

Downloading Dataset and structure:

A dictionary having 162060 samples each of 2 vectors each of length 128 representing time series representation of signals generated by GNU radio under different modulation techniques with different signal to noise ratios (SNRs).

Problem Statement

Given test samples with the same structure classify the samples correctly using deep neural networks and CNNs showing accuracy of prediction of modulation type of each sample and show accuracy of prediction in comparison with amount of noise in the signal .

Features:

Different types of features are used: first, we use raw data of time series of signals; second, features are the first derivative of the data; third, features are the integrals and the fourth features are a combination of the past 3 ones.

Raw time series data:

We will detect signals from their time representation showing value of each signal at a given time where each sample is represented by two vectors one for Quadrature and other for In-phase representation which is a way of representing signals in digital signal processing.

First Derivative:

Since data is time series representation then we can get the derivative by getting the difference of each two consecutive samples for each channel separately and this generates the derivative. This is correct because the derivative is the slope of the tangent by definition and the difference between each two values is one second.

Integral:

We will apply also integration process to our data-set by using scipy cumulative trapezoidal rule integration method as shown in the code below:

```
data_int=integrate.cumtrapz(data, initial=0)
```

In general, using same parameters (raw data case) found at setting our NN and applying them on the integrated version of data-set results in lower accuracy, about 50% maximum accuracy resulted @ 5 layers of NN, 256 input size for each layer, and batch size of 100.

Combined Data:

The data is combined by making more channels, in the previous features we used only 2 channels but now we will use 6 channels two for each type of the first 3 feature types. This will allow our NN to have more features to train on and hopefully more accuracy.

Differentiation features as a detailed use case:

One hidden layer (dense):

Having only one hidden layer with number of units {64,128,256} we observed that as we increase number of units accuracy increases (training, validation and testing).

But it is still low compared to multiple layered models with a maximum accuracy achieved of 21%.

Two hidden layers (dense):

Having two hidden layers with different sets of number of units,

1. We tried making all layers with the same number of units and then made them different trying all combinations to make sense which combinations give best accuracy.
2. We also tried different batch sizes to see their effect.
3. We fixed number of epochs to 100

Conclusions:

- two layers gives better accuracy than one hidden layer with a minimum test accuracy of 44% and maximum of 47.4%
- as we increase batch size number of epochs decrease , running time decreases and accuracy increases (also memory usage increases but we are using colab so it doesn't matter to us)
- We settled with 1000 which is 1/16 of number of samples
- increasing number of units per layer from 128 to 256 increased accuracy by about 0.7% with fixing all other parameters and making number of units the same for 2 layers
- by making one layer 128 units and other one 256 units we notice that accuracy decreases by about 3% than having both of 256 units
- This may mean that having both layers with same number of units increases accuracy or means that as we increase number of units per layer in general accuracy increases

Three hidden layers (dense):

Having two hidden layers with different sets of number of units,

1. least accuracy achieved is 40.5% and maximum accuracy is 47.5% which is almost equivalent to the maximum in two hidden layer model. This means that on increasing another layer we didn't add anything but complexity
2. in general, better results occur when we increase number of units in layers and occur significantly when we make last layer bigger than others, regarding units, and 1st bigger than those in the middle

Four hidden layers (dense):

1. Improved average accuracy by about 3% which is not much compared to complexity added
2. As we increase number of units accuracy tends to increase by a few numbers
3. Maximum accuracy is 46.5% which is less than that of three hidden layers
4. As we increase more layers accuracy doesn't get much better but adds complexity

Raw Data features:

Using Raw data time series representation we observe the following:

1. best accuracy is 64.97% having 4 hidden layers
2. best accuracies at high batch size 700-1000

Integrated Data features:

Using integrated data time series representation we observe the following:

1. best accuracy is 51% having 4 hidden layers
2. best accuracies at high batch size 700-1000
3. CNNs with accuracy 72%

Combined features:

1. best accuracy is 51% using 4 hidden layers
2. high batch size of 700

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Screenshots:

Raw Data tuning:

The screenshot shows a Jupyter Notebook interface with two code cells. The top cell contains code for evaluating a model on test data and printing its metrics. The bottom cell contains code for setting up training parameters and performing training with callbacks.

```
[78] - ls - loss: 1.1500 - acc: 0.5646 - val_loss: 0.9978 - val_acc: 0.6209
    Epoch 85/100
    - ls - loss: 1.1479 - acc: 0.5627 - val_loss: 1.0030 - val_acc: 0.6076
    ↳ Epoch 86/100
        - ls - loss: 1.1431 - acc: 0.5669 - val_loss: 0.9930 - val_acc: 0.6125
    Epoch 87/100
        - ls - loss: 1.1378 - acc: 0.5664 - val_loss: 1.0270 - val_acc: 0.5962
    Epoch 88/100
        - ls - loss: 1.1295 - acc: 0.5682 - val_loss: 0.9973 - val_acc: 0.6046
    Epoch 89/100
        - ls - loss: 1.1367 - acc: 0.5667 - val_loss: 0.9849 - val_acc: 0.6172
    Epoch 90/100
        - ls - loss: 1.1383 - acc: 0.5684 - val_loss: 0.9950 - val_acc: 0.6140
    Epoch 91/100
        - ls - loss: 1.1289 - acc: 0.5708 - val_loss: 0.9958 - val_acc: 0.6162
    Epoch 92/100
        - ls - loss: 1.1250 - acc: 0.5725 - val_loss: 1.0053 - val_acc: 0.6074
    Epoch 93/100
        - ls - loss: 1.1221 - acc: 0.5740 - val_loss: 0.9854 - val_acc: 0.6128
    Epoch 94/100
        - ls - loss: 1.1156 - acc: 0.5755 - val_loss: 1.0189 - val_acc: 0.6039

score = model.evaluate(X_test, Y_test, batch_size=batch_size)
print(model.metrics_names)
print(score)

↳ 81030/81030 [=====] - 0s 5us/step
['loss', 'acc']
[0.9697989894652549, 0.6213871388130134]

[ ] import keras.models as models
# build and train the model
model = models.Sequential()
model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(10, activation='softmax'))
```

```
[77] # Set up some params
nb_epoch = 100 # number of epochs to train on
batch_size = 700 # training batch size

[78] # perform training ...
    - call the main training loop in keras for our network+dataset
filepath = 'convmodrecnets_CNN2_0.5.wts.h5'
history=modell.fit(X_train,
                    Y_train,
                    batch_size=batch_size,
                    epochs=nb_epoch,
                    verbose=2,
                    validation_split=0.05,
                    callbacks = [
                        keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=True, mode='auto'),
                        keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=0, mode='auto')
                    ]
    # we re-load the best weights once training is finished
    modell.load_weights(filepath)

    ↳ Epoch 66/100
        - ls - loss: 1.2392 - acc: 0.5227 - val_loss: 1.0868 - val_acc: 0.5726
    Epoch 67/100
        - ls - loss: 1.2290 - acc: 0.5285 - val_loss: 1.0821 - val_acc: 0.5772
    Epoch 68/100
        - ls - loss: 1.2270 - acc: 0.5295 - val_loss: 1.0760 - val_acc: 0.5809
    Epoch 69/100
        - ls - loss: 1.2174 - acc: 0.5334 - val_loss: 1.0941 - val_acc: 0.5755
    Epoch 70/100
        - ls - loss: 1.2146 - acc: 0.5358 - val_loss: 1.0562 - val_acc: 0.5814
    Epoch 71/100
        - ls - loss: 1.2091 - acc: 0.5389 - val_loss: 1.0534 - val_acc: 0.5879
    Epoch 72/100
```

[76] =====

Layer (type)	Output Shape	Param #
reshape_35 (Reshape)	(None, 2, 128, 1)	0
dropout_80 (Dropout)	(None, 2, 128, 1)	0
flatten_18 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_81 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 128)	32896
dropout_82 (Dropout)	(None, 128)	0
dense3 (Dense)	(None, 128)	16512
dropout_83 (Dropout)	(None, 128)	0
dense4 (Dense)	(None, 64)	8256
dropout_84 (Dropout)	(None, 64)	0
dense5 (Dense)	(None, 11)	715
activation_18 (Activation)	(None, 11)	0
reshape_36 (Reshape)	(None, 11)	0

