In [43]:
```
X_train, X_valid, X_test, y_train, y_valid, y_test = get_train_test_valid_split(data['featu

print(X_train.shape)
print(y_train.shape)
print(X_valid.shape)
print(y_valid.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(36000, 28, 28)
(36000,)
(12000, 28, 28)
(12000,)
(12000, 28, 28)
(12000,)
```

In [44]:
```
# flatten image and normalize between 0 and 1

def flatten_image_set(image_set, pixel_count):
    return np.reshape(image_set, (len(image_set), pixel_count))

X_train_flat = flatten_image_set(X_train, pixel_count)
X_valid_flat = flatten_image_set(X_valid, pixel_count)
X_test_flat  = flatten_image_set(X_test, pixel_count)

X_train_flat.shape
```

Out[44]:
```
(36000, 784)
```

In [45]:
```
# one-hot encode target
class_count = len(set(data['target']))

y_train = to_categorical(y_train, class_count)
y_valid = to_categorical(y_valid, class_count)
y_test = to_categorical(y_test, class_count)

y_train
```

Out[45]:
```
array([[0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       ...,
       [0., 0., 1., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1.]], dtype=float32)
```

In [46]:
```
y_test.shape
```

Out[46]:
```
(12000, 5)
```

CM4, CM5 and CM6 are done in parallel for 3

> different models. All sections have been given the appropriate headings.

CM4 for FCN

Fully-Connected Neural Network

As a baseline model and in order to be able to appreciate CNN better for image classification problems, I will first use an simple fully-connected (aka dense), sequential neural network. A sequential model is a plain stack of layers where each layer has exactly one input tensor and one output tensor.

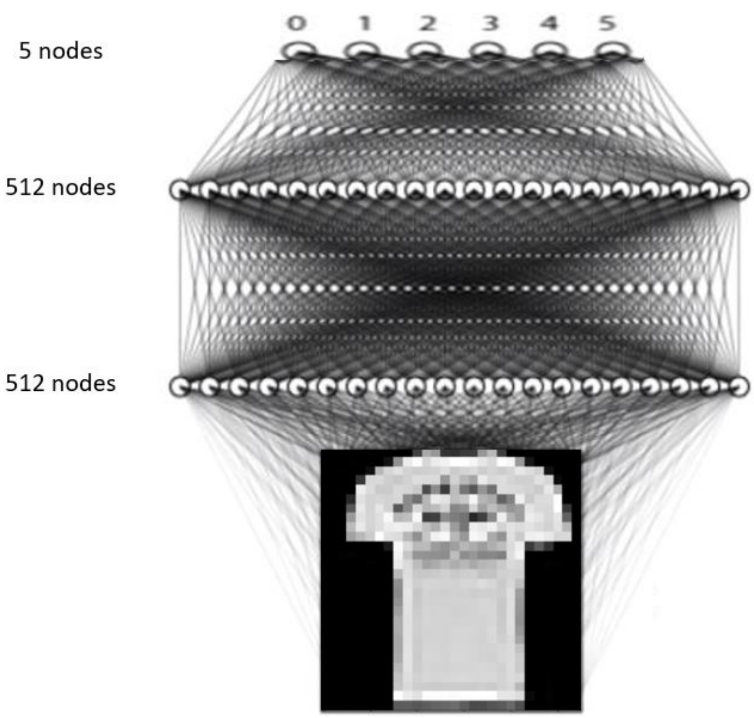
Optimizer: Adam

Activation Functions: ReLU for internal and Softmax for output layer

Regularization Method: Early Stopping and Dropout layers.

Number of parameters: 667,141

Network Architecture: A fully-connected (dense), sequential model



Credits: [https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/ (https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/)](https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/)

CM5 for FCN

Implementation for FCN

In [47]:
```
dense_model = Sequential()
dense_model.add(Dense(512, activation='relu', input_shape=(len(X_train_flat[0]),)))
dense_model.add(Dropout(0))
# input_shape's first argument is the number of dimensions of a single training sample. Son

dense_model.add(Dense(512, activation='relu'))
dense_model.add(Dropout(0))
dense_model.add(Dense(class_count, activation='softmax'))

adam = optimizers.Adam(learning_rate=0.01)
dense_model.compile(optimizer=adam, loss='categorical_crossentropy', metrics=['accuracy'])

# early stopping to avoid overfitting
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=5, verbose=1)
mc = ModelCheckpoint('../model/dense_model/best_model.h5', monitor='val_accuracy', mode='ma

# remember .fit() continues training from where we left off the last time
history_dense_model = dense_model.fit(X_train_flat, y_train,
                                      epochs=10,
                                      validation_data=(X_valid_flat, y_valid),
                                      callbacks=[es, mc])
```

```
Epoch 1/10
1125/1125 [==============================] - 4s 3ms/step - loss: 1.0600 - accuracy:
0.6529 - val_loss: 0.6178 - val_accuracy: 0.7648

Epoch 00001: val_accuracy improved from -inf to 0.76483, saving model to model/dense_
model/best_model.h5
Epoch 2/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.6139 - accuracy:
0.7499 - val_loss: 0.6270 - val_accuracy: 0.7398

Epoch 00002: val_accuracy did not improve from 0.76483
Epoch 3/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5730 - accuracy:
0.7667 - val_loss: 0.6153 - val_accuracy: 0.7562

Epoch 00003: val_accuracy did not improve from 0.76483
Epoch 4/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5564 - accuracy:
0.7715 - val_loss: 0.5476 - val_accuracy: 0.7752

Epoch 00004: val_accuracy improved from 0.76483 to 0.77517, saving model to model/den
se_model/best_model.h5
Epoch 5/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5478 - accuracy:
0.7791 - val_loss: 0.5259 - val_accuracy: 0.7891

Epoch 00005: val_accuracy improved from 0.77517 to 0.78908, saving model to model/den
se_model/best_model.h5
Epoch 6/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5319 - accuracy:
0.7816 - val_loss: 0.5539 - val_accuracy: 0.7827

Epoch 00006: val_accuracy did not improve from 0.78908
Epoch 7/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5299 - accuracy:
```

```
0.7895 - val_loss: 0.5932 - val_accuracy: 0.7587

Epoch 00007: val_accuracy did not improve from 0.78908
Epoch 8/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5328 - accuracy:
0.7828 - val_loss: 0.6128 - val_accuracy: 0.7390

Epoch 00008: val_accuracy did not improve from 0.78908
Epoch 9/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5229 - accuracy:
0.7900 - val_loss: 0.5282 - val_accuracy: 0.7896

Epoch 00009: val_accuracy improved from 0.78908 to 0.78958, saving model to model/den
se_model/best_model.h5
Epoch 10/10
1125/1125 [==============================] - 3s 3ms/step - loss: 0.5187 - accuracy:
0.7926 - val_loss: 0.5283 - val_accuracy: 0.7891

Epoch 00010: val_accuracy did not improve from 0.78958
```

