

# Advanced Image Classification

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**Github Repo** (<https://github.com/amanichopra/CNN-Classification>)

## Resources Used

- <https://zhenye-na.github.io/2018/09/28/pytorch-cnn-cifar10.html> (<https://zhenye-na.github.io/2018/09/28/pytorch-cnn-cifar10.html>)
- [https://www.tensorflow.org/tutorials/keras/save\\_and\\_load](https://www.tensorflow.org/tutorials/keras/save_and_load) ([https://www.tensorflow.org/tutorials/keras/save\\_and\\_load](https://www.tensorflow.org/tutorials/keras/save_and_load))

## Features

- Constructed CNN with Keras for MNIST digits (99% accuracy), MNIST fashion (92% accuracy), CIFAR-10 (73% accuracy), CIFAR-100 fine (43% accuracy), and CIFAR-100 coarse (56% accuracy) datasets.
- Implemented support for saving and loading models to avoid retraining.
- Incorporated functionality for augmentation and random cropping of input data.

## Questions

### 1) How is a CNN superior to standard ANNs for image processing?

The main advantage of CNNs over standard ANNs for image processing is that they preserve the spatial interactions in images. They are also effective in capturing the relevant features of images, similar to process of human vision processing. Just like humans, CNNs begin with simple cells capturing high-level attributes and end with more complex cells capturing low-level attributes.

### 2) Why do we sometimes use pooling in CNNs?

Pooling is useful to help reduce the space complexity of the network and compute fewer parameters. It significantly reduces overhead during training, while still retaining the important features of the image.

### 3) Why do you think the cifar datasets are harder than mnist?

The CIFAR datasets are harder to classify than MNIST probably due to the following reasons:

- CIFAR images are RGB unlike the black & white MNIST images, which adds more complexity.
- CIFAR images have varied backgrounds and orientations for the same objects. For example, airplanes in the dataset are in different settings and are pictured in different angles.
- MNIST has much fewer class labels.

## Evaluation and Hyperparameter Tuning

Let's summarize the results on each dataset.

```
In [1]: from CNN_tuning import getRawData, preprocessData, trainModel, runModel, evalResults
```

```
In [2]: mods = {'mnist_d':None, 'mnist_f':None, 'cifar_10':None, 'cifar_100_c':None, 'cifar_100_f':None}
acc = {dataset: None for dataset in mods}
for dataset in mods:
    raw = getRawData(dataset)
    data = preprocessData(raw, dataset, 'tf_conv')
    model = trainModel(data[0], 'tf_conv', dataset, load=True)
    mods[dataset] = model
    preds = runModel(data[1], model, ALGORITHM='tf_conv')
    acc[dataset] = evalResults(data[1], preds, ALGORITHM='tf_conv')
```

Dataset: mnist\_d  
Shape of xTrain dataset: (60000, 28, 28).  
Shape of yTrain dataset: (60000,).  
Shape of xTest dataset: (10000, 28, 28).  
Shape of yTest dataset: (10000,).  
New shape of xTrain dataset: (60000, 28, 28, 1).  
New shape of xTest dataset: (10000, 28, 28, 1).  
New shape of yTrain dataset: (60000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_CNN.  
Testing TF\_CNN.  
Classifier algorithm: tf\_conv  
Classifier accuracy: 99.080000%

Dataset: mnist\_f  
Shape of xTrain dataset: (60000, 28, 28).  
Shape of yTrain dataset: (60000,).  
Shape of xTest dataset: (10000, 28, 28).  
Shape of yTest dataset: (10000,).  
New shape of xTrain dataset: (60000, 28, 28, 1).  
New shape of xTest dataset: (10000, 28, 28, 1).  
New shape of yTrain dataset: (60000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_CNN.  
Testing TF\_CNN.  
Classifier algorithm: tf\_conv  
Classifier accuracy: 92.920000%

Dataset: cifar\_10  
Shape of xTrain dataset: (50000, 32, 32, 3).  
Shape of yTrain dataset: (50000, 1).  
Shape of xTest dataset: (10000, 32, 32, 3).  
Shape of yTest dataset: (10000, 1).  
New shape of xTrain dataset: (50000, 32, 32, 3).  
New shape of xTest dataset: (10000, 32, 32, 3).  
New shape of yTrain dataset: (50000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_CNN.  
Testing TF\_CNN.  
Classifier algorithm: tf\_conv  
Classifier accuracy: 73.880000%