Total params: 124,171
Trainable params: 124,171
Non-trainable params: 0

[76] CODE TEXT ⌂ CELL ⌄ CELL ✓ CONNECTED | EDITING

[76] #fully connected neural network
dr = 0.3
model = keras.models.Sequential()
model.add(Reshape(in_shp+[1], input_shape=in_shp))
model.add(Dropout(dr))
model.add(Flatten())
model.add(Dense(256, activation='relu', kernel_initializer='he_normal', name="dense1"))
model.add(Dropout(dr))
model.add(Dense(128, activation='relu', kernel_initializer='he_normal', name="dense2"))
model.add(Dropout(dr))
model.add(Dense(128, activation='relu', kernel_initializer='he_normal', name="dense3"))
model.add(Dropout(dr))
model.add(Dense(64, activation='relu', kernel_initializer='he_normal', name="dense4"))
model.add(Dropout(dr))
model.add(Dense(len(classes), kernel_initializer='he_normal', name="dense5"))
model.add(Activation('softmax'))
model.add(Reshape([len(classes)]))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()

[76] Layer (type) Output Shape Param #
=====

Layer (type)	Output Shape	Param #
reshape_35 (Reshape)	(None, 2, 128, 1)	0
dropout_80 (Dropout)	(None, 2, 128, 1)	0
flatten_18 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_81 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 128)	32896

[68] =====

reshape_32 (Reshape) (None, 11) 0

[68] Total params: 133,131
Trainable params: 133,131
Non-trainable params: 0

[69] # Set up some params
nb_epoch = 100 # number of epochs to train on
batch_size = 700 # training batch size

[70] # perform training ...
- call the main training loop in keras for our network+dataset
filepath = 'convmodrecnets_CNN2_0.5.wts.h5'
history=del1.fit(X_train,
Y_train,
batch_size=batch_size,
epochs=nb_epoch,
verbose=2,
validation_split=0.05,
callbacks =[
keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=True, mode='auto'),
keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=0, mode='auto')
])
we re-load the best weights once training is finished
model1.load_weights(filepath)

[70] Epoch 23/100
- 1s - loss: 1.1366 - acc: 0.5608 - val_loss: 1.0823 - val_acc: 0.5745
Epoch 24/100
- 1s - loss: 1.1183 - acc: 0.5684 - val_loss: 1.0723 - val_acc: 0.5871
Epoch 25/100
- 1s - loss: 1.1006 - acc: 0.5769 - val_loss: 1.0543 - val_acc: 0.5896
Epoch 26/100

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```
[68] =====
Layer (type)          Output Shape         Param #
=====
```

- ▷ reshape_31 (Reshape) (None, 2, 128, 1) 0
 ▷ dropout_70 (Dropout) (None, 2, 128, 1) 0
 ▷ flatten_16 (Flatten) (None, 256) 0
 dense1 (Dense) (None, 256) 65792
 dropout_71 (Dropout) (None, 256) 0
 dense2 (Dense) (None, 128) 32896
 dropout_72 (Dropout) (None, 128) 0
 dense3 (Dense) (None, 128) 16512
 dropout_73 (Dropout) (None, 128) 0
 dense4 (Dense) (None, 128) 16512
 dropout_74 (Dropout) (None, 128) 0
 dense5 (Dense) (None, 11) 1419
 activation_16 (Activation) (None, 11) 0
 reshape_32 (Reshape) (None, 11) 0
=====

```
Total params: 133,131
Trainable params: 133,131
Non-trainable params: 0
```

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```
[58] # Set up some params
nb_epoch = 100 # number of epochs to train on
batch_size = 1000 # training batch size
```

```
[59] # perform training ...
# - call the main training loop in keras for our network+dataset
filepath = 'convmodrecnets_CNN2_0.5.wts.h5'
history=modell.fit(X_train,
                    Y_train,
                    batch_size=batch_size,
                    epochs=nb_epoch,
                    validation_split=0.05,
                    callbacks = [
                        keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=True, mode='auto'),
                        keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=0, mode='auto')
                    ]
# we re-load the best weights once training is finished
modell.load_weights(filepath)
```

- ▷ Train on 76978 samples, validate on 4052 samples
 Epoch 1/50
 - 2s - loss: 3.0463 - acc: 0.1765 - val_loss: 2.2358 - val_acc: 0.2078
 Epoch 2/50
 - 1s - loss: 2.2402 - acc: 0.2054 - val_loss: 2.1879 - val_acc: 0.2127
 Epoch 3/50
 - 1s - loss: 2.1942 - acc: 0.2109 - val_loss: 2.1469 - val_acc: 0.2122
 Epoch 4/50
 - 1s - loss: 2.1511 - acc: 0.2120 - val_loss: 2.1033 - val_acc: 0.2394
 Epoch 5/50

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```
[ ] #fully connected neural network
dr = 0.1
modell = keras.models.Sequential()
modell.add(Reshape(in_shp+[1], input_shape=in_shp))
modell.add(Dropout(dr))
modell.add(Flatten())
modell.add(Dense(256, activation='relu', kernel_initializer='he_normal', name="dense1"))
modell.add(Dropout(dr))
modell.add(Dense(256, activation='relu', kernel_initializer='he_normal', name="dense2"))
modell.add(Dropout(dr))
modell.add(Dense(128, activation='relu', kernel_initializer='he_normal', name="dense3"))
modell.add(Dropout(dr))
modell.add(Dense(64, activation='relu', kernel_initializer='he_normal', name="dense4"))
modell.add(Dropout(dr))
modell.add(Dense(len(classes), kernel_initializer='he_normal', name="dense5"))
modell.add(Activation('softmax'))
modell.add(Reshape([len(classes)]))
modell.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
modell.summary()
```

Layer (type)	Output Shape	Param #
reshape_29 (Reshape)	(None, 2, 128, 1)	0
dropout_65 (Dropout)	(None, 2, 128, 1)	0
flatten_15 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_66 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 256)	65792

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```
[59] Epoch 44/50
- 1s - loss: 1.0688 - acc: 0.5928 - val_loss: 1.0394 - val_acc: 0.5962
↳ Epoch 45/50
- 1s - loss: 1.0545 - acc: 0.5984 - val_loss: 1.0290 - val_acc: 0.5982
Epoch 46/50
- 1s - loss: 1.0363 - acc: 0.6032 - val_loss: 1.0190 - val_acc: 0.6160
Epoch 47/50
- 1s - loss: 1.0276 - acc: 0.6083 - val_loss: 1.0133 - val_acc: 0.6115
Epoch 48/50
- 1s - loss: 1.0217 - acc: 0.6084 - val_loss: 0.9989 - val_acc: 0.6150
Epoch 49/50
- 1s - loss: 1.0085 - acc: 0.6123 - val_loss: 0.9953 - val_acc: 0.6162
Epoch 50/50
- 1s - loss: 1.0018 - acc: 0.6167 - val_loss: 0.9910 - val_acc: 0.6153
- 1s - loss: 0.9946 - acc: 0.6174 - val_loss: 0.9885 - val_acc: 0.6212

[60] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

↳ 81030/81030 [=====] - 0s 4us/step
['loss', 'acc']
[0.9838209509524051, 0.6214365039340757]

[ ] import keras.models as models
# Build VT-CNN2 Neural Net model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 Dense layers (ReLU and Softmax)
# - Perform categorical cross entropy optimization
dr = 0.1 # dropout rate (%)
model = keras.models.Sequential()
```

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```
[55] Epoch 30/50
- 7s - loss: 0.9508 - acc: 0.6325 - val_loss: 0.9703 - val_acc: 0.6227
↳ Epoch 31/50
- 7s - loss: 0.9438 - acc: 0.6321 - val_loss: 0.9743 - val_acc: 0.6199
Epoch 32/50
- 7s - loss: 0.9420 - acc: 0.6344 - val_loss: 0.9584 - val_acc: 0.6246
Epoch 33/50
- 7s - loss: 0.9384 - acc: 0.6369 - val_loss: 0.9558 - val_acc: 0.6266
Epoch 34/50
- 7s - loss: 0.9377 - acc: 0.6374 - val_loss: 0.9558 - val_acc: 0.6251
Epoch 35/50
- 7s - loss: 0.9344 - acc: 0.6385 - val_loss: 0.9722 - val_acc: 0.6251
Epoch 36/50
- 7s - loss: 0.9299 - acc: 0.6395 - val_loss: 0.9640 - val_acc: 0.6251
Epoch 37/50
- 7s - loss: 0.9272 - acc: 0.6407 - val_loss: 0.9634 - val_acc: 0.6207
Epoch 38/50
- 7s - loss: 0.9253 - acc: 0.6424 - val_loss: 0.9686 - val_acc: 0.6227

[56] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

↳ 81030/81030 [=====] - 3s 32us/step
['loss', 'acc']
[0.9492381242448846, 0.6300999652605821]

[ ] import keras.models as models
# Build VT-CNN2 Neural Net model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 Dense layers (ReLU and Softmax)
```

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Layer (type)	Output Shape	Param #
reshape_25 (Reshape)	(None, 2, 128, 1)	0
dropout_55 (Dropout)	(None, 2, 128, 1)	0
flatten_13 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_56 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 128)	32896
dropout_57 (Dropout)	(None, 128)	0
dense3 (Dense)	(None, 64)	8256
dropout_58 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 32)	2080
dropout_59 (Dropout)	(None, 32)	0
dense5 (Dense)	(None, 11)	363
activation_13 (Activation)	(None, 11)	0
reshape_26 (Reshape)	(None, 11)	0

