

## Project: Applying various deep learning models & hyperparameters tuning on CIFAR dataset

### Import packages

Keras and CIFAR dataset

In [ ]:

```
! nvidia-smi -L
```

```
GPU 0: Tesla T4 (UUID: GPU-b1af126-2ebd-f024-4d5c-967fe687d151)
```

In [1]:

```
import tensorflow as tf
from tensorflow import keras
from keras.callbacks import ModelCheckpoint, EarlyStopping
from keras.layers import BatchNormalization
from keras.preprocessing.image import ImageDataGenerator

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import MaxNLocator

%matplotlib inline
%config InlineBackend.figure_format = 'retina'
plt.style.use('ggplot')
```

Defining our CIFAR image dimensions with 3 RBG channels, making the overall shape of a image to be 28x28x3

In [2]:

```
img_rows, img_cols, channels = 32, 32, 3
input_shape=(img_rows,img_cols,channels) # shape of input as a tuple

input_shape
```

Out[2]:

```
(32, 32, 3)
```

### Load data

Load the CIFAR 10 dataset from keras built-in datasets

In [3]:

```
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz> (<https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>)  
170500096/170498071 [=====] - 4s 0us/step

In [4]:

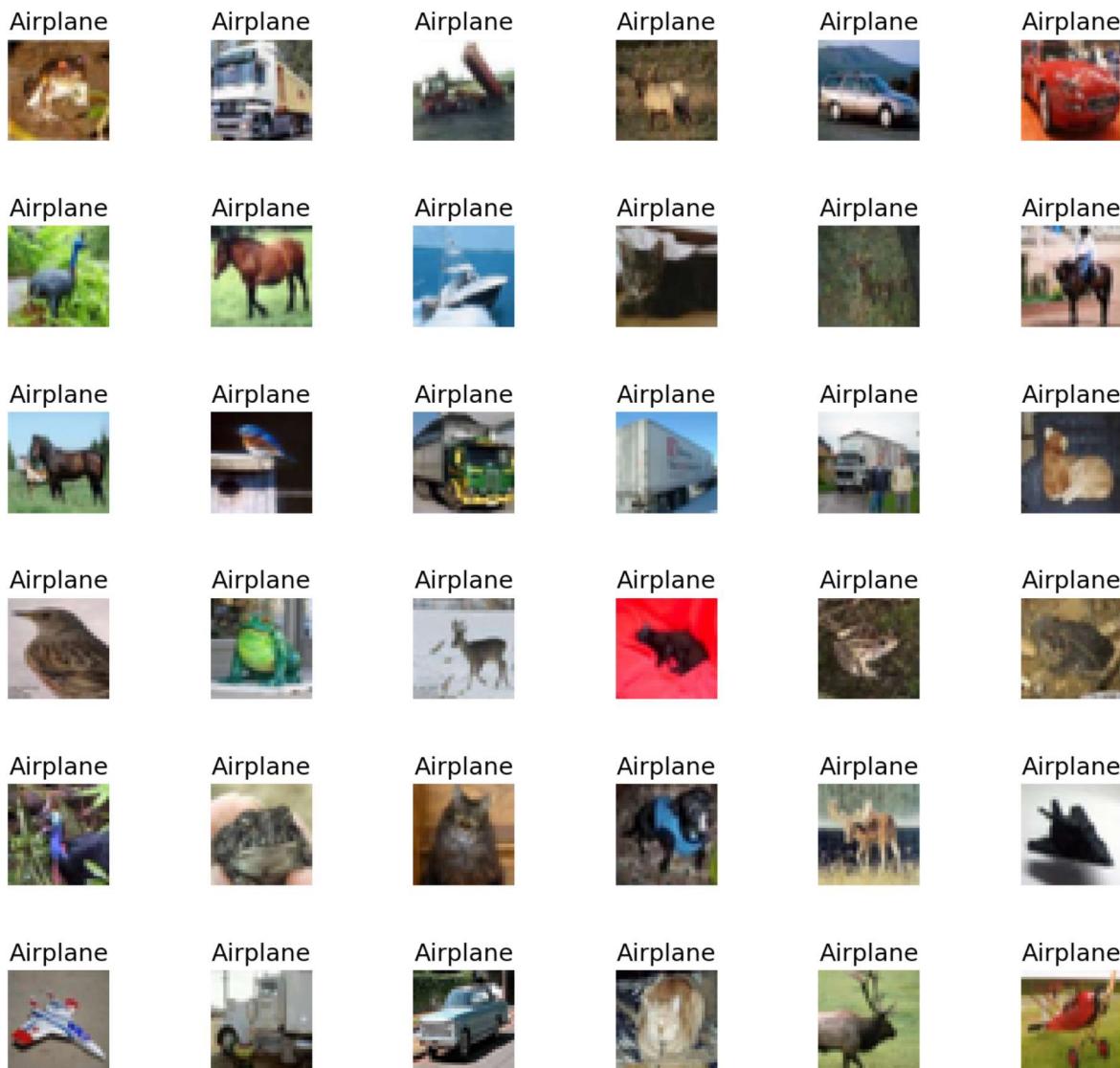
```
print (x_train.shape)
print (y_train.shape)
print (x_test.shape)
print (y_test.shape)
```

