CS-671 Assignment-2

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Contents

1 Aim

To make a CNN model from scratch to classify:

1. MNIST dataset into 10 classes.
2. Images of the line dataset consisting of 96 classes based on 4 kinds of variations(length, width, color, angle).

2 Datasets

Following datasets are provided:

1. 28*28 MNIST Dataset with 60000 images for training 10000 images for testing
2. 28*28*3 Coloured Lines on Black Background (CLBB) Dataset with 750 images of each class for training and 250 images of each class for testing.

3 Task-1 : 10-Class MNIST

3.1 Dataset Preparation

The standard MNIST dataset can be directly loaded by using tf.keras.datasets.mnist.load_data(). We reshaped training and testing data to 4-dimensions(60000, 28. 28, 1) to be able to work with Keras API.

1. Total Data-Samples : 70000
2. Training Samples : 60000
3. Testing Samples : 10000

3.2 Classifier-1

3.2.1 Network Architecture

1. Layer-1 : 7x7 Convolutional Layer with 32 filters and stride of 1
2. Layer-2 : ReLU Activation Layer
3. Layer-3 : Batch Normalization Layer
4. Layer-3 : 2x2 Max Pooling layer with a stride of 2
5. Layer-4 : fully connected layer with 1024 output units
6. Layer-5 : ReLU Activation Layer
7. Layer-5 : Flatten
8. Output-Layer : fully connected layer with 10 output units using softmax activation

Adam optimizer and sparse_categorical_crossentropy was used to compile the model.

3.2.2 Results

$$\text{Confusion Matrix} = \begin{bmatrix} 978 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1130 & 0 & 0 & 1 & 1 & 2 & 1 & 0 & 0 \\ 0 & 2 & 1019 & 0 & 2 & 0 & 1 & 7 & 1 & 0 \\ 2 & 0 & 1 & 988 & 0 & 16 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 974 & 0 & 2 & 0 & 2 & 4 \\ 1 & 0 & 0 & 1 & 0 & 888 & 1 & 0 & 1 & 0 \\ 3 & 3 & 0 & 0 & 3 & 6 & 941 & 0 & 2 & 0 \\ 0 & 3 & 5 & 1 & 1 & 0 & 0 & 1010 & 2 & 6 \\ 5 & 1 & 5 & 1 & 1 & 2 & 3 & 0 & 953 & 3 \\ 2 & 2 & 3 & 0 & 10 & 5 & 0 & 4 & 0 & 983 \end{bmatrix}$$

1. Training Accuracy : 99.88%
2. Testing Accuracy : 98.64%
3. Average F1-score : 98.63%
4. Average Precision : 98.62%
5. Average Recall : 98.64%

3.2.3 Inferences

1. From the accuracy-epochs graph, we can see the train accuracy of model increases, and train loss decreases. While test accuracy also increases, but not the same amount. This shows that model is getting over-fitted and probably we don't even need this more number of epochs.
2. Accuracy obtained is quite high i.e. 99.88% on training data and bit less i.e. 98.64% on test data, which also indicates over-fitting. To decrease over-fitting we added a 0.2 dropout layer before flattening, but results were similar. Nonetheless, accuracy of model is very good.

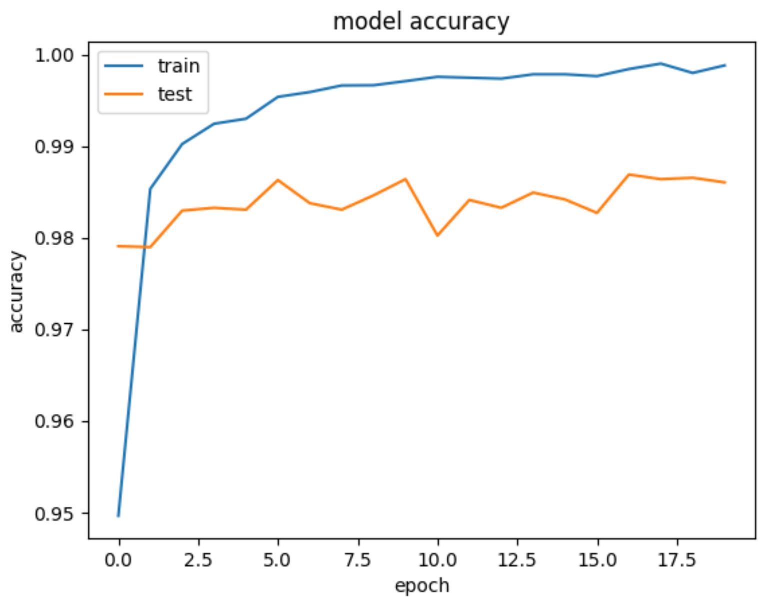


Figure 1: MNIST Data-Set : Accuracy vs Epochs

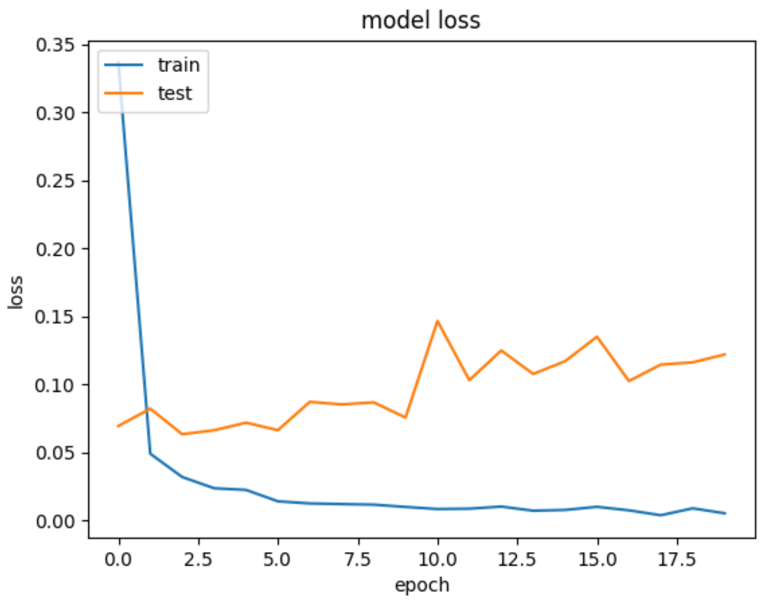


Figure 2: MNIST Data-Set : Loss vs Epochs

4 Task-1 : 96-Class Line-Dataset

4.1 Dataset Preparation

We created data for this classification in classifier's code itself. Creating the images is computationally less expansive than loading them from hard-disk and this does not affect the performance of classifier in any other way. We reshaped training and testing data to 4-dimensions(60000, 28. 28, 3) to be able to work with Keras API.

