Project 2

Artificial Neural Networks and Deep Learning

Images of galaxies obtained by the Sloan Digital Sky Survey (SDSS) have been classified by different people through a participatory science process (see this article: https://arxiv.org/abs/1308.3496). There are tens of thousands of classified examples. However, there are even more images, and classifying them all by humans would take an enormous amount of time.

Our goal is therefore to develop a method to classify these images efficiently. We will use a convolutional neural network.

There are 37 non-exclusive categories (a galaxy can belong to more than one group). Since classification is sometimes ambiguous, participants did not always get the same answers. For each galaxy, the classification result is therefore a probability of belonging to one of the categories. To train the network, we will therefore use the mean squared error (MSE) to compare the probabilities given by the network.

$$MSE = \frac{1}{N} \sum_n (x_n - y_n)^2$$

For our final criterion (i.e., the one we will give as the answer at the very end), we will use the root of the MSE (RMSE): $RMSE = \sqrt{MSE}$. This is therefore a regression problem (37 output values y that we are trying to predict with the model), although the ultimate goal is to classify galaxies.

Step 1: Data exploration

The images are in a folder called images_training_rev1. The probabilities for each class are in the file `training_solutions_rev1.csv`. GalaxyID gives the identifier and each file in the folder corresponds to a GalaxyID (with a .jpg extension). To familiarize yourself with the data:

1. (Optional, not to be displayed in the submission) Import the CSV file and display the first few rows
2. Display the galaxy with the highest probability for each class (a .jpg or .png image). The format is: (dim1, dim2, C) where C=3 in our case. (Please include these images in a single figure, displaying the category name above each image).

Display the resulting figure with a brief explanation. Submit the code used to import the CSV and generate the figure.

```
dir = "docs/courses/epss298_DataAnalysis/projects/proj2"
if isdir(dir)
```

```
    cd(dir)
    Pkg.activate(".")
    Pkg.resolve()
    Pkg.instantiate()
end
```

```
using CSV
using DataFrames

galaxy_data = CSV.read("data/training_solutions_rev1.csv", DataFrame)
transform!(galaxy_data, names(galaxy_data, Float64) .=> x -> Float32.(x);
renamecols=false)

class_columns = names(galaxy_data)[2:end]

DESCRIPTIONS = [
    "Smooth", "Featured or disc", "Star or artifact",
    "Edge on", "Not edge on",
    "Bar through center", "No bar",
    "Spiral", "No Spiral",
    "No bulge", "Just noticeable bulge", "Obvious bulge", "Dominant bulge",
    "Odd Feature", "No Odd Feature",
    "Completely round", "In between", "Cigar shaped",
    "Ring", "Lens or arc", "Disturbed", "Irregular", "Other", "Merger", "Dust
lane",
    "Rounded bulge", "Boxy bulge", "No bulge",
    "Tightly wound arms", "Medium wound arms", "Loose wound arms",
    "1 Spiral Arm", "2 Spiral Arms", "3 Spiral Arms", "4 Spiral Arms",
    "More than four Spiral Arms", "Can't tell how many spiral arms",
]

const CDICT = Dict(class_columns .=> DESCRIPTIONS)
```

```
Dict{String, String} with 37 entries:
  "Class5.1"  => "No bulge"
  "Class8.5"  => "Other"
  "Class7.2"  => "In between"
  "Class11.2" => "2 Spiral Arms"
  "Class11.3" => "3 Spiral Arms"
  "Class3.1"  => "Bar through center"
  "Class8.2"  => "Lens or arc"
  "Class7.1"  => "Completely round"
  "Class6.2"  => "No Odd Feature"
  "Class6.1"  => "Odd Feature"
  "Class2.1"  => "Edge on"
  "Class1.2"  => "Featured or disc"
```

```
  "Class1.1"  => "Smooth"
  "Class1.3"  => "Star or artifact"
  "Class2.2"  => "Not edge on"
  "Class5.4"  => "Dominant bulge"
  "Class10.1" => "Tightly wound arms"
  "Class4.1"  => "Spiral"
  "Class8.1"  => "Ring"
  ⋮           => ⋮
```

```
using FileIO
using Images

load_img(id) = Images.load(File{format"JPEG"}("data/images_training_rev1/
$(id).jpg"))
load_processed_img(id) = Images.load(File{format"JPEG"}("data/
processed_images/$(id).jpg"))
```

