)
| Time: 34s
Epoch 26/120 | Train Loss: 0.3966 (acc. 83.20%) | Val Loss: 0.4327 (acc. 79.83%)
| Time: 34s
Epoch 27/120 | Train Loss: 0.3544 (acc. 84.80%) | Val Loss: 0.4410 (acc. 79.50%)
| Time: 34s
Epoch 28/120 | Train Loss: 0.3779 (acc. 83.60%) | Val Loss: 0.5682 (acc. 78.00%)
| Time: 34s
Epoch 29/120 | Train Loss: 0.3680 (acc. 83.10%) | Val Loss: 0.4246 (acc. 80.00%)
| Time: 34s
Epoch 30/120 | Train Loss: 0.3695 (acc. 83.45%) | Val Loss: 0.4102 (acc. 81.83%)
| Time: 34s
Epoch 31/120 | Train Loss: 0.3606 (acc. 83.85%) | Val Loss: 0.4239 (acc. 79.50%)
| Time: 34s
Epoch 32/120 | Train Loss: 0.3457 (acc. 85.00%) | Val Loss: 0.4096 (acc. 81.83%)
| Time: 34s
Epoch 33/120 | Train Loss: 0.3729 (acc. 83.15%) | Val Loss: 0.4049 (acc. 81.67%)
| Time: 34s
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Epoch 34/120 | Train Loss: 0.3425 (acc. 85.30%) | Val Loss: 0.4355 (acc. 78.67%)
| Time: 34s
Epoch 35/120 | Train Loss: 0.3354 (acc. 85.30%) | Val Loss: 0.4183 (acc. 79.17%)
| Time: 34s
Epoch 36/120 | Train Loss: 0.3577 (acc. 85.05%) | Val Loss: 0.4828 (acc. 80.33%)
| Time: 34s
Epoch 37/120 | Train Loss: 0.3456 (acc. 84.60%) | Val Loss: 0.3931 (acc. 82.50%)
| Time: 34s
Epoch 38/120 | Train Loss: 0.3322 (acc. 85.55%) | Val Loss: 0.3965 (acc. 83.17%)
| Time: 34s
Epoch 39/120 | Train Loss: 0.3058 (acc. 86.40%) | Val Loss: 0.4111 (acc. 82.83%)
| Time: 35s
Epoch 40/120 | Train Loss: 0.3404 (acc. 85.35%) | Val Loss: 0.4212 (acc. 79.83%)
| Time: 34s
Epoch 41/120 | Train Loss: 0.3401 (acc. 85.35%) | Val Loss: 0.4509 (acc. 80.83%)
| Time: 34s
Epoch 42/120 | Train Loss: 0.2948 (acc. 87.25%) | Val Loss: 0.3992 (acc. 82.67%)
| Time: 34s
Epoch 43/120 | Train Loss: 0.3022 (acc. 86.25%) | Val Loss: 0.3992 (acc. 83.00%)
| Time: 34s
Epoch 44/120 | Train Loss: 0.3162 (acc. 86.10%) | Val Loss: 0.4753 (acc. 81.50%)
| Time: 34s
Epoch 45/120 | Train Loss: 0.3307 (acc. 85.55%) | Val Loss: 0.4022 (acc. 82.17%)
| Time: 34s
Epoch 46/120 | Train Loss: 0.3134 (acc. 86.85%) | Val Loss: 0.3986 (acc. 83.33%)
| Time: 34s
Epoch 47/120 | Train Loss: 0.3016 (acc. 86.40%) | Val Loss: 0.5512 (acc. 76.83%)
| Time: 34s
Epoch 48/120 | Train Loss: 0.3121 (acc. 86.80%) | Val Loss: 0.4064 (acc. 82.17%)
| Time: 34s
Epoch 49/120 | Train Loss: 0.3283 (acc. 86.20%) | Val Loss: 0.4151 (acc. 81.83%)
| Time: 34s
Epoch 50/120 | Train Loss: 0.2865 (acc. 87.75%) | Val Loss: 0.4047 (acc. 80.00%)
| Time: 34s
Epoch 51/120 | Train Loss: 0.2695 (acc. 89.45%) | Val Loss: 0.5261 (acc. 78.67%)
| Time: 34s
Epoch 52/120 | Train Loss: 0.2730 (acc. 88.40%) | Val Loss: 0.3803 (acc. 83.00%)
| Time: 34s
Epoch 53/120 | Train Loss: 0.2533 (acc. 89.05%) | Val Loss: 0.3699 (acc. 83.00%)
| Time: 34s
Epoch 54/120 | Train Loss: 0.2447 (acc. 90.15%) | Val Loss: 0.3862 (acc. 82.50%)
| Time: 34s
Epoch 55/120 | Train Loss: 0.2711 (acc. 88.95%) | Val Loss: 0.4081 (acc. 82.17%)
| Time: 34s
Epoch 56/120 | Train Loss: 0.2641 (acc. 88.65%) | Val Loss: 0.3790 (acc. 83.67%)
| Time: 34s
Epoch 57/120 | Train Loss: 0.2395 (acc. 90.30%) | Val Loss: 0.3818 (acc. 84.17%)
| Time: 34s
Epoch 58/120 | Train Loss: 0.2488 (acc. 89.30%) | Val Loss: 0.4039 (acc. 83.33%)
| Time: 34s
Epoch 59/120 | Train Loss: 0.2345 (acc. 89.45%) | Val Loss: 0.4069 (acc. 83.33%)
| Time: 34s
Epoch 60/120 | Train Loss: 0.2545 (acc. 89.45%) | Val Loss: 0.3925 (acc. 81.67%)
| Time: 34s
Epoch 61/120 | Train Loss: 0.2547 (acc. 89.15%) | Val Loss: 0.3998 (acc. 82.00%)
| Time: 34s
Epoch 62/120 | Train Loss: 0.2528 (acc. 89.35%) | Val Loss: 0.3963 (acc. 83.33%)
| Time: 34s
Epoch 63/120 | Train Loss: 0.2303 (acc. 90.40%) | Val Loss: 0.3564 (acc. 84.17%)
| Time: 34s
Epoch 64/120 | Train Loss: 0.2378 (acc. 89.85%) | Val Loss: 0.3902 (acc. 83.17%)
| Time: 34s
Epoch 65/120 | Train Loss: 0.2459 (acc. 90.00%) | Val Loss: 0.4037 (acc. 83.33%)
| Time: 34s
Epoch 66/120 | Train Loss: 0.2132 (acc. 91.40%) | Val Loss: 0.4060 (acc. 82.50%)
| Time: 34s
Epoch 67/120 | Train Loss: 0.2265 (acc. 90.70%) | Val Loss: 0.4332 (acc. 82.83%)
| Time: 34s
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Epoch 68/120 | Train Loss: 0.2146 (acc. 91.25%) | Val Loss: 0.4085 (acc. 82.83%)
| Time: 34s
Epoch 69/120 | Train Loss: 0.2202 (acc. 90.65%) | Val Loss: 0.3930 (acc. 83.83%)
| Time: 34s
Epoch 70/120 | Train Loss: 0.2231 (acc. 90.00%) | Val Loss: 0.3705 (acc. 82.83%)
| Time: 34s
Epoch 71/120 | Train Loss: 0.2257 (acc. 90.90%) | Val Loss: 0.5548 (acc. 79.50%)
| Time: 34s
Epoch 72/120 | Train Loss: 0.2224 (acc. 90.10%) | Val Loss: 0.3889 (acc. 85.33%)
| Time: 34s
Epoch 73/120 | Train Loss: 0.2189 (acc. 90.40%) | Val Loss: 0.3737 (acc. 82.83%)