Dataset: cifar\_100\_c  
Shape of xTrain dataset: (50000, 32, 32, 3).  
Shape of yTrain dataset: (50000, 1).  
Shape of xTest dataset: (10000, 32, 32, 3).  
Shape of yTest dataset: (10000, 1).  
New shape of xTrain dataset: (50000, 32, 32, 3).  
New shape of xTest dataset: (10000, 32, 32, 3).  
New shape of yTrain dataset: (50000, 20).  
New shape of yTest dataset: (10000, 20).  
Building and training TF\_CNN.  
Testing TF\_CNN.  
Classifier algorithm: tf\_conv  
Classifier accuracy: 56.560000%

Dataset: cifar\_100\_f

```
Shape of xTrain dataset: (50000, 32, 32, 3).
Shape of yTrain dataset: (50000, 1).
Shape of xTest dataset: (10000, 32, 32, 3).
Shape of yTest dataset: (10000, 1).
New shape of xTrain dataset: (50000, 32, 32, 3).
New shape of xTest dataset: (10000, 32, 32, 3).
New shape of yTrain dataset: (50000, 100).
New shape of yTest dataset: (10000, 100).
Building and training TF_CNN.
Testing TF_CNN.
Classifier algorithm: tf_conv
Classifier accuracy: 43.940000%
```

Increasing the accuracy of the CNN was a tedious but rewarding task. At first, the CNN architecture for each dataset only had one convolution layer, followed by a dropout layer. This resulted in decent accuracy (95% for MNIST datasets and 35%-50% for CIFAR datasets). To increase the accuracy further, I added more convolutional layers with increasing numbers of filters for each subsequent layer. Additionally, I added BatchNormalization layers to help with regularization and accelerating the training process. Lastly, despite the time complexity, I trained the CNNs for many epochs ~35.

## CNN Architecture and Hyperparameters

### MNIST Digits

```
In [3]: mods['mnist_d'].summary()
```

Model: "sequential\_21"

Layer (type)	Output Shape	Param #
=====		
conv2d_73 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_27 (MaxPooling)	(None, 13, 13, 32)	0
dropout_75 (Dropout)	(None, 13, 13, 32)	0
conv2d_74 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_28 (MaxPooling)	(None, 5, 5, 64)	0
dropout_76 (Dropout)	(None, 5, 5, 64)	0
conv2d_75 (Conv2D)	(None, 3, 3, 128)	73856
max_pooling2d_29 (MaxPooling)	(None, 1, 1, 128)	0
dropout_77 (Dropout)	(None, 1, 1, 128)	0
flatten_19 (Flatten)	(None, 128)	0
dense_44 (Dense)	(None, 256)	33024
dropout_78 (Dropout)	(None, 256)	0
dense_45 (Dense)	(None, 10)	2570
=====		
Total params: 128,266		
Trainable params: 128,266		
Non-trainable params: 0		

conv\_1\_num\_filters: 32

conv\_2\_num\_filters: 64

conv\_3\_num\_filters: 128

dropout: 0.2

num\_hidden\_layers = 1

neurons\_per\_hidden\_layer = 256

pool\_size = 2x2

## MNIST Fashion

```
In [4]: mods['mnist_f'].summary()
```

Model: "sequential\_17"

Layer (type)	Output Shape	Param #
=====		
conv2d_57 (Conv2D)	(None, 26, 26, 32)	320
batch_normalization_43 (Batch Normalization)	(None, 26, 26, 32)	128
conv2d_58 (Conv2D)	(None, 24, 24, 32)	9248
batch_normalization_44 (Batch Normalization)	(None, 24, 24, 32)	128
dropout_59 (Dropout)	(None, 24, 24, 32)	0
conv2d_59 (Conv2D)	(None, 22, 22, 64)	18496
max_pooling2d_23 (MaxPooling2D)	(None, 11, 11, 64)	0
dropout_60 (Dropout)	(None, 11, 11, 64)	0
conv2d_60 (Conv2D)	(None, 9, 9, 128)	73856
batch_normalization_45 (Batch Normalization)	(None, 9, 9, 128)	512
dropout_61 (Dropout)	(None, 9, 9, 128)	0
flatten_15 (Flatten)	(None, 10368)	0
dense_36 (Dense)	(None, 256)	2654464
batch_normalization_46 (Batch Normalization)	(None, 256)	1024
dropout_62 (Dropout)	(None, 256)	0
dense_37 (Dense)	(None, 10)	2570
=====		
Total params: 2,760,746		
Trainable params: 2,759,850		
Non-trainable params: 896		

conv\_1\_num\_filters: 32

conv\_2\_num\_filters: 32

conv\_3\_num\_filters: 64

conv\_4\_num\_filters: 128

dropout: 0.2

num\_hidden\_layers = 1

neurons\_per\_hidden\_layer = 256

pool\_size = 2x2

**CIFAR-10**

```
In [5]: mods['cifar_10'].summary()
```

Model: "sequential\_18"

