```
In [1]:
         #Figure creation for CNN and NAS comparison paper
         # Date Created: 09-11-2021
         # Created by Matthew Hall
         # Last Edited: 04-03-2022
         import tensorflow as tf
         import numpy as np
         from tensorflow.keras import Input, Model
         from tensorflow.keras.layers import Dense, concatenate
         import keras as keras
         from keras import backend as K
         from keras.models import Sequential
         from keras.layers import Dense, Activation, Reshape
         from keras.layers import Conv1D, MaxPooling1D, Flatten, GlobalAveragePooling1D, Dropout
         import os
         from os.path import dirname, join as pjoin
         import scipy.io as sio
         import h5py
         import matplotlib as mpl
         import matplotlib.pyplot as plt
         import matplotlib.pyplot
         from scipy.fft import fft, fftfreq
         from datetime import datetime
         import random
In [2]:
         # Networks to be tested
```

```
In [2]: # Networks to be tested

model_dir = 'Z:\\SmithLab\\prjNAS\\NASNet'

limiter =150
gamma = 0.15
gammas = np.arange(1,10)/10
gammas =0.15
numLines =800
ntimepts = 52

netnames =[]
numcnn =1

netnames.append('SmithCNNnet') #best trained network
netnames.append('NAS_full') #original nas network
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```
# evaluate mat files as one large chunk
#data returned was used to determine the realtime test across a random sample of all co

data_dir = 'Z:/SmithLab/prjNAS/NASNet/test_all/' #all areas in one file
testingFile = []
for file in os.listdir(data_dir): # pull all training files from directory
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if file.endswith(".mat"):
        testingFile.append(file)
nset = len(testingFile) # singular testing file
#Time testing on full file (random choice over all areas)
#print('Testing on ' + str(nsets) + ' files.')
for j in range(nset): # loop over the different testing files
        f_waves = h5py.File(data_dir + '/' + testingFile[j],mode='r') # load testing f
        testacc = []
        fozle = testingFile[j]
        file edit = fozle.rfind(' ')
        datastr = fozle[file_edit+1: len(fozle)-4]
        print(fozle)
        waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
        #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
        for netname in netnames:
            match = netnames.index(netname)
            model path = pjoin(model dir, netname)
            model = keras.models.load model(model path)
            if match < numcnn:</pre>
                x_test = waveforms[:, 1:(52+1)] # waveform voltage values
                y_test = waveforms[:, 0] # waveform labels
                x test = np.expand dims(x test, axis=2)
                #predicts CNN = model.predict(x test,verbose =0)
                #print(netname +area+" has acc of: "+str(predicts) +" with " +str(model
                #print(predicts CNN.shape)
                #timetest
                time diffs = []
                for i in np.arange(1,100):
                    x_test_400 = x_test[np.random.choice(len(waveforms),400),:]
                    t1 = datetime.now().now()
                    predicts scrub = model.predict(x test 400, verbose =0)
                    t2 = datetime.now().now()
                    time diff = (t2-t1)/400
                    time diffs.append(time diff.total seconds())
                print(f'Time Diff CNN: {np.mean(time_diffs)} var: {np.var(time_diffs)}'
            else:
                #print('we made it')
                x_test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
                \#x test = np.expand dims(x test, axis=2)
                y_test = waveforms[:, 0] # waveform labels
                #predicts NAS = model.predict(x test, verbose =0)
                #print(netname +area+" has acc of: "+str(predicts) +" with " +str(model
                #print(predicts NAS.shape)
                #timetest
                time diffs = []
                for i in np.arange(1,100):
                    x_test_400 = x_test[np.random.choice(len(waveforms),400),:]
                    t1 = datetime.now().now()
```

```
predicts_scrub = model.predict(x_test_400,verbose =0)
                              t2 = datetime.now().now()
                              time diff = (t2-t1)/400
                              time_diffs.append(time_diff.total_seconds())
                          print(f'Time Diff NAS: {np.mean(time diffs)} var: {np.var(time diffs)}'
                          # NAS 2.144 times faster than CNN at 113.52% of the variance
                          # CNN classifies 6907 waveforms/sec
                          # NAS classifies 14805 waveforms/sec
         full test.mat
         Time Diff CNN: 0.0002552121212121212 var: 1.2651553792470156e-06
         Time Diff NAS: 6.484848484848485e-05 var: 2.97684113865932e-10
In [20]:
          #figure 3 - gamma sweeps and accuracy across each area
          # data was placed into an excel spreadsheet
          data_dir = 'Z:/SmithLab/prjNAS/NASNet/tests_byarea/' #all areas in separate files
          testingFiles = []
          for file in os.listdir(data dir): # pull all training files from directory
              if file.endswith(".mat"):
                  testingFiles.append(file)
          nsets = len(testingFiles) # number of training files
          for j in range(nsets): # loop over the different testing files
                  f_waves = h5py.File(data_dir + '/' + testingFiles[j],mode='r') # Load testing
                  testacc = []
                  fozle = testingFiles[j]
                  file edit = fozle.rfind(' ')
                  datastr
                            = fozle[file edit+1: len(fozle)-4]
                  print(fozle)
                  waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
                  #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
                  for netname in netnames:
                      match = netnames.index(netname)
                      model_path = pjoin(model_dir, netname)
                      model = keras.models.load model(model path)
                      if match < numcnn:</pre>
                          x test = waveforms[:, 1:(52+1)] # waveform voltage values
                          y_test = waveforms[:, 0] # waveform labels
                          x test = np.expand dims(x test, axis=2)
                          predicts CNN = model.predict(x test,verbose =0)
                          print(netname +" has acc of: "+str(predicts CNN) +" with " +str(model.c
                          #print(predicts CNN.shape)
                      else:
                          #print('we made it')
                          x_test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
                          #x_test = np.expand_dims(x_test, axis=2)
                          y test = waveforms[:, 0] # waveform labels
                          predicts_NAS = model.predict(x_test,verbose =0)
                          print(netname +" has acc of: "+str(predicts NAS) +" with " +str(model.c
```

```
#print(predicts NAS.shape)
best g NAS = 0
best_g_NN = 0
g of CNN = 0.2
g_of_NAS = 0.2
ranger = np.arange(0,len(y_test),1)
spikes_are = ranger[y_test == 1]
noise_are = ranger[y_test == 0]
for gamma in np.arange(0.01, 0.99, 0.01):
    predlabel_CNN = predicts_CNN[:,0] > gamma
    predlabel_NAS = predicts_NAS[:,0] > (gamma)
    CNN acc = sum(y test == predlabel CNN)/len(y test)
    NAS_acc = sum(y_test == predlabel_NAS)/len(y_test)
    ranger
    #CNN_spike_acc = sum(y_test[spikes_are] == predlabel_CNN[spikes_are])/len(s
    #NAS spike acc = sum(y test[spikes are] == predlabel NAS[spikes are])/len(s
    CNN_noise_acc = sum(y_test[noise_are] == predlabel_CNN[noise_are])/len(noise_are)
    NAS_noise_acc = sum(y_test[noise_are] == predlabel_NAS[noise_are])/len(nois
    if best g CNN < (CNN acc):</pre>
        best g CNN = (CNN acc)
        g_of_CNN = gamma
    if best_g_NAS < (NAS_acc):</pre>
        best_g_NAS = (NAS_acc)
        g of NAS = gamma
    #print("Gamma: %f\tCNN %f\tNAS %f spikes:\tCNN %f\tNAS %f" %(gamma, CNN_acc
    #print("%f\t%f\t%f\t%f\t%f" %(gamma, CNN_acc*100, NAS_acc*100, CNN_spike_ac
    print("%f\t%f\t%f" %(gamma, CNN_acc*100, NAS_acc*100))
print("Best gamma -\tCNN: %f \tNAS: %f" %(g of CNN, g of NAS))
\#gamma = g_of
predlabel CNN = predicts CNN[:,0] > g of CNN
predlabel_NAS = predicts_NAS[:,0] > (g_of_NAS)
CNN acc = sum(y test == predlabel CNN)/len(y test)
NAS_acc = sum(y_test == predlabel_NAS)/len(y_test)
print("Best ACC:\tCNN %f\tNAS %f" %(CNN_acc*100, NAS_acc*100))
best_g_NAS = 0
best g CNN = 0
g_of_CNN = 0.48
g_of_NAS = 0.48
ranger = np.arange(0,len(y test),1)
spikes_are = ranger[y_test == 1]
print("Best gamma -\tCNN: %f \tNAS: %f" %(g of CNN, g of NAS))
predlabel CNN = predicts CNN[:,0] > g of CNN
predlabel NAS = predicts NAS[:,0] > (g of NAS)
CNN_acc = sum(y_test == predlabel_CNN)/len(y_test)
NAS_acc = sum(y_test == predlabel_NAS)/len(y_test)
print("Best ACC:\tCNN %f\tNAS %f" %(CNN_acc*100, NAS_acc*100))
```

```
test_FEF.mat
SmithCNNnet has acc of: [[0.70802605]
[0.93216443]
[0.74365234]
```

```
[0.2768412]
 [0.90511584]
 [0.5531881 ]] with 222576 params.
NAS_full has acc of: [[0.36806393]
 [0.8682376]
 [0.5341552]
 [0.27719992]
 [0.7985201
 [0.3755422 ]] with 2701 params.
0.010000
                 71.571404
                                  70.467355
0.020000
                 71.709988
                                  70.533009
0.030000
                 71.914201
                                  70.581014
0.040000
                 72.167157
                                  70.627668
0.050000
                 72.438155
                                  70.669233
                 72.723729
                                  70.712789
0.060000
0.070000
                 73.020757
                                  70.753961
0.080000
                 73.316212
                                  70.795723
0.090000
                 73.602130
                                  70.838813
0.100000
                 73.885590
                                  70.886130
                                  70.934258
0.110000
                 74.167256
0.120000
                 74.446931
                                  70.984623
0.130000
                 74.716405
                                  71.037422
0.140000
                                  71.098700
                 74.988091
0.150000
                 75.242669
                                  71.170278
0.160000
                 75.493855
                                  71.251098
0.170000
                 75.744034
                                  71.338997
                                  71.438793
0.180000
                 75.986002
0.190000
                 76.222465
                                  71.560220
0.200000
                 76.447915
                                  71.704752
                 76.670146
0.210000
                                  71.862287
0.220000
                 76.893089
                                  72.033588
0.230000
                 77.110551
                                  72.223298
0.240000
                 77.322826
                                  72.421932
0.250000
                                  72.624572
                 77.520845
0.260000
                 77.714833
                                  72.839354
0.270000
                 77.911623
                                  73.056423
0.280000
                 78.092706
                                  73.276982
0.290000
                 78.267423
                                  73.509930
0.300000
                                  73.731398
                 78.438281
0.310000
                 78.595201
                                  73.939077
0.320000
                 78.741995
                                  74.135720
0.330000
                 78.884192
                                  74.323489
0.340000
                 79.014959
                                  74.504695
0.350000
                 79.138942
                                  74.664295
0.360000
                 79,252257
                                  74.805631
0.370000
                 79.359427
                                  74.919045
0.380000
                 79.450670
                                  75.015498
0.390000
                 79.532473
                                  75.093663
0.400000
                 79.595472
                                  75.154696
0.410000
                 79.653162
                                  75.186773
0.420000
                 79.698881
                                  75.180702
0.430000
                 79.722601
                                  75.179866
0.440000
                 79.733318
                                  75.144594
0.450000
                 79.724543
                                  75.094327
0.460000
                 79.700381
                                  75.023732
0.470000
                                  74.937406
                 79.658496
0.480000
                 79.615161
                                  74.825271
0.490000
                 79.546754
                                  74.697281
0.500000
                 79.463156
                                  74.550906
0.510000
                 79.370513
                                  74.389388
0.520000
                 79.252552
                                  74.221652
0.530000
                 79.112494
                                  74.036464
0.540000
                 78.961522
                                  73.844197
```

```
0.550000
                 78.800865
                                 73.636617
                                 73.423727
                 78.602944
0.560000
0.570000
                 78.400451
                                 73.198841
0.580000
                 78.177262
                                 72.967909
0.590000
                 77.944905
                                 72.726236
0.600000
                 77.694481
                                 72.468290
0.610000
                 77.431840
                                 72.202430
0.620000
                 77.148478
                                 71.931235
0.630000
                 76.844346
                                 71.645489
0.640000
                 76.520648
                                 71.349813
0.650000
                 76.185914
                                 71.043640
                                 70.727734
0.660000
                 75.826255
0.670000
                 75.431790
                                 70.410771
0.680000
                 75.024101
                                 70.084320
0.690000
                 74.580746
                                 69.742359
0.700000
                 74.110599
                                 69.381914
0.710000
                 73.627694
                                 69.008539
0.720000
                 73.105608
                                 68.626340
0.730000
                 72.555747
                                 68.224599
0.740000
                 71.972432
                                 67.805898
0.750000
                 71.360235
                                 67.374170
0.760000
                 70.705071
                                 66.913338
0.770000
                 70.030293
                                 66.427140
0.780000
                 69.309328
                                 65.895468
0.790000
                 68.547928
                                 65.331473
0.800000
                 67.760228
                                 64.724143
0.810000
                 66.935485
                                 64.058729
0.820000
                 66.087366
                                 63.329677
0.830000
                 65.204933
                                 62.518601
0.840000
                 64.296003
                                 61.626410
0.850000
                 63.360698
                                 60.639019
                 62.402558
0.860000
                                 59.527424
0.870000
                 61.415880
                                 58.295484
0.880000
                 60.389062
                                  56.903329
0.890000
                 59.311904
                                 55.341546
0.900000
                 58.187797
                                 53.607135
0.910000
                 56.986066
                                 51.695967
0.920000
                 55.688521
                                 49.580218
0.930000
                 54.267214
                                 47.297076
0.940000
                 52.676254
                                 44.855293
0.950000
                 50.849077
                                 42.298770
0.960000
                 48.705454
                                  39.642180
0.970000
                46.046529
                                 36.948203
0.980000
                42.597002
                                 34.256143
                CNN: 0.440000
                                 NAS: 0.410000
Best gamma -
Best ACC:
                 CNN 79.733318
                                 NAS 75.186773
Best gamma -
                 CNN: 0.480000
                                 NAS: 0.480000
Best ACC:
                CNN 79.615161
                                 NAS 74.825271
test M1.mat
SmithCNNnet has acc of: [[0.9706267]
 [0.9853221]
 [0.743441 ]
 [0.24973476]
 [0.01425135]
 [0.00252596]] with 222576 params.
NAS full has acc of: [[0.9627198]
 [0.9995914]
 [0.88791865]
 [0.14881828]
 [0.02733597]
 [0.00186482]] with 2701 params.
0.010000
                                  74.654075
                 74.209000
0.020000
                 76.235840
                                 76.560580
```