| Time: 34s
Epoch 74/120 | Train Loss: 0.2150 (acc. 91.35%) | Val Loss: 0.3786 (acc. 85.00%)
| Time: 34s
Epoch 75/120 | Train Loss: 0.1934 (acc. 91.40%) | Val Loss: 0.4055 (acc. 84.50%)
| Time: 34s
Epoch 76/120 | Train Loss: 0.2077 (acc. 91.25%) | Val Loss: 0.3716 (acc. 83.33%)
| Time: 34s
Epoch 77/120 | Train Loss: 0.1775 (acc. 92.90%) | Val Loss: 0.3672 (acc. 85.33%)
| Time: 34s
Epoch 78/120 | Train Loss: 0.1895 (acc. 91.70%) | Val Loss: 0.3786 (acc. 85.17%)
| Time: 34s
Epoch 79/120 | Train Loss: 0.1848 (acc. 92.00%) | Val Loss: 0.3830 (acc. 84.50%)
| Time: 34s
Epoch 80/120 | Train Loss: 0.1781 (acc. 92.90%) | Val Loss: 0.3858 (acc. 84.50%)
| Time: 34s
Epoch 81/120 | Train Loss: 0.1880 (acc. 92.50%) | Val Loss: 0.3819 (acc. 84.33%)
| Time: 34s
Epoch 82/120 | Train Loss: 0.1884 (acc. 92.70%) | Val Loss: 0.4351 (acc. 84.17%)
| Time: 34s
Epoch 83/120 | Train Loss: 0.2066 (acc. 92.20%) | Val Loss: 0.4312 (acc. 84.50%)
| Time: 34s
Epoch 84/120 | Train Loss: 0.1839 (acc. 92.30%) | Val Loss: 0.3898 (acc. 84.67%)
| Time: 34s
Epoch 85/120 | Train Loss: 0.1813 (acc. 92.65%) | Val Loss: 0.4003 (acc. 84.67%)
| Time: 34s
Epoch 86/120 | Train Loss: 0.1831 (acc. 92.30%) | Val Loss: 0.3869 (acc. 84.67%)
| Time: 34s
Epoch 87/120 | Train Loss: 0.1765 (acc. 93.15%) | Val Loss: 0.3765 (acc. 84.50%)
| Time: 34s
Epoch 88/120 | Train Loss: 0.1671 (acc. 93.00%) | Val Loss: 0.3776 (acc. 84.17%)
| Time: 34s
Epoch 89/120 | Train Loss: 0.1641 (acc. 93.55%) | Val Loss: 0.3761 (acc. 85.50%)
| Time: 34s
Epoch 90/120 | Train Loss: 0.1715 (acc. 92.65%) | Val Loss: 0.4062 (acc. 84.83%)
| Time: 34s
Epoch 91/120 | Train Loss: 0.1762 (acc. 92.65%) | Val Loss: 0.3752 (acc. 85.67%)
| Time: 34s
Epoch 92/120 | Train Loss: 0.1673 (acc. 93.35%) | Val Loss: 0.4252 (acc. 83.67%)
| Time: 34s
Epoch 93/120 | Train Loss: 0.1655 (acc. 93.70%) | Val Loss: 0.3844 (acc. 85.33%)
| Time: 34s
Epoch 94/120 | Train Loss: 0.1607 (acc. 93.30%) | Val Loss: 0.3873 (acc. 85.83%)
| Time: 34s
Epoch 95/120 | Train Loss: 0.1577 (acc. 93.45%) | Val Loss: 0.3750 (acc. 84.67%)
| Time: 34s
Epoch 96/120 | Train Loss: 0.1712 (acc. 93.15%) | Val Loss: 0.3911 (acc. 85.67%)
| Time: 34s
Epoch 97/120 | Train Loss: 0.1462 (acc. 94.35%) | Val Loss: 0.3730 (acc. 85.67%)
| Time: 34s
Epoch 98/120 | Train Loss: 0.1576 (acc. 93.35%) | Val Loss: 0.4075 (acc. 84.67%)
| Time: 34s
Epoch 99/120 | Train Loss: 0.1636 (acc. 93.60%) | Val Loss: 0.3994 (acc. 85.17%)
| Time: 34s
Epoch 100/120 | Train Loss: 0.1412 (acc. 94.25%) | Val Loss: 0.4108 (acc.
85.17%) | Time: 34s
Epoch 101/120 | Train Loss: 0.1632 (acc. 93.05%) | Val Loss: 0.3921 (acc.
86.17%) | Time: 34s
```

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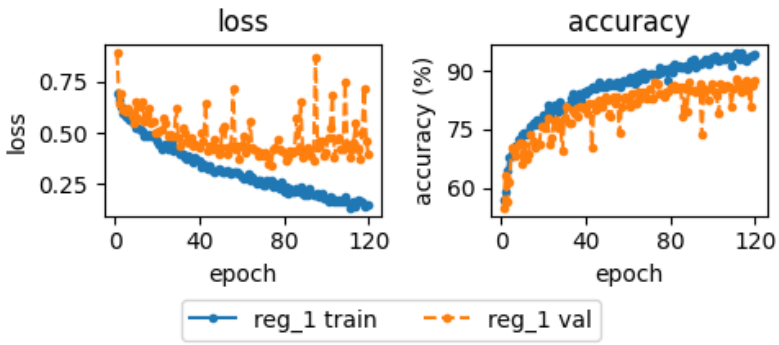
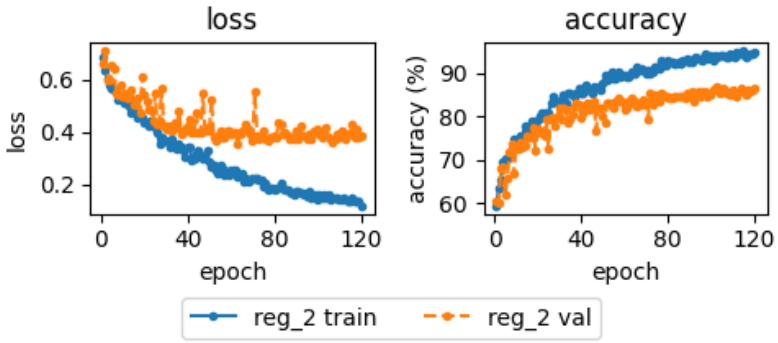
Epoch 102/120 | Train Loss: 0.1473 (acc. 94.10%) | Val Loss: 0.3816 (acc.
86.50%) | Time: 34s
Epoch 103/120 | Train Loss: 0.1616 (acc. 93.85%) | Val Loss: 0.3904 (acc.
86.83%) | Time: 34s
Epoch 104/120 | Train Loss: 0.1503 (acc. 94.05%) | Val Loss: 0.4195 (acc.
85.33%) | Time: 34s
Epoch 105/120 | Train Loss: 0.1607 (acc. 93.95%) | Val Loss: 0.3830 (acc.
86.17%) | Time: 34s
Epoch 106/120 | Train Loss: 0.1445 (acc. 94.15%) | Val Loss: 0.3717 (acc.
86.67%) | Time: 34s
Epoch 107/120 | Train Loss: 0.1506 (acc. 93.90%) | Val Loss: 0.3647 (acc.
85.50%) | Time: 34s
Epoch 108/120 | Train Loss: 0.1465 (acc. 93.80%) | Val Loss: 0.3742 (acc.
85.67%) | Time: 34s
Epoch 109/120 | Train Loss: 0.1480 (acc. 94.65%) | Val Loss: 0.3903 (acc.
85.17%) | Time: 34s
Epoch 110/120 | Train Loss: 0.1402 (acc. 93.95%) | Val Loss: 0.3808 (acc.
86.33%) | Time: 34s
Epoch 111/120 | Train Loss: 0.1420 (acc. 93.65%) | Val Loss: 0.4025 (acc.
85.33%) | Time: 34s
Epoch 112/120 | Train Loss: 0.1481 (acc. 94.80%) | Val Loss: 0.4009 (acc.
84.50%) | Time: 34s
Epoch 113/120 | Train Loss: 0.1451 (acc. 94.60%) | Val Loss: 0.3759 (acc.
85.83%) | Time: 34s
Epoch 114/120 | Train Loss: 0.1347 (acc. 94.50%) | Val Loss: 0.3902 (acc.
86.50%) | Time: 34s
Epoch 115/120 | Train Loss: 0.1350 (acc. 95.25%) | Val Loss: 0.3958 (acc.
85.83%) | Time: 34s
Epoch 116/120 | Train Loss: 0.1492 (acc. 93.60%) | Val Loss: 0.4291 (acc.
85.17%) | Time: 34s
Epoch 117/120 | Train Loss: 0.1390 (acc. 94.25%) | Val Loss: 0.3823 (acc.
86.33%) | Time: 35s
Epoch 118/120 | Train Loss: 0.1388 (acc. 94.50%) | Val Loss: 0.4105 (acc.
85.83%) | Time: 34s
Epoch 119/120 | Train Loss: 0.1387 (acc. 94.65%) | Val Loss: 0.3825 (acc.
86.17%) | Time: 34s
Epoch 120/120 | Train Loss: 0.1183 (acc. 94.95%) | Val Loss: 0.3888 (acc.