```
(50000, 32, 32, 3)
(50000, 1)
(10000, 32, 32, 3)
(10000, 1)
```

In [5]:

# Visualising the dataset

```
labels = ['Airplane', 'Automobile', 'Bird', 'Cat', 'Deer', 'Dog', 'Frog', 'Horse', 'Ship',  
  
R = 6  
C = 6  
fig, axes = plt.subplots(R, C, figsize=(12,12))  
axes = axes.ravel()  
Y_true = np.argmax(y_train, axis=1)  
  
for i in np.arange(0, R*C):  
    axes[i].imshow(x_train[i])  
    axes[i].set_title(labels[Y_true[i]])  
    axes[i].axis('off')  
    plt.subplots_adjust(wspace=1)
```



## Data preprocessing

Normalisation on x dataset and use one-hot encoding on the categorical values in y

In [6]:

```
num_classes = 10

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

x_train /= 255
x_test /= 255

print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')

y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
x_train shape: (50000, 32, 32, 3)
50000 train samples
10000 test samples
```

## Model 1: Multi-Layer Perceptron

In [20]:

```
model = keras.Sequential()

model.add(keras.layers.Dense(128, activation='relu', input_shape=input_shape))
model.add(BatchNormalization())
model.add(keras.layers.Dropout(0.2))

model.add(keras.layers.Dense(128, activation='relu'))
model.add(BatchNormalization())
model.add(keras.layers.Dropout(0.4))

model.add(tf.keras.layers.Flatten())
model.add(keras.layers.Dense(num_classes, activation='softmax'))
```

In [21]:

```
model.summary()
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
<hr/>		
dense_6 (Dense)	(None, 32, 32, 128)	512
<hr/>		
batch_normalization_4 (Batch Normalization)	(None, 32, 32, 128)	512
<hr/>		
dropout_4 (Dropout)	(None, 32, 32, 128)	0
<hr/>		
dense_7 (Dense)	(None, 32, 32, 128)	16512
<hr/>		
batch_normalization_5 (Batch Normalization)	(None, 32, 32, 128)	512
<hr/>		
dropout_5 (Dropout)	(None, 32, 32, 128)	0
<hr/>		
flatten_2 (Flatten)	(None, 131072)	0
<hr/>		
dense_8 (Dense)	(None, 10)	1310730
<hr/>		
Total params: 1,328,778		
Trainable params: 1,328,266		
Non-trainable params: 512		

---

In [22]:

```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

In [23]:

```
batch_size = 100
epochs = 100
```

In [24]:

```
es = EarlyStopping(monitor='val_accuracy', mode='max', min_delta=0.01, patience=5, verbose=1)

model_log = model.fit(x_train, y_train,
                      batch_size=batch_size,
                      epochs=epochs,
                      validation_split = 0.1,
                      callbacks=[es])