		rigu
0.030000	77.485720	77.866144
0.040000	78.400613	78.861329
0.050000	79.154720	79.634245
0.060000	79.799345	80.288173
0.070000	80.365836	80.863428
0.080000		
	80.865990	81.359470
0.090000	81.305807	81.796388
0.100000	81.720007	82.188273
0.110000	82.092139	82.543282
0.120000	82.432923	82.864381
0.130000	82.756449	83.153930
0.140000	83.060425	83.431748
0.150000	83.336895	83.688264
0.160000	83.610062	83.920981
0.170000	83.877498	84.146755
0.180000	84.127474	84.358439
0.190000	84.355405	84.553471
0.200000	84.579561	84.733538
0.210000	84.793537	84.902211
0.220000	84.995109	85.073176
0.230000	85.189804	85.230051
0.240000	85.377219	85.376208
0.250000	85.546566	85.509420
0.260000	85.709576	85.634341
0.270000	85.859575	85.751037
0.280000	85.999462	85.847912
0.290000	86.131124	85.941957
0.300000	86.248562	86.027776
0.310000	86.359932	86.118989
0.320000	86.462605	86.193079
0.330000	86.559548	86.261775
0.340000	86.639907	86.328516
0.350000	86.717637	86.387976
0.360000	86.788154	86.435706
0.370000	86.849367	86.489369
0.380000	86.909973	86.530357
0.390000	86.964579	86.572155
0.400000	87.002332	86.603368
0.410000	87.036377	86.632626
0.420000	87.067590	86.647660
0.430000	87.095702	86.656559
0.440000	87.121050	86.658177
0.450000	87.133657	86.648671
0.460000	87.140196	86.638222
0.470000	87.138039	86.623256
0.480000	87.129612	86.606402
0.490000	87.106286	86.582267
0.500000	87.079253	86.544245
0.510000	87.047163	86.509459
0.520000	86.989118	86.454313
0.530000	86.934849	86.396268
0.540000	86.856378	86.323460
0.550000	86.774199	86.250045
0.560000	86.666941	86.170967
0.570000	86.560559	86.082855
0.580000	86.453369	85.992249
0.590000	86.323864	85.885800
0.600000	86.196787	85.768699
0.610000	86.056361	85.643981
0.620000	85.896721	85.504903
0.630000	85.735666	85.358612
0.640000	85.553442	85.205917
0.650000	85.363062	85.045603
0.660000	85.169715	84.873020
0.670000	84.972795	84.701246
0.070000	U-T + J / L / J J	J/U1240

```
84.741425
0.680000
                                 84.510123
                                 84.303496
0.690000
                 84.502843
                 84.255968
0.700000
                                 84.088710
0.710000
                 84.000127
                                 83.864218
0.720000
                 83.721836
                                 83.632241
0.730000
                 83.418265
                                 83.386243
0.740000
                 83.109031
                                 83.117661
0.750000
                 82.784562
                                 82.842808
0.760000
                 82.447081
                                 82.530204
0.770000
                 82.091263
                                 82.206408
0.780000
                 81.726276
                                 81.867444
0.790000
                                 81.506570
                 81.331830
0.800000
                 80.911023
                                 81.131269
0.810000
                 80.476801
                                 80.749429
0.820000
                 80.017434
                                 80.363813
0.830000
                 79.509662
                                 79.944153
0.840000
                 78.959688
                                 79.508718
                                 79.051305
0.850000
                 78.402231
0.860000
                 77.800280
                                 78.595847
0.870000
                 77.154374
                                 78.119289
0.880000
                 76.488311
                                 77.616101
0.890000
                 75.755034
                                 77.071520
0.900000
                 74.995803
                                 76.506378
0.910000
                 74.208460
                                 75.882854
                                 75.202431
0.920000
                 73.367454
0.930000
                 72.478112
                                 74.412594
0.940000
                 71.482321
                                 73.480982
0.950000
                 70.316104
                                 72.362292
                                 70.932549
0.960000
                 68.883461
0.970000
                 66.990372
                                 68.975281
0.980000
                 64.030976
                                 66.051412
Best gamma -
                CNN: 0.460000
                                 NAS: 0.440000
Best ACC:
                CNN 87.140196
                                 NAS 86.658177
Best gamma -
                CNN: 0.480000
                                 NAS: 0.480000
                 CNN 87.129612
Best ACC:
                                 NAS 86.606402
test PFC.mat
SmithCNNnet has acc of: [[9.9264956e-01]
 [9.9045038e-01]
 [9.9495506e-01]
 [7.2709165e-16]
 [3.0571908e-02]
 [2.1777382e-06]] with 222576 params.
NAS full has acc of: [[9.6726519e-01]
 [8.8205469e-01]
 [9.8557377e-01]
 [5.8659911e-04]
 [5.3554392e-01]
 [1.3933411e-05] with 2701 params.
0.010000
                 79.840256
                                 74.170469
0.020000
                 81.265502
                                 75.748212
0.030000
                82.164532
                                 76.839785
0.040000
                 82.827356
                                 77.687143
                 83.352926
                                 78.381875
0.050000
                 83.798081
                                 78.984566
0.060000
0.070000
                 84.165276
                                 79.512138
0.080000
                 84.480799
                                 80.013228
                                 80.453927
0.090000
                 84.768160
0.100000
                 85.028394
                                 80.862976
0.110000
                 85.263954
                                 81.256524
0.120000
                 85.476520
                                 81.612157
0.130000
                 85.673585
                                 81.952612
0.140000
                 85.855987
                                 82.270266
0.150000
                 86.025213
                                 82.563117
```