1. Total Data-Samples : 96000
2. Training Samples : 72000
3. Testing Samples : 24000

4.2 Classifier-1

4.2.1 Network Architecture

1. Layer-1 : 7x7 Convolutional Layer with 32 filters and stride of 1
2. Layer-2 : ReLU Activation Layer
3. Layer-3 : Batch Normalization Layer
4. Layer-3 : 2x2 Max Pooling layer with a stride of 2
5. Layer-4 : fully connected layer with 1024 output units
6. Layer-5 : ReLU Activation Layer
7. Layer-5 : Flatten
8. Output-Layer : fully connected layer with 96 output units using softmax activation

Adam optimizer and sparse_categorical_crossentropy was used to compile the model.

4.2.2 Results

1. Training Accuracy : 98.97%
2. Testing Accuracy : 98.96%
3. Average F1-score : 98.61%
4. Average Precision : 98.44%
5. Average Recall : 98.96%

4.2.3 Inferences

1. Using given architecture only, we good get quite good results. As train accuracy and test accuracy are quite similar, model is not over-fitted.

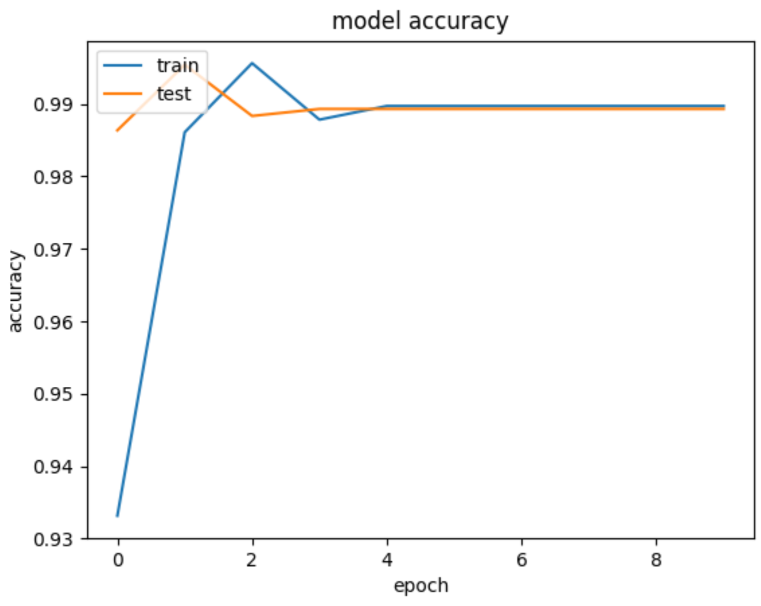


Figure 3: Line Data-Set : Accuracy vs Epochs

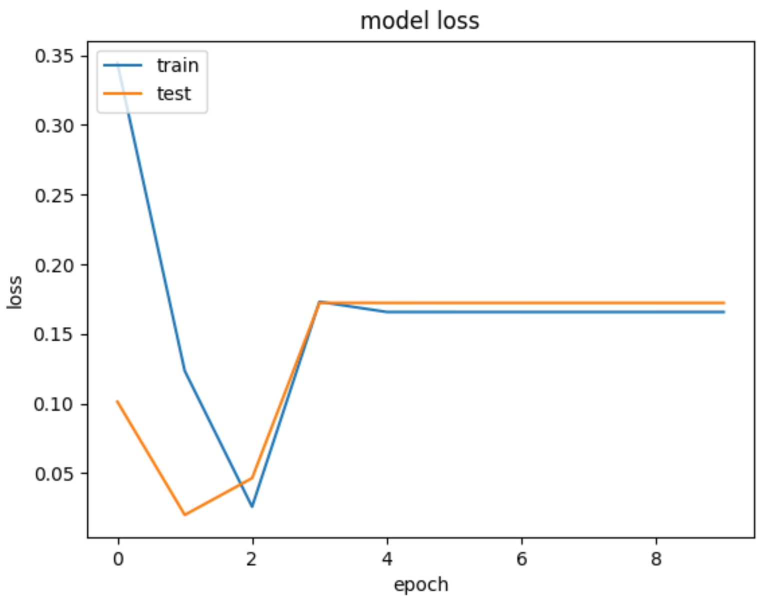


Figure 4: Line Data-Set : Loss vs Epochs

5 Task-2 : Multi-headed Classification for Line Data-set

5.1 Dataset Preparation

The data-set contained 96000 images of shape 28*28*3. In order to prepare the data, we first flattened each data image to a single vector with pixel values between 0 and 1. This resulted in a 2352-dimensional feature representing a single image. Next we partitioned data into training and testing set.

1. Total Data-Samples : 96000
2. Training Samples : 72000
3. Testing Samples : 24000

5.2 Classifier-1

5.2.1 Network Architecture

1. Colour-Head : Binary Cross-entropy loss with sigmoid activation.
2. Length-Head : Binary Cross-entropy loss with sigmoid activation.
3. Width-Head :Binary Cross-entropy loss with sigmoid activation.
4. Angle-Head : Categorical Cross-entropy loss with softmax activation.

Adam Optimizer was used. The learning rate was set to 0.0001 and decay to 0.00001 The model was run for 15 epochs.