```
Total params: 109,387
Trainable params: 109,387
Non-trainable params: 0
```

Code Editor 1:

```
[55]
- 7s - loss: 0.9766 - acc: 0.6223 - val_loss: 0.9722 - val_acc: 0.6207
Epoch 26/50
- 7s - loss: 0.9690 - acc: 0.6221 - val_loss: 0.9670 - val_acc: 0.6281
Epoch 27/50
- 7s - loss: 0.9624 - acc: 0.6277 - val_loss: 0.9664 - val_acc: 0.6182
Epoch 28/50
- 7s - loss: 0.9616 - acc: 0.6280 - val_loss: 0.9710 - val_acc: 0.6190
Epoch 29/50
- 7s - loss: 0.9505 - acc: 0.6311 - val_loss: 0.9698 - val_acc: 0.6251
Epoch 30/50
- 7s - loss: 0.9508 - acc: 0.6325 - val_loss: 0.9703 - val_acc: 0.6227
Epoch 31/50
- 7s - loss: 0.9438 - acc: 0.6321 - val_loss: 0.9743 - val_acc: 0.6199
Epoch 32/50
- 7s - loss: 0.9420 - acc: 0.6344 - val_loss: 0.9584 - val_acc: 0.6246
Epoch 33/50
- 7s - loss: 0.9384 - acc: 0.6369 - val_loss: 0.9558 - val_acc: 0.6266
Epoch 34/50
- 7s - loss: 0.9377 - acc: 0.6374 - val_loss: 0.9558 - val_acc: 0.6251
Epoch 35/50
- 7s - loss: 0.9344 - acc: 0.6385 - val_loss: 0.9722 - val_acc: 0.6251
Epoch 36/50
- 7s - loss: 0.9299 - acc: 0.6395 - val_loss: 0.9640 - val_acc: 0.6251
Epoch 37/50
- 7s - loss: 0.9272 - acc: 0.6407 - val_loss: 0.9634 - val_acc: 0.6207
Epoch 38/50
- 7s - loss: 0.9253 - acc: 0.6424 - val_loss: 0.9686 - val_acc: 0.6227

[56] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)
```

Code Editor 2:

```
[44]
- 6s - loss: 1.0119 - acc: 0.6112 - val_loss: 1.0169 - val_acc: 0.6091
Epoch 25/50
- 6s - loss: 1.0038 - acc: 0.6155 - val_loss: 1.0072 - val_acc: 0.6096
Epoch 26/50
- 6s - loss: 0.9979 - acc: 0.6167 - val_loss: 0.9939 - val_acc: 0.6172
Epoch 27/50
- 6s - loss: 0.9923 - acc: 0.6177 - val_loss: 1.0049 - val_acc: 0.6066
Epoch 28/50
- 6s - loss: 0.9921 - acc: 0.6189 - val_loss: 0.9905 - val_acc: 0.6101
Epoch 29/50
- 6s - loss: 0.9836 - acc: 0.6232 - val_loss: 0.9865 - val_acc: 0.6153
Epoch 30/50
- 6s - loss: 0.9783 - acc: 0.6225 - val_loss: 0.9904 - val_acc: 0.6172
Epoch 31/50
- 6s - loss: 0.9777 - acc: 0.6262 - val_loss: 0.9920 - val_acc: 0.6130
Epoch 32/50
- 6s - loss: 0.9708 - acc: 0.6269 - val_loss: 0.9921 - val_acc: 0.6192
Epoch 33/50
- 6s - loss: 0.9703 - acc: 0.6275 - val_loss: 0.9897 - val_acc: 0.6162
Epoch 34/50
- 6s - loss: 0.9667 - acc: 0.6296 - val_loss: 0.9938 - val_acc: 0.6177

[ ] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

[ ] 81030/81030 [=====] - 2s 27us/step
['loss', 'acc']
[0.993114006822098, 0.6144267573656601]
```

Code Editor 3:

```
[40] Epoch 43/50
- 6s - loss: 1.0032 - acc: 0.6149 - val_loss: 0.9797 - val_acc: 0.6212
Epoch 44/50
- 6s - loss: 0.9989 - acc: 0.6173 - val_loss: 0.9802 - val_acc: 0.6239
Epoch 45/50
- 6s - loss: 0.9961 - acc: 0.6194 - val_loss: 0.9753 - val_acc: 0.6234
Epoch 46/50
- 6s - loss: 0.9995 - acc: 0.6180 - val_loss: 0.9809 - val_acc: 0.6197
Epoch 47/50
- 6s - loss: 0.9996 - acc: 0.6184 - val_loss: 0.9827 - val_acc: 0.6229
Epoch 48/50
- 6s - loss: 0.9931 - acc: 0.6213 - val_loss: 0.9783 - val_acc: 0.6259
Epoch 49/50
- 6s - loss: 0.9917 - acc: 0.6212 - val_loss: 0.9797 - val_acc: 0.6207
Epoch 50/50
- 6s - loss: 0.9909 - acc: 0.6204 - val_loss: 0.9785 - val_acc: 0.6187

[ ] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

[ ] 81030/81030 [=====] - 2s 31us/step
['loss', 'acc']
[0.9702621066722245, 0.6247686062784646]

[ ] import keras.models as models
# Build a VGGNet model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 2DConv/ReLU layers
# - Pass through 2 Dense layers (ReLU and Softmax)
# - Perform categorical cross entropy optimization
```

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```
[40] Epoch 37/50
  - 6s - loss: 1.0242 - acc: 0.6099 - val_loss: 0.9999 - val_acc: 0.6130
  ↳ Epoch 38/50
    - 6s - loss: 1.0230 - acc: 0.6078 - val_loss: 1.0043 - val_acc: 0.6128
    Epoch 39/50
    - 6s - loss: 1.0164 - acc: 0.6108 - val_loss: 0.9865 - val_acc: 0.6145
    Epoch 40/50
    - 6s - loss: 1.0149 - acc: 0.6116 - val_loss: 0.9867 - val_acc: 0.6229
    Epoch 41/50
    - 6s - loss: 1.0127 - acc: 0.6118 - val_loss: 0.9824 - val_acc: 0.6192
    Epoch 42/50
    - 6s - loss: 1.0121 - acc: 0.6132 - val_loss: 0.9885 - val_acc: 0.6194
    Epoch 43/50
    - 6s - loss: 1.0107 - acc: 0.6142 - val_loss: 0.9897 - val_acc: 0.6180
    Epoch 44/50
    - 6s - loss: 1.0032 - acc: 0.6149 - val_loss: 0.9797 - val_acc: 0.6212
    Epoch 45/50
    - 6s - loss: 0.9989 - acc: 0.6173 - val_loss: 0.9802 - val_acc: 0.6239
    Epoch 46/50
    - 6s - loss: 0.9961 - acc: 0.6194 - val_loss: 0.9753 - val_acc: 0.6234
    Epoch 47/50
    - 6s - loss: 0.9995 - acc: 0.6180 - val_loss: 0.9809 - val_acc: 0.6197
    Epoch 48/50
    - 6s - loss: 0.9996 - acc: 0.6184 - val_loss: 0.9827 - val_acc: 0.6229
    Epoch 49/50
    - 6s - loss: 0.9931 - acc: 0.6213 - val_loss: 0.9783 - val_acc: 0.6259
    Epoch 50/50
    - 6s - loss: 0.9917 - acc: 0.6212 - val_loss: 0.9797 - val_acc: 0.6207
Epoch 50/50
- 6s - loss: 0.9909 - acc: 0.6204 - val_loss: 0.9785 - val_acc: 0.6187
```

score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)

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```
Layer (type)          Output Shape         Param #
=====
reshape_17 (Reshape)  (None, 2, 128, 1)   0
dropout_37 (Dropout) (None, 2, 128, 1)   0
flatten_9 (Flatten)  (None, 256)          0
dense1 (Dense)        (None, 128)          32896
dropout_38 (Dropout) (None, 128)          0
dense2 (Dense)        (None, 64)           8256
dropout_39 (Dropout) (None, 64)           0
dense3 (Dense)        (None, 32)           2080
dropout_40 (Dropout) (None, 32)           0
dense6 (Dense)        (None, 11)           363
activation_9 (Activation) (None, 11)       0
reshape_18 (Reshape)  (None, 11)           0
=====
Total params: 43,595
Trainable params: 43,595
Non-trainable params: 0
```

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```

dropout_33 (Dropout)      (None, 2, 128, 1)    0
flatten_8 (Flatten)       (None, 256)          0
dense1 (Dense)            (None, 256)          65792
dropout_34 (Dropout)       (None, 256)          0
dense2 (Dense)             (None, 64)           16448
dropout_35 (Dropout)       (None, 64)           0
dense3 (Dense)             (None, 32)           2080
dropout_36 (Dropout)       (None, 32)           0
dense6 (Dense)             (None, 11)           363
activation_8 (Activation)  (None, 11)           0
reshape_16 (Reshape)        (None, 11)           0
=====
Total params: 84,683
Trainable params: 84,683
Non-trainable params: 0