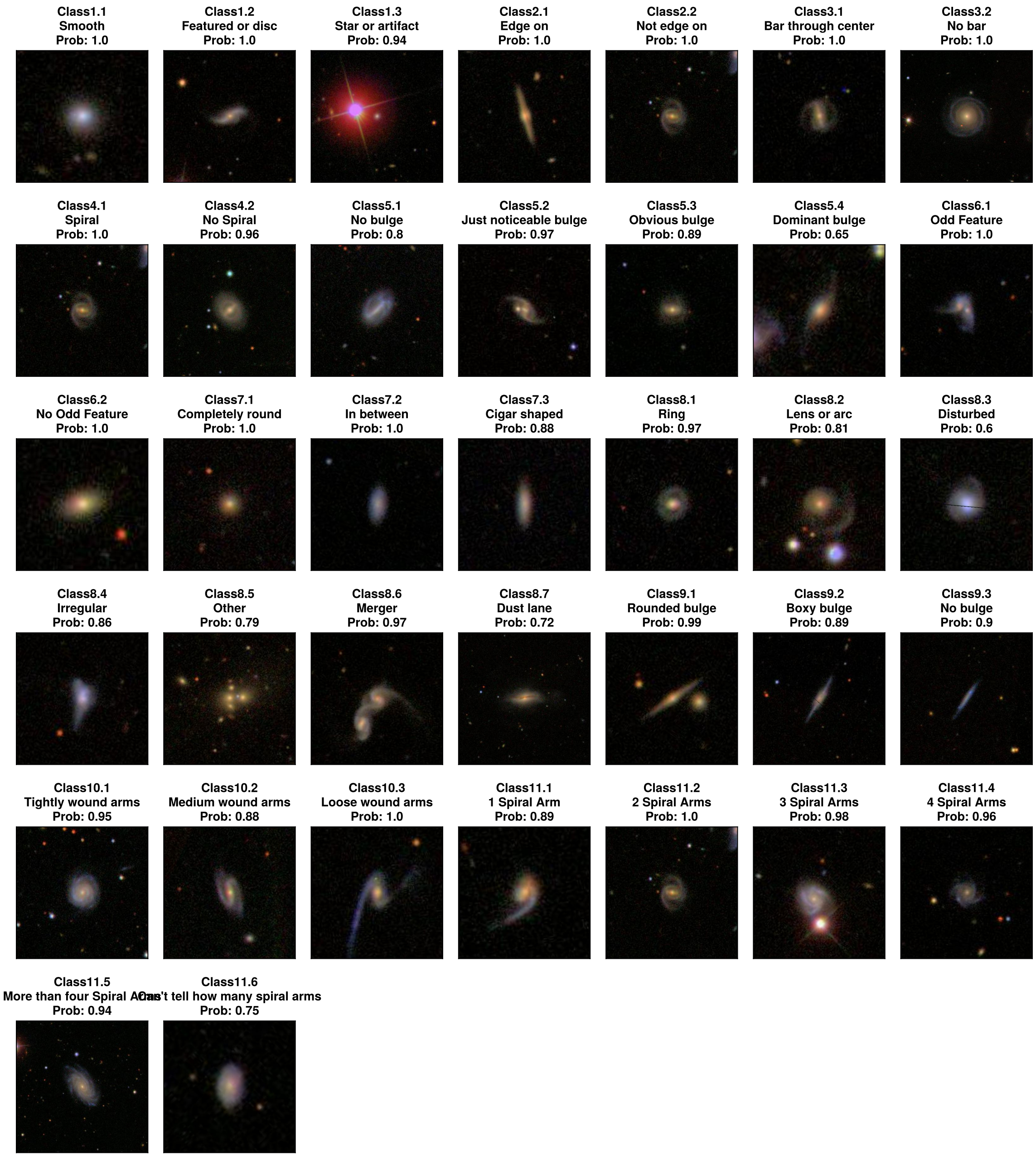
```
load_processed_img (generic function with 1 method)
```

```
# Find the galaxy with highest probability for each class
highest_prob_df = DataFrame(
    map(class_columns) do Class
        max_idx = argmax(galaxy_data[!, Class])
        GalaxyID = galaxy_data[max_idx, :GalaxyID]
        Probability = galaxy_data[max_idx, Class]
        (; Class, GalaxyID, Probability)
    end
)
```

```
37×3 DataFrame
 Row │ Class      GalaxyID  Probability
     │ String     Int64     Float32
─────┼──────────────────────────────────
   1 │ Class1.1     105447     1.0
   2 │ Class1.2     100859     1.0
   3 │ Class1.3     356310     0.935147
   4 │ Class2.1     344604     1.0
   5 │ Class2.2     105009     1.0
   6 │ Class3.1     205541     1.0
   7 │ Class3.2     185561     1.0
   8 │ Class4.1     105009     1.0
  ⋮  │     ⋮          ⋮           ⋮
  31 │ Class10.3    416488     0.996952
  32 │ Class11.1    848818     0.886363
  33 │ Class11.2    105009     1.0
```

```
  34 │ Class11.3    121006     0.975913
  35 │ Class11.4    233081     0.957
  36 │ Class11.5    495381     0.938881
  37 │ Class11.6    598442     0.753082
                          22 rows omitted
```

```
using CairoMakie
using CairoMakie: Axis

num_classes = nrow(highest_prob_df)

function plot_images(df, load; width=150, height=150)
    fig = Figure()
    # Calculate grid dimensions - aim for roughly square layout
    ncols = ceil(Int, sqrt(num_classes))
    nrows = ceil(Int, num_classes / ncols)
    # Load and display each image
    for (i, row) in enumerate(eachrow(highest_prob_df))
        row_idx = div(i - 1, ncols) + 1
        col_idx = mod(i - 1, ncols) + 1
        title = "$(row.Class)\n$(CDICT[row.Class])\nProb:
$(round(row.Probability, digits=2))"
        ax = Axis(fig[row_idx, col_idx]; width, height, title,)
        hidedecorations!(ax)
        image!(ax, load(row.GalaxyID))
    end
    resize_to_layout!(fig)
    return fig
end

plot_images(highest_prob_df, load_img)
```



Step 2: Prepare the images

The initial format of the images is not optimal. The format is large (424x424) and there is a lot of empty space around the galaxies. Write a code that performs the following tasks:

Crop, resize, and save images

1. Crop the image to reduce the size by half around the center (212x212)
2. Reduce the resolution so that the image has 64 pixels on each side
3. Save all pre-processed images in a new folder

```julia
using ProgressMeter
using DataAugmentation

@views function preprocess_image(img; crop_size=212)
    cropped_img = DataAugmentation.apply(
        DataAugmentation.CenterCrop((crop_size, crop_size)),
        DataAugmentation.Image(img)
    ) |> DataAugmentation.itemdata
    return imresize(cropped_img, (64, 64))
end

function process_and_save_images(galaxy_ids, path)
    mkpath(path)
    @showprogress "Processing images..." for id in galaxy_ids
        img_path = joinpath(path, "$(id).jpg")
        !isfile(img_path) && save(img_path, preprocess_image(load_img(id)))
    end
end

# Process and save all images
process_and_save_images(galaxy_data.GalaxyID, "data/processed_images")
```

```
Processing images...   2%|█                                       |  ETA:
0:00:06Processing images... 100%|████████████████████████████████████████| Time:
0:00:01
```

Data split, Dataset, and DataLoader

4. Using the GalaxyID from the CSV, randomly split the data into two subsets: training and testing. We want 20% of the images to be used exclusively for testing.
5. Define a Dataset that can import the data and probabilities for each class (one for training, one for testing).
6. From the two Datasets, create two Dataloaders that use subsets of 64 images.

