

**Machine Learning Project Report**  
on  
**Kaggle's**  
**Cdiscount's Image Classification Challenge**

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# Chapter 1

## Introduction and Problem Description

Image classification is a necessary task these days as most of the data that is available today is in non-textual format. Image classification refers to assigning images to different classes based on certain features that are extracted from images. Complex models of deep learning such as a deep neural network, convolutional neural network are known to perform good for this task. We have used convolutional neural network.

This challenge is from one of the ongoing competitions on kaggle.com. CDiscount is a french e-commerce company which has a lot of images of all the products that it sells and it wants to classify the products in different categories based the image of the product. The current process that is employed by Cdiscount is applying machine learning techniques to the text description of a product to determine its category.

This challenge asks for taking the potential of their method to a whole new level by applying machine learning techniques to images. However, this task is multiclass classification as each image can belong to more than one classes which makes it even more complex.

## Chapter 2

### Related work

We have referred the following machine learning tasks in order to get an insight about which machine learning techniques to use for classification of images.

- MNIST: This dataset contains images of handwritten digits from 0 – 9. The images are in gray scale. The resolution of images being small, a deep neural net gave good results for the same.
- CIFAR-10: This dataset contains various RGB images belonging to 10 classes. We referred Navin Manaswi's article on how to build an image classifier using TF Learn
- The classification task at hand requires much complex network and hence we referred to Andrew Ng's course on Convolutional Neural Network on Coursera.
- Apart from this, for data preprocessing and analysis we have referred kernels on Kaggle.com in order to get an idea about the same.

# Chapter 3

## Dataset Description

### Dataset Description:

- 9 million products which is almost half of their current catalogue
- Over 15 million images at resolution of 180 x 180
- More than 5000 categories of the products

### Description of files:

**train.bson** : This file contains a list of 7,069,896 dictionaries, one dictionary per product. Each dictionary has a product id (key: `_id`), the category id of the product (key: `category_id`) and 1 – 4 images of the product. The images are stored in a list (key: `imgs`). Each list of image(s) contains a single dictionary per image, format: `{'picture': b'...binary string...'}`. The binary string is the binary representation of the Image in JPEG format.

**train.bson.torrent**: Torrent file for downloading the train.bson file. The size of the train.bson file is 58.2 GB.

**test.bson**: This file contains a list of 1,768,182 products in the same format as the train.bson file. Only difference is that, the `category_id` is not included in this file. Our objective is to determine the same.

**test.bson.torrent**: Torrent file for downloading the test.bson file. The size of the test.bson file is 14.5 GB.

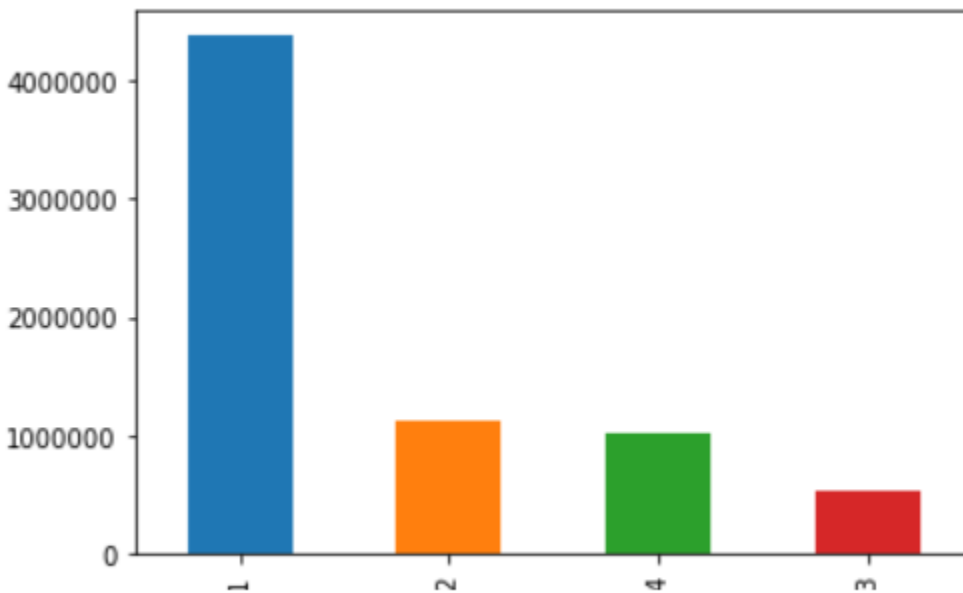
**train\_example.bson**: This contains the first 100 records of the train.bson file.