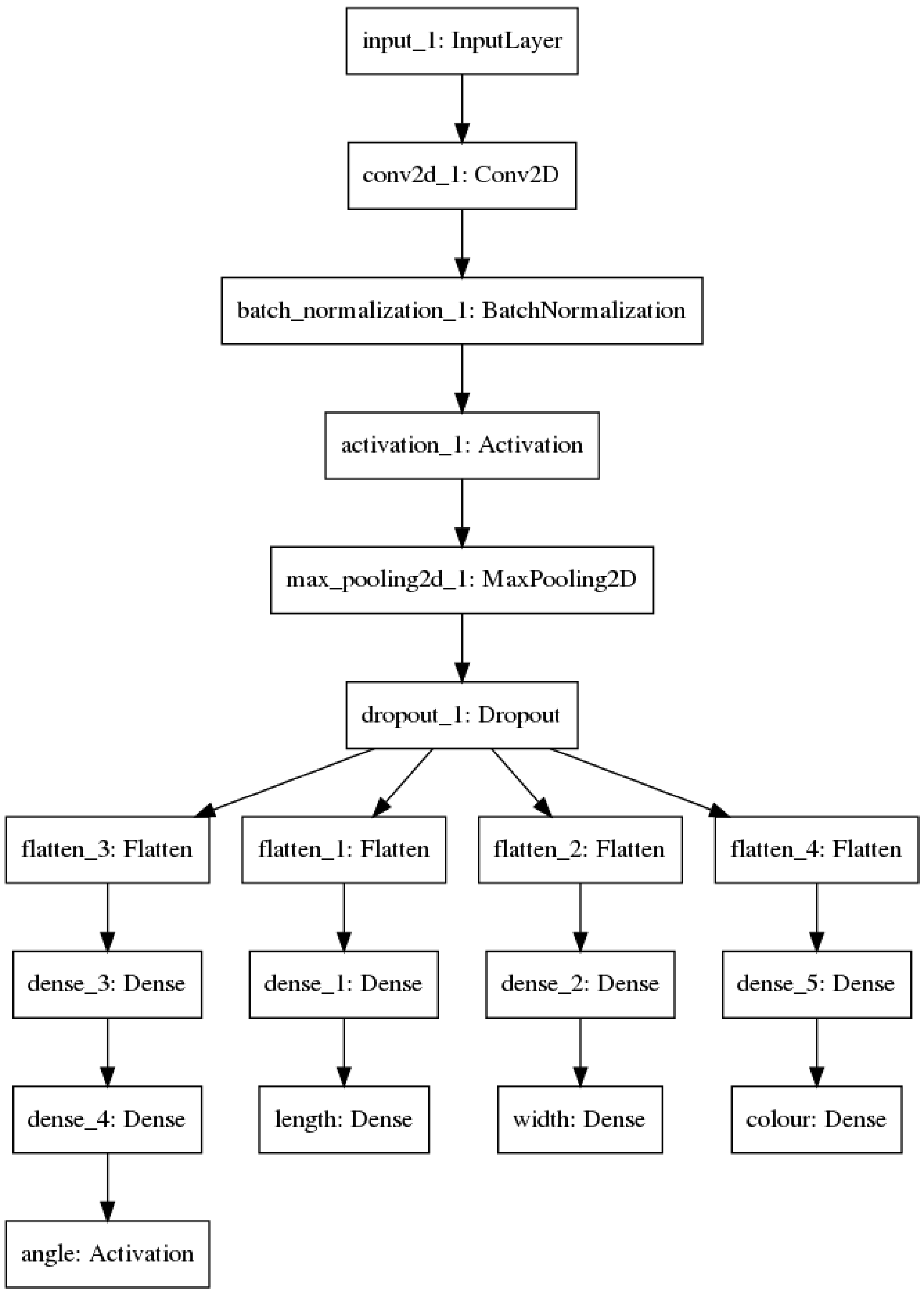


Figure 5: Multi-Head CNN Architecture

5.2.2 Results

1. Training Accuracy : 100.0%

2. Testing Accuracy : 100.00%

Since the all points are correctly classified, the recall, precision and f-score for all classes are 1.
Thus rather than making a table, I have put all the f-score in a plot.

