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MATH 6373 Final Exam Part 1: Application of Convolution Neural Network on Fonts Dataset for Classification

1. Data Set Presentation

The set of data, Character Font Images Dataset, is obtained from University of California Irvine's machine learning repository and may be found in the following link:

<https://archive.ics.uci.edu/ml/datasets/Character+Font+Images>

We will select 8 fonts among the 50 fonts available, each font considered as a class for prediction.

The image height and width in this sample are always 20x20, 400 columns grayscale pixels representing images of characters and numbers.

Furthermore, we will combine the 8 fonts csv files together and create a "true class" column based on the given font for classification.

The input variables (based on computer vision):

- | | | |
|--|--|--|
| • CL1 – Castellar:
size(CL1) = 1056 | • CL4 – English:
size(CL4) = 968 | • CL7 – Matura:
size(CL7) = 956 |
| • CL2 – Rage:
size(CL2) = 976 | • CL5 – Gloucester:
size(CL5) = 956 | • CL8 – Californian:
size(CL8) = 1004 |
| • CL3 – French:
size(CL3) = 984 | • CL6 – Brush:
size(CL6) = 956 | |

There is no categorical variable and the output variable in which we will attempt to classify would be the class of fonts.

Some potential use cases include:

- Optical character recognition: The dataset can be used to train machine learning models for recognizing and transcribing handwritten text into digital format.
- Handwriting analysis: The dataset can be used to develop algorithms that can identify individual handwriting styles and distinguish between different writers.
- Signature verification: The dataset can be used to train models that can identify and verify signatures on documents.
- Linguistics research: The dataset can be used to study the characteristics of different alphabets and scripts, and to investigate the similarities and differences between handwriting styles across different languages and cultures.
- Education: The dataset can be used to develop educational tools and resources for teaching handwriting and handwriting recognition to students.

Data Preparation:

In total, there are about 7856 cases in this dataset. All classes of chosen datasets are fairly balanced as observed in our original proposal. But we want to increase the number of cases per class in order to have a more robust neural network. We will implement horizontal flipping, in which we will flip the images horizontally to increase the number of cases by a multiple of 2 to each class, while also maintaining the original pixelated data.

The new dataset with horizontally flipped images will contain 15712 total cases:

- CL1 – Castellar:
size(CL1) = 2112
- CL2 – Rage:
size(CL2) = 1952
- CL3 – French:
size(CL3) = 1968
- CL4 – English:
size(CL4) = 1936
- CL5 – Gloucester:
size(CL5) = 1912
- CL6 – Brush:
size(CL6) = 1912
- CL7 – Matura:
size(CL7) = 1912
- CL8 – Californian:
size(CL8) = 2008

Each font case from our dataset is represented by a row of 400 pixels, we then can reshape the 400 pixels from dimensions of (15712 x 400) into (15712 x 20 x 20), thereby representing a grid of 20 x 20 for imaging. A single case of the font is represented by (1 x 20 x 20), where we will reserve 90% of total cases for training and 10% for testing.

Below is the code that was used to reshape the 400 pixels into a 20 x 20 format, then flip horizontally.

```
In [5]: # reshape the 400 pixel to a 20 x 20
x = dfs.loc[:,dfs.columns.str.startswith('r')].values
print(x.shape)
x = x.reshape(-1, 20, 20)
print(x.shape)
```

executed in 24ms, finished 13:39:35 2023-05-02

```
(7856, 400)
(7856, 20, 20)
```

```
In [6]: # function to rotate image
def rotation(img_mat):
    return np.fliplr(img_mat)
```

executed in 9ms, finished 13:39:36 2023-05-02

```
In [7]: # create empty array to store the images
x_rotated = np.zeros((7856*2, 20, 20))
```

executed in 17ms, finished 13:39:38 2023-05-02

```
In [8]: # flip each array once and store in new array
for i in range(x.shape[0]):
    x_rotated[2*i] = x[i]
    x_rotated[(2*i)+1] = rotation(x[i])
x_rotated.shape
```

executed in 46ms, finished 13:39:38 2023-05-02

```
Out[8]: (15712, 20, 20)
```

Below is an example of the fonts and their respective horizontal flipping applied.

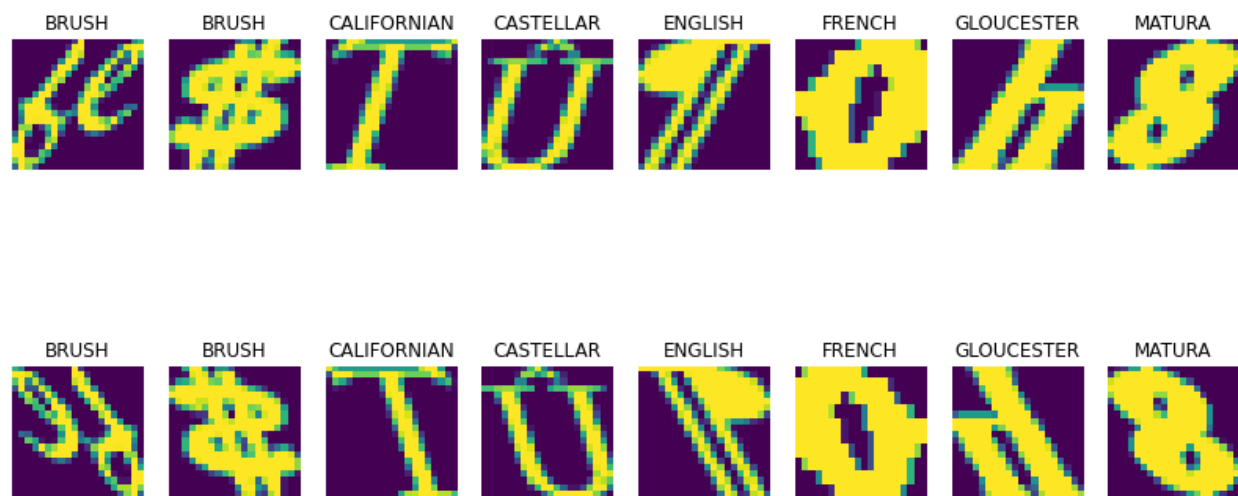


Figure 1: Fonts with their respective horizontal flipping applied below

2. CNN Architecture & First Automatic Training

Our CNN model will feature the following architecture:

Input → Convolution #1 → Maxpool #1 → Convolution #2 → Maxpool #2 → flattening layer (F) → hidden layer (H) → pre-output → softmax → probability output

We will attempt the following sensitivity changes on our parameters:

1. Number of channels in convolution layer 1, CL1
 - a. Varying numbers: 8, 16, 24
2. Kernel size of convolution layer 1, KL1
 - a. Varying window sizes: 3x3, 5x5
3. Number of channels in convolution layer 2, CL2
 - a. Same number of channels as first convolutional layer
4. Kernel size of convolution layer 2, KL2
 - a. Varying window sizes: 2x2, 3x3

We will try $h = \text{dim}(F)/2$ for our first run of automatic training, F = dimension of our flattened layer; note this can be improved later on after our first run-through.

All max pool layers will be kept at stride=2 and window 2x2 with no padding.

