Project Report

Gotta Plot 'Em All | PokeNet

Reid, Brandon
Vangala, Sravani
Buchireddy, Shreya Reddy

06/25/2020

Participation

Reid, Brandon | Team Lead | Machine Learning - spent the project specializing and studying machine learning. Built a CNN for image classification of Pokemon.

Vangala, Sravani | Data Analysis - worked on data analysis, feature extraction, and data visualization, also scribed/voiced the project presentation.

Buchireddy, Shreya Reddy | Data Analysis - worked on data analysis, feature extraction, and data visualization, also scribed/voiced the project presentation.

Image Dataset

pokemon.zip

The Complete Pokemon Dataset

Workflow & Collaboration

The collaboration of this project was done via slack communication, as well as email. The shared codebase was managed through github. Image datasets were too large to store on github so we shared them through google drive via zip file. The github repository included two notebooks, one for data visualization, and one for our machine learning model. For the machine learning portion of this project we imported Tensorflow into our Jupyter Workbook using Python.

The project directory is as followed:

```
.
├──── PlotEmAll.ipynb - data visualization
├──── PokeNet.ipynb - CNN Image Classification
├──── PokeNet.pdf - PDF of CNN workbook
├──── ProjectProposal.pdf
├──── ProjectReport.pdf
├──── Datasets
└──── README.md
```

Abstract

Pokemon is a global icon for children and adults everywhere. It is a TV series that has expanded into video games, card games, movies, merchandise, and everything in-between. The motivation behind this project is to further understand the dynamics of the pokemon universe through data, while also having fun and learning in the process. Given how popular pokemon is, there is an extremely large amount of data to use for analysis and visualization. For the machine learning portion of this project we would easily be able to scrub the web for images of pokemon very easily.

The desired outcome of this project was to incorporate different data science concepts using an accumulation of pokemon data we found through various sources like kaggle and google images. The main goal of this project was split into two desired outcomes, provide statistical analysis and data visualization, and utilize pokemon data for machine learning purposes.

Our goal with the machine learning portion of the project was to do something both fun and challenging. A very well known tool in the world of Pokemon is a “Pokedex” where a pokemon trainer can use it to discover and analyze pokemon as they come across them in the wild. This provided the project inspiration to attempt to create the building blocks of a real world machine learning “Pokedex” that could essentially take an image of a pokemon and predict its name using a standard Convolutional Neural Network. As more libraries like TensorFlow become more robust, projects like this show how easy it can be to get a small and simple Convolutional Neural Network running.

With this, we could expand outside of this project in the future, to create a fun mobile application that could be used to take a picture of a pokemon with your phone, and it could provide you a prediction with the name, stats, etc. of the pokemon. This is just one example of what could be done, since this project is using a standard Convolutional Neural Network, we could expand it to do image recognition on all types of datasets.

Design

As stated above, this project uses Python for management, analysis, and visualization of our datasets, and also uses Python with TensorFlow for our Convolutional Neural Network. The code for this project was managed in two Jupyter Workbooks, one for data visualization and one for our CNN. The following sections will attempt to describe what a CNN is, it's architecture, etc. This report makes the assumption that the user has a basic understanding of neural networks.

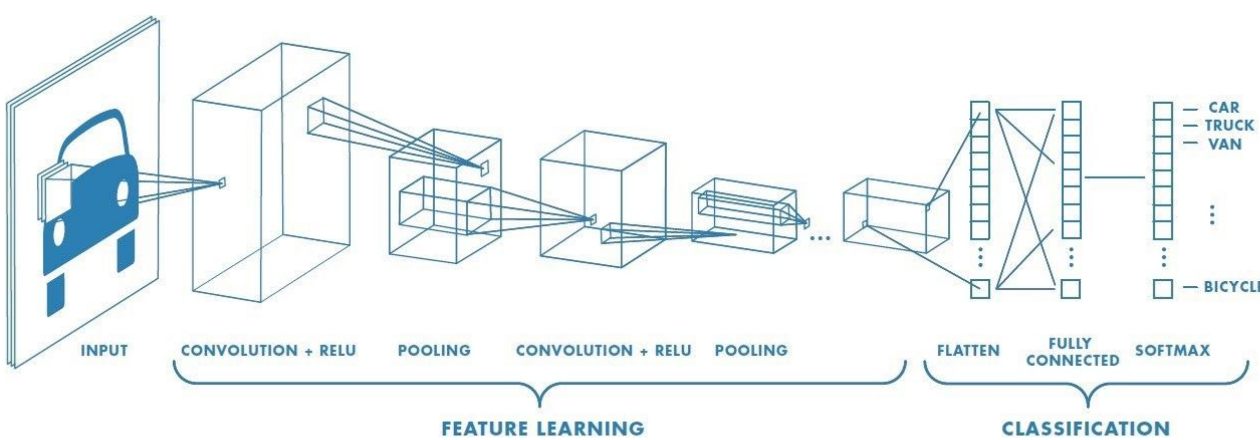
The goal of this project was not to go extremely in depth with the building blocks of a CNN, but provide an example of how simple and quick it can be to utilizing libraries like TensorFlow to get around some of the grunt work of building a neural network while also having fun in the process.

Convolutional Neural Networks (CNN)

Essentially, similar to neural networks, CNN's are made up of layers of neurons that have specific weights and biases that are learned in an unsupervised approach. The CNN will take an input image, assign those weights and biases to various features of the image to attempt to find patterns and distinctions. CNNs are useful in reducing larger images down to a form which is easy to process, while also maintaining critical features for good predicted outcomes.

A simple CNN consists of the following layers:

- Input layer
- Convo layer (Convo + ReLU)
- Pooling layer
- Fully connected(FC) layer
- Softmax/logistic layer



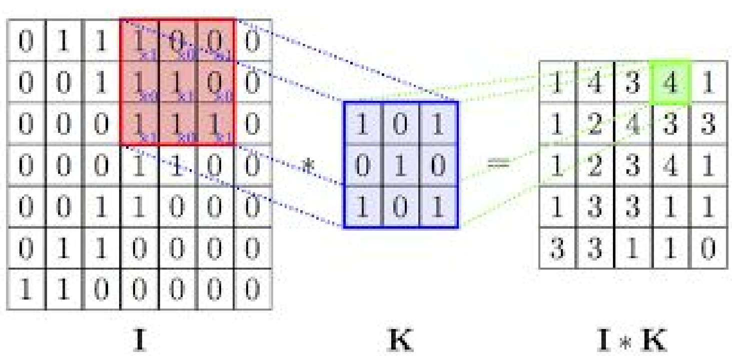
Input Layer

This is the layer that houses image data. In order to prepare image data for the input layer, images must be in the form of an array, represented in a three dimensional matrix. Similar to one of our class assignments where we get a three dimensional array of RGB color percentages of an image,. Images must be reshaped into a single dimension as well.

In order to properly prepare images for the Conv Layer, they must also be shuffled, and resized to standard image sizes. For this project we resize images down to 96 x 96.

Convolution Layer

This layer can be thought of as the main feature extraction layer, where it will attempt to gather features using edge detection. All images are made of dark and light horizontal and vertical edges. Convolution works to separate an image into many distinct features based on these edges. You can think of a face, and how the nose has distinct edges. Without going into too much detail, convolution uses dot product (matrix multiplication) to filter out these edge features. Stepping over a grid of pixels a certain number of times until the whole image is covered. Below is an example of convolution, you can think of K as a small feature (edge) of an image, and the red space is a section of a bigger image, the 1's are edges. You can see how weights are then calculated using the dot product.



In the diagram above you'll see Convo + ReLU, ReLU is the process of changing negative values during this process to 0.

Pooling Layer

A layer used between two convolution layers, used to reduce spatial complexity of an image after it's been convoluted. Without this step it would be too costly on computation when we start training on our dataset.

Fully Connected Layer

This layer takes the output of the previous layers, flattens them and turns them into a single vector that can be an input for the next stage. Then takes the inputs from the feature analysis and applies weights to make a prediction.

Milestones

The following milestones will provide details for direction in building the CNN, and what was accomplished. For further code details please refer to the codebase.

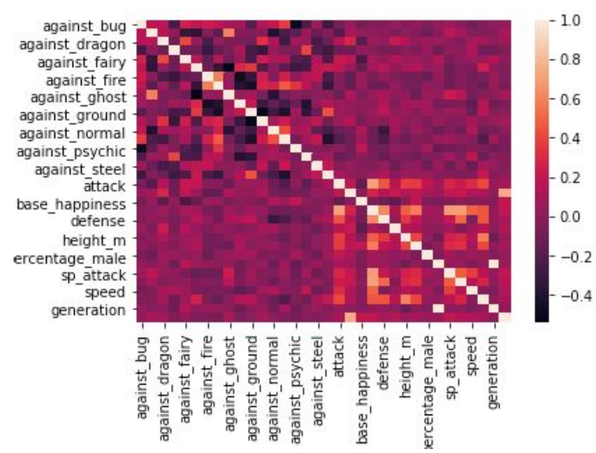
Part 1. Data Analysis | Data Visualization

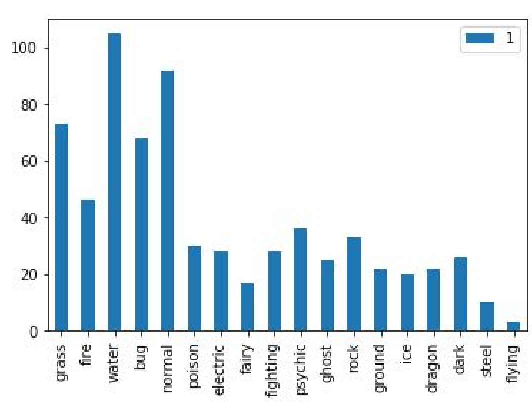
✔ *Distribution of Pokemon Types*

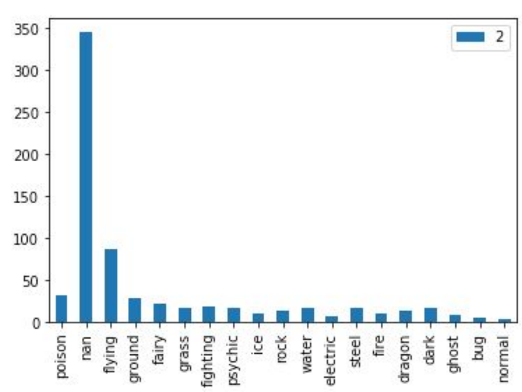
✔ *Single vs dual types using attack and special attack attributes*

✔ *Heatmap showing correlation between pokemon base stats*

✔ *Plot legendary vs non-legendary Pokemon*







Part 2. Machine learning | Convolutional Neural Network

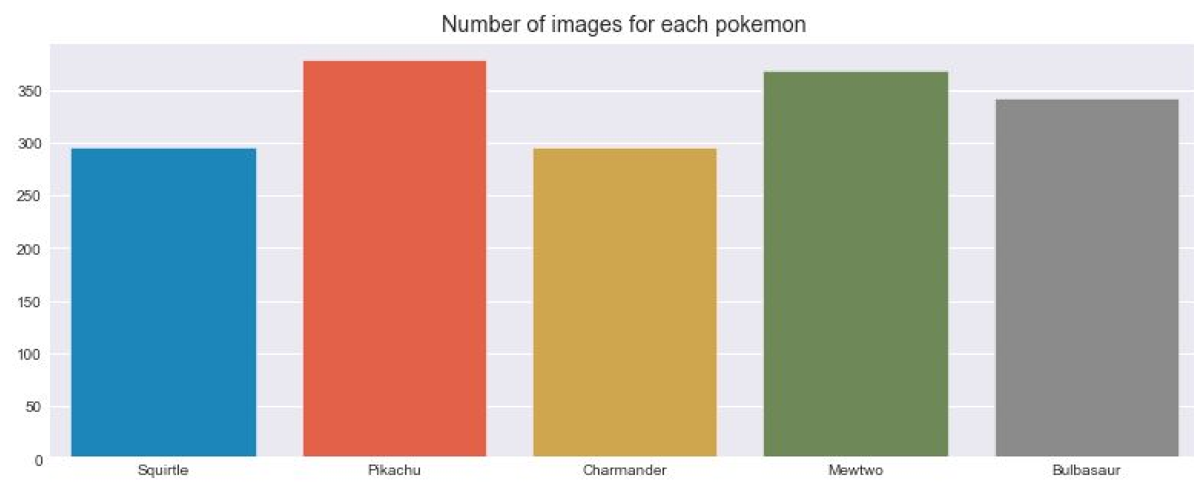
✔️ *Crawl Web for Images of Pokemon for dataset*