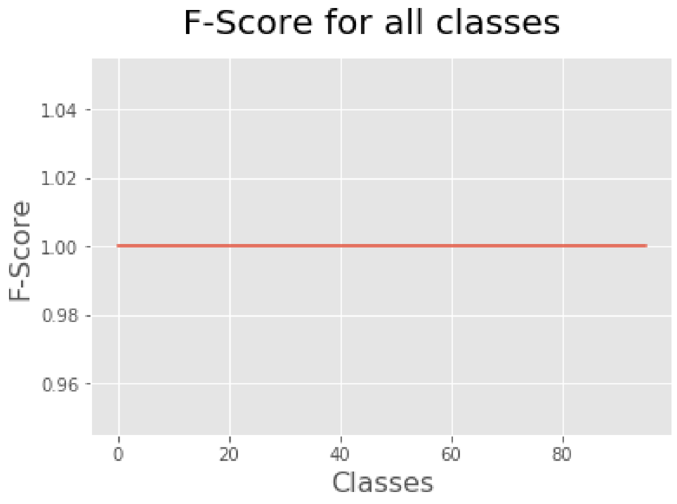


Figure 6: Multi-head Classification : F-Score for all classes

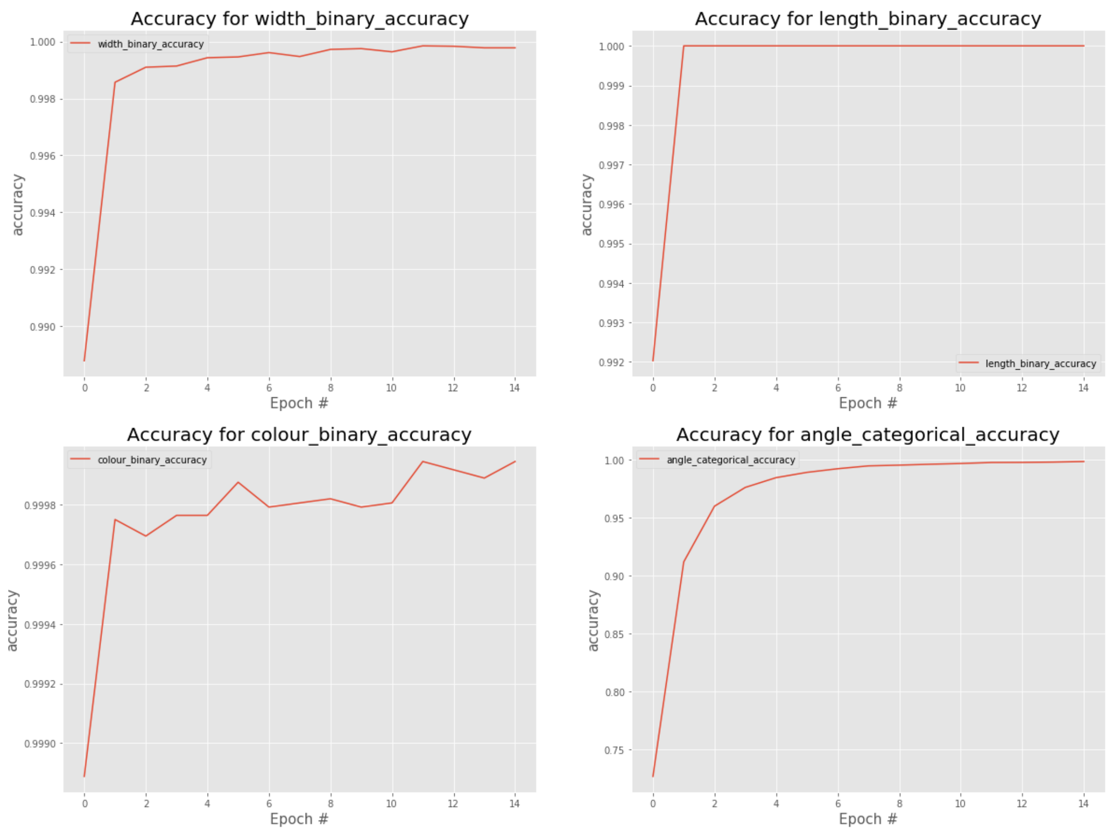


Figure 7: Multi-head Classification : Accuracy for various heads vs Epochs

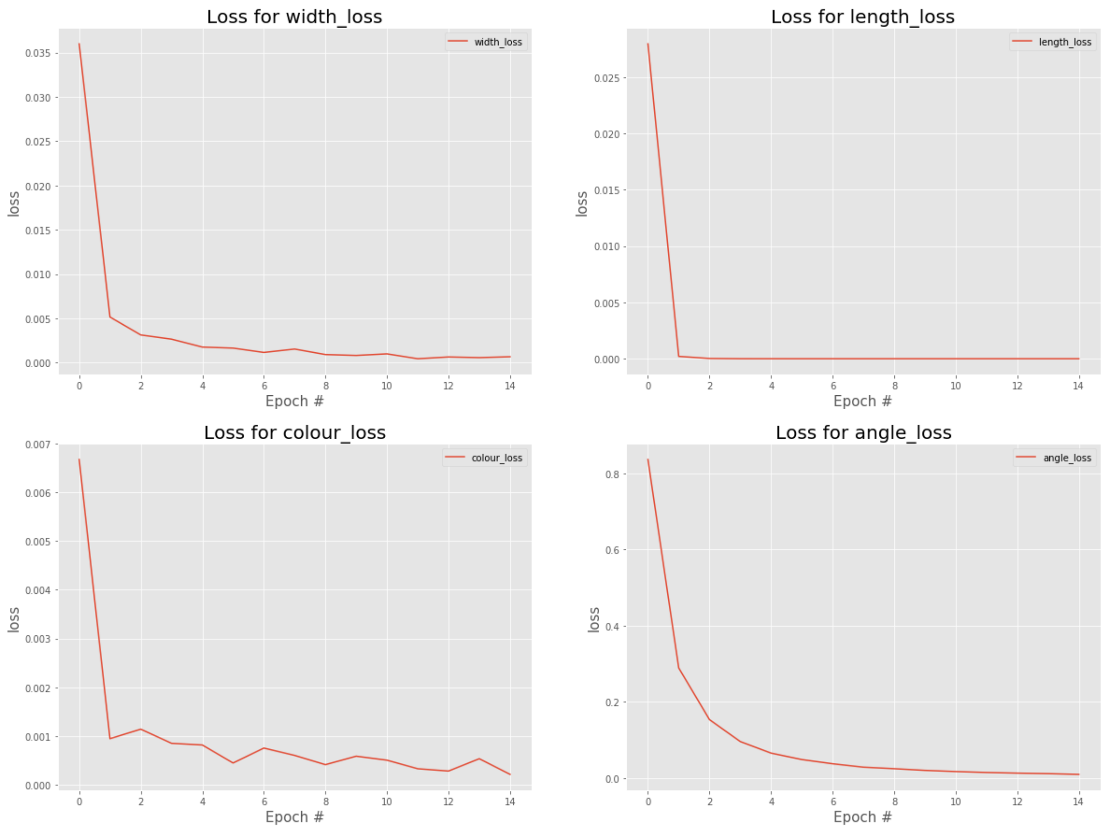


Figure 8: Multi-head Classification : Loss for various heads vs Epochs

5.2.3 Inferences

It is evident from the graphs that the bottle-neck for the accuracy are the angle classification head and the colour classification head. Having said that, the model performed very well, with no point being mis-classified.
One advantage of using Multi-head classification is follows:
Suppose we have trained we now want our model to detect Green Lines as well (they have been added to the data-set). Now, we only have to train the colour head of the model separately and the model would start recognizing the Green Lines. This is despite the fact that the other classification head have never actually seen a Green Line.

