ANNs vs CNNs

Agenda

- Image classification using ANNs
- Challenges with ANNs
- CNNs over ANNs

Image classification using ANNs

Image classification using ANNs

Let’s say we want to build a neural network using ANNs to classify an input image as a cat or a dog. For this, we'll be using a set of images of cats and dogs.

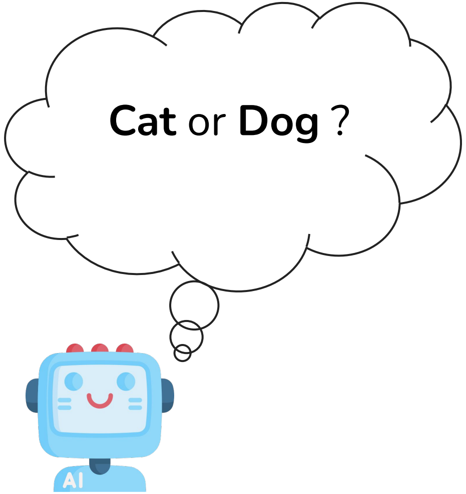


Image classification using ANNs

- If the images are RGB, we know that each image will have 3 channels, which will be represented by 3 matrices - each matrix numerically representing the pixel intensity values from that channel.

- The information about brightness, contrast, edges, shape, texture, shadows etc. of an image **does not depend on color.** So the RGB representation of images only adds to the complexity, and may be replaced by their grayscale version instead.

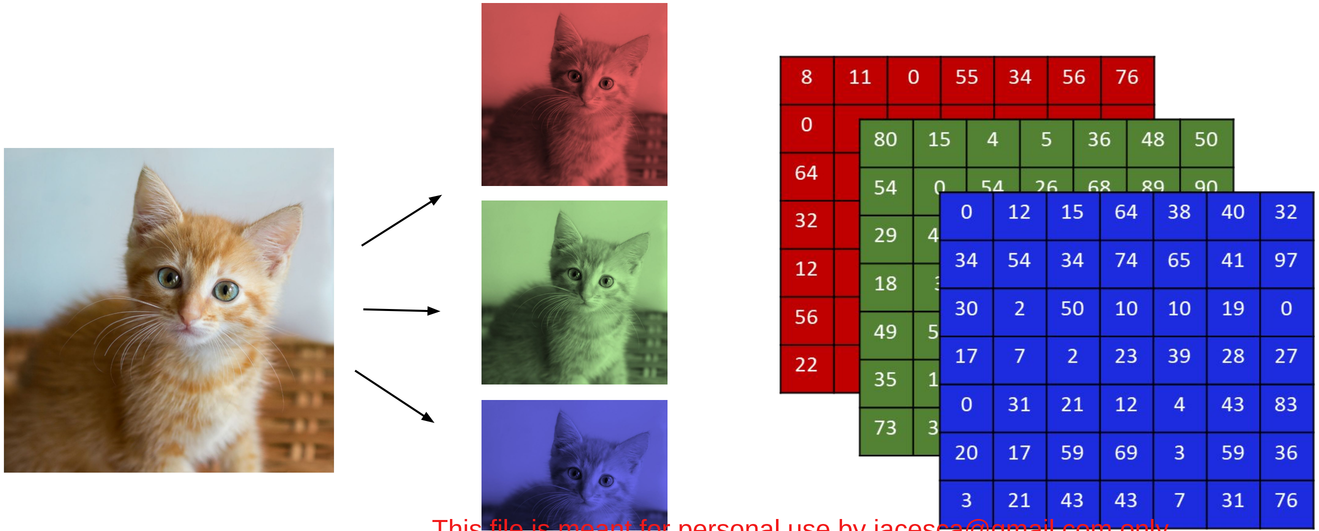
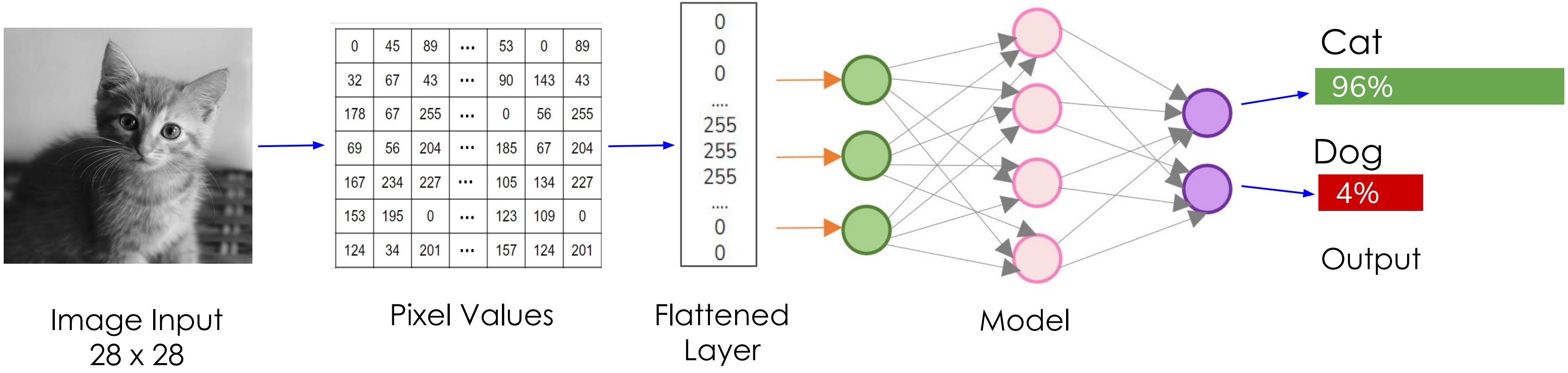