**category\_names.7z**: This shows the hierarchy of classification. The labels are in French. `Category_id` corresponds to the label in lowest level(level 3) category.

**sample\_submission.7z**: Shows the required format for submission.

## Data Distribution

The dictionaries of product have images, and the number of images per product are 1 – 4. The visualization of this distribution is shown below.



*Figure 1: Images per product*

For convenience, we have observed the distribution of classes for the training example which is a subset of the train dataset.

### Distribution of products over classes for train sample

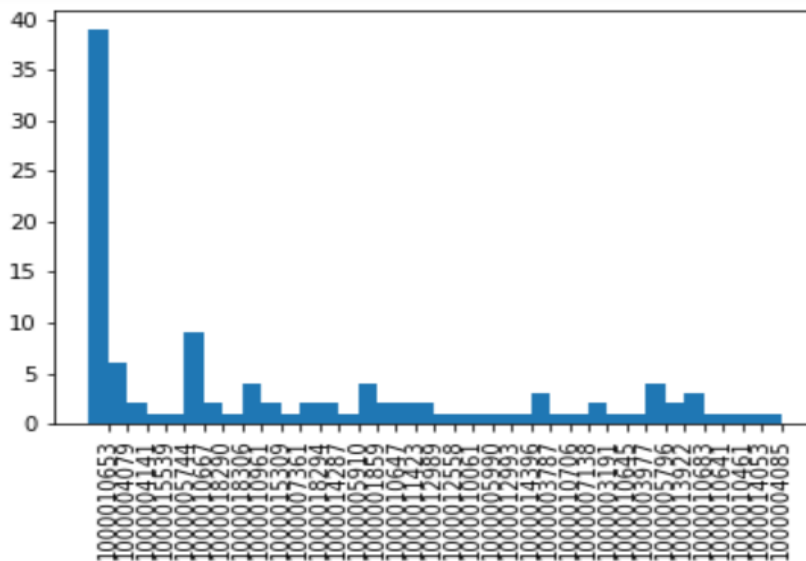
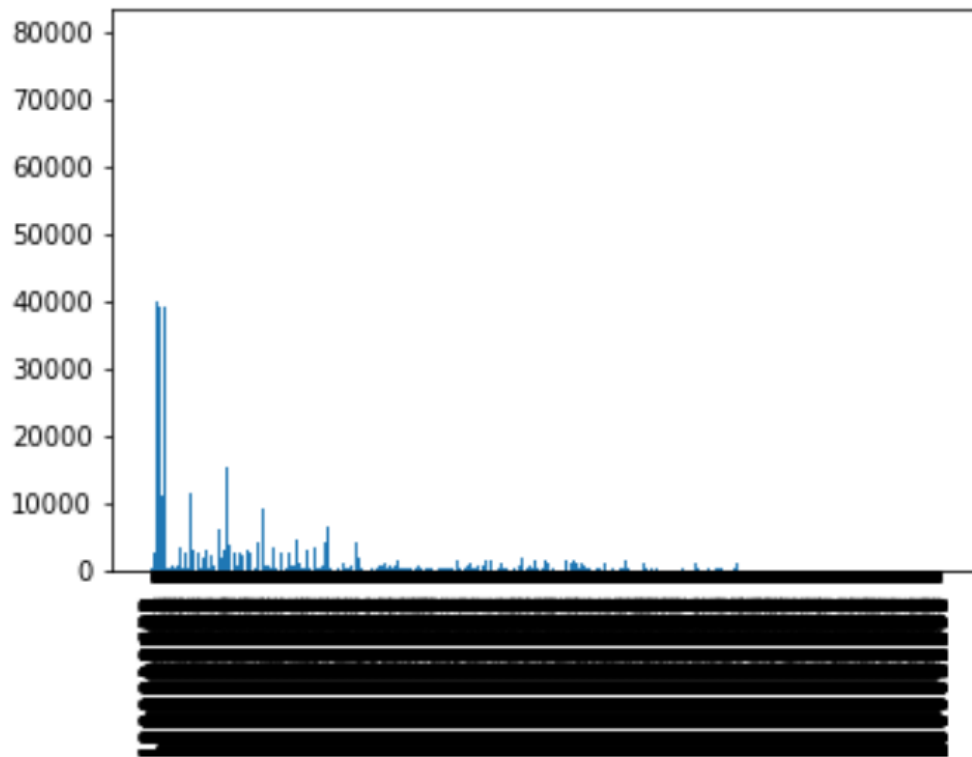