6 Task-3 : 10-Class MNIST Dataset

6.1 Architecture

```
_________________________________________________________________
Layer (type)                 Output Shape              Param \#
=================================================================
conv2d_1 (Conv2D)            (None, 24, 24, 32)        832
```

```
_________________________________________________________________
activation_1 (Activation)    (None, 24, 24, 32)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 24, 24, 32)        128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 32)        0
_________________________________________________________________
dense_1 (Dense)              (None, 12, 12, 1024)      33792
_________________________________________________________________
activation_2 (Activation)    (None, 12, 12, 1024)      0
_________________________________________________________________
flatten_1 (Flatten)          (None, 147456)            0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                1474570
=================================================================
Total params: 1,509,322
Trainable params: 1,509,258
Non-trainable params: 64
_________________________________________________________________
```

6.2 Test Image 1

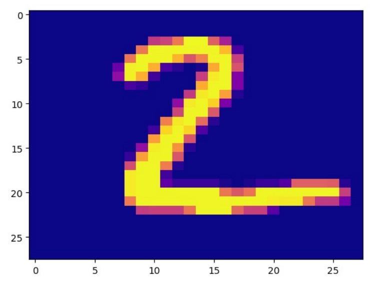


Figure 9: Test Image 1

6.2.1 Visualizing Intermediate Layer Activations

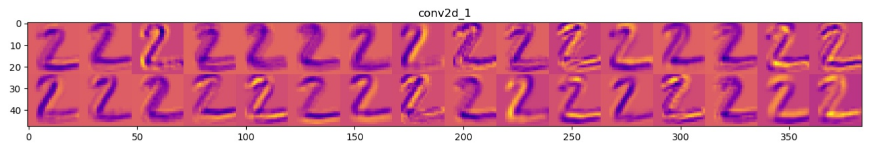


Figure 10: Conv2D Layer

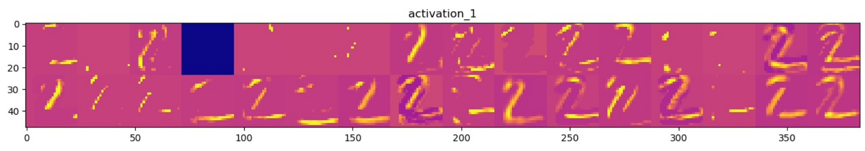


Figure 11: Activation Layer

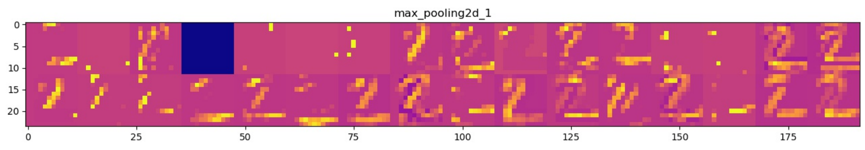


Figure 12: Max Pooling Layer

6.2.2 Visualizing Convnet Filters

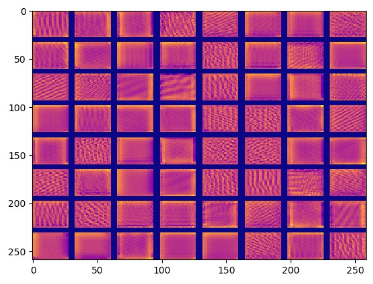
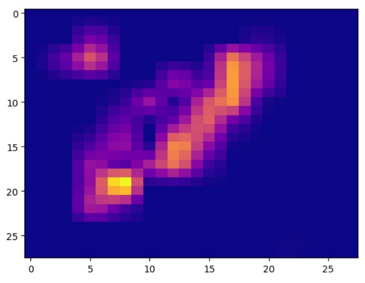
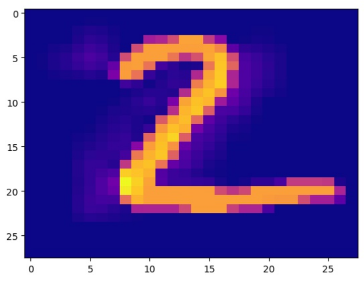