Layer (type)	Output Shape	Param #
=====		
conv2d_61 (Conv2D)	(None, 30, 30, 32)	896
batch_normalization_47 (Batch Normalization)	(None, 30, 30, 32)	128
conv2d_62 (Conv2D)	(None, 28, 28, 32)	9248
batch_normalization_48 (Batch Normalization)	(None, 28, 28, 32)	128
dropout_63 (Dropout)	(None, 28, 28, 32)	0
conv2d_63 (Conv2D)	(None, 26, 26, 64)	18496
max_pooling2d_24 (MaxPooling2D)	(None, 13, 13, 64)	0
dropout_64 (Dropout)	(None, 13, 13, 64)	0
conv2d_64 (Conv2D)	(None, 11, 11, 128)	73856
batch_normalization_49 (Batch Normalization)	(None, 11, 11, 128)	512
dropout_65 (Dropout)	(None, 11, 11, 128)	0
flatten_16 (Flatten)	(None, 15488)	0
dense_38 (Dense)	(None, 256)	3965184
batch_normalization_50 (Batch Normalization)	(None, 256)	1024
dropout_66 (Dropout)	(None, 256)	0
dense_39 (Dense)	(None, 10)	2570
=====		
Total params: 4,072,042		
Trainable params: 4,071,146		
Non-trainable params: 896		



conv\_1\_num\_filters: 32  
conv\_2\_num\_filters: 32  
conv\_3\_num\_filters: 64  
conv\_4\_num\_filters: 128  
dropout: 0.2  
num\_hidden\_layers = 1  
neurons\_per\_hidden\_layer = 256  
pool\_size = 2x2

### **CIFAR-100 (Coarse Labels)**

```
In [6]: mods['cifar_100_c'].summary()
```

Model: "sequential\_20"

Layer (type)	Output Shape	Param #
=====		
conv2d_69 (Conv2D)	(None, 30, 30, 32)	896
batch_normalization_55 (Batch Normalization)	(None, 30, 30, 32)	128
conv2d_70 (Conv2D)	(None, 28, 28, 32)	9248
batch_normalization_56 (Batch Normalization)	(None, 28, 28, 32)	128
dropout_71 (Dropout)	(None, 28, 28, 32)	0
conv2d_71 (Conv2D)	(None, 26, 26, 64)	18496
max_pooling2d_26 (MaxPooling2D)	(None, 13, 13, 64)	0
dropout_72 (Dropout)	(None, 13, 13, 64)	0
conv2d_72 (Conv2D)	(None, 11, 11, 128)	73856
batch_normalization_57 (Batch Normalization)	(None, 11, 11, 128)	512
dropout_73 (Dropout)	(None, 11, 11, 128)	0
flatten_18 (Flatten)	(None, 15488)	0
dense_42 (Dense)	(None, 256)	3965184
batch_normalization_58 (Batch Normalization)	(None, 256)	1024
dropout_74 (Dropout)	(None, 256)	0
dense_43 (Dense)	(None, 20)	5140
=====		
Total params: 4,074,612		
Trainable params: 4,073,716		
Non-trainable params: 896		

