

Skin Cancer MNIST HAM10000:

A comparative Study of Different Machine Learning Approaches

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Problem

A comparative study of different machine learning approaches on the Skin Cancer MNIST: HAM10000 database. We compare different Neural Network models to determine which has the best testing accuracy on this dataset, including:

- Linear
- MLP
- CNN
- Deep CNN
- Three Custom models
- DenseNet-121

Dataset

Skin Cancer MNIST: HAM10000

Samples: 9958 Usable, 10015 Total

Images: 36x36 RGB images (3x36x36)

Table Data: 3 Features (Age, Sex, Localization)

Classes: 7 (Lesion Type)

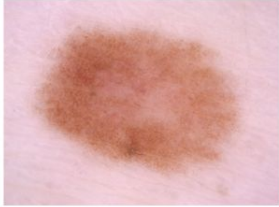
Train / Val / Test % split of dataset: 72 / 8 / 20



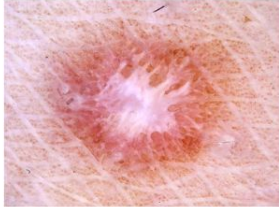
Nevus

Classes (Lesion Types)

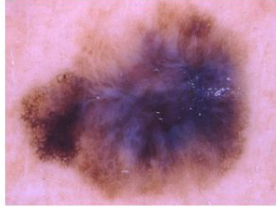
Nevus



Dermatofibroma



Melanoma



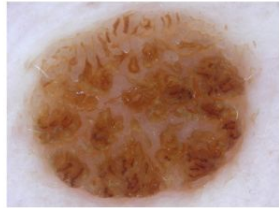
Vascular



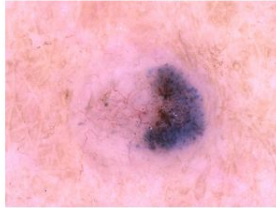
Pigmented
Bowen's



Pigmented Benign
Keratosis



Basal Cell
Carcinoma



Cancerous:

Pigmented Bowen's

Basal Cell Carcinoma

Melanoma

Non-Cancerous:

Pigmented Benign keratosis

Dermatofibroma

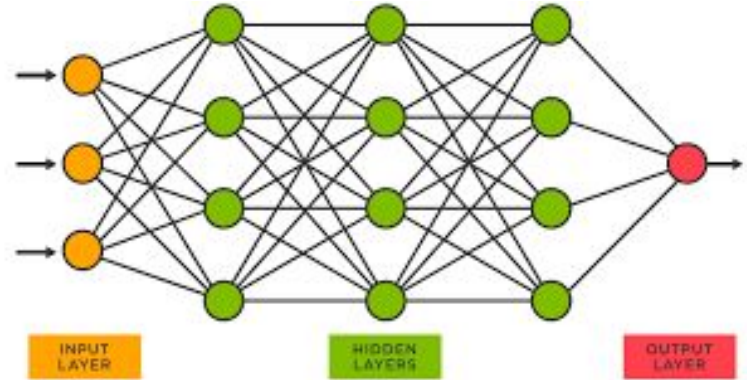
Nevus

Vascular

Neural Network Design Overview

Two data variables: image data and metadata

Epochs and batch size were determined individually for each model to maximize accuracy



Neural Network Design (Linear)

```
m = LinearModel()
xs, xs2, ys = next(iter(train_dataloader))
print(xs.shape, xs2.shape)
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

```
=====
      Kernel Shape Output Shape   Params Mult-Adds
Layer
0_flat      -      [30, 3888]      -      -
1_output    [3891, 7]      [30, 7]  27.244k  27.237k
=====
```

```

Totals
Total params      27.244k
Trainable params  27.244k
Non-trainable params    0.0
Mult-Adds        27.237k
=====
```

Imgs and data are combined after layer 0

Training: 30 Epochs, Batches of 100

Avg Epoch: 0.16s

Total Training Time: 4.79s

Final Results:

train_loss=0.87, train_acc=0.70, val_loss=0.85, val_acc=0.70

Testing Accuracy: 68.71 %

Neural Network Design (MLP)