Our output dimensions for each layer can be computed with the following formulas:

$\text{Width}_{\text{out}} = (\text{Width}_{\text{in}} - \text{Kernel size} + 2 * \text{padding size}) / (\text{stride size}) + 1$

$\text{Height}_{\text{out}} = (\text{Height}_{\text{in}} - \text{Kernel size} + 2 * \text{padding size}) / (\text{stride size}) + 1$

Dimensions of our varying CNN models:

Case Model	CL1	KL1	Output Dim1	Maxpool1	Output Dim2	CL2	KL2	Output Dim3	Maxpool2	Output Dim4	Flattened	H = F/2	Output Layer
Model_8_3_16_2	8	3x3	18x18x8	2x2	9x9x8	16	2x2	8x8x16	2x2	4x4x16	256	128	8
Model_8_3_16_3	8	3x3	18x18x8	2x2	9x9x8	16	3x3	7x7x16	2x2	3x3x16	144	72	8
Model_8_3_8_3	8	3x3	18x18x8	2x2	9x9x8	8	3x3	7x7x8	2x2	3x3x8	72	36	8
Model_8_3_8_2	8	3x3	18x18x8	2x2	9x9x8	8	2x2	8x8x8	2x2	4x4x8	128	64	8
Model_8_5_24_2	8	5x5	16x16x8	2x2	8x8x8	24	2x2	7x7x24	2x2	3x3x24	216	108	8
Model_8_5_24_3	8	5x5	16x16x8	2x2	8x8x8	24	3x3	6x6x24	2x2	3x3x24	216	108	8
Model_16_5_32_2	16	5x5	16x16x16	2x2	8x8x16	32	2x2	7x7x32	2x2	3x3x32	288	144	8
Model_16_5_32_3	16	5x5	16x16x16	2x2	8x8x16	32	3x3	6x6x32	2x2	3x3x32	288	144	8
Model_24_5_48_2	24	5x5	16x16x24	2x2	8x8x24	48	2x2	7x7x58	2x2	3x3x48	432	216	8
Model_24_5_48_3	24	5x5	16x16x24	2x2	8x8x24	48	3x3	6x6x48	2x2	3x3x48	432	216	8
Model_16_3_16_2	16	3x3	18x18x16	2x2	9x9x16	16	2x2	8x8x16	2x2	4x4x16	256	128	8
Model_16_5_16_3	16	5x5	16x16x16	2x2	8x8x16	16	3x3	6x6x16	2x2	3x3x16	144	72	8

Example for the naming convention of our models: Model_8_3_16_2

- 8 channels in convolution layer 1
- 3x3 kernel size in convolution layer 1
- 16 channels in convolution layer 2
- 2x2 kernel size in convolution layer 2

From our table column naming convention:

- Case model: models with different cases
- CL1: channels of convolution layer 1
- KL1: kernel size of convolution layer 1
- Output Dim1: dimensions of convolution layer 1
- Maxpool1: max pool of stride 2 applied to convolution layer 1
- Output Dim2: dimensions of max pool 1
- CL2: channels of convolution layer 2
- KL2: kernel size of convolution layer 2
- Output Dim3: dimensions of convolution layer 2
- Maxpool2: max pool of stride 2 applied to convolution layer 2
- Output Dim4: dimensions of max pool 2
- Flattened: dimension of flattened max pool 2 output
- H = hidden layer dimensions after flattening
- Output layer: size of predicted class

Selection of Best Epoch criterion:

We can select the best epoch for individual models by observing the loss and accuracy during training. We should look for an epoch where the loss decreasing stabilizes, no longer decreasing for each epoch thereafter. The epoch should also be where accuracy of test set < accuracy of train set but high enough to be considered a good result. Each “best epoch” will be shown on the respective training curves.

Learning Algorithm Parameters:

- Batch size: 100; recommended between [80, $\sqrt{\text{trainset size}}=118$]
- Optimizer: categorical cross entropy for multi-class classification tasks
- Learning rate: 0.003, epoch: 150
- Dropout: dropout layer with value of 0.2 to increase robustness
- Activation function: RELU used in convolution and hidden layers
- Kernel Initializer: glorot uniform

Parsimony Ratio:

Number of information = number of classes to predict * training set cases = 8 * 14140 = 113120

Model	# of Parameters	# of Information	Parsimony Ratio
Model_8_3_16_2	34536	113120	3.28
Model_8_3_16_3	12272	113120	9.22
Model_8_3_8_3	3588	113120	31.53
Model_8_3_8_2	9120	113120	12.40
Model_8_5_24_2	25308	113120	4.47
Model_8_5_24_3	26268	113120	4.31
Model_16_5_32_2	45272	113120	2.50
Model_16_5_32_3	47832	113120	2.36
Model_24_5_48_2	100544	113120	1.13
Model_24_5_48_3	106304	113120	1.06
Model_16_3_16_2	35128	113120	3.22
Model_16_5_16_3	13504	113120	8.38

Weights and Thresholds of CNN:

Model Name: model_8_3_16_2			
Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_32	72	8	80
max_pooling2d_32	-	-	0
conv2d_33	512	16	528
max_pooling2d_33	-	-	0
flatten_16	-	-	0
dense_32	32768	128	32896
dropout_16	-	-	0
dense_33	1024	8	1032
Model Name: model_8_3_16_3			
Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_34	72	8	80
max_pooling2d_34	-	-	0
conv2d_35	1152	16	1168
max_pooling2d_35	-	-	0
flatten_17	-	-	0
dense_34	10368	72	10440
dropout_17	-	-	0
dense_35	576	8	584
Model Name: model_8_3_8_3			
Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_30	72	8	80
max_pooling2d_30	-	-	0
conv2d_31	576	8	584
max_pooling2d_31	-	-	0
flatten_15	-	-	0
dense_30	2592	36	2628
dropout_15	-	-	0
dense_31	288	8	296

Model Name: model_8_3_8_2

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_28	72	8	80
max_pooling2d_28	-	-	0
conv2d_29	256	8	264
max_pooling2d_29	-	-	0
flatten_14	-	-	0
dense_28	8192	64	8256
dropout_14	-	-	0
dense_29	512	8	520

Model Name: model_8_5_24_2

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_36	200	8	208
max_pooling2d_36	-	-	0
conv2d_37	768	24	792
max_pooling2d_37	-	-	0
flatten_18	-	-	0
dense_36	23328	108	23436
dropout_18	-	-	0
dense_37	864	8	872

Model Name: model_8_5_24_3

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_38	200	8	208
max_pooling2d_38	-	-	0
conv2d_39	1728	24	1752
max_pooling2d_39	-	-	0
flatten_19	-	-	0
dense_38	23328	108	23436
dropout_19	-	-	0
dense_39	864	8	872

Model Name: model_16_5_32_2

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_44	400	16	416
max_pooling2d_44	-	-	0
conv2d_45	2048	32	2080
max_pooling2d_45	-	-	0
flatten_22	-	-	0
dense_44	41472	144	41616
dropout_22	-	-	0
dense_45	1152	8	1160

Model Name: model_16_5_32_3

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_46	400	16	416
max_pooling2d_46	-	-	0
conv2d_47	4608	32	4640
max_pooling2d_47	-	-	0
flatten_23	-	-	0
dense_46	41472	144	41616
dropout_23	-	-	0
dense_47	1152	8	1160

Model Name: model_24_5_48_2

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_48	600	24	624
max_pooling2d_48	-	-	0
conv2d_49	4608	48	4656
max_pooling2d_49	-	-	0
flatten_24	-	-	0
dense_48	93312	216	93528
dropout_24	-	-	0
dense_49	1728	8	1736

Model Name: model_24_5_48_3

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_50	600	24	624
max_pooling2d_50	-	-	0
conv2d_51	10368	48	10416
max_pooling2d_51	-	-	0
flatten_25	-	-	0
dense_50	93312	216	93528
dropout_25	-	-	0
dense_51	1728	8	1736

