Assessing Model Complexity

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In the deep neural network domain, training on a deeper neural architecture often yields a better result, since deeper hidden layers can capture more complex features. However, is it true regardless of any other factors? So in this project, I will try to investigate whether a more complex DNN will always yield better performance.

In [8]:

```
import tensorflow as tf
import numpy as np
```

In this project, I will use a subset of the MNIST training dataset, since training DNNs on the whole MNIST dataset often yield accuracy higher than 99%, which makes us hard to tell whether a model is better or not.
In this case, I only choose 2000 samples for training. Besides, I will try to resize the image from 28x28 into 32x32, for some of our models used later on are required to have an input image size of at least 32x32.

In [9]:

```
mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

x_train = np.expand_dims(x_train, axis=-1)
x_train = tf.image.resize(x_train, [32, 32]) / 255.
x_train = x_train[:2000]

y_train = y_train[:2000]
y_train = tf.keras.utils.to_categorical(y_train, 10)

x_test = np.expand_dims(x_test, axis=-1)
x_test = tf.image.resize(x_test, [32, 32]) / 255.

y_test = tf.keras.utils.to_categorical(y_test, 10)

print("x_train", x_train.shape)
print("y_train", y_train.shape)
print("x_test", x_test.shape)
print("y_test", y_test.shape)
```

```
x_train (2000, 32, 32, 1)
y_train (2000, 10)
x_test (10000, 32, 32, 1)
y_test (10000, 10)
```

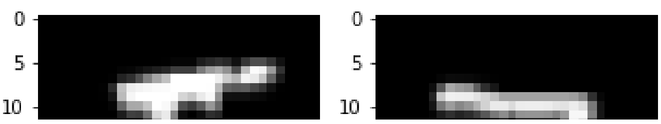
Let's visualize some sample images.

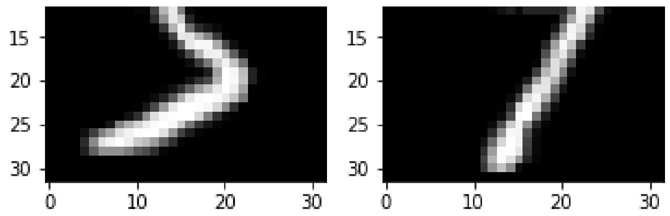
In [10]:

```
import matplotlib.pyplot as plt
fig, axes = plt.subplots(1, 2)
axes[0].imshow(x_train[0,:,:,0], cmap="gray")
axes[1].imshow(x_test[0,:,:,0], cmap="gray")
```

Out[10]:

```
<matplotlib.image.AxesImage at 0x7f6274196fd0>
```





In this project, I will use three kinds of different deep neural networks:

1. **Customize CNN (inspired from VGG, the simplest model here)**
2. **DesneNet-121**
3. **ResNet-152**

In [11]:

```
model1 = tf.keras.Sequential([
  tf.keras.Input(shape=(32, 32, 1)),
  tf.keras.layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
  tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
  tf.keras.layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
  tf.keras.layers.MaxPooling2D(pool_size=(2, 2)),
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(10, activation="softmax"),
])
model2 = tf.keras.applications.DenseNet121(weights=None, input_shape=(32, 32, 1), classe
s=10)
model3 = tf.keras.applications.ResNet152(weights=None, input_shape=(32, 32, 1), classes=
10)
models = [model1, model2, model3]
```

Now we assess the number of parameters for each model. Since DenseNet and ResNet have a huge amount of neurons, I use logarithmic count for the y-axis.

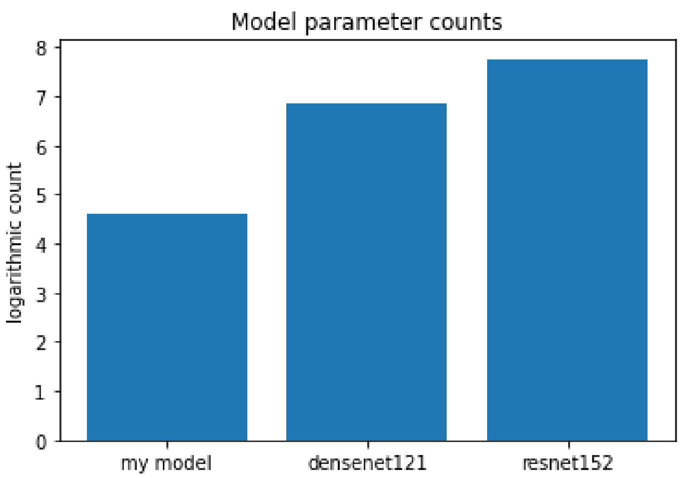
In [18]:

```
n_params = []
for model in models:
  n_params.append(np.log10(model.count_params()))

names = ["my model", "densenet121", "resnet152"]
plt.bar(names, n_params, align="center")
plt.ylabel("logarithmic count")
plt.title("Model parameter counts")
```

Out[18]:

```
Text(0.5, 1.0, 'Model parameter counts')
```



As we can see, DenseNet has approximately 100 times more parameters than our customized model, and ResNet even has 10 times more parameters than DenseNet.