86.50%) | Time: 34s
Training Time: 4112s
```





0.9.1 Adding one more convolutional layer

[22]:
```
net_config2 = {**default_net_config,
    "cv_layers": [
        {"out_channels": 64, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": True},
        {"out_channels": 128, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 256, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 512, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 512, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
    ],
    "fc_layers": [
        {"out_features": 512, "batch_norm": True, "dropout_rate": 0.4},
        {"out_features": 256, "batch_norm": True, "dropout_rate": 0.2},
    ],
}

configs2 = [
    {**default_config, "label": "reg_3", "net_config": net_config2},
    {**default_config, "label": "reg_4", "net_config": net_config2, "train_config": train_config1}
]

results = result_handler(configs2, device)
plot_scores(results)
```

```
Experiment: reg_3
Epoch 1/120 | Train Loss: 0.7206 (acc. 55.15%) | Val Loss: 0.7543 (acc. 56.83%)
| Time: 67s
Epoch 2/120 | Train Loss: 0.6802 (acc. 57.90%) | Val Loss: 0.7889 (acc. 58.50%)
| Time: 67s
Epoch 3/120 | Train Loss: 0.6636 (acc. 60.65%) | Val Loss: 0.6234 (acc. 63.00%)
| Time: 67s
Epoch 4/120 | Train Loss: 0.6367 (acc. 63.45%) | Val Loss: 0.5956 (acc. 68.83%)
| Time: 67s
Epoch 5/120 | Train Loss: 0.6149 (acc. 66.10%) | Val Loss: 0.6728 (acc. 61.50%)
| Time: 67s
Epoch 6/120 | Train Loss: 0.6022 (acc. 66.60%) | Val Loss: 0.6197 (acc. 65.00%)
| Time: 67s
Epoch 7/120 | Train Loss: 0.5728 (acc. 70.70%) | Val Loss: 0.5960 (acc. 68.67%)
| Time: 67s
Epoch 8/120 | Train Loss: 0.5657 (acc. 71.15%) | Val Loss: 0.7474 (acc. 61.00%)
| Time: 67s
```

```
Epoch 9/120 | Train Loss: 0.5561 (acc. 71.15%) | Val Loss: 0.5889 (acc. 70.33%)
| Time: 67s
Epoch 10/120 | Train Loss: 0.5503 (acc. 72.65%) | Val Loss: 0.5609 (acc. 71.17%)
| Time: 67s
Epoch 11/120 | Train Loss: 0.5269 (acc. 72.90%) | Val Loss: 0.5995 (acc. 64.33%)
| Time: 67s
Epoch 12/120 | Train Loss: 0.5106 (acc. 74.65%) | Val Loss: 0.5758 (acc. 72.50%)
| Time: 67s
Epoch 13/120 | Train Loss: 0.5094 (acc. 75.35%) | Val Loss: 0.5395 (acc. 74.83%)
| Time: 67s
Epoch 14/120 | Train Loss: 0.4990 (acc. 75.45%) | Val Loss: 0.5470 (acc. 74.00%)
| Time: 67s
Epoch 15/120 | Train Loss: 0.4923 (acc. 76.70%) | Val Loss: 0.6012 (acc. 68.67%)
| Time: 67s
Epoch 16/120 | Train Loss: 0.4936 (acc. 76.90%) | Val Loss: 0.4990 (acc. 74.83%)
| Time: 67s
Epoch 17/120 | Train Loss: 0.4631 (acc. 79.30%) | Val Loss: 0.5559 (acc. 72.17%)
| Time: 67s
Epoch 18/120 | Train Loss: 0.4567 (acc. 78.95%) | Val Loss: 0.5044 (acc. 73.50%)
| Time: 67s
Epoch 19/120 | Train Loss: 0.4417 (acc. 78.95%) | Val Loss: 0.5147 (acc. 75.83%)
| Time: 67s
Epoch 20/120 | Train Loss: 0.4621 (acc. 78.85%) | Val Loss: 0.4939 (acc. 78.17%)
| Time: 67s
Epoch 21/120 | Train Loss: 0.4443 (acc. 79.30%) | Val Loss: 0.5131 (acc. 75.17%)
| Time: 67s
Epoch 22/120 | Train Loss: 0.4118 (acc. 80.95%) | Val Loss: 0.6186 (acc. 73.50%)
| Time: 67s
Epoch 23/120 | Train Loss: 0.4778 (acc. 76.40%) | Val Loss: 0.4806 (acc. 78.00%)
| Time: 67s
Epoch 24/120 | Train Loss: 0.4142 (acc. 80.80%) | Val Loss: 0.4869 (acc. 77.17%)
| Time: 67s
Epoch 25/120 | Train Loss: 0.4148 (acc. 80.40%) | Val Loss: 0.4357 (acc. 78.00%)
| Time: 67s
Epoch 26/120 | Train Loss: 0.4125 (acc. 81.50%) | Val Loss: 0.4279 (acc. 81.17%)
| Time: 67s
Epoch 27/120 | Train Loss: 0.3962 (acc. 81.20%) | Val Loss: 0.4663 (acc. 79.33%)
| Time: 67s
Epoch 28/120 | Train Loss: 0.3772 (acc. 84.10%) | Val Loss: 0.4881 (acc. 78.50%)
| Time: 67s
Epoch 29/120 | Train Loss: 0.3432 (acc. 84.60%) | Val Loss: 0.4451 (acc. 81.00%)
| Time: 67s
Epoch 30/120 | Train Loss: 0.3646 (acc. 83.65%) | Val Loss: 0.4301 (acc. 81.17%)
| Time: 67s
Epoch 31/120 | Train Loss: 0.3487 (acc. 84.25%) | Val Loss: 0.5731 (acc. 76.00%)
| Time: 67s
Epoch 32/120 | Train Loss: 0.3363 (acc. 84.75%) | Val Loss: 0.5071 (acc. 76.17%)
| Time: 67s
Epoch 33/120 | Train Loss: 0.3626 (acc. 83.65%) | Val Loss: 0.3897 (acc. 82.50%)
| Time: 67s
Epoch 34/120 | Train Loss: 0.3289 (acc. 85.75%) | Val Loss: 0.3771 (acc. 86.00%)
| Time: 67s
Epoch 35/120 | Train Loss: 0.3029 (acc. 87.25%) | Val Loss: 0.4087 (acc. 84.00%)
| Time: 67s
Epoch 36/120 | Train Loss: 0.3089 (acc. 86.50%) | Val Loss: 0.3707 (acc. 84.00%)
| Time: 67s
Epoch 37/120 | Train Loss: 0.3221 (acc. 86.55%) | Val Loss: 0.4977 (acc. 80.00%)
| Time: 67s
Epoch 38/120 | Train Loss: 0.2892 (acc. 87.15%) | Val Loss: 0.3727 (acc. 85.17%)
| Time: 67s
Epoch 39/120 | Train Loss: 0.2993 (acc. 87.10%) | Val Loss: 0.4675 (acc. 81.17%)
| Time: 67s
Epoch 40/120 | Train Loss: 0.3062 (acc. 86.55%) | Val Loss: 0.3523 (acc. 84.83%)
| Time: 67s
Epoch 41/120 | Train Loss: 0.2927 (acc. 87.40%) | Val Loss: 0.3551 (acc. 83.83%)
| Time: 67s
Epoch 42/120 | Train Loss: 0.2845 (acc. 87.90%) | Val Loss: 0.3976 (acc. 83.50%)
| Time: 67s
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Epoch 43/120 | Train Loss: 0.2866 (acc. 88.35%) | Val Loss: 0.6133 (acc. 78.50%)
| Time: 67s
Epoch 44/120 | Train Loss: 0.2843 (acc. 88.35%) | Val Loss: 0.3339 (acc. 85.50%)
| Time: 67s
Epoch 45/120 | Train Loss: 0.2659 (acc. 89.25%) | Val Loss: 0.3488 (acc. 84.67%)
| Time: 67s
Epoch 46/120 | Train Loss: 0.2761 (acc. 88.70%) | Val Loss: 0.3933 (acc. 86.33%)
| Time: 67s
Epoch 47/120 | Train Loss: 0.2852 (acc. 87.85%) | Val Loss: 0.3365 (acc. 84.83%)
| Time: 67s
Epoch 48/120 | Train Loss: 0.2639 (acc. 88.00%) | Val Loss: 0.3755 (acc. 84.00%)
| Time: 67s
Epoch 49/120 | Train Loss: 0.2497 (acc. 89.95%) | Val Loss: 0.7493 (acc. 73.17%)
| Time: 67s
Epoch 50/120 | Train Loss: 0.2600 (acc. 89.60%) | Val Loss: 0.2911 (acc. 88.33%)
