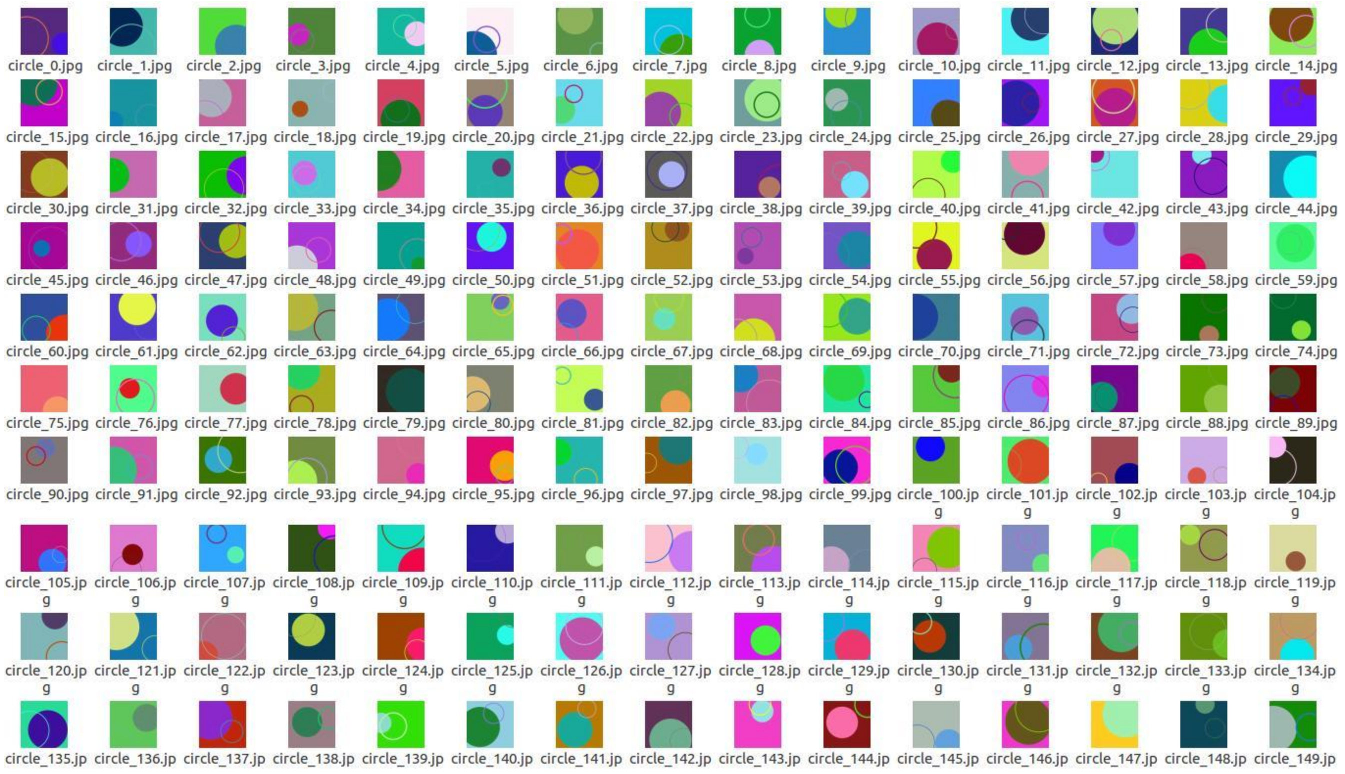
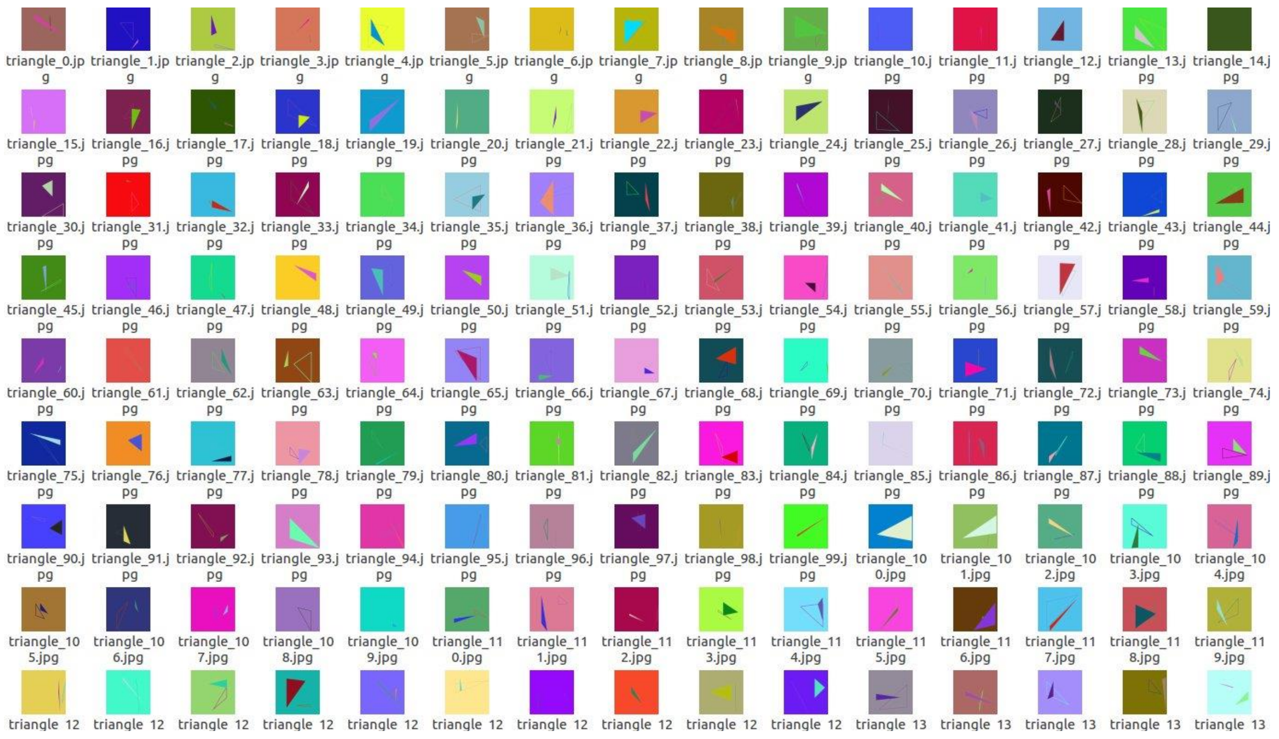
Single Output with Multi-Class Classification

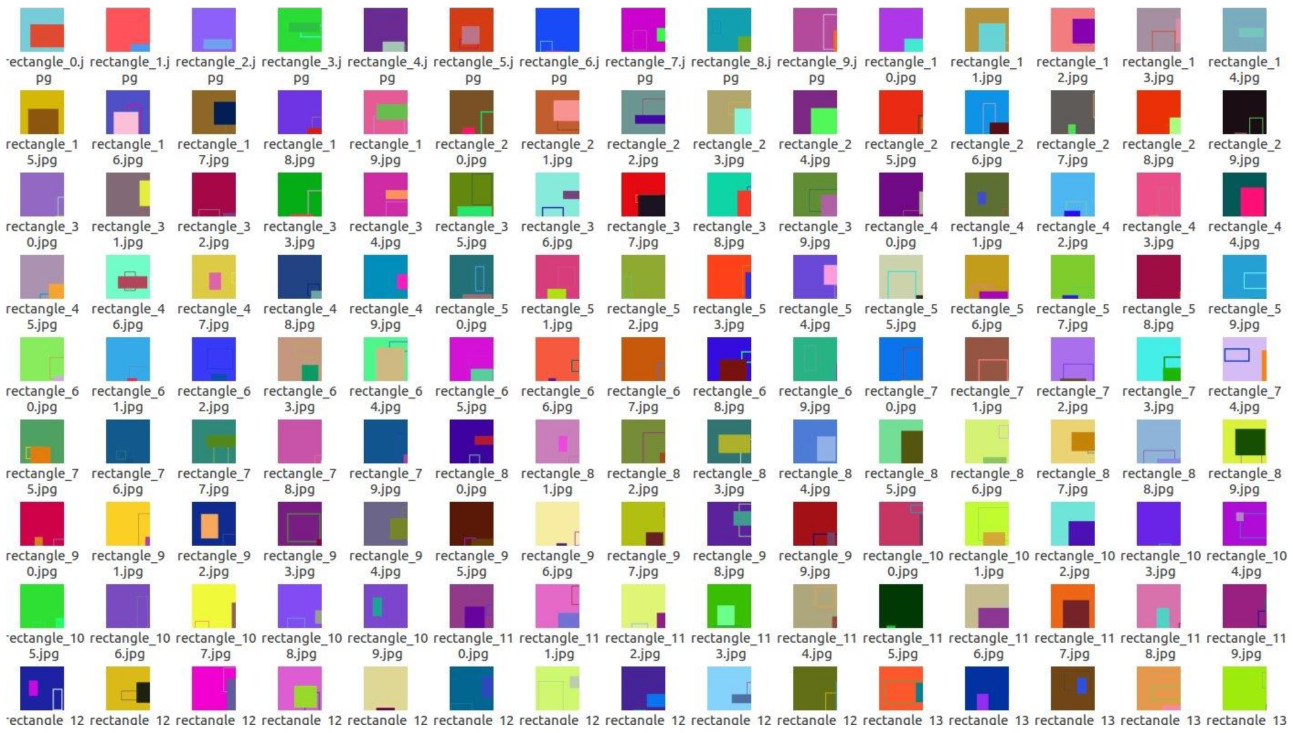
The convolutional neural network will learn using supervised training in Keras. The training and validation datasets will have a supervised output of a single label for each class in a 300 by 300 image. The dataset consisting of circles, triangles, squares and rectangles is created by the program draw.py. It uses multiprocessing of independent pool workers to draw these shapes and saving these shapes in ".png" format. Draw.py uses the cairo library for drawing the shapes and the random library to randomize the location and size of these shapes. Each 300 by 300 image will have two variations, which are the linear contours and the fill of the shape pertaining to the same class. To execute the file, simply run python draw.py --draw-func draw_circle --num-images 2000 --file-dir training_set/circle/circle_, where draw-func represents the drawing function that draws either circle, triangle, square or rectangle or a combination of these shapes if needed. There are 2,000 images per data shape with a total of 8,000 images for the training dataset. The validation dataset consists of 400 images per data shape with a total of 1,600 images, which is 20% of the training dataset.