```

```
[31] # Set up some params
nb_epoch = 50 # number of epochs to train on
batch_size = 100 # training batch size
```

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```

[32] Epoch 39/50
- 7s - loss: 0.9876 - acc: 0.6220 - val_loss: 0.9711 - val_acc: 0.6264
  Epoch 40/50
- 8s - loss: 0.9774 - acc: 0.6254 - val_loss: 0.9851 - val_acc: 0.6165
Epoch 41/50
- 8s - loss: 0.9764 - acc: 0.6259 - val_loss: 0.9670 - val_acc: 0.6199
Epoch 42/50
- 7s - loss: 0.9731 - acc: 0.6261 - val_loss: 0.9534 - val_acc: 0.6306
Epoch 43/50
- 8s - loss: 0.9736 - acc: 0.6258 - val_loss: 0.9611 - val_acc: 0.6234
Epoch 44/50
- 7s - loss: 0.9655 - acc: 0.6294 - val_loss: 0.9735 - val_acc: 0.6209
Epoch 45/50
- 8s - loss: 0.9606 - acc: 0.6308 - val_loss: 0.9644 - val_acc: 0.6227
Epoch 46/50
- 8s - loss: 0.9617 - acc: 0.6314 - val_loss: 0.9684 - val_acc: 0.6347
Epoch 47/50
- 8s - loss: 0.9624 - acc: 0.6309 - val_loss: 0.9609 - val_acc: 0.6283

  score = model.evaluate(X_test, Y_test, batch_size=batch_size)
  print(model.metrics_names)
  print(score)

  81030/81030 [=====] - 3s 32us/step
  ['loss', 'acc']
  [0.9578799731990985, 0.6293101338640924]
```

```
[ ] import keras.models as models
# Build UT-CNN2 Neural Net model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 2DConv/ReLU layers
#   - Pass through 2 Dense Layers (ReLU and Softmax)
```

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```

[31] # Set up some params
nb_epoch = 50 # number of epochs to train on
batch_size = 100 # training batch size

# perform training ...
# - call the main training loop in keras for our network+dataset
filepath = 'convmodrecnets_CNN2_0.5.wts.h5'
history=modell.fit(X_train,
                    Y_train,
                    batch_size=batch_size,
                    epochs=nb_epoch,
                    verbose=1,
                    validation_split=0.05,
                    callbacks=[keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=True, mode='auto'),
                               keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=0, mode='auto')])
# we re-load the best weights once training is finished
modell.load_weights(filepath)

... Train on 76978 samples, validate on 4052 samples
Epoch 1/50
- 8s - loss: 2.3993 - acc: 0.1863 - val_loss: 2.0778 - val_acc: 0.2110
Epoch 2/50
- 7s - loss: 1.9942 - acc: 0.2577 - val_loss: 1.8586 - val_acc: 0.2747
Epoch 3/50
- 8s - loss: 1.8152 - acc: 0.3080 - val_loss: 1.6678 - val_acc: 0.3736
Epoch 4/50
- 8s - loss: 1.6798 - acc: 0.3739 - val_loss: 1.5821 - val_acc: 0.4158
Epoch 5/50
```

Layer (type) **Output Shape** **Param #**

[30] reshape_13 (Reshape)	(None, 2, 128, 1)	0
dropout_27 (Dropout)	(None, 2, 128, 1)	0
flatten_7 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_28 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 64)	16448
dropout_29 (Dropout)	(None, 64)	0
dense3 (Dense)	(None, 64)	4160
dropout_30 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 32)	2080
dropout_31 (Dropout)	(None, 32)	0
dense5 (Dense)	(None, 32)	1056
dropout_32 (Dropout)	(None, 32)	0
dense6 (Dense)	(None, 11)	363
activation_7 (Activation)	(None, 11)	0
reshape_14 (Reshape)	(None, 11)	0

Epoch 22/50
- 7s - loss: 1.0282 - acc: 0.6043 - val_loss: 1.0013 - val_acc: 0.6086
Epoch 23/50
- 8s - loss: 1.0225 - acc: 0.6056 - val_loss: 0.9970 - val_acc: 0.6155
Epoch 24/50
- 7s - loss: 1.0137 - acc: 0.6101 - val_loss: 1.0200 - val_acc: 0.6096
Epoch 25/50
- 7s - loss: 1.0055 - acc: 0.6118 - val_loss: 0.9914 - val_acc: 0.6143
Epoch 26/50
- 7s - loss: 1.0008 - acc: 0.6159 - val_loss: 0.9764 - val_acc: 0.6170
Epoch 27/50
- 8s - loss: 0.9906 - acc: 0.6180 - val_loss: 0.9816 - val_acc: 0.6182
Epoch 28/50
- 7s - loss: 0.9929 - acc: 0.6179 - val_loss: 1.0085 - val_acc: 0.6145
Epoch 29/50
- 7s - loss: 0.9857 - acc: 0.6209 - val_loss: 0.9932 - val_acc: 0.6167
Epoch 30/50
- 7s - loss: 0.9793 - acc: 0.6219 - val_loss: 0.9794 - val_acc: 0.6190
Epoch 31/50
- 8s - loss: 0.9796 - acc: 0.6223 - val_loss: 0.9816 - val_acc: 0.6209

```

score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

81030/81030 [=====] - 2s 27us/step
['loss', 'acc']
[0.9702057201332777, 0.623596200760163]

```

```

import keras.models as models
# Build VT-CNN2 Neural Net model using Keras primitives --

```


Epoch 17/50
- 7s - loss: 1.1150 - acc: 0.5683 - val_loss: 1.0537 - val_acc: 0.5911
Epoch 18/50
- 8s - loss: 1.0865 - acc: 0.5812 - val_loss: 1.0368 - val_acc: 0.5965
Epoch 19/50
- 7s - loss: 1.0663 - acc: 0.5895 - val_loss: 1.0327 - val_acc: 0.5987
Epoch 20/50
- 8s - loss: 1.0522 - acc: 0.5945 - val_loss: 1.0169 - val_acc: 0.6007
Epoch 21/50
- 8s - loss: 1.0396 - acc: 0.6006 - val_loss: 1.0249 - val_acc: 0.6081
Epoch 22/50
- 7s - loss: 1.0282 - acc: 0.6043 - val_loss: 1.0013 - val_acc: 0.6086
Epoch 23/50
- 8s - loss: 1.0225 - acc: 0.6056 - val_loss: 0.9970 - val_acc: 0.6155
Epoch 24/50
- 7s - loss: 1.0137 - acc: 0.6101 - val_loss: 1.0200 - val_acc: 0.6096
Epoch 25/50
- 7s - loss: 1.0055 - acc: 0.6118 - val_loss: 0.9914 - val_acc: 0.6143
Epoch 26/50
- 7s - loss: 1.0008 - acc: 0.6159 - val_loss: 0.9764 - val_acc: 0.6170
Epoch 27/50
- 8s - loss: 0.9906 - acc: 0.6180 - val_loss: 0.9816 - val_acc: 0.6182
Epoch 28/50
- 7s - loss: 0.9929 - acc: 0.6179 - val_loss: 1.0085 - val_acc: 0.6145
Epoch 29/50
- 7s - loss: 0.9857 - acc: 0.6209 - val_loss: 0.9932 - val_acc: 0.6167
Epoch 30/50
- 7s - loss: 0.9793 - acc: 0.6219 - val_loss: 0.9794 - val_acc: 0.6190
Epoch 31/50
- 8s - loss: 0.9796 - acc: 0.6223 - val_loss: 0.9816 - val_acc: 0.6209

```

score = model1.evaluate(X_test, Y_test, batch_size=batch_size)

```

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Layer (type)	Output Shape	Param #
reshape_9 (Reshape)	(None, 2, 128, 1)	0
dropout_15 (Dropout)	(None, 2, 128, 1)	0
flatten_5 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_16 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 64)	16448
dropout_17 (Dropout)	(None, 64)	0
dense3 (Dense)	(None, 64)	4160
dropout_18 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 64)	4160
dropout_19 (Dropout)	(None, 64)	0
dense5 (Dense)	(None, 64)	4160
dropout_20 (Dropout)	(None, 64)	0
dense6 (Dense)	(None, 11)	715
activation 5 (Activation)	(None, 11)	0