Library used: `GoogleImageCrawler`

```
2020-06-25 00:54:16,335 - INFO - icrawler.crawler - start crawling...
2020-06-25 00:54:16,336 - INFO - icrawler.crawler - starting 1 feeder threads...
2020-06-25 00:54:16,337 - INFO - feeder - thread feeder-001 exit
2020-06-25 00:54:16,337 - INFO - icrawler.crawler - starting 1 parser threads...
2020-06-25 00:54:16,339 - INFO - icrawler.crawler - starting 1 downloader threads...
2020-06-25 00:54:16,919 - INFO - parser - parsing result page https://www.google.com/search?q=Detective+Pikachu+Squ
irtle&ijn=0&start=0&tbs=&tbm=isch
2020-06-25 00:54:17,095 - INFO - downloader - image #1  https://i.ytimg.com/vi/wbFt4PpwggQ/maxresdefault.jpg
2020-06-25 00:54:17,716 - INFO - downloader - image #2  https://cdn.vox-cdn.com/thumbor/7CFvl9b0UpEQviCDY0RfXzHBoZ0
=/1400x0/filters:no_upscale()/cdn.vox-cdn.com/uploads/chorus_asset/file/16023556/Screen_Shot_2019_04_10_at_5.06.16_
PM.png
2020-06-25 00:54:17,752 - INFO - downloader - image #3  https://i.ytimg.com/vi/DPE3J9ama_E/maxresdefault.jpg
2020-06-25 00:54:17,913 - INFO - downloader - image #4  https://images-wixmp-ed30a86b8c4ca887773594c2.wixmp.com/f/2
95fb76c-7179-4c70-a508-a1cce61a876f/dd4aps3-5c7a8849-aab1-4f8f-933e-84240f3c1c35.png?token=eyJ0eXAiOiJKV1QiLCJhbGci
OiJIUzI1NiJ9.eyJzdWIiOiJ1cm46YXBwOiIsImlzcyI6InVybjphcHA6Iiwib2JqIjpbW3sicGF0aCI6IlwvZlwvMjk1ZmI3NmMtNzE3OS00YzcwLW
E1MDgtYTFjY2U2MWE4NzZmXC9kZDRhcHMzLTVjN2E4ODQ5LWFhYjEtNGY4Zi05MzNlLTg0MjQwZjNjMWMzNS5wbmcifV1dLCJhdWQiOlsidXJuOnNlc
nZpY2U6ZmlsZS5kb3dubG9hZCJdfQ.yolWSOEufTtHvpjGsDVvkogEkh8gJSk7EaYolU4_rsM
2020-06-25 00:54:18,029 - INFO - downloader - image #5  https://cdna.artstation.com/p/assets/images/images/017/754/
158/large/julie-tardieu-06.jpg?1557228628
2020-06-25 00:54:18,265 - INFO - downloader - image #6  https://www.thehdroom.com/wp-content/uploads/2019/04/new-de
tective-pikachu-footage.jpg
```

✔️ *Get Top 5 Pokemon with 200+ images*

```
Total number of pokemon: 5
Total number of images: 1679
```



✔ *Prepare images for input layer - Shuffle, Resize, Reshape, and Scale*

Each of the above pokemon have their own directories that we loop over, shuffle the image paths and then resize each image into an array with their associated labels (pokemon). This is in preparation for the input layer.

You can see we shuffle our images, so we get an unbiased dataset. Resize the images, to 96 x 96, and then like we discussed in the design section we must reshape our image array down to one column, and a good practice is to scale the images.

`to_categorical` is a Keras/TensorFlow tool to prepare our labels/classes for our model.

```
    IMG_SIZE = 96
    random.seed(SEED)
    random.shuffle(image_paths)
    ...
    data.append(cv.resize(image, (IMG_SIZE, IMG_SIZE)))
    labels.append(pokemon.index(poke))

    X = np.array(data).reshape(-1, IMG_SIZE, IMG_SIZE, 3) / 255.0
    y = to_categorical(labels, num_classes=len(pokemon))
```

```
/Users/brandonreid/Science/pokemon/Mewtwo/ed9eb0e7d3494c6992e06196f5b7cc05.svg -> UNREADABLE
/Users/brandonreid/Science/pokemon/Bulbasaur/000007.gif -> UNREADABLE
1677  TOTAL IMAGES PROCESSED
```

✔ *Implement Cross Validation*

Here we create our test cases from our dataset, a very popular cross validation method is `test_train_split`

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size = 0.2, random_state = SEED)
```

❌ *Image Data Augmentation*

After some research/studying we came across data augmentation methods in order to help better train our CNN. Data Augmentation essentially takes images from a dataset and creates many different variations of each image, like rotation, transformations, hue and color changes, etc. Data Augmentation can greatly improve a training model.

However attempting data augmentation with TensorFlow tools was found extremely slow, and CPU intensive. For now we decided against this approach.

Issues found here: https://github.com/keras-team/keras/issues/12683

✔️ *Build the model*

While pruning through the image data we crawled for, we noticed many of the images were higher resolution, or of larger sizes, and we also had over a thousand of them. After further research into CNNs it was clear that a VGGNet Architecture is most beneficial for Large-Scale image Recognition.

```
model = Sequential() # set up the modal for sequential layers

# SEQUENCE LAYER: CONV => RELU => POOL
model.add(Conv2D(32, (3, 3), padding="same", input_shape=IMAGE_DIMS))
#CONV
model.add(Activation("relu")) #RELU
model.add(BatchNormalization(axis=-1))
model.add(MaxPooling2D(pool_size=(3, 3))) # POOL
model.add(Dropout(0.25)) #Dropout to next sequence

# SEQUENCE LAYER: (CONV => RELU) * 2 => POOL
model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=1))
```

```
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25)) # Dropout to next sequence

# SEQUENCE LAYER: (CONV => RELU) * 2 => POOL
model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25)) # Dropout to next sequence

# SEQUENCE LAYER: first (and only) set of FC => RELU layers
model.add(Flatten())
model.add(Dense(1024))
model.add(Activation("relu"))
model.add(BatchNormalization())
model.add(Dropout(0.5)) # Dropout to next sequence

# softmax classifier
model.add(Dense(len(pokemon))) # Dense is number of classes to
predict
model.add(Activation("softmax"))
```

✔️ *Train the Model*

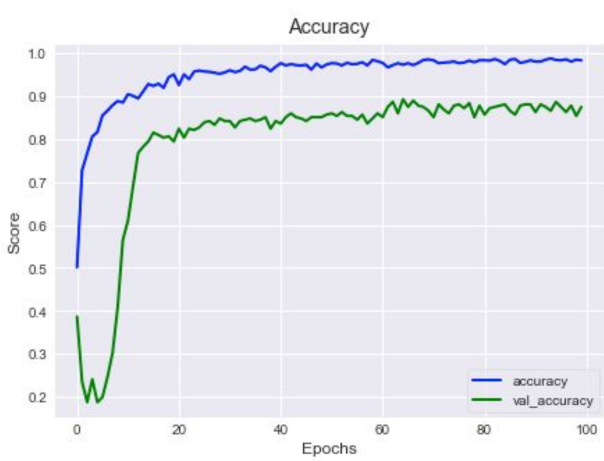
Here is where the magic happens. We fit our model with our cross validated datasets, and provide a number of epochs to train on. From what we've researched, the more epochs the better usually, but for time sake, we went with 100. This means the model will learn and train itself 100 times.

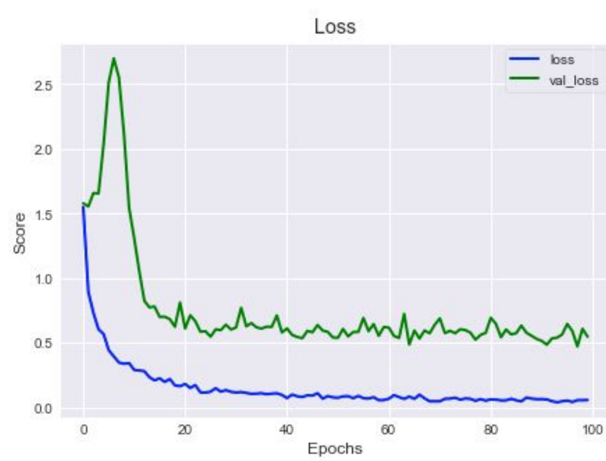
```
model.fit(X_train, y_train, batch_size=BS,
                epochs=EPOCHS, verbose=1, validation_data=(X_test,
y_test))
```

```
Epoch 97/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.0402 - accuracy: 0.9858 - val_loss: 0.5903 - val_accuracy: 0.8631
Epoch 98/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0544 - accuracy: 0.9806 - val_loss: 0.4704 - val_accuracy: 0.8780
Epoch 99/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0546 - accuracy: 0.9851 - val_loss: 0.6073 - val_accuracy: 0.8542
Epoch 100/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0561 - accuracy: 0.9836 - val_loss: 0.5463 - val_accuracy: 0.8750
```

✔️ *Analyze Accuracy and Loss on Training Model*

You can see from the plots below, we start to get a pretty great accuracy percentage even after 20 epochs. Ideally, we would like to get that green val_accuracy line closer to the blue accuracy line. There's definitely room for improvement in our model, but what a great outcome for a first build CNN.





✔️ *Make Predictions*

Before we can make a prediction we need to process our images that we want to predict, just like we do for our images before they go into the image layer. So we will take our images and resize, reshape and scale them.

```
image = cv.resize(image, (IMG_SIZE, IMG_SIZE))
image = image.reshape(-1, IMG_SIZE, IMG_SIZE, 3) / 255.0

preds = model.predict(image) # run prediction
```

Perfect predictions with pikachu and bulbasaur across the board! You'll see we even get a perfect prediction with detective pikachu. The first time we ran our model, detective pikachu would fail to predict correctly. Our assumptions were that the dataset of images did not consist of images of detective pikachu. Our model must not have gathered features of pikachu ever being "fuzzy".

Once we retrained our model with some images from the detective pikachu movie, you can see we get perfect predictions.

Predicted: Pikachu 100.0%

Predicted: Pikachu 57.41%

Predicted: Pikachu 99.97%

Predicted: Bulbasaur 99.98%

Predicted: Bulbasaur 100.0%

Predicted: Bulbasaur 100.0%

❌ *Prediction Failures*

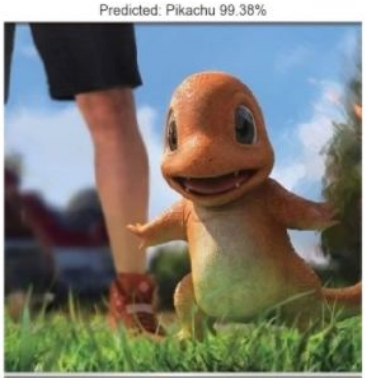
We can see below that our model is not perfect. The toy version of squirtle fails to predict accurately. Our assumption is that the edges throw off the model with the waves of water.

Predicted: Squirtle 100.0%

Predicted: Bulbasaur 89.24%

Predicted: Squirtle 100.0%

Below we can see that the charmander from the detective pikachu movie fails to predict accurately. Charmander was the only pokemon we didn't crawl for from the detective pikachu movie. This shows that our model is most likely making features based on the edges and smoothness of the character.



Predicted: Pikachu 99.38%

Predicted: Charmander 99.96%

Predicted: Charmander 99.97%

Reference Material

https://medium.com/@kelfun5354/building-a-simple-pokemon-convolutional-neural-net-cc724a8fb47d

https://www.pyimagesearch.com/2018/04/16/keras-and-convolutional-neural-networks-cnns/

https://www.youtube.com/watch?v=FmpDIaiMIeA

https://www.geeksforgeeks.org/image-classifier-using-cnn/

https://www.pyimagesearch.com/2019/07/08/keras-imagedatagenerator-and-data-augmentation/

https://missinglink.ai/guides/convolutional-neural-networks/fully-connected-layers-convolutional-neural-networks-complete-guide/

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

https://towardsdatascience.com/step-by-step-vgg16-implementation-in-keras-for-beginners-a833c686ae6c

PlotEmAll

June 25, 2020

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[7]:
```
#Loading Dataset for Building the Model
data = pd.read_csv('datasets_2756_4568_pokemon.csv')
data.head(16)
```

[7]:
```
                                  abilities  against_bug  against_dark  \
0               ['Overgrow', 'Chlorophyll']         1.00           1.0
1               ['Overgrow', 'Chlorophyll']         1.00           1.0
2               ['Overgrow', 'Chlorophyll']         1.00           1.0
3                  ['Blaze', 'Solar Power']         0.50           1.0
4                  ['Blaze', 'Solar Power']         0.50           1.0
5                  ['Blaze', 'Solar Power']         0.25           1.0
6                   ['Torrent', 'Rain Dish']         1.00           1.0
7                   ['Torrent', 'Rain Dish']         1.00           1.0
8                   ['Torrent', 'Rain Dish']         1.00           1.0
9               ['Shield Dust', 'Run Away']         1.00           1.0
10                            ['Shed Skin']         1.00           1.0
11          ['Compoundeyes', 'Tinted Lens']         0.50           1.0
12              ['Shield Dust', 'Run Away']         0.50           1.0
13                            ['Shed Skin']         0.50           1.0
14                       ['Swarm', 'Sniper']         0.50           1.0
15  ['Keen Eye', 'Tangled Feet', 'Big Pecks']         0.50           1.0