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0.160000	86.180165	82.843826
0.170000	86.324782	83.108258
0.180000	86.461197	83.360095
0.190000	86.590248	83.598627
0.200000	86.710902	83.833541
0.210000	86.826712	84.054245
0.220000	86.936839	84.258027
0.230000	87.045285	84.469237
0.240000	87.145723	84.668756
0.250000	87.239250	84.856907
0.260000	87.328449	85.034207
0.270000	87.414806	85.212088
0.280000	87.499160	85.385642
0.290000	87.590491	85.546794
0.300000	87.668386	85.700519
0.310000	87.743569	85.850626
0.320000	87.814360	85.991497
0.330000	87.884570	86.131852
0.340000	87.953875	86.264391
0.350000	88.015106	86.388985
0.360000	88.072398	86.513192
0.370000	88.124780	86.622995
0.380000	88.176646	86.734542
0.390000	88.230708	86.835690
0.400000	88.285610	86.938583
0.410000	88.333859	87.027459
0.420000	88.376165	87.117562
0.430000	88.412723	87.196749
0.440000	88.446633	87.278327
0.450000	88.480801	87.352541
0.460000	88.511675	87.414289
0.470000	88.546619	87.480106
0.480000	88.565350	87.539077
0.490000	88.586148	87.594108
0.500000	88.604879	87.637448
0.510000	88.611855	87.682080
0.520000	88.620187	87.713406
0.530000	88.624062	87.738725
0.540000	88.620187	87.764238
0.550000	88.606687	87.782194
0.560000	88.599066	87.791366
0.570000	88.582079	87.790785
0.580000	88.561539	87.775089
0.590000	88.529115	87.748284
0.600000	88.486937	87.724515
0.610000	88.450056	87.679819
0.620000	88.397932	87.627049
0.630000	88.342385	87.559940
0.640000	88.285933	87.473776
0.650000	88.209329	87.373597
0.660000	88.124780	87.259079
0.670000	88.038488	87.134291
0.680000	87.942959	86.985346
0.690000	87.828505	86.814311
0.700000	87.692737	86.621897
0.710000	87.556323	86.396930
0.720000	87.399627	86.137277
0.730000	87.219743	85.853856
0.740000	87.037470	85.537170
0.750000	86.845637	85.190580
0.760000	86.624933	84.782241
0.770000	86.377746	84.342124
0.780000	86.107049	83.850786
0.790000	85.815748	83.289498
0.800000	85.496866	82.650702

```
0.810000
                 85.134903
                                 81.935043
0.820000
                 84.738642
                                 81.110937
0.830000
                 84.303822
                                 80.158233
0.840000
                 83.828438
                                 79.068597
0.850000
                 83.280520
                                 77.828338
0.860000
                 82.680672
                                 76.415041
0.870000
                 82.011647
                                 74.796993
0.880000
                 81.249677
                                 72.952105
0.890000
                 80.387786
                                 70.801899
0.900000
                 79.425329
                                 68.313694
0.910000
                 78.312570
                                 65.519331
0.920000
                 76.976071
                                 62.397883
0.930000
                 75.406982
                                 58.869582
0.940000
                 73.528055
                                 54.955678
0.950000
                 71.233491
                                 50.573883
                 68.372341
0.960000
                                 45.713928
0.970000
                                 40.324268
                 64.553191
0.980000
                 59.206872
                                 34.726047
Best gamma -
                CNN: 0.530000
                                 NAS: 0.560000
Best ACC:
                CNN 88.624062
                                 NAS 87.791366
Best gamma -
                CNN: 0.480000
                                 NAS: 0.480000
                CNN 88.565350
Best ACC:
                                 NAS 87.539077
test V4.mat
SmithCNNnet has acc of: [[0.95236915]
 [0.9909262]
 [0.99970496]
 [0.10696539]
 [0.00127164]
 [0.7000898 ]] with 222576 params.
NAS full has acc of: [[9.2407745e-01]
 [7.5693905e-01]
 [9.0013546e-01]
 . . .
 [2.7215630e-02]
 [1.3545156e-04]
 [7.6440048e-01]] with 2701 params.
0.010000
                 80.655888
                                 77.552278
0.020000
                 82.116413
                                 78.939478
0.030000
                83.030064
                                 79.851220
0.040000
                83.694208
                                 80.546302
0.050000
                 84.228075
                                 81.113667
0.060000
                 84.678372
                                 81.610771
0.070000
                85.062123
                                 82.048211
                                 82.434172
0.080000
                85.390328
0.090000
                 85.686441
                                 82.778649
0.100000
                 85.951667
                                 83.108311
                                 83.407989
0.110000
                 86.204889
0.120000
                 86.427376
                                 83.688382
0.130000
                                 83.942459
                 86.636051
0.140000
                                 84.185486
                 86.829910
0.150000
                 87.016488
                                 84.408375
0.160000
                 87.182222
                                 84.628249
0.170000
                 87.335201
                                 84.828487
0.180000
                                 85.013909
                 87.484563
0.190000
                 87.623880
                                 85.196067
0.200000
                 87.759482
                                 85.371495
0.210000
                 87.882477
                                 85.539288
0.220000
                 88.002409
                                 85.691664
0.230000
                 88.122290
                                 85.839670
0.240000
                 88.231324
                                 85.982202
0.250000
                 88.337545
                                 86.116246
0.260000
                 88.437236
                                 86.242908
0.270000
                 88.536426
                                 86.372030
0.280000
                 88.632854
                                 86.488396
```

		Figu
0.290000	88.723255	86.601096
0.300000	88.806674	86.710230
0.310000	88.885223	86.818259
0.320000	88.960205	86.921265
0.330000	89.032475	87.023368
0.340000	89.101933	87.116431
0.350000	89.166419	87.208388
0.360000	89.226787	87.291105
0.370000	89.278968	87.371361
0.380000	89.329894	87.444535
0.390000	89.370374	87.523686
0.400000	89.413816	87.590533
0.410000	89.448269	87.651955
0.420000	89.485584	87.707853
0.430000	89.513860	87.763550
0.440000	89.533848	87.810859
0.450000	89.544546	87.862036
0.460000	89.548212	87.897142
0.470000		
	89.550924	87.928933
0.480000	89.554640	87.955300
0.490000	89.545550	87.973832
0.500000	89.534250	87.986538
0.510000	89.516321	87.998190
0.520000	89.478302	87.994574
0.530000	89.439229	87.988748
0.540000	89.397393	87.970768
0.550000	89.349330	87.934960
0.560000	89.288310	87.896389
0.570000	89.216893	87.840792
		87.770330
0.580000	89.139199	
0.590000	89.051108	87.678121
0.600000	88.953726	87.573808
0.610000	88.847154	87.448854
0.620000	88.737568	87.309687
0.630000	88.619043	87.146715
0.640000	88.483291	86.958983
0.650000	88.334481	86.737400
0.660000	88.180448	86.483424
0.670000	88.010093	86.210313
0.680000	87.813722	85.910785
0.690000	87.623629	85.558222
0.700000	87.401394	85.168645
0.710000	87.177853	84.732562
0.720000	86.922421	84.227472
0.730000	86.645342	83.695263
0.740000	86.352243	83.087870
0.750000	86.038753	82.420562
0.760000	85.697590	81.661195
0.770000	85.327299	80.830361
0.780000	84.937721	79.913948
0.790000	84.527201	78.883831
0.800000	84.073038	77.742873
0.810000	83.568501	76.482535
0.820000	83.039054	75.093075
0.830000	82.458480	73.570324
0.840000	81.817538	71.910063
0.850000	81.121753	70.092154
0.860000	80.371075	68.090479
0.870000	79.548629	65.901776
0.880000	78.628198	63.539653
0.890000	77.622037	60.954442
0.900000	76.493936	58.164974
0.910000	75.222298	55.174516
0.920000	73.786432	51.962827
0.930000	72.143197	48.567775
0.230000	, _ • ±¬J±J/	-0.507775