Figure 13: Conv net Filters of dense$_1 Layer$

6.2.3 Visualizing Heatmaps of class activations



(a) Heatmap of activation_2 Layer



(b) Superimposed Image

6.3 Test Image 2

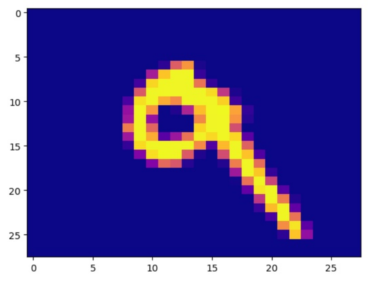


Figure 15: Test Image 2

6.3.1 Visualizing Intermediate Layer Activations

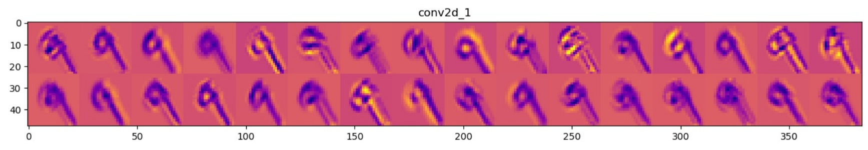


Figure 16: Conv2D Layer

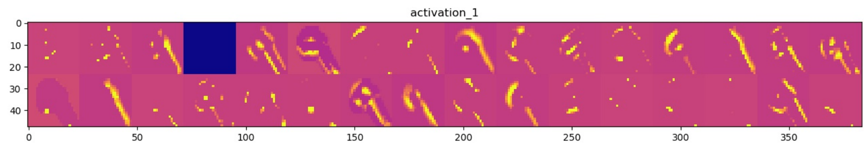


Figure 17: Activation Layer

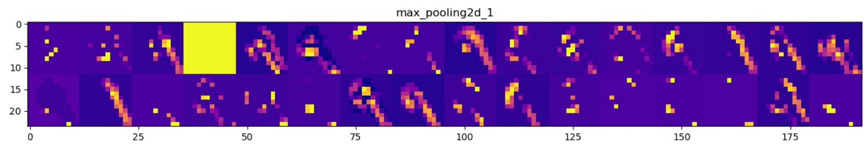


Figure 18: Max Pooling Layer

6.3.2 Visualizing Convnet Filters

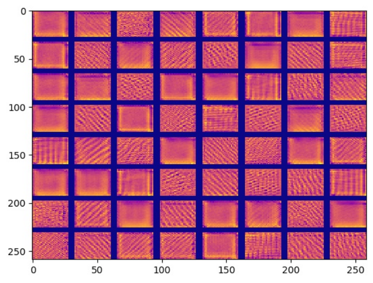
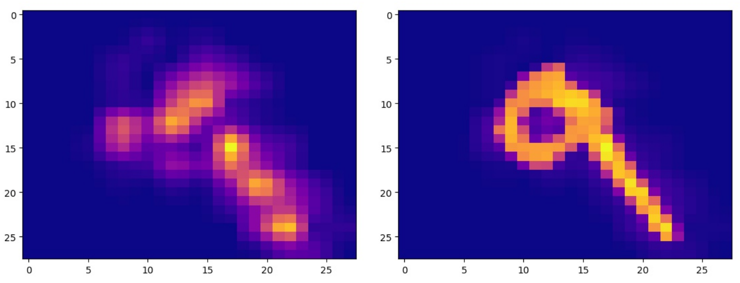


Figure 19: Convnet Filters of dense$_1$*Layer*

6.3.3 Visualizing Heatmaps of class activations



(a) Heatmap of activation_2 Layer (b) Superimposed Image

6.4 Test Image 3

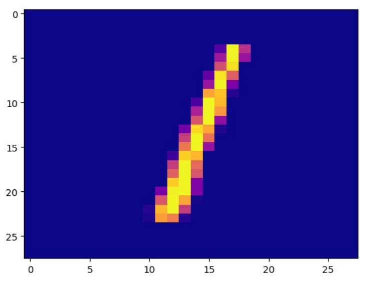


Figure 21: Test Image 3

6.4.1 Visualizing Intermediate Layer Activations

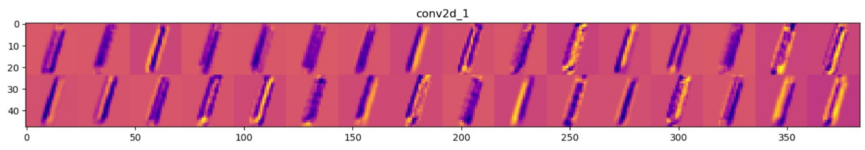


Figure 22: Conv2D Layer

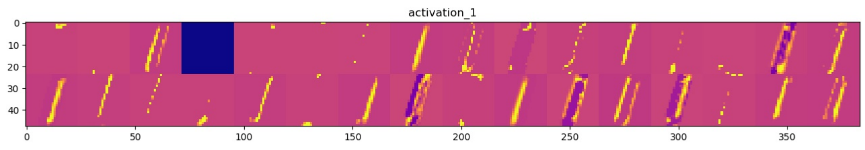


Figure 23: Activation Layer

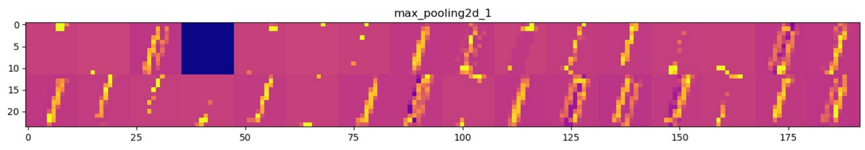


Figure 24: Max Pooling Layer

6.4.2 Visualizing Convnet Filters

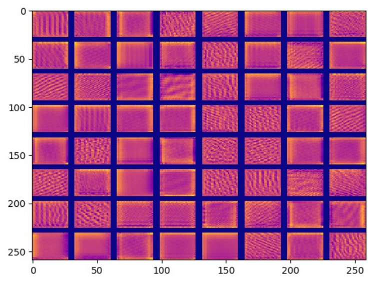
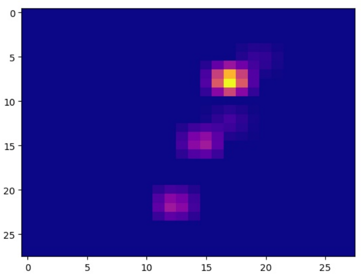
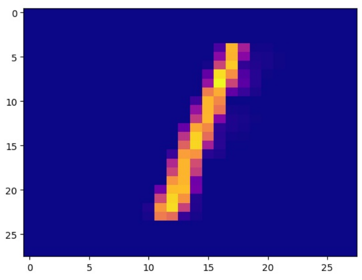