Figure 2: Number of images per category id

The values on the X axis is the category into which the images belong to. The Y axis shows the count of images in each class.

The distribution of all images in the training set is shown in the following plot.



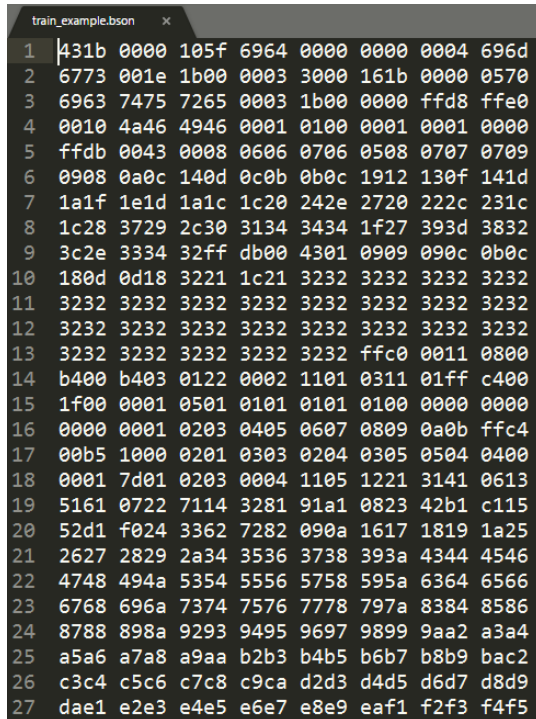
*Figure 3: This plot shows that the dataset has class imbalance distribution.*



## Chapter 4

### Preprocessing Techniques

- The image data is given in the bson (binary json) format



1	431b	0000	105f	6964	0000	0000	0004	696d
2	6773	001e	1b00	0003	3000	161b	0000	0570
3	6963	7475	7265	0003	1b00	0000	ffd8	ffe0
4	0010	4a46	4946	0001	0100	0001	0001	0000
5	ffdb	0043	0008	0606	0706	0508	0707	0709
6	0908	0a0c	140d	0c0b	0b0c	1912	130f	141d
7	1a1f	1e1d	1a1c	1c20	242e	2720	222c	231c
8	1c28	3729	2c30	3134	3434	1f27	393d	3832
9	3c2e	3334	32ff	db00	4301	0909	090c	0b0c
10	180d	0d18	3221	1c21	3232	3232	3232	3232
11	3232	3232	3232	3232	3232	3232	3232	3232
12	3232	3232	3232	3232	3232	3232	3232	3232
13	3232	3232	3232	3232	3232	ffc0	0011	0800
14	b400	b403	0122	0002	1101	0311	01ff	c400
15	1f00	0001	0501	0101	0101	0100	0000	0000
16	0000	0001	0203	0405	0607	0809	0a0b	ffc4
17	00b5	1000	0201	0303	0204	0305	0504	0400
18	0001	7d01	0203	0004	1105	1221	3141	0613
19	5161	0722	7114	3281	91a1	0823	42b1	c115
20	52d1	f024	3362	7282	090a	1617	1819	1a25
21	2627	2829	2a34	3536	3738	393a	4344	4546
22	4748	494a	5354	5556	5758	595a	6364	6566
23	6768	696a	7374	7576	7778	797a	8384	8586
24	8788	898a	9293	9495	9697	9899	9aa2	a3a4
25	a5a6	a7a8	a9aa	b2b3	b4b5	b6b7	b8b9	bac2
26	c3c4	c5c6	c7c8	c9ca	d2d3	d4d5	d6d7	d8d9
27	dae1	e2e3	e4e5	e6e7	e8e9	eaf1	f2f3	f4f5