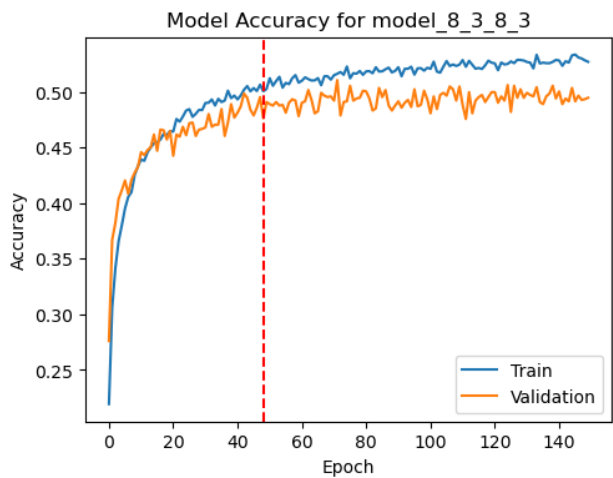
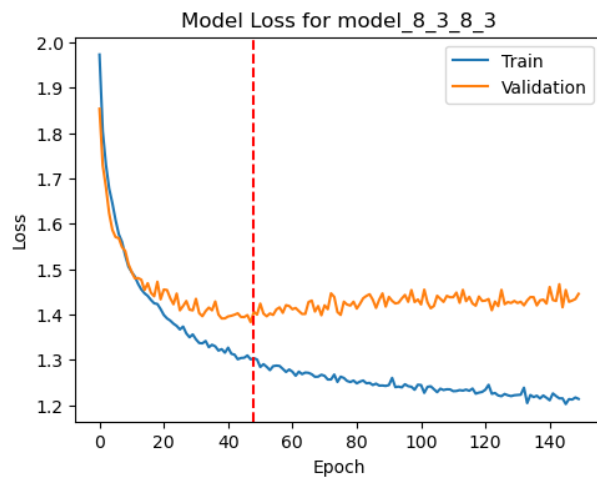
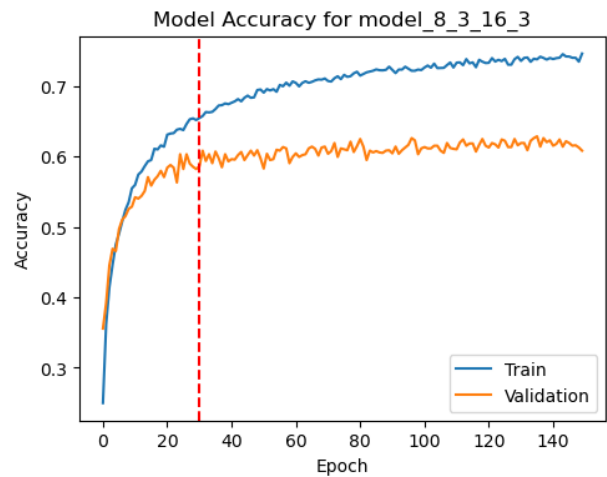
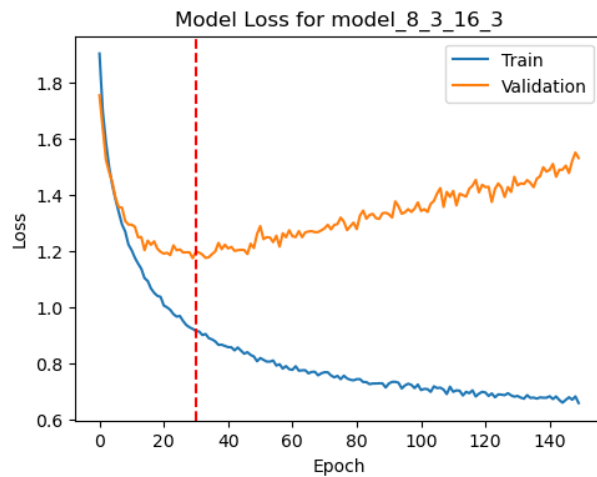
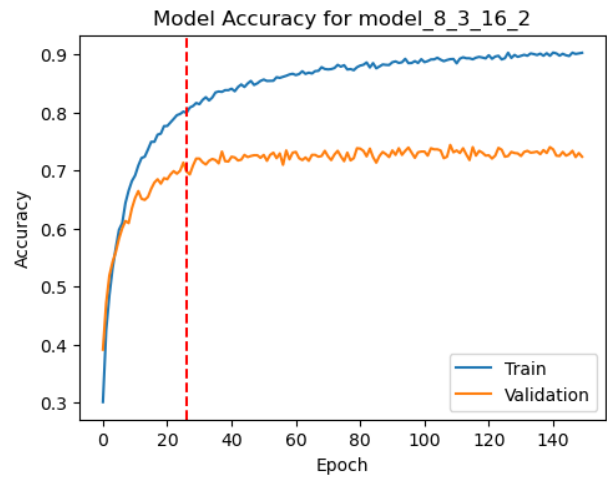
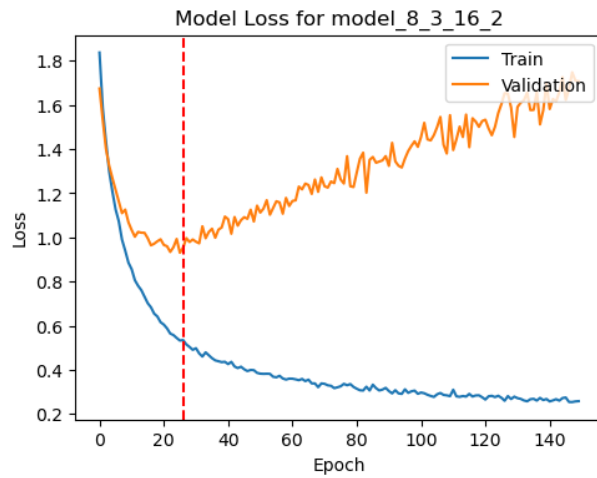
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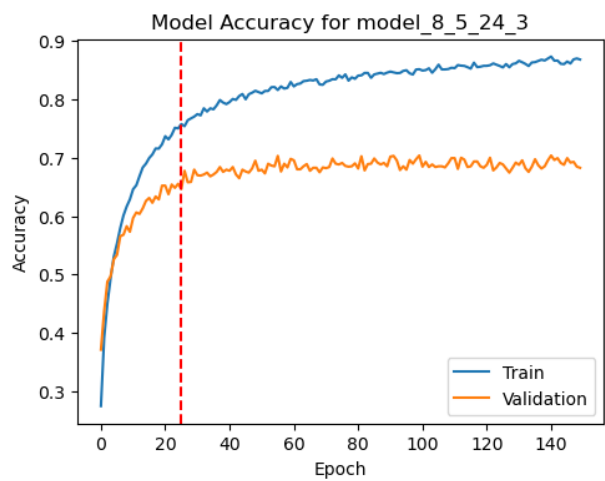
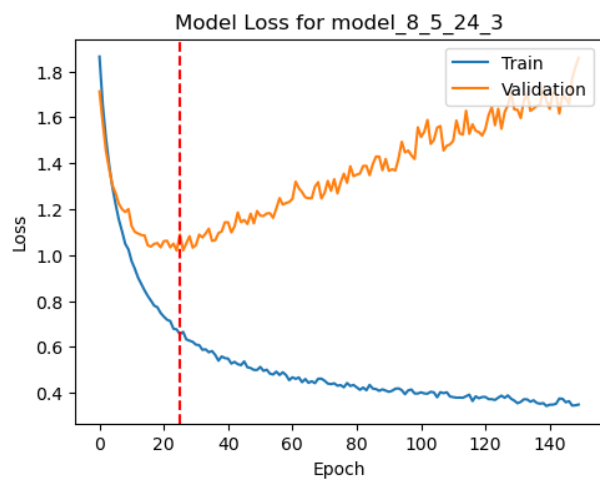
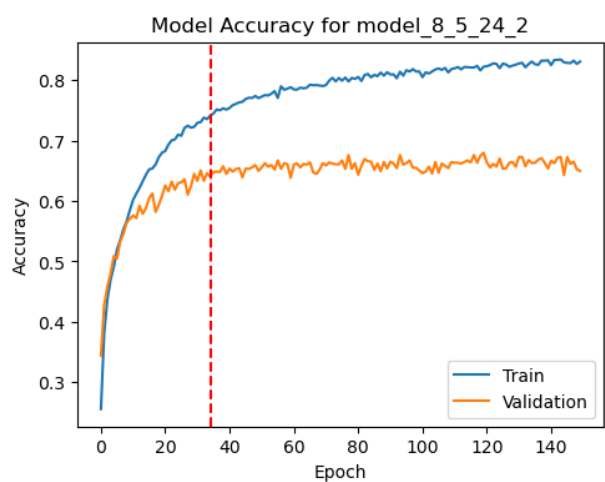
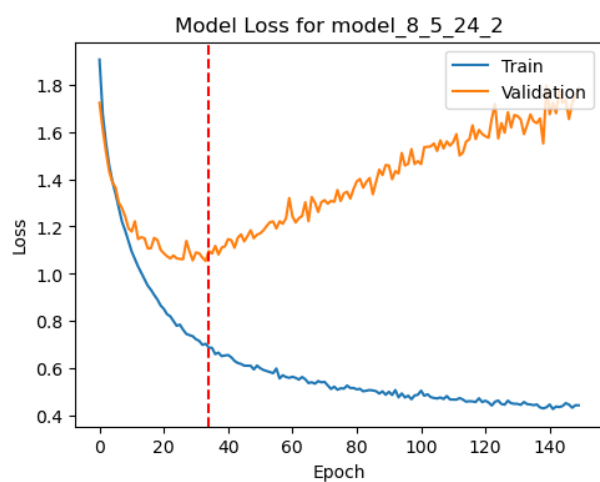
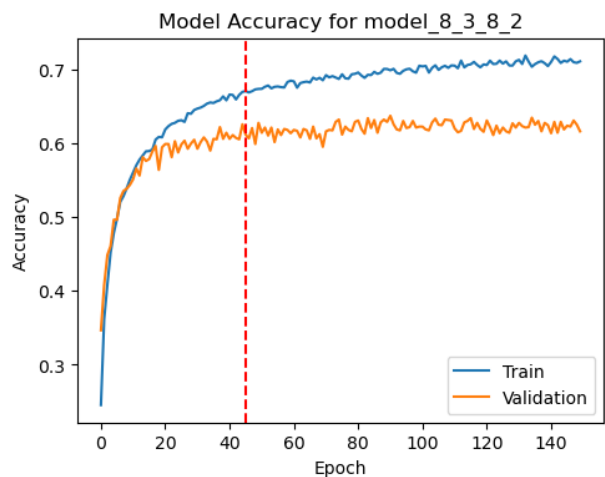
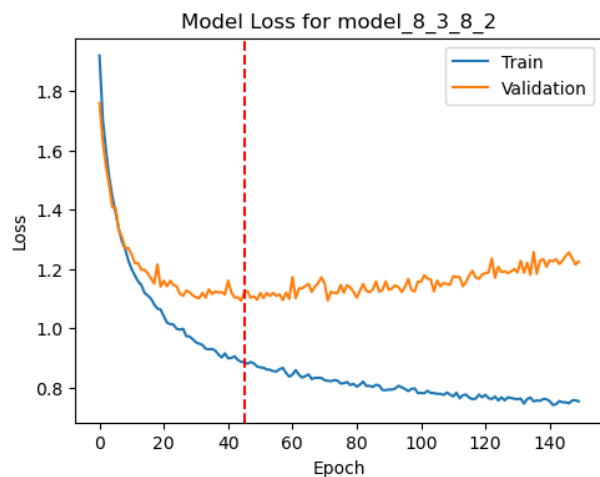
Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_40	144	16	160
max_pooling2d_40	-	-	0
conv2d_41	1024	16	1040
max_pooling2d_41	-	-	0
flatten_20	-	-	0
dense_40	32768	128	32896
dropout_20	-	-	0
dense_41	1024	8	1032