Image classification using ANNs

- For that reason, **we will use the Grayscale color space**, which isolates the color information into a single channel.

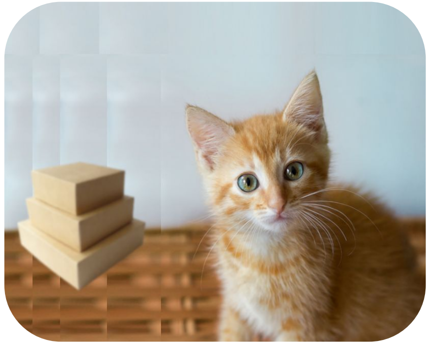
- In ANNs, one neuron would be used for each input. Here the inputs are the pixel values in an image. For an image with 28 x 28 pixels, the flattened input layer will have 28*28 = 784 inputs.

- Every node/element in the output vector refers to an output class.
  The input sample is labeled according to the class with the highest score.



Challenges with image classification using ANNs

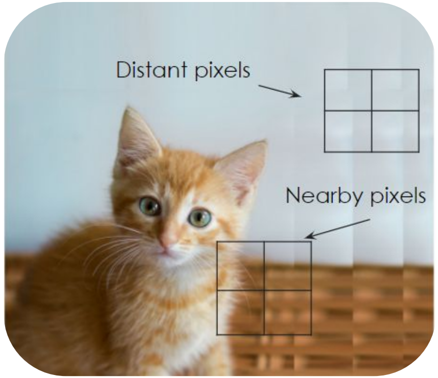
1. Spatial and translational invariance



Translational invariance

One of the main disadvantages of ANNs is that **they are not translation invariant.** For example: Even though the cat may be present in the center, the left or the right corner of an image, ANNs would try to learn the location the cat is present as an indicator of its presence, and this may give inconsistent results.

Another problem with ANNs is that **they lose spatial information** after getting the image matrix converted into a flattened array. This means ANNs do not leverage the fact that nearby pixels are more strongly related than distant ones.