In [48]:

```
dense_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_9 (Dense)              (None, 512)               401920    
_________________________________________________________________
dropout_6 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_10 (Dense)             (None, 512)               262656    
_________________________________________________________________
dropout_7 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 5)                 2565      
=================================================================
Total params: 667,141
Trainable params: 667,141
Non-trainable params: 0
_________________________________________________________________
```

In [49]:

```
# # save model configuration

# model_config = dense_model.to_json()

# with open("../model/config/dense_model.json", "w") as json_file:
#     json_file.write(model_config)
```

CM6 for FCN

Results Analysis for FCN

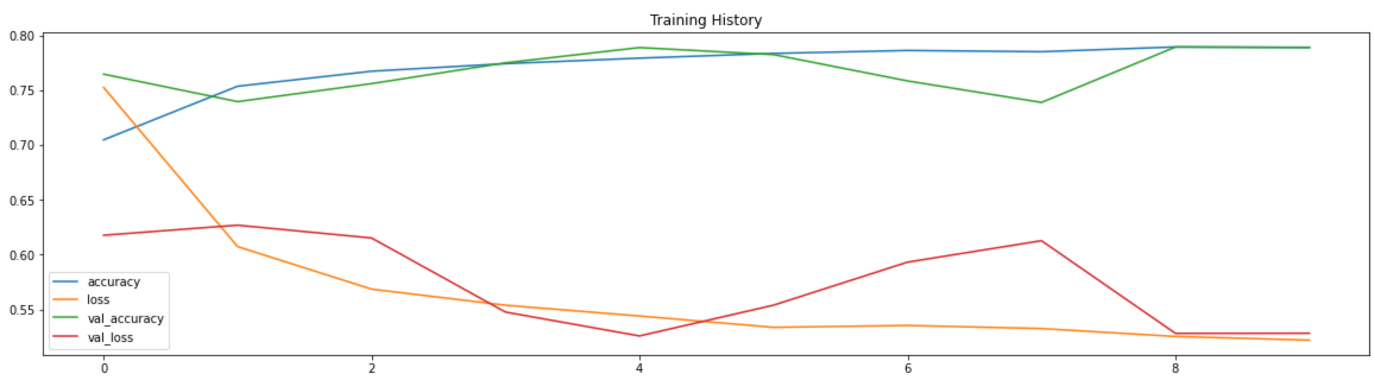
In [50]:
```python
# evaluate the model
train_loss, train_acc = dense_model.evaluate(X_train_flat, y_train, verbose=0)
test_loss, test_acc = dense_model.evaluate(X_test_flat, y_test, verbose=0)

print("Accuracy:")
print('Train: %.3f, Test: %.3f' % (train_acc, test_acc))
print("Loss:")
print('Train: %.3f, Test: %.3f' % (train_loss, test_loss))
```

```
Accuracy:
Train: 0.797, Test: 0.782
Loss:
Train: 0.499, Test: 0.545
```

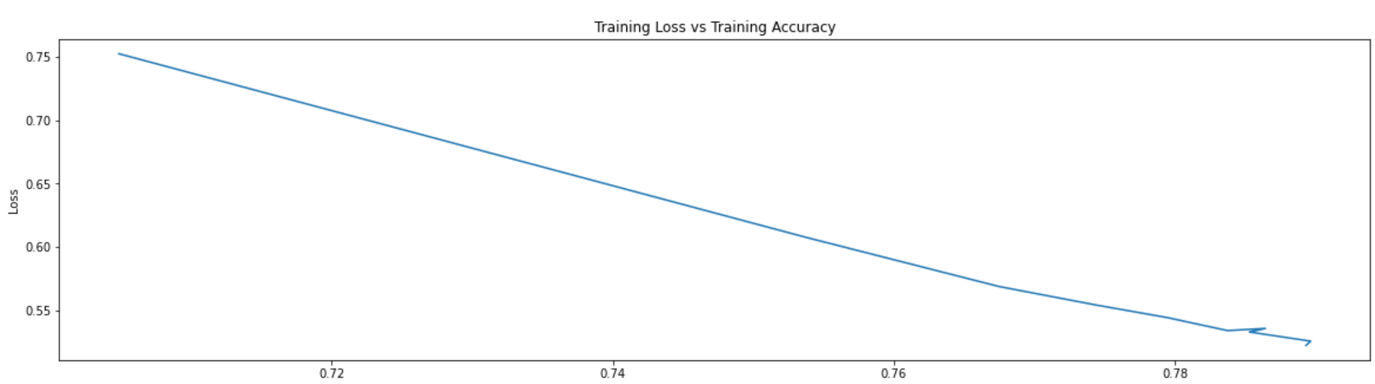
In [113]:
```python
plt.plot(history_dense_model.history['accuracy'])
plt.plot(history_dense_model.history['loss'])
plt.plot(history_dense_model.history['val_accuracy'])
plt.plot(history_dense_model.history['val_loss'])
plt.legend(['accuracy', 'loss', 'val_accuracy', 'val_loss'])
plt.title("Training History")
```