```
m = MLPModel()
xs, xs2, ys = next(iter(train_dataloader))
print(xs.shape, xs2.shape)
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

```
=====
```

	Kernel Shape	Output Shape	Params	Mult-Adds
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Layer	Kernel Shape	Output Shape	Params	Mult-Adds
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0_flat	-	[30, 3888]	-	-
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1_ll	[3891, 200]	[30, 200]	778.4k	778.2k
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2_relu	-	[30, 200]	-	-
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3_output	[200, 7]	[30, 7]	1.407k	1.4k
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```
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```

	Totals
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Total params	779.807k
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Trainable params	779.807k
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Non-trainable params	0.0
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Mult-Adds	779.6k
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```
=====
```

Imgs and data are combined after layer 0

Training: 30 Epochs, Batches of 100

Avg Epoch: 0.50s

Total Training Time: 15.06s

Final Results:

train_loss=0.83, train_acc=0.71, val_loss=0.78, val_acc=0.73

Testing Accuracy: 72.07 %

Neural Network Design (CNN)

```
m = CNNModel()
xs, xs2, ys = next(iter(train_dataloader))
print(xs.shape, xs2.shape)
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

	Kernel Shape	Output Shape	Params	Mult-Adds
Layer				
0_conv.Conv2d_0	[3, 5, 3, 3]	[30, 5, 36, 36]	140.0	174.96k
1_conv.MaxPool2d_1	-	[30, 5, 18, 18]	-	-
2_relu	-	[30, 5, 18, 18]	-	-
3_flat	-	[30, 1620]	-	-
4_ll	[1623, 200]	[30, 200]	324.8k	324.6k
5_relu	-	[30, 200]	-	-
6_output	[200, 7]	[30, 7]	1.407k	1.4k

	Totals
Total params	326.347k
Trainable params	326.347k
Non-trainable params	0.0
Mult-Adds	500.96k

Imgs and data are combined after layer 3

Training: 30 Epochs, Batches of 100

Avg Epoch: 0.49s

Total Training Time: 14.74s

Final Results:

train_loss=0.61, train_acc=0.78, val_loss=0.68, val_acc=0.74

Testing Accuracy: 75.99 %

Neural Network Design (Deep CNN)

```
m = DCNNModel()  
xs, xs2, ys = next(iter(train_dataloader))  
print(xs.shape, xs2.shape)  
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

Layer	Kernel Shape	Output Shape	Params	Mult-Adds
0_conv.Conv2d_0	[3, 10, 5, 5]	[30, 10, 36, 36]	760.0	972.0k
1_conv.MaxPool2d_1	-	[30, 10, 18, 18]	-	-
2_conv.Conv2d_2	[10, 20, 3, 3]	[30, 20, 18, 18]	1.82k	583.2k
3_conv.MaxPool2d_3	-	[30, 20, 9, 9]	-	-
4_relu	-	[30, 20, 9, 9]	-	-
5_flat	-	[30, 1620]	-	-
6_ll	[1623, 200]	[30, 200]	324.8k	324.6k
7_relu	-	[30, 200]	-	-
8_output	[200, 7]	[30, 7]	1.407k	1.4k

Totals	
Total params	328.787k
Trainable params	328.787k
Non-trainable params	0.0
Mult-Adds	1.8812M

Imgs and data are combined after layer 3

Training: 30 Epochs, Batches of 100

Avg Epoch: 0.85s

Total Training Time: 25.59s

Final Results:

train_loss=0.50, train_acc=0.81, val_loss=0.63, val_acc=0.77

Testing Accuracy: 77.90 %

Neural Network Design (Custom 1)

```
m = CustomModel11()
xs, xs2, ys = next(iter(train_dataloader))
print(xs.shape, xs2.shape)
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