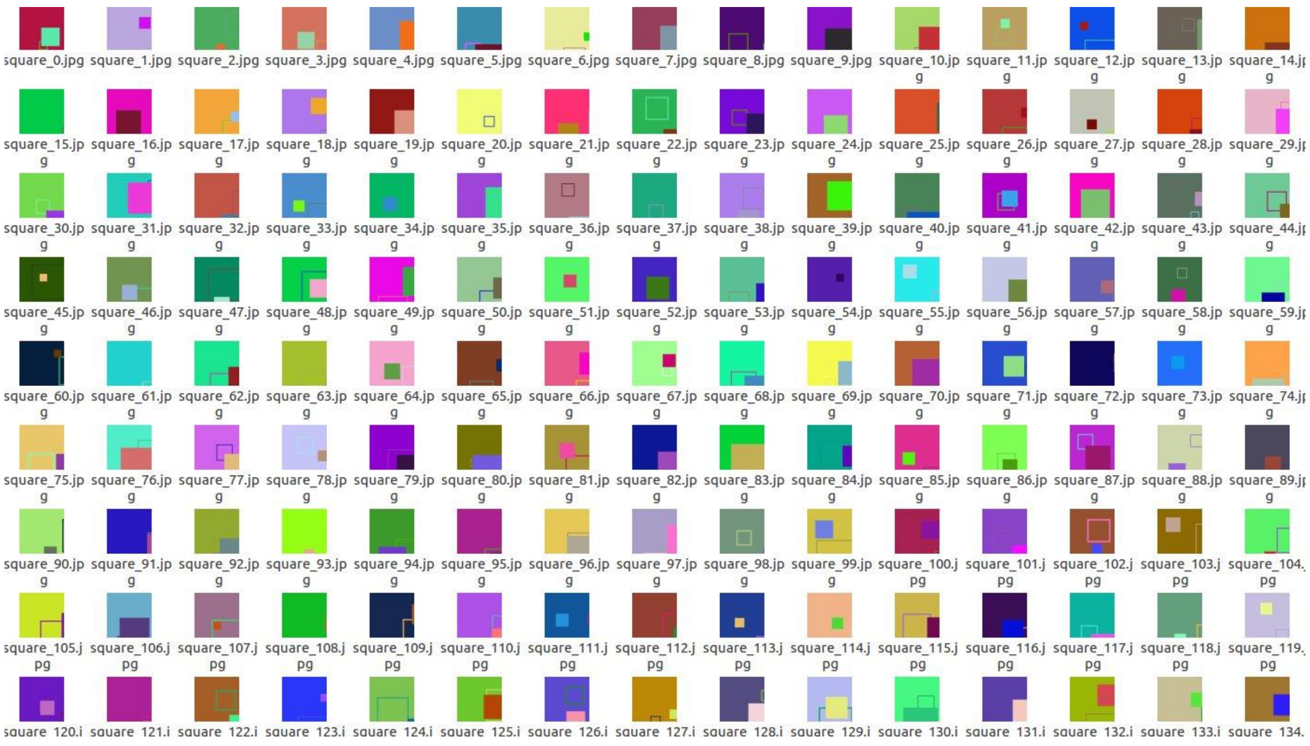
A single PNG image file has a better pixel precision, but it comes at a cost of having twice or even three times as much data storage as a JPEG file. Since the training data tend to increase when the architecture of the convolutional neural network has more layers, it is efficient



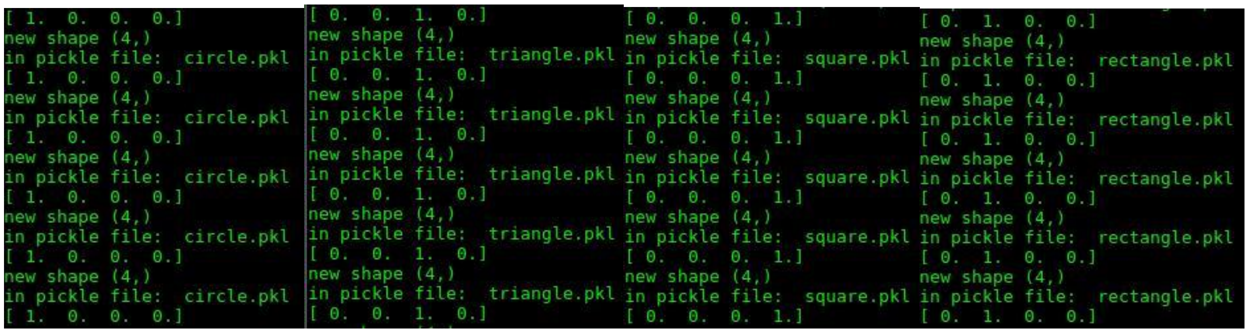
to reduce the size of the images by converting from PNG to JPEG. The program reduce_images_pickle.py reduces image sizes by adjusting a ratio of height and base decrease. It then saves the images in pickle file, where the same pickle file is opened to save the newly reduced size images into a folder.







After each image file size is reduced, pickletestcats.py is the main file that will process the reduced sized images. It is a multiprocessing program of independent pool workers, which uses the Pillow 3 module to open JPEG image files. The pool workers individually convert the JPEG image file into a numpy array of shape (300, 300, 3), where 300 represents the width and the height of the image and 3 represents the color format. The image's corresponding output label (y_label) is generated by using the Keras library of to_categorical encoding. The encoding transforms integers into different binary 1 and 0 encodings of output classes. These classes are circle, rectangle, triangle, and square. The numpy array's total size of 2000 images per shape is reduced by a half if the numpy data structure is a float-16 instead of float-32. After the execution of the program for each shape in the training and validation data, there will be eight pickle files called “circle.pkl”, “triangle.pkl”, “square.pkl”, “rectangle.pkl”, “valid_circle.pkl”, “valid_triangle.pkl”, “valid_square.pkl” and “valid_rectangle.pkl”. A tuple of (image data, output y label) is returned by the pool workers.



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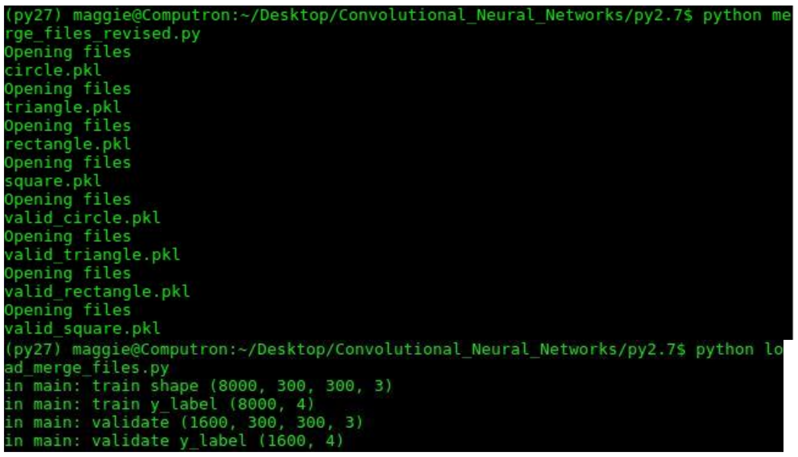
The combined pickled data of all the shapes represent the training dataset and the validation dataset, which is needed for the convolutional neural network to learn. The file merge_files_revised.py merges the shapes by using the Loader class, which is a multiprocessing module, to load the images and store them in a very large list. All the pool workers execute the loading of the images and the appending of the tuple (image data, output y label) independently. Therefore, a global storage of each large dataset list per shape is needed because each pool worker needs access to the it. I tried allocating the list using “None” times number of images. The numpy array is organized in a tuple, so the list allocation doesn't work in numpy arrays or in tuples. Memmap would not work either because the merged dataset contains a tuple, not a single memory array. After the loaded data is stored in the large lists, the program uses list concatenation to merge all the shapes together, forming the training and validation dataset.

Since the dataset is a very large list, joblib does a successful job dumping and compressing into a file, which will be loaded from load_merge_files.py. The reason for having one file for merging the dataset and another file for loading the merged dataset is that it is better to shuffle the dataset before loading into the convolutional neural network. Although the Keras' generator automatically shuffles with each run of an epoch, it is a good practice to shuffle the training dataset to allow for randomization of images. The program shuffles the dataset and loads the previously merged files by organizing the tuple into two different lists. The first one contains the numpy pixel data and the second list contains its corresponding y label output, which is needed for a supervised training of the neural network. The large list is being stored using the numpy array's memory mapping because each shape of the data pixel array is (300, 300, 3) and its corresponding y output label is (4,) where 4 represents the number of classes to be learned by the convolutional neural network.



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Opening files
triangle.pkl
Opening files
rectangle.pkl
Opening files
square.pkl
Opening files
valid_circle.pkl
Opening files
valid_triangle.pkl
Opening files
valid_rectangle.pkl
Opening files
valid_square.pkl
(py27) maggie@Computron:~/Desktop/Convolutional_Neural_Networks/py2.7$ python lo
ad_merge_files.py
in main: train shape (8000, 300, 300, 3)
in main: train y_label (8000, 4)
in main: validate (1600, 300, 300, 3)
in main: validate y_label (1600, 4)
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Background data without the Shape Contours

It is redundant for the convolutional neural network in cnn_copy_sobel_test.py to obtain pixelized convolutions from background pixels that do not have object contours. An image preprocessing function is needed before the image data are inputted into the first two-dimensional convolution of the network. This function get_edges is responsible for cropping the image and reducing the background space. The input image needs to be converted into grayscale for the Sobel algorithm to process. Since findContours of the opencv2 module alters the original image, a copy of the input image is needed. After finding the contours in both the x and y directions of the Sobel algorithm, the gradients in both directions clarify the contour boundaries of the image. The combined gradient adds the weights in gradients from x and y derivatives, which finalizes the pixels for the image contours.

When the coordinates of the contours are detected, the rectangular boundaries are drawn around it by using opencv2's rectangle method. A list for x coordinates and another list for y coordinates stores all the x and y coordinates returned by findContours. The minimum and maximum values of the x and y lists will determine the area of the cropping region. The locations of the rectangles are in (x,y) coordinates where the cropped version will be from the top left corner (smallest_x, smallest_y) and the bottom right opposite corner (largest_x, largest y). The original input image will be cropped by slicing the coordinates of the original array.