Display the same figure as in Step 1, but with the images modified, explaining how the modifications were made. Submit the code used to modify the images and generate the figure.

```julia
using MLUtils
```

```
@views function get_labels(source, ids)
    idx = searchsortedfirst.(Ref(source.GalaxyID), ids)
    return source[idx, 2:end]
end
```

```
get_labels (generic function with 1 method)
```

```
# 5. Define a Julia Dataset equivalent for training and testing
struct GalaxyDataset{I,L,F}
    ids::I
    labels::L
    load::F
end

transform_img(img) = permutedims(channelview(img), (2, 3, 1))

function Base.getindex(dataset::GalaxyDataset, idx)
    ids = dataset.ids[idx]
    img_arrays = convert(Array{Float32,4}, stack(transform_img ∘ dataset.load,
ids; dims=4))
    labels = convert(Matrix{Float32}, stack(get_labels.(Ref(dataset.labels),
ids); dims=2))
    return img_arrays, labels
end

Base.length(dataset::GalaxyDataset) = length(dataset.ids)

train_ids, test_ids = splitobs(galaxy_data.GalaxyID, at=0.8, shuffle=true)

# Create training and testing datasets
train_dataset = GalaxyDataset(
    train_ids,
    galaxy_data,
    load_processed_img
)

test_dataset = GalaxyDataset(
    test_ids,
    galaxy_data,
    load_processed_img
)
```

```
GalaxyDataset{SubArray{Int64, 1, SentinelArrays.ChainedVector{Int64,
Vector{Int64}}, Tuple{Vector{Int64}}, false}, DataFrame,
typeof(load_processed_img)}([382929, 544106, 446979, 964338, 347181, 846886,
122933, 938653, 218078, 520163  …  505764, 994191, 508567, 224858, 680758,
```

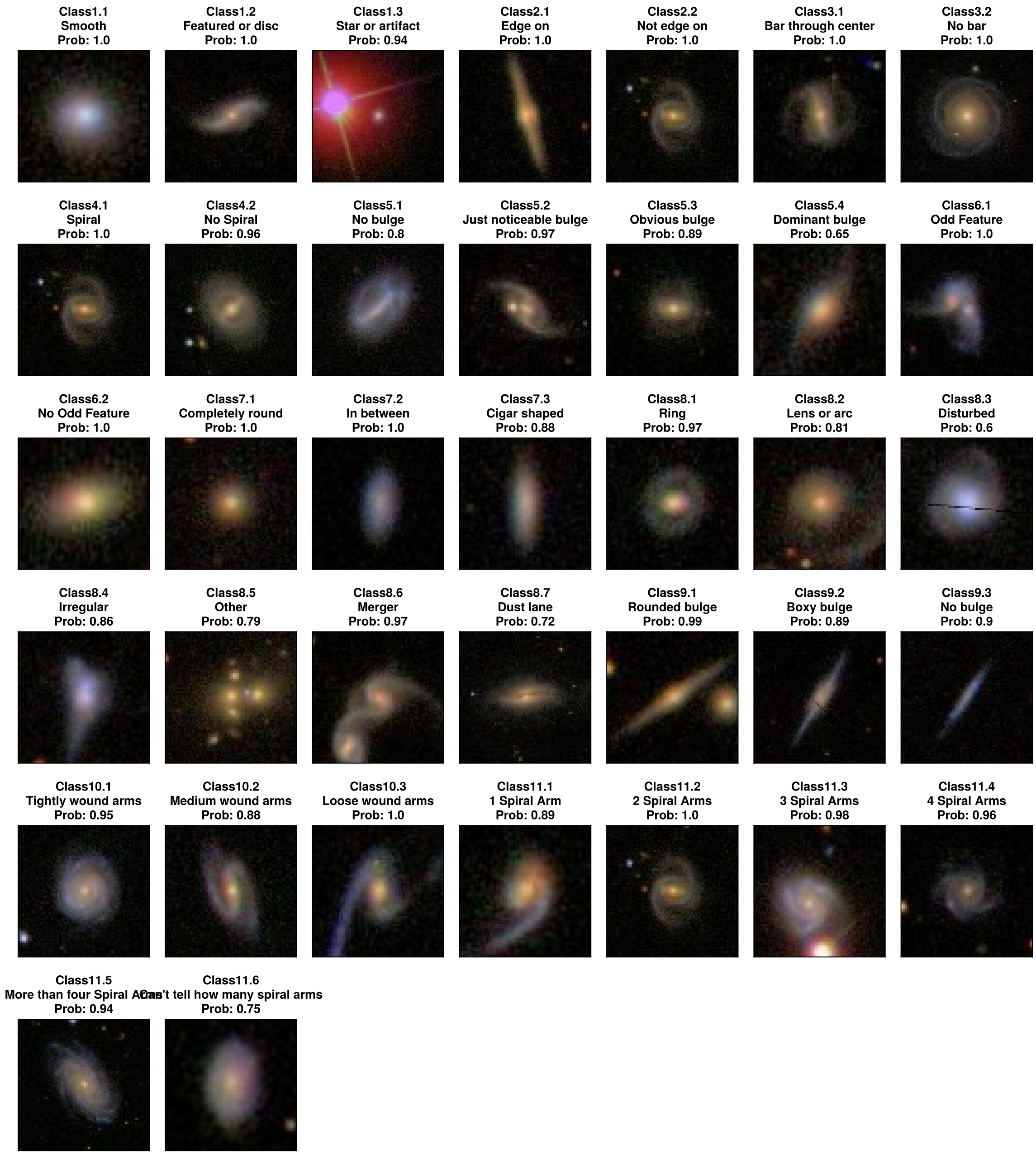
```
295420, 571359, 482977, 214376, 898745], 61578×38 DataFrame
   Row │ GalaxyID  Class1.1  Class1.2  Class1.3  Class2.1   Class2.2  Class3.1
…
       │ Int64     Float32   Float32   Float32   Float32    Float32   Float32
…
───────┼─────────────────────────────────────────────────────────────────────────
     1 │   100008  0.383147  0.616853  0.0       0.0        0.616853  0.038452
…
     2 │   100023  0.327001  0.663777  0.009222  0.0311783  0.632599  0.46737
     3 │   100053  0.765717  0.177352  0.056931  0.0        0.177352  0.0
     4 │   100078  0.693377  0.238564  0.068059  0.0        0.238564  0.109493
     5 │   100090  0.933839  0.0       0.066161  0.0        0.0       0.0
…
     6 │   100122  0.738832  0.238159  0.023009  0.0        0.238159  0.0
     7 │   100123  0.462492  0.456033  0.081475  0.0        0.456033  0.0
     8 │   100128  0.687783  0.288344  0.023873  0.0        0.288344  0.069098
   ⋮   │    ⋮         ⋮         ⋮         ⋮         ⋮          ⋮         ⋮     ⋱
 61572 │   999900  0.460239  0.511396  0.028365  0.109439   0.401957  0.0
…
 61573 │   999936  0.545443  0.454557  0.0       0.0568196  0.397737  0.126909
 61574 │   999948  0.510379  0.489621  0.0       0.0592069  0.430414  0.0
 61575 │   999950  0.901216  0.098784  0.0       0.0        0.098784  0.0
 61576 │   999958  0.202841  0.777376  0.019783  0.116962   0.660414  0.067245
…
 61577 │   999964  0.091     0.909     0.0       0.04545    0.86355   0.022452
 61578 │   999967  0.767     0.14      0.093     0.0        0.14      0.0
                                               32 columns and 61563 rows
omitted, load_processed_img)
```

