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Problem Statement

Goal of this Project

Showing that
GoogleNet is a better
model than AlexNet by
using a real dataset



Rebuilt models with different hyperparameters

How results change?











- 1) Random image selection from dataset
- 2) Image Preprocessing
- 3) Creating Custom Dataset
- 4) Train and validation dataset separation
- 5) Model Finetuning
- 6) Parameters Selection
- 7) Training
- B) Evaluation of Model using Test dataset
- 9) Doing some predictions
- 10) Comparison of Models





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Chess Board Image Size for Training & Validation: 1000 Board Image

Chess Board Image Size for Test: 200 Board Image



Are they little amount?







1. Taking FEN notations and converting FEN to label

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Label size = 13

emptyGrid = 0

blackPawn = 1

whitePawn = 2

blackBishop = 3

whiteBishop = 4

blackRock = 5

whiteRock = 6

blackKnight = 7

whiteKnight = 8

blackQueen = 9

whiteQueen = 10

blackKing = 11

whiteKing = 12

FEN Notation:

./dataset/train\2K5-1N1PN3-8-3r2k1-8-1R1B1B1b-8-6R1.jpeg

Labels:

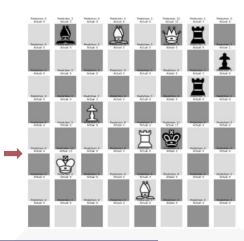




- 2. Convert image to gray scale
- 3. Taking out grids of the board as 64 images







dataset separation 5) Model Finetuning

from dataset

Parameters Selection 6)

Training

1)

Evaluation of Model using Test dataset

Random image selection

Image Preprocessing

Train and validation

Creating Custom Dataset

9) Doing some predictions

10) Comparison of Models **Dataset for Training & Validation:**

 $1000 \times 64 = 64000 \text{ Image}$

Dataset for Test: $200 \times 64 = 12800 \text{ Image}$



4. Resize Images to (224,224)

5. Convert gray Images to 3 channel Images



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```
transform = transforms.Compose([
  transforms.ToTensor(),
  transforms.Normalize(
  mean=[0.485, 0.456, 0.406],
  std=[0.229, 0.224, 0.225]
class CustomDataset(torch.utils.data.Dataset):
   def init (self, imageX, labelX):
       self.images = imageX
       self.labels = labelX
       self.transform = transform
   def getitem (self, index):
       img = self.transform(self.images[index])
       label = self.labels[index]
       return img, label
   def len (self):
       return len(self.images)
```

Convert to tensor format!





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Train and Validation Split= 0.2
Train Dataset = 80%
Validation Dataset = 20%

Create Data Loaders for train, validation and test datasets!