45.025018

0.940000

70.242822

```
0.950000
                         68.008265
                                          41.391208
                         65.296944
                                          37.821632
         0.960000
         0.970000
                         61.883360
                                          34.596484
         0.980000
                         57.289493
                                          32.057376
         Best gamma -
                         CNN: 0.480000 NAS: 0.510000
         Best ACC:
                         CNN 89.554640
                                          NAS 87.998190
         Best gamma -
                         CNN: 0.480000
                                          NAS: 0.480000
         Best ACC:
                         CNN 89.554640
                                          NAS 87.955300
In [17]:
          #figure 3 on excel CNNnas.xlsx
          #range and variance
          # 10 fold cross validation on test data
          data_dir_base = 'Z:/SmithLab/prjNAS/NASNet/tests_byarea_kfold/' #all areas in separate
          area_names = ["PFC","M1","V4", "FEF"]
          \#area\ names = \lceil "V4" \rceil
          area var = np.zeros([4,4])
          for area in area_names:
              data dir = data dir base + area+ '/'
              testingFiles = []
              for file in os.listdir(data dir): # pull all training files from directory
                  if file.endswith(".mat"):
                      testingFiles.append(file)
              nsets = len(testingFiles) # number of training files
              print(area)
              kfold = np.zeros([nsets, 4]) #contains accuracy at 0.2 for NAS/CNN, and 0.48 for NA
              for j in range(nsets): # loop over the different testing files
                      f_waves = h5py.File(data_dir + '/' + testingFiles[j],mode='r') # Load test
                      testacc = []
                      fozle = testingFiles[j]
                      file_edit = fozle.rfind('_')
                      datastr
                                = fozle[file edit+1: len(fozle)-4]
                      print(fozle)
                      waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
                      #waveforms = waveforms[np.random.choice(Len(waveforms),5000000), :]
                      for netname in netnames:
                          match = netnames.index(netname)
                          model_path = pjoin(model_dir, netname)
                          model = keras.models.load model(model path)
                           if match < numcnn:</pre>
                               x_test = waveforms[:, 1:(52+1)] # waveform voltage values
                               y test = waveforms[:, 0] # waveform labels
                               x test = np.expand dims(x test, axis=2)
                               predicts_CNN = model.predict(x_test, verbose =0)
                           else:
                               #print('we made it')
                               x_test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
                               \#x test = np.expand dims(x test, axis=2)
                               v test = waveforms[:, 0] # waveform Labels
                               predicts NAS = model.predict(x test,verbose =0)
                      predlabel CNNpt2 = predicts CNN[:,0] > 0.2
                      predlabel CNNpt48 = predicts CNN[:,0] > 0.48
                      predlabel NASpt2 = predicts NAS[:,0] > 0.2
                      predlabel NASpt48 = predicts NAS[:,0] > 0.48
```

```
Figure Prep - CNN-NAS

kfold[j, 0] = sum(y_test == predlabel_NASpt2)/len(y_test)
kfold[j, 1] = sum(y_test == predlabel_CNNpt2)/len(y_test)
kfold[j, 2] = sum(y_test == predlabel_NASpt48)/len(y_test)
kfold[j, 3] = sum(y_test == predlabel_CNNpt48)/len(y_test)

area_var[area_names.index(area)] = [np.var(kfold[:, 0]), np.var(kfold[:, 1]), np.v

print("gamma=0.2 \t\tNAS\t\tCNN\t\tgamma=0.48 NAS\t\tCNN")
print("average acc: ", np.mean(kfold[:, 0]), np.mean(kfold[:, 1]), np.mean(kfold[:, print("var:\t ", np.var(kfold[:, 0]), np.var(kfold[:, 1]), np.var(kfold[:, 2]),n

PFC
test_1.mat
test_2.mat
test_3.mat
test_3.mat
```

```
PFC
test 1.mat
test 10.mat
test 2.mat
test_3.mat
test 4.mat
test 5.mat
test 6.mat
test_7.mat
test_8.mat
test_9.mat
gamma=0.2
                        NAS
                                         CNN
                                                         gamma=0.48 NAS
                                                                                  CNN
average acc: 0.8383354085811361 0.8671090227863454 0.8753907695497561 0.885653497206439
             8.156480794596731e-07 7.056196930351562e-07 8.191190105021668e-07 7.6674691
var:
49886502e-07
test_1.mat
test_10.mat
test_2.mat
test_3.mat
test_4.mat
test 5.mat
test 6.mat
test_7.mat
test 8.mat
test 9.mat
gamma=0.2
                        NAS
                                         CNN
                                                         gamma=0.48 NAS
                                                                                  CNN
average acc: 0.84733537668137 0.8457956113339868 0.866064018453336 0.8712961201528735
             4.201065338185848e-07 5.760230707739078e-07 9.007338597599479e-07 9.7252980
48907775e-07
test_1.mat
test 10.mat
test 2.mat
test_3.mat
test_4.mat
test_5.mat
test 6.mat
test 7.mat
test_8.mat
test_9.mat
gamma=0.2
                        NAS
                                         CNN
                                                         gamma=0.48 NAS
                                                                                  CNN
average acc: 0.8537149448458514 0.8775948163249849 0.8795529979728001 0.895546404669909
             9.593496016125697e-07 5.086381887970802e-07 6.414652197802632e-07 6.1869209
59731345e-07
FEF
test 1.mat
test 10.mat
test 2.mat
test_3.mat
test 4.mat
test 5.mat
```

```
test 6.mat
         test 7.mat
         test 8.mat
         test_9.mat
                                                                  gamma=0.48 NAS
                                 NAS
                                                  CNN
                                                                                           CNN
         gamma=0.2
         average acc: 0.7170475224482281 0.7644791508629807 0.7482527089678372 0.796151608961875
         var:
                      4.209654443091048e-07 3.7383588497614953e-07 5.752884279937727e-07 5.020865
         312099486e-07
In [18]:
          print(area_names)
          print(area var)
          print("gamma=0.2 \t\tNAS\t\tCNN\t\tgamma=0.48 NAS\t\tCNN")
          print("average var: ", np.mean(area_var[:, 0]), np.mean(area_var[:, 1]), np.mean(area_v
          ['PFC', 'M1', 'V4', 'FEF']
          [[8.15648079e-07 7.05619693e-07 8.19119011e-07 7.66746915e-07]
          [4.20106534e-07 5.76023071e-07 9.00733860e-07 9.72529805e-07]
          [9.59349602e-07 5.08638189e-07 6.41465220e-07 6.18692096e-07]
          [4.20965444e-07 3.73835885e-07 5.75288428e-07 5.02086531e-07]]
                                 NAS
                                                  CNN
                                                                  gamma=0.48 NAS
         gamma=0.2
         average var: 6.540174147999831e-07 5.410292093955734e-07 7.341516295090377e-07 7.150138
         367656277e-07
In [21]:
          # buffer load all predictions here
          #figure 3 - gamma sweeps and accuracy across each area
          data dir = 'Z:/SmithLab/prjNAS/NASNet/test all/' #all areas in one file
          testingFiles = []
          for file in os.listdir(data dir): # pull all training files from directory
              if file.endswith(".mat"):
                  testingFiles.append(file)
          nsets = len(testingFiles) # singular testing file
          for j in range(nsets): # loop over the different testing files
                  f waves = h5py.File(data dir + '/' + testingFiles[j],mode='r') # load testing
                  testacc = []
                  fozle = testingFiles[j]
                  file edit = fozle.rfind(' ')
                            = fozle[file edit+1: len(fozle)-4]
                  print(fozle)
                  waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
                  #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
                  for netname in netnames:
                      match = netnames.index(netname)
                      model path = pjoin(model dir, netname)
                      model = keras.models.load model(model path)
                      if match < numcnn:</pre>
                          x_test = waveforms[:, 1:(52+1)] # waveform voltage values
                          y test = waveforms[:, 0] # waveform labels
                          x test = np.expand dims(x test, axis=2)
                          predicts CNNall = model.predict(x test,verbose =0)
                          #print(netname +" has acc of: "+str(predicts_CNNall) +" with " +str(mod
                           #print(predicts CNN.shape)
                      else:
```

```
#print('we made it')
        x test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
        #x_test = np.expand_dims(x_test, axis=2)
        y_test = waveforms[:, 0] # waveform labels
        predicts_NASall = model.predict(x_test,verbose =0)
        #print(netname +" has acc of: "+str(predicts NASall) +" with " +str(mod
        #print(predicts_NAS.shape)
best g NAS = 0
best g CNN = 0
g_of_CNN = 0.2
g_of_NAS = 0.2
ranger = np.arange(0,len(y_test),1)
spikes are = ranger[y test == 1]
noise_are = ranger[y_test == 0]
for gamma in np.arange(0.01, 0.99, 0.01):
    predlabel CNN = predicts CNNall[:,0] > gamma
    predlabel_NAS = predicts_NASall[:,0] > (gamma)
    CNN_acc = sum(y_test == predlabel_CNN)/len(y_test)
    NAS acc = sum(y test == predlabel NAS)/len(y test)
    ranger
    #CNN_spike_acc = sum(y_test[spikes_are] == predlabel_CNN[spikes_are])/len(s
    #NAS_spike_acc = sum(y_test[spikes_are] == predlabel_NAS[spikes_are])/len(s
    CNN_noise_acc = sum(y_test[noise_are] == predlabel_CNN[noise_are])/len(noise_are)
    NAS_noise_acc = sum(y_test[noise_are] == predlabel_NAS[noise_are])/len(nois
    if best_g_CNN < (CNN_acc):</pre>
        best_g_CNN = (CNN_acc)
        g_of_CNN = gamma
    if best g NAS < (NAS acc):</pre>
        best_g_NAS = (NAS_acc)
        g_of_NAS = gamma
    #print("Gamma: %f\tCNN %f\tNAS %f spikes:\tCNN %f\tNAS %f" %(gamma, CNN acc
    \#print("\%f\t\%f\t\%f\t\%f" \%(gamma, CNN\_acc*100, NAS\_acc*100, CNN\_spike\_ac)
    print("%f\t%f\t%f" %(gamma, CNN_acc*100, NAS_acc*100))
print("Best gamma -\tCNN: %f \tNAS: %f" %(g_of_CNN, g_of_NAS))
\#gamma = g_of
predlabel CNN = predicts CNNall[:,0] > g of CNN
predlabel_NAS = predicts_NASall[:,0] > (g_of_NAS)
CNN_acc = sum(y_test == predlabel_CNN)/len(y_test)
NAS acc = sum(y test == predlabel NAS)/len(y test)
print("Best ACC:\tCNN %f\tNAS %f" %(CNN_acc*100, NAS_acc*100))
best_g_NAS = 0
best g CNN = 0
g 	ext{ of } CNN = 0.48
g_of_NAS = 0.48
ranger = np.arange(0,len(y_test),1)
spikes_are = ranger[y_test == 1]
print("Best gamma -\tCNN: %f \tNAS: %f" %(g_of_CNN, g_of_NAS))
predlabel_CNN = predicts_CNNall[:,0] > g_of_CNN
predlabel_NAS = predicts_NASall[:,0] > (g_of_NAS)
CNN_acc = sum(y_test == predlabel_CNN)/len(y_test)
```