6. Create DataLoaders with batch size

```
train_loader = DataLoader(train_dataset, batchsize=32)
test_loader = DataLoader(test_dataset, batchsize=32)
```

```
385-element DataLoader(::GalaxyDataset{SubArray{Int64, 1,
SentinelArrays.ChainedVector{Int64, Vector{Int64}}, Tuple{Vector{Int64}},
false}, DataFrame, typeof(load_processed_img)}, batchsize=32)
  with first element:
  (64×64×3×32 Array{Float32, 4}, 37×32 Matrix{Float32},)
```

```
plot_images(highest_prob_df, load_processed_img)
```



Step 3: Defining a CNN

The data is now ready to be analyzed. Next, we need to define a CNN that will take the 64x64 images with 3 colors as input and give us a probability for the 37 classes as output. To start, define a CNN with the following elements (this is an adaptation of the CNN we used with the FashionMNIST data):

1. Convolution layer with 6 output filters, a 5-pixel kernel, and a padding of 3.
2. Convolution layer with 16 output filters, a 5-pixel kernel, and a padding of 3.
3. Fully connected layer with 120 output neurons
4. Fully connected layer with 84 output neurons
5. Final layer with logits for the 37 classes.
6. We need to convert the 37 classes to probabilities. Which function seen in class allows us to convert logits to a value between 0 and 1? (Note: The probabilities are not mutually exclusive!)

After each convolution layer, use batch normalization, ReLU activation, and pooling with a kernel size of 2. Between the fully connected layers, use a ReLU activation function (except at the output of the final layer). Don't forget to flatten the images between the last convolution layer and the first fully connected layer.

In the report, explain the general structure and function of the different layers. Submit the code that defines this CNN.

```
function get_output_width(width, kernel_size; stride=1, padding=0, dilation=1)
    floor(Int,
        (width + 2 * padding - dilation * (kernel_size - 1) - 1) / stride + 1
    )
end

using Chain: @chain

@chain 64 begin
    get_output_width(5; padding=3)
    get_output_width(2; stride=2)
    get_output_width(5; padding=3)
    get_output_width(2; stride=2)
end
```

```
17
```

```
using Random
using Lux
using Optimisers
using Zygote

rng = Random.default_rng()
Random.seed!(rng, 42)

function build_cnn_model(; num_classes=37, pad=3)
    return Chain(
        Chain(
            Conv((5, 5), 3 => 6; pad),
```

```
            BatchNorm(6, relu),
            MaxPool((2, 2)),
        ),
        Chain(
            Conv((5, 5), 6 => 16; pad),
            BatchNorm(16, relu),
            MaxPool((2, 2)),
        ),
        FlattenLayer(; N=3),
        Chain(
            Dense(4624 => 120, relu),
            Dense(120 => 84, relu),
            Dense(84 => num_classes, sigmoid);
            name="Fully connected layer"
        )
    )
end

# Initialize the model
model = build_cnn_model()
```

```
Chain(
    layer_1 = Chain(
        layer_1 = Conv((5, 5), 3 => 6, pad=3),  # 456 parameters
        layer_2 = BatchNorm(6, relu, affine=true, track_stats=true),  # 12
parameters, plus 13
        layer_3 = MaxPool((2, 2)),
    ),
    layer_2 = Chain(
        layer_1 = Conv((5, 5), 6 => 16, pad=3),  # 2_416 parameters
        layer_2 = BatchNorm(16, relu, affine=true, track_stats=true),  # 32
parameters, plus 33
        layer_3 = MaxPool((2, 2)),
    ),
    layer_3 = FlattenLayer{Static.StaticInt{3}}(static(3)),
    layer_4 = Fully connected layer(
        layer_1 = Dense(4624 => 120, relu),  # 555_000 parameters
        layer_2 = Dense(120 => 84, relu),  # 10_164 parameters
        layer_3 = Dense(84 => 37, σ),   # 3_145 parameters
    ),
)         # Total: 571_225 parameters,
          #        plus 46 states.
```

Create dummy input to test the model

```
ps, st = Lux.setup(rng, model);
x = rand(rng, Float32, 64, 64, 3, 2)  # (height, width, channels, batch_size)
model(x, ps, Lux.testmode(st))
```

```
(Float32[0.5226176 0.5963492; 0.7555507 0.75195336; … ; 0.43180552 0.5062954;
0.64954376 0.6692772], (layer_1 = (layer_1 = NamedTuple(), layer_2 =
(running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var =
Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}()), layer_3 =
NamedTuple()), layer_2 = (layer_1 = NamedTuple(), layer_2 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}()), layer_3 =
NamedTuple()), layer_3 = NamedTuple(), layer_4 = (layer_1 = NamedTuple(),
layer_2 = NamedTuple(), layer_3 = NamedTuple())))
```

Step 4: Training the network

Once the network is defined, it must be trained to recognize galaxies. Adapt the training and testing loops we saw in class. Use the following hyperparameters, then train the model.