conv\_1\_num\_filters: 32

conv\_2\_num\_filters: 32

conv\_3\_num\_filters: 64

conv\_4\_num\_filters: 128

dropout: 0.2

num\_hidden\_layers = 1

neurons\_per\_hidden\_layer = 256

pool\_size = 2x2

## CIFAR-100 (Fine Labels)

For the CIFAR-100 dataset with fine labels, I used KerasTuner to optimize hyperparameters by building several models. The process is highlighted below.

```
# note that data refers to the cifar_100_f dataset
def buildTuneModel(hp):
    mod = tf.keras.models.Sequential()
    mod.add(tf.keras.layers.Conv2D(filters=hp.Int('input_num_filters', min_value=32, max_value=256, step=32), kernel_size=(3, 3), activation="relu", input_shape=data[0][0][0].shape))
    mod.add(tf.keras.layers.BatchNormalization())
    tf.keras.layers.Dropout(hp.Float('input_dropout', min_value=0.0, max_value=0.5, default=0.25, step=0.05))
    for i in range(hp.Int('num_conv_layers', 1, 5)):
        mod.add(tf.keras.layers.Conv2D(filters=hp.Int('conv_{i}_num_filters', min_value=32, max_value=256, step=32), kernel_size=(3, 3), activation="relu"))
        mod.add(tf.keras.layers.BatchNormalization())
        mod.add(tf.keras.layers.Dropout(hp.Float('conv_{i}_dropout', min_value=0.0, max_value=0.5, default=0.25, step=0.05)))
    mod.add(tf.keras.layers.Flatten())
    for i in range(hp.Int('num_hid_layers', 1, 5)):
        mod.add(tf.keras.layers.Dense(hp.Int('hid_{i}_num_neurons', min_value=32, max_value=256, step=32), activation="relu"))
        mod.add(tf.keras.layers.BatchNormalization())
        mod.add(tf.keras.layers.Dropout(hp.Float('hid_{i}_dropout', min_value=0.0, max_value=0.5, default=0.25, step=0.05)))
    mod.add(tf.keras.layers.Dense(data[0][1].shape[1], activation=tf.nn.softmax))
    mod.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return mod

from kerastuner.tuners import RandomSearch
from kerastuner.engine.hyperparameters import HyperParameters
import pickle
```

```
tuner = RandomSearch(buildTuneModel, objective='val_accuracy', max_trials=20
, executions_per_trial=2)
tuner.search_space_summary()
tuner.search(x=data[0][0], y=data[0][1], epochs=3, validation_data=data[1])
with open(f'tuner.pkl', "wb") as f:
    pickle.dump(tuner, f)
```

Now, let's load the tuner and identify the optimal hyperparameters.

```
In [9]: import pickle
import tensorflow as tf

with open(f'tuner.pkl', 'rb') as f:
    tuner = pickle.load(f)

bestMod = tuner.get_best_models()[0]
bestHps = tuner.get_best_hyperparameters()[0]
```

```
In [10]: bestMod.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 30, 30, 192)	5376
batch_normalization (Batch Normalization)	(None, 30, 30, 192)	768
conv2d_1 (Conv2D)	(None, 28, 28, 96)	165984
batch_normalization_1 (Batch Normalization)	(None, 28, 28, 96)	384
dropout_1 (Dropout)	(None, 28, 28, 96)	0
conv2d_2 (Conv2D)	(None, 26, 26, 96)	83040
batch_normalization_2 (Batch Normalization)	(None, 26, 26, 96)	384
dropout_2 (Dropout)	(None, 26, 26, 96)	0
flatten (Flatten)	(None, 64896)	0
dense (Dense)	(None, 160)	10383520
batch_normalization_3 (Batch Normalization)	(None, 160)	640
dropout_3 (Dropout)	(None, 160)	0
dense_1 (Dense)	(None, 160)	25760
batch_normalization_4 (Batch Normalization)	(None, 160)	640
dropout_4 (Dropout)	(None, 160)	0
dense_2 (Dense)	(None, 100)	16100
=====		
Total params: 10,682,596		
Trainable params: 10,681,188		
Non-trainable params: 1,408		

```
In [11]: for hp in bestHps._hps.keys():
          print('{}: {}'.format(hp, bestHps.get(hp)))
```

```
input_num_filters: 192
input_dropout: 0.2
num_conv_layers: 2
conv_{i}_num_filters: 96
conv_{i}_dropout: 0.2
num_hid_layers: 2
hid_{i}_num_neurons: 160
hid_{i}_dropout: 0.05
```

## Visualizations