```
185 train_set, validation_set = torch.utils.data.random_split(custom_dataset,[int(train_split),int(validation_split)])
```

186 train loader = torch.utils.data.DataLoader(dataset=train set, batch size=batch size,shuffle=True)

187 validation loader = torch.utils.data.DataLoader(dataset=validation set, batch size=batch size,shuffle=True)

188 test_loader = torch.utils.data.DataLoader(dataset=test_custom_dataset, batch_size=batch_size,shuffle=False)

18





(2): ReLU(inplace=True)

(5): ReLU(inplace=True)

(3): Dropout(p=0.5, inplace=False)

(4): Linear(in features=4096, out features=4096, bias=True)

(6): Linear(in features=4096, out features=13, bias=True)

Freeze initial layers, train classifiers for both models!

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```
(conv1): BasicConv2d(
AlexNet(
                                                                                                          (conv): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
(bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
  (features): Sequential(
                                                                                                         maxpool1): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=True)
                                                                                                         (conv2): BasicConv2d(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
                                                                                                          (conv): Conv2d(64, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
                                                                                                          (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track running stats=True)
    (1): ReLU(inplace=True)
                                                                                                          (conv): Conv2d(64, 192, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (2): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
                                                                                                          (bn): BatchNorm2d(192, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
                                                                                                         (maxpool2): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=True)
    (3): Conv2d(64, 192, kernel size=(5, 5), stride=(1, 1), padding=(2, 2))
                                                                                                         inception3a): Inception(
                                                                                                          (branch1): BasicConv2d(
    (4): ReLU(inplace=True)
                                                                                                             (conv): Conv2d(192, 64, kernel_size=(1, 1), stride=(1, 1), bias=False)
                                                                                                             (bn): BatchNorm2d(64, eps=0.001, momentum=0.1, affine=True, track running stats=True)
    (5): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
                                                                                                             (0): BasicConv2d(
    (6): Conv2d(192, 384, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
                                                                                                               (conv): Conv2d(192, 96, kernel_size=(1, 1), stride=(1, 1), bias=False)
                                                                                                               (bn): BatchNorm2d(96, eps=0.001, momentum=0.1, affine=True, track running stats=True)
    (7): ReLU(inplace=True)
                                                                                                               (conv): Conv2d(96, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                                                                                                               (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track_running_stats=True)
    (8): Conv2d(384, 256, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
                                                                                                             (0): BasicConv2d(
                                                                                                               (conv): Conv2d(192, 16, kernel size=(1, 1), stride=(1, 1), bias=False)
    (10): Conv2d(256, 256, kernel size=(3, 3), stride=(1, 1), padding=(1, 1))
                                                                                                               (bn): BatchNorm2d(16, eps=0.001, momentum=0.1, affine=True, track running stats=True)
    (11): ReLU(inplace=True)
                                                                                                               (conv): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
                                                                                                               (bn): BatchNorm2d(32, eps=0.001, momentum=0.1, affine=True, track running stats=True)
     (12): MaxPool2d(kernel size=3, stride=2, padding=0, dilation=1, ceil mode=False)
  (avgpool): AdaptiveAvgPool2d(output size=(6, 6))
  (classifier): Sequential(
                                                                                                              (conv): Conv2d(512, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
                                                                                                              (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track running stats=True)
    (0): Dropout(p=0.5, inplace=False)
                                                                                                            (fc1): Linear(in features=2048, out features=1024, bias=True)
                                                                                                            (fc2): Linear(in_features=1024, out_features=1000, bias=True)
    (1): Linear(in features=9216, out features=4096, bias=True)
                                                                                                            (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track running stats=True)
```

(conv): BasicConv2d(

(conv): Conv2d(528, 128, kernel size=(1, 1), stride=(1, 1), bias=False) (bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track running stats=True)

(bn): BatchNorm2d(128, eps=0.001, momentum=0.1, affine=True, track running stats=True)

(fc1): Linear(in features=2048, out features=1024, bias=True) (fc2): Linear(in features=1024, out features=1000, bias=True)

(avgpool): AdaptiveAvgPool2d(output size=(1, 1)) (dropout): Dropout(p=0.2, inplace=False) (fc): Linear(in features=1024, out features=13, bias=True)

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```
319 AlexNetModel = model
320 batch_size = 64
321 learning_rate = 0.001
322 weight_decay = 0.0000001
323 num_epochs = 10
324 #momentum = 0.9
325
326 criterion = nn.CrossEntropyLoss()
327 #optimizer = torch.optim.Adam(model.classifier.parameters(), lr=learning_rate)
328 optimizer = torch.optim.Adam(filter(lambda x: x.requires_grad, model.parameters()), lr=learning_rate)
329 #optimizer = optim.SGD(model.classifier.parameters(), lr=learning_rate, momentum=momentum)
```

- For Each epoch
- Set model to training mode for training, eval mode for validation
- Iterate through all batches of images and labels
- Take model output
- Calculate the loss using CrossEntropyLoss
- > Empties the gradient tensors from previous batch in training mode
- Perform back-propagation in training mode
- Update the weight parameters in training mode
- Calculate train and val loss
- Calculate train and val accuracy