Out[113]:
```
Text(0.5, 1.0, 'Training History')
```



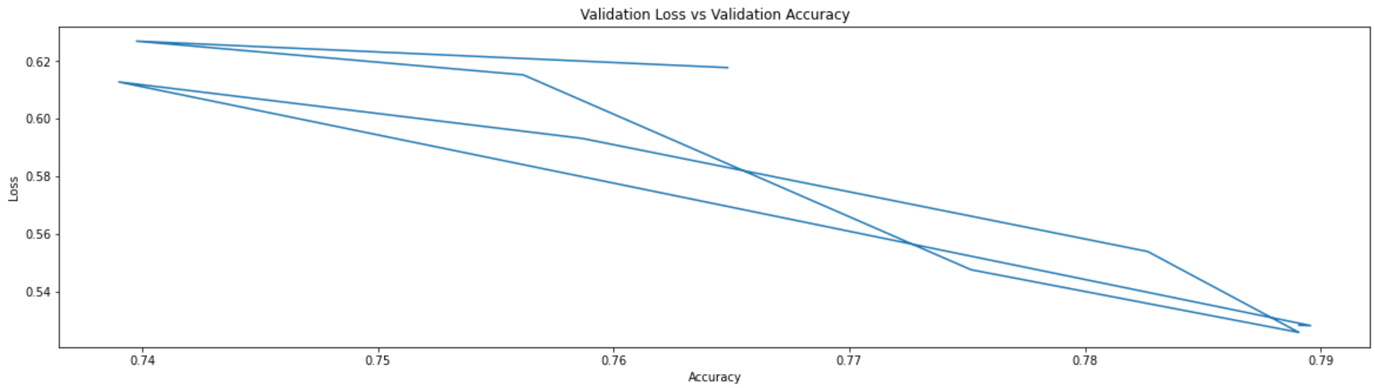
In [114]:
```python
plt.plot(history_dense_model.history['accuracy'], history_dense_model.history['loss'])
plt.title("Training Loss vs Training Accuracy")
plt.xlabel("Accuracy")
plt.ylabel("Loss")
```

Out[114]:
```
Text(0, 0.5, 'Loss')
```



In [115]:
```
plt.plot(history_dense_model.history['val_accuracy'], history_dense_model.history['val_los
plt.title("Validation Loss vs Validation Accuracy")
plt.xlabel("Accuracy")
plt.ylabel("Loss")
```

Out[115]: Text(0, 0.5, 'Loss')



The training loss decreases smoothly against accuracy but the validation loss does not.

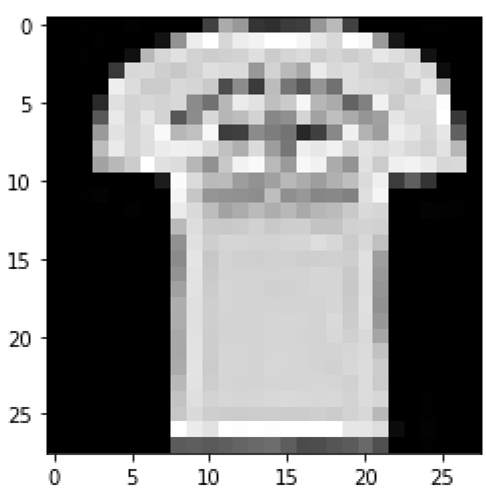
Testing on a random image

In [54]:
```
X_test[0].reshape(int(np.sqrt(pixel_count)), int(np.sqrt(pixel_count))).shape
```

Out[54]: (28, 28)

In [55]:
```
plt.imshow(X_test[0].reshape(int(np.sqrt(pixel_count)), int(np.sqrt(pixel_count))), cmap="g
```

Out[55]: <matplotlib.image.AxesImage at 0x7f21000f0fd0>



In [56]:
```
X_test_flat[0].shape
```

Out[56]: (784,)

In [57]:
```
test = np.expand_dims(X_test_flat[0], axis=0)
test.shape
```

Out[57]:
```
(1, 784)
```

In [58]:
```
dense_model.predict(test)
```

Out[58]:
```
array([[6.8528615e-02, 8.9717156e-01, 3.3814643e-02, 1.2754760e-04,
        3.5769388e-04]], dtype=float32)
```

In [59]:
```
np.argmax(dense_model.predict(test))
```

Out[59]:
```
1
```

In [60]:
```
y_test[0]
```

Out[60]:
```
array([0., 1., 0., 0., 0.], dtype=float32)
```

CM4

Convolution Neural Networks

I now turn to CNNs.

Optimizer: Adam

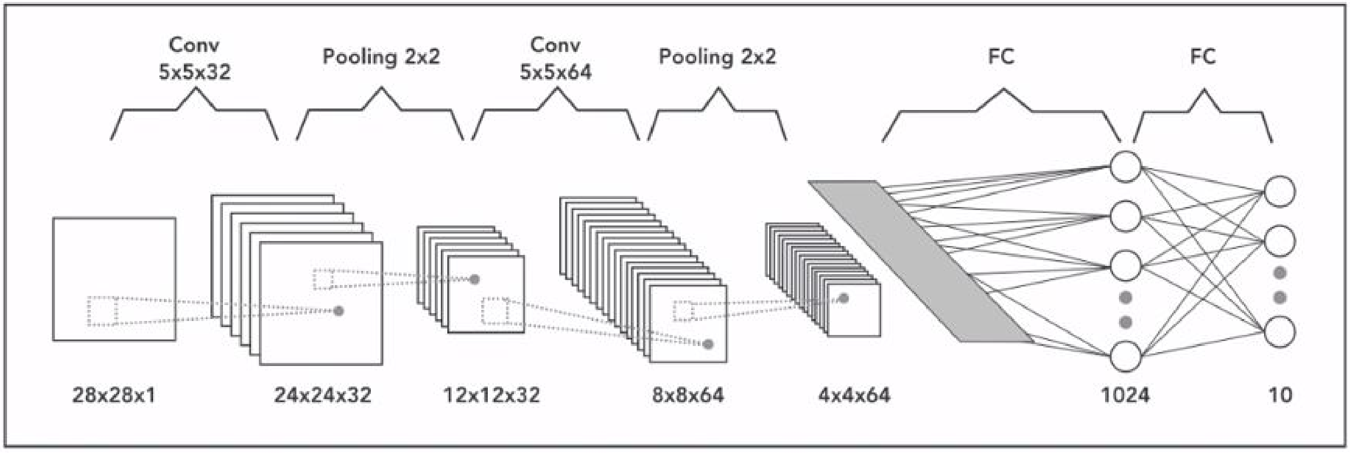
Activation Functions: ReLU for internal and Softmax for output layer

Regularization Method: Early Stopping and Dropouts

Number of parameters: 110,309

Network Architecture: A convolution neural network with 32 and 64 kernels

> ## Note:
>
> The image shows 10 units in the softmax layer. However, 5 are implemented for this application.