| Time: 67s
Epoch 51/120 | Train Loss: 0.2528 (acc. 89.40%) | Val Loss: 0.3326 (acc. 86.00%)
| Time: 67s
Epoch 52/120 | Train Loss: 0.2187 (acc. 90.60%) | Val Loss: 0.4604 (acc. 82.83%)
| Time: 67s
Epoch 53/120 | Train Loss: 0.2296 (acc. 90.75%) | Val Loss: 0.3377 (acc. 86.00%)
| Time: 67s
Epoch 54/120 | Train Loss: 0.2347 (acc. 90.05%) | Val Loss: 0.4674 (acc. 82.50%)
| Time: 67s
Epoch 55/120 | Train Loss: 0.2162 (acc. 90.70%) | Val Loss: 0.3766 (acc. 85.00%)
| Time: 67s
Epoch 56/120 | Train Loss: 0.1940 (acc. 92.00%) | Val Loss: 0.3656 (acc. 86.33%)
| Time: 67s
Epoch 57/120 | Train Loss: 0.1849 (acc. 92.70%) | Val Loss: 0.3781 (acc. 85.67%)
| Time: 67s
Epoch 58/120 | Train Loss: 0.2236 (acc. 90.80%) | Val Loss: 0.7648 (acc. 75.83%)
| Time: 67s
Epoch 59/120 | Train Loss: 0.1955 (acc. 91.55%) | Val Loss: 0.4405 (acc. 84.00%)
| Time: 67s
Epoch 60/120 | Train Loss: 0.2079 (acc. 91.60%) | Val Loss: 0.3520 (acc. 87.00%)
| Time: 67s
Epoch 61/120 | Train Loss: 0.2027 (acc. 91.70%) | Val Loss: 0.3833 (acc. 86.17%)
| Time: 67s
Epoch 62/120 | Train Loss: 0.2129 (acc. 90.40%) | Val Loss: 0.3591 (acc. 86.00%)
| Time: 67s
Epoch 63/120 | Train Loss: 0.1757 (acc. 92.80%) | Val Loss: 0.3098 (acc. 88.33%)
| Time: 67s
Epoch 64/120 | Train Loss: 0.1723 (acc. 92.95%) | Val Loss: 0.3120 (acc. 87.50%)
| Time: 67s
Epoch 65/120 | Train Loss: 0.1906 (acc. 92.45%) | Val Loss: 0.3507 (acc. 86.83%)
| Time: 67s
Epoch 66/120 | Train Loss: 0.1713 (acc. 92.95%) | Val Loss: 0.3310 (acc. 87.17%)
| Time: 67s
Epoch 67/120 | Train Loss: 0.1631 (acc. 93.30%) | Val Loss: 0.2971 (acc. 89.00%)
| Time: 67s
Epoch 68/120 | Train Loss: 0.1673 (acc. 93.75%) | Val Loss: 0.3352 (acc. 88.67%)
| Time: 67s
Epoch 69/120 | Train Loss: 0.1557 (acc. 93.70%) | Val Loss: 0.4033 (acc. 87.17%)
| Time: 67s
Epoch 70/120 | Train Loss: 0.1711 (acc. 93.10%) | Val Loss: 0.3080 (acc. 89.67%)
| Time: 67s
Epoch 71/120 | Train Loss: 0.1537 (acc. 93.90%) | Val Loss: 0.3449 (acc. 86.83%)
| Time: 67s
Epoch 72/120 | Train Loss: 0.1642 (acc. 93.20%) | Val Loss: 0.3177 (acc. 88.00%)
| Time: 67s
Epoch 73/120 | Train Loss: 0.1374 (acc. 94.15%) | Val Loss: 0.2684 (acc. 88.83%)
| Time: 67s
Epoch 74/120 | Train Loss: 0.1266 (acc. 95.05%) | Val Loss: 0.2855 (acc. 88.83%)
| Time: 67s
Epoch 75/120 | Train Loss: 0.1609 (acc. 93.70%) | Val Loss: 0.3289 (acc. 89.33%)
| Time: 67s
Epoch 76/120 | Train Loss: 0.1678 (acc. 92.65%) | Val Loss: 0.2932 (acc. 88.17%)
| Time: 67s
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Epoch 77/120 | Train Loss: 0.1437 (acc. 94.80%) | Val Loss: 0.4449 (acc. 85.17%)
| Time: 67s
Epoch 78/120 | Train Loss: 0.1824 (acc. 92.70%) | Val Loss: 0.3284 (acc. 87.00%)
| Time: 67s
Epoch 79/120 | Train Loss: 0.1366 (acc. 94.65%) | Val Loss: 0.3170 (acc. 87.33%)
| Time: 67s
Epoch 80/120 | Train Loss: 0.1377 (acc. 94.35%) | Val Loss: 0.3692 (acc. 87.50%)
| Time: 67s
Epoch 81/120 | Train Loss: 0.1326 (acc. 95.30%) | Val Loss: 0.2757 (acc. 87.67%)
| Time: 67s
Epoch 82/120 | Train Loss: 0.1139 (acc. 95.55%) | Val Loss: 0.3848 (acc. 87.17%)
| Time: 68s
Epoch 83/120 | Train Loss: 0.1520 (acc. 93.85%) | Val Loss: 0.3718 (acc. 86.00%)
| Time: 67s
Epoch 84/120 | Train Loss: 0.1272 (acc. 95.35%) | Val Loss: 0.3369 (acc. 87.00%)
| Time: 67s
Epoch 85/120 | Train Loss: 0.1166 (acc. 95.50%) | Val Loss: 0.2958 (acc. 89.67%)
| Time: 67s
Epoch 86/120 | Train Loss: 0.1233 (acc. 95.45%) | Val Loss: 0.3126 (acc. 88.50%)
| Time: 67s
Epoch 87/120 | Train Loss: 0.1655 (acc. 94.05%) | Val Loss: 0.3738 (acc. 87.67%)
| Time: 67s
Epoch 88/120 | Train Loss: 0.1296 (acc. 94.65%) | Val Loss: 0.2697 (acc. 90.00%)
| Time: 67s
Epoch 89/120 | Train Loss: 0.1159 (acc. 95.75%) | Val Loss: 0.5481 (acc. 85.00%)
| Time: 67s
Epoch 90/120 | Train Loss: 0.1388 (acc. 94.20%) | Val Loss: 0.4467 (acc. 87.17%)
| Time: 67s
Epoch 91/120 | Train Loss: 0.1342 (acc. 94.90%) | Val Loss: 0.2801 (acc. 90.83%)
| Time: 67s
Epoch 92/120 | Train Loss: 0.1434 (acc. 94.15%) | Val Loss: 0.3517 (acc. 88.50%)
| Time: 67s
Epoch 93/120 | Train Loss: 0.1240 (acc. 95.05%) | Val Loss: 0.2855 (acc. 89.83%)
| Time: 67s
Epoch 94/120 | Train Loss: 0.0916 (acc. 96.35%) | Val Loss: 0.3218 (acc. 90.33%)
| Time: 67s
Epoch 95/120 | Train Loss: 0.0975 (acc. 96.00%) | Val Loss: 0.5325 (acc. 85.17%)
| Time: 67s
Epoch 96/120 | Train Loss: 0.1017 (acc. 96.30%) | Val Loss: 0.3723 (acc. 88.00%)
| Time: 67s
Epoch 97/120 | Train Loss: 0.1237 (acc. 94.30%) | Val Loss: 0.2634 (acc. 91.00%)
| Time: 67s
Epoch 98/120 | Train Loss: 0.1012 (acc. 95.90%) | Val Loss: 0.3041 (acc. 90.33%)
| Time: 67s
Epoch 99/120 | Train Loss: 0.1016 (acc. 96.25%) | Val Loss: 0.3535 (acc. 88.33%)
| Time: 67s
Epoch 100/120 | Train Loss: 0.0990 (acc. 95.95%) | Val Loss: 0.2743 (acc.
91.17%) | Time: 67s
Epoch 101/120 | Train Loss: 0.1105 (acc. 95.70%) | Val Loss: 0.2681 (acc.
90.33%) | Time: 67s
Epoch 102/120 | Train Loss: 0.1064 (acc. 96.00%) | Val Loss: 0.4660 (acc.
88.00%) | Time: 67s
Epoch 103/120 | Train Loss: 0.1173 (acc. 95.05%) | Val Loss: 0.2934 (acc.
89.83%) | Time: 67s
Epoch 104/120 | Train Loss: 0.1039 (acc. 95.80%) | Val Loss: 0.2386 (acc.
91.50%) | Time: 67s
Epoch 105/120 | Train Loss: 0.1126 (acc. 96.50%) | Val Loss: 0.3063 (acc.
90.83%) | Time: 67s
Epoch 106/120 | Train Loss: 0.1080 (acc. 96.30%) | Val Loss: 0.3350 (acc.
89.67%) | Time: 67s
Epoch 107/120 | Train Loss: 0.0932 (acc. 96.20%) | Val Loss: 0.2827 (acc.
90.33%) | Time: 67s
Epoch 108/120 | Train Loss: 0.0998 (acc. 96.50%) | Val Loss: 0.3170 (acc.
89.67%) | Time: 67s
Epoch 109/120 | Train Loss: 0.1282 (acc. 95.30%) | Val Loss: 0.3020 (acc.
89.50%) | Time: 67s
Epoch 110/120 | Train Loss: 0.0889 (acc. 96.60%) | Val Loss: 0.4448 (acc.