Layer	Kernel Shape	Output Shape	Params	Mult-Adds
0_conv.Conv2d_0	[3, 10, 5, 5]	[30, 10, 36, 36]	760.0	972.0k
1_conv.MaxPool2d_1	-	[30, 10, 18, 18]	-	-
2_conv.Conv2d_2	[10, 20, 5, 5]	[30, 20, 18, 18]	5.02k	1.62M
3_conv.MaxPool2d_3	-	[30, 20, 9, 9]	-	-
4_conv.Conv2d_4	[20, 40, 5, 5]	[30, 40, 9, 9]	20.04k	1.62M
5_conv.MaxPool2d_5	-	[30, 40, 3, 3]	-	-
6_relu	-	[30, 40, 3, 3]	-	-
7_flat	-	[30, 360]	-	-
8_ll	[363, 200]	[30, 200]	72.8k	72.6k
9_mlp.Linear_0	[200, 100]	[30, 100]	20.1k	20.0k
10_mlp.ReLU_1	-	[30, 100]	-	-
11_mlp.Linear_2	[100, 200]	[30, 200]	20.2k	20.0k
12_mlp.Linear_0	[200, 100]	[30, 100]	-	20.0k
13_mlp.ReLU_1	-	[30, 100]	-	-
14_mlp.Linear_2	[100, 200]	[30, 200]	-	20.0k
15_relu	-	[30, 200]	-	-
16_output	[200, 7]	[30, 7]	1.407k	1.4k

Totals	
Total params	140.327k
Trainable params	140.327k
Non-trainable params	0.0
Mult-Adds	4.366M

Imgs and data are combined after layer 7

Training: 30 Epochs, Batches of 100

Avg Epoch: 1.06s

Total Training Time: 31.79s

Final Results:

train_loss=0.54, train_acc=0.79, val_loss=0.64, val_acc=0.77

Testing Accuracy:

78.30 %

Neural Network Design (Custom 2)

```
m = CustomModel2()  
xs, xs2, ys = next(iter(train_dataloader))  
print(xs.shape, xs2.shape)  
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

Layer	Kernel Shape	Output Shape	Params	Mult-Adds
0_conv.Conv2d_0	[3, 25, 5, 5]	[30, 25, 36, 36]	1.9k	2.43M
1_conv.MaxPool2d_1	-	[30, 25, 12, 12]	-	-
2_conv.ReLU_2	-	[30, 25, 12, 12]	-	-
3_conv.Conv2d_3	[25, 50, 3, 3]	[30, 50, 12, 12]	11.3k	1.62M
4_conv.MaxPool2d_4	-	[30, 50, 4, 4]	-	-
5_conv.ReLU_5	-	[30, 50, 4, 4]	-	-
6_flat	-	[30, 800]	-	-
7_ll	[803, 200]	[30, 200]	160.8k	160.6k
8_mlp.Linear_0	[200, 100]	[30, 100]	20.1k	20.0k
9_mlp.ReLU_1	-	[30, 100]	-	-
10_mlp.Linear_2	[100, 200]	[30, 200]	20.2k	20.0k
11_mlp.Linear_0	[200, 100]	[30, 100]	-	20.0k
12_mlp.ReLU_1	-	[30, 100]	-	-
13_mlp.Linear_2	[100, 200]	[30, 200]	-	20.0k
14_output	[200, 7]	[30, 7]	1.407k	1.4k

	Totals
Total params	215.707k
Trainable params	215.707k
Non-trainable params	0.0
Mult-Adds	4.292M

Imgs and data are combined after layer 7

Training: 45 Epochs, Batches of 130

Avg Epoch: 1.44s

Total Training Time: 64.96s

Final Results:

train_loss=0.51, train_acc=0.81, val_loss=0.65, val_acc=0.77

Testing Accuracy: 78.20 %

Neural Network Design (Custom 3)

```
m = CustomModel3()  
xs, xs2, ys = next(iter(train_dataloader))  
print(xs.shape, xs2.shape)  
summary(m, xs, xs2);
```