Credits: [https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/ (https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/)](https://www.linkedin.com/learning/neural-networks-and-convolutional-neural-networks-essential-training/)

In [61]:
```
def calculate_image_dims(original_dim, filter_size, stride, padding):
    return ((original_dim - filter_size + 2*padding) / stride) + 1
```

In [62]:
```
X_train = X_train.reshape(-1, 28, 28, 1)
X_valid = X_valid.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)

print(X_train.shape)
print(y_train.shape)
print(X_valid.shape)
print(y_valid.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(36000, 28, 28, 1)
(36000, 5)
(12000, 28, 28, 1)
(12000, 5)
(12000, 28, 28, 1)
(12000, 5)
```

In [62]:
```
```

This time around, we don't have to and should not flatten the image since we will now be convolving kernels on the image matrix.

CM 5 for CNN

Implementation for CNN

In [63]:

```
cnn = Sequential()
cnn.add(Conv2D(32, kernel_size=(3,3), input_shape=X_train[0].shape, padding='same', activat
# same means when stride is 1, pad zeros to keep same dimensions as opposed to using only
cnn.add(MaxPooling2D(pool_size=(2, 2)))
cnn.add(Conv2D(32, kernel_size=(3,3), padding='same', activation='relu'))
cnn.add(MaxPooling2D(pool_size=(2, 2)))
cnn.add(Flatten())
cnn.add(Dense(64,activation='relu'))
cnn.add(Dense(class_count,activation='softmax'))

# compile architecture
adam = optimizers.Adam(learning_rate=0.01)
cnn.compile(optimizer=adam, loss='categorical_crossentropy', metrics=['accuracy'])
print(cnn.summary())
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 32)        320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 14, 14, 32)        9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 7, 7, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 1568)              0
_________________________________________________________________
dense_12 (Dense)             (None, 64)                100416
_________________________________________________________________
dense_13 (Dense)             (None, 5)                 325
=================================================================
Total params: 110,309
Trainable params: 110,309
Non-trainable params: 0
_________________________________________________________________
None
```

In [64]:

```
# early stopping to avoid overfitting
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=5, verbose=1)
mc = ModelCheckpoint('../model/cnn/best_model.h5', monitor='val_accuracy', mode='max', verl

# perform training
history_cnn = cnn.fit(X_train, y_train,
                      epochs=10,
                      validation_data=(X_valid, y_valid),
                      callbacks=[es, mc])
```

```
Epoch 1/10
1125/1125 [==============================] - 33s 3ms/step - loss: 0.6851 - accuracy: 0.71
70 - val_loss: 0.4136 - val_accuracy: 0.8355

Epoch 00001: val_accuracy improved from -inf to 0.83550, saving model to model/cnn/best_m
odel.h5
Epoch 2/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.3938 - accuracy: 0.844
2 - val_loss: 0.3612 - val_accuracy: 0.8605

Epoch 00002: val_accuracy improved from 0.83550 to 0.86050, saving model to model/cnn/bes
t_model.h5
Epoch 3/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.3469 - accuracy: 0.861
4 - val_loss: 0.3570 - val_accuracy: 0.8635

Epoch 00003: val_accuracy improved from 0.86050 to 0.86350, saving model to model/cnn/bes
t_model.h5
Epoch 4/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.3358 - accuracy: 0.865
2 - val_loss: 0.3660 - val_accuracy: 0.8519

Epoch 00004: val_accuracy did not improve from 0.86350
Epoch 5/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.3101 - accuracy: 0.874
5 - val_loss: 0.4012 - val_accuracy: 0.8457

Epoch 00005: val_accuracy did not improve from 0.86350
Epoch 6/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.3043 - accuracy: 0.881
8 - val_loss: 0.3381 - val_accuracy: 0.8708

Epoch 00006: val_accuracy improved from 0.86350 to 0.87083, saving model to model/cnn/bes
t_model.h5
Epoch 7/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.2852 - accuracy: 0.888
4 - val_loss: 0.3559 - val_accuracy: 0.8633

Epoch 00007: val_accuracy did not improve from 0.87083
Epoch 8/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.2893 - accuracy: 0.886
4 - val_loss: 0.4200 - val_accuracy: 0.8436

Epoch 00008: val_accuracy did not improve from 0.87083
Epoch 9/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.2746 - accuracy: 0.892
7 - val_loss: 0.3930 - val_accuracy: 0.8473
```

```
Epoch 00009: val_accuracy did not improve from 0.87083
Epoch 10/10
1125/1125 [==============================] - 4s 3ms/step - loss: 0.2810 - accuracy: 0.890
6 - val_loss: 0.3455 - val_accuracy: 0.8654

Epoch 00010: val_accuracy did not improve from 0.87083
```

In [65]:
```
# cnn.save('cnn_model/')
# cnn.save_weights('cnn_model_weights/')
```