85.83%) | Time: 67s
```

```
Epoch 111/120 | Train Loss: 0.0856 (acc. 96.65%) | Val Loss: 0.2558 (acc.
90.00%) | Time: 67s
Epoch 112/120 | Train Loss: 0.0883 (acc. 96.85%) | Val Loss: 0.2908 (acc.
90.17%) | Time: 67s
Epoch 113/120 | Train Loss: 0.0900 (acc. 96.55%) | Val Loss: 0.2865 (acc.
90.67%) | Time: 67s
Epoch 114/120 | Train Loss: 0.0760 (acc. 97.10%) | Val Loss: 0.2750 (acc.
91.33%) | Time: 67s
Epoch 115/120 | Train Loss: 0.0827 (acc. 96.75%) | Val Loss: 0.2618 (acc.
92.17%) | Time: 67s
Epoch 116/120 | Train Loss: 0.1015 (acc. 96.25%) | Val Loss: 0.2775 (acc.
90.33%) | Time: 67s
Epoch 117/120 | Train Loss: 0.0798 (acc. 96.95%) | Val Loss: 0.3634 (acc.
88.17%) | Time: 67s
Epoch 118/120 | Train Loss: 0.0842 (acc. 96.95%) | Val Loss: 0.2854 (acc.
90.67%) | Time: 67s
Epoch 119/120 | Train Loss: 0.0669 (acc. 97.25%) | Val Loss: 0.2490 (acc.
91.83%) | Time: 67s
Epoch 120/120 | Train Loss: 0.0740 (acc. 97.15%) | Val Loss: 0.3117 (acc.
91.67%) | Time: 67s
Training Time: 8018s

Experiment: reg_4
Epoch 1/120 | Train Loss: 0.7047 (acc. 55.85%) | Val Loss: 0.6922 (acc. 62.00%)
| Time: 67s
Epoch 2/120 | Train Loss: 0.6393 (acc. 63.35%) | Val Loss: 0.6482 (acc. 59.83%)
| Time: 67s
Epoch 3/120 | Train Loss: 0.6206 (acc. 66.35%) | Val Loss: 0.6200 (acc. 64.17%)
| Time: 67s
Epoch 4/120 | Train Loss: 0.5876 (acc. 68.50%) | Val Loss: 0.6980 (acc. 62.17%)
| Time: 67s
Epoch 5/120 | Train Loss: 0.5801 (acc. 69.85%) | Val Loss: 0.6019 (acc. 66.17%)
| Time: 67s
Epoch 6/120 | Train Loss: 0.5693 (acc. 68.80%) | Val Loss: 0.5931 (acc. 68.17%)
| Time: 67s
Epoch 7/120 | Train Loss: 0.5562 (acc. 72.05%) | Val Loss: 0.5676 (acc. 69.17%)
| Time: 67s
Epoch 8/120 | Train Loss: 0.5508 (acc. 73.50%) | Val Loss: 0.6502 (acc. 65.50%)
| Time: 67s
Epoch 9/120 | Train Loss: 0.5197 (acc. 73.90%) | Val Loss: 0.5756 (acc. 72.00%)
| Time: 67s
Epoch 10/120 | Train Loss: 0.5229 (acc. 74.70%) | Val Loss: 0.6711 (acc. 62.50%)
| Time: 67s
Epoch 11/120 | Train Loss: 0.5215 (acc. 75.45%) | Val Loss: 0.5439 (acc. 74.50%)
| Time: 67s
Epoch 12/120 | Train Loss: 0.4906 (acc. 76.55%) | Val Loss: 0.5044 (acc. 76.67%)
| Time: 67s
Epoch 13/120 | Train Loss: 0.4835 (acc. 77.25%) | Val Loss: 0.4873 (acc. 75.83%)
| Time: 67s
Epoch 14/120 | Train Loss: 0.4614 (acc. 79.60%) | Val Loss: 0.6430 (acc. 69.33%)
| Time: 67s
Epoch 15/120 | Train Loss: 0.4500 (acc. 79.40%) | Val Loss: 0.6143 (acc. 72.00%)
| Time: 67s
Epoch 16/120 | Train Loss: 0.4687 (acc. 78.00%) | Val Loss: 0.5107 (acc. 77.00%)
| Time: 67s
Epoch 17/120 | Train Loss: 0.4408 (acc. 79.45%) | Val Loss: 0.5049 (acc. 75.50%)
| Time: 67s
Epoch 18/120 | Train Loss: 0.4183 (acc. 81.80%) | Val Loss: 0.4865 (acc. 76.50%)
| Time: 67s
Epoch 19/120 | Train Loss: 0.4158 (acc. 81.90%) | Val Loss: 0.4882 (acc. 78.50%)
| Time: 67s
Epoch 20/120 | Train Loss: 0.3973 (acc. 81.45%) | Val Loss: 0.5123 (acc. 77.67%)
| Time: 67s
Epoch 21/120 | Train Loss: 0.3712 (acc. 83.45%) | Val Loss: 0.4798 (acc. 78.33%)
| Time: 67s
Epoch 22/120 | Train Loss: 0.4021 (acc. 83.05%) | Val Loss: 0.5558 (acc. 74.17%)
| Time: 67s
Epoch 23/120 | Train Loss: 0.3716 (acc. 83.20%) | Val Loss: 0.4363 (acc. 81.33%)
```

```
| Time: 67s
Epoch 24/120 | Train Loss: 0.3868 (acc. 81.95%) | Val Loss: 0.7918 (acc. 69.50%)
| Time: 67s
Epoch 25/120 | Train Loss: 0.3843 (acc. 82.60%) | Val Loss: 0.4914 (acc. 79.17%)
| Time: 67s
Epoch 26/120 | Train Loss: 0.3303 (acc. 86.25%) | Val Loss: 0.3908 (acc. 81.83%)
| Time: 67s
Epoch 27/120 | Train Loss: 0.3031 (acc. 86.35%) | Val Loss: 0.4620 (acc. 81.67%)
| Time: 67s
Epoch 28/120 | Train Loss: 0.2944 (acc. 87.65%) | Val Loss: 0.4229 (acc. 80.83%)
| Time: 67s
Epoch 29/120 | Train Loss: 0.3225 (acc. 85.80%) | Val Loss: 0.3870 (acc. 83.83%)
| Time: 67s
Epoch 30/120 | Train Loss: 0.3118 (acc. 87.05%) | Val Loss: 0.3783 (acc. 83.17%)
| Time: 67s
Epoch 31/120 | Train Loss: 0.2989 (acc. 86.45%) | Val Loss: 0.3883 (acc. 84.67%)
| Time: 67s
Epoch 32/120 | Train Loss: 0.2765 (acc. 88.50%) | Val Loss: 0.3599 (acc. 85.33%)
| Time: 67s
Epoch 33/120 | Train Loss: 0.2972 (acc. 87.10%) | Val Loss: 0.3706 (acc. 84.83%)
| Time: 67s
Epoch 34/120 | Train Loss: 0.2757 (acc. 89.10%) | Val Loss: 0.3927 (acc. 83.50%)
| Time: 68s
Epoch 35/120 | Train Loss: 0.2514 (acc. 90.20%) | Val Loss: 0.3298 (acc. 86.00%)
| Time: 68s
Epoch 36/120 | Train Loss: 0.2860 (acc. 87.55%) | Val Loss: 0.3622 (acc. 85.00%)
| Time: 67s
Epoch 37/120 | Train Loss: 0.2438 (acc. 89.35%) | Val Loss: 0.3580 (acc. 85.50%)
| Time: 67s
Epoch 38/120 | Train Loss: 0.2286 (acc. 90.60%) | Val Loss: 0.3856 (acc. 84.00%)
| Time: 67s
Epoch 39/120 | Train Loss: 0.2383 (acc. 90.10%) | Val Loss: 0.3534 (acc. 85.33%)
| Time: 67s
Epoch 40/120 | Train Loss: 0.2089 (acc. 91.50%) | Val Loss: 0.3663 (acc. 85.00%)
| Time: 68s
Epoch 41/120 | Train Loss: 0.2168 (acc. 91.05%) | Val Loss: 0.3586 (acc. 84.17%)
| Time: 67s
Epoch 42/120 | Train Loss: 0.2216 (acc. 90.95%) | Val Loss: 0.4370 (acc. 84.33%)
| Time: 70s
Epoch 43/120 | Train Loss: 0.2208 (acc. 90.60%) | Val Loss: 0.3776 (acc. 85.50%)
| Time: 67s
Epoch 44/120 | Train Loss: 0.2285 (acc. 90.15%) | Val Loss: 0.3789 (acc. 84.67%)
| Time: 67s
Epoch 45/120 | Train Loss: 0.2159 (acc. 90.85%) | Val Loss: 0.4297 (acc. 86.50%)
| Time: 67s