Figure 25: Convnet Filters of $\text{dense}_1 Layer$

6.4.3 Visualizing Heatmaps of class activations


(a) Heatmap of activation_2 Layer


(b) Superimposed Image

7 Task 3 : 96-Class Line Dataset

7.1 Architecture

```
____________________________________________________________________________________________________
Layer (type)                     Output Shape          Param #     Connected to
====================================================================================================
input_1 (InputLayer)             (None, 28, 28, 3)     0
____________________________________________________________________________________________________
conv2d_1 (Conv2D)                (None, 28, 28, 32)    896         input_1[0][0]
____________________________________________________________________________________________________
activation_1 (Activation)        (None, 28, 28, 32)    0           conv2d_1[0][0]
____________________________________________________________________________________________________
batch_normalization_1 (BatchNor (None, 28, 28, 32)    128         activation_1[0][0]
____________________________________________________________________________________________________
max_pooling2d_1 (MaxPooling2D)  (None, 9, 9, 32)      0           batch_normalization_1[0][
____________________________________________________________________________________________________
dropout_1 (Dropout)              (None, 9, 9, 32)      0           max_pooling2d_1[0][0]
____________________________________________________________________________________________________
conv2d_2 (Conv2D)                (None, 9, 9, 64)      18496       dropout_1[0][0]
____________________________________________________________________________________________________
activation_2 (Activation)        (None, 9, 9, 64)      0           conv2d_2[0][0]
____________________________________________________________________________________________________
batch_normalization_2 (BatchNor (None, 9, 9, 64)      256         activation_2[0][0]
____________________________________________________________________________________________________
conv2d_3 (Conv2D)                (None, 9, 9, 64)      36928       batch_normalization_2[0][
____________________________________________________________________________________________________
conv2d_4 (Conv2D)                (None, 9, 9, 32)      9248        dropout_1[0][0]
____________________________________________________________________________________________________
conv2d_5 (Conv2D)                (None, 9, 9, 32)      9248        dropout_1[0][0]
____________________________________________________________________________________________________
conv2d_6 (Conv2D)                (None, 9, 9, 32)      9248        dropout_1[0][0]
____________________________________________________________________________________________________
activation_3 (Activation)        (None, 9, 9, 64)      0           conv2d_3[0][0]
____________________________________________________________________________________________________
activation_4 (Activation)        (None, 9, 9, 32)      0           conv2d_4[0][0]
____________________________________________________________________________________________________
activation_5 (Activation)        (None, 9, 9, 32)      0           conv2d_5[0][0]
```

```
__________________________________________________________________________________________
activation_6 (Activation)       (None, 9, 9, 32)     0           conv2d_6[0][0]
__________________________________________________________________________________________
batch_normalization_3 (BatchNor (None, 9, 9, 64)     256         activation_3[0][0]
__________________________________________________________________________________________
batch_normalization_4 (BatchNor (None, 9, 9, 32)     128         activation_4[0][0]
__________________________________________________________________________________________
batch_normalization_5 (BatchNor (None, 9, 9, 32)     128         activation_5[0][0]
__________________________________________________________________________________________
batch_normalization_6 (BatchNor (None, 9, 9, 32)     128         activation_6[0][0]
__________________________________________________________________________________________
max_pooling2d_2 (MaxPooling2D)  (None, 4, 4, 64)     0           batch_normalization_3[0][
__________________________________________________________________________________________
max_pooling2d_3 (MaxPooling2D)  (None, 4, 4, 32)     0           batch_normalization_4[0][
__________________________________________________________________________________________
max_pooling2d_4 (MaxPooling2D)  (None, 4, 4, 32)     0           batch_normalization_5[0][
__________________________________________________________________________________________
max_pooling2d_5 (MaxPooling2D)  (None, 4, 4, 32)     0           batch_normalization_6[0][
__________________________________________________________________________________________
dropout_2 (Dropout)             (None, 4, 4, 64)     0           max_pooling2d_2[0][0]
__________________________________________________________________________________________
dropout_3 (Dropout)             (None, 4, 4, 32)     0           max_pooling2d_3[0][0]
__________________________________________________________________________________________
dropout_4 (Dropout)             (None, 4, 4, 32)     0           max_pooling2d_4[0][0]
__________________________________________________________________________________________
dropout_5 (Dropout)             (None, 4, 4, 32)     0           max_pooling2d_5[0][0]
__________________________________________________________________________________________
flatten_1 (Flatten)             (None, 1024)         0           dropout_2[0][0]
__________________________________________________________________________________________
flatten_2 (Flatten)             (None, 512)          0           dropout_3[0][0]
__________________________________________________________________________________________
flatten_3 (Flatten)             (None, 512)          0           dropout_4[0][0]
__________________________________________________________________________________________
flatten_4 (Flatten)             (None, 512)          0           dropout_5[0][0]
__________________________________________________________________________________________
dense_1 (Dense)                 (None, 12)           12300       flatten_1[0][0]
__________________________________________________________________________________________
dense_2 (Dense)                 (None, 1)            513         flatten_2[0][0]
__________________________________________________________________________________________
dense_3 (Dense)                 (None, 1)            513         flatten_3[0][0]
__________________________________________________________________________________________
dense_4 (Dense)                 (None, 1)            513         flatten_4[0][0]
__________________________________________________________________________________________
angle_output (Activation)       (None, 12)           0           dense_1[0][0]
__________________________________________________________________________________________
color_output (Activation)       (None, 1)            0           dense_2[0][0]
__________________________________________________________________________________________
length_output (Activation)      (None, 1)            0           dense_3[0][0]
__________________________________________________________________________________________
width_output (Activation)       (None, 1)            0           dense_4[0][0]
```

```
==================================================================================
Total params: 98,927
Trainable params: 98,415
Non-trainable params: 512
----------------------------------------------------------------------------------
```