Figure 4: Image data in bson format

- We converted the bson data files into json

```
{
  '_id': 0,
  'imgs': [
    {
      'picture': b'BINARY STRING FOR IMAGE 1'
    },
    {
      'picture': b'BINARY STRING FOR IMAGE 2'
    }
  ],
  'category_id': 1000010653
}
```

Figure 5 Image data in json format

- We have one dictionary per product. As seen the keys in dictionary for each product are '\_id' – product id, 'category\_id' – Category ID of the product, 'imgs' – a dictionary containing all the images of that product.
- The image data is in hex format (e.g \xff), we have converted the images in the encoded format to RGB values, and these RGB values of the pixels of image serves as raw features for the learner.
- RGB values range from 0-255, the size of each image is 180\*180\*3 where 180\*180 is the dimension of the image and 3 is the number of channels.
- We plotted these using the matplotlib to view the images, here are a few of them



Figure 6: Sample training images.

## The raw pixels of images act as features

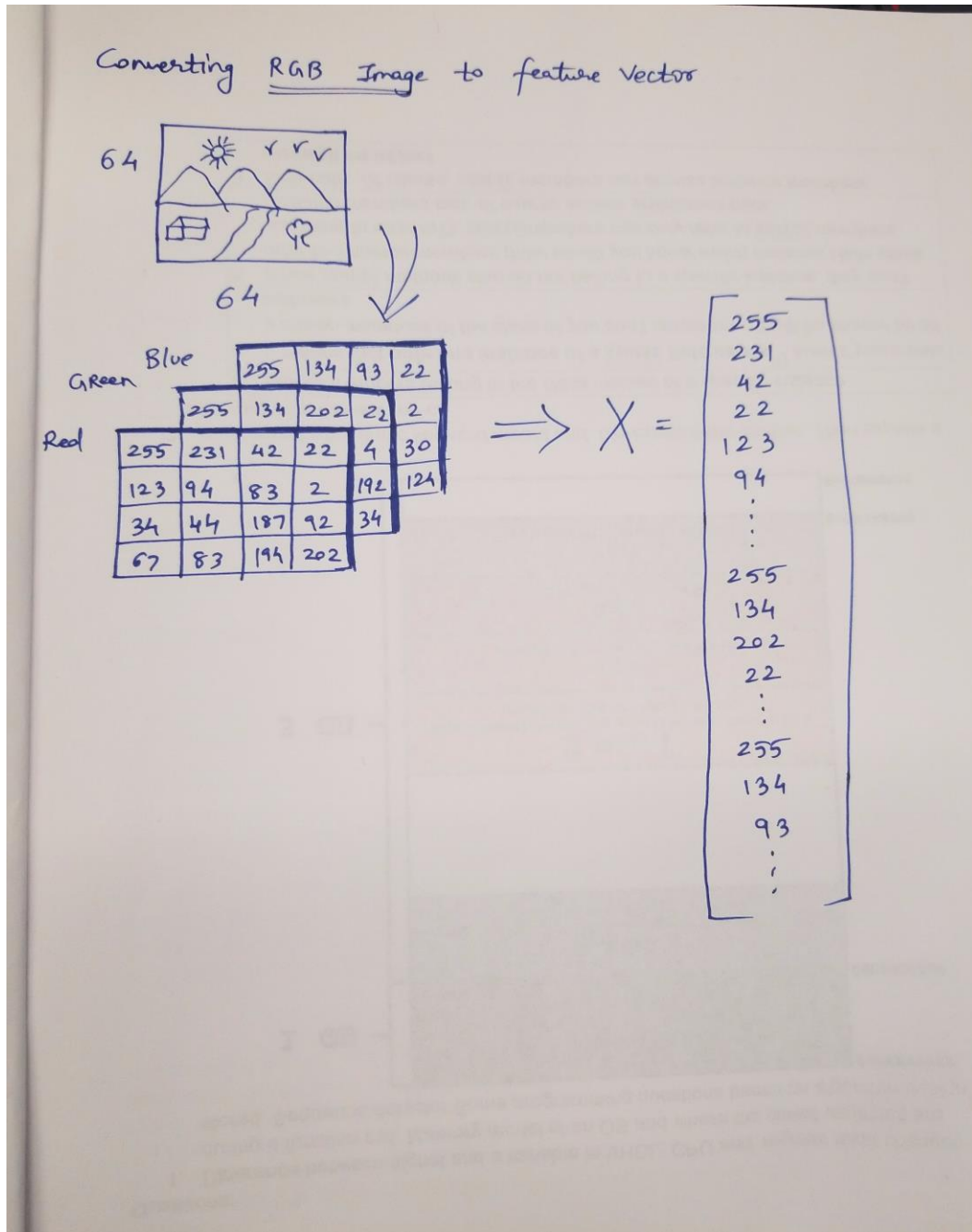


Figure 7: Converting pixel values to single feature vector.

## Chapter 5

### Our proposed solution, and methods:

We have used convolutional neural network for the purpose of image classification.

Why CNN and not other classifier studied in this course?