The layers of the convolutional neural network will gather pixels from images that are cropped and will not see the original image. To maintain the scale consistency of the size of the input image at 300 pixels by 300 pixels in RGB format, the cropped image needs to be resized in aspect ratio with a fixed width of 300 pixels. The flatten() layer of the convolutional neural network requires the input images to have the same numpy shape array; get_edges must return the same shape of (300, 300, 3). A white background of 300 pixels by 300 pixels is created and converted into an 8-bit unsigned integer numpy array. By using the paste function from the Pillow library, the resized cropped image is pasted onto the white background. The pasted, cropped image is converted back into a 32-bit numpy float value because Keras processes numpy arrays in 32-bit float values.

Convolutional Neural Network Architecture

This convolutional neural network architecture uses the Keras Sequential model that acts as instances being layered on top of each other. The convolutional layers in the beginning of the neural network gather pixels of each input data. Depending on the quality and quantity of the image data, the number of output filters will vary. The output filters are the third dimensionality of the convolutional neural layer at the z axis where a rise in output filters and convolutional layers increases the parameter of the network. Increasing the number of filters is necessary as the training data increases, so 128 filters for the first layer of the second convolutional neural network is sufficient for 8,000 JPEG images. The convolutional layer will operate for each 6 pixels by 6 pixels square area in a single 300 pixels by 300 pixels image with a stride of (1,1) overlap. Padding might be needed since 600 doesn't divide evenly by 36. “Valid” padding means that there won’t be additional padding around the borders of the input image whereas "same" padding means padding around the input to create the same dimensions as the output filters. “Same” padding drastically increases the parameters of the network. For instance, a “valid” padding with two convolutional layers and a 3-layer perceptron has 5,063,428 parameters while the “same” padding of the equivalent architecture results in 9,623,422 parameters. The rectifier activation function outputs from the first layer of the convolutional neural network. It is an easier option than the sigmoid activation function because the rectifier activation function max(0, x) creates nonlinearity with the summation of weights without as much computation as the sigmoid activation function.

After the 6 pixels by 6 pixels convolutions are individually formed and activated with the rectifier, the 6 pixels by 6 pixels pool size will down-sample the number of pixels per output filter for the first convolutional layer. Then, a second two-dimensional convolutional neural layer is added to the Sequential model. To enable a growth of learning, the number of output filters is increased twice as much from 128 in the first layer to 256 in the second convolutional layer. The stride is still (1,1) by default in Keras with a convolution size of (6,6) with no padding. The relu activation is also the summation output from the second convolutional layer. After the convolutional filters are created in the second layer, the pixels will be downsampled through maxpool. Maxpooling determines whether each pixel is similar or belong to the surrounding pixels. If it is, the pixel will be visible in the down-sampled layer whereas the pixel removed in the maxpool layer if not.

After the formation of two convolutional layers with maxpool in between, the flattening of these layers allows the convolutional network to be fed into a traditional fully connected neural network. Keras requires that the flattening of the pixelized data input to have a defined shape in the format (width, height, color). The drawback of using convolutional layers is that the images must be the same size. However, convolutional layers are capable of extracting pixels and characteristics from the image data and processes them in layered filters. The basic multi-layer perceptron is not capable of directly extracting features from pixels. In the fully connected layer of the network, a Dense layer is added onto the Sequential model. A Dense layer represents a basic perceptron where 512 neurons are fully connected from the flattening layer to the output of the first Dense layer. The output again will be summed and calculated by the rectifier function. The dropout at the rate of 0.35 is added for the neural network to prevent overfitting. The neurons will be dropped out from the network, removing their connective weight functionality from the next Dense layer of the network.

The final layer will have four units because the number of output classes is four. The activation function for the last layer will be softmax, which squashes the probabilities of the output classes from zero to one. After the architecture of the neural network is defined as a Sequential model, the convolutional and dense layers for the single-label output with multi-class classification will be compiled. The optimizer for compiling the convolutional neural network is one of the most crucial parameters of the learning process. This is because the optimizer determines the learning rate, decay and momentum of the network for correct weight updates during the forward-pass and backpropogation.

Data input into the convolutional neural network architecture

After the architecture of the network, the optimizer and the loss functions are defined, the convolutional neural network will be feed the input images. Keras image generator uses data augmentation to create variations of the image data ranging from scaling, rotating to flipping in a default batch size of 32 per data input. The training data generator consists of rescaling at 1./255, shearing at 0.2, zooming at 0.2, horizontal flip and preprocessing function get_edges.

Training and validation data generators will fit the Sequential model on batches of 32 with real-time data augmentation (Keras.io). The validate data generator will be rescaled at 1./255 and will also be preprocessed with the function get_edges. Fitting the validation and training data generator will "compute quantities required for feature-wise normalization such as standard deviation, mean, and principal components if ZCA whitening is applied," (Keras.io). Data augmentation will prevent overfitting if the augmented data has informative pixels. The early stopping of the convolutional neural network is applied to also prevent overfitting. The network will stop training after three epochs of nondecreasing improvement in the loss values. Finally, after the convolutional neural network is learning through adjusting weight parameters through supervised training with categorical cross entropy loss, the Sequential model is evaluated on a validation set in terms of the validation loss and the validation accuracy. The layers of the model and their corresponding output shapes are printed via the summary() method. The Sequential model is saved as a hierarchical data format (HDF5) file and will be loaded in another file for the testing set, which will predict and evaluate the output classes of the input image data. The testing set file makes predictions based from the trained model that has the network architecture, weight and loss values and optimizer.

Cropped Shapes with Different Dimensions Using Spatial Pyramid Pooling

The spatial pyramid pooling functions as a layer in between the convolutional layers. It will be used to see if the loss of the convolutional neural network can be reduced. The program cnn_sobel_main.py saves the cropped images of different dimensions, 300 pixels by 300 pixels and 300 pixels by 150 pixels in their respective folders. The images are pickled into a tuple of image data array and output labels, merged and split into two separate lists of image data and categorical label encodings for training and validation sets. The cnn_sobel_spp.py file does not use the preprocessing function get_edges because the processed images are already cropped, scaled and saved accordingly in cnn_sobel_main.py. The architecture with spatial pyramid pooling will use Keras Sequential layered model. Spatial pyramid pooling allows different image sizes to be incorporated into the convolutional neural network by replacing the flatten layer with the spatial pyramid pooling([1, 2, 4]) layer. The max-pool layer is also not needed into between the two-dimensional convolutional layer. The parameter [1, 2, 4] list array represents 3 regions with 1, 2x2 and 4x4 max pools, which creates 21 outputs per feature map, (yhenon/keras-spp). The architecture of the network is as follows: convolutional two-dimensional layer, max-pool layer, dropout layer, spatial pyramid pooling layer, dense Layer, dropout layer and dense layer for output classes. The Sequential model is then fitted for the training dataset with 300 pixels by 300 pixels and the other training dataset with 300 pixels by 150 pixels.

Inception Model using Keras Functional API

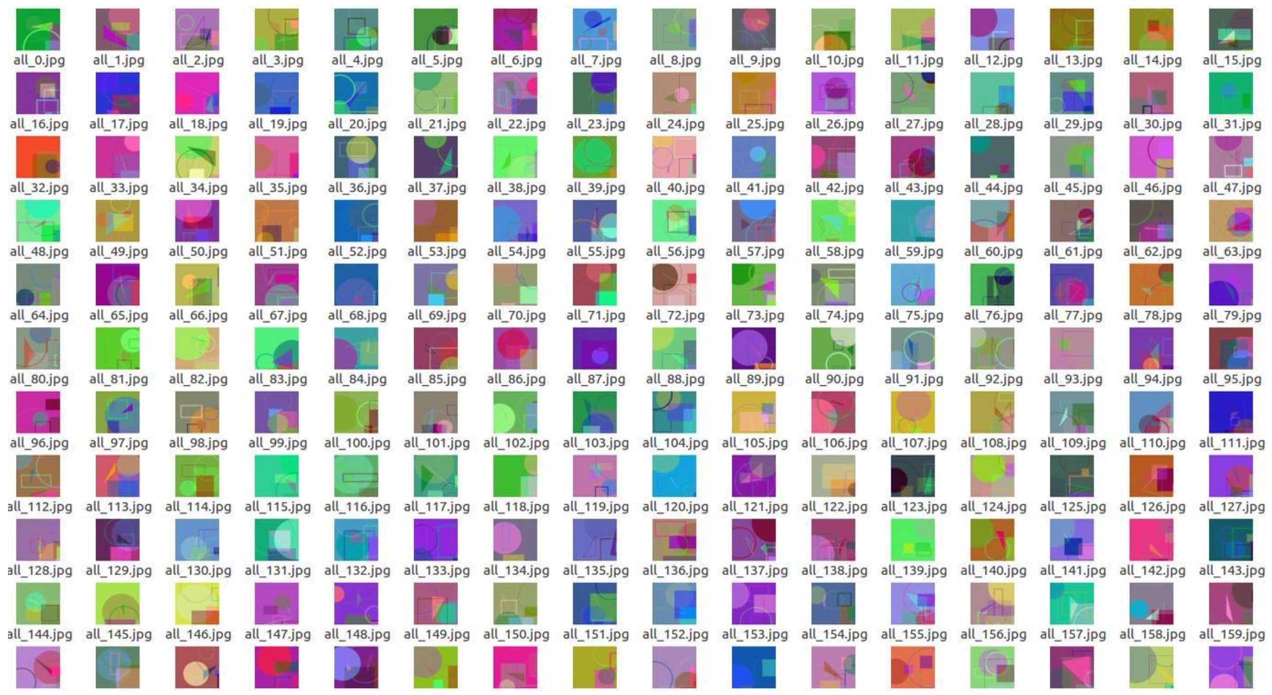
A smaller version of Google's Inception model architecture can be created using Keras functional API. The Input instance allows a defined image size of the shape (300, 300, 3), where Input represents the input data being loaded from the pickle file. The Inception module architecture consists of piling two-dimensional convolutions on top of each other; these layers are called towers. The first layer of the tower will obtain the vectors of input image matrices from Input(). It is followed by the second consecutive layer of the two-dimensional convolutional layer, which will obtain the output from the first layer of the tower. The layering of these two consecutive convolutional layers can continue to as many towers as needed. The layers of the tower are concatenated into a single output and then flattened for the towered layers to feed into the fully connected layer. The fully connected layer follows the dense instance where the first dense layer gets data from the flattened output. There will be dropout after the first dense layer, which gets its input from the first fully connected layer. The functional input into the layer modules continues as needed where the final dense layer contains four neurons for soft-max activation to a probabilistic output class. An inception model is then created from the functional layering by using the model instance where the inputs represent the input data and the outputs represent the resulting layer, which is the fully connected layer. The data generator, early stopping and the fitting of the inception model remains the same as the previous convolutional neural network file.