1. MSE objective function
2. Adam optimizer
3. 6 epochs

Record the value of the objective function for each epoch, for the training and test data separately. Once training is complete, display the evolution of the objective function for the training and test data.

In the report, explain the training process and display the evolution of the objective function. Submit the code used to train the network.

```
using Printf

function evaluate_model(model, ps, st, dataloader, lossfn)
    total_loss = 0.0f0
    total_batches = 0
    st = Lux.testmode(st)
    @showprogress "Testing..." for (x, y) in dataloader
        # Forward pass
        y_pred = first(model(x, ps, st))
        # Compute loss
        loss = lossfn(y_pred, y)
        total_loss += loss
```

```julia
        total_batches += 1
    end
    return total_loss / total_batches
end

function init_evaluate_model(model, ps, st, train_loader, test_loader,
lossfn=MSELoss(); verbose=true)
    train_loss = evaluate_model(model, ps, st, train_loader, lossfn)
    test_loss = evaluate_model(model, ps, st, test_loader, lossfn)
    if verbose
        @printf "Initial: Train Loss %4.5f, Test Loss %4.5f\n" train_loss
test_loss
    end
    return train_loss, test_loss
end
```

```
init_evaluate_model (generic function with 2 methods)
```

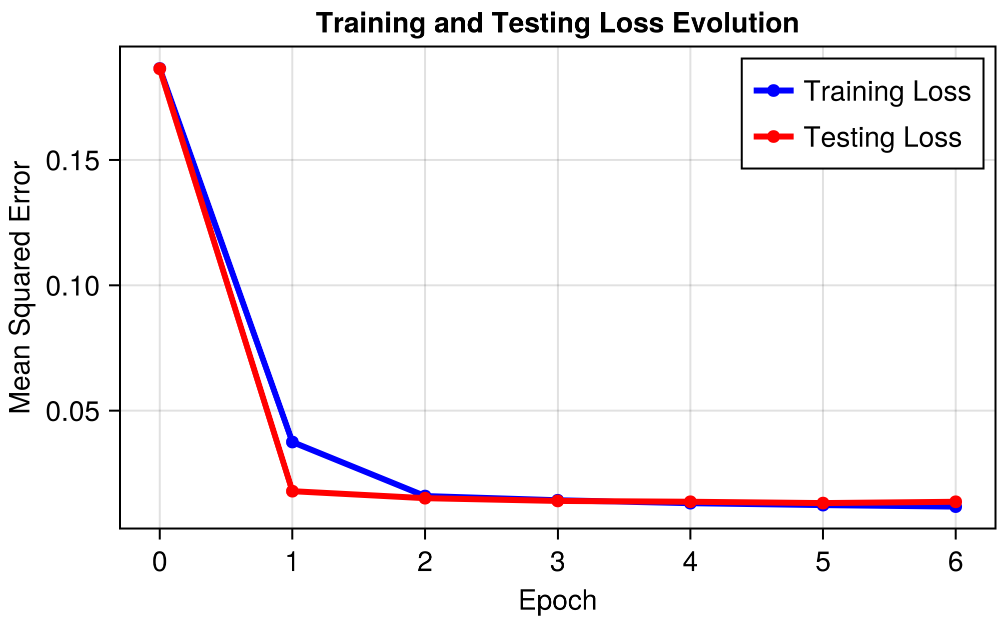
```julia
using JLD2

function train_model!(model, ps, st, train_loader, test_loader;
op=Adam(0.003f0), epochs=6)
    train_state = Training.TrainState(model, ps, st, op)

    ad = AutoZygote()
    lossfn = MSELoss()

    # Initialize arrays to store losses
    train_losses = Float32[]
    test_losses = Float32[]

    for epoch in 1:epochs
        # Training phase
        total_loss = 0.0f0
        total_batches = 0

        @showprogress "Training..." for data in train_loader
            _, loss, _, train_state = Training.single_train_step!(
                ad, lossfn,
                data, train_state
            )
            total_loss += loss
            total_batches += 1
        end
        # Calculate average training loss for this epoch
        train_loss = total_loss / total_batches
        push!(train_losses, train_loss)
```

```
        test_loss = evaluate_model(model, train_state.parameters,
train_state.states, test_loader, lossfn)
        push!(test_losses, test_loss)
        @printf "Epoch [%3d]: Train Loss %4.5f, Test Loss %4.5f\n" epoch
train_loss test_loss
    end

    return train_state, train_losses, test_losses
end

# load file if it exists
epochs = 6
if isfile("trained_model.jld2")
    @load "trained_model.jld2" ps_trained st_trained train_losses test_losses
else
    # Evaluate initial losses before training
    initial_train_loss, initial_test_loss = init_evaluate_model(model, ps, st,
train_loader, test_loader; verbose=true)

    # Train the model and record both training and testing losses
    train_state, train_losses, test_losses = train_model!(model, ps, st,
train_loader, test_loader; epochs)

    # Append training losses to the initial losses
    prepend!(train_losses, initial_train_loss)
    prepend!(test_losses, initial_test_loss)

    ps_trained, st_trained = train_state.parameters, train_state.states
    @save "trained_model.jld2" ps_trained st_trained train_losses test_losses
end
```

```
4-element Vector{Symbol}:
 :ps_trained
 :st_trained
 :train_losses
 :test_losses
```

```
# Visualize the evolution of the training and testing loss
fig = Figure()
ax = Axis(fig[1, 1],
    xlabel="Epoch",
    ylabel="Mean Squared Error",
    title="Training and Testing Loss Evolution",
)
scatterlines!(0:epochs, train_losses, linewidth=3, color=:blue,
label="Training Loss")
```

```
scatterlines!(0:epochs, test_losses, linewidth=3, color=:red, label="Testing
Loss")
axislegend(ax, position=:rt)

fig
```