```
Number of images: 128000, Number of batches: 1600
Epoch: [1/10] | Train Loss: 0.074 | Train Accuracy: 0.986 | Val Loss: 0.010 | Val Accuracy: 0.998|
Validation Loss Decreased: inf ---> 0.009990 ---> Saving Model
Epoch: [2/10] | Train Loss: 0.065 | Train Accuracy: 0.994 | Val Loss: 0.004 | Val Accuracy: 0.999|
Validation Loss Decreased: 0.009990 ---> 0.003745 ---> Saving Model
Epoch: [3/10] | Train Loss: 0.055 | Train Accuracy: 0.996 | Val Loss: 0.002 | Val Accuracy: 1.000|
Validation Loss Decreased: 0.003745 ---> 0.002439 ---> Saving Model
Epoch: [4/10] | Train Loss: 0.035 | Train Accuracy: 0.997 | Val Loss: 0.001 | Val Accuracy: 1.000
Validation Loss Decreased: 0.002439 ---> 0.001436 ---> Saving Model
Epoch: [5/10] | Train Loss: 0.048 | Train Accuracy: 0.997 | Val Loss: 0.034 | Val Accuracy: 0.999|
Epoch: [6/10] | Train Loss: 0.035 | Train Accuracy: 0.998 | Val Loss: 0.007 | Val Accuracy: 0.999|
Epoch: [7/10] | Train Loss: 0.044 | Train Accuracy: 0.998 | Val Loss: 0.004 | Val Accuracy: 1.000|
Epoch: [8/10] | Train Loss: 0.054 | Train Accuracy: 0.998 | Val Loss: 0.001 | Val Accuracy: 1.000 |
Validation Loss Decreased: 0.001436 ---> 0.001176 ---> Saving Model
Epoch: [9/10] | Train Loss: 0.040 | Train Accuracy: 0.998 | Val Loss: 0.004 | Val Accuracy: 1.000|
Epoch: [10/10] | Train Loss: 0.050 | Train Accuracy: 0.998 | Val Loss: 0.000 | Val Accuracy: 1.000|
Validation Loss Decreased: 0.001176 ---> 0.000061 ---> Saving Model
```





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```
395 with torch.no.grad():
396 model.eval()
397 correct = 0
388 total = 0
398 for images, labels in test_loader:
400 images = images.to(device)
401 labels = labels.to(device)
402 #(no grad calculation)
403
404 outputs = model(images)
405
406 # Get predictions and calculate accuracy
407 __, predicted = torch.max(outputs.data, 1)
408 total += labels.size(0)
409 correct += (predicted == labels).sum().item()
410
411 print('Accuracy of the network on the 12800 test images: {} %'.format(100 * correct / total))
```

AlexNet

```
Number of images: 64000, Number of batches: 800
Epoch: [1/10] | Train Loss: 0.120 | Train Accuracy: 0.974 | Val Loss: 0.011 | Val Accuracy: 0.997 |
Validation Loss Decreased: inf ---> 0.010798 ---> Saving Model
Epoch: [2/10] | Train Loss: 0.046 | Train Accuracy: 0.991 | Val Loss: 0.008 | Val Accuracy: 0.998 |
Validation Loss Decreased: 0.010798 ---> 0.007895 ---> Saving Model
Epoch: [3/10] | Train Loss: 0.054 | Train Accuracy: 0.992 | Val Loss: 0.008 | Val Accuracy: 0.998 |
Validation Loss Decreased: 0.007895 ---> 0.007894 ---> Saving Model
Epoch: [4/10] | Train Loss: 0.054 | Train Accuracy: 0.994 | Val Loss: 0.003 | Val Accuracy: 0.999 |
Validation Loss Decreased: 0.007894 ---> 0.002764 ---> Saving Model
Epoch: [5/10] | Train Loss: 0.042 | Train Accuracy: 0.995 | Val Loss: 0.002 | Val Accuracy: 0.999 |
Validation Loss Decreased: 0.002764 ---> 0.001925 ---> Saving Model
Epoch: [6/10] | Train Loss: 0.037 | Train Accuracy: 0.996 | Val Loss: 0.012 | Val Accuracy: 0.998
Epoch: [7/10] | Train Loss: 0.050 | Train Accuracy: 0.996 | Val Loss: 0.003 | Val Accuracy: 1.000
Epoch: [8/10] | Train Loss: 0.059 | Train Accuracy: 0.996 | Val Loss: 0.004 | Val Accuracy: 0.999
Epoch: [9/10] | Train Loss: 0.047 | Train Accuracy: 0.997 | Val Loss: 0.003 | Val Accuracy: 1.000
Epoch: [10/10] | Train Loss: 0.052 | Train Accuracy: 0.997 | Val Loss: 0.001 | Val Accuracy: 1.000
Accuracy of the network on the 12800 test images: 99.984375 %
```