We have used the image in their raw format as features for the classifier to learn on. As CNN has the special functionality of using convolution layers, it can learn from the RGB pixels of Image.

Also unlike other datasets, in images it is not necessary that all the images are similar say centered in same place, orientation, lightening etc. The CNN model works efficiently because it learns from the convolutions of image which contains only the important features in an image.

Consider the following classifiers:

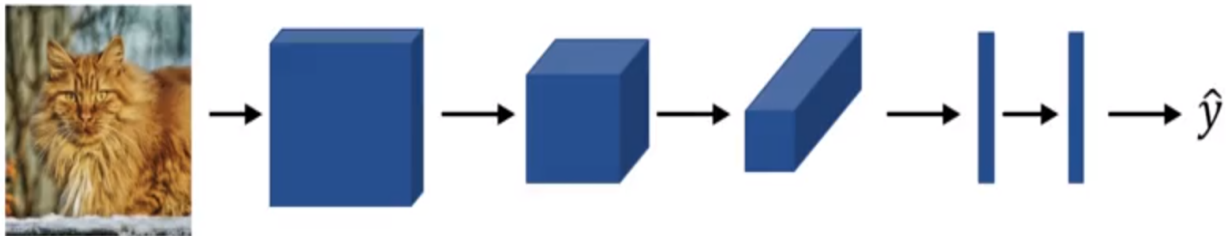
- Perceptron
- Decision Tree
- Linear SVM
- Naïve Bayes
- Random Forests

Neural Networks were used for the character recognition, but in that case the images were gray scale.

In case of more complex Image Classification tasks like this, CNN is known to have performed the best, also these classifiers don't perform well with the RGB values of the images as features.

## General Architecture of a Convolutional Neural Net

Training set  $(x^{(1)}, y^{(1)}) \dots (x^{(m)}, y^{(m)})$ .



Andrew Ng

Figure 8: CNN Example

### Learning Procedure

- 1) Firstly, the images from the BSON format are converted to the RGB which is the standard format for images.
- 2) The image is fed into the network, its dimension is  $H \times W \times 3$ ,  $H$  is the height of image,  $W$  is the width of image
- 3) Next the image undergoes the convolution and pooling layers.