Epoch 1/100
450/450 [=====] - 12s 25ms/step - loss: 6.9604 - accuracy: 0.3006 - val_loss: 3.5947 - val_accuracy: 0.1716
Epoch 2/100
450/450 [=====] - 11s 24ms/step - loss: 2.0942 - accuracy: 0.3845 - val_loss: 1.5738 - val_accuracy: 0.4508
Epoch 3/100
450/450 [=====] - 11s 24ms/step - loss: 1.5435 - accuracy: 0.4581 - val_loss: 1.4987 - val_accuracy: 0.4858
Epoch 4/100
450/450 [=====] - 11s 24ms/step - loss: 1.4606 - accuracy: 0.4919 - val_loss: 1.4596 - val_accuracy: 0.4954
Epoch 5/100
450/450 [=====] - 11s 24ms/step - loss: 1.4217 - accuracy: 0.5033 - val_loss: 1.4678 - val_accuracy: 0.4828
Epoch 6/100
450/450 [=====] - 11s 24ms/step - loss: 1.3973 - accuracy: 0.5148 - val_loss: 1.4464 - val_accuracy: 0.4970
Epoch 7/100
450/450 [=====] - 11s 24ms/step - loss: 1.3821 - accuracy: 0.5208 - val_loss: 1.4664 - val_accuracy: 0.4874
Epoch 8/100
450/450 [=====] - 11s 24ms/step - loss: 1.3754 - accuracy: 0.5165 - val_loss: 1.4754 - val_accuracy: 0.4894
Epoch 9/100
450/450 [=====] - 11s 24ms/step - loss: 1.3674 - accuracy: 0.5207 - val_loss: 1.5325 - val_accuracy: 0.4742
Epoch 10/100
450/450 [=====] - 11s 24ms/step - loss: 1.3471 - accuracy: 0.5273 - val_loss: 1.4554 - val_accuracy: 0.4902
Epoch 11/100
450/450 [=====] - 11s 24ms/step - loss: 1.3386 - accuracy: 0.5334 - val_loss: 1.4589 - val_accuracy: 0.4840
Restoring model weights from the end of the best epoch.
Epoch 00011: early stopping
```

In [25]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Test loss: 1.450524091720581  
 Test accuracy: 0.49140000343322754

In [ ]:

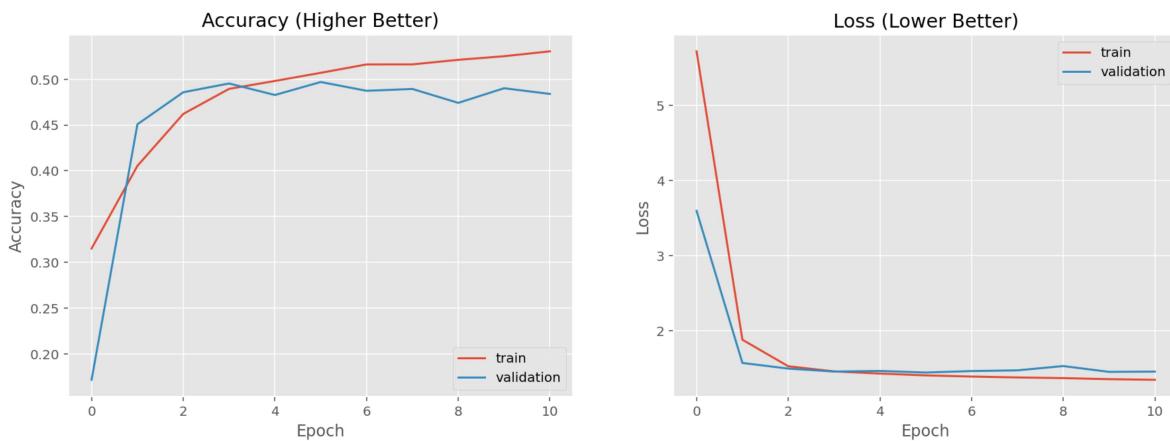
```
model.save("MLPmodel.h5")
```

In [26]:

```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,5))

ax1.plot(model_log.history['accuracy'])
ax1.plot(model_log.history['val_accuracy'])
ax1.set_title('Accuracy (Higher Better)')
ax1.set(xlabel='Epoch', ylabel='Accuracy')
ax1.legend(['train', 'validation'], loc='lower right')

ax2.plot(model_log.history['loss'])
ax2.plot(model_log.history['val_loss'])
ax2.set_title('Loss (Lower Better)')
ax2.set(xlabel='Epoch', ylabel='Loss')
ax2.legend(['train', 'validation'], loc='upper right')
ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
```



## Model 2: Convolutional Neural Network with LeNet

In [ ]:

```
# Lenet-5

model = tf.keras.Sequential()

model.add(tf.keras.layers.Conv2D(6, kernel_size=(5,5),
                               strides=(1,1),
                               padding='same',
                               input_shape=input_shape,
                               use_bias=True,
                               kernel_initializer='glorot_uniform',
                               bias_initializer='zeros'))

model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))

model.add(tf.keras.layers.Conv2D(16, kernel_size=(5,5),
                               padding='valid'))
model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(tf.keras.layers.Dropout(0.2))

model.add(tf.keras.layers.Conv2D(120, kernel_size=(5,5),
                               padding='valid'))
model.add(tf.keras.layers.Activation('relu'))
model.add(tf.keras.layers.Dropout(0.4))

model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(84))

model.add(tf.keras.layers.Dense(num_classes))
model.add(tf.keras.layers.Activation('softmax'))
```

In [ ]:

```
model.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d (Conv2D)	(None, 32, 32, 6)	456
activation (Activation)	(None, 32, 32, 6)	0
max_pooling2d (MaxPooling2D)	(None, 16, 16, 6)	0
conv2d_1 (Conv2D)	(None, 12, 12, 16)	2416
activation_1 (Activation)	(None, 12, 12, 16)	0
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 16)	0
dropout_2 (Dropout)	(None, 6, 6, 16)	0
conv2d_2 (Conv2D)	(None, 2, 2, 120)	48120
activation_2 (Activation)	(None, 2, 2, 120)	0
dropout_3 (Dropout)	(None, 2, 2, 120)	0
flatten_1 (Flatten)	(None, 480)	0
dense_3 (Dense)	(None, 84)	40404
dense_4 (Dense)	(None, 10)	850
activation_3 (Activation)	(None, 10)	0
<hr/>		
Total params:	92,246	
Trainable params:	92,246	
Non-trainable params:	0	

In [ ]:

```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [ ]:

```
batch_size = 100
num_classes = 10
epochs = 100
```

In [ ]:

```
es = EarlyStopping(monitor='val_accuracy', mode='max', min_delta=0.01, patience=10, verbose=1)

model_log = model.fit(x_train, y_train,
                      batch_size=batch_size,
                      epochs=epochs,
                      validation_split = 0.1,
                      callbacks=[es]
)
```

```
Epoch 1/50
450/450 [=====] - 32s 5ms/step - loss: 1.9666 - accuracy: 0.2709 - val_loss: 1.5181 - val_accuracy: 0.4460
Epoch 2/50
450/450 [=====] - 2s 4ms/step - loss: 1.5142 - accuracy: 0.4530 - val_loss: 1.3070 - val_accuracy: 0.5216
Epoch 3/50
450/450 [=====] - 2s 4ms/step - loss: 1.3660 - accuracy: 0.5120 - val_loss: 1.2481 - val_accuracy: 0.5540
Epoch 4/50
450/450 [=====] - 2s 5ms/step - loss: 1.3037 - accuracy: 0.5308 - val_loss: 1.1796 - val_accuracy: 0.5812
Epoch 5/50
450/450 [=====] - 2s 4ms/step - loss: 1.2498 - accuracy: 0.5549 - val_loss: 1.1560 - val_accuracy: 0.5920
Epoch 6/50
450/450 [=====] - 2s 4ms/step - loss: 1.1992 - accuracy: 0.5710 - val_loss: 1.0993 - val_accuracy: 0.6110
Epoch 7/50
450/450 [=====] - 2s 4ms/step - loss: 1.1560 - accuracy: 0.5920 - val_loss: 1.0993 - val_accuracy: 0.6110
```

In [ ]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.8936426639556885
Test accuracy: 0.6919999718666077
```

In [ ]:

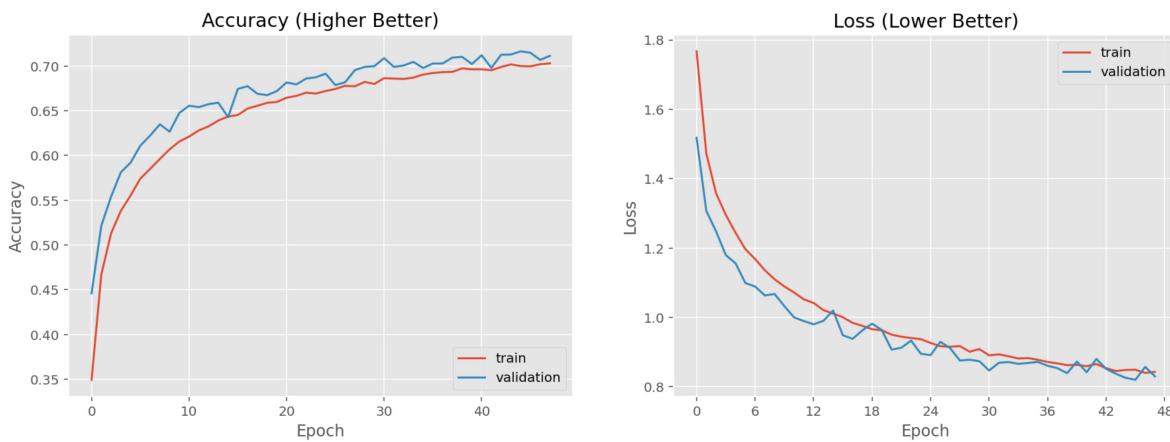
```
model.save("CNNmodel.h5")
```

In [ ]:

```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,5))

ax1.plot(model_log.history['accuracy'])
ax1.plot(model_log.history['val_accuracy'])
ax1.set_title('Accuracy (Higher Better)')
ax1.set(xlabel='Epoch', ylabel='Accuracy')
ax1.legend(['train', 'validation'], loc='lower right')

ax2.plot(model_log.history['loss'])
ax2.plot(model_log.history['val_loss'])
ax2.set_title('Loss (Lower Better)')
ax2.set(xlabel='Epoch', ylabel='Loss')
ax2.legend(['train', 'validation'], loc='upper right')
ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
```