    against_dragon  against_electric  against_fairy  against_fight  \
0              1.0               0.5            0.5           0.50
1              1.0               0.5            0.5           0.50
2              1.0               0.5            0.5           0.50
3              1.0               1.0            0.5           1.00
4              1.0               1.0            0.5           1.00
5              1.0               2.0            0.5           0.50
6              1.0               2.0            1.0           1.00
7              1.0               2.0            1.0           1.00
8              1.0               2.0            1.0           1.00
```

9	1.0	1.0	1.0	0.50
10	1.0	1.0	1.0	0.50
11	1.0	2.0	1.0	0.25
12	1.0	1.0	0.5	0.25
13	1.0	1.0	0.5	0.25
14	1.0	1.0	0.5	0.25
15	1.0	2.0	1.0	1.00

	against_fire	against_flying	against_ghost	…	percentage_male	\
0	2.0	2.0	1.0	…	88.1	
1	2.0	2.0	1.0	…	88.1	
2	2.0	2.0	1.0	…	88.1	
3	0.5	1.0	1.0	…	88.1	
4	0.5	1.0	1.0	…	88.1	
5	0.5	1.0	1.0	…	88.1	
6	0.5	1.0	1.0	…	88.1	
7	0.5	1.0	1.0	…	88.1	
8	0.5	1.0	1.0	…	88.1	
9	2.0	2.0	1.0	…	50.0	
10	2.0	2.0	1.0	…	50.0	
11	2.0	2.0	1.0	…	50.0	
12	2.0	2.0	1.0	…	50.0	
13	2.0	2.0	1.0	…	50.0	
14	2.0	2.0	1.0	…	50.0	
15	1.0	1.0	0.0	…	50.0	

	pokedex_number	sp_attack	sp_defense	speed	type1	type2	weight_kg	\
0	1	65	65	45	grass	poison	6.9	
1	2	80	80	60	grass	poison	13.0	
2	3	122	120	80	grass	poison	100.0	
3	4	60	50	65	fire	NaN	8.5	
4	5	80	65	80	fire	NaN	19.0	
5	6	159	115	100	fire	flying	90.5	
6	7	50	64	43	water	NaN	9.0	
7	8	65	80	58	water	NaN	22.5	
8	9	135	115	78	water	NaN	85.5	
9	10	20	20	45	bug	NaN	2.9	
10	11	25	25	30	bug	NaN	9.9	
11	12	90	80	70	bug	flying	32.0	
12	13	20	20	50	bug	poison	3.2	
13	14	25	25	35	bug	poison	10.0	
14	15	15	80	145	bug	poison	29.5	
15	16	35	35	56	normal	flying	1.8	

	generation	is_legendary
0	1	0
1	1	0

```
2            1            0
3            1            0
4            1            0
5            1            0
6            1            0
7            1            0
8            1            0
9            1            0
10           1            0
11           1            0
12           1            0
13           1            0
14           1            0
15           1            0

[16 rows x 41 columns]
```

[9]:
```
#Checking the shape of the dataframe
data.shape
```

[9]:
```
(801, 41)
```

[10]:
```
#displaying all the coloumn names
data.columns
```

[10]:
```
Index(['abilities', 'against_bug', 'against_dark', 'against_dragon',
       'against_electric', 'against_fairy', 'against_fight', 'against_fire',
       'against_flying', 'against_ghost', 'against_grass', 'against_ground',
       'against_ice', 'against_normal', 'against_poison', 'against_psychic',
       'against_rock', 'against_steel', 'against_water', 'attack',
       'base_egg_steps', 'base_happiness', 'base_total', 'capture_rate',
       'classfication', 'defense', 'experience_growth', 'height_m', 'hp',
       'japanese_name', 'name', 'percentage_male', 'pokedex_number',
       'sp_attack', 'sp_defense', 'speed', 'type1', 'type2', 'weight_kg',
       'generation', 'is_legendary'],
      dtype='object')
```

[11]:
```
#Descriptive statistics using describe
data.describe()
```

[11]:
```
       against_bug  against_dark  against_dragon  against_electric  \
count   801.000000    801.000000      801.000000        801.000000
mean      0.996255      1.057116        0.968789          1.073970
std       0.597248      0.438142        0.353058          0.654962
min       0.250000      0.250000        0.000000          0.000000
25%       0.500000      1.000000        1.000000          0.500000
50%       1.000000      1.000000        1.000000          1.000000
```

```
75%        1.000000      1.000000        1.000000          1.000000
max        4.000000      4.000000        2.000000          4.000000

       against_fairy  against_fight  against_fire  against_flying  \
count     801.000000     801.000000    801.000000      801.000000
mean        1.068976       1.065543      1.135456        1.192884
std         0.522167       0.717251      0.691853        0.604488
min         0.250000       0.000000      0.250000        0.250000
25%         1.000000       0.500000      0.500000        1.000000
50%         1.000000       1.000000      1.000000        1.000000
75%         1.000000       1.000000      2.000000        1.000000
max         4.000000       4.000000      4.000000        4.000000

       against_ghost  against_grass  …    height_m          hp  \
count     801.000000     801.000000  …  781.000000  801.000000
mean        0.985019       1.034020  …    1.163892   68.958801
std         0.558256       0.788896  …    1.080326   26.576015
min         0.000000       0.250000  …    0.100000    1.000000
25%         1.000000       0.500000  …    0.600000   50.000000
50%         1.000000       1.000000  …    1.000000   65.000000
75%         1.000000       1.000000  …    1.500000   80.000000
max         4.000000       4.000000  …   14.500000  255.000000

       percentage_male  pokedex_number   sp_attack  sp_defense       speed  \
count       703.000000      801.000000  801.000000  801.000000  801.000000
mean         55.155761      401.000000   71.305868   70.911361   66.334582
std          20.261623      231.373075   32.353826   27.942501   28.907662
min           0.000000        1.000000   10.000000   20.000000    5.000000
25%          50.000000      201.000000   45.000000   50.000000   45.000000
50%          50.000000      401.000000   65.000000   66.000000   65.000000
75%          50.000000      601.000000   91.000000   90.000000   85.000000
max         100.000000      801.000000  194.000000  230.000000  180.000000

        weight_kg  generation  is_legendary
count  781.000000  801.000000    801.000000
mean    61.378105    3.690387      0.087391
std    109.354766    1.930420      0.282583
min      0.100000    1.000000      0.000000
25%      9.000000    2.000000      0.000000
50%     27.300000    4.000000      0.000000
75%     64.800000    5.000000      0.000000
max    999.900000    7.000000      1.000000

[8 rows x 34 columns]
```

[12]:

```
data.dtypes
```

[12]:
```
abilities               object
against_bug            float64
against_dark           float64
against_dragon         float64
against_electric       float64
against_fairy          float64
against_fight          float64
against_fire           float64
against_flying         float64
against_ghost          float64
against_grass          float64
against_ground         float64
against_ice            float64
against_normal         float64
against_poison         float64
against_psychic        float64
against_rock           float64
against_steel          float64
against_water          float64
attack                   int64
base_egg_steps           int64
base_happiness           int64
base_total               int64
capture_rate            object
classfication           object
defense                  int64
experience_growth        int64
height_m               float64
hp                       int64
japanese_name           object
name                    object
percentage_male        float64
pokedex_number           int64
sp_attack                int64
sp_defense               int64
speed                    int64
type1                   object
type2                   object
weight_kg              float64
generation               int64
is_legendary             int64
dtype: object
```

[14]:
```
missing_values_count = data.isnull().sum()
missing_values_count
```

[14]:

```
abilities              0
against_bug            0
against_dark           0
against_dragon         0
against_electric       0
against_fairy          0
against_fight          0
against_fire           0
against_flying         0
against_ghost          0
against_grass          0
against_ground         0
against_ice            0
against_normal         0
against_poison         0
against_psychic        0
against_rock           0
against_steel          0
against_water          0
attack                 0
base_egg_steps         0
base_happiness         0
base_total             0
capture_rate           0
classfication          0
defense                0
experience_growth      0
height_m              20
hp                     0
japanese_name          0
name                   0
percentage_male       98
pokedex_number         0
sp_attack              0
sp_defense             0
speed                  0
type1                  0
type2                384
weight_kg             20
generation             0
is_legendary           0
dtype: int64
```

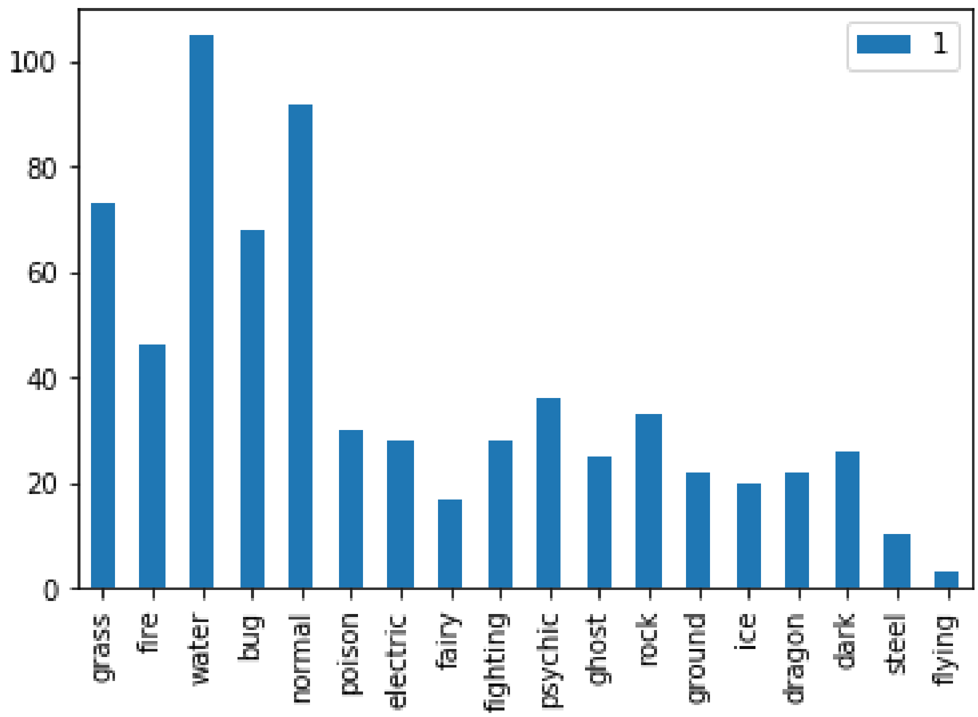
[32]:

```
#removing the data that has the null values.
data = data.dropna(subset=['percentage_male','weight_kg'])
data.shape
```

[32]: (684, 41)

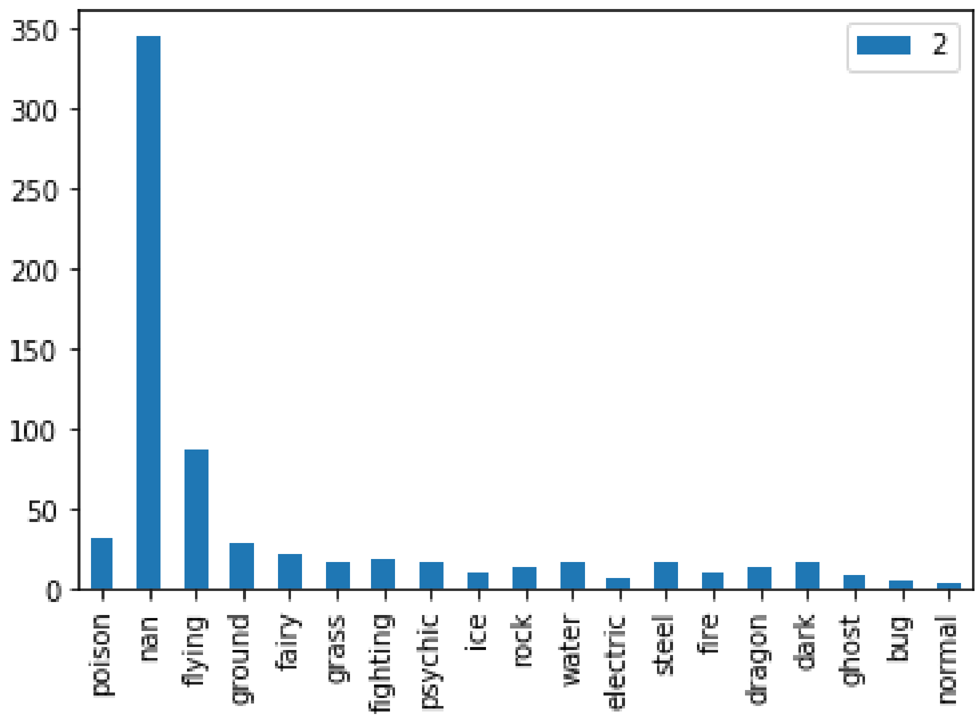
[33]:
```
#Distribution of the types
from collections import Counter

type_counts = Counter(data['type1'])
type1 = pd.DataFrame.from_dict(type_counts, orient='index')
ax=type1.plot(kind='bar')
ax.legend('1')
```

[33]: <matplotlib.legend.Legend at 0x2692a44d188>



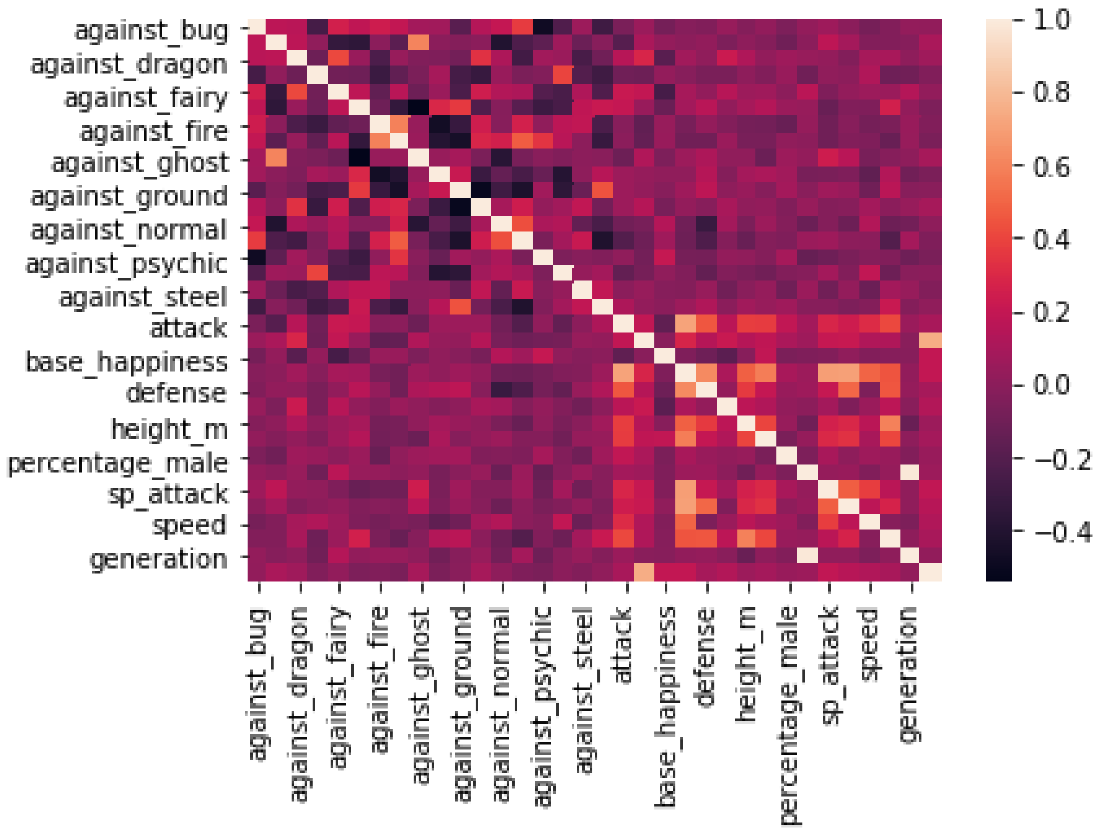
[34]:
```
type_counts = Counter(data['type2'])
type1 = pd.DataFrame.from_dict(type_counts, orient='index')
ax=type1.plot(kind='bar')
ax.legend('2')
```

[34]: <matplotlib.legend.Legend at 0x2692a51af48>

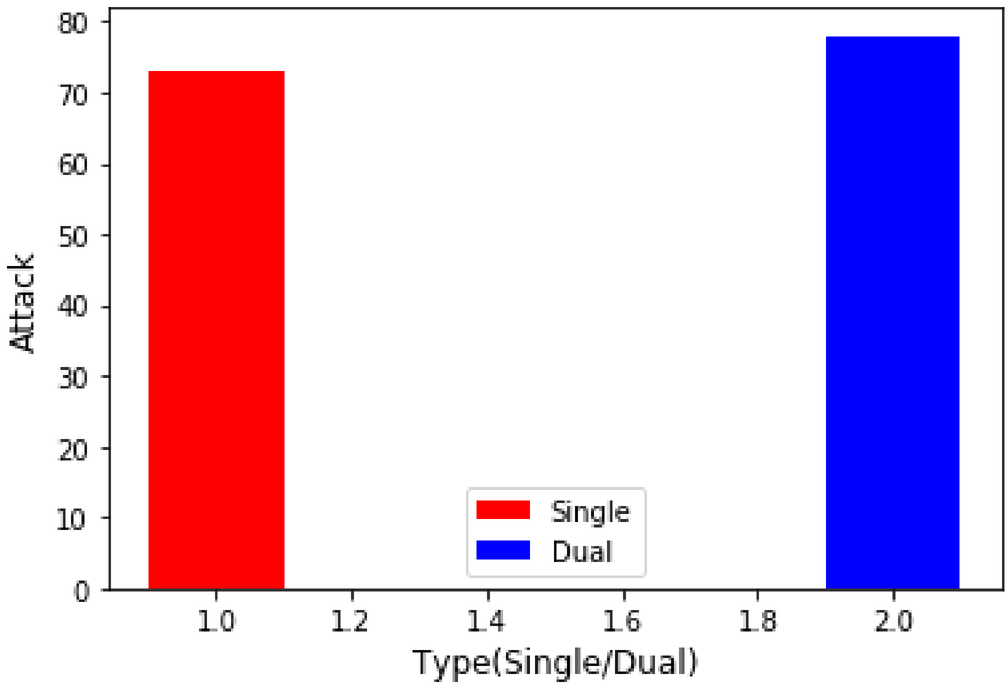


[35]:
```
#correlation between the data by heat map
corr = data.corr()
sns.heatmap(corr)
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x2692a61d7c8>

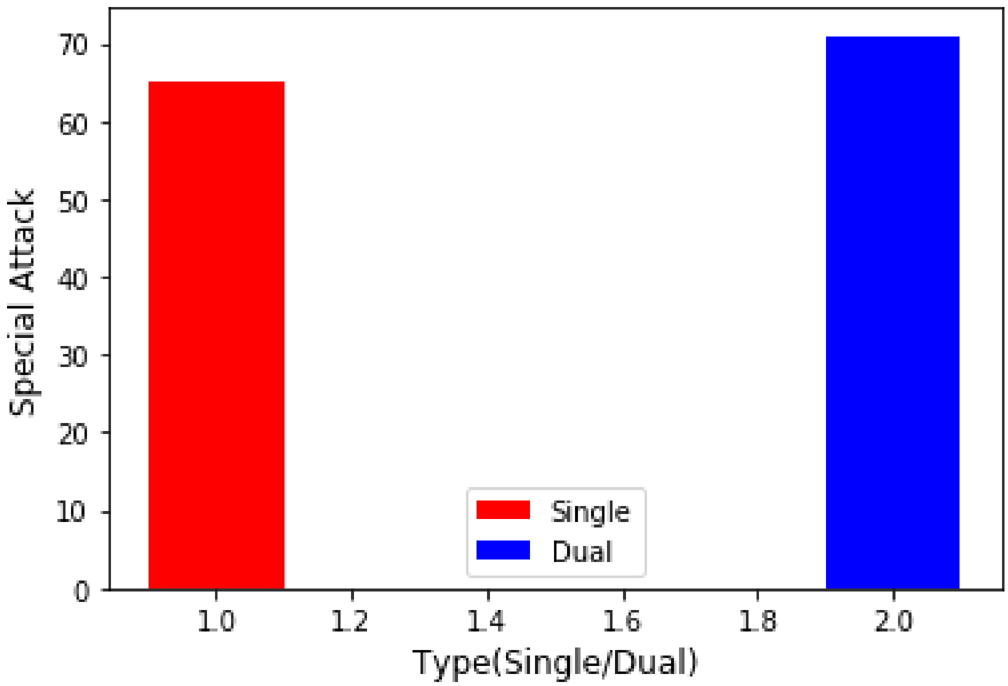



```
[36]: #Differentiating single vs dual types using attack and special attack␣
      ↪atttributes
      df = data.rename(columns={'type1': 'Type_1', 'type2': 'Type_2'})
      df.fillna(value='missing', axis=1, inplace=True)
      single = df[df['Type_2'].str.contains('missing')]
      dual = df[~df['Type_2'].str.contains('missing')]
      atk_single = round(np.sum(single['attack'].values, axis = 0) / single.shape[0])
      spatk_single = round(np.sum(single['sp_attack'].values, axis = 0) / single.
      ↪shape[0])
      atk_dual = round(np.sum(dual['attack'].values, axis = 0) / dual.shape[0])
      spatk_dual = round(np.sum(dual['sp_attack'].values, axis = 0) / dual.shape[0])
      x = np.array([1,2])
      y = np.array([atk_single,atk_dual])
      plt.bar(x[0],y[0],color='r',label = 'Single',width = 0.2)
      plt.bar(x[1],y[1],color='b', label = 'Dual',width = 0.2)
      plt.xlabel("Type(Single/Dual)",fontsize = 12)
      plt.ylabel("Attack",fontsize = 12)
      plt.legend()
      plt.show()
```