Multi-output (Y-label) Multi-Class Classification

The multi-output classification is different from the single-output classification during the compilation of the Sequential model as well at the last dense layer. The last dense layer is responsible for generating the output classes in supervised training. At the last dense layer, the number of neurons, which is the number of classes, remains the same. The sigmoid activation function is used instead of soft-max because soft-max makes it more evident for a single output classification. Multi-label classification does not have a chance probability of an image pertaining to a single class. A multi-label output image contains multiple classes, so the sigmoid activation will smooth out multiple probabilities of classes pertaining to the data image. The loss function for the Sequential model will be in binary cross-entropy instead of categorical cross-entropy because the binary cross-entropy represents an array of zero or one label of an input image where zero doesn't belong to the class and one belongs to the class. For instance, the array [1 1 1 1] represents that the input image has all the shapes belonging to all the classes.

The difference between the single-label output with multi-class classification and multi-label output with multi-class classification is that the multi-label output will learn the intersection of different shapes from different classes not just a single class. The training dataset will consist of two or more classes on a single image consisting of the labels (circle, triangle, square, rectangle), (circle, rectangle), (circle, rectangle, square), (circle, square), (circle, triangle), (circle, triangle, rectangle), (circle, triangle, square), (rectangle, square), (triangle, rectangle), (triangle, rectangle, square) and (triangle, square) to create a consistent layered effect of the images, the same images from the previous training dataset on single-label output is used. For the layering of the shapes on top of each other, each pickle file representing a shape is loaded and returned as a numpy array. Concatenating the numpy array, rather than as a list in the single-label output, will combine the layers of the image data, creating an intersection of different shapes.