## Model 3: Three-Block VGG Architecture

In [ ]:

```
model = keras.Sequential()

model.add(keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=input_shape, padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(32, (3,3), activation='relu', padding = 'same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.2))

model.add(keras.layers.Conv2D(64, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.4))

model.add(keras.layers.Conv2D(128, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(128, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.5))

model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(128, activation='relu'))
model.add(BatchNormalization())
model.add(keras.layers.Dropout(0.5))

model.add(keras.layers.Dense(num_classes, activation='softmax'))
```

In [ ]:

```
model.summary()
```

Model: "sequential\_10"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d_47 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_40 (Batch Normalization)	(None, 32, 32, 32)	128
conv2d_48 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_41 (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d_23 (MaxPooling)	(None, 16, 16, 32)	0
dropout_32 (Dropout)	(None, 16, 16, 32)	0
conv2d_49 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_42 (Batch Normalization)	(None, 16, 16, 64)	256
conv2d_50 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_43 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_24 (MaxPooling)	(None, 8, 8, 64)	0
dropout_33 (Dropout)	(None, 8, 8, 64)	0
conv2d_51 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_44 (Batch Normalization)	(None, 8, 8, 128)	512
conv2d_52 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_45 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_25 (MaxPooling)	(None, 4, 4, 128)	0
dropout_34 (Dropout)	(None, 4, 4, 128)	0
flatten_9 (Flatten)	(None, 2048)	0
dense_19 (Dense)	(None, 128)	262272
batch_normalization_46 (Batch Normalization)	(None, 128)	512
dropout_35 (Dropout)	(None, 128)	0
dense_20 (Dense)	(None, 10)	1290
<hr/>		
Total params: 552,874		
Trainable params: 551,722		
Non-trainable params: 1,152		

In [ ]:

```
# opt = keras.optimizers.SGD(Learning_rate=0.001, momentum=0.9)

model.compile(optimizer="adam",
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

In [ ]:

```
batch_size = 100
num_classes = 10
epochs = 100
```

In [ ]:

```
es = EarlyStopping(monitor='val_accuracy', mode='max', min_delta=0.01, patience=10, verbose=0

model_log = model.fit(x_train, y_train,
                      batch_size=batch_size,
                      epochs=epochs,
                      validation_split = 0.1,
                      callbacks=[es]
                     )
```

```
Epoch 1/100
450/450 [=====] - 7s 13ms/step - loss: 2.1703 - accuracy: 0.3228 - val_loss: 2.2065 - val_accuracy: 0.2778
Epoch 2/100
450/450 [=====] - 6s 12ms/step - loss: 1.2921 - accuracy: 0.5336 - val_loss: 1.0135 - val_accuracy: 0.6388
Epoch 3/100
450/450 [=====] - 6s 13ms/step - loss: 1.0433 - accuracy: 0.6285 - val_loss: 0.9237 - val_accuracy: 0.6754
Epoch 4/100
450/450 [=====] - 6s 13ms/step - loss: 0.9130 - accuracy: 0.6769 - val_loss: 0.9453 - val_accuracy: 0.6742
Epoch 5/100
450/450 [=====] - 6s 13ms/step - loss: 0.8251 - accuracy: 0.7091 - val_loss: 0.7566 - val_accuracy: 0.7334
Epoch 6/100
450/450 [=====] - 6s 13ms/step - loss: 0.7512 - accuracy: 0.7383 - val_loss: 0.7229 - val_accuracy: 0.7552
Epoch 7/100
450/450 [=====] - 6s 13ms/step - loss: 0.7229 - accuracy: 0.7552
```

In [ ]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.47637563943862915
Test accuracy: 0.8496999740600586
```

In [ ]:

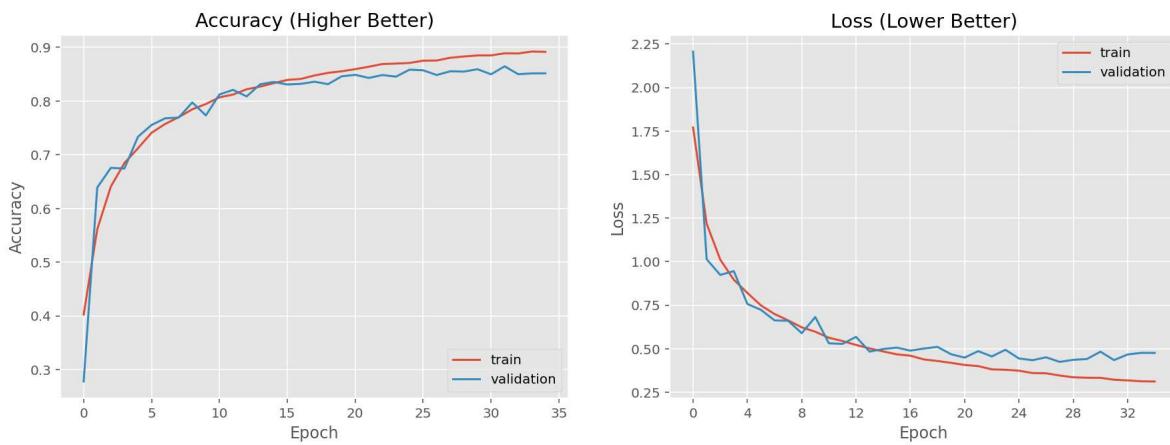
```
model.save("VGGmodel.h5")
```

In [ ]:

```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,5))

ax1.plot(model_log.history['accuracy'])
ax1.plot(model_log.history['val_accuracy'])
ax1.set_title('Accuracy (Higher Better)')
ax1.set(xlabel='Epoch', ylabel='Accuracy')
ax1.legend(['train', 'validation'], loc='lower right')
# ax1.xaxis.set_major_locator(MaxNLocator(integer=True))

ax2.plot(model_log.history['loss'])
ax2.plot(model_log.history['val_loss'])
ax2.set_title('Loss (Lower Better)')
ax2.set(xlabel='Epoch', ylabel='Loss')
ax2.legend(['train', 'validation'], loc='upper right')
ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
```



## Data Augmentation

Data augmentation using keras Image Data Generator on VGG model

In [13]:

```
model = keras.Sequential()

model.add(keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=input_shape, padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(32, (3,3), activation='relu', padding = 'same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.2))

model.add(keras.layers.Conv2D(64, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.3))

model.add(keras.layers.Conv2D(128, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.Conv2D(128, (3, 3), activation='relu',padding='same'))
model.add(BatchNormalization())
model.add(keras.layers.MaxPooling2D((2, 2)))
model.add(keras.layers.Dropout(0.4))

model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(128, activation='relu'))
model.add(BatchNormalization())
model.add(keras.layers.Dropout(0.5))

model.add(keras.layers.Dense(num_classes, activation='softmax'))
```

In [14]:

```
model.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d_6 (Conv2D)	(None, 32, 32, 32)	896
batch_normalization_7 (Batch Normalization)	(None, 32, 32, 32)	128
conv2d_7 (Conv2D)	(None, 32, 32, 32)	9248
batch_normalization_8 (Batch Normalization)	(None, 32, 32, 32)	128
max_pooling2d_3 (MaxPooling2D)	(None, 16, 16, 32)	0
dropout_4 (Dropout)	(None, 16, 16, 32)	0
conv2d_8 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_9 (Batch Normalization)	(None, 16, 16, 64)	256
conv2d_9 (Conv2D)	(None, 16, 16, 64)	36928
batch_normalization_10 (Batch Normalization)	(None, 16, 16, 64)	256
max_pooling2d_4 (MaxPooling2D)	(None, 8, 8, 64)	0
dropout_5 (Dropout)	(None, 8, 8, 64)	0
conv2d_10 (Conv2D)	(None, 8, 8, 128)	73856
batch_normalization_11 (Batch Normalization)	(None, 8, 8, 128)	512
conv2d_11 (Conv2D)	(None, 8, 8, 128)	147584
batch_normalization_12 (Batch Normalization)	(None, 8, 8, 128)	512
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_6 (Dropout)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0
dense_2 (Dense)	(None, 128)	262272
batch_normalization_13 (Batch Normalization)	(None, 128)	512
dropout_7 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1290
<hr/>		
Total params: 552,874		
Trainable params: 551,722		
Non-trainable params: 1,152		

In [15]:

```
# opt = keras.optimizers.SGD(Learning_rate=0.001, momentum=0.9)

model.compile(optimizer="adam",
              loss='categorical_crossentropy',
              metrics=['accuracy'])

batch_size = 100
num_classes = 10
epochs = 100
```

In [16]:

```
datagen = ImageDataGenerator(  
    # featurewise_center=True,  
    # featurewise_std_normalization=True,  
    rotation_range=15,  
    width_shift_range=0.1,  
    height_shift_range=0.1,  
    horizontal_flip=True,  
    validation_split=0.0)  
  
# compute quantities required for featurewise normalization  
# (std, mean, and principal components if ZCA whitening is applied)  
datagen.fit(x_train)  
  
es = EarlyStopping(monitor='val_accuracy', mode='max', min_delta=0.01, patience=5, verbose=  
  