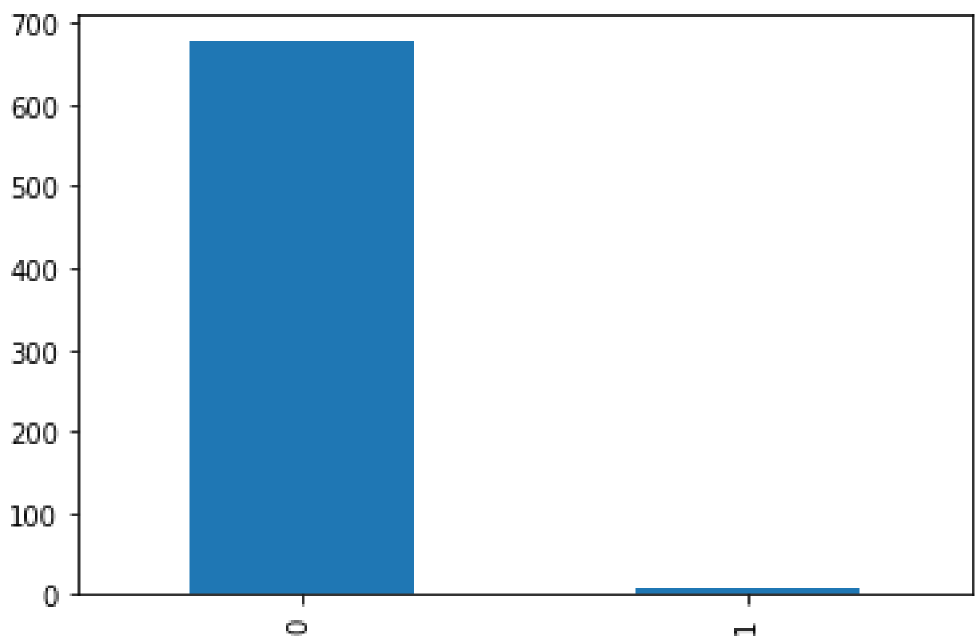
[37]:

```
x = np.array([1,2])
y = np.array([spatk_single,spatk_dual])
plt.bar(x[0],y[0],color='r',label = 'Single',width = 0.2)
plt.bar(x[1],y[1],color='b', label = 'Dual',width = 0.2)
plt.xlabel("Type(Single/Dual)",fontsize = 12)
plt.ylabel("Special Attack",fontsize = 12)
plt.legend()
plt.show()
```



[38]:
```
#Finding out the count of legendary and non legendary pokemons
data['is_legendary'].value_counts().plot.bar()
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x2692a72d748>



```
[ ]:
```

PokeNet

June 25, 2020

[1]:
```
# Importing all necessary libraries
import numpy as np
import pandas as pd
import cv2 as cv # requires manual install to Anaconda
import os
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns
import warnings
import gc
import requests
import random
from icrawler.builtin import GoogleImageCrawler # requires manual install to␣
 ↪Anaconda
from sklearn.model_selection import train_test_split

# Keras, Tensorflow stuff for CNN/VGG
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
from keras import backend as K
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers import GlobalAveragePooling2D, Lambda, Conv2D, MaxPooling2D,␣
 ↪Dropout, Dense, Flatten, Activation
from keras.layers.normalization import BatchNormalization
from keras.optimizers import SGD, RMSprop, Adam

# plot style preferences
style.use('fivethirtyeight')
sns.set_style("darkgrid")

%matplotlib inline
```

```
Using TensorFlow backend.
```

[197]:
```
# Crawl for images of specified pokemon
pokemon = ['Pikachu', 'Squirtle', 'Bulbasaur', 'Charmander', 'Mewtwo']
```

```python
for i in pokemon:
    crawler = GoogleImageCrawler(storage={'root_dir': 'dataset/' + i})
    crawler.crawl(keyword=i, max_num=500, min_size=(96,96))

# ran this later to get detective pikachu images from google
# have to manual go through images to get outliers and then add the good ones
# to our main dataset manually
for i in pokemon:
    crawler = GoogleImageCrawler(storage={'root_dir': 'outliers/' + i})
    crawler.crawl(keyword='Detective Pikachu ' + i, max_num=100,␣
 ↪min_size=(96,96))
```

```
2020-06-25 00:54:16,335 - INFO - icrawler.crawler - start crawling…
2020-06-25 00:54:16,336 - INFO - icrawler.crawler - starting 1 feeder threads…
2020-06-25 00:54:16,337 - INFO - feeder - thread feeder-001 exit
2020-06-25 00:54:16,337 - INFO - icrawler.crawler - starting 1 parser threads…
2020-06-25 00:54:16,339 - INFO - icrawler.crawler - starting 1 downloader
threads…
2020-06-25 00:54:16,919 - INFO - parser - parsing result page https://www.google
.com/search?q=Detective+Pikachu+Squirtle&ijn=0&start=0&tbs=&tbm=isch
2020-06-25 00:54:17,095 - INFO - downloader - image #1
https://i.ytimg.com/vi/wbFt4PpwggQ/maxresdefault.jpg
2020-06-25 00:54:17,716 - INFO - downloader - image #2  https://cdn.vox-cdn.com/
thumbor/7CFvl9b0UpEQviCDY0RfXzHBoZ0=/1400x0/filters:no_upscale()/cdn.vox-cdn.com
/uploads/chorus_asset/file/16023556/Screen_Shot_2019_04_10_at_5.06.16_PM.png
2020-06-25 00:54:17,752 - INFO - downloader - image #3
https://i.ytimg.com/vi/DPE3J9ama_E/maxresdefault.jpg
2020-06-25 00:54:17,913 - INFO - downloader - image #4  https://images-wixmp-ed3
0a86b8c4ca887773594c2.wixmp.com/f/295fb76c-7179-4c70-a508-a1cce61a876f/dd4aps3-5
c7a8849-aab1-4f8f-933e-84240f3c1c35.png?token=eyJ0eXAiOiJKV1QiLCJhbGciOiJIUzI1Ni
J9.eyJzdWIiOiJ1cm46YXBwOiIsImlzcyI6InVybjphcHA6Iiwib2JqIjpbW3sicGF0aCI6IlwvZlwvM
jk1ZmI3NmMtNzE3OS00YzcwLWE1MDgtYTFjY2U2MWE4NzZmXC9kZDRhcHMzLTVjN2E4ODQ5LWFhYjEtN
GY4Zi05MzNlLTg0MjQwZjNjMWMzNS5wbmcifV1dLCJhdWQiOlsidXJuOnNlcnZpY2U6ZmlsZS5kb3dub
G9hZCJdfQ.yolWSOEufTtHvpjGsDVvkogEkh8gJSk7EaYolU4_rsM
2020-06-25 00:54:18,029 - INFO - downloader - image #5
https://cdna.artstation.com/p/assets/images/images/017/754/158/large/julie-
tardieu-06.jpg?1557228628
2020-06-25 00:54:18,265 - INFO - downloader - image #6
https://www.thehdroom.com/wp-content/uploads/2019/04/new-detective-pikachu-
footage.jpg
2020-06-25 00:54:18,621 - INFO - downloader - image #7
https://cdn1.thr.com/sites/default/files/2019/05/detective_pikachu-bulbasaur-
publicity-h_2019.jpg
2020-06-25 00:54:18,641 - INFO - downloader - image #8  https://cdn.vox-cdn.com/
thumbor/g0daWh_TciOX-n5x5viFl0pllmE=/1400x1400/filters:format(png)/cdn.vox-cdn.c
om/uploads/chorus_asset/file/16022665/Screen_Shot_2019_04_10_at_12.26.32_PM.png
2020-06-25 00:54:18,907 - INFO - downloader - image #9  https://nerdist.com/wp-
```

content/uploads/2019/05/Detective-Pikachu-casting-1200x676.jpg
2020-06-25 00:54:19,100 - INFO - downloader - image #10
https://cdn.dribbble.com/users/2367883/screenshots/6477123/shot-
cropped-1557766487823.png
2020-06-25 00:54:19,379 - INFO - downloader - image #11
https://thepopinsider.com/wp-
content/uploads/2019/04/DetectivePikachu_Squirtle.jpg
2020-06-25 00:54:20,120 - INFO - downloader - image #12
http://ricedigital.co.uk/wp-content/uploads/2019/05/Squirtle-555x350.jpg
2020-06-25 00:54:20,929 - INFO - downloader - image #13
https://i.pinimg.com/originals/95/91/34/95913461a301b5215953a491ad57bcb1.gif
2020-06-25 00:54:22,236 - INFO - downloader - image #14 https://66.media.tumblr.
com/6ac780a38a8d9eafed01daf41d6cd45b/tumblr_ps1sykZPEV1vplr8j_400.png
2020-06-25 00:54:22,637 - INFO - downloader - image #15
https://www.thesun.co.uk/wp-content/uploads/2019/04/asc-composite-
detectivepikachu.jpg?strip=all&quality=100&w=1200&h=800&crop=1
2020-06-25 00:54:22,810 - INFO - downloader - image #16 https://external-preview
.redd.it/9XiADhPsTauolR5moAjku0g7oi2Gm1TZ1dB9dlqSjRc.jpg?auto=webp&s=5d6316c1478
5f103d838b5ca1d7e8bb0a868bafa
2020-06-25 00:54:24,014 - INFO - downloader - image #17 https://www.channelnewsa
sia.com/image/11313830/1x1/600/600/303b5411eb34a1eaeed382ebde634b24/Bg/pokemon.j
pg
2020-06-25 00:54:24,174 - INFO - downloader - image #18
https://s3.amazonaws.com/prod-
media.gameinformer.com/styles/full/s3/2018/11/12/77db3cda/pikachumovie.jpg
2020-06-25 00:54:24,414 - INFO - downloader - image #19
https://i.redd.it/ce5pubg191u21.jpg
2020-06-25 00:54:24,497 - INFO - downloader - image #20 https://cdn.vox-cdn.com/
thumbor/sQXDUl49gchks_fgxkqvaXji4pI=/1400x1400/filters:format(jpeg)/cdn.vox-
cdn.com/uploads/chorus_asset/file/13430765/detective_pikachu_trailer_24_1920.jpg
2020-06-25 00:54:24,607 - INFO - downloader - image #21
https://d13ezvd6yrslxm.cloudfront.net/wp/wp-content/images/detective-pikachu-
poster-cropped-700x339.jpeg
2020-06-25 00:54:25,204 - INFO - downloader - image #22 https://poketouch.files.
wordpress.com/2018/11/pokemon_detective_pikachu_movie_bulbasaur_morelull_and_jus
tice_smith_holding_pikachu.png
2020-06-25 00:54:25,973 - INFO - downloader - image #23 https://imagenes.milenio
.com/Byd9it6e0jOav0llTLNEsLNZgb8=/958x596/https://www.milenio.com/uploads/media/
2019/04/10/el-meme-vamo-a-calmano_23_0_1607_1000.jpg
2020-06-25 00:54:26,152 - INFO - downloader - image #24
https://cdn.images.express.co.uk/img/dynamic/36/750x445/1044754.jpg
2020-06-25 00:54:26,288 - INFO - downloader - image #25
https://i.ytimg.com/vi/M3E_g0z9Cys/maxresdefault.jpg
2020-06-25 00:54:26,647 - INFO - downloader - image #26
https://static0.srcdn.com/wordpress/wp-content/uploads/2018/11/Detective-
Pikachu-Squirtle.jpg
2020-06-25 00:54:26,935 - INFO - downloader - image #27
https://i.imgur.com/misRiiZ.png