In [66]:
```
# CM6 for CNN

## Results Analysis for CNN
```

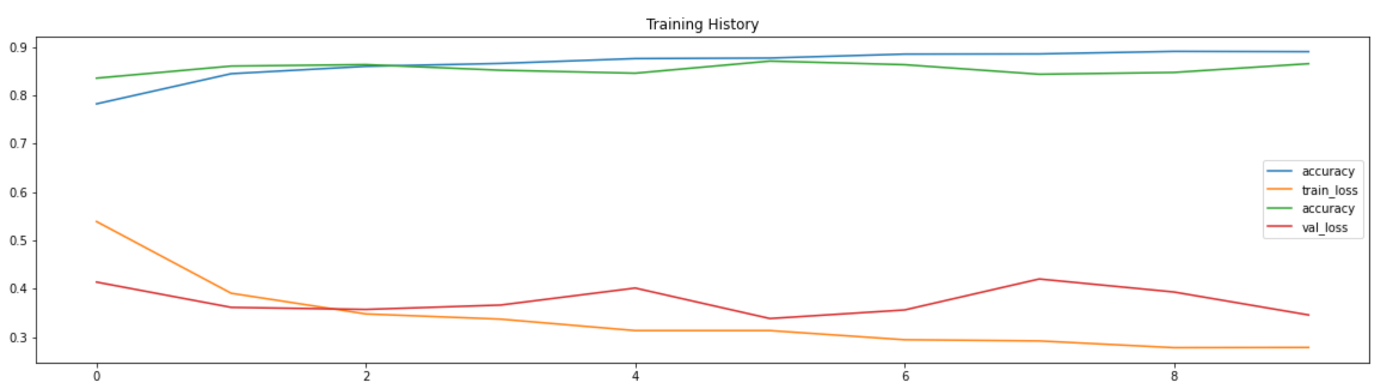
In [67]:
```
# evaluate the model
train_loss, train_acc = cnn.evaluate(X_train, y_train, verbose=0)
test_loss, test_acc = cnn.evaluate(X_test, y_test, verbose=0)

print("Accuracy:")
print('Train: %.3f, Valid: %.3f' % (train_acc, test_acc))
print("Loss:")
print('Train: %.3f, Valid: %.3f' % (train_loss, test_loss))
```

```
Accuracy:
Train: 0.901, Valid: 0.866
Loss:
Train: 0.247, Valid: 0.359
```

In [116]:
```
plt.plot(history_cnn.history['accuracy'])
plt.plot(history_cnn.history['loss'])
plt.plot(history_cnn.history['val_accuracy'])
plt.plot(history_cnn.history['val_loss'])
plt.legend(['accuracy', 'train_loss', 'accuracy', 'val_loss'])
plt.title("Training History")
```

Out[116]:
```
Text(0.5, 1.0, 'Training History')
```

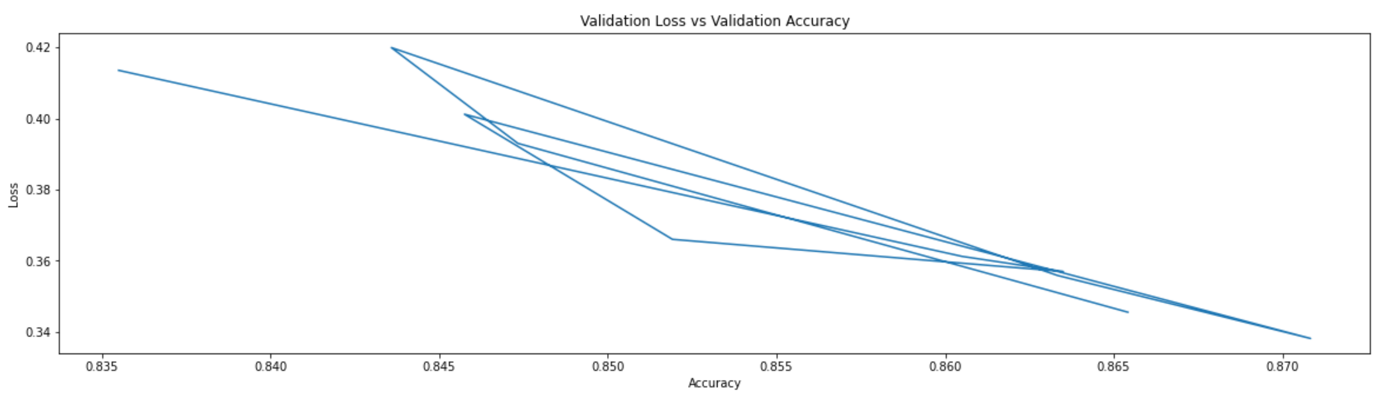


In [117]:
```
plt.plot(history_cnn.history['accuracy'], history_cnn.history['loss'])
plt.title("Training Loss vs Training Accuracy")
plt.xlabel("Accuracy")
plt.ylabel("Loss")
```

Out[117]:
```
Text(0, 0.5, 'Loss')
```

In [118]:
```
plt.plot(history_cnn.history['val_accuracy'], history_cnn.history['val_loss'])
plt.title("Validation Loss vs Validation Accuracy")
plt.xlabel("Accuracy")
plt.ylabel("Loss")
```

Out[118]:
```
Text(0, 0.5, 'Loss')
```



The training loss decreases smoothly against accuracy but the validation loss does not.

CM4

Resnet50

I now turn to the famous Resnet50 architecture that has proven to be very successful in computer vision applications.

Optimizer: Adam

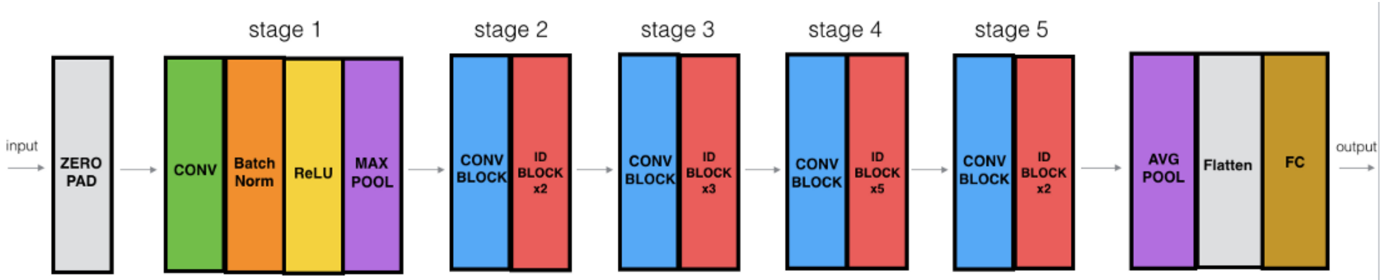
Activation Functions: ReLU for internal and Softmax for output layer

Regularization Method: Dropout and Early Stopping

Number of parameters:

Trainable params: 23,528,320 Non-trainable params: 53,120

Network Architecture: Resnet50 with batch normalization, skip connection and average and max-pooling



Credits: [https://github.com/priya-dwivedi/Deep-Learning/ (https://github.com/priya-dwivedi/Deep-Learning/)](https://github.com/priya-dwivedi/Deep-Learning/)