Now let's train our model.

In [13]:

```
history_lst = []
for model in models:
  model.compile(loss="categorical_crossentropy", optimizer="sgd", metrics=["accuracy"])
  history = model.fit(x_train, y_train, batch_size=64, epochs=5, validation_split=0.1)
  history_lst.append(history)
```

```
Epoch 1/5
29/29 [==============================] - 1s 13ms/step - loss: 2.2972 - accuracy: 0.1189 -
val_loss: 2.2388 - val_accuracy: 0.2950
Epoch 2/5
29/29 [==============================] - 0s 5ms/step - loss: 2.2384 - accuracy: 0.1855 -
val_loss: 2.1699 - val_accuracy: 0.4850
Epoch 3/5
29/29 [==============================] - 0s 5ms/step - loss: 2.1671 - accuracy: 0.2957 -
val_loss: 2.0746 - val_accuracy: 0.5800
Epoch 4/5
29/29 [==============================] - 0s 5ms/step - loss: 2.0640 - accuracy: 0.3688 -
val_loss: 1.9046 - val_accuracy: 0.6250
Epoch 5/5
29/29 [==============================] - 0s 5ms/step - loss: 1.8728 - accuracy: 0.4736 -
val_loss: 1.6361 - val_accuracy: 0.6400
Epoch 1/5
29/29 [==============================] - 13s 180ms/step - loss: 2.0422 - accuracy: 0.3084
- val_loss: 2.3033 - val_accuracy: 0.1200
Epoch 2/5
29/29 [==============================] - 2s 61ms/step - loss: 0.8533 - accuracy: 0.7604 -
val_loss: 2.3136 - val_accuracy: 0.1150
Epoch 3/5
29/29 [==============================] - 2s 62ms/step - loss: 0.4131 - accuracy: 0.8826 -
val_loss: 2.3327 - val_accuracy: 0.0600
Epoch 4/5
29/29 [==============================] - 2s 61ms/step - loss: 0.2576 - accuracy: 0.9375 -
val_loss: 2.3722 - val_accuracy: 0.0900
Epoch 5/5
29/29 [==============================] - 2s 61ms/step - loss: 0.1764 - accuracy: 0.9674 -
val_loss: 2.3983 - val_accuracy: 0.0600
Epoch 1/5
29/29 [==============================] - 19s 251ms/step - loss: 3.6443 - accuracy: 0.1678
- val_loss: 338010.2812 - val_accuracy: 0.1150
Epoch 2/5
29/29 [==============================] - 4s 142ms/step - loss: 3.3629 - accuracy: 0.3278
- val_loss: 9801.8379 - val_accuracy: 0.1050
Epoch 3/5
29/29 [==============================] - 4s 144ms/step - loss: 2.7190 - accuracy: 0.4323
- val_loss: 2018.0312 - val_accuracy: 0.1000
Epoch 4/5
29/29 [==============================] - 4s 142ms/step - loss: 1.7933 - accuracy: 0.5593
- val_loss: 794.3433 - val_accuracy: 0.1050
Epoch 5/5
29/29 [==============================] - 4s 143ms/step - loss: 1.7522 - accuracy: 0.6577
- val_loss: 115.0957 - val_accuracy: 0.1000
```

After training is done, let's check the accuracy of training data and validation data, respectively.