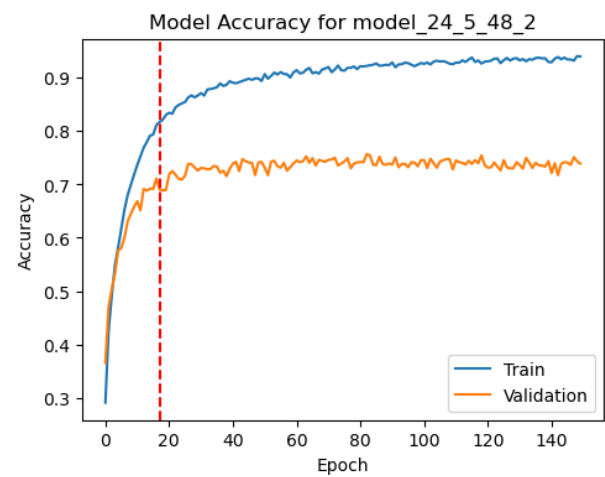
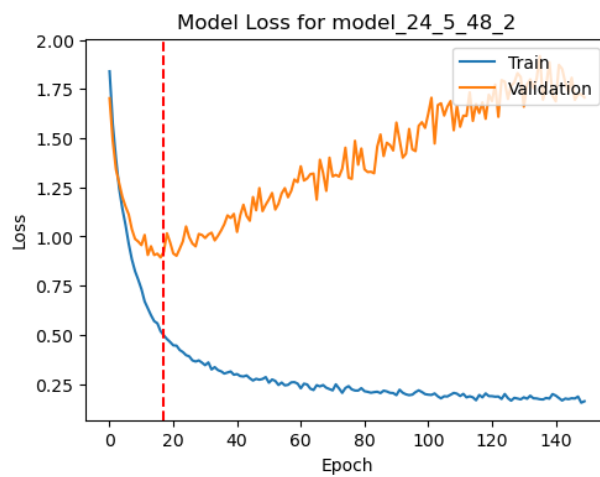
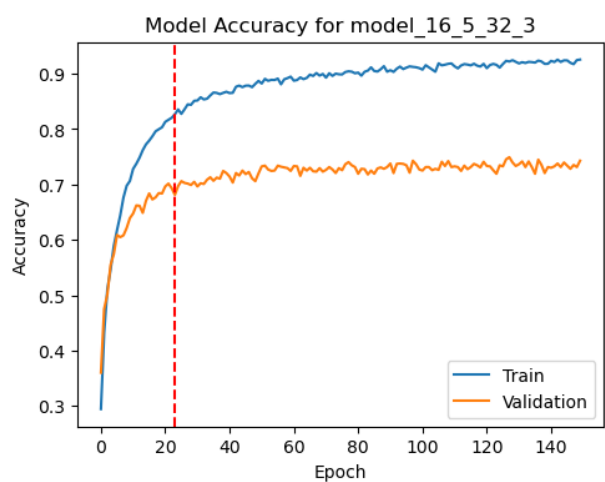
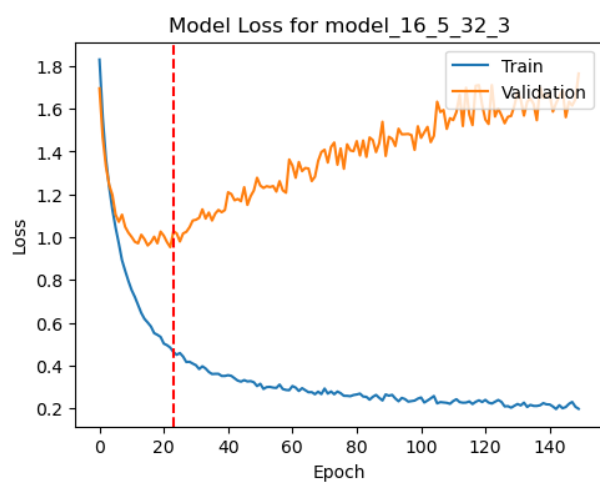
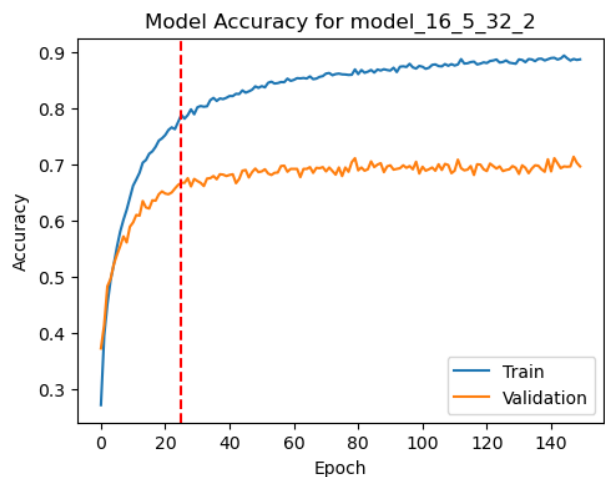
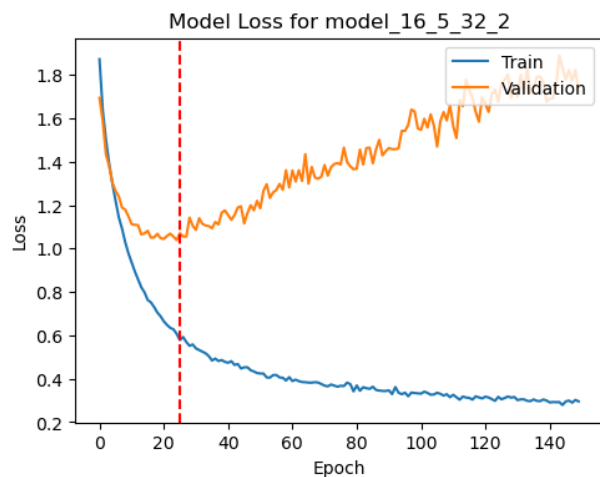
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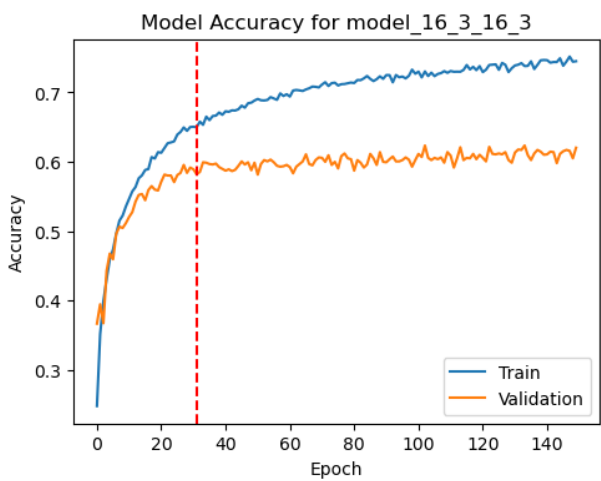
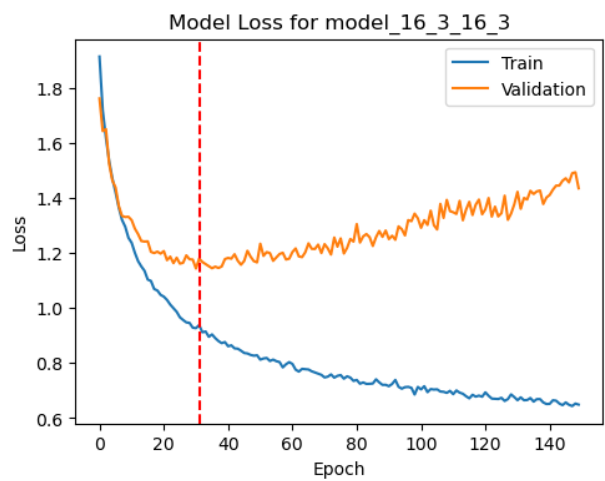
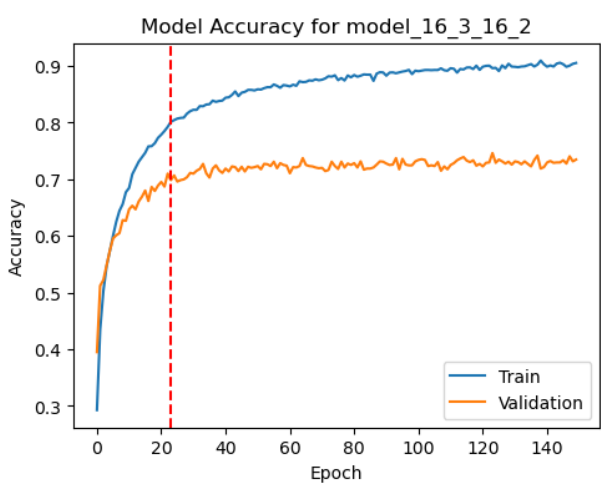
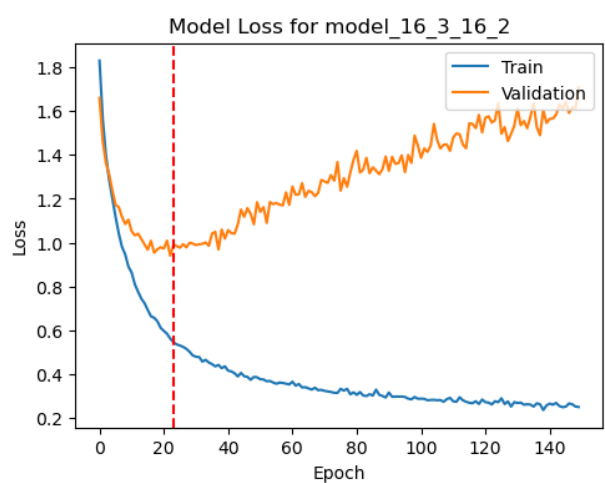
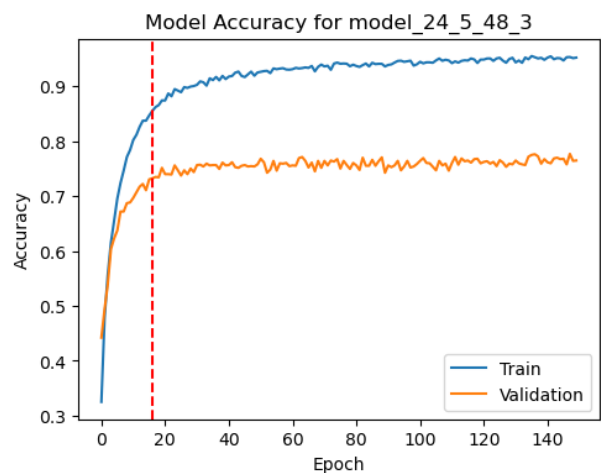
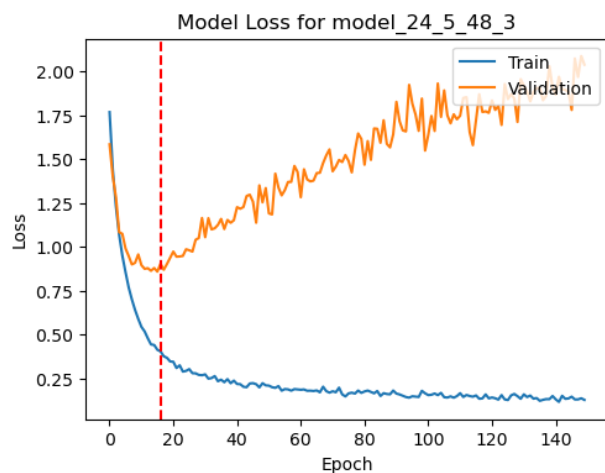
Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_42	144	16	160
max_pooling2d_42	-	-	0
conv2d_43	2304	16	2320
max_pooling2d_43	-	-	0
flatten_21	-	-	0
dense_42	10368	72	10440
dropout_21	-	-	0
dense_43	576	8	584