```
torch.Size([30, 3, 36, 36]) torch.Size([30, 3])
```

Layer	Kernel Shape	Output Shape	Params	Mult-Adds
0_conv.Conv2d_0	[3, 25, 5, 5]	[30, 25, 36, 36]	1.9k	2.43M
1_conv.MaxPool2d_1	-	[30, 25, 12, 12]	-	-
2_conv.ReLU_2	-	[30, 25, 12, 12]	-	-
3_conv.Conv2d_3	[25, 50, 3, 3]	[30, 50, 12, 12]	11.3k	1.62M
4_conv.MaxPool2d_4	-	[30, 50, 4, 4]	-	-
5_conv.ReLU_5	-	[30, 50, 4, 4]	-	-
6_flat	-	[30, 800]	-	-
7_lstm	-	[30, 200]	1.4448M	1.44M
8_ll	[203, 200]	[30, 200]	40.8k	40.6k
9_mlp.Linear_0	[200, 100]	[30, 100]	20.1k	20.0k
10_mlp.ReLU_1	-	[30, 100]	-	-
11_mlp.Linear_2	[100, 200]	[30, 200]	20.2k	20.0k
12_mlp.Linear_0	[200, 100]	[30, 100]	-	20.0k
13_mlp.ReLU_1	-	[30, 100]	-	-
14_mlp.Linear_2	[100, 200]	[30, 200]	-	20.0k
15_output	[200, 7]	[30, 7]	1.407k	1.4k

	Totals
Total params	1.540507M
Trainable params	1.540507M
Non-trainable params	0.0
Mult-Adds	5.612M

Imgs and data are combined after layer 7

Training: 45 Epochs, Batches of 150

