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# IMAGE RECOGNITION IN DATA SCIENCE

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***Abstract: Image recognition is one of the most important fields of image processing and computer vision. The CNN's are a very effective class of neural networks that is highly effective at the task of image classifying, object detection and other computer vision problems.optical character recognition (OCR), A scanner can identify the characters in the image to convert the texts in an image to a text file. Image data will help to understand the image recognition, image data will explain about pixel.***

**Keywords:** *Neural network, pixel, computer vision pattern analysis, OCR (optical character recognition), image data, machine learning.*

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## I INTRODUCTION

Image recognition is about the pixel and pattern analysis of an image to recognize the image as a particular object.

### Image Recognition

Just like the phrase "What-you-see-is-what-you-get" says, human brains make vision easy. It doesn't take any effort for humans to tell apart a dog, a cat or a flying saucer. But this process is quite hard for a computer to imitate: they only seem easy because God designs our brains incredibly good in recognizing images. A common example of image recognition is optical character recognition (OCR). A scanner can identify the characters in the image to convert the texts in an image to a text file. With the same process, OCR can be applied to recognize the text of a license plate in an image.

To understand image recognition we should go with image data.

### Introduction and Understand Image Data:

An image is made of "pixels". In a black-and-white image each pixel(A pixel is the smallest unit of a digital image or graphic that can be displayed and represented on a digital display device. Pixels are combined to form a complete image, video, text or any visible thing on a computer display) is represented by a number ranging from 0 to 255. Most images today use 24-bit color or higher. An RGB color image means the color in a pixel is the combination of Red, Green and Blue, each of the colors ranging from 0 to 255. The RGB color system constructs all the colors from the combination of the Red, Green and Blue colors. So a pixel contains a set of three values RGB(102, 255, 102) refers to color #66ff66 color name is "Screamin".

The MNIST database (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems. The training dataset in Keras has 60,000 records and the test dataset has 10,000 records. Each record has 28 x 28 pixels.

### How does image recognition work

How do we train a computer to tell one image apart from another image? The process of an image recognition model is no different from the process of machine learning modeling. I list the modeling process for image recognition in Step 1 through 4.

## II STEPS

**Modeling Step 1: Extract pixel features from an image**

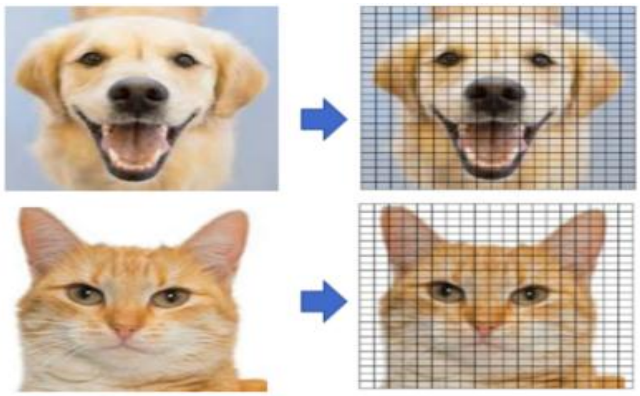


Figure (A)

First, a great number of characteristics, called features are extracted from the image. An image is actually made of "pixels", as shown in **Figure (A).** Each pixel is represented by a number or a set of numbers — and the range of these numbers is called the color depth (or bit depth). In other words, the color depth indicates the maximum number of potential colors that can be used in an image. In an (8-bit) greyscale image (black and white) each pixel has one value that ranges from 0 to 255. Most images today use 24-bit color or higher. An RGB color image means the color in a pixel is the combination of red, green and blue. Each of the colors ranges from 0 to 255. This RGB color generator shows how any color can be generated by RGB. So a pixel contains a set of three values RGB(102, 255, 102) refers to color #66ff66. An image 800 pixel wide, 600 pixels high has 800 x 600 = 480,000 pixels = 0.48 megapixels ("megapixel" is 1 million pixels). An image with a resolution of 1024×768 is a grid with 1,024 columns and 768 rows, which therefore contains 1,024 × 768 = 0.78 megapixels.

**Modeling Step 2: Prepare labeled images to train the model**

Once each image is converted to thousands of features, with the known labels of the images we can use them to train a model. **Figure (B)** shows many labeled images that belong to different categories such as "dog" or "fish". The more images we can use for each category, the better a model can be trained to tell an image whether is a dog or a fish image. Here we already know the category that an image belongs to and we use them to train the model. This is called supervised machine learning.