7.2 Test Image 1

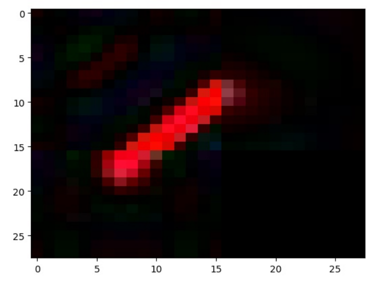


Figure 27: Test Image 1

7.2.1 Visualizing Intermediate Layer Activations

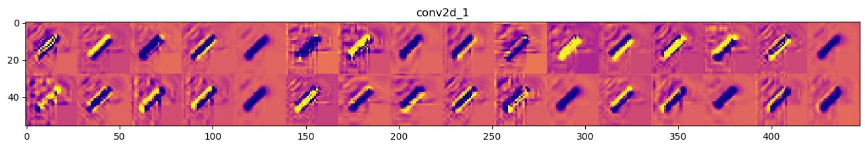


Figure 28: Conv2D_1 Layer

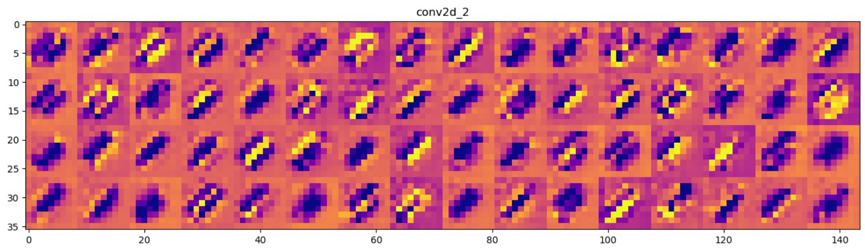


Figure 29: Conv2D_2 Layer

7.2.2 Visualizing Convnet Filters

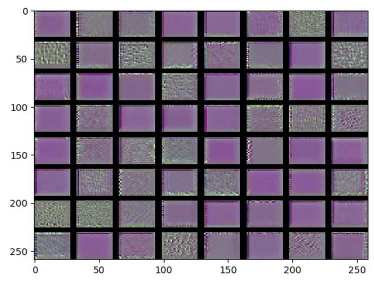


Figure 30: Conv net Filters of conv2d_2 Layer

7.3 Test Image 2

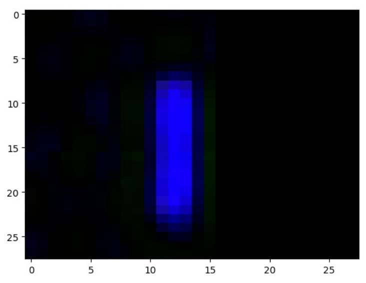


Figure 31: Test Image 2

7.3.1 Visualizing Intermediate Layer Activations

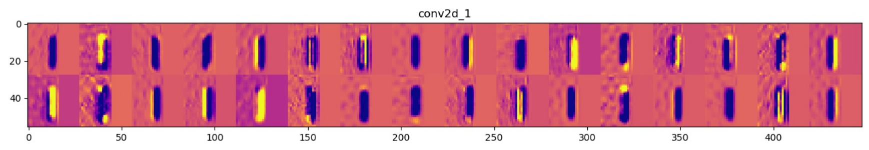


Figure 32: Conv2D_1 Layer

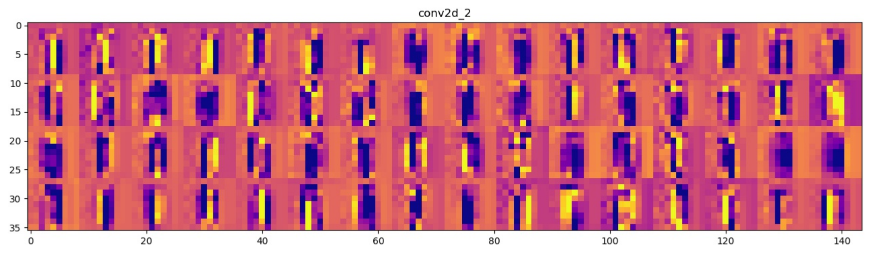


Figure 33: Conv2D_2 Layer

7.3.2 Visualizing Convnet Filters

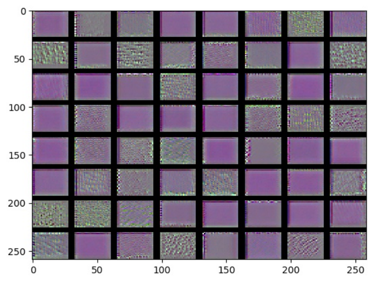


Figure 34: Conv net Filters of conv2d_2 Layer

7.4 Test Image 3

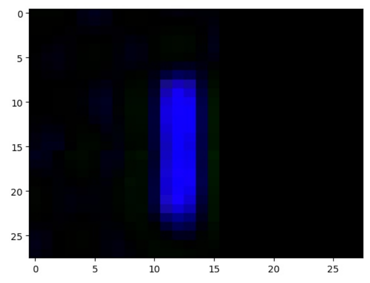


Figure 35: Test Image 3

7.4.1 Visualizing Intermediate Layer Activations

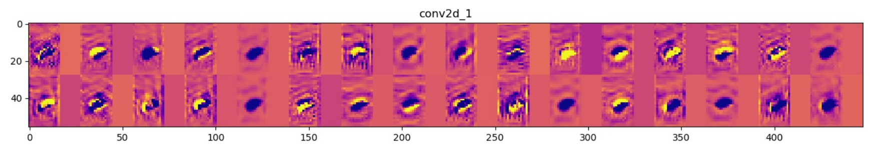


Figure 36: Conv2D_1 Layer

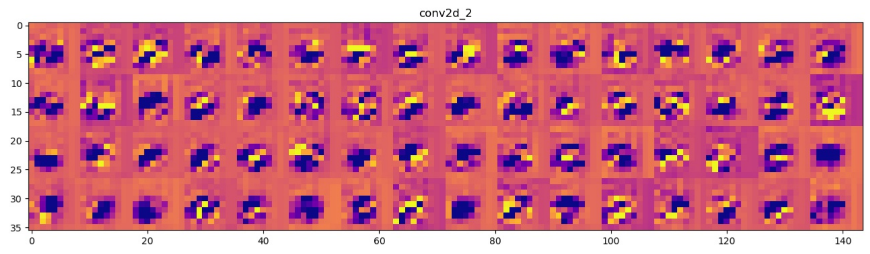


Figure 37: Conv2D_2 Layer

7.4.2 Visualizing Convnet Filters

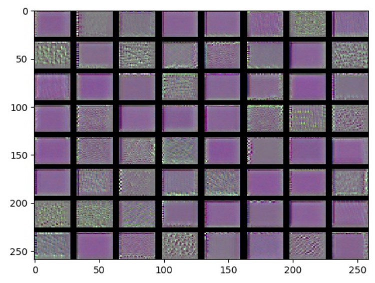


Figure 38: Conv net Filters of conv2d_2 Layer

References

[1] $www.pyimagesearch.com/2018/06/04/keras - multiple - outputs - and - multiple - losses/$