Avg Epoch: 3.00s

Total Training Time: 135.06s

Final Results:

train_loss=0.45, train_acc=0.83, val_loss=0.73, val_acc=0.77

Testing Accuracy:

75.94 %

Neural Network Design (DenseNet-121)

DenseNet uses a combination of many layers.

It has:

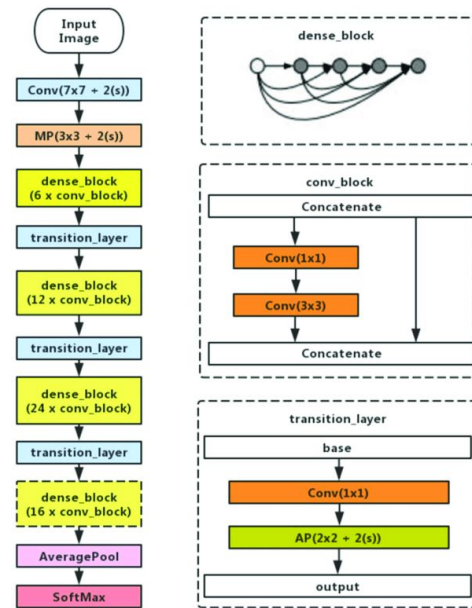
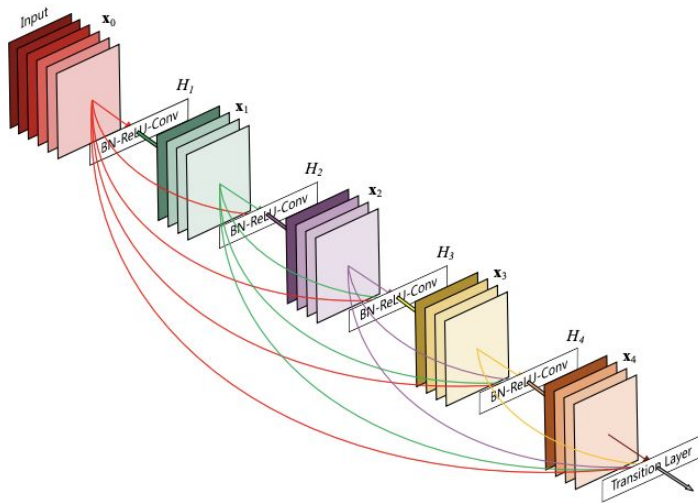
1 7x7 Convolutions,

58 3x3 Convolutions,

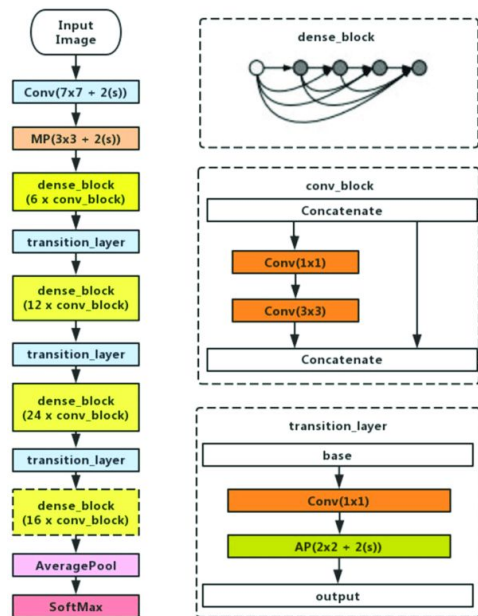
61 1x1 Convolutions,

4 AvgPools,

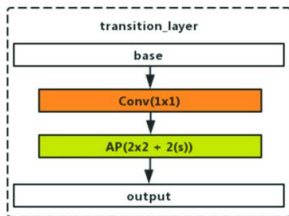
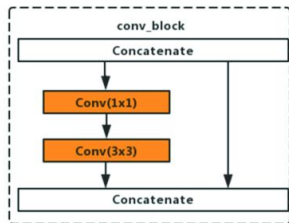
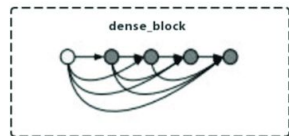
and 1 fully connected layer



Neural Network Design (DenseNet-121)



	Totals
Total params	6.961116M
Trainable params	6.961116M
Non-trainable params	0.0
Mult-Adds	64.705141M



Imgs and data are combined after layer 7

365 layers

Training: 45 Epochs, Batches of 150

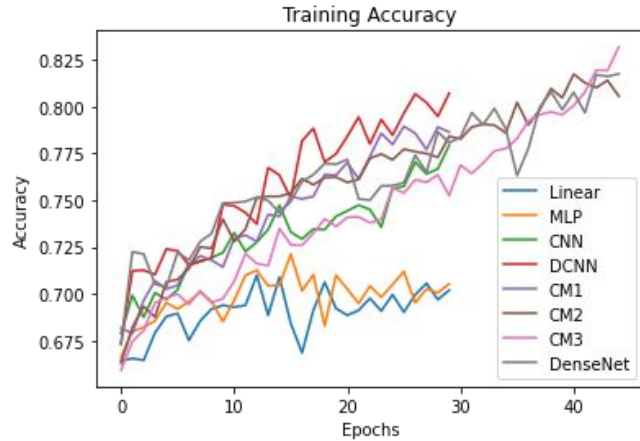
Avg Epoch: 35.43s **Total Training Time:** 1594.15s