CM5 for Resnet50

Implementation for ResNet50

In [71]:
```
X_train = X_train.reshape(-1, 28, 28)
X_valid = X_valid.reshape(-1, 28, 28)
X_test = X_test.reshape(-1, 28, 28)

print(X_train.shape)
print(y_train.shape)
print(X_valid.shape)
print(y_valid.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(36000, 28, 28)
(36000, 5)
(12000, 28, 28)
(12000, 5)
(12000, 28, 28)
(12000, 5)
```

In [72]:
```
def pad_numpy_images(images, padding=((2,2),(2,2))):
    padded_images = np.zeros((images.shape[0], images[0].shape[0] + (padding[0][0] + paddi
    images.shape[1] + (padding[1][0] + padding[1][1])))

    for i, image in enumerate(images):
        padded_images[i] = np.pad(image, padding, 'constant')

    return padded_images

X_train_padded = pad_numpy_images(X_train, padding=((2,2),(2,2)))
X_valid_padded = pad_numpy_images(X_valid, padding=((2,2),(2,2)))
X_test_padded = pad_numpy_images(X_test, padding=((2,2),(2,2)))

print(X_train_padded.shape)
print(y_train.shape)
print(X_valid_padded.shape)
print(y_valid.shape)
print(X_test_padded.shape)
print(y_test.shape)
```

```
(36000, 32, 32)
(36000, 5)
(12000, 32, 32)
(12000, 5)
(12000, 32, 32)
(12000, 5)
```

In [73]:
```
img_height, img_width, img_channels = 32, 32, 1
# if imagenet weights are being loaded,
# input must have a static square shape (one of (128, 128), (160, 160), (192, 192), or (224
base_model = applications.resnet50.ResNet50(weights= None, include_top=False, input_shape=
```

In [74]:
```
base_model.summary()
```

```
Model: "resnet50"
__________________________________________________________________________________________
____________
Layer (type)                    Output Shape         Param #     Connected to
==========================================================================================
============
input_1 (InputLayer)            [(None, 32, 32, 1)]  0
__________________________________________________________________________________________
____________
conv1_pad (ZeroPadding2D)       (None, 38, 38, 1)    0           input_1[0][0]
__________________________________________________________________________________________
____________
conv1_conv (Conv2D)             (None, 16, 16, 64)   3200        conv1_pad[0][0]
__________________________________________________________________________________________
____________
conv1_bn (BatchNormalization)   (None, 16, 16, 64)   256         conv1_conv[0][0]
__________________________________________________________________________________________
____________
conv1_relu (Activation)         (None, 16, 16, 64)   0           conv1_bn[0][0]
```

In [75]:
```
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.7)(x)

output_layer = Dense(class_count, activation= 'softmax')(x)
resnet50 = Model(inputs = base_model.input, outputs = output_layer)

adam = optimizers.Adam(learning_rate=0.01)
resnet50.compile(optimizer=adam, loss='categorical_crossentropy', metrics=['accuracy'])
```

In [76]:
```
resnet50.summary()
```

```
Model: "model"
_____________________________________________________________________________________
_____________
Layer (type)                   Output Shape         Param #     Connected to
=====================================================================================
=============
input_1 (InputLayer)           [(None, 32, 32, 1)]  0

_____________________________________________________________________________________
_____________
conv1_pad (ZeroPadding2D)      (None, 38, 38, 1)    0           input_1[0][0]

_____________________________________________________________________________________
_____________
conv1_conv (Conv2D)            (None, 16, 16, 64)   3200        conv1_pad[0][0]

_____________________________________________________________________________________
_____________
conv1_bn (BatchNormalization)  (None, 16, 16, 64)   256         conv1_conv[0][0]

_____________________________________________________________________________________
_____________
conv1_relu (Activation)        (None, 16, 16, 64)   0           conv1_bn[0][0]
```

In [77]:
```
# early stopping to avoid overfitting
es = EarlyStopping(monitor='val_accuracy', mode='max', patience=5, verbose=1)
mc = ModelCheckpoint('../model/resnet50/best_model.h5', monitor='val_accuracy', mode='max'

# perform training
history_resnet50 = resnet50.fit(X_train_padded, y_train,
                    epochs=10,
                    validation_data=(X_valid_padded, y_valid),
                    callbacks=[es, mc],
                    batch_size=64)
```

```
Epoch 1/10
563/563 [==============================] - 35s 52ms/step - loss: 3.5523 - accuracy: 0.424
2 - val_loss: 10307.9961 - val_accuracy: 0.2051

Epoch 00001: val_accuracy improved from -inf to 0.20508, saving model to model/resnet50/b
est_model.h5
Epoch 2/10
563/563 [==============================] - 28s 50ms/step - loss: 2.9423 - accuracy: 0.536
5 - val_loss: 435.4293 - val_accuracy: 0.2488

Epoch 00002: val_accuracy improved from 0.20508 to 0.24883, saving model to model/resnet5
0/best_model.h5
Epoch 3/10
563/563 [==============================] - 28s 50ms/step - loss: 2.9818 - accuracy: 0.607
0 - val_loss: 2.7941 - val_accuracy: 0.6457

Epoch 00003: val_accuracy improved from 0.24883 to 0.64567, saving model to model/resnet5
0/best_model.h5
Epoch 4/10
563/563 [==============================] - 28s 49ms/step - loss: 1.8069 - accuracy: 0.646
8 - val_loss: 2.8662 - val_accuracy: 0.5717

Epoch 00004: val_accuracy did not improve from 0.64567
Epoch 5/10
563/563 [==============================] - 28s 49ms/step - loss: 1.5992 - accuracy: 0.683
5 - val_loss: 1602.0485 - val_accuracy: 0.3451

Epoch 00005: val_accuracy did not improve from 0.64567
Epoch 6/10
563/563 [==============================] - 27s 48ms/step - loss: 1.6312 - accuracy: 0.592
9 - val_loss: 0.8337 - val_accuracy: 0.6108

Epoch 00006: val_accuracy did not improve from 0.64567
Epoch 7/10
563/563 [==============================] - 28s 49ms/step - loss: 1.0525 - accuracy: 0.691
7 - val_loss: 29141.9473 - val_accuracy: 0.1257

Epoch 00007: val_accuracy did not improve from 0.64567
Epoch 8/10
563/563 [==============================] - 28s 49ms/step - loss: 1.4849 - accuracy: 0.616
9 - val_loss: 3.8383 - val_accuracy: 0.4089

Epoch 00008: val_accuracy did not improve from 0.64567
Epoch 00008: early stopping
```