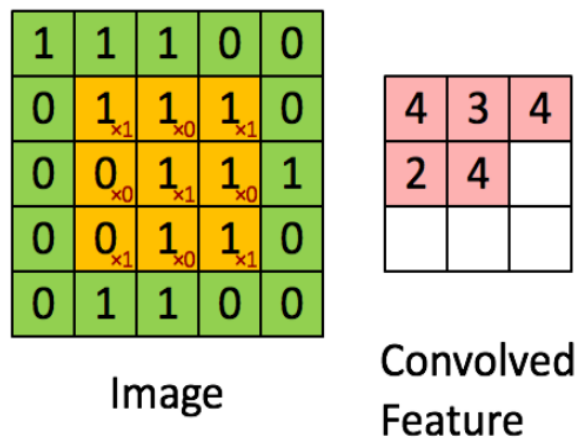


Figure 9: Example of Convolution

4) The convolution for RGB image happens as shown

Convolutions on RGB image

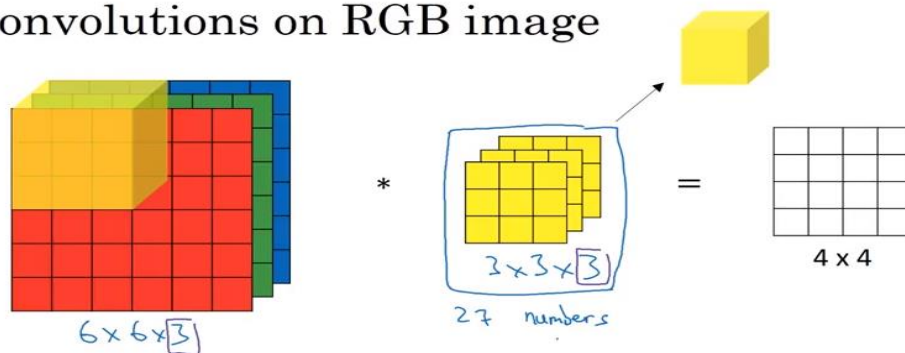
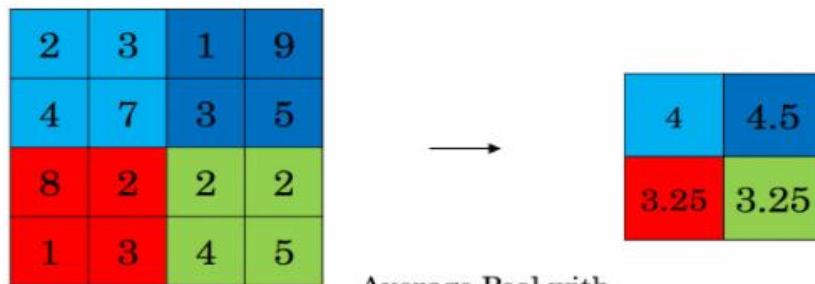


Figure 10: Example of Convolution for RGB

5) There are different kinds of pooling, for examples: Average Pooling, Max Pooling etc.

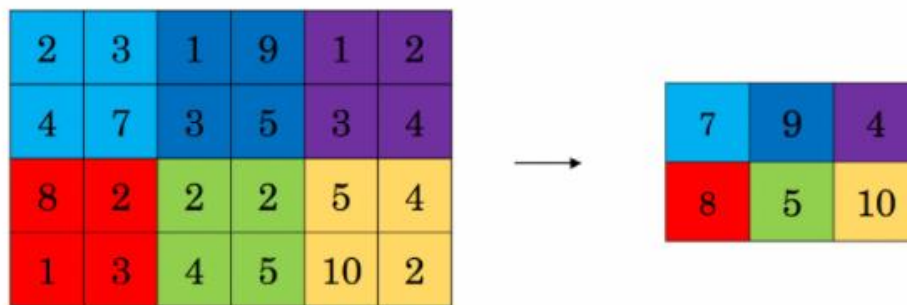
## Average Pool



Average Pool with a 2 by 2 filter and stride 2.

Figure 11: Example of average pooling

## Max Pooling



Max Pool with a 2 by 2 filter and stride 2.

Figure 12: Example of max pooling.

- 6) The activation function used is ReLU function, filters act as weights of Network.
- 7) The last layer in the ConvNet is the fully connected layer, and uses the softmax function which gives final output as a probability distribution over classes, the one with the highest confidence is the predicted category for that example.
- 8) The Loss is measured by cross-entropy i.e. log loss function.

Following is the architecture of our Convolutional Neural Network.