Epoch 46/120 | Train Loss: 0.2089 (acc. 91.30%) | Val Loss: 0.3336 (acc. 86.67%)
| Time: 67s
Epoch 47/120 | Train Loss: 0.1955 (acc. 92.10%) | Val Loss: 0.5513 (acc. 81.50%)
| Time: 67s
Epoch 48/120 | Train Loss: 0.2087 (acc. 91.45%) | Val Loss: 0.3444 (acc. 86.33%)
| Time: 67s
Epoch 49/120 | Train Loss: 0.2035 (acc. 91.45%) | Val Loss: 0.4692 (acc. 85.33%)
| Time: 67s
Epoch 50/120 | Train Loss: 0.1823 (acc. 91.95%) | Val Loss: 0.3462 (acc. 87.33%)
| Time: 67s
Epoch 51/120 | Train Loss: 0.1732 (acc. 93.45%) | Val Loss: 0.3008 (acc. 89.00%)
| Time: 67s
Epoch 52/120 | Train Loss: 0.1742 (acc. 92.75%) | Val Loss: 0.3278 (acc. 87.33%)
| Time: 67s
Epoch 53/120 | Train Loss: 0.1615 (acc. 93.55%) | Val Loss: 0.3221 (acc. 88.00%)
| Time: 67s
Epoch 54/120 | Train Loss: 0.1429 (acc. 94.00%) | Val Loss: 0.3693 (acc. 87.00%)
| Time: 67s
Epoch 55/120 | Train Loss: 0.1290 (acc. 94.85%) | Val Loss: 0.4544 (acc. 86.17%)
| Time: 67s
Epoch 56/120 | Train Loss: 0.1425 (acc. 94.20%) | Val Loss: 0.3564 (acc. 87.17%)
| Time: 67s
Epoch 57/120 | Train Loss: 0.1544 (acc. 93.95%) | Val Loss: 0.3282 (acc. 88.33%)
```

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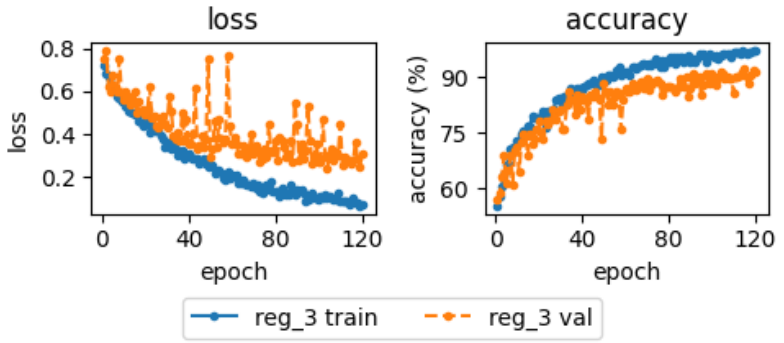
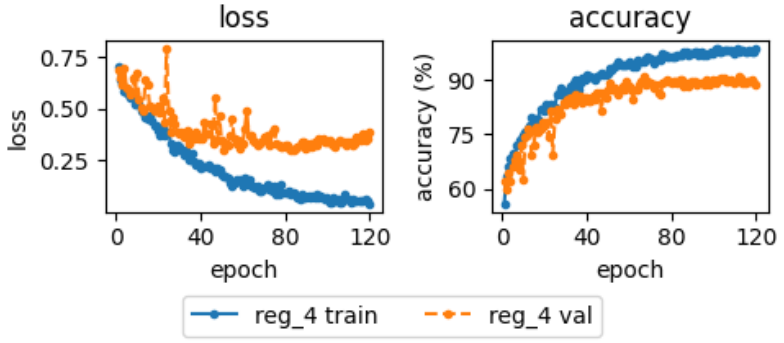
| Time: 67s
Epoch 58/120 | Train Loss: 0.1483 (acc. 94.25%) | Val Loss: 0.3485 (acc. 87.33%)
| Time: 67s
Epoch 59/120 | Train Loss: 0.1574 (acc. 93.95%) | Val Loss: 0.3070 (acc. 89.50%)
| Time: 67s
Epoch 60/120 | Train Loss: 0.1253 (acc. 95.10%) | Val Loss: 0.3293 (acc. 88.17%)
| Time: 67s
Epoch 61/120 | Train Loss: 0.1670 (acc. 94.75%) | Val Loss: 0.4046 (acc. 87.50%)
| Time: 67s
Epoch 62/120 | Train Loss: 0.1581 (acc. 93.65%) | Val Loss: 0.4881 (acc. 84.83%)
| Time: 67s
Epoch 63/120 | Train Loss: 0.1563 (acc. 93.85%) | Val Loss: 0.3700 (acc. 87.50%)
| Time: 67s
Epoch 64/120 | Train Loss: 0.1228 (acc. 95.65%) | Val Loss: 0.3689 (acc. 87.33%)
| Time: 67s
Epoch 65/120 | Train Loss: 0.1254 (acc. 95.05%) | Val Loss: 0.3460 (acc. 88.83%)
| Time: 67s
Epoch 66/120 | Train Loss: 0.1189 (acc. 95.20%) | Val Loss: 0.3387 (acc. 89.50%)
| Time: 67s
Epoch 67/120 | Train Loss: 0.1289 (acc. 95.00%) | Val Loss: 0.3249 (acc. 91.00%)
| Time: 67s
Epoch 68/120 | Train Loss: 0.1008 (acc. 96.10%) | Val Loss: 0.3334 (acc. 88.83%)
| Time: 67s
Epoch 69/120 | Train Loss: 0.0984 (acc. 96.20%) | Val Loss: 0.3412 (acc. 89.50%)
| Time: 67s
Epoch 70/120 | Train Loss: 0.1160 (acc. 95.95%) | Val Loss: 0.3617 (acc. 89.17%)
| Time: 67s
Epoch 71/120 | Train Loss: 0.1178 (acc. 95.65%) | Val Loss: 0.3561 (acc. 88.67%)
| Time: 67s
Epoch 72/120 | Train Loss: 0.1307 (acc. 94.50%) | Val Loss: 0.3677 (acc. 87.83%)
| Time: 67s
Epoch 73/120 | Train Loss: 0.1076 (acc. 95.65%) | Val Loss: 0.3262 (acc. 88.83%)
| Time: 67s
Epoch 74/120 | Train Loss: 0.1048 (acc. 96.10%) | Val Loss: 0.3870 (acc. 86.33%)
| Time: 67s
Epoch 75/120 | Train Loss: 0.1219 (acc. 95.70%) | Val Loss: 0.4031 (acc. 86.17%)
| Time: 67s
Epoch 76/120 | Train Loss: 0.0832 (acc. 97.15%) | Val Loss: 0.3331 (acc. 89.33%)
| Time: 67s
Epoch 77/120 | Train Loss: 0.0879 (acc. 96.85%) | Val Loss: 0.3198 (acc. 89.50%)
| Time: 67s
Epoch 78/120 | Train Loss: 0.1347 (acc. 96.40%) | Val Loss: 0.3182 (acc. 90.00%)
| Time: 67s
Epoch 79/120 | Train Loss: 0.0964 (acc. 96.50%) | Val Loss: 0.3149 (acc. 89.50%)
| Time: 67s
Epoch 80/120 | Train Loss: 0.0950 (acc. 96.25%) | Val Loss: 0.3244 (acc. 89.33%)
| Time: 67s
Epoch 81/120 | Train Loss: 0.0960 (acc. 96.45%) | Val Loss: 0.3273 (acc. 89.67%)
| Time: 67s
Epoch 82/120 | Train Loss: 0.0992 (acc. 96.45%) | Val Loss: 0.3052 (acc. 89.50%)
| Time: 67s
Epoch 83/120 | Train Loss: 0.0868 (acc. 97.05%) | Val Loss: 0.3015 (acc. 89.00%)
| Time: 67s
Epoch 84/120 | Train Loss: 0.0902 (acc. 96.65%) | Val Loss: 0.2983 (acc. 90.00%)
| Time: 67s
Epoch 85/120 | Train Loss: 0.0824 (acc. 96.75%) | Val Loss: 0.3060 (acc. 90.00%)
| Time: 67s
Epoch 86/120 | Train Loss: 0.0683 (acc. 97.70%) | Val Loss: 0.3179 (acc. 88.17%)
| Time: 67s
Epoch 87/120 | Train Loss: 0.0651 (acc. 97.65%) | Val Loss: 0.3229 (acc. 89.17%)
| Time: 67s
Epoch 88/120 | Train Loss: 0.0832 (acc. 96.70%) | Val Loss: 0.3387 (acc. 88.33%)
| Time: 67s
Epoch 89/120 | Train Loss: 0.0677 (acc. 97.15%) | Val Loss: 0.3406 (acc. 89.17%)
| Time: 67s
Epoch 90/120 | Train Loss: 0.0668 (acc. 97.25%) | Val Loss: 0.3052 (acc. 89.67%)
| Time: 67s
Epoch 91/120 | Train Loss: 0.0771 (acc. 97.55%) | Val Loss: 0.3154 (acc. 89.83%)
```

```
| Time: 67s
Epoch 92/120 | Train Loss: 0.0714 (acc. 97.60%) | Val Loss: 0.3325 (acc. 88.83%)
| Time: 67s
Epoch 93/120 | Train Loss: 0.0774 (acc. 97.05%) | Val Loss: 0.3195 (acc. 89.17%)
| Time: 67s
Epoch 94/120 | Train Loss: 0.0665 (acc. 97.60%) | Val Loss: 0.3369 (acc. 89.33%)
| Time: 67s
Epoch 95/120 | Train Loss: 0.0829 (acc. 96.95%) | Val Loss: 0.3272 (acc. 89.33%)
| Time: 67s
Epoch 96/120 | Train Loss: 0.0704 (acc. 97.35%) | Val Loss: 0.3520 (acc. 88.83%)
| Time: 67s
Epoch 97/120 | Train Loss: 0.0814 (acc. 96.75%) | Val Loss: 0.3474 (acc. 90.00%)
| Time: 67s
Epoch 98/120 | Train Loss: 0.0725 (acc. 97.10%) | Val Loss: 0.3524 (acc. 88.67%)
| Time: 67s
Epoch 99/120 | Train Loss: 0.0598 (acc. 97.70%) | Val Loss: 0.3396 (acc. 89.50%)
| Time: 67s
Epoch 100/120 | Train Loss: 0.0665 (acc. 97.20%) | Val Loss: 0.3376 (acc.