The file merge_pkl_files.py is an option for merge where the intersections of shapes are created by draw.py. It does so by returning each pickled shape as a numpy array and merging them into layers in the next corresponding file. Since each pickled file from the training dataset consists of 2,000 images per shape, the memory mapping of numpy arrays are used for numpy array data in the shape (number of shapes, 300, 300, 3) and their categorical encoding in the shape (number of shapes, 4). The Loader() class uses multiprocessing of independent pool workers to return serialized pickled numpy arrays into function results(), where list arrays are stored globally. A pickle file called individual_data_shapes.pkl is created to represent the memory mapping of the pixelized data of each shape dataset for training and validation. The program load_merge_intersection.py merges all numpy arrays that describes each shape's pixels into layers in the next corresponding file. Each numpy array of data pixels represents a layer of information rather than as a merged list. So, the training dataset will consist of a combination of each shape layer, creating layered intersections of the same shape data of the original dataset. This is for the addition of the convolutional neural network where each training data will have multiple outputs as a label of shapes instead of a single output. This creates two pickle files by running the same program twice with different variables and pickle files called intersection_shapes_one.pkl and intersection_shapes_two.pkl. The point of these pickle files is for another program, save_pickle_images.py, to save these as images by loading the intersected layers of these pickle files.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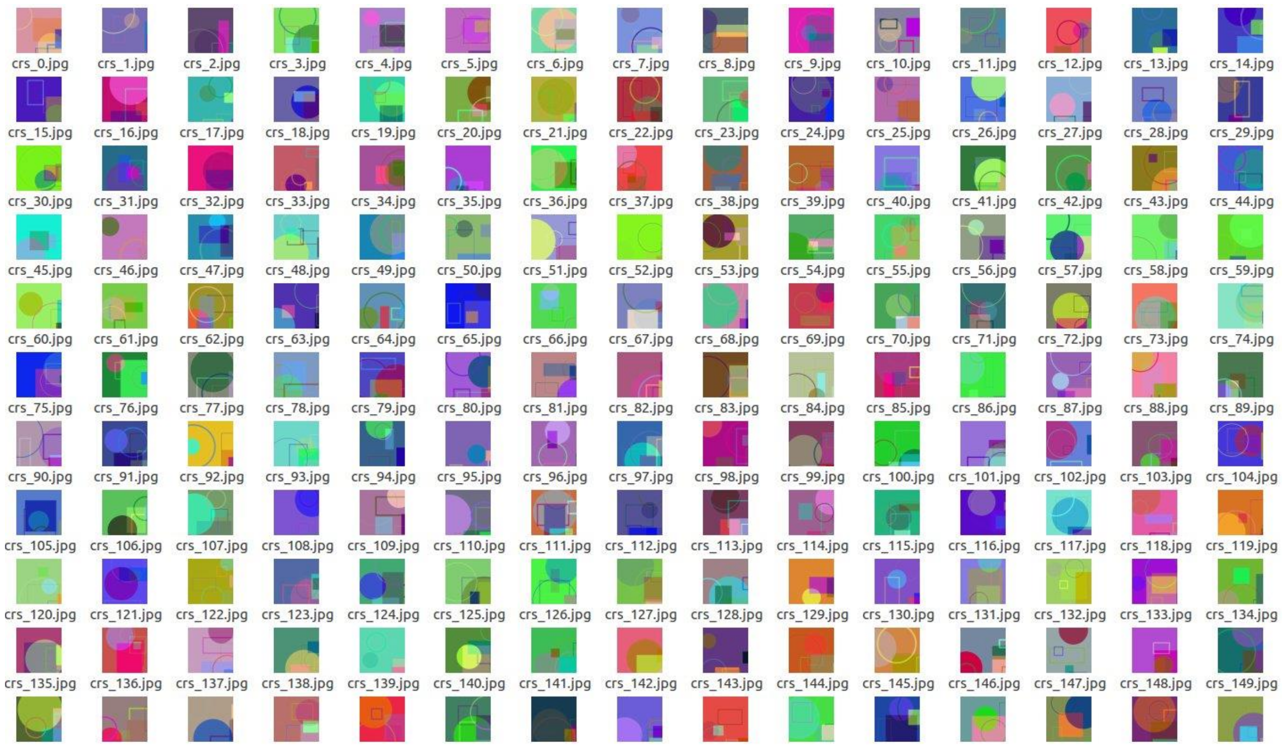
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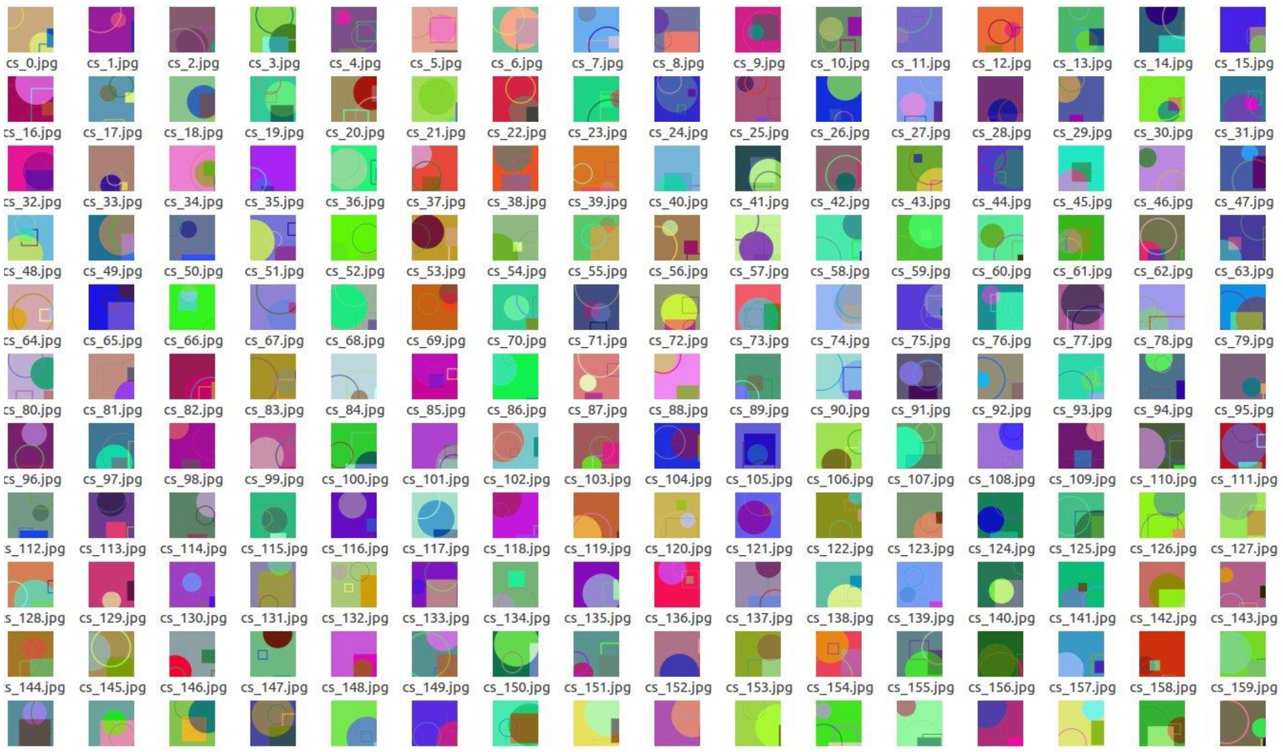
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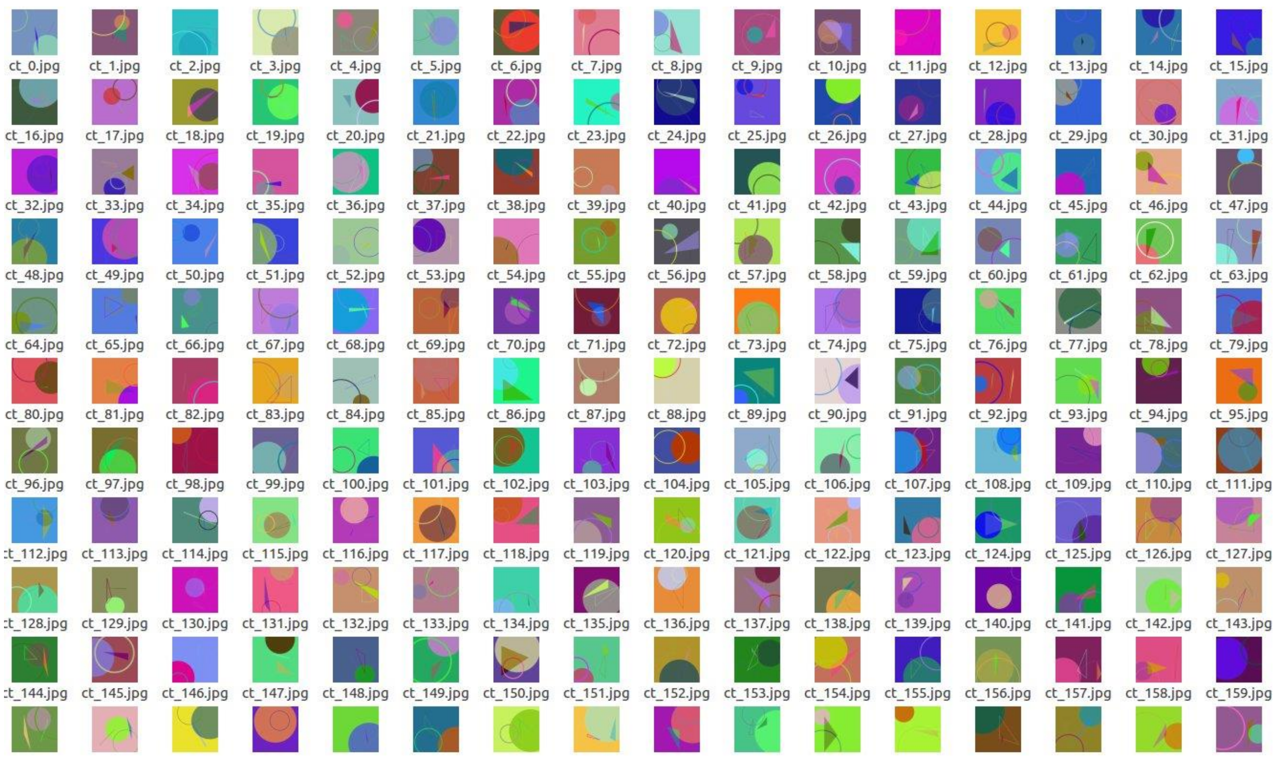
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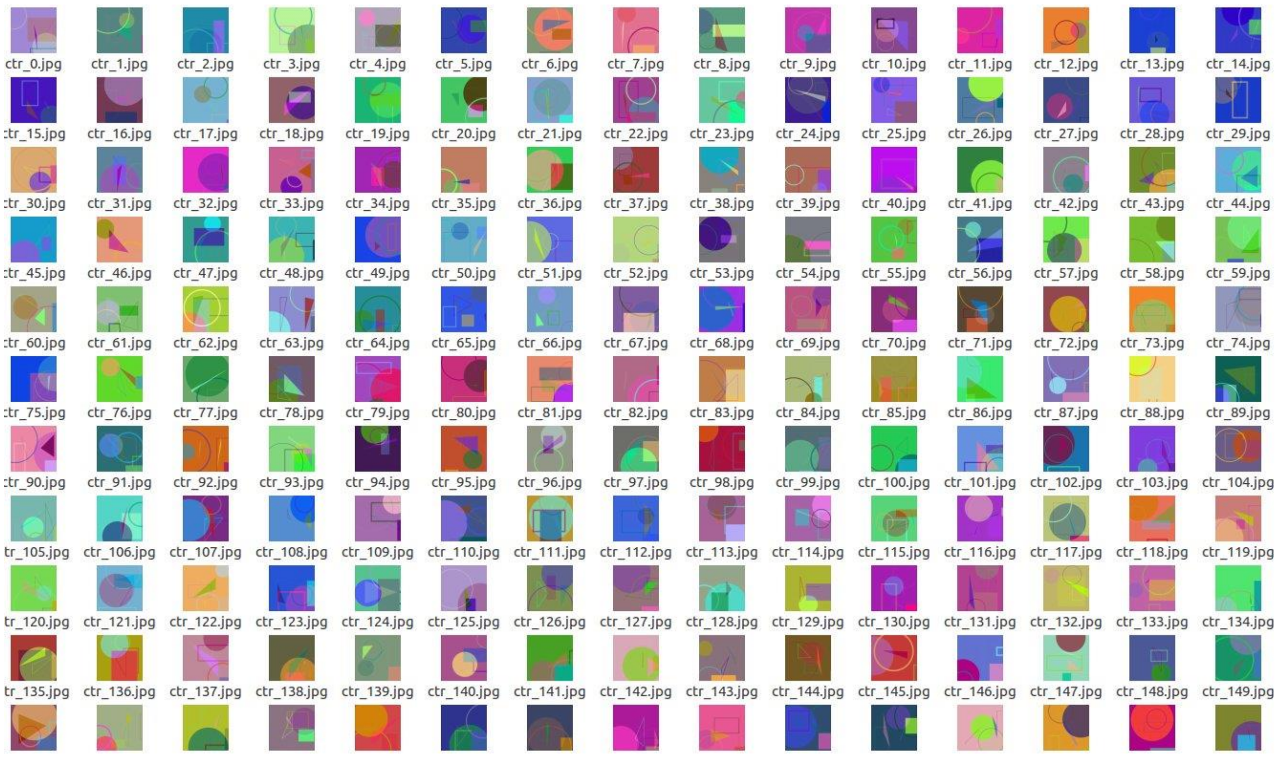
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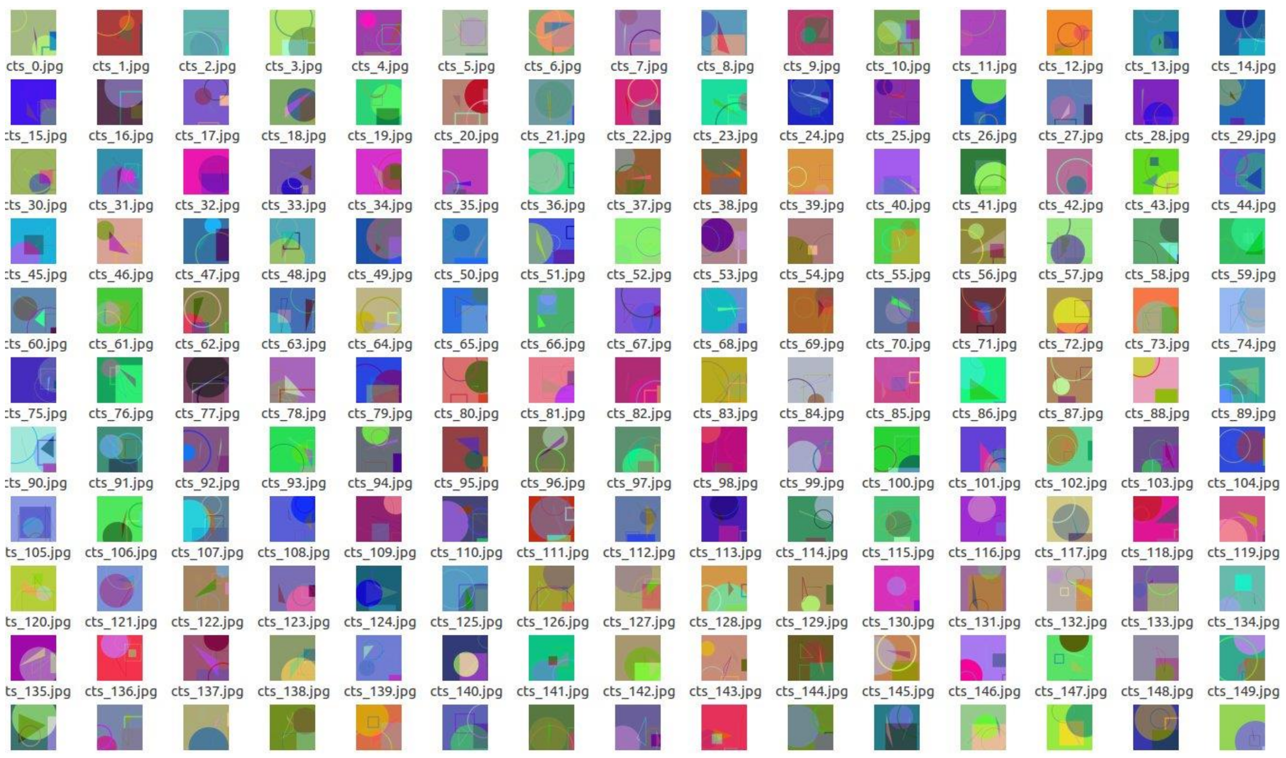
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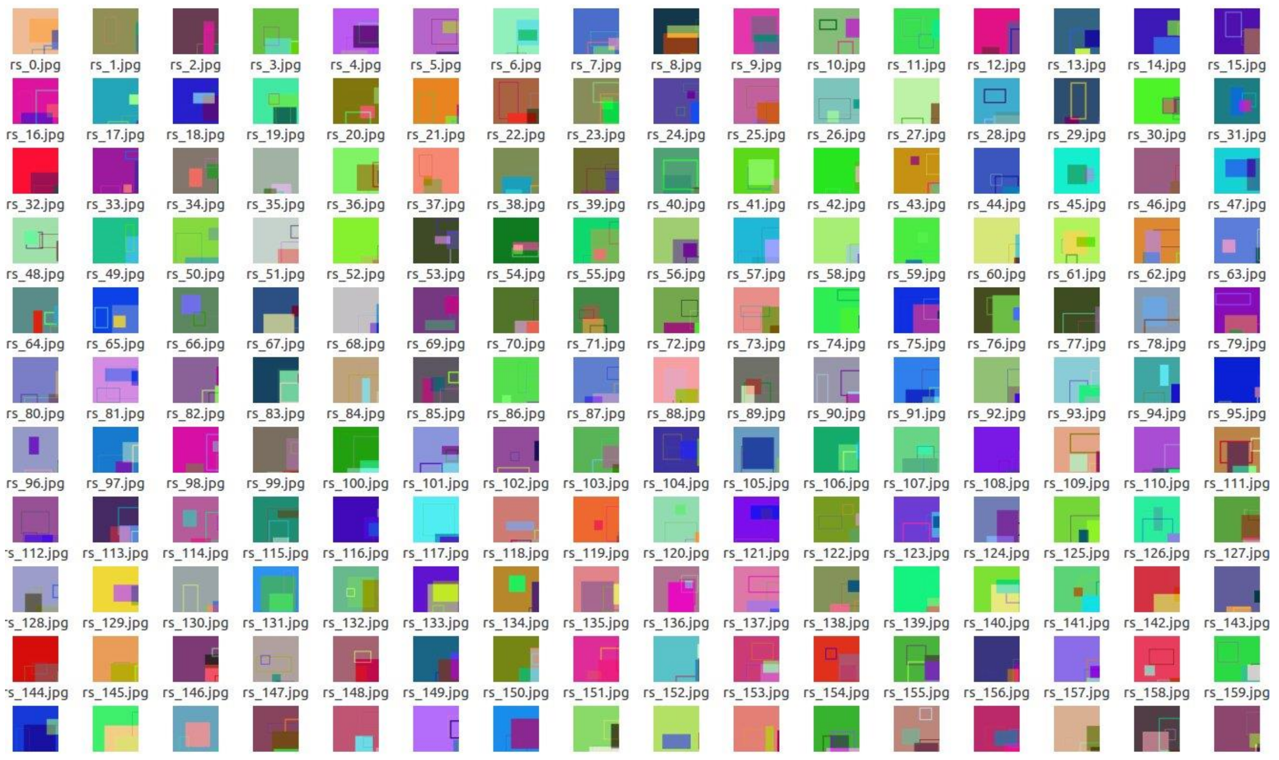
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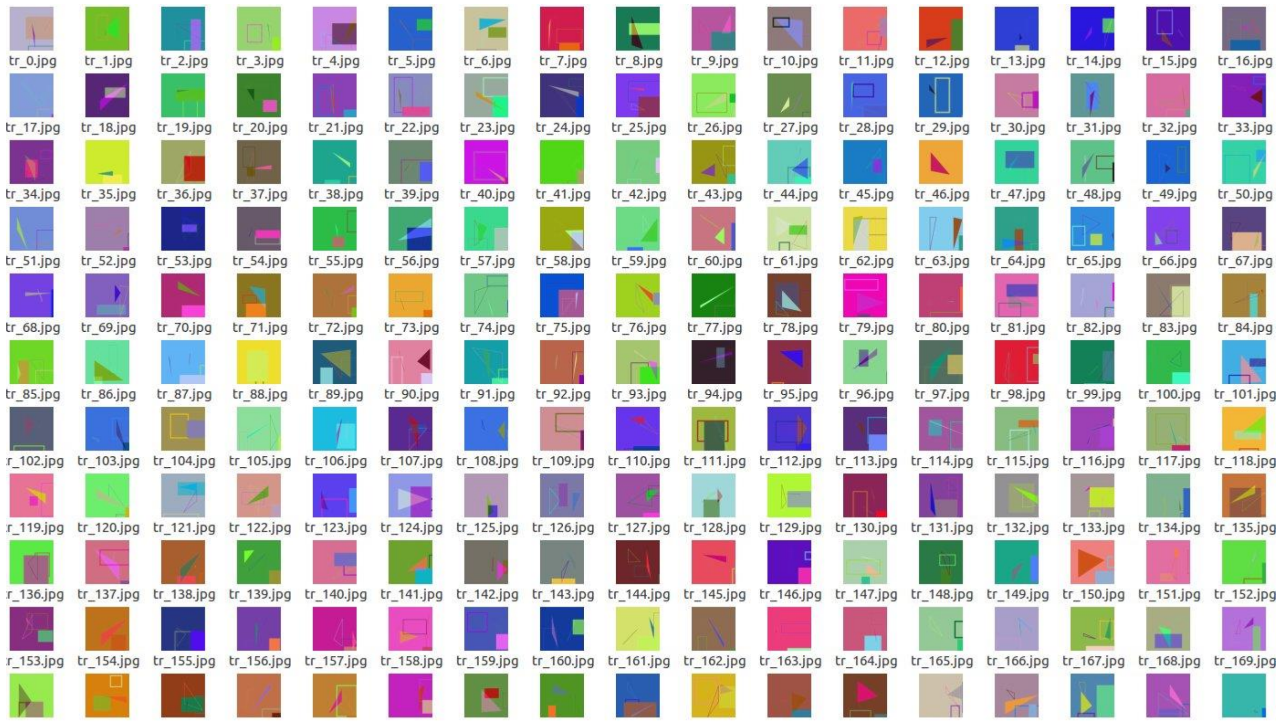
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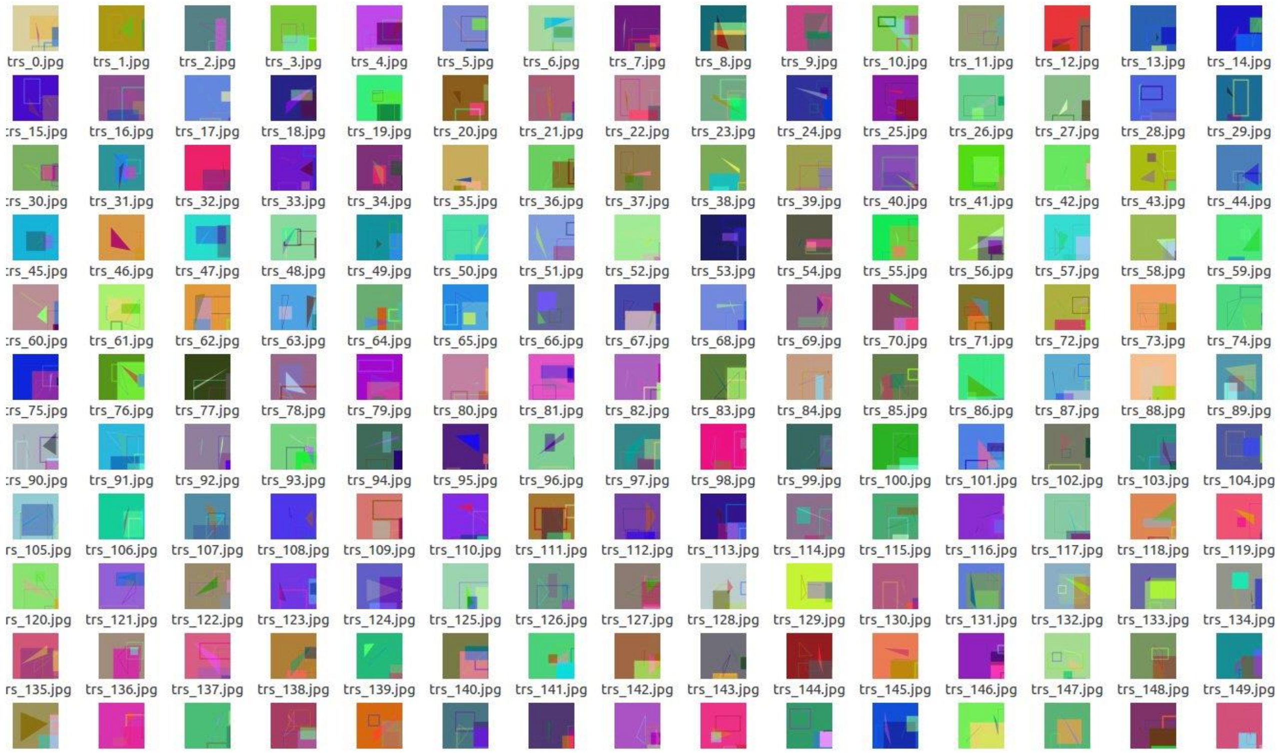
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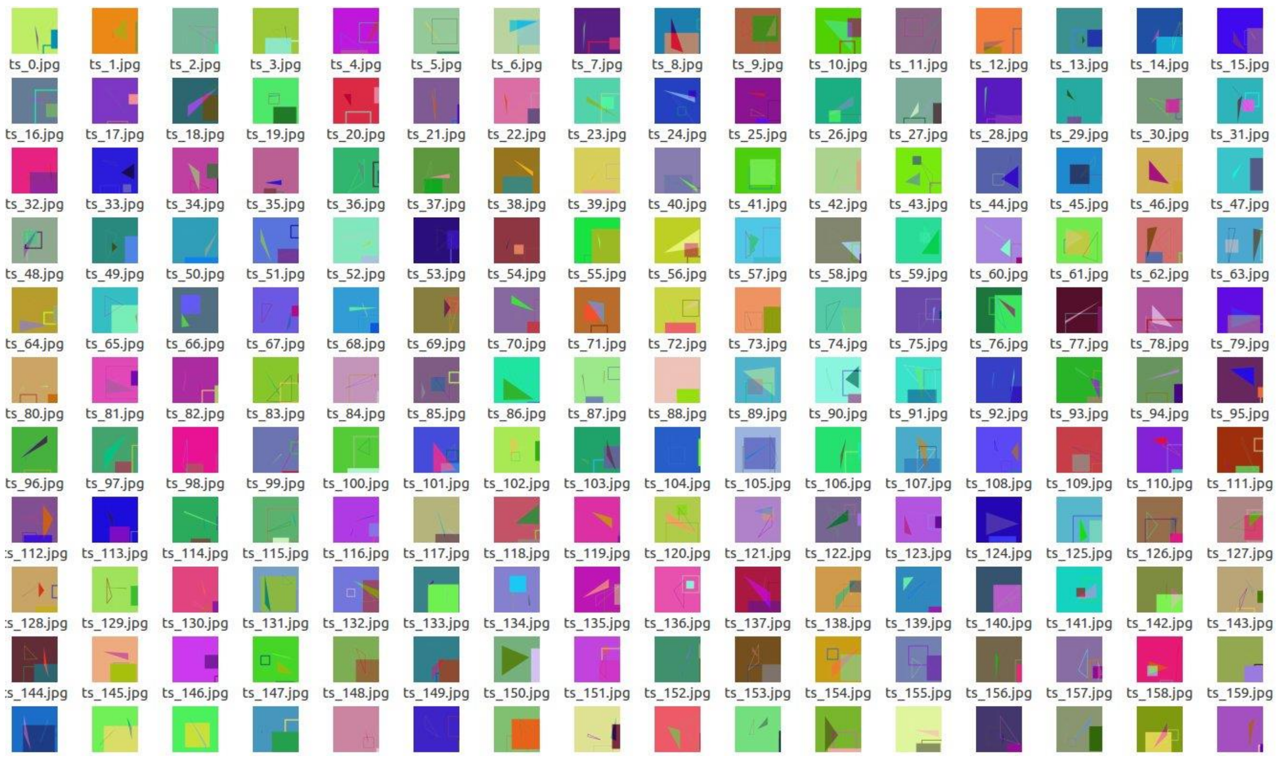
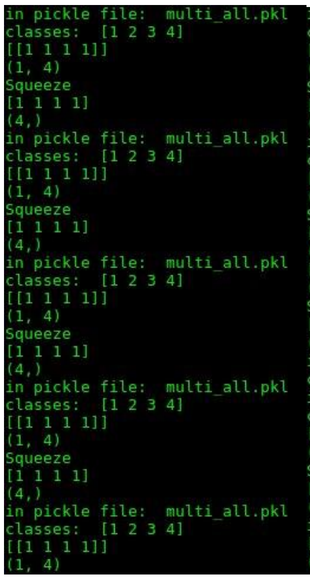
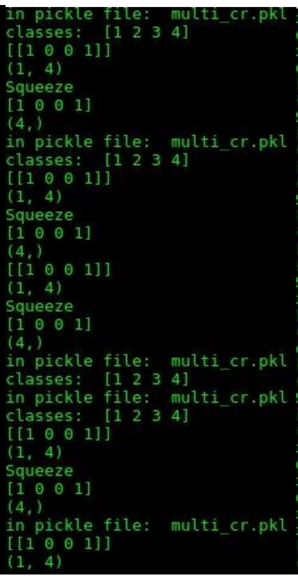