Step 5: Model evaluation

With the trained model, what is the RMSE value for the test data? For reference, a simple solution that uses the average color of the 100 central pixels (10x10) gives an RMSE of 0.16194. How does your neural network compare to this method? The dataset we are studying was used in a Kaggle competition several years ago: https://www.kaggle.com/c/galaxy-zoo-the-galaxy-challenge. Several people have attempted to find a solution that gives the smallest possible RMSE. The solutions are ranked in the Leaderboard tab. How does the solution obtained in Step 4 rank? In the report, report the RMSE and discuss the comparison with a simplistic method (central pixels). Submit the code used to calculate the RMSE.

```
cnn_rmse = sqrt(test_losses[end])
simple_rmse_ref = 0.16194
improvement = round(((simple_rmse_ref - cnn_rmse) / simple_rmse_ref * 100),
digits=2)

@info "CNN RMSE on train data: " sqrt(train_losses[end])
```

```
@info "CNN RMSE on test data: " sqrt(test_losses[end])
@info "Improvement: $(improvement) %"

if cnn_rmse < simple_rmse_ref
    println("\nOur CNN model outperforms the simple central pixels method!")
    println("This demonstrates that the CNN can learn complex patterns across
the entire image rather than just using the central region.")
else
    println("\nOur CNN model doesn't outperform the simple method yet.")
    println("This could be due to several factors:")
    println("1. Limited training epochs")
    println("2. Model architecture might need optimization")
    println("3. Learning rate or other hyperparameters might need tuning")
end
```

```
┌ Info: CNN RMSE on train data:
└   sqrt(train_losses[end]) = 0.108268715f0
┌ Info: CNN RMSE on test data:
└   sqrt(test_losses[end]) = 0.11684338f0
[ Info: Improvement: 27.85 %

Our CNN model outperforms the simple central pixels method!
This demonstrates that the CNN can learn complex patterns across the entire
image rather than just using the central region.
```

Step 6: Model modification

In class, we saw different ways to improve model performance (regularization, dropout, data augmentation, adding layers, changing the model configuration or training process). Modify the model and evaluate the effect of the changes on training. You can also completely redefine the model, either using a known architecture (e.g., ResNet) or an original architecture. How does the performance compare to that of Steps 3-4-5? Can you explain why the changes had this effect?

Grading scale:

1. Any simple modification to the model ensures at least 6/10
2. Additional modifications are worth 1 point each, up to a total of 10/10
3. Rewriting a completely different architecture with a similar or larger number of parameters and at least two hidden layers automatically earns full points (10/10)
4. Model performance does not earn any additional points. The goal is really to get you to explore possible modifications! In the report, indicate what modifications you made, the effect they had, and why they had that effect. Also include a comparison of the RMSE with the previous steps. Submit the modified code for this section.