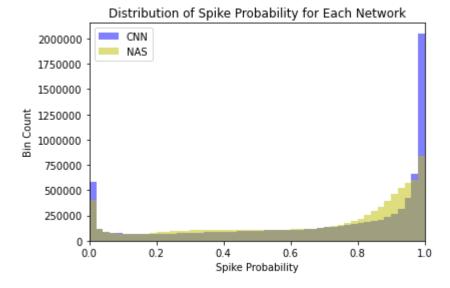
```
NAS_acc = sum(y_test == predlabel_NAS)/len(y_test)
print("Best ACC:\tCNN %f\tNAS %f" %(CNN_acc*100, NAS_acc*100))
\max idx = []
X_{maxes} = np.amax(x_{test,1})
pos = 0
for mx in X_maxes:
    max_val = np.where(x_test[pos,:] == mx)
    max_val_val = max_val[0]
    max_idx.append(max_val_val[0])
    pos = pos + 1
min_idx = []
X_{mins} = np.amin(x_{test,1})
pos = 0
for mins in X_mins:
    min_val = np.where(x_test[pos,:] == mins)
    min_val_val = min_val[0]
    min_idx.append(min_val_val[0])
    pos = pos + 1
y_test_idx= []
y_test_idx_noise= []
max_idx_spike = []
p_{CNN_spike} = []
p_NAS_spike = []
p_{CNN_noise} = []
p NAS noise = []
max_idx_noise = []
for p in np.arange(0,len(y_test)-1):
    if y test[p] == 1:
        y_{test_idx} = p
        max_idx_spike.append(max_idx[y_test_idx])
        p_CNN_spike.append(predicts_CNNall[y_test_idx,0])
        p_NAS_spike.append(predicts_NASall[y_test_idx,0])
    else:
        y_{\text{test_idx_noise}} = p
        max_idx_noise.append(max_idx[y_test_idx_noise])
        p CNN noise.append(predicts CNNall[y test idx noise,0])
        p_NAS_noise.append(predicts_NASall[y_test_idx_noise,0])
```

```
full_test.mat
0.010000
                75.399687
                                 73.332895
0.020000
                76.355027
                                 74.245875
0.030000
                77.003570
                                 74.865972
0.040000
                77.524393
                                 75.345776
0.050000
                77.975146
                                 75.733071
0.060000
                78.382560
                                 76.070779
                                 76.368722
0.070000
                78.754500
                79.093945
                                 76.638219
0.080000
                79.407453
                                 76.879293
0.090000
0.100000
                79.704296
                                 77.106276
0.110000
                79.986642
                                 77.318409
0.120000
                80.252333
                                 77.515307
                                 77.699808
0.130000
                80.504979
0.140000
                80.749682
                                 77.879887
0.150000
                80.978403
                                 78.052465
                81.198071
                                 78.222567
0.160000
0.170000
                81.411799
                                 78.387631
0.180000
                81.616815
                                 78.550331
0.190000
                81.812316
                                 78.717012
```

		5
0.200000	82.000029	78.889501
0.210000	82.181054	79.061859
0.220000	82.358736	79.234491
0.230000	82.532545	79.413371
0.240000	82.699105	79.591306
0.250000	82.854545	79.765115
0.260000	83.004979	79.939562
0.270000	83.153951	80.114317
0.280000	83.293308	80.283870
0.290000	83.428321	80.455589
0.300000	83.555480	80.618784
0.310000	83.673883	80.775829
0.320000	83.784806	80.922469
0.330000	83.892044	81.063971
0.340000	83.990691	81.198918
0.350000	84.083409	81.321391
0.360000	84.168592	81.431709
0.370000	84.246889	81.527485
0.380000	84.317607	81.612360
0.390000	84.381198	81.688721
0.400000	84.434415	81.753290
0.410000	84.481550	81.801008
0.420000	84.522480	81.828332
0.430000	84.550101	81.855094
0.440000	84.569186	81.863828
0.450000	84.575478	81.863630
0.460000	84.571793	81.848539
0.470000	84.559242	81.825637
0.480000	84.542478	81.788523
0.490000	84.509610	81.740740
0.500000	84.468504	81.679195
0.510000	84.419070	81.611392
0.520000	84.349903	81.531874
0.530000	84.270473	81.442565
0.540000	84.180285	81.345051
0.550000	84.082155	81.235394
0.560000	83.961420	81.120335
0.570000	83.834910	80.993044
0.580000	83.697026	80.856810
0.590000	83.547098	80.706530
0.600000	83.385784	80.545095
0.610000	83.215715	80.370791
0.620000	83.029982	80.187269
0.630000	82.832182	79.988402
0.640000	82.618245	79.775378
0.650000	82.391746	
		79.546613
0.660000	82.151113	79.301953
0.670000	81.890448	79.051013
0.680000	81.610974	78.782770
0.690000	81.312514	78.489666
0.700000		
	80.990041	78.175234
0.710000	80.660000	77.837692
0.720000	80.298324	77.473958
0.730000	79.911402	77.089204
0.740000	79.504670	76.671043
0.750000	79.076434	76.227813
0.760000	78.615868	75.734721
0.770000	78.132643	75.207386
0.780000	77.619025	74.629760
0.790000	77.074409	73.997277
0.800000	76.499467	73.305571
0.810000	75.887389	72.547557
0.820000	75.249450	71.713722
0.830000	74.570493	70.786519
0.840000	73.852662	69.767005
3.0-0000	. 3.032002	32.707003

```
0.850000
                73.097442
                                 68.641122
                72.303877
                                 67.390258
0.860000
0.870000
                71.462869
                                 66.006262
0.880000
                                 64.469610
                70.563320
0.890000
                69.594482
                                 62.749436
0.900000
                68.556566
                                 60.846356
0.910000
                67.422290
                                 58.758488
0.920000
                66.162307
                                 56.465627
0.930000
                64.754024
                                 53.970554
                63.143364
0.940000
                                 51.283335
0.950000
                 61.255211
                                 48.414619
0.960000
                58.981060
                                 45.383004
                56.084216
                                 42.233812
0.970000
0.980000
                52.140997
                                 39.042501
Best gamma -
                CNN: 0.450000
                                 NAS: 0.440000
Best ACC:
                CNN 84.575478
                                 NAS 81.863828
                CNN: 0.480000
Best gamma -
                                 NAS: 0.480000
Best ACC:
                CNN 84.542478
                                 NAS 81.788523
```

```
In [7]:
         # supplemental figure
         # Distribution of spike probability for each Network
         p_CNN_spike = []
         p_NAS_spike = []
         p CNN noise = []
         p NAS noise = []
         plt.figure()
         kwargs = dict(alpha=0.5, bins=50)
         plt.hist(predicts_CNNall[:,0], **kwargs, label = "CNN",color='b')
         plt.hist(predicts_NASall[:,0], **kwargs, label = "NAS",color='y')
         plt.legend()
         plt.xlabel("Spike Probability")
         plt.ylabel("Bin Count")
         plt.title("Distribution of Spike Probability for Each Network")
         plt.xlim([0, 1])
         plt.ticklabel_format(useOffset=False, style='plain')
         plt.show()
```