# fits the model on batches with real-time data augmentation:  
model_log=model.fit(datagen.flow(x_train, y_train, batch_size=batch_size),  
                     steps_per_epoch=len(x_train) /batch_size, epochs=epochs,  
                     validation_data=(x_test,y_test),  
                     callbacks=[es])
```

```
Epoch 1/100  
500/500 [=====] - 26s 50ms/step - loss: 2.1648 - accuracy: 0.3082 - val_loss: 1.5311 - val_accuracy: 0.4442  
Epoch 2/100  
500/500 [=====] - 25s 50ms/step - loss: 1.3347 - accuracy: 0.5162 - val_loss: 1.3702 - val_accuracy: 0.5492  
Epoch 3/100  
500/500 [=====] - 25s 50ms/step - loss: 1.1237 - accuracy: 0.5979 - val_loss: 0.9982 - val_accuracy: 0.6584  
Epoch 4/100  
500/500 [=====] - 24s 49ms/step - loss: 1.0026 - accuracy: 0.6491 - val_loss: 0.8909 - val_accuracy: 0.6901  
Epoch 5/100  
500/500 [=====] - 25s 50ms/step - loss: 0.9166 - accuracy: 0.6777 - val_loss: 0.9179 - val_accuracy: 0.6884  
Epoch 6/100  
500/500 [=====] - 25s 50ms/step - loss: 0.8550 - accuracy: 0.7046 - val_loss: 0.9841 - val_accuracy: 0.6825  
Epoch 7/100  
500/500 [=====] - 25s 50ms/step - loss: 0.7880 - accuracy: 0.7310 - val_loss: 0.7366 - val_accuracy: 0.7442  
Epoch 8/100  
500/500 [=====] - 25s 49ms/step - loss: 0.7555 - accuracy: 0.7390 - val_loss: 0.6518 - val_accuracy: 0.7757  
Epoch 9/100  
500/500 [=====] - 25s 49ms/step - loss: 0.7290 - accuracy: 0.7509 - val_loss: 0.7363 - val_accuracy: 0.7505  
Epoch 10/100  
500/500 [=====] - 25s 50ms/step - loss: 0.7040 - accuracy: 0.7599 - val_loss: 0.7704 - val_accuracy: 0.7398  
Epoch 11/100  
500/500 [=====] - 25s 49ms/step - loss: 0.6792 - accuracy: 0.7632 - val_loss: 0.6213 - val_accuracy: 0.7893  
Epoch 12/100  
500/500 [=====] - 25s 50ms/step - loss: 0.6562 - accuracy: 0.7761 - val_loss: 0.7071 - val_accuracy: 0.7668  
Epoch 13/100
```

```
500/500 [=====] - 25s 50ms/step - loss: 0.6299 - accuracy: 0.7846 - val_loss: 0.5605 - val_accuracy: 0.8092
Epoch 14/100
500/500 [=====] - 25s 49ms/step - loss: 0.6189 - accuracy: 0.7900 - val_loss: 0.5936 - val_accuracy: 0.8005
Epoch 15/100
500/500 [=====] - 25s 49ms/step - loss: 0.6034 - accuracy: 0.7940 - val_loss: 0.5924 - val_accuracy: 0.8032
Epoch 16/100
500/500 [=====] - 25s 50ms/step - loss: 0.5923 - accuracy: 0.7967 - val_loss: 0.4953 - val_accuracy: 0.8343
Epoch 17/100
500/500 [=====] - 25s 50ms/step - loss: 0.5744 - accuracy: 0.8037 - val_loss: 0.5454 - val_accuracy: 0.8148
Epoch 18/100
500/500 [=====] - 25s 49ms/step - loss: 0.5693 - accuracy: 0.8050 - val_loss: 0.7702 - val_accuracy: 0.7523
Epoch 19/100
500/500 [=====] - 25s 50ms/step - loss: 0.5504 - accuracy: 0.8135 - val_loss: 0.5374 - val_accuracy: 0.8190
Epoch 20/100
500/500 [=====] - 25s 50ms/step - loss: 0.5562 - accuracy: 0.8096 - val_loss: 0.4751 - val_accuracy: 0.8406
Epoch 21/100
500/500 [=====] - 25s 50ms/step - loss: 0.5440 - accuracy: 0.8159 - val_loss: 0.5357 - val_accuracy: 0.8253
Restoring model weights from the end of the best epoch.
Epoch 00021: early stopping
```

In [17]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.4953373074531555
Test accuracy: 0.8342999815940857
```

In [ ]:

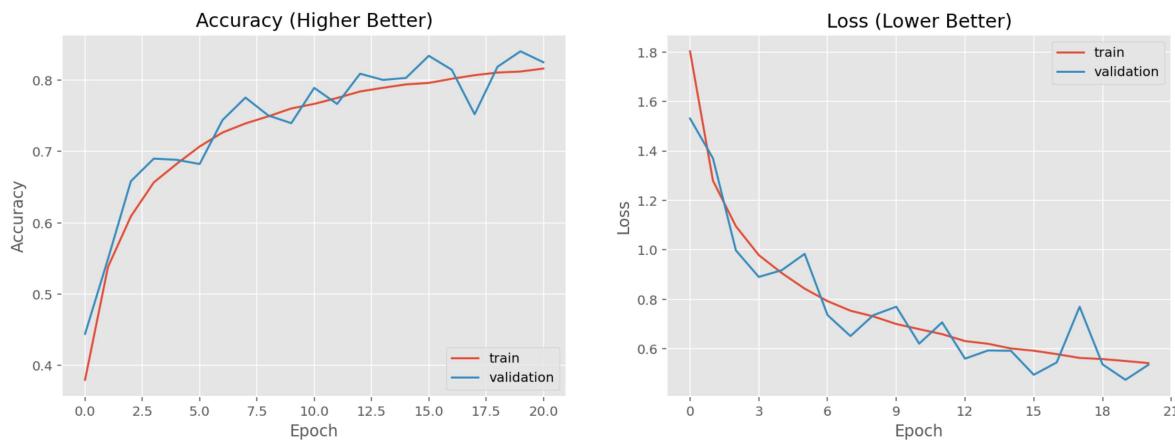
```
model.save("DataAugmentVGG.h5")
```

In [18]:

```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,5))

ax1.plot(model_log.history['accuracy'])
ax1.plot(model_log.history['val_accuracy'])
ax1.set_title('Accuracy (Higher Better)')
ax1.set(xlabel='Epoch', ylabel='Accuracy')
ax1.legend(['train', 'validation'], loc='lower right')
# ax1.xaxis.set_major_locator(MaxNLocator(integer=True))

ax2.plot(model_log.history['loss'])
ax2.plot(model_log.history['val_loss'])
ax2.set_title('Loss (Lower Better)')
ax2.set(xlabel='Epoch', ylabel='Loss')
ax2.legend(['train', 'validation'], loc='upper right')
ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
```



## Check the Predictions

In [ ]:

```
pred = model.predict(x_test)

# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(pred, axis=1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(y_test, axis=1)
```

In [ ]:

```
R = 5
C = 5
fig, axes = plt.subplots(R, C, figsize=(12,12))
axes = axes.ravel()

for i in np.arange(0, R*C):
    axes[i].imshow(x_test[i])
    axes[i].set_title("True: %s \nPredict: %s" % (labels[Y_true[i]], labels[Y_pred_classes[i]]))
    axes[i].axis('off')
plt.subplots_adjust(wspace=1)
```

◀ ▶

True: Cat  
Predict: CatTrue: Ship  
Predict: ShipTrue: Ship  
Predict: ShipTrue: Airplane  
Predict: AirplaneTrue: Frog  
Predict: FrogTrue: Frog  
Predict: FrogTrue: Automobile  
Predict: AutomobileTrue: Frog  
Predict: FrogTrue: Cat  
Predict: CatTrue: Automobile  
Predict: AutomobileTrue: Airplane  
Predict: AirplaneTrue: Truck  
Predict: TruckTrue: Dog  
Predict: DogTrue: Horse  
Predict: HorseTrue: Truck  
Predict: TruckTrue: Ship  
Predict: ShipTrue: Dog  
Predict: DogTrue: Horse  
Predict: HorseTrue: Ship  
Predict: ShipTrue: Frog  
Predict: FrogTrue: Horse  
Predict: HorseTrue: Airplane  
Predict: AirplaneTrue: Deer  
Predict: DeerTrue: Truck  
Predict: TruckTrue: Dog  
Predict: Deer

## Check the wrong Predictions

In [ ]:

```
R = 5
C = 5
fig, axes = plt.subplots(R, C, figsize=(12,12))
axes = axes.ravel()

misclassified_idx = np.where(Y_pred_classes != Y_true)[0]
for i in np.arange(0, R*C):
    axes[i].imshow(x_test[misclassified_idx[i]])
    axes[i].set_title("True: %s \nPredicted: %s" % (labels[Y_true[misclassified_idx[i]]], labels[Y_pred_classes[misclassified_idx[i]]]))
    axes[i].axis('off')
plt.subplots_adjust(wspace=1)
```