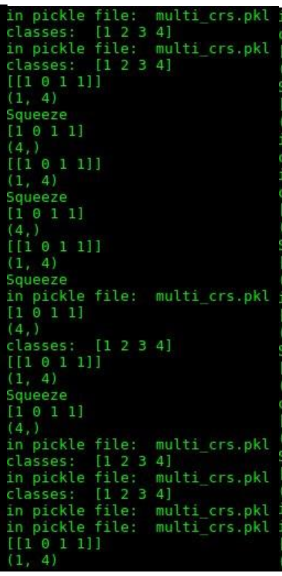
After the images for the multi-label output with multi-class classification are created, the images will be organized in a pickle file like the one with the single-label output. The difference is in the second data structure, which is y-label, that is part of the (data image, y-label) tuple. This y-label will be created by the multi-label binarizer class. It is a numpy array in binary representing zero for no class representation and one for class representation. For example, an image that consists of all shapes will have the y-label [1 1 1 1]. An image that has a circle, triangle and rectangle will have the y_label [1 1 0 1]. The numpy.squeeze function is needed to remove the extra shape axis created by multi-label binarizer so that Keras can process the numpy list structure correctly.



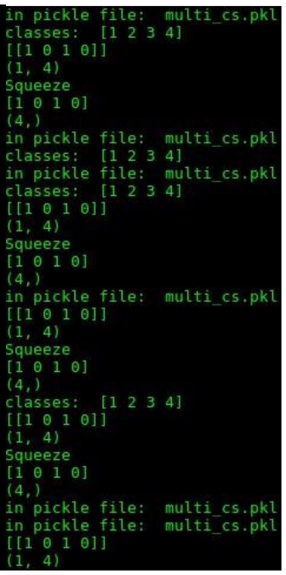
```
in pickle file:  multi_all.pkl
classes:  [1 2 3 4]
[[1 1 1 1]]
(1, 4)
Squeeze
[1 1 1 1]
(4,)
in pickle file:  multi_all.pkl
classes:  [1 2 3 4]
[[1 1 1 1]]
(1, 4)
Squeeze
[1 1 1 1]
(4,)
in pickle file:  multi_all.pkl
classes:  [1 2 3 4]
[[1 1 1 1]]
(1, 4)
Squeeze
[1 1 1 1]
(4,)
in pickle file:  multi_all.pkl
classes:  [1 2 3 4]
[[1 1 1 1]]
(1, 4)
Squeeze
[1 1 1 1]
(4,)
in pickle file:  multi_all.pkl
classes:  [1 2 3 4]
[[1 1 1 1]]
(1, 4)
```



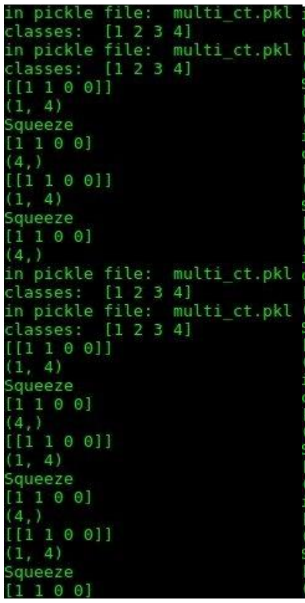
```
in pickle file:  multi_cr.pkl
classes:  [1 2 3 4]
[[1 0 0 1]]
(1, 4)
Squeeze
[1 0 0 1]
(4,)
in pickle file:  multi_cr.pkl
classes:  [1 2 3 4]
[[1 0 0 1]]
(1, 4)
Squeeze
[1 0 0 1]
(4,)
[[1 0 0 1]]
(1, 4)
Squeeze
[1 0 0 1]
(4,)
in pickle file:  multi_cr.pkl
classes:  [1 2 3 4]
in pickle file:  multi_cr.pkl
classes:  [1 2 3 4]
[[1 0 0 1]]
(1, 4)
Squeeze
[1 0 0 1]
(4,)
in pickle file:  multi_cr.pkl
[[1 0 0 1]]
(1, 4)
```



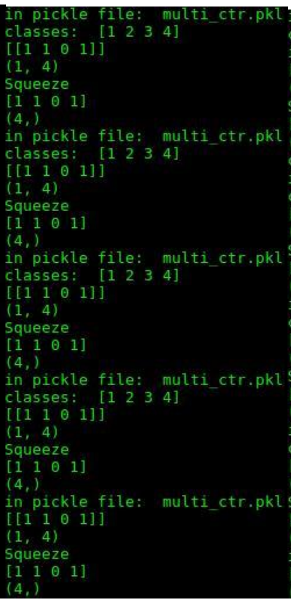
```
in pickle file:  multi_crs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_crs.pkl
classes:  [1 2 3 4]
[[1 0 1 1]]
(1, 4)
Squeeze
[1 0 1 1]
(4,)
[[1 0 1 1]]
(1, 4)
Squeeze
[1 0 1 1]
(4,)
[[1 0 1 1]]
(1, 4)
Squeeze
in pickle file:  multi_crs.pkl
[1 0 1 1]
(4,)
classes:  [1 2 3 4]
[[1 0 1 1]]
(1, 4)
Squeeze
[1 0 1 1]
(4,)
in pickle file:  multi_crs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_crs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_crs.pkl
in pickle file:  multi_crs.pkl
[[1 0 1 1]]
(1, 4)
```



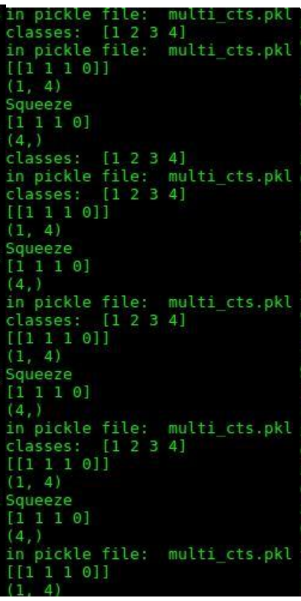
```
in pickle file:  multi_cs.pkl
classes:  [1 2 3 4]
[[1 0 1 0]]
(1, 4)
Squeeze
[1 0 1 0]
(4,)
in pickle file:  multi_cs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_cs.pkl
classes:  [1 2 3 4]
[[1 0 1 0]]
(1, 4)
Squeeze
[1 0 1 0]
(4,)
in pickle file:  multi_cs.pkl
[[1 0 1 0]]
(1, 4)
Squeeze
[1 0 1 0]
(4,)
classes:  [1 2 3 4]
[[1 0 1 0]]
(1, 4)
Squeeze
[1 0 1 0]
(4,)
in pickle file:  multi_cs.pkl
in pickle file:  multi_cs.pkl
[[1 0 1 0]]
(1, 4)
```



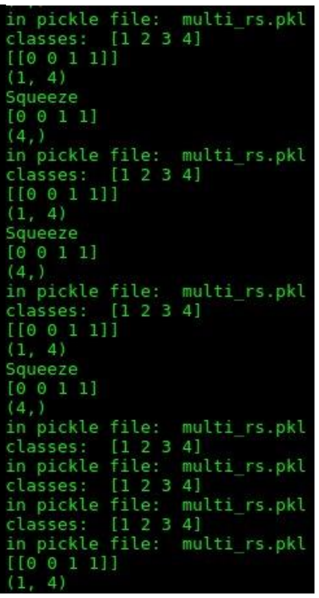
```
in pickle file:  multi_ct.pkl
classes:  [1 2 3 4]
in pickle file:  multi_ct.pkl
classes:  [1 2 3 4]
[[1 1 0 0]]
(1, 4)
Squeeze
[1 1 0 0]
(4,)
[[1 1 0 0]]
(1, 4)
Squeeze
[1 1 0 0]
(4,)
in pickle file:  multi_ct.pkl
classes:  [1 2 3 4]
in pickle file:  multi_ct.pkl
classes:  [1 2 3 4]
[[1 1 0 0]]
(1, 4)
Squeeze
[1 1 0 0]
(4,)
[[1 1 0 0]]
(1, 4)
Squeeze
[1 1 0 0]
(4,)
[[1 1 0 0]]
(1, 4)
Squeeze
[1 1 0 0]
```