```
2020-06-25 00:54:27,042 - INFO - downloader - image #28
https://cdn.mos.cms.futurecdn.net/MphYS8aibgiFZVT3de4bSV.jpg
2020-06-25 00:54:27,108 - INFO - downloader - image #29
https://i.redd.it/yh6woxws11y11.png
2020-06-25 00:54:27,527 - INFO - downloader - image #30
https://static1.srcdn.com/wordpress/wp-content/uploads/2018/11/Detective-
Pikachu-Every-Pokemon.jpg
2020-06-25 00:54:28,071 - INFO - downloader - image #31
https://miro.medium.com/max/1200/1*pIhWVOtVAJDUmUJP1jRtVQ.png
2020-06-25 00:54:28,246 - INFO - downloader - image #32
https://media.comicbook.com/2018/11/detective-pikachu-starter-
header-1143895-1280x0.jpeg
2020-06-25 00:54:28,320 - INFO - downloader - image #33 https://cdn.vox-cdn.com/
thumbor/Itoov8zegYkBSrG7ea35aU82bc8=/1400x0/filters:no_upscale()/cdn.vox-cdn.com
/uploads/chorus_asset/file/16023618/Screen_Shot_2019_04_10_at_5.19.56_PM.png
2020-06-25 00:54:28,464 - ERROR - downloader - Response status code 404, file
http://mouse.latercera.com/wp-content/uploads/2019/05/detective-pikachu-1.jpg
2020-06-25 00:54:28,582 - INFO - downloader - image #34
https://d1lss44hh2trtw.cloudfront.net/assets/article/2019/02/26/all-pokemon-in-
detective-pikachu_feature.jpg
2020-06-25 00:54:34,696 - ERROR - downloader - Exception caught when downloading
file https://sm.ign.com/t/ign_ap/gallery/e/every-poke/every-pokemon-in-the-
detective-pikachu-movie_pexr.1080.jpg, error:
HTTPSConnectionPool(host='sm.ign.com', port=443): Read timed out. (read
timeout=5), remaining retry times: 2
2020-06-25 00:54:35,358 - INFO - downloader - image #35
https://sm.ign.com/t/ign_ap/gallery/e/every-poke/every-pokemon-in-the-detective-
pikachu-movie_pexr.1080.jpg
2020-06-25 00:54:35,476 - INFO - downloader - image #36
https://pbs.twimg.com/media/D3zpHLvU0AE3s5b.jpg
2020-06-25 00:54:36,012 - INFO - downloader - image #37 https://nerdist.com/wp-
content/uploads/2019/02/Detective-Pikachu-Braviary.png
2020-06-25 00:54:36,450 - INFO - downloader - image #38
https://movies.mxdwn.com/wp-content/uploads/2019/04/download.jpg
2020-06-25 00:54:36,507 - INFO - downloader - image #39 https://cdn.vox-cdn.com/
thumbor/v2U85x7stV62ecUKZmjqSjpPzNY=/0x0:1024x500/1200x800/filters:focal(236x289
:398x451)/cdn.vox-cdn.com/uploads/chorus_image/image/63721566/Banner.0.jpg
2020-06-25 00:54:36,661 - INFO - downloader - image #40
https://ae01.alicdn.com/kf/Haffd9ac9cbe841f2881061343a89f883x/Takara-Tomy-
Pokemon-Detective-pikachu-Psyduck-Mewtwo-Bulbasaur-Squirtle-Eevee-anime-action-
toy-figures-model.jpg_q50.jpg
2020-06-25 00:54:36,892 - INFO - downloader - image #41
https://media.distractify.com/brand-img/I5aSU-EaQ/480x252/detective-
pikachu-1557498103339.jpg
2020-06-25 00:54:36,948 - INFO - downloader - image #42
https://i.imgur.com/GERfojf.jpg?fb
2020-06-25 00:54:37,048 - INFO - downloader - image #43 https://pyxis.nymag.com/
v1/imgs/4a9/af5/e736d91cd589d1fe2545d1bb1d00b7ba95-08-psyduck.rsquare.w700.jpg
```

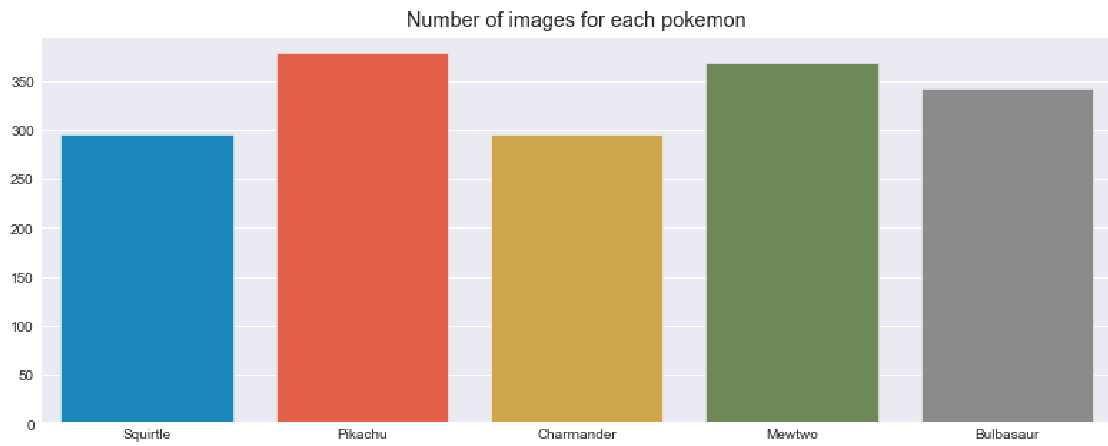
```
2020-06-25 00:54:37,125 - INFO - downloader - image #44
https://d1lss44hh2trtw.cloudfront.net/assets/editorial/2019/02/det-pikachu-
bulbasaur.jpg
2020-06-25 00:54:37,383 - INFO - downloader - image #45 https://images-wixmp-ed3
0a86b8c4ca887773594c2.wixmp.com/f/295fb76c-7179-4c70-a508-a1cce61a876f/dcrxray-e
f618793-8f15-4bee-b1b2-250d0808a43b.png?token=eyJ0eXAiOiJKV1QiLCJhbGciOiJIUzI1Ni
J9.eyJzdWIiOiJ1cm46YXBwOiIsImlzcyI6InVybjphcHA6Iiwib2JqIjpbW3sicGF0aCI6IlwvZlwvM
jk1ZmI3NmMtNzE3OS00YzcwLWE1MDgtYTFjY2U2MWE4NzZmXC9kY3J4cmF5LWVmNjE4NzkzLThmMTUtN
GJlZS1iMWIyLTI1MGQwODA4YTQzYi5wbmcifV1dLCJhdWQiOlsidXJuOnNlcnZpY2U6ZmlsZS5kb3dub
G9hZCJdfQ.gIMfBE21wUopFBooMZ-DPOb4hFD8sXmQoisRTGM4nNQ
2020-06-25 00:54:37,789 - INFO - downloader - image #46
https://en.freegames66.com/wp-
content/uploads/posts/77eb10760b8342249f490b3ee8e62a64.jpg
2020-06-25 00:54:37,948 - INFO - downloader - image #47 https://www.channelnewsa
sia.com/image/11312896/1x1/600/600/5f39060743064ad8d1928bab67390c09/ge/snorlax-
pokemon-detective-pikachu.png
2020-06-25 00:54:38,306 - INFO - downloader - image #48
https://static1.srcdn.com/wordpress/wp-content/uploads/2019/02/Detective-
Pikachu-Pokemon-Header.jpg
2020-06-25 00:54:38,416 - INFO - downloader - image #49 https://img.ifunny.co/im
ages/8f875b92c29da85d0db757abb6b9dfd793e72846880d56e3cb62bb61ea510ca0_1.jpg
2020-06-25 00:54:38,440 - INFO - downloader - image #50 https://pyxis.nymag.com/
v1/imgs/635/968/cdd9e17681dc850b2dee6eb0f51d667313-06-detective-
pikachu.rsquare.w700.jpg
2020-06-25 00:54:38,791 - INFO - downloader - downloaded images reach max num,
thread downloader-001 is ready to exit
2020-06-25 00:54:38,792 - INFO - downloader - thread downloader-001 exit
2020-06-25 00:54:39,407 - INFO - icrawler.crawler - Crawling task done!
2020-06-25 00:54:39,444 - INFO - parser - downloaded image reached max num,
thread parser-001 is ready to exit
2020-06-25 00:54:39,445 - INFO - parser - thread parser-001 exit
```

[2]:
```
#constants
DATA_DIR = '/Users/brandonreid/Science/pokemon'
IMG_SIZE = 96
LEARN_RATE = 1e-4
IMAGE_DIMS = (IMG_SIZE, IMG_SIZE, 3)
EPOCHS = 100
SEED = 42
FIG_SIZE = (12, 5)
BS = 32
```

[3]:
```
# obtain number of images for each pokemon
pokemon = os.listdir(DATA_DIR)
print('Total number of pokemon:', len(pokemon))

images = {}
```

```python
for poke in pokemon:
    images[poke] = len(os.listdir(os.path.join(DATA_DIR, poke)))

print('Total number of images:', sum(list(images.values())))

classes = list(images.keys())
counts = list(images.values())

fig = plt.figure(figsize = FIG_SIZE)
sns.barplot(x=classes, y=counts).set_title('Number of images for each pokemon')
plt.show()
```

```
Total number of pokemon: 5
Total number of images: 1679
```



[4]:
```python
data = [] # List for data (images)
labels = [] # List for data labels

# Loop through pokemon classes
for poke in pokemon:
    path = os.path.join(DATA_DIR, poke) # dir of pokemon

    # randomize image paths before resizing them
    image_paths = sorted(list(os.listdir(path)))
    random.seed(SEED)
    random.shuffle(image_paths)

    # loop over each image of pokemon
    for img in image_paths:
        image = cv.imread(os.path.join(path, img))
        try:
```

```
            data.append(cv.resize(image, (IMG_SIZE, IMG_SIZE))) # add resized␣
↪image to dataset
            labels.append(pokemon.index(poke)) # add label as index of pokemon
        except: # error handling for unreadable images
            print(os.path.join(path, img), '-> UNREADABLE')
            continue

print(len(data), " TOTAL IMAGES PROCESSED")
```

```
/Users/brandonreid/Science/pokemon/Mewtwo/ed9eb0e7d3494c6992e06196f5b7cc05.svg
-> UNREADABLE
/Users/brandonreid/Science/pokemon/Bulbasaur/000007.gif -> UNREADABLE
1677  TOTAL IMAGES PROCESSED
```

[5]:
```
X = np.array(data).reshape(-1, IMG_SIZE, IMG_SIZE, 3) / 255.0 # Reshape and␣
↪scale images
y = to_categorical(labels, num_classes = len(pokemon)) # Labelize

print("[INFO] data matrix: {:.2f}MB".format(
        X.nbytes / (1024 * 1000.0)))
```

```
[INFO] data matrix: 362.23MB
```

[6]:
```
# Cross Validation
# Popular method to train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size = 0.2, random_state = SEED)
```

[7]:
```
# Defining ImageDataGenerator & construct data augmentation
# useful for fitting model to provide different image types, angles, rotations,␣
↪etc.
# I have excluded this due to how much time it adds to trail the modal
# after looking further https://github.com/keras-team/keras/issues/12683
# this is a known issue
aug = ImageDataGenerator(rotation_range = 25, # Degree range for random␣
↪rotations
                        width_shift_range = 0.1, # Range for horizontal shift
                        height_shift_range = 0.1, # Range for vertical shift
                        zoom_range = 0.2, # Range for random zoom
                        horizontal_flip = True, # Randomly flip inputs␣
↪horizontally
                        shear_range = 0.2, # Shear Intensity
                        fill_mode="nearest")

aug.fit(X_train) # ideally would augment training image set
```

[8]:

```python
model = Sequential() # set up the modal for sequential layers

# SEQUENCE LAYER: CONV => RELU => POOL
model.add(Conv2D(32, (3, 3), padding="same", input_shape=IMAGE_DIMS)) #CONV
model.add(Activation("relu")) #RELU
model.add(BatchNormalization(axis=-1))
model.add(MaxPooling2D(pool_size=(3, 3))) # POOL
model.add(Dropout(0.25)) #Dropout to next sequence

# SEQUENCE LAYER: (CONV => RELU) * 2 => POOL
model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(Conv2D(64, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=1))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25)) # Dropout to next sequence

# SEQUENCE LAYER: (CONV => RELU) * 2 => POOL
model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(Conv2D(128, (3, 3), padding="same"))
model.add(Activation("relu"))
model.add(BatchNormalization(axis=-1))

model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25)) # Dropout to next sequence

# SEQUENCE LAYER: first (and only) set of FC => RELU layers
model.add(Flatten())
model.add(Dense(1024))
model.add(Activation("relu"))
model.add(BatchNormalization())
model.add(Dropout(0.5)) # Dropout to next sequence

# softmax classifier
model.add(Dense(len(pokemon))) # Dense is number of classes to predict
model.add(Activation("softmax"))

model.summary()

# optimizer
```

```
model.compile(Adam(lr=LEARN_RATE), loss='categorical_crossentropy',␣
↪metrics=["accuracy"])
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 96, 96, 32)        896
_________________________________________________________________
activation_1 (Activation)    (None, 96, 96, 32)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 96, 96, 32)        128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 32, 32, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 32, 32, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 32, 32, 64)        18496
_________________________________________________________________
activation_2 (Activation)    (None, 32, 32, 64)        0
_________________________________________________________________
batch_normalization_2 (Batch (None, 32, 32, 64)        256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 32, 32, 64)        36928
_________________________________________________________________
activation_3 (Activation)    (None, 32, 32, 64)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 32, 32, 64)        128
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 64)        0
_________________________________________________________________
dropout_2 (Dropout)          (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 16, 16, 128)       73856
_________________________________________________________________
activation_4 (Activation)    (None, 16, 16, 128)       0
_________________________________________________________________
batch_normalization_4 (Batch (None, 16, 16, 128)       512
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 16, 16, 128)       147584
_________________________________________________________________
activation_5 (Activation)    (None, 16, 16, 128)       0
_________________________________________________________________
batch_normalization_5 (Batch (None, 16, 16, 128)       512
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 8, 8, 128)         0
_________________________________________________________________
```