GoogleNet

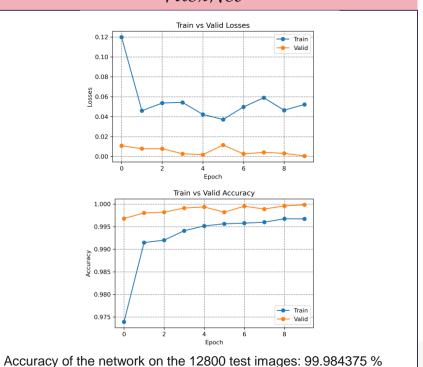
```
Number of images: 64000, Number of batches: 800
Epoch: [1/10] | Train Loss: 0.257 | Train Accuracy: 0.949 | Val Loss: 0.066 | Val Accuracy: 0.986|
Validation Loss Decreased: inf ---> 0.065633 ---> Saving Model
Epoch: [2/10] | Train Loss: 0.064 | Train Accuracy: 0.986 | Val Loss: 0.035 | Val Accuracy: 0.994|
Validation Loss Decreased: 0.065633 ---> 0.035024 ---> Saving Model
Epoch: [3/10] | Train Loss: 0.044 | Train Accuracy: 0.990 | Val Loss: 0.027 | Val Accuracy: 0.994|
Validation Loss Decreased: 0.035024 ---> 0.027179 ---> Saving Model
Epoch: [4/10] | Train Loss: 0.037 | Train Accuracy: 0.991 | Val Loss: 0.025 | Val Accuracy: 0.993|
Validation Loss Decreased: 0.027179 ---> 0.024920 ---> Saving Model
Epoch: [5/10] | Train Loss: 0.029 | Train Accuracy: 0.993 | Val Loss: 0.017 | Val Accuracy: 0.996|
Validation Loss Decreased: 0.024920 ---> 0.016835 ---> Saving Model
Epoch: [6/10] | Train Loss: 0.027 | Train Accuracy: 0.993 | Val Loss: 0.016 | Val Accuracy: 0.996|
Validation Loss Decreased: 0.016835 ---> 0.015948 ---> Saving Model
Epoch: [7/10] | Train Loss: 0.025 | Train Accuracy: 0.993 | Val Loss: 0.016 | Val Accuracy: 0.996|
Epoch: [8/10] | Train Loss: 0.023 | Train Accuracy: 0.994 | Val Loss: 0.014 | Val Accuracy: 0.996|
Validation Loss Decreased: 0.015948 ---> 0.014224 ---> Saving Model
Epoch: [9/10] | Train Loss: 0.021 | Train Accuracy: 0.994 | Val Loss: 0.015 | Val Accuracy: 0.995|
                                                            Wal Loss: 0.013 | Val Accuracy: 0.996|
Validation Loss Decreased: 0.014224 ---> 0.012909 ---> Saving Model
Accuracy of the network on the 12800 test images: 99.578125 %
```