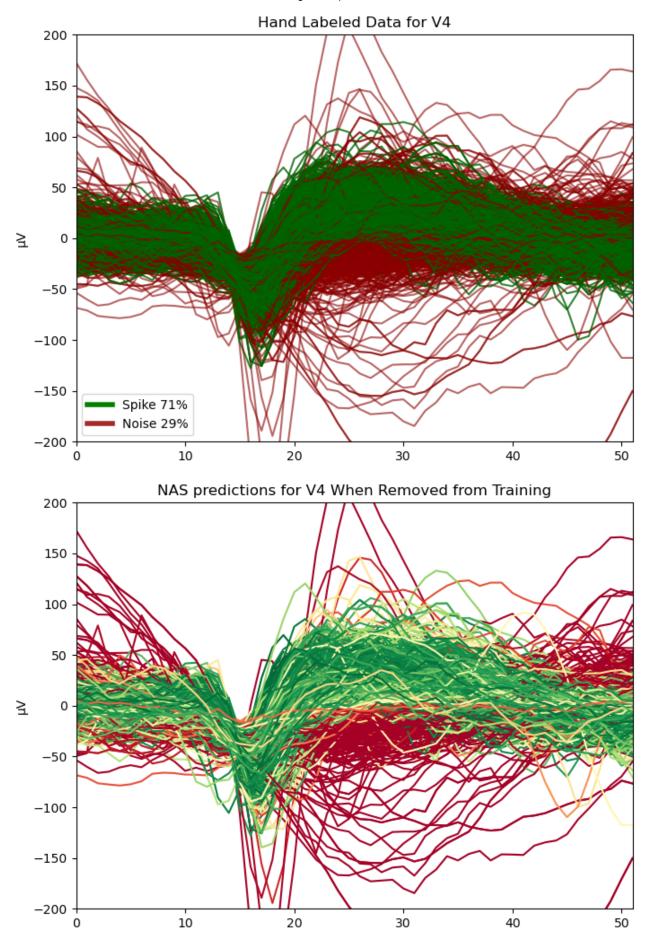


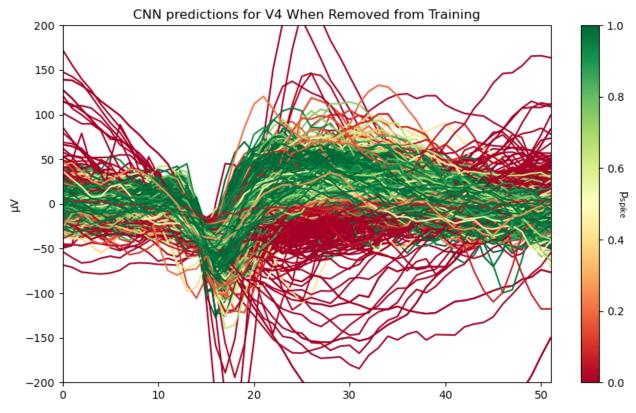
```
In [10]:
    #figure 4 - comparison to hand label distribution
    #over a single chanel of v4
    data_dir = 'Z:/SmithLab/prjNAS/NASNet/tests_m1/v4_ch/' #all areas in separate files
    testingFiles = []
```

```
for file in os.listdir(data dir): # pull all training files from directory
    if file.endswith(".mat"):
        testingFiles.append(file)
nsets = len(testingFiles) # number of training files
for j in range(nsets): # loop over the different testing files
        f waves = h5py.File(data dir + '/' + testingFiles[j],mode='r') # load testing
        testacc = []
        fozle = testingFiles[j]
        file_edit = fozle.rfind('_')
        datastr = fozle[file edit+1: len(fozle)-4]
        print(fozle)
        waveforms = np.transpose(f_waves['waveData'][()]) #load all waveforms
        #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
        for netname in netnames:
            match = netnames.index(netname)
            model path = pjoin(model dir, netname)
            model = keras.models.load_model(model_path)
            if match < numcnn:</pre>
                x test = waveforms[:, 1:(52+1)] # waveform voltage values
                y test = waveforms[:, 0] # waveform labels
                x_test = np.expand_dims(x_test, axis=2)
                predicts_CNN = model.predict(x_test,verbose =0)
                print(netname +" has acc of: "+str(predicts CNN) +" with " +str(model.c
                #print(predicts CNN.shape)
            else:
                #print('we made it')
                x test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
                #x_test = np.expand_dims(x_test, axis=2)
                y test = waveforms[:, 0] # waveform labels
                predicts NAS = model.predict(x test,verbose =0)
                print(netname +" has acc of: "+str(predicts NAS) +" with " +str(model.c
                #print(predicts NAS.shape)
        best g NAS = 0
        best g CNN = 0
        g of CNN = 0.2
        g_of_NAS = 0.2
        ranger = np.arange(0,len(y_test),1)
        spikes are = ranger[y test == 1]
        noise_are = ranger[y_test == 0]
        lims = 200
        #ch = fozle[fozle.find('_SNR')-2:fozle.find('_SNR')]
        ch = fozle[fozle.find('ch')+2:fozle.find('ch')+3]
        lab = 'V4'
        rngvals = np.random.choice(len(predicts NAS),3000)
        t = np.arange(0,52)
        plt.figure(figsize=(8, 6),dpi=100)
        for r in rngvals:
            if y_test[r] == 1:
                plt.plot(t,x_test[r,:],c='darkgreen', alpha=0.8)
            else:
```

```
plt.plot(t,x_test[r,:],c='darkred', alpha=0.6)
         plt.title('Hand Labeled Data for ' +lab)
         plt.ylabel(u'\u03bcV')
         plt.xlim([0, 51])
         plt.ylim([-lims ,lims])
         custom_lines = [mpl.lines.Line2D([0], [0], color='g', lw=4),
                 mpl.lines.Line2D([0], [0], color='brown', lw=4)]
         plt.legend(custom_lines, ['Spike ' + str(round(sum(y_test)*100/len(y_test)))+'%
         plt.show()
         n lines = 10
         c = np.arange(1, n_lines + 1)
         norm = mpl.colors.Normalize(vmin=0, vmax=1)
         cmap = mpl.cm.ScalarMappable(norm=norm, cmap='RdYlGn')
         cmap.set_array([])
         fig, ax = plt.subplots(figsize=(8, 6),dpi=100)
        for r in rngvals:
             ax.plot(t, x_test[r,:], c=cmap.to_rgba(predicts_NAS[r,0]))
         #fig.colorbar(cmap)
         plt.title('NAS predictions for ' +lab +' When Removed from Training')
        plt.ylabel(u'\u03bcV')
        plt.xlim([0, 51])
         plt.ylim([-lims ,lims])
         plt.show()
        fig, ax = plt.subplots(figsize=(10, 6), dpi=100)
         for r in rngvals:
             ax.plot(t, x test[r,:], c=cmap.to rgba(predicts CNN[r,0]))
         cbar = fig.colorbar(cmap)
         params = {'mathtext.default': 'regular' }
         plt.rcParams.update(params)
         cbar.ax.set_ylabel('$p_{spike}$', rotation=270)
         plt.title('CNN predictions for ' +lab+' When Removed from Training')
         plt.ylabel(u'\u03bcV')
        plt.xlim([0, 51])
         plt.ylim([-lims,lims])
         plt.show()
test V4 ch46.mat
SmithCNNnet has acc of: [[5.7647729e-01]
```

```
test_V4_ch46.mat
SmithCNNnet has acc of: [[5.7647729e-01]
  [4.4530813e-07]
  [8.0015409e-01]
  ...
  [8.9890397e-01]
  [9.9204135e-01]
  [9.8123592e-01]] with 222576 params.
NAS_full has acc of: [[0.53182775]
  [0.00352195]
  [0.59787434]
  ...
  [0.94488055]
  [0.85020876]
  [0.88086283]] with 2701 params.
```