90.17%) | Time: 67s
Epoch 101/120 | Train Loss: 0.0456 (acc. 98.50%) | Val Loss: 0.3500 (acc.
89.00%) | Time: 67s
Epoch 102/120 | Train Loss: 0.0472 (acc. 98.50%) | Val Loss: 0.3313 (acc.
90.17%) | Time: 67s
Epoch 103/120 | Train Loss: 0.0674 (acc. 97.70%) | Val Loss: 0.3263 (acc.
90.17%) | Time: 67s
Epoch 104/120 | Train Loss: 0.0554 (acc. 97.95%) | Val Loss: 0.3132 (acc.
90.67%) | Time: 67s
Epoch 105/120 | Train Loss: 0.0589 (acc. 98.00%) | Val Loss: 0.3411 (acc.
90.67%) | Time: 67s
Epoch 106/120 | Train Loss: 0.0456 (acc. 98.05%) | Val Loss: 0.3470 (acc.
89.83%) | Time: 67s
Epoch 107/120 | Train Loss: 0.0433 (acc. 98.30%) | Val Loss: 0.3356 (acc.
89.67%) | Time: 67s
Epoch 108/120 | Train Loss: 0.0856 (acc. 98.25%) | Val Loss: 0.3408 (acc.
90.00%) | Time: 67s
Epoch 109/120 | Train Loss: 0.0578 (acc. 97.95%) | Val Loss: 0.3249 (acc.
89.50%) | Time: 68s
Epoch 110/120 | Train Loss: 0.0625 (acc. 97.45%) | Val Loss: 0.3357 (acc.
89.33%) | Time: 68s
Epoch 111/120 | Train Loss: 0.0448 (acc. 98.60%) | Val Loss: 0.3400 (acc.
89.50%) | Time: 68s
Epoch 112/120 | Train Loss: 0.0578 (acc. 97.95%) | Val Loss: 0.3215 (acc.
90.83%) | Time: 67s
Epoch 113/120 | Train Loss: 0.0525 (acc. 98.15%) | Val Loss: 0.3348 (acc.
90.50%) | Time: 68s
Epoch 114/120 | Train Loss: 0.0510 (acc. 98.00%) | Val Loss: 0.3671 (acc.
89.17%) | Time: 67s
Epoch 115/120 | Train Loss: 0.0532 (acc. 97.95%) | Val Loss: 0.3569 (acc.
89.33%) | Time: 68s
Epoch 116/120 | Train Loss: 0.0564 (acc. 97.85%) | Val Loss: 0.3501 (acc.
89.50%) | Time: 68s
Epoch 117/120 | Train Loss: 0.0544 (acc. 98.00%) | Val Loss: 0.3818 (acc.
89.67%) | Time: 67s
Epoch 118/120 | Train Loss: 0.0606 (acc. 97.85%) | Val Loss: 0.3494 (acc.
90.17%) | Time: 67s
Epoch 119/120 | Train Loss: 0.0563 (acc. 97.65%) | Val Loss: 0.3548 (acc.
89.33%) | Time: 68s
Epoch 120/120 | Train Loss: 0.0384 (acc. 98.65%) | Val Loss: 0.3839 (acc.
88.67%) | Time: 67s
Training Time: 8039s
```



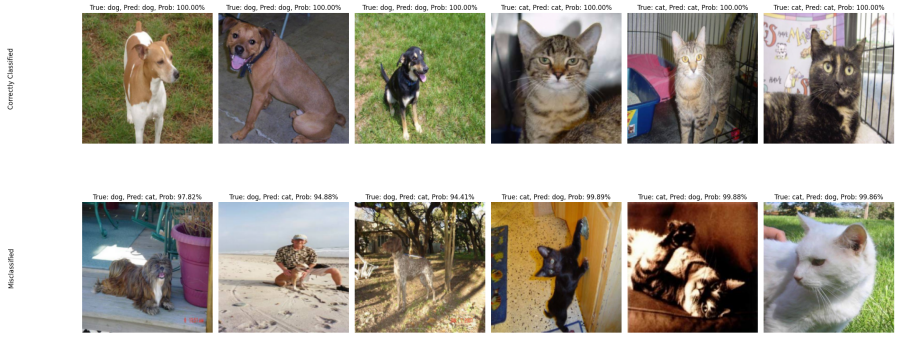


0.10 Predict

[27]:
```
test_image = "data/test/cats/cat.1306.jpg"
net_config2 = {**default_net_config,
    "cv_layers": [
        {"out_channels": 64, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":␣
↪2, "batch_norm": True},
        {"out_channels": 128, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 256, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 512, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
        {"out_channels": 512, "kernel_size": 3, "stride": 1, "padding": 1, "max_pool": 2, "max_pool_stride":
↪ 2, "batch_norm": True},
    ],
    "fc_layers": [
        {"out_features": 512, "batch_norm": True, "dropout_rate": 0.4},
        {"out_features": 256, "batch_norm": True, "dropout_rate": 0.2},
    ],
}
model = ConvolutionalNetwork(net_config2)
predict(model, device, "models/reg_4.pth", "results/reg_4.csv")
plot_individual_feature_maps(model, device, test_image, "results/feature_maps_reg_4.png")
```

```
Total Correctly Classified: 366 | Total Misclassified: 34 | Accuracy: 91.5%
Class-wise Correctly Classified Counts:
```

```
- Class cat: 175
- Class dog: 191
Class-wise Misclassified Counts:
- Class cat: 25
- Class dog: 9
Cat Accuracy: 87.5% | Dog Accuracy: 95.5%
```