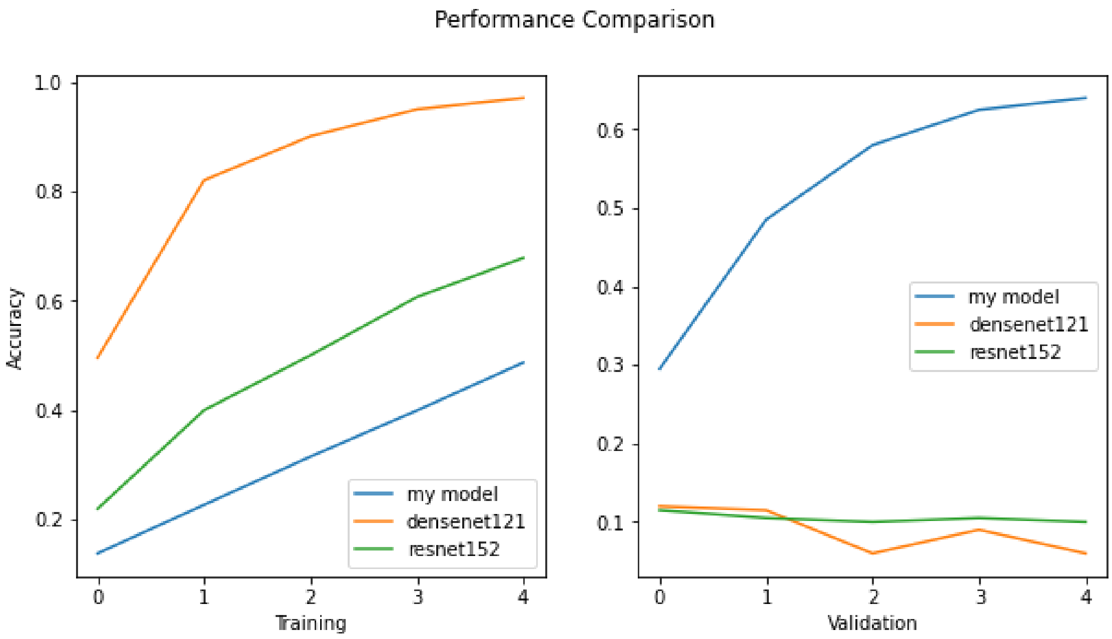
In [36]:

```
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
for name, history in zip(names, history_lst):
  axes[0].plot(history.history['accuracy'], label=name)
  axes[1].plot(history.history['val_accuracy'], label=name)
axes[0].set_xlabel("Training")
axes[1].set_xlabel("Validation")
axes[0].set_ylabel("Accuracy")
axes[0].legend(loc="best")
axes[1].legend(loc="best")
plt.suptitle("Performance Comparison")
```

Out[36]:

Out[36]:

Text(0.5, 0.98, 'Performance Comparison')



From the above, we observe that although our customized model yields the worst accuracy on the training data, it turns out to have the best validation accuracy. This is the phenomenon of overfitting for the DenseNet and ResNet cases since their parameter counts are too high.
To ensure this is the problem of overfitting, let's check the test set performance.

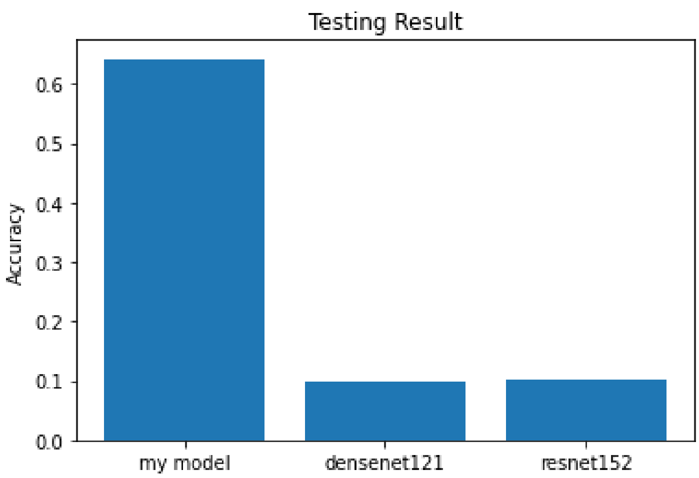
In [46]:

```
results = []
for model in models:
  score = model.evaluate(x_test, y_test)
  results.append(score[1])
plt.bar(names, results, align="center")
plt.ylabel("Accuracy")
plt.title("Testing Result")
```

```
313/313 [==============================] - 1s 2ms/step - loss: 1.6349 - accuracy: 0.6420
313/313 [==============================] - 5s 15ms/step - loss: 2.4087 - accuracy: 0.0974
313/313 [==============================] - 10s 32ms/step - loss: 116.2906 - accuracy: 0.1
013
```

Out[46]:

Text(0.5, 1.0, 'Testing Result')



As we can see, our simplest model outperforms the others. But, we shall not blame the designer of DenseNet and ResNet, since our training data is too small.
In the next section, I try to increase the training data size from 2000 to 10000, and I want to see if there is any difference.