Final Results:

train_loss=0.48, train_acc=0.82, val_loss=0.63, val_acc=0.78

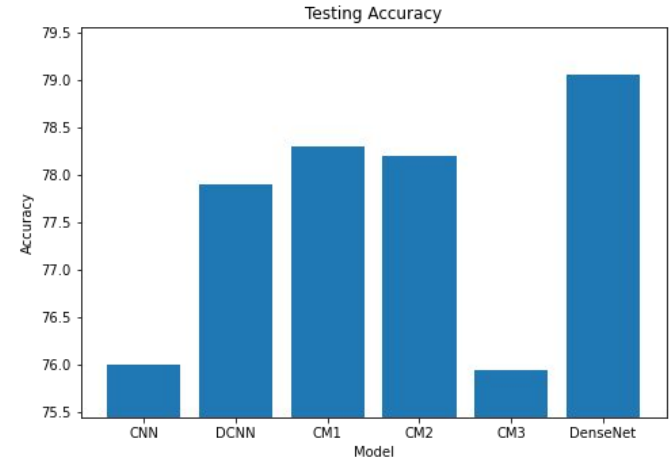
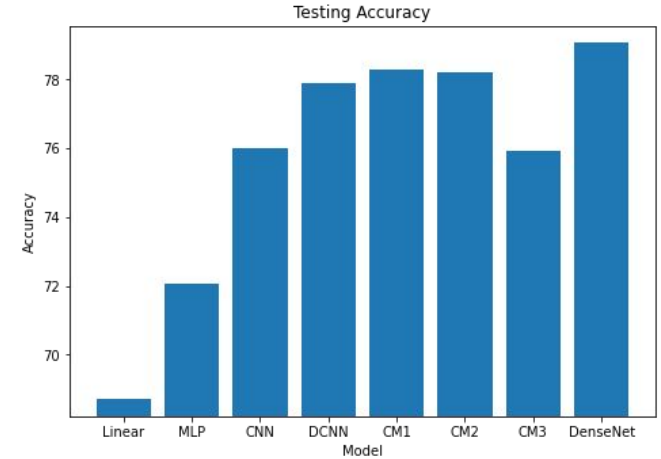
Testing Accuracy: 79.06 %

Neural Network Designs Compared



The DenseNet Model performed the best, with 79.1% test accuracy

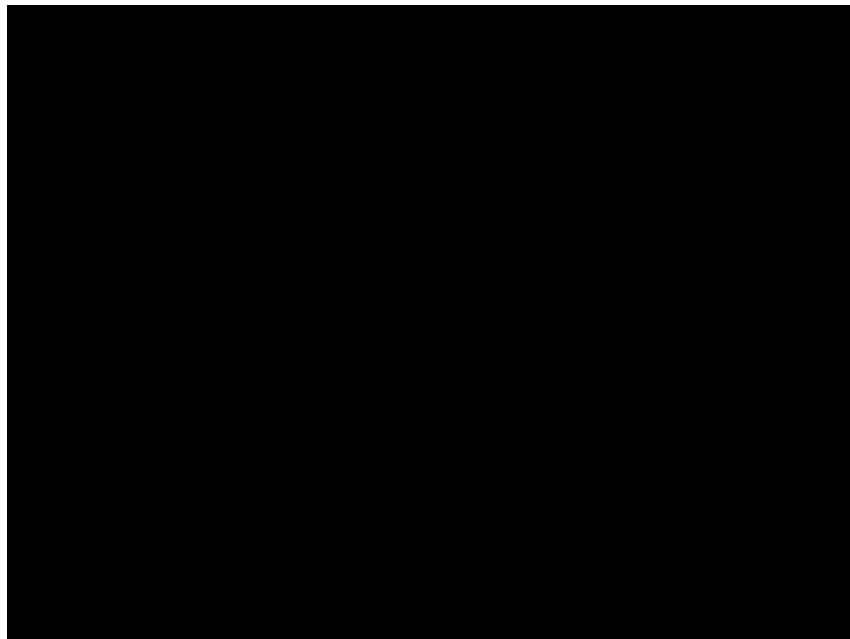
The Linear model meanwhile performed the worst, with only 68.7% test accuracy



Real-life Applications

- Dermatologists could use the application to quickly classify large quantities of lesion images as cancerous or non-cancerous. Though due to inaccuracies they would likely be restricted to using this as a helper tool in diagnosing lesions.
- Medical Practitioners could also use the application to decide how urgently they may need to refer a patient to a dermatologist if a given image is predicted as cancerous or non-cancerous.

Deployment Demo



Deployment Application