Using ResNet for Galaxy Classification

```
using Boltz, Metalhead, Lux

# Function to create a modified ResNet for our galaxy classification task
function build_resnet_model(; num_classes=37)
    # Get the base ResNet-18 model
    resnet = Vision.ResNet(18)

    # Extract all layers except the final classification layer
    base_layers = resnet.layer.layer_1

    # Create a new final layer for our 37-class multi-label classification
    final_layer = Chain(
        AdaptiveMeanPool((1, 1)),
        FlattenLayer(; N=3),
        Dense(512 => num_classes, sigmoid)
    )

    # Combine the base layers with our new classification head
    return Chain(base_layers, final_layer)
end

# Initialize the ResNet model
resnet_model = build_resnet_model()
resnet_ps, resnet_st = Lux.setup(rng, resnet_model)

# Show model structure
resnet_model
```

```
Chain(
    layer_1 = Chain(
        layer_1 = Chain(
            layer_1 = Conv((7, 7), 3 => 64, pad=3, stride=2, use_bias=false),
# 9_408 parameters
            layer_2 = BatchNorm(64, relu, affine=true, track_stats=true),  #
128 parameters, plus 129
            layer_3 = MaxPool((3, 3), pad=1, stride=2),
        ),
        layer_2 = Chain(
            layer_1 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = NoOpLayer(),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 64 => 64, pad=1, use_bias=false),
# 36_864 parameters
                    layer_2 = BatchNorm(64, affine=true, track_stats=true),  #
128 parameters, plus 129
```

```
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 64 => 64, pad=1, use_bias=false),
# 36_864 parameters
                    layer_5 = BatchNorm(64, affine=true, track_stats=true),  #
128 parameters, plus 129
                ),
            ),
            layer_2 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = NoOpLayer(),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 64 => 64, pad=1, use_bias=false),
# 36_864 parameters
                    layer_2 = BatchNorm(64, affine=true, track_stats=true),  #
128 parameters, plus 129
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 64 => 64, pad=1, use_bias=false),
# 36_864 parameters
                    layer_5 = BatchNorm(64, affine=true, track_stats=true),  #
128 parameters, plus 129
                ),
            ),
        ),
        layer_3 = Chain(
            layer_1 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = Chain(
                    layer_1 = Conv((1, 1), 64 => 128, stride=2,
use_bias=false),  # 8_192 parameters
                    layer_2 = BatchNorm(128, affine=true, track_stats=true),
# 256 parameters, plus 257
                ),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 64 => 128, pad=1, stride=2,
use_bias=false),  # 73_728 parameters
                    layer_2 = BatchNorm(128, affine=true, track_stats=true),
# 256 parameters, plus 257
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 128 => 128, pad=1, use_bias=false),
# 147_456 parameters
                    layer_5 = BatchNorm(128, affine=true, track_stats=true),
# 256 parameters, plus 257
                ),
            ),
            layer_2 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = NoOpLayer(),
                layer_2 = Chain(
```

```
                    layer_1 = Conv((3, 3), 128 => 128, pad=1, use_bias=false),
# 147_456 parameters
                    layer_2 = BatchNorm(128, affine=true, track_stats=true),
# 256 parameters, plus 257
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 128 => 128, pad=1, use_bias=false),
# 147_456 parameters
                    layer_5 = BatchNorm(128, affine=true, track_stats=true),
# 256 parameters, plus 257
                ),
            ),
        ),
        layer_4 = Chain(
            layer_1 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = Chain(
                    layer_1 = Conv((1, 1), 128 => 256, stride=2,
use_bias=false),  # 32_768 parameters
                    layer_2 = BatchNorm(256, affine=true, track_stats=true),
# 512 parameters, plus 513
                ),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 128 => 256, pad=1, stride=2,
use_bias=false),  # 294_912 parameters
                    layer_2 = BatchNorm(256, affine=true, track_stats=true),
# 512 parameters, plus 513
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 256 => 256, pad=1, use_bias=false),
# 589_824 parameters
                    layer_5 = BatchNorm(256, affine=true, track_stats=true),
# 512 parameters, plus 513
                ),
            ),
            layer_2 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = NoOpLayer(),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 256 => 256, pad=1, use_bias=false),
# 589_824 parameters
                    layer_2 = BatchNorm(256, affine=true, track_stats=true),
# 512 parameters, plus 513
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 256 => 256, pad=1, use_bias=false),
# 589_824 parameters
                    layer_5 = BatchNorm(256, affine=true, track_stats=true),
# 512 parameters, plus 513
                ),
            ),
```

```
        ),
        layer_5 = Chain(
            layer_1 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = Chain(
                    layer_1 = Conv((1, 1), 256 => 512, stride=2,
use_bias=false),  # 131_072 parameters
                    layer_2 = BatchNorm(512, affine=true, track_stats=true),
# 1_024 parameters, plus 1_025
                ),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 256 => 512, pad=1, stride=2,
use_bias=false),  # 1_179_648 parameters
                    layer_2 = BatchNorm(512, affine=true, track_stats=true),
# 1_024 parameters, plus 1_025
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 512 => 512, pad=1, use_bias=false),
# 2_359_296 parameters
                    layer_5 = BatchNorm(512, affine=true, track_stats=true),
# 1_024 parameters, plus 1_025
                ),
            ),
            layer_2 = Parallel(
                connection = addact(NNlib.relu, ...),
                layer_1 = NoOpLayer(),
                layer_2 = Chain(
                    layer_1 = Conv((3, 3), 512 => 512, pad=1, use_bias=false),
# 2_359_296 parameters
                    layer_2 = BatchNorm(512, affine=true, track_stats=true),
# 1_024 parameters, plus 1_025
                    layer_3 = WrappedFunction(relu),
                    layer_4 = Conv((3, 3), 512 => 512, pad=1, use_bias=false),
# 2_359_296 parameters
                    layer_5 = BatchNorm(512, affine=true, track_stats=true),
# 1_024 parameters, plus 1_025
                ),
            ),
        ),
    ),
    layer_2 = Chain(
        layer_1 = AdaptiveMeanPool((1, 1)),
        layer_2 = FlattenLayer{Static.StaticInt{3}}(static(3)),
        layer_3 = Dense(512 => 37, σ),  # 18_981 parameters
    ),
)         # Total: 11_195_493 parameters,
          #        plus 9_620 states.
```

Testing the ResNet Model with Sample Data

```
# Create dummy input to test the model
x_test = rand(rng, Float32, 64, 64, 3, 2)  # (height, width, channels,
batch_size)
resnet_model(x_test, resnet_ps, Lux.testmode(resnet_st))
```

```
(Float32[0.30450302 0.30915502; 0.37083414 0.3660484; … ; 0.6346178
0.65124583; 0.30676535 0.30921096], (layer_1 = (layer_1 = (layer_1 =
NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}()),
layer_3 = NamedTuple()), layer_2 = (layer_1 = (layer_1 = NamedTuple(), layer_2
= (layer_1 = NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training =
Val{false}()), layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 =
(running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0], training = Val{false}()))), layer_2 = (layer_1 =
NamedTuple(), layer_2 = (layer_1 = NamedTuple(), layer_2 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}()), layer_3 = NamedTuple(), layer_4 =
NamedTuple(), layer_5 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}
()))))), layer_3 = (layer_1 = (layer_1 = (layer_1 = NamedTuple(), layer_2 =
(running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0], training = Val{false}())), layer_2 = (layer_1 =
NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}()),
layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}()))), layer_2 = (layer_1 = NamedTuple(), layer_2 =
(layer_1 = NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
```

```
0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0
…  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}
()), layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}())))), layer_4 = (layer_1 = (layer_1 = (layer_1 =
NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}())),
layer_2 = (layer_1 = NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training =
Val{false}()), layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 =
(running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0,
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1.0, 1.0, 1.0, 1.0], training = Val{false}()))), layer_2 = (layer_1 =
NamedTuple(), layer_2 = (layer_1 = NamedTuple(), layer_2 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}()), layer_3 = NamedTuple(), layer_4 =
NamedTuple(), layer_5 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}
()))), layer_5 = (layer_1 = (layer_1 = (layer_1 = NamedTuple(), layer_2 =
(running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0], training = Val{false}())), layer_2 = (layer_1 =
NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0],
running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …
1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}()),
layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 = (running_mean =
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}()))), layer_2 = (layer_1 = NamedTuple(), layer_2 =
(layer_1 = NamedTuple(), layer_2 = (running_mean = Float32[0.0, 0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0
…  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0], training = Val{false}
()), layer_3 = NamedTuple(), layer_4 = NamedTuple(), layer_5 = (running_mean =
```

```
Float32[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0  …  0.0, 0.0, 0.0,
0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0], running_var = Float32[1.0, 1.0, 1.0, 1.0,
1.0, 1.0, 1.0, 1.0, 1.0, 1.0  …  1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,
1.0], training = Val{false}()))))), layer_2 = (layer_1 = NamedTuple(), layer_2
= NamedTuple(), layer_3 = NamedTuple())))
```