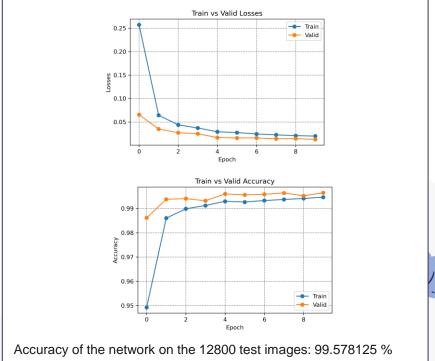


Evaluation of Model using Test dataset

AlexNet



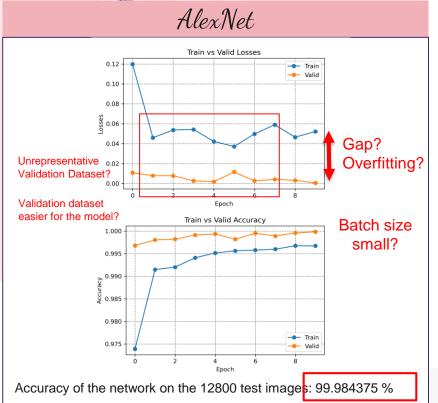
GoogleNet



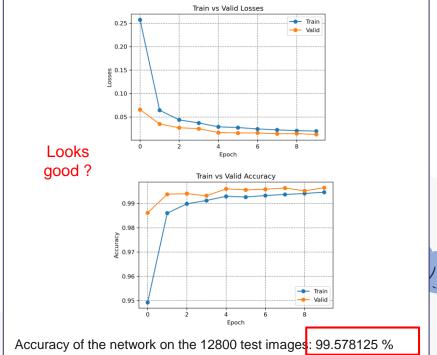
133



No Underfit







133



AlexNet



Better Accuracy than GoogleNet



GAP between losses and Overfit



No Underfit



Validation dataset is easier to predict



Unrepresentative Validation Dataset



More parameters to learn

GoogleNet



AlexNet has better Accuracy



No gap and Overfit



No Underfit



More smooth (no noisy movements)



Curves looks good!



Less parameters to learn





Better!

AlexNet



Better Accuracy than GoogleNet



GAP between losses and Overfit



No Underfit



validation dataset is easier to predict



Unrepresentative Validation Dataset



More parameters to learn

GoogleNet



AlexNet has better Accuracy



No gap ne overfit



No Underfit



More smooth (no noisy movements)



Curves looks good!



Less parameters to learn



Some Predictions



426

427

Actual FEN

1Q5k-4BR2-8-5B1p-1K1N4-8-8-7n

AlexNet FEN

1Q5k-4BR2-8-5B@p-1K1N4-8-8-7n



GoogleNet FEN

1Q5k-4BR2-8-5B1p-1K1N4-8-8-7n







Some Predictions

Actual FEN

rn1qr1k1-ppp3pp-8-5Q2-3Nn3-1P1P2P1-PB3PBP-R3K2R

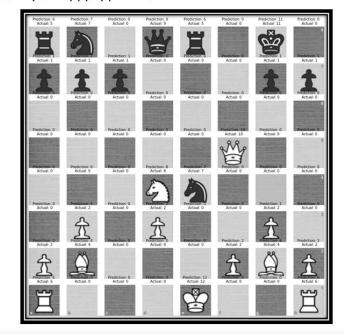
AlexNet FEN

rn1qr1k1-ppp3pp-8-5Q2-3Nn3-1P1P2P1-PB3PBP-R3K2R



GoogleNet FEN

Rn1qR1k1-ppp3pp-8-5Q2-3Nn3-1P1P2P1-PB3PBP-R3K2R







Some Predictions



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Actual FEN

4kb1r-5ppp-4pn2-p1pp4-4P3-2P1BP2-PP3P1P-R4K1R

AlexNet FEN

4kb1r-5ppp-4pn2-p1pp4-4P3-2P1pP2-PP3p1P-R4K1R



GoogleNet FEN

4kk1r-5pbp-4pn2-p1pp4-4p3-2p1BP2-pP3P1P-R4K1R







Apply Different Hyperparameters Train & Test Models with different

hyperparameters Get Results

Final report

Final presentation

Compare Results

- Learning rate
- Optimizer
- Batch size
- Regularization
- Dropout

Analyizing Models

- Train & val accuracy
- Train & val loss
- PR & ROC curves can be used!
- Different performans metrics?

Final Work



Conclusion

- Finetuning methods were used. Initial layers were freezed and classifier layers were trained.
- Both models gives high accuracies.
- After analyzing results and performans metrics, It is shown that GoogleNet model looks more stable and suitable for the problem.
- However AlexNet has higher accuracy.
- And AlexNet predicts better.
- AlexNet has overfit and unrepresentative validation dataset problem.
- Models may predict false when chess pieces are so different than dataset.









Thank you for listening!