CM6 for Resnet50

Results Analysis for Resnet50

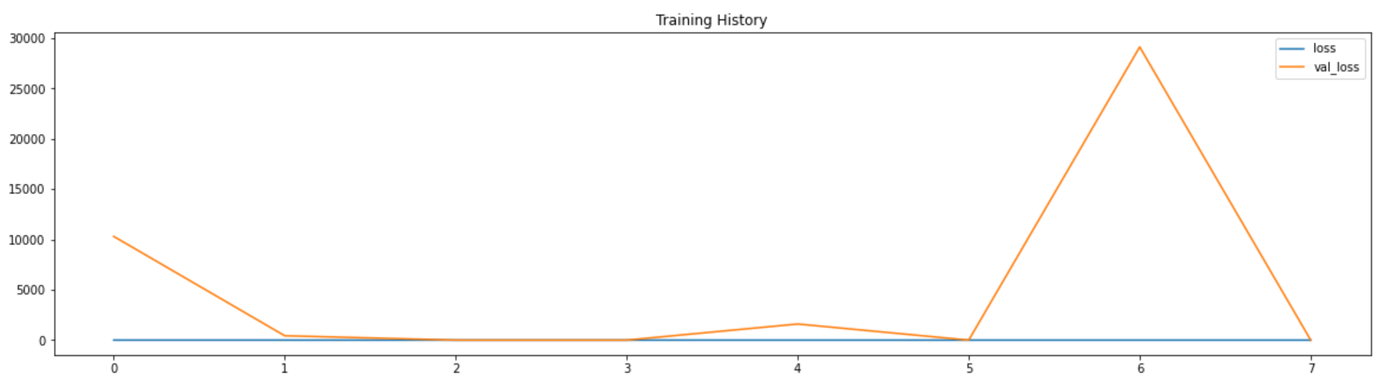
In [78]:
```
# evaluate the model
train_loss, train_acc = resnet50.evaluate(X_train_padded, y_train, verbose=0)
test_loss, test_acc = resnet50.evaluate(X_test_padded, y_test, verbose=0)

print("Accuracy:")
print('Train: %.3f, Valid: %.3f' % (train_acc, test_acc))
print("Loss:")
print('Train: %.3f, Valid: %.3f' % (train_loss, test_loss))
```

```
Accuracy:
Train: 0.400, Valid: 0.404
Loss:
Train: 4.156, Valid: 4.245
```

In [123]:
```
plt.plot(history_resnet50.history['loss'])
plt.plot(history_resnet50.history['val_loss'])
plt.legend(['loss', 'val_loss'])
plt.title("Training History")
```

Out[123]: `Text(0.5, 1.0, 'Training History')`



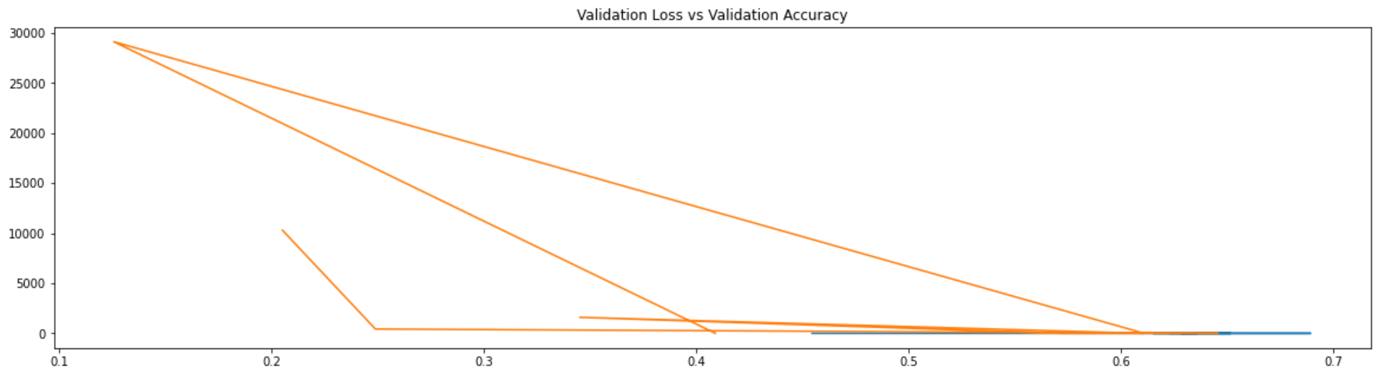
In [125]:
```
plt.plot(history_resnet50.history['accuracy'])
plt.plot(history_resnet50.history['val_accuracy'])
plt.legend(['accuracy', 'val_accuracy'])
plt.title("Training History")
```

Out[125]: `Text(0.5, 1.0, 'Training History')`

```
In [120]: plt.plot(history_resnet50.history['accuracy'], history_resnet50.history['loss'])
          plt.title("Training Loss vs Training Accuracy")

          plt.plot(history_resnet50.history['val_accuracy'], history_resnet50.history['val_loss'])
          plt.title("Validation Loss vs Validation Accuracy")
```

```
Out[120]: Text(0.5, 1.0, 'Validation Loss vs Validation Accuracy')
```