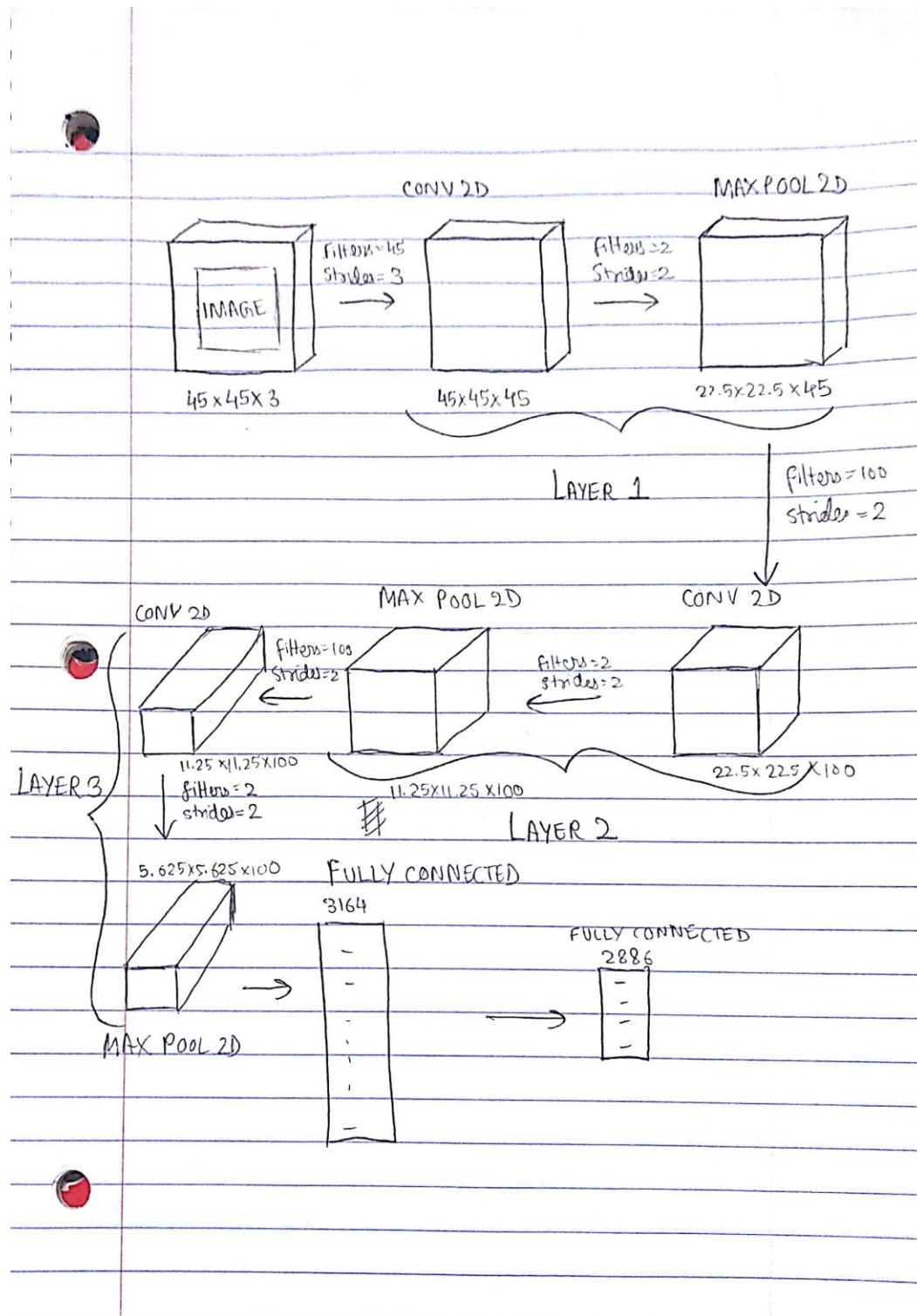


Figure 13: Network architecture of our model



About this ConvNet:

- The Image is rescaled from 180\*180 to 45\*45
- Layer 1 consists of convolutional layer and max pool layer
- After passing through this network, the network starts learning and essential features are retained, and passed to the next layer
- The second layer is also convolution and max pooling where more learning happens. The formula for the dimensions of image that goes into next layer is as follows:

Layer  $l$  is convolution layer

$f^{[l]}$  = filter size

Dimension of filter

$p^{[l]}$  = padding

$s^{[l]}$  = stride

$n_c^{[l]}$  = # of filters

$$f^{[l]} \times f^{[l]} \times n_c^{[l]}$$

Input:  $n_H^{[l-1]} \times n_W^{[l-1]} \times n_C^{[l-1]}$

Output:  $n_H^{[l]} \times n_W^{[l]} \times n_C^{[l]}$

$$n_H^{[l]} = \left\lfloor \frac{n_H^{[l-1]} + 2p^{[l]} - f^{[l]}}{s^{[l]}} + 1 \right\rfloor$$

Similarly, for  $n_W^{[l]}$

Figure 14: Formulas for calculating dimensions

- After layer three, next is the fully connected layer, the activation function used in the last layer is softmax, which converts the predictions to a probability distribution because we have categories of images.