Spatial invariance

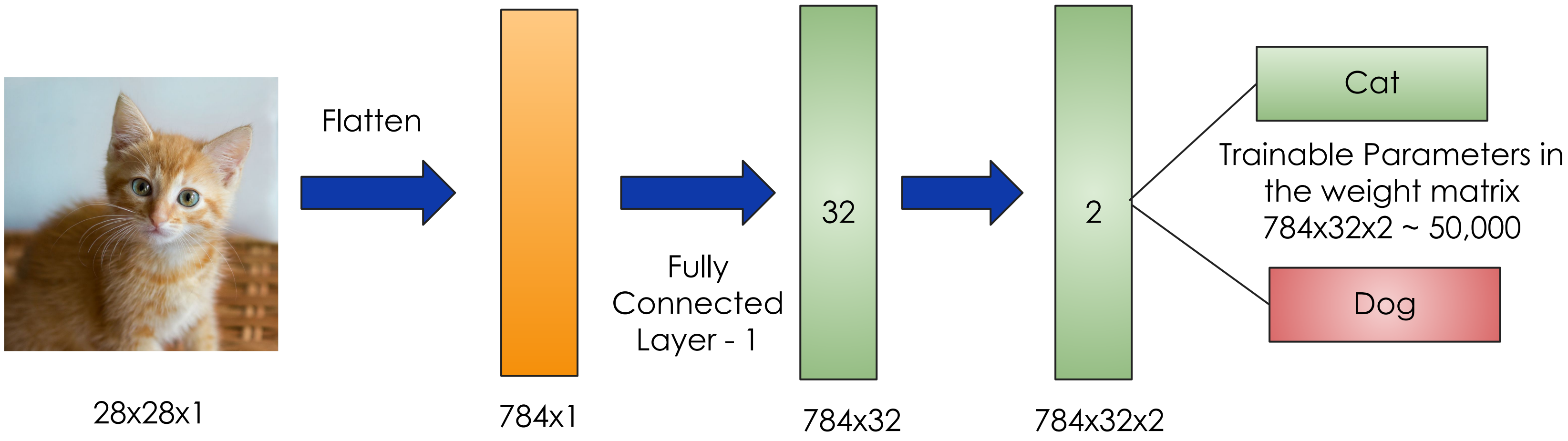
2. Extracting important features

- Yet another disadvantage of ANNs for image classification, has to do with **detecting which features of an image are important and which ones are not.** When detecting the presence of the object, there is no use of looking at the background or other features of an image. There is unfortunately no scope to use this idea in a traditional ANN, which may give importance to every pixel in an image, and will hence try to learn the background of the object as well.

  For example: A cat remains a cat whether it is in the garden or on a table. However, an ANN will wrongly learn about the background and assume that a cat appears in a specific background.

3. The computationally expensive nature of ANNs

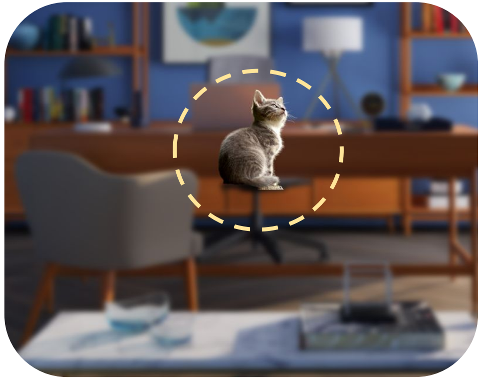
- To add to that, **ANNs are also very computationally expensive.**
- To use an ANN, we would first have to flatten the input. Using just two fully-connected layers (of 32 and 2 nodes each) on the input image of 28x28x1, we observe that there are already **about 50,000 trainable parameters,** and this would just increase with an increase in the number of layers.



Why CNNs over ANNs?

Spatial and translational invariance of CNNs

- CNNs have the inbuilt property of handling positional shifts, or translations of a given image. They are **spatially and translationally invariant.**
- In the below example, we have three images of a cat. It obviously remains a cat regardless of whether it appears in the left, the center or the top right corner of the image. Unlike ANNs, **CNNs are able to understand this**, as you would expect for any practical computer vision model.
- So how are CNNs able to accomplish this?


Spatial and translational invariance of CNNs

- CNNs achieve this through the use of **convolutional and pooling layers.**
- Convolutional layers extract the right set of features from the image by applying filters that match those patterns in the image. Since the same filter is applied through a sliding mechanism throughout the whole image, **the features of the image get detected irrespective of their position.**
- The result of the convolutional layer is sent to the pooling layer. The pooling layer reduces the image complexity and size, and extracts the important features from the pooling patch. This achieves the dual task of **eliminating unwanted background features**, as well as the translational invariance of **removing the information about the exact position** of the object in the image.
- This is why CNNs will likely work well even for shifted objects in images, even if the CNN is not explicitly trained on images with such variability.
- Each layer in the CNN introduces some amount of translational invariance, and the more layers we add, the more effective it usually becomes.

Extracting important Features in CNNs

- **CNNs automatically detect or learn the important features of an image without any human supervision.** For example: In an image dataset of handwritten digits, CNNs learn the distinctive features for each digit by themselves, by learning the best filter values through backpropagation.

- Convolutional filters change the input in such a way that only **the important features are extracted.**

  In the below images, detecting the presence of the dog does not require extracting information about the background (depicted in red lines). We only need to extract the relevant features of the dog, and ignore all other information. This is achieved using convolution and pooling.