Automatic Training Loss and Accuracy for First Run:









3. Epoch k* of Best Performance for Each CNN Model

Model Name	Epoch	Training Time
model_8_3_16_2	26	0.7
model_8_3_16_3	30	0.75
model_8_3_8_3	48	0.76
model_8_3_8_2	45	0.72
model_8_5_24_2	34	0.79
model_8_5_24_3	25	0.93
model_16_5_32_2	25	1.14
model_16_5_32_3	23	1.58
model_24_5_48_2	17	1.76
model_24_5_48_3	16	1.77
model_16_3_16_2	23	0.88
model_16_3_16_3	31	0.97

Note: training time is in seconds (s)

4. Compare Best Performance Amongst Difference CNN Models

Model Name	Train Accuracy (Best Epoch)	Test Accuracy (Best Epoch)	Best Epoch	Robustness Ratios
model_8_3_16_2	0.8	0.71	26	0.89
model_8_3_16_3	0.65	0.58	30	0.89
model_8_3_8_3	0.51	0.5	48	0.98
model_8_3_8_2	0.67	0.63	45	0.93
model_8_5_24_2	0.74	0.65	34	0.88
model_8_5_24_3	0.75	0.66	25	0.87
model_16_5_32_2	0.78	0.66	25	0.86
model_16_5_32_3	0.82	0.69	23	0.84
model_24_5_48_2	0.81	0.71	17	0.88
model_24_5_48_3	0.85	0.73	16	0.86
model_16_3_16_2	0.79	0.71	23	0.9
model_16_3_16_3	0.65	0.59	31	0.91

For the performance of our models, the best was a test accuracy of 73% obtained by model_24_5_48_3, followed by model_8_3_16_2, model_24_5_48_2, and model_16_3_16_2. All four models have relatively similar robustness ratios which are in the range [0.86, 0.9]. We select model_24_5_48_3, for having the highest test accuracy, and for the other 3, we select the one with the highest robustness ratio, which would be model_16_3_16_2 with an accuracy of 71% and robustness ratio of 0.9. When comparing the two models, model_16_3_16_2's worst class of prediction was English with an accuracy of 61%, while it's best class of prediction was Castellar at 83%. Model_24_5_48_3's worst class of prediction was Rage at 64% while its best class was Castellar at 90%. For sake of accuracy, we will pick the best model as model_24_5_48_3.