In [47]:

```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

x_train = np.expand_dims(x_train, axis=-1)
x_train = tf.image.resize(x_train, [32, 32]) / 255.
x_train = x_train[:10000]

y_train = y_train[:10000]
y_train = tf.keras.utils.to_categorical(y_train, 10)

x_test = np.expand_dims(x_test, axis=-1)
x_test = tf.image.resize(x_test, [32, 32]) / 255.

y_test = tf.keras.utils.to_categorical(y_test, 10)

print("x_train", x_train.shape)
print("y_train", y_train.shape)
print("x_test", x_test.shape)
print("y_test", y_test.shape)
```

```
x_train (10000, 32, 32, 1)
y_train (10000, 10)
x_test (10000, 32, 32, 1)
y_test (10000, 10)
```

And do something the same as before.

In [48]:

```
history_lst = []
for model in models:
  model.compile(loss="categorical_crossentropy", optimizer="sgd", metrics=["accuracy"])
  history = model.fit(x_train, y_train, batch_size=64, epochs=5, validation_split=0.1)
  history_lst.append(history)
```

```
Epoch 1/5
141/141 [==============================] - 1s 6ms/step - loss: 1.4023 - accuracy: 0.5864
- val_loss: 0.6152 - val_accuracy: 0.8380
Epoch 2/5
141/141 [==============================] - 1s 4ms/step - loss: 0.7856 - accuracy: 0.7405
- val_loss: 0.4641 - val_accuracy: 0.8540
Epoch 3/5
141/141 [==============================] - 1s 4ms/step - loss: 0.6227 - accuracy: 0.7966
- val_loss: 0.3893 - val_accuracy: 0.8890
Epoch 4/5
141/141 [==============================] - 1s 4ms/step - loss: 0.5046 - accuracy: 0.8365
- val_loss: 0.3504 - val_accuracy: 0.8900
Epoch 5/5
141/141 [==============================] - 1s 4ms/step - loss: 0.4315 - accuracy: 0.8650
- val_loss: 0.3216 - val_accuracy: 0.9060
Epoch 1/5
141/141 [==============================] - 20s 86ms/step - loss: 0.2058 - accuracy: 0.941
7 - val_loss: 2.2179 - val_accuracy: 0.1390
Epoch 2/5
141/141 [==============================] - 8s 60ms/step - loss: 0.0864 - accuracy: 0.9771
- val_loss: 0.5395 - val_accuracy: 0.8320
Epoch 3/5
141/141 [==============================] - 9s 60ms/step - loss: 0.0494 - accuracy: 0.9887
- val_loss: 0.1101 - val_accuracy: 0.9670
Epoch 4/5
141/141 [==============================] - 8s 60ms/step - loss: 0.0275 - accuracy: 0.9954
- val_loss: 0.0953 - val_accuracy: 0.9730
Epoch 5/5
141/141 [==============================] - 8s 60ms/step - loss: 0.0160 - accuracy: 0.9989
- val_loss: 0.0879 - val_accuracy: 0.9730
Epoch 1/5
141/141 [==============================] - 34s 165ms/step - loss: 0.8585 - accuracy: 0.76
66 - val_loss: 2.4046 - val_accuracy: 0.1760
Epoch 2/5
141/141 [==============================] - 20s 142ms/step - loss: 0.4221 - accuracy: 0.88
```