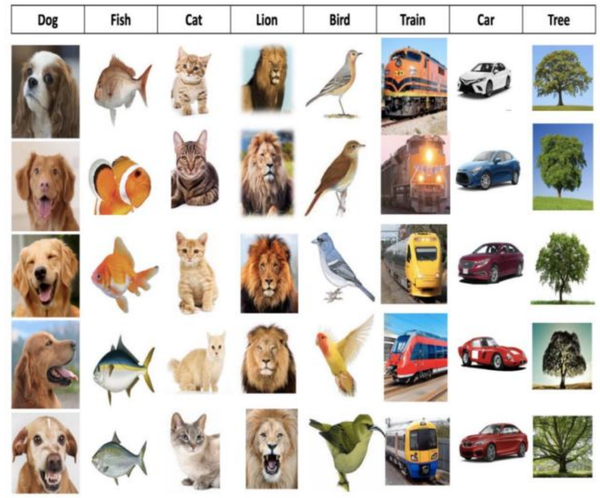



Figure (B)

**Modeling Step 3: Train the model to be able to categorize images**

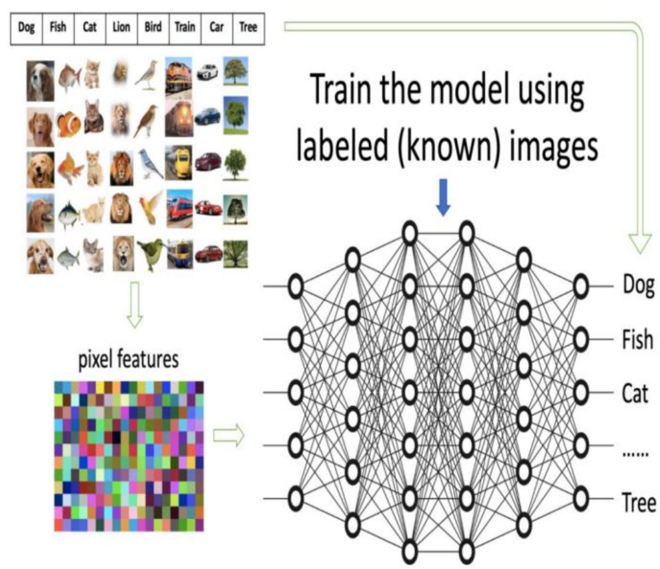
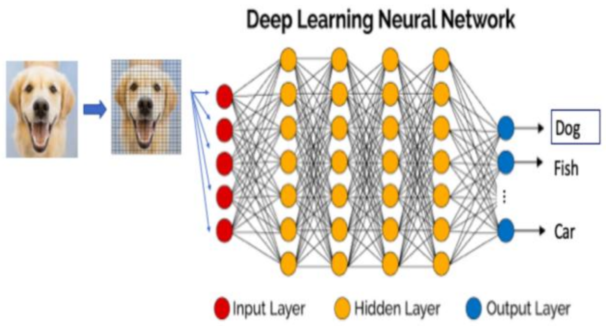



Figure (C)

**Figure (C)** demonstrates how a model is trained with the pre-labelled images. The huge networks in the middle can be considered as a giant filter. The images in their extracted forms enter the input side and the labels are in the output side. The purpose here is to train the networks such that an image with its features coming from the input will match the label in the right.

**Modeling Step 4: Recognize (or predict) a new image to be one of the categories**




Once a model is trained, it can be used to recognize(or predict) an unknown image. **Figure (D)** shows a new image is recognized as a dog image. Notice that the new image will also go through the pixel feature extraction process.

## III IMPLIMENTATION

If image is non blur we can easily recognize. What if a image is blur? If image is blur we can use the image data process. Image process will tell about the "pixel" as we shared information above. Combination of pixel is a image. We can recognize the each pixel color and fill that particular color in that pixel. Repeat this for each pixel. Then we get perfect, non-blur image.

We usually takes photo in our camera. Few time we may face few issue the main issue is that "obstracal".

obstracal is that "the object between the target and the camera"(example like a the player inside the net while playing) by using the same image data(pixel science) we can clear the obstracle and make obstracal free photo.

Concentrate on each pixel comparing the color of corresponding pixel and fix the average color to that particular pixel. this way we can clear the obstracal in the picture.

## IV BENIFITS

A) We can get the clear photo using the image processing.

B) We can convert blur image to normal HD image.

C)The Benefits of Image Recognition

Image recognition can really help you with digital marketing. By integrating the application's programming interface to your text-based analytic platforms, you will be able to offer visual insights to your customers without the expensive product creation that uses logo detection. Image recognition can also help you monitor ROI and protect your brand. You will be able to track how a sponsorship is doing with image and logo detection and this will help you determine how much revenue you will get in return. Therefore, integrating an image recognition application programming interface is an easy way of giving your customers the best service.

## V CONCLUSION

The processing of images is faster and more cost-effective. One needs less time for processing, as well as less film and other photographing equipment. It is more ecological to process images. No processing or fixing chemicals are needed to take and process digital images.

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