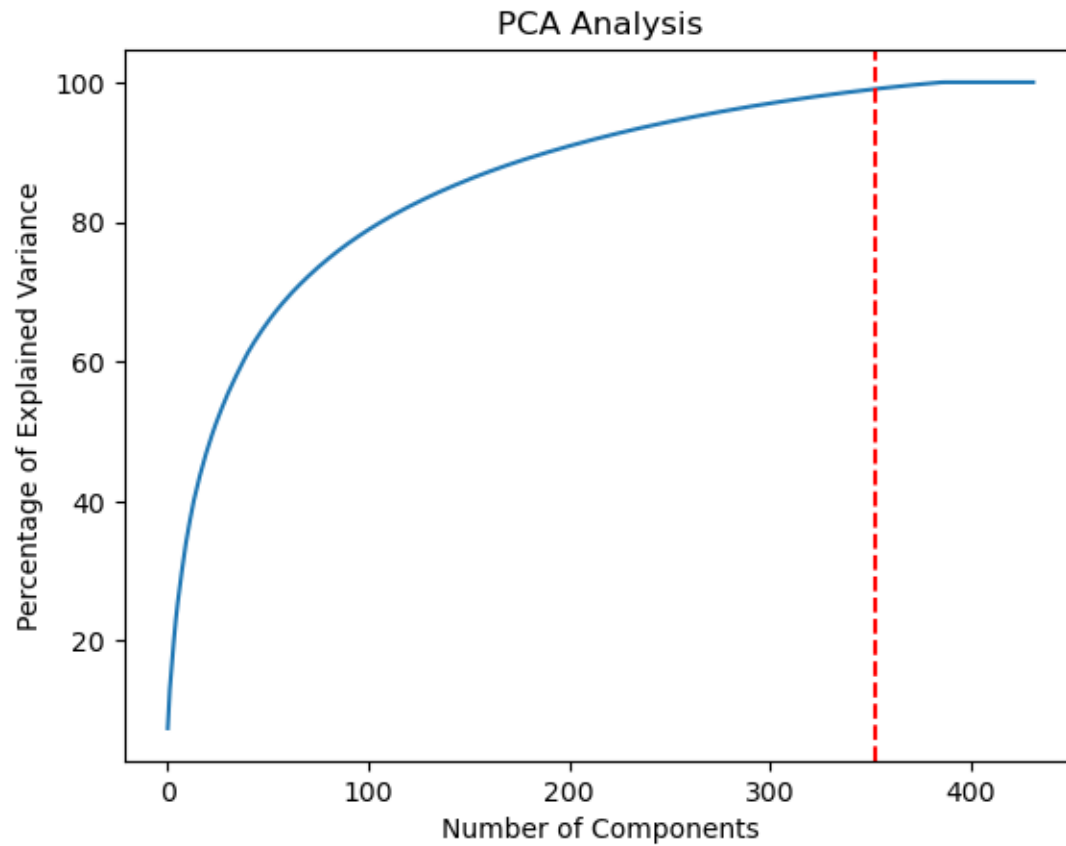
Confusion Matrices of each CNN Model

Model_8_3_16_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	88%	0%	0%	4%	2%	2%	1%	3%
Californian	1%	66%	12%	9%	4%	4%	0%	1%
French	2%	7%	68%	6%	6%	8%	1%	2%
Rage	4%	2%	3%	74%	4%	7%	4%	3%
English	1%	5%	8%	4%	67%	5%	3%	6%
Brush	5%	3%	4%	10%	2%	66%	5%	6%
Gloucester	2%	2%	3%	11%	1%	6%	72%	2%
Matura	8%	2%	4%	5%	6%	3%	3%	71%
Model_8_3_16_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	73%	2%	2%	1%	6%	5%	2%	9%
Californian	3%	54%	17%	3%	11%	4%	3%	2%
French	4%	11%	61%	3%	9%	7%	2%	4%
Rage	8%	7%	2%	52%	8%	15%	5%	3%
English	2%	11%	7%	7%	53%	7%	7%	8%
Brush	5%	8%	8%	6%	5%	58%	5%	5%
Gloucester	9%	5%	2%	5%	9%	11%	55%	2%
Matura	13%	6%	4%	3%	8%	4%	5%	59%
Model_8_3_8_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	65%	4%	1%	3%	2%	3%	13%	9%
Californian	3%	42%	23%	7%	9%	4%	8%	3%
French	5%	10%	53%	3%	7%	7%	9%	5%
Rage	7%	8%	3%	42%	4%	16%	14%	5%
English	7%	10%	7%	6%	38%	5%	14%	13%
Brush	8%	6%	3%	12%	3%	48%	17%	4%
Gloucester	12%	7%	2%	6%	1%	6%	62%	4%
Matura	19%	5%	4%	4%	6%	3%	13%	49%
Model_8_3_8_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	73%	3%	2%	2%	1%	1%	4%	15%
Californian	6%	62%	13%	3%	6%	4%	3%	1%
French	3%	12%	62%	4%	6%	6%	4%	2%
Rage	4%	5%	1%	59%	7%	8%	11%	5%
English	4%	7%	8%	4%	57%	5%	7%	8%
Brush	7%	6%	3%	6%	8%	58%	3%	9%
Gloucester	7%	6%	2%	9%	4%	8%	61%	3%
Matura	9%	3%	4%	4%	7%	2%	6%	68%

Model_8_5_24_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	79%	4%	3%	3%	2%	0%	6%	4%
Californian	1%	70%	12%	4%	5%	3%	2%	1%
French	3%	12%	61%	4%	7%	4%	6%	4%
Rage	7%	5%	4%	60%	4%	11%	9%	0%
English	1%	12%	5%	7%	58%	7%	6%	4%
Brush	6%	5%	4%	10%	7%	56%	7%	5%
Gloucester	6%	8%	2%	4%	2%	5%	68%	5%
Matura	10%	3%	3%	5%	5%	3%	6%	67%
Model_8_5_24_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	82%	3%	1%	4%	1%	1%	2%	7%
Californian	2%	67%	9%	7%	2%	6%	3%	2%
French	2%	7%	65%	4%	9%	6%	3%	4%
Rage	7%	4%	3%	56%	4%	11%	13%	2%
English	4%	8%	7%	5%	60%	4%	6%	5%
Brush	5%	3%	3%	9%	7%	60%	8%	5%
Gloucester	3%	4%	0%	9%	3%	5%	70%	7%
Matura	9%	4%	4%	6%	4%	4%	4%	66%
Model_16_5_32_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	84%	0%	2%	1%	4%	1%	3%	5%
Californian	1%	58%	12%	3%	12%	6%	5%	1%
French	4%	3%	66%	3%	9%	7%	4%	4%
Rage	5%	2%	3%	52%	9%	13%	15%	1%
English	4%	8%	6%	5%	58%	8%	4%	7%
Brush	6%	1%	2%	5%	5%	71%	5%	5%
Gloucester	3%	1%	1%	2%	9%	6%	74%	4%
Matura	6%	3%	3%	2%	8%	5%	4%	70%
Model_16_5_32_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	80%	2%	1%	8%	2%	0%	3%	5%
Californian	1%	75%	7%	4%	5%	4%	1%	1%
French	2%	8%	69%	3%	9%	6%	1%	2%
Rage	5%	5%	5%	69%	2%	7%	3%	4%
English	5%	11%	8%	4%	60%	3%	5%	4%
Brush	4%	6%	3%	10%	5%	65%	5%	2%
Gloucester	6%	4%	1%	8%	3%	6%	69%	2%
Matura	6%	7%	5%	3%	5%	2%	5%	69%