```
In [12]: import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [14]: ann_acc = {'mnist_d':None, 'mnist_f':None, 'cifar_10':None, 'cifar_100_
c':None, 'cifar_100_f':None}
for dataset in ann_acc:
    raw = getRawData(dataset)
    data = preprocessData(raw, dataset, 'tf_net')
    model = trainModel(data[0], 'tf_net', dataset, load=True)
    preds = runModel(data[1], model, ALGORITHM='tf_net')
    ann_acc[dataset] = evalResults(data[1], preds, ALGORITHM='tf_net')
```

Dataset: mnist\_d  
Shape of xTrain dataset: (60000, 28, 28).  
Shape of yTrain dataset: (60000,).  
Shape of xTest dataset: (10000, 28, 28).  
Shape of yTest dataset: (10000,).  
New shape of xTrain dataset: (60000, 784).  
New shape of xTest dataset: (10000, 784).  
New shape of yTrain dataset: (60000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_NN.  
Testing TF\_NN.  
Classifier algorithm: tf\_net  
Classifier accuracy: 98.020000%

Dataset: mnist\_f  
Shape of xTrain dataset: (60000, 28, 28).  
Shape of yTrain dataset: (60000,).  
Shape of xTest dataset: (10000, 28, 28).  
Shape of yTest dataset: (10000,).  
New shape of xTrain dataset: (60000, 784).  
New shape of xTest dataset: (10000, 784).  
New shape of yTrain dataset: (60000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_NN.  
Testing TF\_NN.  
Classifier algorithm: tf\_net  
Classifier accuracy: 88.910000%

Dataset: cifar\_10  
Shape of xTrain dataset: (50000, 32, 32, 3).  
Shape of yTrain dataset: (50000, 1).  
Shape of xTest dataset: (10000, 32, 32, 3).  
Shape of yTest dataset: (10000, 1).  
New shape of xTrain dataset: (50000, 3072).  
New shape of xTest dataset: (10000, 3072).  
New shape of yTrain dataset: (50000, 10).  
New shape of yTest dataset: (10000, 10).  
Building and training TF\_NN.  
Testing TF\_NN.  
Classifier algorithm: tf\_net  
Classifier accuracy: 47.130000%

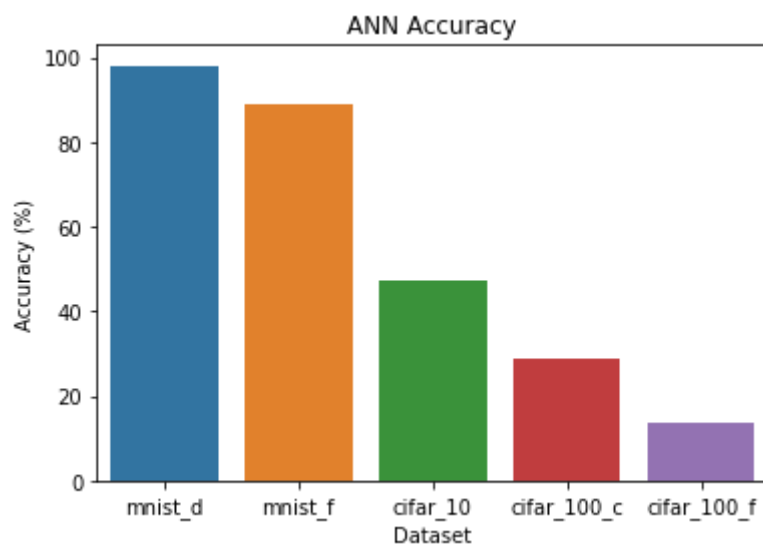
Dataset: cifar\_100\_c  
Shape of xTrain dataset: (50000, 32, 32, 3).  
Shape of yTrain dataset: (50000, 1).  
Shape of xTest dataset: (10000, 32, 32, 3).  
Shape of yTest dataset: (10000, 1).  
New shape of xTrain dataset: (50000, 3072).  
New shape of xTest dataset: (10000, 3072).  
New shape of yTrain dataset: (50000, 20).  
New shape of yTest dataset: (10000, 20).  
Building and training TF\_NN.  
Testing TF\_NN.  
Classifier algorithm: tf\_net  
Classifier accuracy: 28.710000%

Dataset: cifar\_100\_f



```
Shape of xTrain dataset: (50000, 32, 32, 3).  
Shape of yTrain dataset: (50000, 1).  
Shape of xTest dataset: (10000, 32, 32, 3).  
Shape of yTest dataset: (10000, 1).  
New shape of xTrain dataset: (50000, 3072).  
New shape of xTest dataset: (10000, 3072).  
New shape of yTrain dataset: (50000, 100).  
New shape of yTest dataset: (10000, 100).  
Building and training TF_NN.  
Testing TF_NN.  
Classifier algorithm: tf_net  
Classifier accuracy: 13.520000%
```

```
In [15]: fig, ax = plt.subplots()  
sns.barplot(x=list(ann_acc.keys()), y=[acc*100 for acc in ann_acc.values  
()])  
plt.xlabel('Dataset')  
plt.ylabel('Accuracy (%)')  
plt.title('ANN Accuracy')  
fig.savefig('ANN_Accuracy_Plot.pdf')
```



```
In [16]: fig, ax = plt.subplots()
sns.barplot(x=list(acc.keys()), y=[acc*100 for acc in acc.values()])
plt.xlabel('Dataset')
plt.ylabel('Accuracy (%)')
plt.title('CNN Accuracy')
fig.savefig('CNN_Accuracy_Plot.pdf')
```