## Chapter 6

### Experimental Results and Analysis

```
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(84138, 3, 45, 45) (84138, 2886) (21035, 3, 45, 45) (21035, 2886)
```

Figure 15: Shapes of training and testing dataset

```
model.evaluate(X_test, y_test)
```

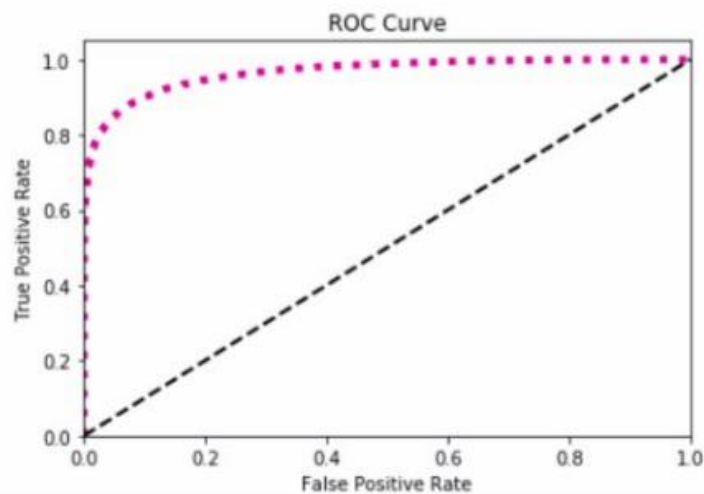
```
[0.36272878533931874]
```

Figure 16: Accuracy of the model

```
from sklearn import metrics  
metrics.auc(fpr["micro"], tpr["micro"])
```

```
0.96593397735438435
```

Figure 17: Area under the curve of the model.



figu

Figure 18: ROC Curve

## **Chapter 7**

### **Conclusion**

We have implemented CNN for image classification. The accuracy of our model is around 36% which can be improved by training it on whole dataset. Due to limited resources available, we couldn't train our model on whole dataset, instead we took 50,000 samples with 2886 classes. We have evaluated the model on three metrics i.e. ROC, AUC and log loss. The AUC was approximately 0.96 and log loss was 2.75 up to two decimal points.

We have used raw pixel values as the input to the network. We can get higher accuracy by extracting features such as corners, edges from the images and passing them to the network as this would make the model less complex and it would run faster.

# Chapter 8

## Contribution of team members

Understanding the Project: Meetika, Priyank, Yash

Defining the scope of the competition: Meetika, Priyank, Yash

Developing project plan and timeline: Priyank

Conducting extensive research: Meetika, Priyank, Yash

Analysis and Data Preprocessing: Meetika, Yash

Writing Project status report: Meetika, Priyank, Yash

Writing the code: Priyank, Meetika, Yash

Final report: Meetika, Yash

## Chapter 9

### References

- <https://www.coursera.org/learn/convolutional-neural-networks/home/info>
- [https://docs.opencv.org/3.0-beta/doc/py\\_tutorials/py\\_feature2d/py\\_table\\_of\\_contents\\_feature2d/py\\_table\\_of\\_contents\\_feature2d.html](https://docs.opencv.org/3.0-beta/doc/py_tutorials/py_feature2d/py_table_of_contents_feature2d/py_table_of_contents_feature2d.html)
- <https://www.kaggle.com/humananalog/keras-generator-for-reading-directly-from-bson>
- <https://www.linkedin.com/pulse/image-classifier-using-tflearn-navin-manaswi>
- [https://www.youtube.com/watch?v=3BXfw\\_1\\_TF4](https://www.youtube.com/watch?v=3BXfw_1_TF4)
- <http://parneetk.github.io/blog/cnn-cifar10/>
- <https://cs231n.github.io/convolutional-networks/>
- <http://cv-tricks.com/tensorflow-tutorial/training-convolutional-neural-network-for-image-classification/>
- <https://www.tensorflow.org/tutorials/layers>