Model_24_5_48_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	83%	0%	3%	2%	1%	6%	3%	3%
Californian	1%	76%	6%	5%	2%	7%	2%	0%
French	4%	5%	74%	3%	3%	5%	3%	3%
Rage	6%	4%	3%	65%	2%	14%	4%	1%
English	3%	9%	7%	9%	60%	5%	3%	4%
Brush	5%	5%	4%	8%	3%	66%	6%	4%
Gloucester	2%	3%	4%	9%	0%	6%	76%	1%
Matura	9%	3%	4%	2%	3%	4%	5%	71%
Model_24_5_48_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	90%	0%	1%	0%	2%	6%	1%	2%
Californian	1%	75%	8%	1%	5%	8%	1%	0%
French	2%	3%	75%	4%	8%	5%	2%	1%
Rage	5%	5%	4%	64%	4%	13%	4%	2%
English	1%	8%	9%	4%	67%	5%	2%	4%
Brush	4%	4%	6%	5%	8%	68%	3%	2%
Gloucester	4%	2%	1%	4%	2%	8%	75%	3%
Matura	6%	6%	4%	2%	6%	4%	2%	72%
Model_16_3_16_2	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	83%	0%	2%	1%	2%	3%	5%	4%
Californian	2%	72%	9%	2%	3%	2%	5%	2%
French	3%	5%	66%	3%	9%	6%	5%	3%
Rage	5%	3%	1%	66%	3%	9%	10%	3%
English	3%	4%	10%	5%	61%	3%	7%	7%
Brush	5%	3%	3%	5%	6%	68%	9%	2%
Gloucester	4%	2%	1%	4%	3%	5%	79%	4%
Matura	5%	2%	1%	3%	6%	4%	5%	76%
Model_16_3_16_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	73%	7%	0%	2%	2%	2%	6%	9%
Californian	2%	61%	11%	5%	8%	5%	4%	2%
French	1%	11%	57%	5%	12%	6%	2%	4%
Rage	5%	7%	2%	45%	7%	21%	11%	3%
English	4%	12%	8%	3%	50%	5%	8%	12%
Brush	8%	7%	2%	4%	4%	61%	7%	6%
Gloucester	8%	12%	1%	6%	3%	11%	56%	5%
Matura	9%	6%	4%	3%	3%	3%	5%	69%

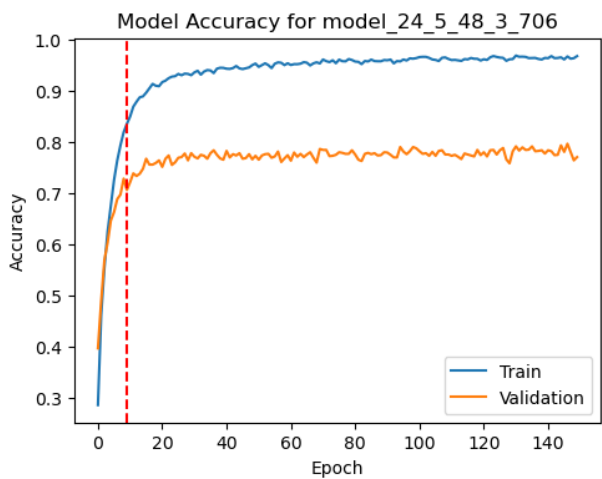
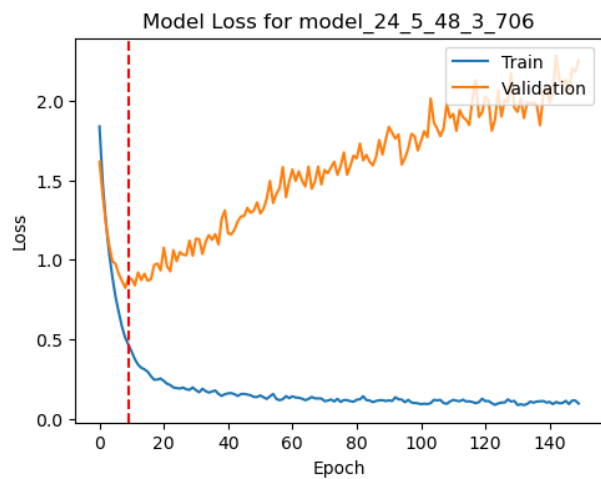
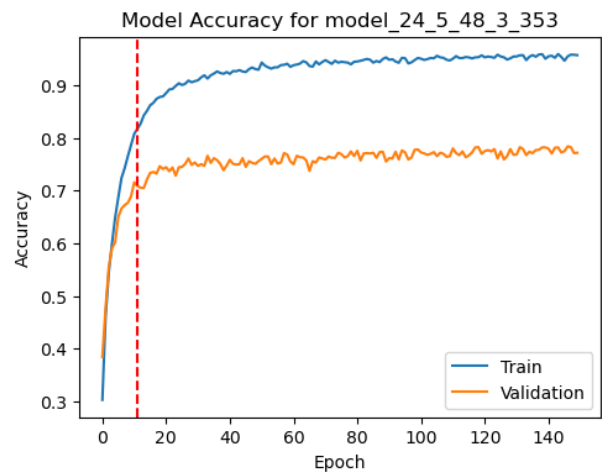
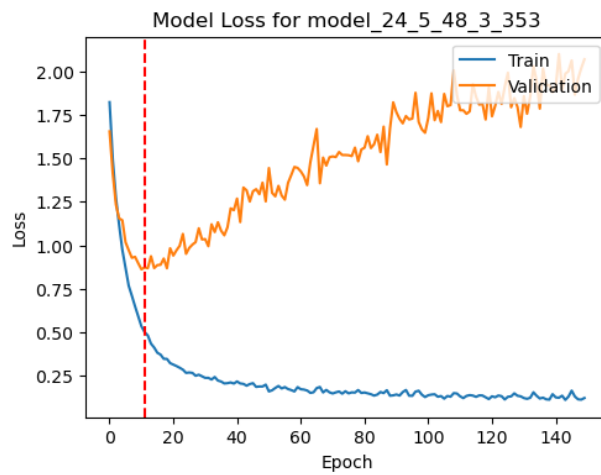
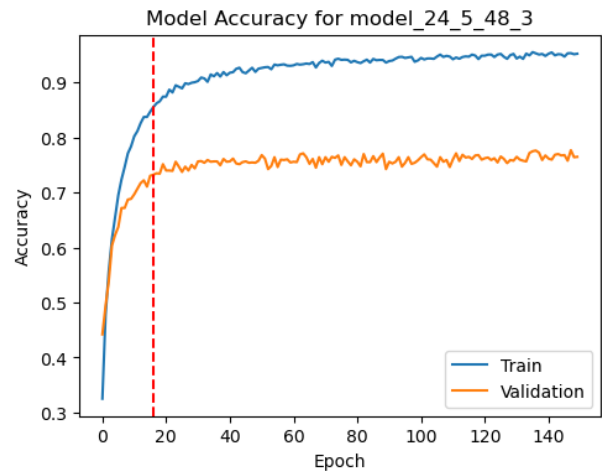
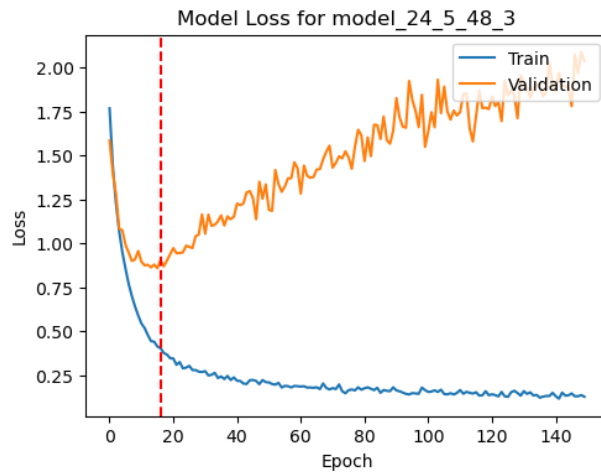
PCA of Model (24-5-48-3)



After running a PCA analysis on this model, we find that the number of components that explain 99% of variance is 353 components. So, our $R = 353$ for our further analysis.

New Analysis with $h=R$ and $h=2R$ for Best Model (24-5-48-3)

Our original hidden layer size was 216, we will now change this to 353 and 706 to compare performance amongst the 3 models (1 original, 2 new models containing new hidden layer sizes).