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[21] `model1.summary()`

Layer (type)	Output Shape	Param #
reshape_7 (Reshape)	(None, 2, 128, 1)	0
dropout_10 (Dropout)	(None, 2, 128, 1)	0
flatten_4 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_11 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 64)	16448
dropout_12 (Dropout)	(None, 64)	0
dense3 (Dense)	(None, 64)	4160
dropout_13 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 64)	4160
dropout_14 (Dropout)	(None, 64)	0
dense5 (Dense)	(None, 11)	715
activation 4 (Activation)	(None, 11)	0
reshape_8 (Reshape)	(None, 11)	0

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Epoch 27/50
- 7s - loss: 1.0073 - acc: 0.6141 - val_loss: 0.9921 - val_acc: 0.6133
Epoch 28/50
- 7s - loss: 0.9968 - acc: 0.6161 - val_loss: 0.9957 - val_acc: 0.6155
Epoch 29/50
- 7s - loss: 0.9943 - acc: 0.6163 - val_loss: 0.9791 - val_acc: 0.6153
Epoch 30/50
- 7s - loss: 0.9920 - acc: 0.6187 - val_loss: 0.9775 - val_acc: 0.6177
Epoch 31/50
- 7s - loss: 0.9921 - acc: 0.6194 - val_loss: 0.9825 - val_acc: 0.6148
Epoch 32/50
- 7s - loss: 0.9822 - acc: 0.6229 - val_loss: 0.9712 - val_acc: 0.6182
Epoch 33/50
- 7s - loss: 0.9771 - acc: 0.6234 - val_loss: 0.9766 - val_acc: 0.6162
Epoch 34/50
- 7s - loss: 0.9796 - acc: 0.6232 - val_loss: 0.9853 - val_acc: 0.6138
Epoch 35/50
- 7s - loss: 0.9778 - acc: 0.6259 - val_loss: 0.9840 - val_acc: 0.6197
Epoch 36/50
- 7s - loss: 0.9739 - acc: 0.6245 - val_loss: 0.9667 - val_acc: 0.6224
Epoch 37/50
- 7s - loss: 0.9735 - acc: 0.6257 - val_loss: 0.9787 - val_acc: 0.6229
Epoch 38/50
- 7s - loss: 0.9648 - acc: 0.6284 - val_loss: 0.9746 - val_acc: 0.6306
Epoch 39/50
- 7s - loss: 0.9602 - acc: 0.6310 - val_loss: 0.9889 - val_acc: 0.6246
Epoch 40/50
- 7s - loss: 0.9630 - acc: 0.6297 - val_loss: 0.9810 - val_acc: 0.6214
Epoch 41/50
- 7s - loss: 0.9586 - acc: 0.6295 - val_loss: 0.9942 - val_acc: 0.6199

```
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```

[17] `model1.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])`

Layer (type)	Output Shape	Param #
reshape_5 (Reshape)	(None, 2, 128, 1)	0
dropout_6 (Dropout)	(None, 2, 128, 1)	0
flatten_3 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_7 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 64)	16448
dropout_8 (Dropout)	(None, 64)	0
dense3 (Dense)	(None, 64)	4160
dropout_9 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 11)	715
activation_3 (Activation)	(None, 11)	0
reshape_6 (Reshape)	(None, 11)	0

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[19] Epoch 42/50
 - 6s - loss: 1.1260 - acc: 0.5751 - val_loss: 1.0802 - val_acc: 0.5948

Epoch 43/50
 - 6s - loss: 1.1230 - acc: 0.5769 - val_loss: 1.0764 - val_acc: 0.5916

Epoch 44/50
 - 6s - loss: 1.1249 - acc: 0.5766 - val_loss: 1.0711 - val_acc: 0.5921

Epoch 45/50
 - 6s - loss: 1.1178 - acc: 0.5781 - val_loss: 1.0722 - val_acc: 0.5982

Epoch 46/50
 - 6s - loss: 1.1116 - acc: 0.5816 - val_loss: 1.0743 - val_acc: 0.5923

Epoch 47/50
 - 6s - loss: 1.1053 - acc: 0.5838 - val_loss: 1.0647 - val_acc: 0.5928

Epoch 48/50
 - 6s - loss: 1.1004 - acc: 0.5852 - val_loss: 1.0617 - val_acc: 0.5901

Epoch 49/50
 - 6s - loss: 1.0898 - acc: 0.5884 - val_loss: 1.0451 - val_acc: 0.6017

Epoch 50/50
 - 6s - loss: 1.0849 - acc: 0.5883 - val_loss: 1.0392 - val_acc: 0.6041

score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

81030/81030 [=====] - 2s 25us/step
['loss', 'acc']
[1.0390372064269358, 0.6059730980109906]

[] import keras.models as models

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The screenshot shows a Jupyter Notebook interface with the following content:

```

[19] Epoch 39/50
- 6s - loss: 1.1481 - acc: 0.5007 - val_loss: 1.0849 - val_acc: 0.5943
  Epoch 40/50
    - 6s - loss: 1.1378 - acc: 0.5719 - val_loss: 1.0876 - val_acc: 0.5911
  Epoch 41/50
    - 6s - loss: 1.1310 - acc: 0.5734 - val_loss: 1.0861 - val_acc: 0.5908
  Epoch 42/50
    - 6s - loss: 1.1338 - acc: 0.5737 - val_loss: 1.0823 - val_acc: 0.5893
  Epoch 43/50
    - 6s - loss: 1.1260 - acc: 0.5751 - val_loss: 1.0802 - val_acc: 0.5948
  Epoch 44/50
    - 6s - loss: 1.1230 - acc: 0.5769 - val_loss: 1.0764 - val_acc: 0.5916
  Epoch 45/50
    - 6s - loss: 1.1249 - acc: 0.5766 - val_loss: 1.0711 - val_acc: 0.5921
  Epoch 46/50
    - 6s - loss: 1.1178 - acc: 0.5781 - val_loss: 1.0722 - val_acc: 0.5982
  Epoch 47/50
    - 6s - loss: 1.1116 - acc: 0.5816 - val_loss: 1.0743 - val_acc: 0.5923
  Epoch 48/50
    - 6s - loss: 1.1053 - acc: 0.5838 - val_loss: 1.0647 - val_acc: 0.5928
  Epoch 49/50
    - 6s - loss: 1.1004 - acc: 0.5852 - val_loss: 1.0617 - val_acc: 0.5901
  Epoch 50/50
    - 6s - loss: 1.0898 - acc: 0.5884 - val_loss: 1.0451 - val_acc: 0.6017
    - 6s - loss: 1.0849 - acc: 0.5883 - val_loss: 1.0392 - val_acc: 0.6041

```

Below the logs, there is a code cell:

```

score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(score)

```

The notebook title is "Untitled2.ipynb".

The screenshot shows a Jupyter Notebook interface with the following content:

Layer (type)	Output Shape	Param #
reshape_5 (Reshape)	(None, 2, 128, 1)	0
dropout_6 (Dropout)	(None, 2, 128, 1)	0
flatten_3 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_7 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 64)	16448
dropout_8 (Dropout)	(None, 64)	0
dense3 (Dense)	(None, 64)	4160
dropout_9 (Dropout)	(None, 64)	0
dense4 (Dense)	(None, 11)	715
activation_3 (Activation)	(None, 11)	0
reshape_6 (Reshape)	(None, 11)	0
Total params: 87,115		
Trainable params: 87,115		

The notebook title is "Untitled2.ipynb".

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```
[15] Epoch 23/50
    - 5s - loss: 1.1272 - acc: 0.5710 - val_loss: 1.0796 - val_acc: 0.5871
    Epoch 24/50
    - 5s - loss: 1.1233 - acc: 0.5740 - val_loss: 1.0829 - val_acc: 0.5829
    Epoch 25/50
    - 5s - loss: 1.1168 - acc: 0.5748 - val_loss: 1.0778 - val_acc: 0.5876
    Epoch 26/50
    - 5s - loss: 1.1086 - acc: 0.5786 - val_loss: 1.0567 - val_acc: 0.5945
    Epoch 27/50
    - 5s - loss: 1.0957 - acc: 0.5834 - val_loss: 1.0687 - val_acc: 0.5896
    Epoch 28/50
    - 5s - loss: 1.0945 - acc: 0.5835 - val_loss: 1.0623 - val_acc: 0.5997
    Epoch 29/50
    - 5s - loss: 1.0846 - acc: 0.5865 - val_loss: 1.0677 - val_acc: 0.5930
    Epoch 30/50
    - 5s - loss: 1.0847 - acc: 0.5848 - val_loss: 1.0666 - val_acc: 0.5943
    Epoch 31/50
    - 5s - loss: 1.0730 - acc: 0.5895 - val_loss: 1.0570 - val_acc: 0.5913

    score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
    print(model1.metrics_names)
    print(score)

    81030/81030 [=====] - 2s 25us/step
    ['loss', 'acc']
    [1.062889713431357, 0.5993582642763967]
```