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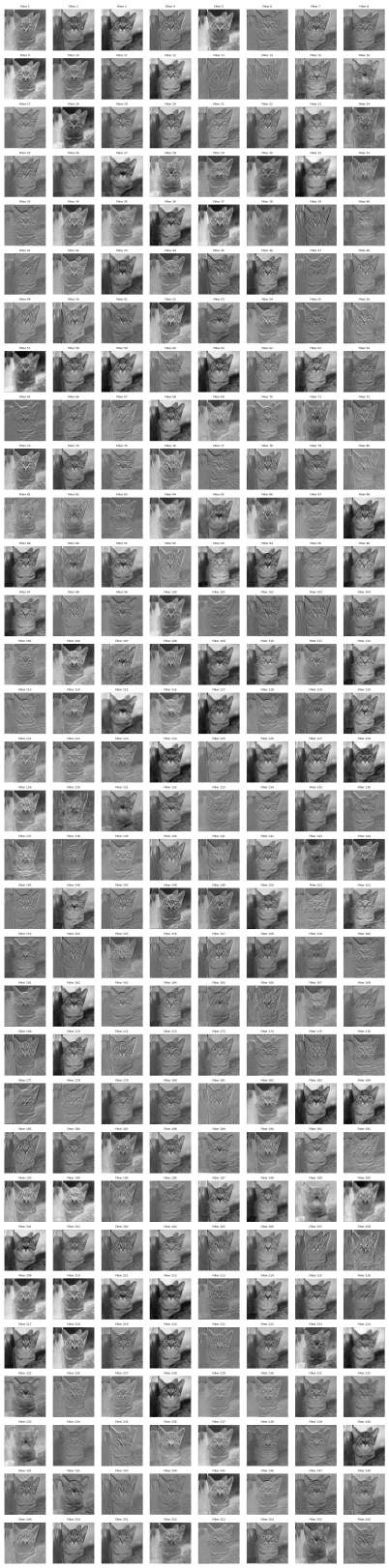


0.11 Transfer Learning

[28]:
```
num_classes = default_config["net_config"]["num_classes"]

model_alexnet = alexnet(weights=AlexNet_Weights.DEFAULT)

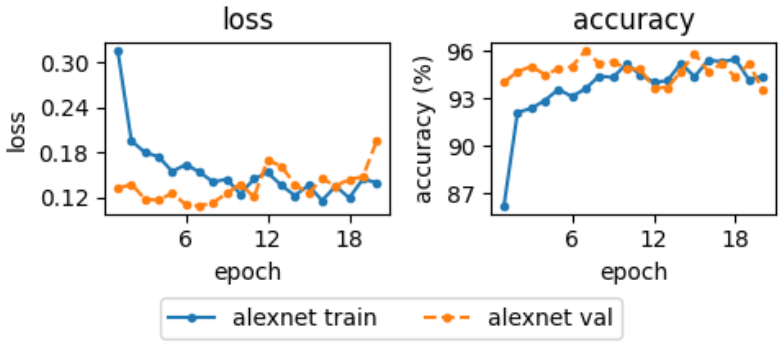
# Freeze all parameters/layers except last one
for name, param in model_alexnet.named_parameters():
    if("bn" not in name):
        param.requires_grad = False

# Change last layer to output 2 classes
model_alexnet.classifier[6] = nn.Linear(4096, num_classes)

config_alexnet = {**default_config, "label": "alexnet", "n_epochs": 20}

results = {}
results["alexnet"] = train_model(model_alexnet, device, config_alexnet)
plot_scores(results)
```

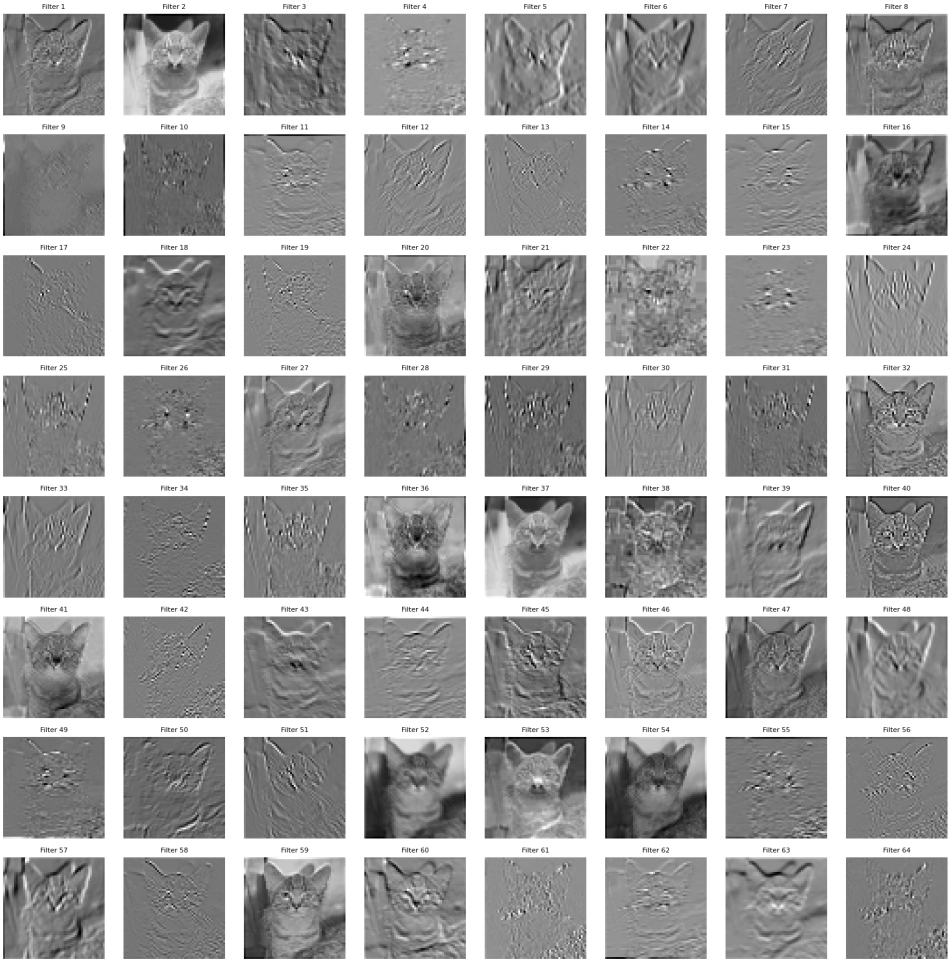
```
Experiment: alexnet
Epoch 1/20 | Train Loss: 0.3162 (acc. 86.20%) | Val Loss: 0.1319 (acc. 94.00%) |
Time: 43s
Epoch 2/20 | Train Loss: 0.1956 (acc. 92.10%) | Val Loss: 0.1380 (acc. 94.67%) |
Time: 38s
Epoch 3/20 | Train Loss: 0.1803 (acc. 92.35%) | Val Loss: 0.1180 (acc. 95.00%) |
Time: 37s
Epoch 4/20 | Train Loss: 0.1746 (acc. 92.85%) | Val Loss: 0.1164 (acc. 94.50%) |
Time: 38s
Epoch 5/20 | Train Loss: 0.1548 (acc. 93.55%) | Val Loss: 0.1260 (acc. 94.83%) |
Time: 37s
Epoch 6/20 | Train Loss: 0.1642 (acc. 93.10%) | Val Loss: 0.1105 (acc. 95.00%) |
Time: 36s
Epoch 7/20 | Train Loss: 0.1540 (acc. 93.60%) | Val Loss: 0.1089 (acc. 96.00%) |
Time: 36s
Epoch 8/20 | Train Loss: 0.1409 (acc. 94.40%) | Val Loss: 0.1133 (acc. 95.17%) |
Time: 35s
Epoch 9/20 | Train Loss: 0.1446 (acc. 94.30%) | Val Loss: 0.1256 (acc. 95.33%) |
Time: 36s
Epoch 10/20 | Train Loss: 0.1248 (acc. 95.15%) | Val Loss: 0.1380 (acc. 94.83%)
| Time: 35s
Epoch 11/20 | Train Loss: 0.1448 (acc. 94.50%) | Val Loss: 0.1210 (acc. 94.83%)
| Time: 36s
Epoch 12/20 | Train Loss: 0.1536 (acc. 94.00%) | Val Loss: 0.1698 (acc. 93.67%)
| Time: 35s
Epoch 13/20 | Train Loss: 0.1365 (acc. 94.10%) | Val Loss: 0.1622 (acc. 93.67%)
| Time: 35s
Epoch 14/20 | Train Loss: 0.1229 (acc. 95.20%) | Val Loss: 0.1379 (acc. 94.67%)
| Time: 35s
Epoch 15/20 | Train Loss: 0.1361 (acc. 94.35%) | Val Loss: 0.1254 (acc. 95.83%)
| Time: 36s
Epoch 16/20 | Train Loss: 0.1163 (acc. 95.40%) | Val Loss: 0.1454 (acc. 94.67%)
| Time: 36s
Epoch 17/20 | Train Loss: 0.1351 (acc. 95.30%) | Val Loss: 0.1353 (acc. 95.17%)
| Time: 40s
Epoch 18/20 | Train Loss: 0.1196 (acc. 95.45%) | Val Loss: 0.1446 (acc. 94.33%)
| Time: 35s
Epoch 19/20 | Train Loss: 0.1448 (acc. 94.15%) | Val Loss: 0.1477 (acc. 95.17%)
| Time: 33s
Epoch 20/20 | Train Loss: 0.1400 (acc. 94.40%) | Val Loss: 0.1953 (acc. 93.50%)
| Time: 33s
Training Time: 724s
```



[26]:
```
model = AlexNet(num_classes=num_classes)
predict(model, device, "models/alexnet.pth", "results/alexnet.csv")
plot_individual_feature_maps(model, device, test_image, "results/feature_maps_alexnet.png")
```

```
Total Correctly Classified: 374 | Total Misclassified: 26 | Accuracy: 93.5%
Class-wise Correctly Classified Counts:
- Class cat: 191
- Class dog: 183
Class-wise Misclassified Counts:
- Class cat: 9
- Class dog: 17
Cat Accuracy: 95.5% | Dog Accuracy: 91.5%
```


Original Image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