Model Name: model_24_5_48_3

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_50	600	24	624
max_pooling2d_50	-	-	0
conv2d_51	10368	48	10416
max_pooling2d_51	-	-	0
flatten_25	-	-	0
dense_50	93312	216	93528
dropout_25	-	-	0
dense_51	1728	8	1736

Model Name: model_24_5_48_3_353

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_52	600	24	624
max_pooling2d_52	-	-	0
conv2d_53	10368	48	10416
max_pooling2d_53	-	-	0
flatten_26	-	-	0
dense_52	152496	353	152849
dropout_26	-	-	0
dense_53	2824	8	2832

Model Name: model_24_5_48_3_706

Layer Name	Trainable Weights Shape	Trainable Bias Shape	Total Parameters
conv2d_54	600	24	624
max_pooling2d_54	-	-	0
conv2d_55	10368	48	10416
max_pooling2d_55	-	-	0
flatten_27	-	-	0
dense_54	304992	706	305698
dropout_27	-	-	0
dense_55	5648	8	5656

Model_24_5_48_3	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	90%	0%	1%	0%	2%	6%	1%	2%
Californian	1%	75%	8%	1%	5%	8%	1%	0%
French	2%	3%	75%	4%	8%	5%	2%	1%
Rage	5%	5%	4%	64%	4%	13%	4%	2%
English	1%	8%	9%	4%	67%	5%	2%	4%
Brush	4%	4%	6%	5%	8%	68%	3%	2%
Gloucester	4%	2%	1%	4%	2%	8%	75%	3%
Matura	6%	6%	4%	2%	6%	4%	2%	72%

Model_24_5_48_3_353	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	81%	2%	1%	1%	6%	3%	3%	4%
Californian	1%	79%	5%	4%	5%	3%	1%	1%
French	1%	9%	67%	4%	7%	6%	4%	3%
Rage	4%	5%	2%	70%	6%	7%	5%	1%
English	2%	5%	10%	4%	67%	1%	4%	7%
Brush	5%	13%	6%	7%	5%	57%	6%	1%
Gloucester	3%	4%	1%	4%	4%	4%	79%	2%
Matura	3%	5%	4%	5%	6%	2%	2%	75%

Model_24_5_48_3_706	Castellar	Californian	French	Rage	English	Brush	Gloucester	Matura
Castellar	79%	2%	2%	3%	3%	2%	2%	7%
Californian	0%	74%	8%	4%	7%	2%	2%	2%
French	2%	9%	69%	6%	8%	3%	2%	2%
Rage	3%	4%	2%	74%	2%	8%	6%	2%
English	2%	7%	7%	5%	68%	2%	4%	5%
Brush	5%	5%	4%	8%	4%	65%	6%	3%
Gloucester	1%	1%	1%	5%	6%	2%	81%	3%
Matura	6%	2%	4%	4%	5%	2%	3%	76%

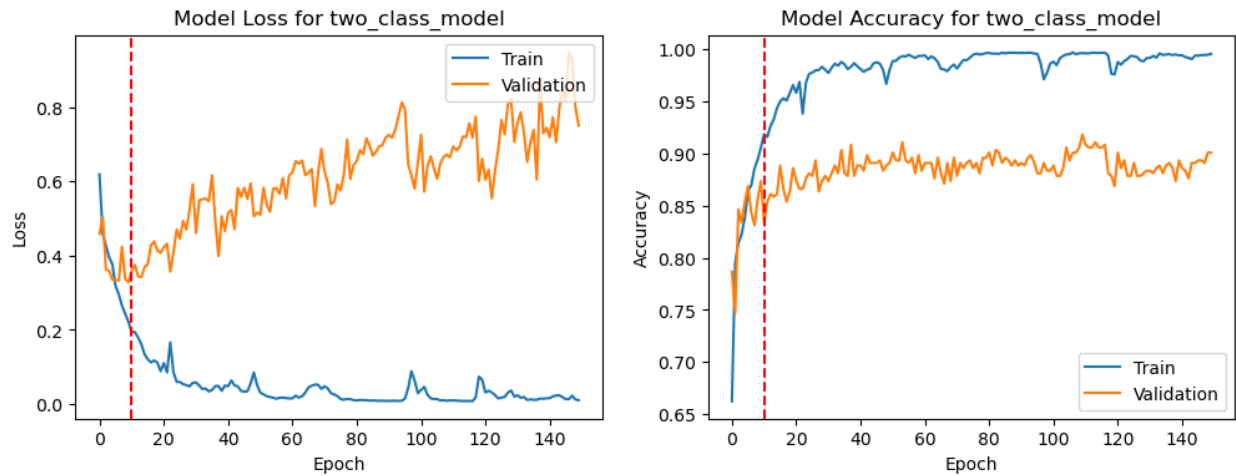
Model	# of Parameters	# of Information	Parsimony Ratio	Best Epoch	Training Time (s)	Robustness Ratio	Train Accuracy (Best Epoch)	Test Accuracy (Best Epoch)
Model_24_5_48_3	106304	113120	1.06	16	1.77	0.86	0.85	0.73
Model_24_5_48_3_353	166722	113120	0.68	11	1.62	0.89	0.81	0.72
Model_24_5_48_3_706	322394	113120	0.35	9	2.1	0.89	0.82	0.73

Our changing of the hidden layer size shows no improvement in test accuracy but improve in robustness ratio. Both increased hidden layer models have 0.89 robustness ratio which is slightly better than our original model. When comparing the confusion matrix of the new models, we can see the h=353 has a maximum of 81% for Castellar and minimum of 57% for Brush; and for h=706, maximum of 81% for Gloucester and minimum of 65% for Brush. Our original model has a max of 90% for Castellar and a min of 64% for Rage. Thus, it is marginally close for our original model and the model with h=706, and based on the parsimony ratio, we should choose h=706 as our best model.

Two Classes Analysis

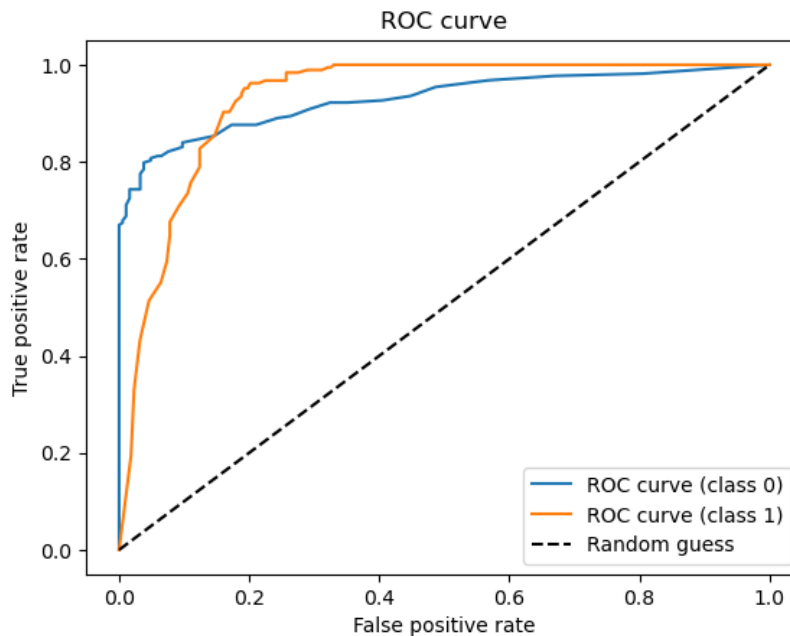
The two highest classes of our classification is Castellar at 79% and Gloucester at 81%.

We proceeded with the best windows+channels and h=706 configurations to implement a new CNN classifier with only these two classes.



Two Class Analysis	Castellar	Gloucester
Castellar	81%	19%
Gloucester	5%	95%

The best epoch for our two-class model is epoch 10. For the confusion matrix, we only slightly increased the accuracy of Castellar compared to our multiclass classifier, from 79% to 81%; while the classification of Gloucester increased drastically from 81% to 95%.



```
Area under the ROC curve (class 0): 0.931  
Area under the ROC curve (class 1): 0.931
```

Based on our AUC curve, we obtain a good classifier as its value is close to 1.