[] import keras.models as models
Build VT-CNN2 Neural Net model using Keras primitives --

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```
[15] Epoch 2/50
    - 5s - loss: 2.0238 - acc: 0.2662 - val_loss: 1.9483 - val_acc: 0.3048
    Epoch 3/50
    - 5s - loss: 1.9338 - acc: 0.3003 - val_loss: 1.8693 - val_acc: 0.3440
    Epoch 4/50
    - 5s - loss: 1.8283 - acc: 0.3363 - val_loss: 1.6690 - val_acc: 0.3702
    Epoch 5/50
    - 5s - loss: 1.6562 - acc: 0.3745 - val_loss: 1.4925 - val_acc: 0.4381
    Epoch 6/50
    - 5s - loss: 1.5196 - acc: 0.4252 - val_loss: 1.3671 - val_acc: 0.4889
    Epoch 7/50
    - 5s - loss: 1.4329 - acc: 0.4509 - val_loss: 1.3132 - val_acc: 0.5010
    Epoch 8/50
    - 5s - loss: 1.3902 - acc: 0.4697 - val_loss: 1.2861 - val_acc: 0.5094
    Epoch 9/50
    - 5s - loss: 1.3766 - acc: 0.4732 - val_loss: 1.2633 - val_acc: 0.5178
    Epoch 10/50
    - 5s - loss: 1.3398 - acc: 0.4902 - val_loss: 1.2274 - val_acc: 0.5437
    Epoch 11/50
    - 5s - loss: 1.3255 - acc: 0.5001 - val_loss: 1.2319 - val_acc: 0.5304
    Epoch 12/50
    - 5s - loss: 1.2929 - acc: 0.5106 - val_loss: 1.1983 - val_acc: 0.5545
    Epoch 13/50
    - 5s - loss: 1.2720 - acc: 0.5172 - val_loss: 1.1942 - val_acc: 0.5610
    Epoch 14/50
    - 5s - loss: 1.2613 - acc: 0.5240 - val_loss: 1.1844 - val_acc: 0.5612
    Epoch 15/50
    - 5s - loss: 1.2430 - acc: 0.5317 - val_loss: 1.1654 - val_acc: 0.5669
    Epoch 16/50
```

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```
[13]
Layer (type)          Output Shape         Param #
reshape_3 (Reshape)    (None, 2, 128, 1)       0
dropout_3 (Dropout)   (None, 2, 128, 1)       0
flatten_2 (Flatten)   (None, 256)            0
dense1 (Dense)        (None, 256)            65792
dropout_4 (Dropout)   (None, 256)            0
dense2 (Dense)        (None, 64)             16448
dropout_5 (Dropout)   (None, 64)             0
dense4 (Dense)        (None, 11)             715
activation_2 (Activation) (None, 11)           0
reshape_4 (Reshape)    (None, 11)             0
=====
Total params: 82,955
Trainable params: 82,955
Non-trainable params: 0
```

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```
[13] reshape_4 (Reshape)    (None, 11)             0
=====
Total params: 82,955
Trainable params: 82,955
Non-trainable params: 0
```

```
[14] # Set up some params
nb_epoch = 50 # number of epochs to train on
batch_size = 100 # training batch size
```

perform training ...
- call the main training loop in keras for our network+dataset
filepath = 'convmodrecnets_CNN2_0.5.wts.h5'
history=modell.fit(X_train,
 Y_train,
 batch_size=batch_size,
 epochs=nb_epoch,
 verbose=2,
 validation_split=0.05,
 callbacks = [
 keras.callbacks.ModelCheckpoint(filepath, monitor='val_loss', verbose=0, save_best_only=True, mode='auto'),
 keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=0, mode='auto')
])
we re-load the best weights once training is finished
modell.load_weights(filepath)

... Train on 76978 samples, validate on 4052 samples
Epoch 1/50
- 5s - loss: 2.5655 - acc: 0.2067 - val loss: 2.0854 - val acc: 0.2246

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```
[11]  - 5s - loss: 2.6830 - acc: 0.4407 - val_loss: 2.9177 - val_acc: 0.4400
Epoch 10/50
- 5s - loss: 2.6502 - acc: 0.4474 - val_loss: 2.9118 - val_acc: 0.4195
Epoch 11/50
- 5s - loss: 2.6083 - acc: 0.4464 - val_loss: 2.8410 - val_acc: 0.4445
Epoch 12/50
- 5s - loss: 2.6039 - acc: 0.4515 - val_loss: 3.0267 - val_acc: 0.4341
Epoch 13/50
- 5s - loss: 2.5554 - acc: 0.4557 - val_loss: 2.9681 - val_acc: 0.4368
Epoch 14/50
- 5s - loss: 2.5539 - acc: 0.4588 - val_loss: 3.0169 - val_acc: 0.4319
Epoch 15/50
- 5s - loss: 2.5469 - acc: 0.4588 - val_loss: 2.9166 - val_acc: 0.4519
Epoch 16/50
- 5s - loss: 2.5225 - acc: 0.4659 - val_loss: 2.8970 - val_acc: 0.4558
```

```
score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)
```

```
81030/81030 [=====] - 2s 23us/step
['loss', 'acc']
[2.8514858320747116, 0.4382697759612459]
```

```
[ ] import keras.models as models
# Build VT-CNN2 Neural Net model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 2DConv/ReLU layers
# - Pass through 3 Dense layers (ReLU and Softmax)
```

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```
[11]  - 5s - loss: 2.6830 - acc: 0.4407 - val_loss: 2.9177 - val_acc: 0.4400
Epoch 10/50
- 5s - loss: 2.6502 - acc: 0.4474 - val_loss: 2.9118 - val_acc: 0.4195
Epoch 11/50
- 5s - loss: 2.6083 - acc: 0.4464 - val_loss: 2.8410 - val_acc: 0.4445
Epoch 12/50
- 5s - loss: 2.6039 - acc: 0.4515 - val_loss: 3.0267 - val_acc: 0.4341
Epoch 13/50
- 5s - loss: 2.5554 - acc: 0.4557 - val_loss: 2.9681 - val_acc: 0.4368
Epoch 14/50
- 5s - loss: 2.5539 - acc: 0.4588 - val_loss: 3.0169 - val_acc: 0.4319
Epoch 15/50
- 5s - loss: 2.5469 - acc: 0.4588 - val_loss: 2.9166 - val_acc: 0.4519
Epoch 16/50
- 5s - loss: 2.5225 - acc: 0.4659 - val_loss: 2.8970 - val_acc: 0.4558
```

```
score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)
```

```
81030/81030 [=====] - 2s 29us/step
['loss', 'acc']
[0.9845394681386099, 0.6212020259119287]
```

```
[ ] import keras.models as models
# Build VT-CNN2 Neural Net model using Keras primitives --
# - Reshape [N,2,128] to [N,1,2,128] on input
# - Pass through 2 2DConv/ReLU layers
# - Pass through 3 Dense layers (ReLU and Softmax)
```

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[7]

Layer (type)	Output Shape	Param #
reshape_1 (Reshape)	(None, 2, 128, 1)	0
dropout_1 (Dropout)	(None, 2, 128, 1)	0
flatten_1 (Flatten)	(None, 256)	0
dense1 (Dense)	(None, 256)	65792
dropout_2 (Dropout)	(None, 256)	0
dense2 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
dense3 (Dense)	(None, 128)	16512
dropout_4 (Dropout)	(None, 128)	0
dense4 (Dense)	(None, 64)	8256
dropout_5 (Dropout)	(None, 64)	0
dense5 (Dense)	(None, 11)	715
activation_1 (Activation)	(None, 11)	0
reshape_2 (Reshape)	(None, 11)	0

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[10]