Training the ResNet Model

```
resnet_epochs = 3
# Evaluate initial performance
if isfile("resnet_trained_model.jld2")
    @load "resnet_trained_model.jld2" resnet_ps_trained resnet_st_trained
resnet_train_losses resnet_test_losses
else
    initial_train_loss, initial_test_loss = init_evaluate_model(resnet_model,
resnet_ps, resnet_st, train_loader, test_loader)
    @printf "Initial ResNet: Train Loss %4.5f, Test Loss %4.5f\n"
initial_train_loss initial_test_loss
    # Train the ResNet model
    resnet_train_state, resnet_train_losses, resnet_test_losses = train_model!
(resnet_model, resnet_ps, resnet_st, train_loader, test_loader;
op=Adam(0.0005f0), epochs=resnet_epochs)

    # Prepend initial losses
    prepend!(resnet_train_losses, initial_train_loss)
    prepend!(resnet_test_losses, initial_test_loss)

    # Save the trained model
    resnet_ps_trained, resnet_st_trained = resnet_train_state.parameters,
resnet_train_state.states
    @save "resnet_trained_model.jld2" resnet_ps_trained resnet_st_trained
resnet_train_losses resnet_test_losses
end
```

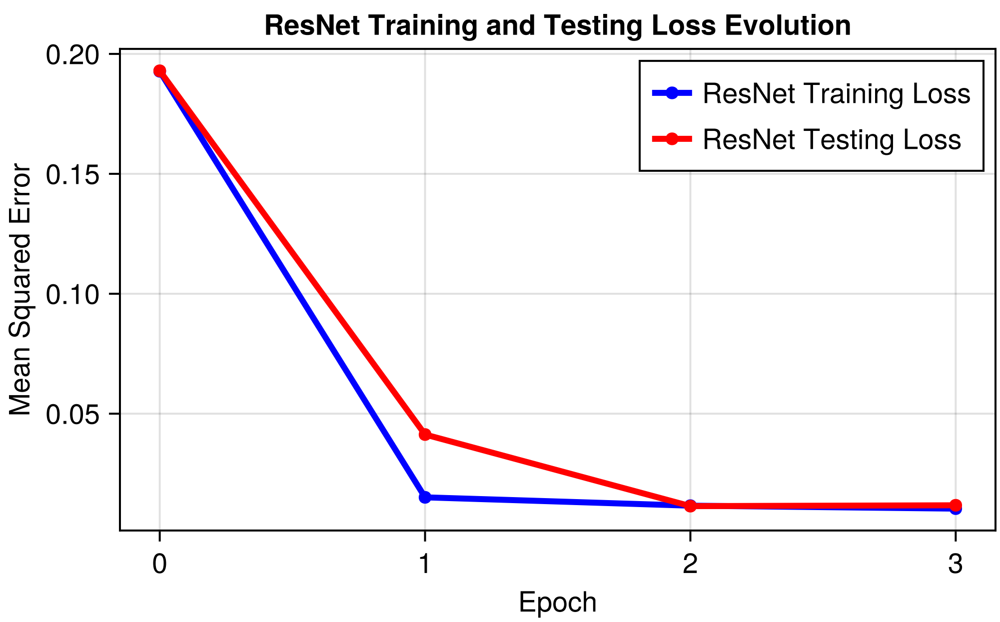
```
4-element Vector{Symbol}:
 :resnet_ps_trained
 :resnet_st_trained
 :resnet_train_losses
 :resnet_test_losses
```

Visualizing ResNet Training Results

```
# Visualize the evolution of the training and testing loss for ResNet
fig = Figure()
ax = Axis(fig[1, 1],
    xlabel="Epoch",
```

```
    ylabel="Mean Squared Error",
    title="ResNet Training and Testing Loss Evolution",
)
scatterlines!(0:resnet_epochs, resnet_train_losses, linewidth=3, color=:blue,
label="ResNet Training Loss")
scatterlines!(0:resnet_epochs, resnet_test_losses, linewidth=3, color=:red,
label="ResNet Testing Loss")
axislegend(ax, position=:rt)

fig
```



Comparing ResNet with Original CNN

```
# Compare RMSE of ResNet with the original CNN
resnet_rmse = sqrt(resnet_test_losses[end])
cnn_rmse = sqrt(test_losses[end])
simple_rmse_ref = 0.16194

@info "Original CNN RMSE: " cnn_rmse
@info "ResNet RMSE: " resnet_rmse
@info "Reference simple method RMSE: " simple_rmse_ref

resnet_improvement = round(((cnn_rmse - resnet_rmse) / cnn_rmse * 100),
digits=2)

if resnet_rmse < cnn_rmse
```

```
    println("\nResNet outperforms our original CNN by
$(resnet_improvement)%!")
    println("The skip connections in ResNet help with gradient flow during
training,
        allowing the network to learn more complex features."
    )
else
    println("\nResNet doesn't outperform our original CNN.")
    println("This could be due to:")
    println("1. Limited training time (ResNet is much larger and needs more
epochs)")
    println("2. Potential overfitting due to the larger model size")
    println("3. The original CNN might be better suited for this specific
dataset size")
end
```

```
┌ Info: Original CNN RMSE:
└   cnn_rmse = 0.11684338f0
┌ Info: ResNet RMSE:
└   resnet_rmse = 0.1086326f0
┌ Info: Reference simple method RMSE:
└   simple_rmse_ref = 0.16194

ResNet outperforms our original CNN by 7.03%!
The skip connections in ResNet help with gradient flow during training,
        allowing the network to learn more complex features.
```

References

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