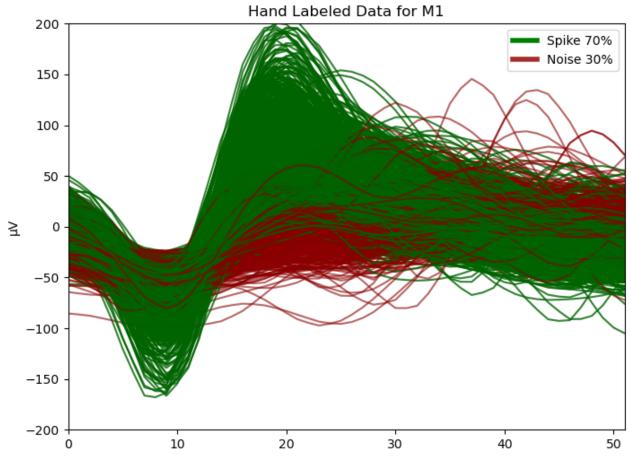
```
In [11]:
          #figure 4 m1 plots
          # uses networks that were trained on lacking m1 data
          data dir = 'Z:/SmithLab/prjNAS/NASNet/small m1/' #all areas in separate files
          testingFiles = []
          for file in os.listdir(data dir): # pull all training files from directory
              if file.endswith(".mat"):
                  testingFiles.append(file)
          nsets = len(testingFiles) # number of training files
          netnames alt = ['CNN4L2d opt noM1','NAS noM1']
          for j in range(nsets): # loop over the different testing files
                  f_waves = h5py.File(data_dir + '/' + testingFiles[j],mode='r') # Load testing
                  testacc = []
                  fozle = testingFiles[j]
                  file_edit = fozle.rfind('_')
                  datastr = fozle[file_edit+1: len(fozle)-4]
                  print(fozle)
                  waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
                  #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
                  for netname in netnames alt:
                      match = netnames alt.index(netname)
                      model_path = pjoin(model_dir, netname)
                      model = keras.models.load model(model path)
                      if match < numcnn:</pre>
                          x_test = waveforms[:, 1:(52+1)] # waveform voltage values
                          y_test = waveforms[:, 0] # waveform labels
                          x test = np.expand dims(x test, axis=2)
                          predicts CNN = model.predict(x test,verbose =0)
```

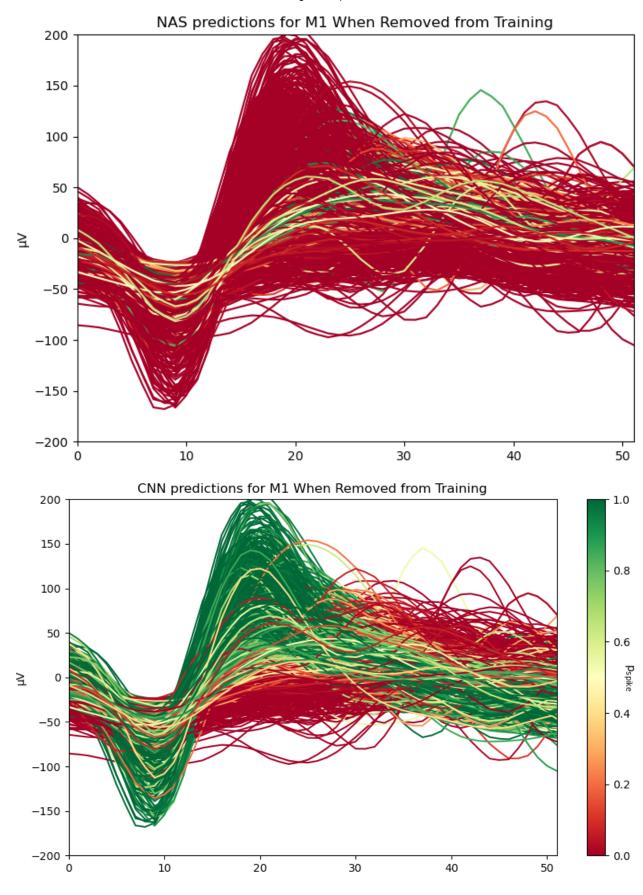
```
print(netname +" has acc of: "+str(predicts CNN) +" with " +str(model.c
        #print(predicts CNN.shape)
    else:
        #print('we made it')
        x test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
        #x_test = np.expand_dims(x_test, axis=2)
        y_test = waveforms[:, 0] # waveform labels
        predicts NAS = model.predict(x test,verbose =0)
        print(netname +" has acc of: "+str(predicts_NAS) +" with " +str(model.c
        #print(predicts_NAS.shape)
best g NAS = 0
best_g_{NN} = 0
g of CNN = 0.2
g_of_NAS = 0.2
ranger = np.arange(0,len(y test),1)
spikes are = ranger[y test == 1]
noise_are = ranger[y_test == 0]
lims = 200
#ch = fozle[fozle.find('_SNR')-2:fozle.find('_SNR')]
ch = fozle[fozle.find('ch')+2:fozle.find('ch')+3]
lab = 'M1'
rngvals = np.random.choice(len(predicts_NAS),3000)
t = np.arange(0,52)
plt.figure(figsize=(8, 6),dpi=100)
for r in rngvals:
    if y test[r] == 1:
        plt.plot(t,x_test[r,:],c='darkgreen', alpha=0.8)
    else:
        plt.plot(t,x_test[r,:],c='darkred', alpha=0.6)
plt.title('Hand Labeled Data for ' +lab)
plt.ylabel(u'\u03bcV')
plt.xlim([0, 51])
plt.ylim([-lims ,lims])
custom lines = [mpl.lines.Line2D([0], [0], color='g', lw=4),
        mpl.lines.Line2D([0], [0], color='brown', lw=4)]
plt.legend(custom lines, ['Spike ' + str(round(sum(y test)*100/len(y test)))+'%
plt.show()
n lines = 10
c = np.arange(1, n lines + 1)
norm = mpl.colors.Normalize(vmin=0, vmax=1)
cmap = mpl.cm.ScalarMappable(norm=norm, cmap='RdYlGn')
cmap.set array([])
fig, ax = plt.subplots(figsize=(8, 6),dpi=100)
for r in rngvals:
    ax.plot(t, x_test[r,:], c=cmap.to_rgba(predicts_NAS[r,0]))
#fig.colorbar(cmap)
plt.title('NAS predictions for ' +lab +' When Removed from Training')
plt.ylabel(u'\u03bcV')
plt.xlim([0, 51])
```

```
plt.ylim([-lims ,lims])
plt.show()

fig, ax = plt.subplots(figsize=(10, 6), dpi=100)
for r in rngvals:
        ax.plot(t, x_test[r,:], c=cmap.to_rgba(predicts_CNN[r,0]))
cbar = fig.colorbar(cmap)
params = {'mathtext.default': 'regular' }
plt.rcParams.update(params)
cbar.ax.set_ylabel('$p_{spike}$', rotation=270)
plt.title('CNN predictions for ' +lab+' When Removed from Training')
plt.ylabel(u'\u03bcV')
plt.xlim([0, 51])
plt.ylim([-lims,lims])
plt.show()
```

```
M1_52_testsmall.mat
CNN4L2d_opt_noM1 has acc of: [[7.1147454e-01]
[9.9899447e-01]
[7.4127906e-06]
...
[7.4729371e-01]
[8.4164274e-01]
[9.8519814e-01]] with 222576 params.
NAS_noM1 has acc of: [[8.5313957e-30]
[0.0000000e+00]
[2.8687716e-04]
...
[1.4983988e-28]
[7.2167754e-02]
[0.0000000e+00]] with 2701 params.
```



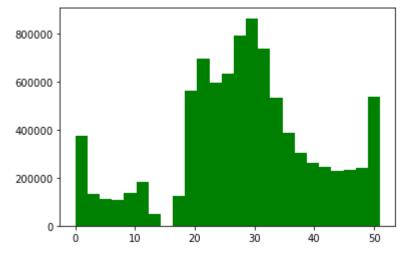


```
In [12]:
    data_dir = 'Z:/SmithLab/prjNAS/NASNet/test_all/' #all areas in one file
    testingFiles = []
    for file in os.listdir(data_dir): # pull all training files from directory
        if file.endswith(".mat"):
```

```
testingFiles.append(file)
          nsets = len(testingFiles) # singular testing file
          for j in range(nsets): # loop over the different testing files
                  f_waves = h5py.File(data_dir + '/' + testingFiles[j],mode='r') # Load testing
                  testacc = []
                  fozle = testingFiles[j]
                  file_edit = fozle.rfind('_')
                           = fozle[file_edit+1: len(fozle)-4]
                  datastr
                  print(fozle)
                  waveforms = np.transpose(f waves['waveData'][()]) #load all waveforms
                  #waveforms = waveforms[np.random.choice(len(waveforms),5000000), :]
                  for netname in netnames:
                      match = netnames.index(netname)
                      model path = pjoin(model dir, netname)
                      model = keras.models.load model(model path)
                      if match < numcnn:</pre>
                          x_test = waveforms[:, 1:(52+1)] # waveform voltage values
                          y test = waveforms[:, 0] # waveform labels
                          x test = np.expand dims(x test, axis=2)
                          #predicts CNNall = model.predict(x test, verbose =0)
                          print(netname +" has acc of: "+str(predicts CNNall) +" with " +str(mode
                          #print(predicts CNN.shape)
                      else:
                          #print('we made it')
                          x_test = waveforms[:, 1:(ntimepts+1)] # waveform voltage values
                          \#x test = np.expand dims(x test, axis=2)
                          y test = waveforms[:, 0] # waveform labels
                          predicts NASall = model.predict(x test,verbose =0)
                          print(netname +" has acc of: "+str(predicts_NASall) +" with " +str(mode
                          #print(predicts NAS.shape)
         full test.mat
         SmithCNNnet has acc of: [[0.7809308]
          [0.97026825]
          [0.9793009]
          [0.93613464]
          [0.5778552 ]
          [0.99800897]] with 222576 params.
         NAS full has acc of: [[0.6798997 ]
          [0.9861808]
          [0.8132093]
          [0.99515414]
          [0.86491585]
          [0.9824934 ]] with 2701 params.
In [13]:
          #figure 5 here, classification of all areas
          #histogram distribution of waveform/spike max and accuracy on that specific bin index
          gamma=0.48
          predlabel_CNN = predicts_CNNall[:,0] > gamma
```