```
Epoch 88/100
- 1s - loss: 1.2030 - acc: 0.5371 - val_loss: 1.0793 - val_acc: 0.5807
Epoch 89/100
- 1s - loss: 1.1995 - acc: 0.5389 - val_loss: 1.0618 - val_acc: 0.5893
Epoch 90/100
- 1s - loss: 1.1943 - acc: 0.5384 - val_loss: 1.0737 - val_acc: 0.5822
Epoch 91/100
- 1s - loss: 1.1892 - acc: 0.5418 - val_loss: 1.0508 - val_acc: 0.5953
Epoch 92/100
- 1s - loss: 1.1895 - acc: 0.5416 - val_loss: 1.0689 - val_acc: 0.5844
Epoch 93/100
- 1s - loss: 1.1851 - acc: 0.5430 - val_loss: 1.0539 - val_acc: 0.5916
Epoch 94/100
- 1s - loss: 1.1826 - acc: 0.5452 - val_loss: 1.0593 - val_acc: 0.5933
Epoch 95/100
- 1s - loss: 1.1802 - acc: 0.5478 - val_loss: 1.0747 - val_acc: 0.5775
Epoch 96/100
- 1s - loss: 1.1728 - acc: 0.5509 - val_loss: 1.0495 - val_acc: 0.5965
Epoch 97/100
- 1s - loss: 1.1751 - acc: 0.5511 - val_loss: 1.0418 - val_acc: 0.5925
Epoch 98/100
- 1s - loss: 1.1636 - acc: 0.5547 - val_loss: 1.0314 - val_acc: 0.6029
Epoch 99/100
- 1s - loss: 1.1596 - acc: 0.5565 - val_loss: 1.0400 - val_acc: 0.6002
Epoch 100/100
- 1s - loss: 1.1594 - acc: 0.5566 - val_loss: 1.0330 - val_acc: 0.6037
```

[11] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
print(model1.metrics_names)
print(score)

81030 [=====] - 0s 5us/step

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```
[10] Epoch 91/100
    - 1s - loss: 1.1892 - acc: 0.5418 - val_loss: 1.0508 - val_acc: 0.5953
  ↗ Epoch 92/100
    - 1s - loss: 1.1895 - acc: 0.5416 - val_loss: 1.0689 - val_acc: 0.5844
  ↗ Epoch 93/100
    - 1s - loss: 1.1851 - acc: 0.5430 - val_loss: 1.0539 - val_acc: 0.5916
  ↗ Epoch 94/100
    - 1s - loss: 1.1826 - acc: 0.5452 - val_loss: 1.0593 - val_acc: 0.5933
  ↗ Epoch 95/100
    - 1s - loss: 1.1802 - acc: 0.5478 - val_loss: 1.0747 - val_acc: 0.5775
  ↗ Epoch 96/100
    - 1s - loss: 1.1728 - acc: 0.5509 - val_loss: 1.0495 - val_acc: 0.5965
  ↗ Epoch 97/100
    - 1s - loss: 1.1751 - acc: 0.5511 - val_loss: 1.0418 - val_acc: 0.5925
  ↗ Epoch 98/100
    - 1s - loss: 1.1636 - acc: 0.5547 - val_loss: 1.0314 - val_acc: 0.6029
  ↗ Epoch 99/100
    - 1s - loss: 1.1596 - acc: 0.5565 - val_loss: 1.0400 - val_acc: 0.6002
  ↗ Epoch 100/100
    - 1s - loss: 1.1594 - acc: 0.5566 - val_loss: 1.0330 - val_acc: 0.6037

[11] score = model1.evaluate(X_test, Y_test, batch_size=batch_size)
      print(model1.metrics_names)
      print(score)

  ↗ 81030 [=====] - 0s 5us/step
    ['loss', 'acc']
    [1.017300804427571, 0.6019005308233571]

[ ] import keras.models as models
  # Build VT-CNN Neural Net model using Keras primitives --
  # -- Reshape [N, 2, 128] to [N, 1, 2, 128] on input
```

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```
[1] 0.6056827691888204, 0.6100826851934411

[12] # Show loss curves
    plt.figure()
    plt.title('Training performance')
    plt.plot(history.epoch, history.history['loss'], label='train loss+error')
    plt.plot(history.epoch, history.history['val_loss'], label='val_error')
    plt.legend()

  ↗ <matplotlib.legend.Legend at 0x7feba46da470>
    Training performance
    train loss+error
    val_error
```

```
[13] def plot_confusion_matrix(cm, title='Confusion matrix', cmap=plt.cm.Blues, labels=[]):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(labels))
    plt.xticks(tick_marks, labels, rotation=45)
    plt.yticks(tick_marks, labels)
```

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[13] plt.xlabel('Predicted label')

```
# Plot confusion matrix
test_Y_hat = model.predict(X_test, batch_size=batch_size)
conf = np.zeros([len(classes),len(classes)])
confm = np.zeros([len(classes),len(classes)])
for i in range(0,X_test.shape[0]):
    j = list(Y_test[i,:].index(1))
    k = int(np.argmax(test_Y_hat[i,:]))
    conf[j,k] = conf[j,k] + 1
for i in range(0,len(classes)):
    confm[i,:] = conf[i,:]/np.sum(conf[i,:])
plot_confusion_matrix(confm, labels=classes)
# on the right its a color chart to indicate that the darker the color the easier and the most to identify
```

True Label	8PSK	AM-DSB	AM-SSB	BPSK	CPFSK	GFSK	PAM4	QAM16	QAM64	QPSK	WBFM
8PSK	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
AM-DSB	0.75	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
AM-SSB	0.70	0.75	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40
BPSK	0.65	0.70	0.75	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45
CPFSK	0.60	0.65	0.70	0.75	0.80	0.75	0.70	0.65	0.60	0.55	0.50
GFSK	0.55	0.60	0.65	0.70	0.75	0.80	0.75	0.70	0.65	0.60	0.55
PAM4	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.75	0.70	0.65	0.60
QAM16	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.75	0.70	0.65
QAM64	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.75	0.70
QPSK	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.75
WBFM	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80

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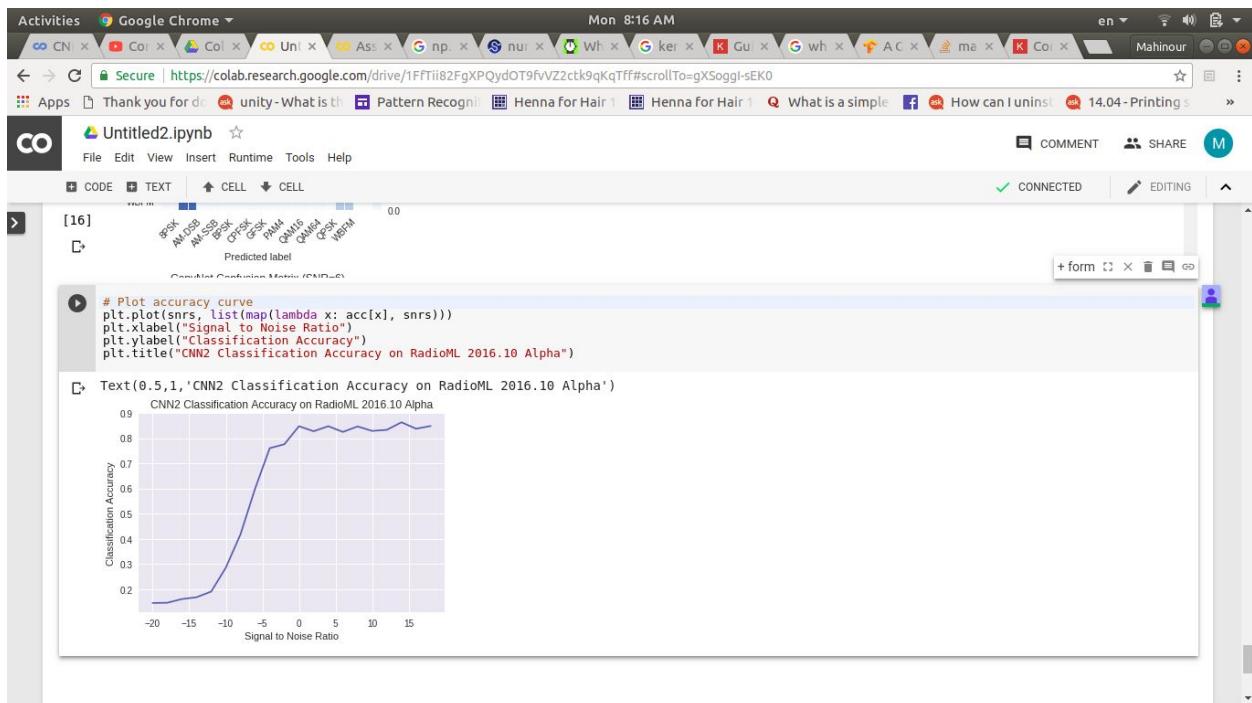
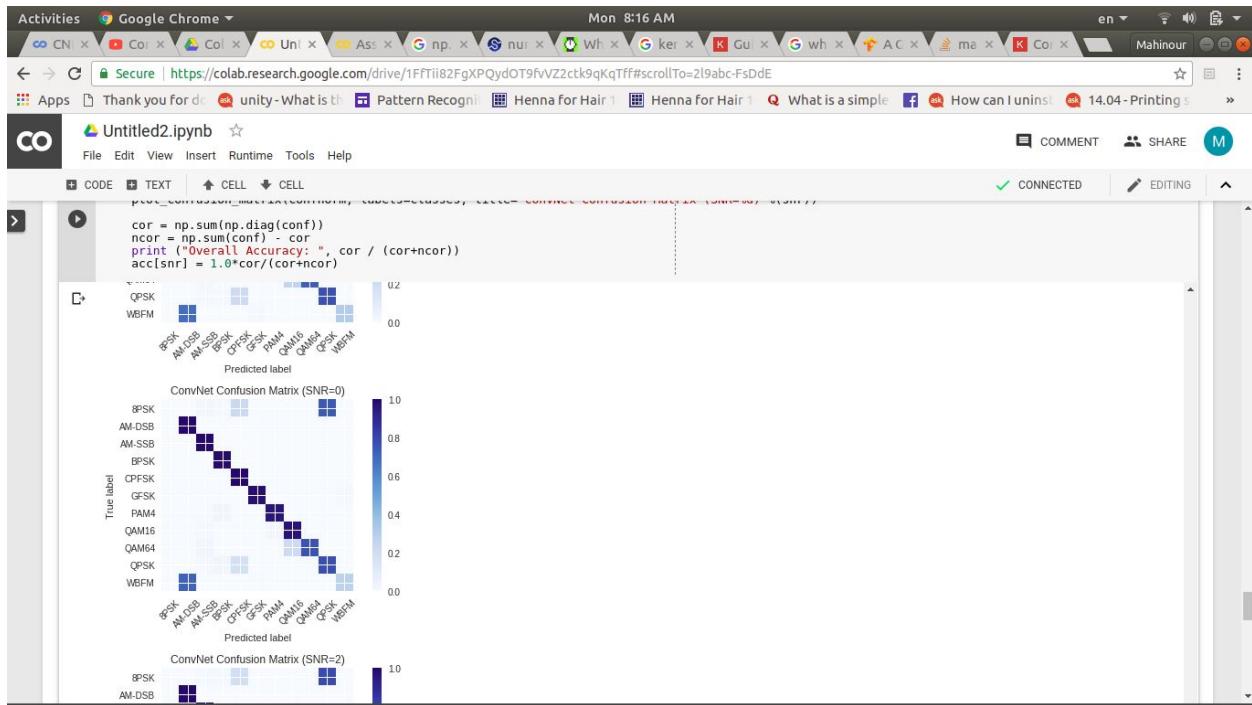
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```
cor = np.sum(np.diag(conf))
ncor = np.sum(conf) - cor
print("Overall Accuracy: ", cor / (cor+ncor))
acc[snr] = 1.0*cor/(cor+ncor)
```