```
dropout_3 (Dropout)          (None, 8, 8, 128)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 8192)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1024)             8389632
_________________________________________________________________
activation_6 (Activation)    (None, 1024)             0
_________________________________________________________________
batch_normalization_6 (Batch (None, 1024)             4096
_________________________________________________________________
dropout_4 (Dropout)          (None, 1024)             0
_________________________________________________________________
dense_2 (Dense)              (None, 5)                5125
_________________________________________________________________
activation_7 (Activation)    (None, 5)                0
=================================================================
Total params: 8,678,149
Trainable params: 8,675,333
Non-trainable params: 2,816
_________________________________________________________________
```

[9]:
```
history = model.fit(X_train, y_train, batch_size=BS,
                 epochs=EPOCHS, verbose=1, validation_data=(X_test, y_test))

# history = model.fit_generator(aug.flow(X_train, y_train, batch_size=BS),
#                     validation_data=(X_test, y_test),
#                     steps_per_epoch=len(X_train) // BS,
#                     epochs=EPOCHS,
#                     verbose=1)
```

```
Train on 1341 samples, validate on 336 samples
Epoch 1/100
1341/1341 [==============================] - 50s 37ms/step - loss: 1.5503 -
accuracy: 0.5019 - val_loss: 1.5788 - val_accuracy: 0.3869
Epoch 2/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.8934 -
accuracy: 0.7278 - val_loss: 1.5542 - val_accuracy: 0.2351
Epoch 3/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.7302 -
accuracy: 0.7673 - val_loss: 1.6577 - val_accuracy: 0.1875
Epoch 4/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.6033 -
accuracy: 0.8061 - val_loss: 1.6550 - val_accuracy: 0.2411
Epoch 5/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.5659 -
accuracy: 0.8166 - val_loss: 2.0370 - val_accuracy: 0.1875
Epoch 6/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.4423 -
```

```
accuracy: 0.8553 - val_loss: 2.5136 - val_accuracy: 0.1994
Epoch 7/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.3935 -
accuracy: 0.8665 - val_loss: 2.7008 - val_accuracy: 0.2470
Epoch 8/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.3460 -
accuracy: 0.8792 - val_loss: 2.5530 - val_accuracy: 0.3036
Epoch 9/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.3364 -
accuracy: 0.8889 - val_loss: 2.1155 - val_accuracy: 0.4107
Epoch 10/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.3412 -
accuracy: 0.8852 - val_loss: 1.5435 - val_accuracy: 0.5655
Epoch 11/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.2893 -
accuracy: 0.9045 - val_loss: 1.3093 - val_accuracy: 0.6101
Epoch 12/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.2845 -
accuracy: 0.9008 - val_loss: 1.0530 - val_accuracy: 0.6905
Epoch 13/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.2791 -
accuracy: 0.8949 - val_loss: 0.8240 - val_accuracy: 0.7679
Epoch 14/100
1341/1341 [==============================] - 49s 36ms/step - loss: 0.2316 -
accuracy: 0.9113 - val_loss: 0.7726 - val_accuracy: 0.7827
Epoch 15/100
1341/1341 [==============================] - 49s 36ms/step - loss: 0.2086 -
accuracy: 0.9284 - val_loss: 0.7797 - val_accuracy: 0.7946
Epoch 16/100
1341/1341 [==============================] - 50s 37ms/step - loss: 0.2235 -
accuracy: 0.9239 - val_loss: 0.6989 - val_accuracy: 0.8155
Epoch 17/100
1341/1341 [==============================] - 50s 37ms/step - loss: 0.1965 -
accuracy: 0.9292 - val_loss: 0.7002 - val_accuracy: 0.8095
Epoch 18/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.2179 -
accuracy: 0.9195 - val_loss: 0.6816 - val_accuracy: 0.8036
Epoch 19/100
1341/1341 [==============================] - 50s 37ms/step - loss: 0.1692 -
accuracy: 0.9441 - val_loss: 0.6231 - val_accuracy: 0.8065
Epoch 20/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1628 -
accuracy: 0.9508 - val_loss: 0.8104 - val_accuracy: 0.7946
Epoch 21/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1800 -
accuracy: 0.9262 - val_loss: 0.6092 - val_accuracy: 0.8244
Epoch 22/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1489 -
```

```
accuracy: 0.9508 - val_loss: 0.7116 - val_accuracy: 0.8036
Epoch 23/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1712 -
accuracy: 0.9396 - val_loss: 0.6660 - val_accuracy: 0.8244
Epoch 24/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1150 -
accuracy: 0.9575 - val_loss: 0.5849 - val_accuracy: 0.8214
Epoch 25/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1136 -
accuracy: 0.9597 - val_loss: 0.5881 - val_accuracy: 0.8274
Epoch 26/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1205 -
accuracy: 0.9575 - val_loss: 0.5462 - val_accuracy: 0.8393
Epoch 27/100
1341/1341 [==============================] - 53s 40ms/step - loss: 0.1470 -
accuracy: 0.9567 - val_loss: 0.6029 - val_accuracy: 0.8423
Epoch 28/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1203 -
accuracy: 0.9545 - val_loss: 0.5968 - val_accuracy: 0.8333
Epoch 29/100
1341/1341 [==============================] - 53s 40ms/step - loss: 0.1324 -
accuracy: 0.9523 - val_loss: 0.6392 - val_accuracy: 0.8482
Epoch 30/100
1341/1341 [==============================] - 52s 38ms/step - loss: 0.1193 -
accuracy: 0.9553 - val_loss: 0.6015 - val_accuracy: 0.8423
Epoch 31/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1140 -
accuracy: 0.9605 - val_loss: 0.6175 - val_accuracy: 0.8423
Epoch 32/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1176 -
accuracy: 0.9560 - val_loss: 0.7695 - val_accuracy: 0.8274
Epoch 33/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1106 -
accuracy: 0.9590 - val_loss: 0.6264 - val_accuracy: 0.8423
Epoch 34/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1038 -
accuracy: 0.9687 - val_loss: 0.6512 - val_accuracy: 0.8452
Epoch 35/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1052 -
accuracy: 0.9620 - val_loss: 0.6187 - val_accuracy: 0.8482
Epoch 36/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1085 -
accuracy: 0.9627 - val_loss: 0.6091 - val_accuracy: 0.8423
Epoch 37/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1002 -
accuracy: 0.9709 - val_loss: 0.6233 - val_accuracy: 0.8452
Epoch 38/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.1053 -
```

```
accuracy: 0.9672 - val_loss: 0.6216 - val_accuracy: 0.8512
Epoch 39/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.1078 -
accuracy: 0.9582 - val_loss: 0.7105 - val_accuracy: 0.8244
Epoch 40/100
1341/1341 [==============================] - 50s 37ms/step - loss: 0.0949 -
accuracy: 0.9687 - val_loss: 0.5789 - val_accuracy: 0.8423
Epoch 41/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.0712 -
accuracy: 0.9769 - val_loss: 0.6102 - val_accuracy: 0.8363
Epoch 42/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.0977 -
accuracy: 0.9717 - val_loss: 0.5599 - val_accuracy: 0.8512
Epoch 43/100
1341/1341 [==============================] - 54s 40ms/step - loss: 0.0847 -
accuracy: 0.9746 - val_loss: 0.5439 - val_accuracy: 0.8601
Epoch 44/100
1341/1341 [==============================] - 52s 39ms/step - loss: 0.0788 -
accuracy: 0.9724 - val_loss: 0.5344 - val_accuracy: 0.8512
Epoch 45/100
1341/1341 [==============================] - 49s 37ms/step - loss: 0.0923 -
accuracy: 0.9717 - val_loss: 0.5910 - val_accuracy: 0.8482
Epoch 46/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0901 -
accuracy: 0.9732 - val_loss: 0.5803 - val_accuracy: 0.8423
Epoch 47/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.1081 -
accuracy: 0.9620 - val_loss: 0.6365 - val_accuracy: 0.8512
Epoch 48/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0662 -
accuracy: 0.9761 - val_loss: 0.5934 - val_accuracy: 0.8512
Epoch 49/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0865 -
accuracy: 0.9672 - val_loss: 0.5836 - val_accuracy: 0.8512
Epoch 50/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0762 -
accuracy: 0.9739 - val_loss: 0.5401 - val_accuracy: 0.8571
Epoch 51/100
1341/1341 [==============================] - 51s 38ms/step - loss: 0.0734 -
accuracy: 0.9769 - val_loss: 0.5372 - val_accuracy: 0.8601
Epoch 52/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.0840 -
accuracy: 0.9761 - val_loss: 0.6061 - val_accuracy: 0.8542
Epoch 53/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0853 -
accuracy: 0.9717 - val_loss: 0.5482 - val_accuracy: 0.8631
Epoch 54/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0701 -
```

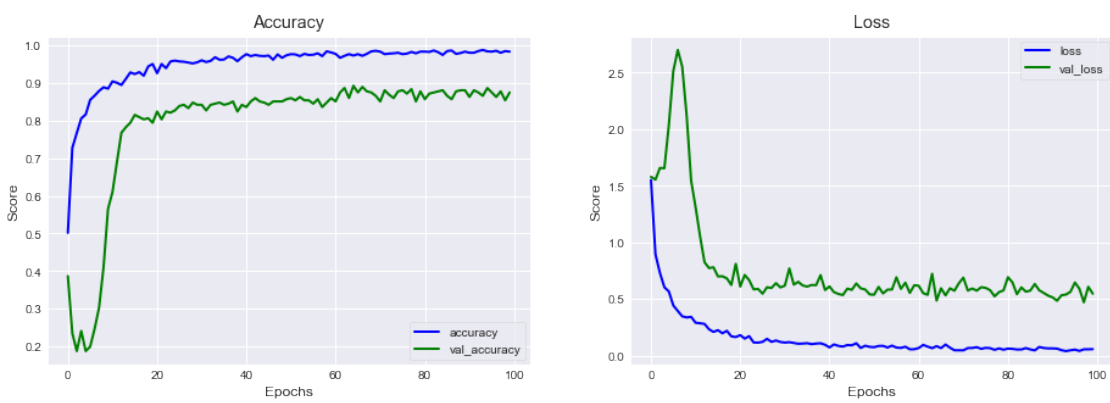
```
accuracy: 0.9776 - val_loss: 0.5821 - val_accuracy: 0.8542
Epoch 55/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0875 -
accuracy: 0.9746 - val_loss: 0.5832 - val_accuracy: 0.8542
Epoch 56/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.0700 -
accuracy: 0.9754 - val_loss: 0.6908 - val_accuracy: 0.8452
Epoch 57/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0667 -
accuracy: 0.9791 - val_loss: 0.5891 - val_accuracy: 0.8571
Epoch 58/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.0778 -
accuracy: 0.9717 - val_loss: 0.6435 - val_accuracy: 0.8363
Epoch 59/100
1341/1341 [==============================] - 49s 36ms/step - loss: 0.0545 -
accuracy: 0.9843 - val_loss: 0.5528 - val_accuracy: 0.8482
Epoch 60/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0552 -
accuracy: 0.9814 - val_loss: 0.6210 - val_accuracy: 0.8601
Epoch 61/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0658 -
accuracy: 0.9776 - val_loss: 0.6162 - val_accuracy: 0.8512
Epoch 62/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0934 -
accuracy: 0.9672 - val_loss: 0.5510 - val_accuracy: 0.8750
Epoch 63/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.0785 -
accuracy: 0.9724 - val_loss: 0.5361 - val_accuracy: 0.8869
Epoch 64/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0643 -
accuracy: 0.9769 - val_loss: 0.7227 - val_accuracy: 0.8601
Epoch 65/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0828 -
accuracy: 0.9732 - val_loss: 0.4851 - val_accuracy: 0.8929
Epoch 66/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0649 -
accuracy: 0.9769 - val_loss: 0.5938 - val_accuracy: 0.8750
Epoch 67/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0968 -
accuracy: 0.9724 - val_loss: 0.5318 - val_accuracy: 0.8899
Epoch 68/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0688 -
accuracy: 0.9776 - val_loss: 0.5941 - val_accuracy: 0.8780
Epoch 69/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0459 -
accuracy: 0.9843 - val_loss: 0.5724 - val_accuracy: 0.8750
Epoch 70/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0460 -
```