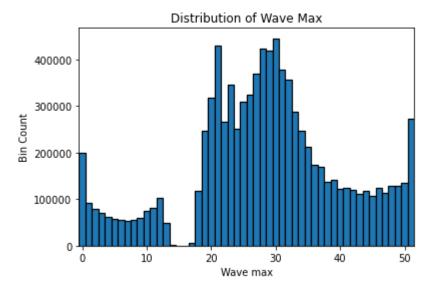
```
predlabel NAS = predicts NASall[:,0] > (gamma)
# Get the histogramp
Y,X = np.histogram(max_idx, 52,range=((0,51)))
bins = 52
t waves = np.zeros(bins)
cor_waves = np.zeros((bins,2))
err waves = np.zeros(bins)
for maxW in np.arange(0,52):
    idx = 0
    for maxval in max idx:
        t_waves[maxval] = t_waves[maxval] + 1
        if predlabel_CNN[idx] == y_test[idx]:
            cor_waves[maxval,1] = cor_waves[maxval,1] + 1
        if predlabel_NAS[idx] == y_test[idx]:
            cor waves[maxval,0] = cor waves[maxval,0] + 1
        idx = idx + 1
```

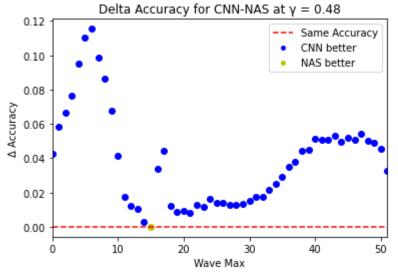
```
In [14]:
          Ys,Xs = np.histogram(max_idx_spike, 52,range=((0,51)))
          bins = 52
          t_spike = np.zeros(bins)
          cor spike = np.zeros((bins,2))
          for maxW in np.arange(0,52):
              idx = 0
              for maxval in max idx:
                   if y_test[idx] == 1:
                       t spike[maxval] = t spike[maxval] + 1
                       if predlabel_CNN[idx] == y_test[idx]:
                           cor spike[maxval,1] = cor spike[maxval,1] + 1
                       if predlabel NAS[idx] == y test[idx]:
                           cor_spike[maxval,0] = cor_spike[maxval,0] + 1
                   idx = idx + 1
          n, bins, patches = plt.hist(max_idx, 25, color='green')
          bin centers = 0.5 * (bins[:-1] + bins[1:])
          plt.show()
```



```
In [15]:
#binned accuracy for each network type over relative waveform max
p_NAS = cor_waves[:,0]/t_waves
p_CNN = cor_waves[:,1]/t_waves
''''
''''
```

```
norm1 = p NAS/np.linalg.norm(p NAS)
norm2 = p CNN/np.linalg.norm(p CNN)
col = bin centers - min(bin centers)
col /= max(col)
c map = plt.cm.get cmap('binary', 15)
p both = np.concatenate([p NAS, p CNN])
cm = c map(p both)
norm1 = p NAS/np.linalg.norm(p NAS)
norm2 = p CNN/np.linalg.norm(p CNN)
col = bin_centers - min(bin_centers)
col /= max(col)
c map = plt.cm.get cmap('binary', 15)
p_both = np.concatenate([p_NAS, p_CNN])
cm = c map(p both)
# histograms and delta accuracies
Y,X = np.histogram(max idx, 52, range=(0,52))
x span = X.max()-X.min()
bin_centers = 0.5 * (X[:-1] + X[1:])
\#ax = plt.bar(X[:-1], Y, color=cm[0:51,:], width=X[1]-X[0])
ax = plt.bar(X[:-1],Y,width=X[1]-X[0],edgecolor='black', linewidth=1.2)
plt.xlim([0-0.5,51+0.5])
#sm = plt.cm.ScalarMappable(cmap=c map, norm=plt.Normalize(min(p both), max(p both)))
#sm.set array([])
#cbar = plt.colorbar(sm)
plt.title("Distribution of Wave Max")
plt.xlabel('Wave max')
plt.ylabel('Bin Count')
plt.show()
plt.figure()
idxa = 0
CNNbetterc =0
for p in p_CNN:
    if p-p NAS[idxa] > 0:
        plt.scatter(idxa,p-p NAS[idxa],c='b')
        CNNbetterc = CNNbetterc+1
    else:
        plt.scatter(idxa,p-p NAS[idxa],c='y')
    idxa = idxa+1
#plt.plot(np.arange(0,52),p CNN-p NAS,'b')
plt.plot(np.arange(0,52),np.zeros([52, 1]),'r--')
plt.title(u"Delta Accuracy for CNN-NAS at \u03B3 = 0.48")
plt.xlabel('Wave Max')
plt.ylabel(u'\u0394 Accuracy')
legend elements = [mpl.lines.Line2D([0], [0], color='r', linestyle='--', label='Same Ac
    mpl.lines.Line2D([0], [0], color='w', marker='o', label='CNN better', markerfacecol
           mpl.lines.Line2D([0], [0], marker='o', color='w', label='NAS better', marker
plt.legend(handles=legend elements, loc='upper right')
plt.xlim([0, 51])
plt.show()
print(CNNbetterc)
```

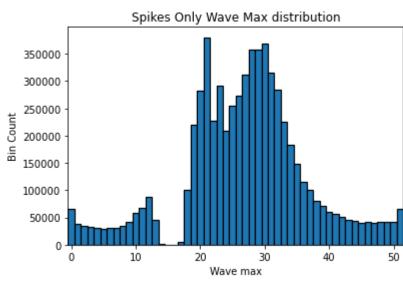




51

```
In [16]:
          #binned accuracy for each network type over relative spike waveform max
          p_NAS = cor_spike[:,0]/t_spike
          p_CNN = cor_spike[:,1]/t_spike
          norm1 = p NAS/np.linalg.norm(p NAS)
          norm2 = p_CNN/np.linalg.norm(p_CNN)
          col = bin_centers - min(bin_centers)
          col /= max(col)
          c_map = plt.cm.get_cmap('binary', 15)
          p_both = np.concatenate([p_NAS, p_CNN])
          cm = c_map(p_both)
          Y,X = np.histogram(max_idx_spike, 52, range=(0,52))
          x_span = X.max()-X.min()
          ax = plt.bar(X[:-1],Y,width=X[1]-X[0],edgecolor='black', linewidth=1.2)
          plt.xlim([0-0.5,51+0.5])
          #sm = plt.cm.ScalarMappable(cmap=c map, norm=plt.Normalize(min(p both), max(p both)))
          #sm.set_array([])
          plt.title("Spikes Only Wave Max distribution")
          plt.xlabel('Wave max')
```

```
plt.ylabel('Bin Count')
plt.show()
. . .
plt.figure()
idxa = 0
CNNbetterc =0
for p in p_CNN:
    if p-p NAS[idxa] > 0:
        plt.scatter(idxa,p-p NAS[idxa],c='b')
        CNNbetterc = CNNbetterc+1
    else:
        plt.scatter(idxa,p-p_NAS[idxa],c='y')
    idxa = idxa+1
#plt.plot(np.arange(0,52),p_CNN-p_NAS,'b')
plt.plot(np.arange(0,52),np.zeros([52, 1]),'r--')
plt.title(u"Delta Accuracy for CNN-NAS at \u03B3 = 0.48 (Spikes Only)")
plt.xlabel('Wave Max')
plt.ylabel(u'\u0394 Accuracy')
#plt.legend(['Same Accuracy', 'CNN better', 'NAS better'])
legend_elements = [mpl.lines.Line2D([0], [0], color='r', linestyle='--', label='Same Ac
    mpl.lines.Line2D([0], [0], color='w', marker='o', label='CNN better', markerfacecol
           mpl.lines.Line2D([0], [0], marker='o', color='w', label='NAS better', marker
plt.legend(handles=legend elements, loc='upper right')
plt.xlim([0, 51])
plt.show()
print(CNNbetterc)
```



47