Computational advantage of CNNs

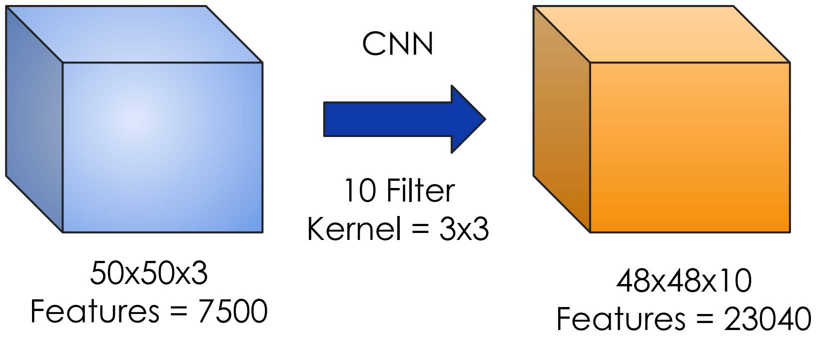
Weight sharing: In the convolution process, we apply the same filter to every patch of the image.

As a result:

- **It reduces the number of weights that must be learned**, which reduces training time and cost.
- **It makes the filter search insensitive to the location** of the important features in the image.

Let's say we have an image of size 50 x 50 x 3 (i.e. 7500 Pixels or Features)

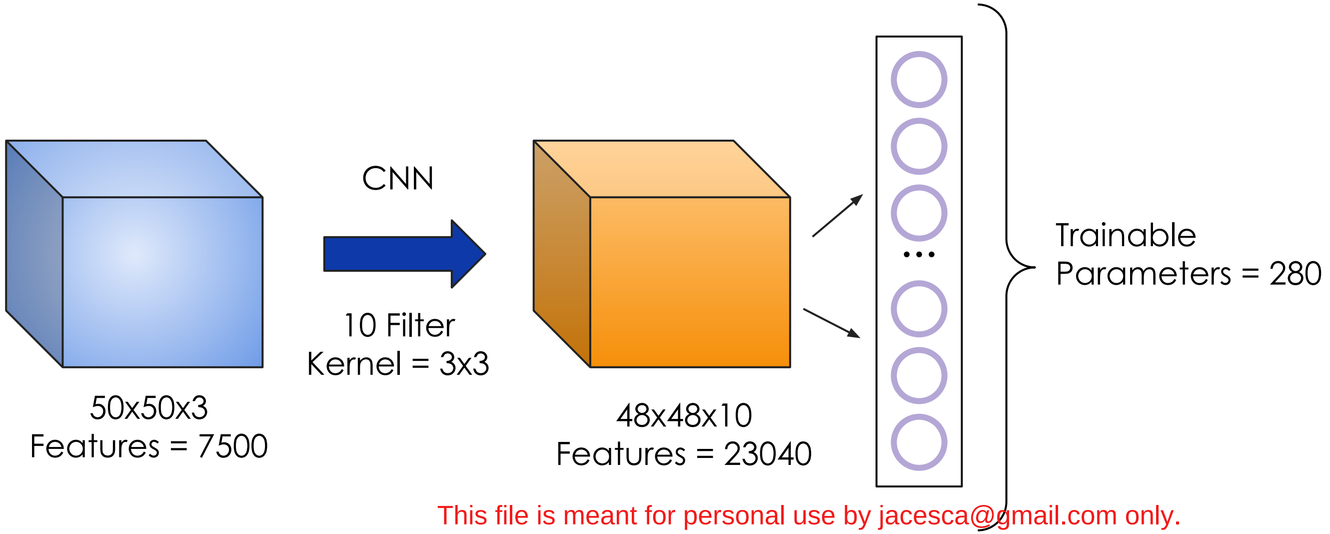
- Taking a CNN Layer with 10 filters and a kernel size of 3x3, we'll have the given output of size 48x48x10 size having 23040 features.



Computational Advantage of CNNs

- **However unlike in ANNs, the number of trainable parameters still remains a small fraction** of the features and does not scale with that large number.

- **Number of Trainable Parameters**
  = (filter size x No. of channels + bias) x No. of filters
  = (3 x 3 x 3 + 1) x 10 = **280**



Summary

- CNNs perform better than ANNs in the crucial task of **capturing the relevant features from an image**, by ignoring any spatial and translational transformations.
- The use of filters in a CNN helps us reduce the dimensionality of the image and extract only the important and required information.
- Convolutional filters require exponentially less trainable parameters in comparison to the fully-connected dense layers required in ANNs, and **this gives CNNs a computational advantage over ANNs as well.**

Thank You