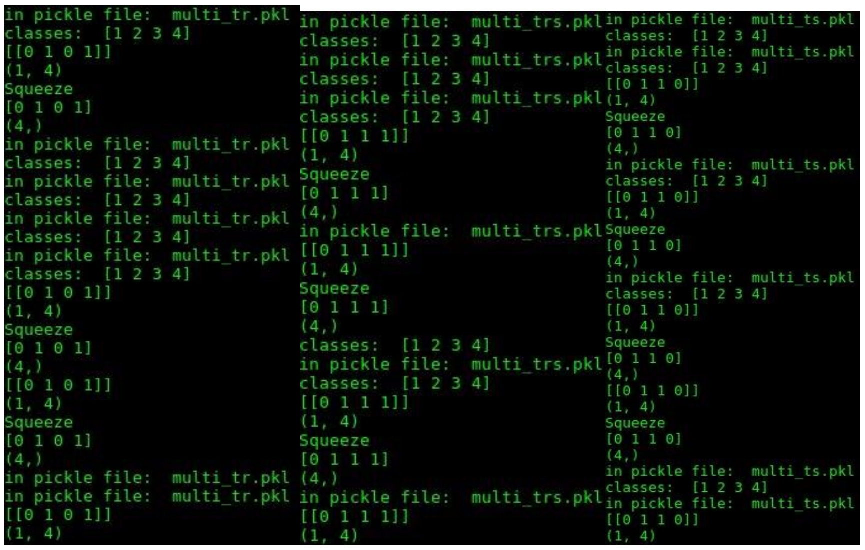
```
in pickle file:  multi_ctr.pkl
classes:  [1 2 3 4]
[[1 1 0 1]]
(1, 4)
Squeeze
[1 1 0 1]
(4,)
in pickle file:  multi_ctr.pkl
classes:  [1 2 3 4]
[[1 1 0 1]]
(1, 4)
Squeeze
[1 1 0 1]
(4,)
in pickle file:  multi_ctr.pkl
classes:  [1 2 3 4]
[[1 1 0 1]]
(1, 4)
Squeeze
[1 1 0 1]
(4,)
in pickle file:  multi_ctr.pkl
classes:  [1 2 3 4]
[[1 1 0 1]]
(1, 4)
Squeeze
[1 1 0 1]
(4,)
in pickle file:  multi_ctr.pkl
[[1 1 0 1]]
(1, 4)
Squeeze
[1 1 0 1]
(4,)
```



```
in pickle file:  multi_cts.pkl
classes:  [1 2 3 4]
in pickle file:  multi_cts.pkl
[[1 1 1 0]]
(1, 4)
Squeeze
[1 1 1 0]
(4,)
classes:  [1 2 3 4]
in pickle file:  multi_cts.pkl
classes:  [1 2 3 4]
[[1 1 1 0]]
(1, 4)
Squeeze
[1 1 1 0]
(4,)
in pickle file:  multi_cts.pkl
classes:  [1 2 3 4]
[[1 1 1 0]]
(1, 4)
Squeeze
[1 1 1 0]
(4,)
in pickle file:  multi_cts.pkl
classes:  [1 2 3 4]
[[1 1 1 0]]
(1, 4)
Squeeze
[1 1 1 0]
(4,)
in pickle file:  multi_cts.pkl
[[1 1 1 0]]
(1, 4)
```



```
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
[[0 0 1 1]]
(1, 4)
Squeeze
[0 0 1 1]
(4,)
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
[[0 0 1 1]]
(1, 4)
Squeeze
[0 0 1 1]
(4,)
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
[[0 0 1 1]]
(1, 4)
Squeeze
[0 0 1 1]
(4,)
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_rs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_rs.pkl
[[0 0 1 1]]
(1, 4)
```

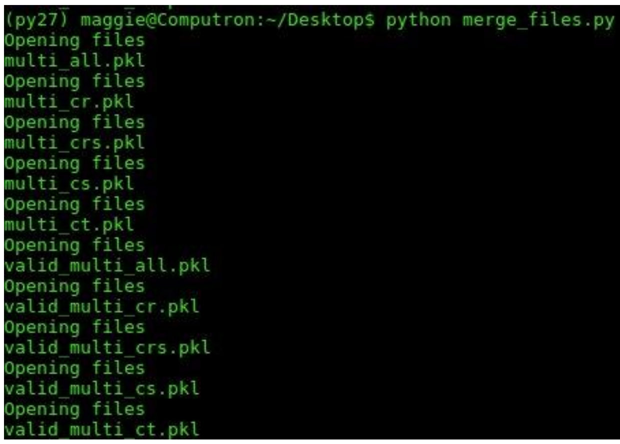


```
in pickle file:  multi_tr.pkl
classes:  [1 2 3 4]
[[0 1 0 1]]
(1, 4)
Squeeze
[0 1 0 1]
(4,)
in pickle file:  multi_tr.pkl
classes:  [1 2 3 4]
in pickle file:  multi_tr.pkl
classes:  [1 2 3 4]
in pickle file:  multi_tr.pkl
classes:  [1 2 3 4]
in pickle file:  multi_tr.pkl
classes:  [1 2 3 4]
[[0 1 0 1]]
(1, 4)
Squeeze
[0 1 0 1]
(4,)
[[0 1 0 1]]
(1, 4)
Squeeze
[0 1 0 1]
(4,)
in pickle file:  multi_tr.pkl
in pickle file:  multi_tr.pkl
[[0 1 0 1]]
(1, 4)
```

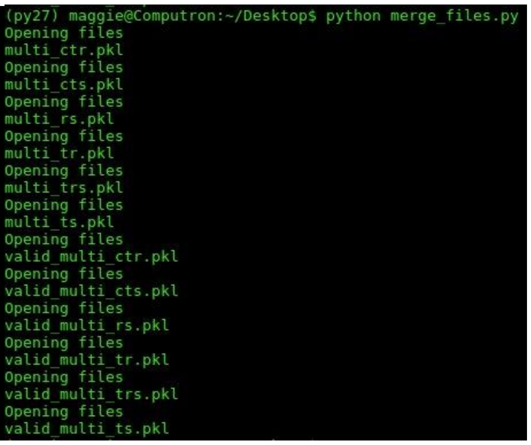
```
in pickle file:  multi_trs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_trs.pkl
classes:  [1 2 3 4]
in pickle file:  multi_trs.pkl
classes:  [1 2 3 4]
[[0 1 1 1]]
(1, 4)
Squeeze
[0 1 1 1]
(4,)
in pickle file:  multi_trs.pkl
[[0 1 1 1]]
(1, 4)
Squeeze
[0 1 1 1]
(4,)
classes:  [1 2 3 4]
in pickle file:  multi_trs.pkl
classes:  [1 2 3 4]
[[0 1 1 1]]
(1, 4)
Squeeze
[0 1 1 1]
(4,)
in pickle file:  multi_trs.pkl
[[0 1 1 1]]
(1, 4)
```

```
in pickle file:  multi_ts.pkl
classes:  [1 2 3 4]
in pickle file:  multi_ts.pkl
classes:  [1 2 3 4]
[[0 1 1 0]]
(1, 4)
Squeeze
[0 1 1 0]
(4,)
in pickle file:  multi_ts.pkl
classes:  [1 2 3 4]
[[0 1 1 0]]
(1, 4)
Squeeze
[0 1 1 0]
(4,)
in pickle file:  multi_ts.pkl
classes:  [1 2 3 4]
[[0 1 1 0]]
(1, 4)
Squeeze
[0 1 1 0]
(4,)
[[0 1 1 0]]
(1, 4)
Squeeze
[0 1 1 0]
(4,)
in pickle file:  multi_ts.pkl
classes:  [1 2 3 4]
in pickle file:  multi_ts.pkl
[[0 1 1 0]]
(1, 4)
```

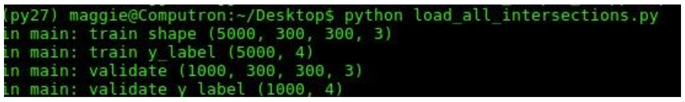
After these pickle files are created, the program merge_files.py merges all types of intersections into a single large list for training and validation data. It is very similar to the merge_files.py for single label output for multi-class classification. The difference is that there are a lot more files to load and merge. Since each intersection dataset consists of 2,000 images with a total of 22,000 images is a lot of repetitive data, half of each dataset is merged instead of the entire set with a total of 11,000 images. The validation data for the intersections consists of 200 images for each multi-label class, with a total of 2200, which is 20% of the training dataset. It dumps all the merged dataset, training dataset and validation dataset into a pickle file called data_shapes.pkl in order for load_all_intersections.py to create two large lists of the intersected data: the numpy image data list and its corresponding multi-label output. Similar to the single-label output, the multi-label output for the training dataset and the validation dataset are shuffled in order to randomize the data input for the convolutional neural network.



```
(py27) maggie@Computron:~/Desktop$ python merge_files.py
Opening files
multi_all.pkl
Opening files
multi_cr.pkl
Opening files
multi_crs.pkl
Opening files
multi_cs.pkl
Opening files
multi_ct.pkl
Opening files
valid_multi_all.pkl
Opening files
valid_multi_cr.pkl
Opening files
valid_multi_crs.pkl
Opening files
valid_multi_cs.pkl
Opening files
valid_multi_ct.pkl
```



```
(py27) maggie@Computron:~/Desktop$ python merge_files.py
Opening files
multi_ctr.pkl
Opening files
multi_cts.pkl
Opening files
multi_rs.pkl
Opening files
multi_tr.pkl
Opening files
multi_trs.pkl
Opening files
multi_ts.pkl
Opening files
valid_multi_ctr.pkl
Opening files
valid_multi_cts.pkl
Opening files
valid_multi_rs.pkl
Opening files
valid_multi_tr.pkl
Opening files
valid_multi_trs.pkl
Opening files
valid_multi_ts.pkl
```



```
(py27) maggie@Computron:~/Desktop$ python load_all_intersections.py
in main: train shape (5000, 300, 300, 3)
in main: train y_label (5000, 4)
in main: validate (1000, 300, 300, 3)
in main: validate y label (1000, 4)
```

Conclusion of the optimal Convolutional Neural Network Architecture

It is unclear which neural network architecture works better for generalization: 2 Dense layers or 3 Dense layers with the final Dense layer representing the output classes of the convolutional neural network. I am not sure if the white background from the cropped images should pertain to a class. Will that decrease the loss of the neural network? The lowest loss I can obtain from training the network is 0.3466. This has the architecture in the chart below:

adamax = Adamax(lr=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0) #prev 0.002

Number of Filters	64		128			512	512	512	4
Layer Type	CONV_2D	MAX POOL	CONV_2D	MAXPOOL	Flatten()	Dense()	Dense()	Dense()	Dense()
Conv. Size	(6,6)	(6,6)	(6,6)	(6,6)		Dropout (0.35)	Dropout (0.35)	Dropout (0.35)	
Padding	valid		valid						
Activation	relu		relu			relu	relu	relu	softmax

Epoch 30/50

250/250 [==============================] - 233s - loss: 0.3466 - acc: 0.8096 - val_loss: 0.3560 - val_acc: 0.7869

Test loss: 4.95138476849

Test accuracy 0.673125

Total params: 4,041,156

Trainable params: 4,041,156

Layer(type)	Output Shape	Param #
conv2d_1(Conv2D)	(None, 295, 295, 64)	6976

max_pooling2d_1(MaxPooling2D)	(None, 49, 49, 64)	0
conv2d_2(Conv2D)	(None, 44, 44, 128)	295040
max_pooling2d_2(MaxPooling2D)	(None, 7, 7, 128)	0
flatten_1(Flatten)	(None, 6272)	0
dense_1(Dense)	(None, 512)	3211776
dropout_1(Dropout)	(None, 512)	0
dense_2(Dense)	(None, 512)	262656
dropout_2(Dropout)	(None, 512)	0
dense_3(Dense)	(None, 512)	262656
dropout_3(Dropout)	(None, 512)	0
dense_4(Dense)	(None, 4)	2052