```
accuracy: 0.9858 - val_loss: 0.6388 - val_accuracy: 0.8661
Epoch 71/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0455 -
accuracy: 0.9836 - val_loss: 0.6877 - val_accuracy: 0.8512
Epoch 72/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0655 -
accuracy: 0.9769 - val_loss: 0.5737 - val_accuracy: 0.8810
Epoch 73/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0665 -
accuracy: 0.9784 - val_loss: 0.5921 - val_accuracy: 0.8690
Epoch 74/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0734 -
accuracy: 0.9791 - val_loss: 0.5728 - val_accuracy: 0.8601
Epoch 75/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.0587 -
accuracy: 0.9806 - val_loss: 0.6036 - val_accuracy: 0.8780
Epoch 76/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0675 -
accuracy: 0.9769 - val_loss: 0.5974 - val_accuracy: 0.8810
Epoch 77/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0648 -
accuracy: 0.9784 - val_loss: 0.5772 - val_accuracy: 0.8720
Epoch 78/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0498 -
accuracy: 0.9828 - val_loss: 0.5228 - val_accuracy: 0.8839
Epoch 79/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.0625 -
accuracy: 0.9791 - val_loss: 0.5604 - val_accuracy: 0.8512
Epoch 80/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.0510 -
accuracy: 0.9836 - val_loss: 0.5755 - val_accuracy: 0.8780
Epoch 81/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0609 -
accuracy: 0.9836 - val_loss: 0.6922 - val_accuracy: 0.8571
Epoch 82/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0585 -
accuracy: 0.9828 - val_loss: 0.6459 - val_accuracy: 0.8720
Epoch 83/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0529 -
accuracy: 0.9866 - val_loss: 0.5417 - val_accuracy: 0.8750
Epoch 84/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0531 -
accuracy: 0.9821 - val_loss: 0.6018 - val_accuracy: 0.8780
Epoch 85/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.0653 -
accuracy: 0.9746 - val_loss: 0.5642 - val_accuracy: 0.8810
Epoch 86/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.0535 -
```

```
accuracy: 0.9851 - val_loss: 0.5734 - val_accuracy: 0.8661
Epoch 87/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0449 -
accuracy: 0.9866 - val_loss: 0.6318 - val_accuracy: 0.8571
Epoch 88/100
1341/1341 [==============================] - 48s 36ms/step - loss: 0.0754 -
accuracy: 0.9776 - val_loss: 0.5764 - val_accuracy: 0.8780
Epoch 89/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0662 -
accuracy: 0.9799 - val_loss: 0.5530 - val_accuracy: 0.8810
Epoch 90/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0626 -
accuracy: 0.9836 - val_loss: 0.5291 - val_accuracy: 0.8810
Epoch 91/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0628 -
accuracy: 0.9806 - val_loss: 0.5133 - val_accuracy: 0.8631
Epoch 92/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0606 -
accuracy: 0.9806 - val_loss: 0.4840 - val_accuracy: 0.8810
Epoch 93/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0467 -
accuracy: 0.9851 - val_loss: 0.5326 - val_accuracy: 0.8750
Epoch 94/100
1341/1341 [==============================] - 45s 34ms/step - loss: 0.0386 -
accuracy: 0.9881 - val_loss: 0.5385 - val_accuracy: 0.8661
Epoch 95/100
1341/1341 [==============================] - 45s 33ms/step - loss: 0.0459 -
accuracy: 0.9843 - val_loss: 0.5629 - val_accuracy: 0.8869
Epoch 96/100
1341/1341 [==============================] - 44s 33ms/step - loss: 0.0517 -
accuracy: 0.9836 - val_loss: 0.6448 - val_accuracy: 0.8750
Epoch 97/100
1341/1341 [==============================] - 46s 35ms/step - loss: 0.0402 -
accuracy: 0.9858 - val_loss: 0.5903 - val_accuracy: 0.8631
Epoch 98/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0544 -
accuracy: 0.9806 - val_loss: 0.4704 - val_accuracy: 0.8780
Epoch 99/100
1341/1341 [==============================] - 47s 35ms/step - loss: 0.0546 -
accuracy: 0.9851 - val_loss: 0.6073 - val_accuracy: 0.8542
Epoch 100/100
1341/1341 [==============================] - 46s 34ms/step - loss: 0.0561 -
accuracy: 0.9836 - val_loss: 0.5463 - val_accuracy: 0.8750
```

[10]:
```
# Plot learning curves
train_loss = history.history['loss']
val_loss = history.history['val_loss']
```

```python
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

acc_df = pd.Series(train_acc)
val_acc_df = pd.Series(val_acc)
loss_df = pd.Series(train_loss)
val_loss_df = pd.Series(val_loss)

fig = plt.figure(figsize = (14, 5))

plt.subplot(121)
sns.lineplot(data=acc_df, color='blue', label="accuracy", linewidth=2).
 ↪set_title("Accuracy")
sns.lineplot(data=val_acc_df, color='green', label="val_accuracy", linewidth=2).
 ↪set(xlabel='Epochs', ylabel='Score')
plt.legend(loc='lower right')

plt.subplot(122)
sns.lineplot(data=loss_df, color='blue', label="loss", linewidth=2).
 ↪set_title("Loss")
sns.lineplot(data=val_loss_df, color='green', label="val_loss", linewidth=2).
 ↪set(xlabel='Epochs', ylabel='Score')
plt.legend(loc='upper right')
plt.show()
```



[11]:
```python
# return image as array from web using requests
def get_image(url):
    r = requests.get(url, stream = True).raw
    return np.asarray(bytearray(r.read()), dtype="uint8")
```

[66]:
```python
# prediction and plot function for image
def predict_image(url, row, pos):
```

```
    # process image
    image = get_image(url)
    image = cv.imdecode(image, cv.IMREAD_COLOR)
    original_img = image
    image = cv.resize(image, (IMG_SIZE, IMG_SIZE)) # Resizing image to (96, 96)
    image = image.reshape(-1, IMG_SIZE, IMG_SIZE, 3) / 255.0 # Reshape and␣
↪scale resized image

    # run prediction
    preds = model.predict(image) # Predicting image
    pred_class = np.argmax(preds) # Defining predicted class

    # plot image with prediction outcome
    plots.add_subplot(row, 3, pos)
    plt.imshow(original_img[:, :, ::-1])
    plt.title(f'Predicted: {pokemon[pred_class]} {round(preds[0][pred_class] *␣
↪100, 2)}%')
    plt.axis('off')
```

[102]:

```
# predict pikachu images from web
pikachu3D = 'https://www.nme.com/wp-content/uploads/2019/05/
↪MV5BZTNmOGE1ZmQtYjZmYy00MDhkLThkZjYtNzkyZDYxNTA5ZTE0XkEyXkFqcGdeQXVyNjg2NjQwMDQ@.
↪jpg'
pikachuToy = 'https://soranews24.com/wp-content/uploads/sites/3/2019/11/pk-3.
↪png?w=640&h=426'
pikachuOG = 'https://encrypted-tbn0.gstatic.com/images?
↪q=tbn%3AANd9GcQxX6o-s7rgiQGUrqeJJCws4uPLz9AxUqVMcA&usqp=CAU'

plots = plt.figure(figsize = (20, 20))

predict_image(pikachu3D, 1, 1)
predict_image(pikachuToy, 1, 2)
predict_image(pikachuOG, 1, 3)

plt.show()
```

Predicted: Pikachu 100.0%

Predicted: Pikachu 57.41%

Predicted: Pikachu 99.97%

[103]:
```
# predict mewtwo images from web
mewtwo3D = 'https://cdn.now.howstuffworks.com/media-content/
 ↪3beb4197-0e43-4943-95b8-c432f6b0071a-1920-1080.jpg'
mewtwoToy = 'https://target.scene7.com/is/image/Target/
 ↪GUEST_e5bb766e-140c-48ad-a323-1fde69087fed?wid=488&hei=488&fmt=pjpeg'
mewtwoOG = 'https://m.media-amazon.com/images/M/
 ↪MV5BNjk1NTc3MDEtZDM4ZS00YzE2LThhNjEtMzdmZDcwMGJiNTA5XkEyXkFqcGdeQW1yb3NzZXI@.
 ↪_V1_UX477_CR0,0,477,268_AL_.jpg'

plots = plt.figure(figsize = (20, 20))

predict_image(mewtwo3D, 2, 1)
predict_image(mewtwoToy, 2, 2)
predict_image(mewtwoOG, 2, 3)

plt.show()
```

[104]:
```
# predict squirtle images from web
squirtle3D = 'https://66.media.tumblr.com/6ac780a38a8d9eafed01daf41d6cd45b/
 ↪tumblr_ps1sykZPEV1vplr8j_400.png'
squirtleToy = 'https://ae01.alicdn.com/kf/Hf096a66261864013886bd82540d9f4757/
 ↪GK-Anime-Bulbasaur-Squirtle-Charmander-pikaqu-Charizard-Resin-Statue-Figure-Small-Fire-Drag
 ↪jpg'
squirtleOG = 'https://aguycalledkane.files.wordpress.com/2017/04/squirtle.png?
 ↪w=840'

plots = plt.figure(figsize = (20, 20))

predict_image(squirtle3D, 3, 1)
predict_image(squirtleToy, 3, 2)
predict_image(squirtleOG, 3, 3)
```

```python
plt.show()

# Failure with Toy image: Predicted was Bulbasaur, most likely do to edges in image
```

[105]:
```python
# predict bulbasuar images from web
bulbasuar3D = 'https://cdn1.thr.com/sites/default/files/2019/05/detective_pikachu-bulbasaur-publicity-h_2019.jpg'
bulbasuarOG = 'https://i.pinimg.com/736x/6f/aa/74/6faa74e32ce5f00f2dbc9c0b095cda52.jpg'
bulbasuarToy = 'https://www.choozily.com/wp-content/uploads/Funko-Pop-Bulbasaur-Pokemon-Vinyl-Figure-Choozily.jpg'

plots = plt.figure(figsize = (20, 20))

predict_image(bulbasuar3D, 1, 1)
predict_image(bulbasuarToy, 1, 2)
predict_image(bulbasuarOG, 1, 3)

plt.show()
```

[107]:

```
# predict charmander images from web
charmanderToy = 'https://ak1.ostkcdn.com/images/products/is/images/direct/
↪2c9a494898df8ce9f85130f15683fdd2d80b9c51/
↪Warp-Gadgets-Pok%C3%A9mon-Bundle-Funko-Pop-Charmander-and-Bulbasaur-2-Items.
↪jpg'
charmander3D = 'https://i.pinimg.com/474x/48/8f/c4/
↪488fc45206b15c68313706ca638d9441.jpg'
charmanderOG = 'https://i.ebayimg.com/images/g/-Z4AAOSwkShY8ocn/s-l400.jpg'

plots = plt.figure(figsize = (20, 20))

predict_image(charmander3D, 1, 1)
predict_image(charmanderToy, 1, 2)
predict_image(charmanderOG, 1, 3)

plt.show()

# Failure: 3D image from detective pikachu movie, Predicted Pikachu
```

[ ]:

```
## References
# https://medium.com/@kelfun5354/
↪building-a-simple-pokemon-convolutional-neural-net-cc724a8fb47d
# https://www.pyimagesearch.com/2018/04/16/
↪keras-and-convolutional-neural-networks-cnns/
# https://www.youtube.com/watch?v=FmpDIaiMIeA
# https://www.geeksforgeeks.org/image-classifier-using-cnn/
# https://www.pyimagesearch.com/2019/07/08/
↪keras-imagedatagenerator-and-data-augmentation/

## TODO
```

```
# Data/Image augmentation optimization
# crawl for more images on 3D versions
# Provide callback to fit model to monitor best fits
```