```
PS C:\Users\[redacted]\project> python CancerPrediction.py
CSV file path: CancerData/deployment_data.csv
Images folder path: C:/Users/[redacted]/project/CancerData/deployment_images
```

```
Loading from dcnn_model.pt
```

Img	Predicted
0	bkl
1	bcc
2	nv
3	nv
4	akiec
5	bkl
6	bcc
7	bcc
8	vasc
9	mel
10	akiec
11	bcc
12	nv
13	nv
14	nv
15	mel
16	nv
17	bkl
18	akiec
19	bkl
20	bkl

```
PS C:\Users\[redacted]\project> █
```

The user specifies a path for the .csv file containing image metadata, and then the folder path containing the images

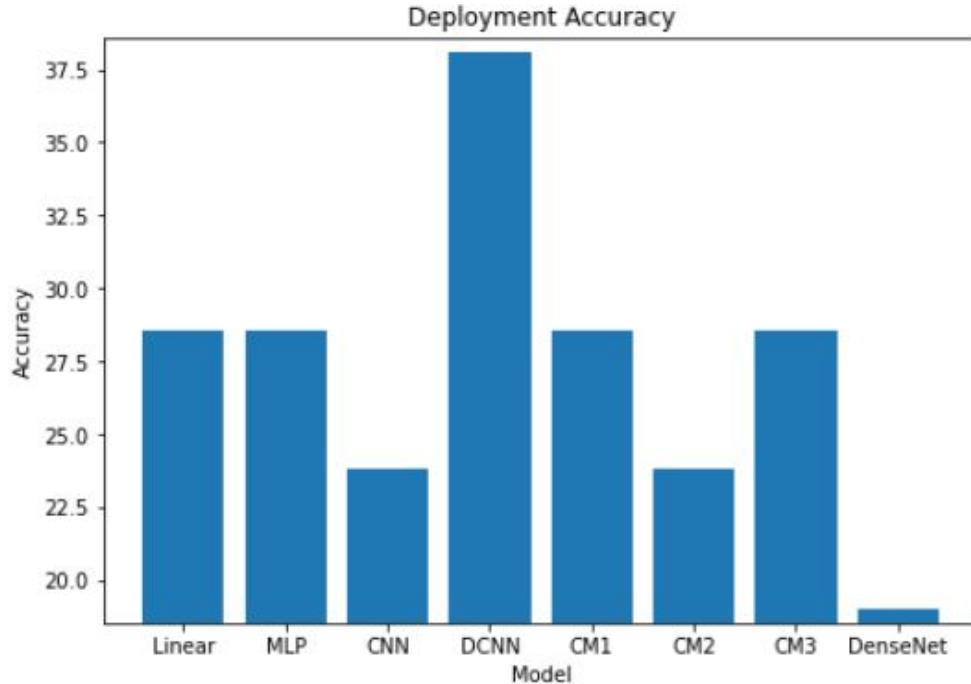
Deployment Overview

- Using 21 samples with 3 for each class of lesion
- Each sample has an 36x36 RGB image (3x36x36), and
- data containing the age, sex, and localization for each sample
- Each model was tested on the deployment data, which was collected from images found online



Melanoma

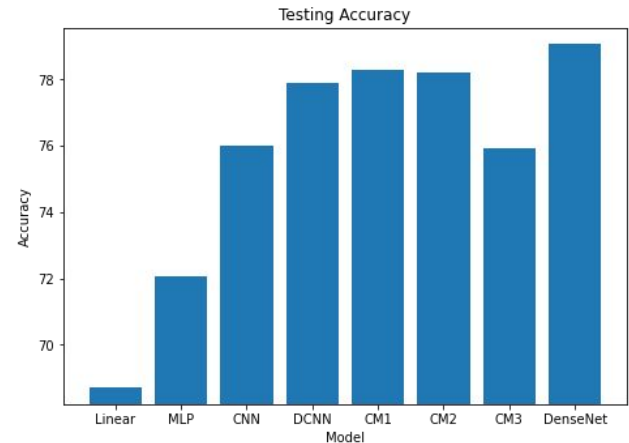
Deployment Results



Significant differences in accuracy between deployment and testing

The DCNN Model performed the best, with 38% accuracy

DenseNet meanwhile performed the worst, with only 19% accuracy



Deployment Problems

- Looking at the true positives and false positives of each class we noticed a large amount of false positives of Nevus lesions using the deployment data, and many of the predictions in testing showed a similar result, where most of the accuracy came from the many nevus samples, while predicting other kinds of lesions incorrectly.
- We found the majority of samples in the MNIST Skin Cancer dataset are Nevus lesions. This, combined with how similar Nevus lesions may look to other types of lesions, the models often predict most images as Nevus.
- This causes the training and testing accuracy to be significantly higher than they should be, as shown by the deployment accuracy, where there are an equal number of samples of each class.

References

[Skin Cancer MNIST: HAM10000 | Kaggle](#)

[DenseNet121 | pytorch | Kaggle](#)

[Architecture of DenseNet-121 \(opengenius.org\)](#)