Overall Accuracy: 0.14537335648722402
Overall Accuracy: 0.14622757434259032
Overall Accuracy: 0.16099605522682445
Overall Accuracy: 0.16819875776397517
Overall Accuracy: 0.19061441702951137
Overall Accuracy: 0.28546840422916153
Overall Accuracy: 0.41758510898848883
Overall Accuracy: 0.5992102665356444
Overall Accuracy: 0.759899117271664
Overall Accuracy: 0.7755856966707768
Overall Accuracy: 0.8473566641846612
Overall Accuracy: 0.827203159713651
Overall Accuracy: 0.847239114570664
Overall Accuracy: 0.8244575936883629
Overall Accuracy: 0.8463426607756505
Overall Accuracy: 0.8284797630799605
Overall Accuracy: 0.8327543424317618
Overall Accuracy: 0.8627646326276464
Overall Accuracy: 0.8371520078837152
Overall Accuracy: 0.8481075697211156

True Label	8PSK	AM-DSB	AM-SSB	BPSK	CPFSK
8PSK	1.00	0.95	0.90	0.85	0.80
AM-DSB	0.95	1.00	0.95	0.90	0.85
AM-SSB	0.90	0.95	1.00	0.95	0.90
BPSK	0.85	0.90	0.95	1.00	0.95
CPFSK	0.80	0.85	0.90	0.95	1.00



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```

Epoch 51/100
[20] - 1s - loss: 0.9055 - acc: 0.6479 - val_loss: 0.9602 - val_acc: 0.6276
Epoch 52/100
[20] - 1s - loss: 0.9003 - acc: 0.6484 - val_loss: 0.9566 - val_acc: 0.6288
Epoch 53/100
[20] - 1s - loss: 0.8972 - acc: 0.6486 - val_loss: 0.9529 - val_acc: 0.6347
Epoch 54/100
[20] - 1s - loss: 0.8963 - acc: 0.6510 - val_loss: 0.9722 - val_acc: 0.6325
Epoch 55/100
[20] - 1s - loss: 0.8885 - acc: 0.6555 - val_loss: 0.9617 - val_acc: 0.6399
Epoch 56/100
[20] - 1s - loss: 0.8854 - acc: 0.6534 - val_loss: 0.9718 - val_acc: 0.6338
Epoch 57/100
[20] - 1s - loss: 0.8820 - acc: 0.6565 - val_loss: 0.9528 - val_acc: 0.6365
Epoch 58/100
[20] - 1s - loss: 0.8817 - acc: 0.6570 - val_loss: 0.9549 - val_acc: 0.6382
Epoch 59/100
[20] - 1s - loss: 0.8792 - acc: 0.6567 - val_loss: 0.9625 - val_acc: 0.6343
Epoch 60/100
[20] - 1s - loss: 0.8763 - acc: 0.6592 - val_loss: 0.9654 - val_acc: 0.6340
Epoch 61/100
[20] - 1s - loss: 0.8747 - acc: 0.6594 - val_loss: 0.9592 - val_acc: 0.6325
Epoch 62/100
[20] - 1s - loss: 0.8678 - acc: 0.6619 - val_loss: 0.9710 - val_acc: 0.6355

[21] score = model.evaluate(X_test, Y_test, batch_size=batch_size)
print(model.metrics_names)
print(score)

[21] 81030/81030 [=====] - 0s 5us/step
['loss', 'acc']
[0.9580647699782234, 0.6355423914627442]

```

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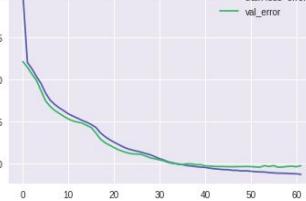
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```

[22] # Show loss curves
plt.figure()
plt.title('Training performance')
plt.plot(history.epoch, history.history['loss'], label='train loss+error')
plt.plot(history.epoch, history.history['val_loss'], label='val_error')
plt.legend()

[22] <matplotlib.legend.Legend at 0x7feb98fedd68>
Training performance


```

```

[23] def plot_confusion_matrix(cm, title='Confusion matrix', cmap=plt.cm.Blues, labels=[]):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(labels))
    plt.xticks(tick_marks, labels, rotation=45)
    plt.yticks(tick_marks, labels)
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

```

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```
[24] # Plot confusion matrix
test_Y_hat = model.predict(X_test, batch_size=batch_size)
conf = np.zeros([len(classes),len(classes)])
confnorm = np.zeros([len(classes),len(classes)])
for i in range(0,len(classes)):
    for j in range(0,len(classes)):
        k = int(y_test[i,j])
        l = int(np.argmax(test_Y_hat[i,:]))
        conf[j,k] = conf[j,k] + 1
        confnorm[j,:] = conf[j,:] / np.sum(conf[j,:])
plot_confusion_matrix(confnorm, labels=classes)
# on the right its a color chart to indicate that the darker the color the easier and the most to identify
```

```
[25] # Plot confusion matrix
acc = 0.
```

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```
[25]
    conf[i,k] = conf[i,k] + 1
    confnorm[i,:] = conf[i,:] / np.sum(conf[i,:])
plt.figure()
plot_confusion_matrix(confnorm, labels=classes, title="ConvNet Confusion Matrix (SNR=%d) "%(snr))

cor = np.sum(np.diag(conf))
ncor = np.sum(conf) - cor
print("Overall Accuracy: ", cor / (cor+ncor))
acc[snr] = 1.0*cor/(cor+ncor)
```

Overall Accuracy: 0.1538079880922848
Overall Accuracy: 0.14966822315065126
Overall Accuracy: 0.16247534516765286
Overall Accuracy: 0.1759006211180124
Overall Accuracy: 0.21504596032897919
Overall Accuracy: 0.27760019678511881
Overall Accuracy: 0.478569791574822
Overall Accuracy: 0.637216895360315
Overall Accuracy: 0.7702395964691047
Overall Accuracy: 0.8589395807644883
Overall Accuracy: 0.8602630925788036
Overall Accuracy: 0.84571710688711884
Overall Accuracy: 0.8805643395767453
Overall Accuracy: 0.9154339250493096
Overall Accuracy: 0.8465881197839961
Overall Accuracy: 0.9010365251727542
Overall Accuracy: 0.9255583126550868
Overall Accuracy: 0.8528019925280199
Overall Accuracy: 0.887410692288741
Overall Accuracy: 0.9287848605577689