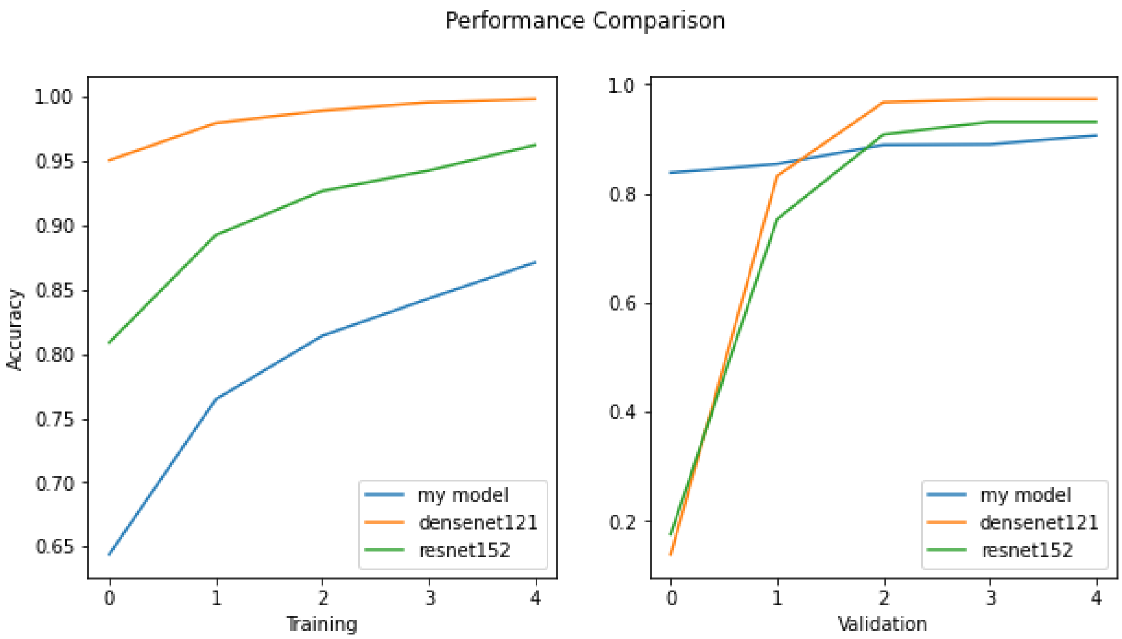
```
09 - val_loss: 0.8126 - val_accuracy: 0.7530
Epoch 3/5
141/141 [==============================] - 20s 142ms/step - loss: 0.2851 - accuracy: 0.92
48 - val_loss: 0.2990 - val_accuracy: 0.9080
Epoch 4/5
141/141 [==============================] - 20s 141ms/step - loss: 0.2148 - accuracy: 0.93
87 - val_loss: 0.2197 - val_accuracy: 0.9310
Epoch 5/5
141/141 [==============================] - 20s 142ms/step - loss: 0.1498 - accuracy: 0.96
34 - val_loss: 0.2238 - val_accuracy: 0.9310
```

In [49]:

```
fig, axes = plt.subplots(1, 2, figsize=(10, 5))
for name, history in zip(names, history_lst):
  axes[0].plot(history.history['accuracy'], label=name)
  axes[1].plot(history.history['val_accuracy'], label=name)
axes[0].set_xlabel("Training")
axes[1].set_xlabel("Validation")
axes[0].set_ylabel("Accuracy")
axes[0].legend(loc="best")
axes[1].legend(loc="best")
plt.suptitle("Performance Comparison")
```

Out[49]:

```
Text(0.5, 0.98, 'Performance Comparison')
```



Here, we see that DensetNet and ResNet not only perform better during the training stage, they also have a good performance on the validation stage after 2 epochs.
Finally, let's see the test set performance:

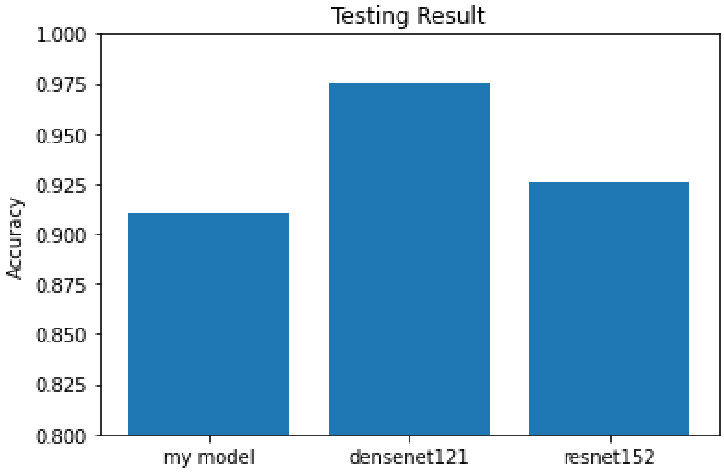
In [52]:

```
results = []
for model in models:
  score = model.evaluate(x_test, y_test)
  results.append(score[1])
plt.bar(names, results, align="center")
plt.ylabel("Accuracy")
plt.ylim((0.8, 1))
plt.title("Testing Result")
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.3194 - accuracy: 0.9103
313/313 [==============================] - 5s 15ms/step - loss: 0.0780 - accuracy: 0.9757
313/313 [==============================] - 10s 31ms/step - loss: 0.2479 - accuracy: 0.926
0
```

Out[52]:

```
Text(0.5, 1.0, 'Testing Result')
```



Compared to the data volume that has merely 2000, DenseNet and ResNet can perform well as long as the training data is sufficient enough. Therefore, we can conclude:

1. **If data volume is small, we shall use simpler model for training in order to prevent overfitting.**
2. **If we have sufficient training data, we could use more complex model in order to boost performance.**