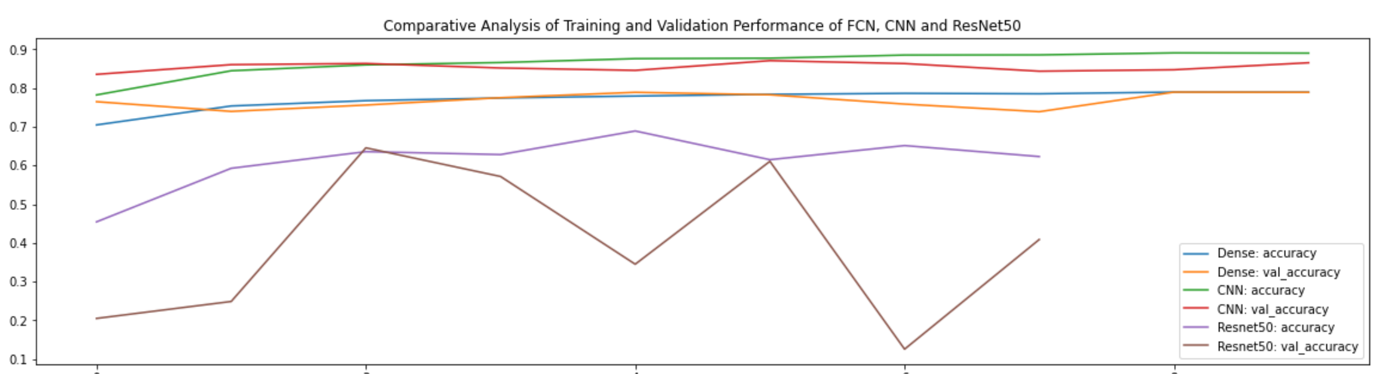


Comparative Analysis

Fully-Connected Neural Network vs CNN vs ResNet50

```
In [121]: plt.plot(history_dense_model.history['accuracy'])
          plt.plot(history_dense_model.history['val_accuracy'])
          plt.plot(history_cnn.history['accuracy'])
          plt.plot(history_cnn.history['val_accuracy'])
          plt.plot(history_resnet50.history['accuracy'])
          plt.plot(history_resnet50.history['val_accuracy'])
          plt.legend(['Dense: accuracy', 'Dense: val_accuracy', 'CNN: accuracy', 'CNN: val_accuracy',
          plt.title("Comparative Analysis of Training and Validation Performance of FCN, CNN and ResN
```

```
Out[121]: Text(0.5, 1.0, 'Comparative Analysis of Training and Validation Performance of FCN, CNN a
          nd ResNet50')
```



1. FCN: Adam works better mostly. Also, adding dropouts decreased the performance considerably.
2. CCN: As was expected, CNNs in general perform way better than simple FCNs in such tasks.

3. ResNet50: It it too slow to train and very computationally expensive. Due to limited time and computing resources, I only kept the epochs to 10 but they can be increased to test how the model performs.

Kaggle Predictions

In [96]:
```
kaggle_data = np.load(r'.data/fashion_mnist_dataset_kaggle_test.npy', allow_pickle=True).i
```

In [97]:
```
kaggle_data['features'].shape
```

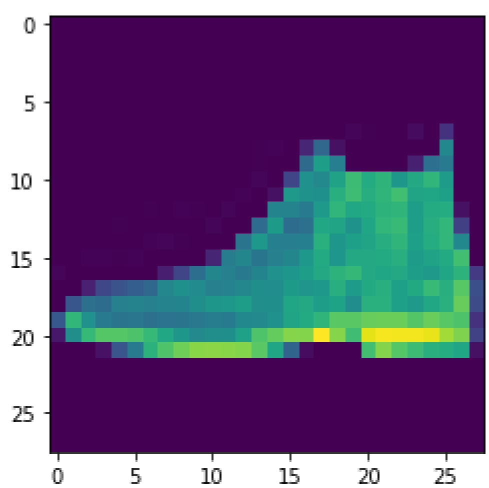
Out[97]: (10000, 28, 28)

In [98]:
```
pixel_count = kaggle_data['features'][0].shape[0] * kaggle_data['features'][0].shape[1]
pixel_count
```

Out[98]: 784

In [99]:
```
plt.imshow(kaggle_data['features'][0])
```

Out[99]: <matplotlib.image.AxesImage at 0x7f20f8433e90>



In [100]:
```
test_flat = flatten_image_set(kaggle_data['features'], pixel_count)
test_flat.shape
```

Out[100]: (10000, 784)

In [101]:
```
test = np.expand_dims(kaggle_data['features'], axis=0).reshape(-1, 28, 28, 1)
test.shape
```

Out[101]: (10000, 28, 28, 1)

In [102]:
```
test_padded = pad_numpy_images(kaggle_data['features'], padding=((2,2),(2,2))).reshape(-1,
test_padded.shape
```

Out[102]: (10000, 32, 32, 1)

In [103]:
```
dense_model_preds = np.argmax(dense_model.predict(test_flat), axis=1) + 1
cnn_preds = np.argmax(cnn.predict(test), axis=1) + 1
resnet50_preds = np.argmax(resnet50.predict(test_padded), axis=1) + 1

print("Dense: ", dense_model_preds)
print("CNN: ", cnn_preds)
print("Resnet50: ", cnn_preds)
```

```
Dense:  [4 3 2 ... 4 2 4]
CNN:  [4 3 2 ... 4 2 4]
Resnet50:  [4 3 2 ... 4 2 4]
```

In [104]:
```
df = pd.DataFrame({ "target" : dense_model_preds,
            }).reset_index().rename(columns={"index":"Id"})

df.to_csv("output/dense_kaggle_predictions.csv", index=False)
```

In [105]:
```
df = pd.DataFrame({ "target" : cnn_preds,
            }).reset_index().rename(columns={"index":"Id"})

df.to_csv("output/cnn_kaggle_predictions.csv", index=False)
```

In [106]:
```
df = pd.DataFrame({ "target" : resnet50_preds,
            }).reset_index().rename(columns={"index":"Id"})

df.to_csv("output/resnet50_kaggle_predictions.csv", index=False)
```

In [107]:
```
# !zip -r log.zip ./model/
```

```
updating: model/ (stored 0%)
updating: model/cnn/ (stored 0%)
updating: model/cnn/best_model.h5 (deflated 35%)
updating: model/resnet50/ (stored 0%)
updating: model/resnet50/best_model.h5 (deflated 24%)
updating: model/dense_model/ (stored 0%)
updating: model/dense_model/best_model.h5 (deflated 39%)
```

In [108]:
```
# files.download('log.zip')
```

```
<IPython.core.display.Javascript object>

<IPython.core.display.Javascript object>
```

In [108]:
```
```