Deep Learning for Computer Vision
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Lecture No. 44
CNNs for Object Detection-I

We have so far seen neural networks in its most simplest form, feed forward neural networks, learnt back propagation, seen how different variants of gradient descent can be used. Learnt a few practical tricks while training neural networks, we then moved on to convolutional neural networks, the building blocks of computer vision. We saw how they can be trained using back propagation, we saw various kinds of architectures in CNNs.

And then we also saw last week on how one can visualize and understand what CNNs are learning as well as explain their predictions. But in all these lectures so far, we focused on the task being classification, given an image our objective was to classify what object was in the image. You could extend that to regression where you predict a real value by changing the cross entropy loss to a mean square error.

However, there are many other kinds of vision tasks that are possible and we will now move on to those tasks in this week. We will start with one of the most used tasks today which is object detection.

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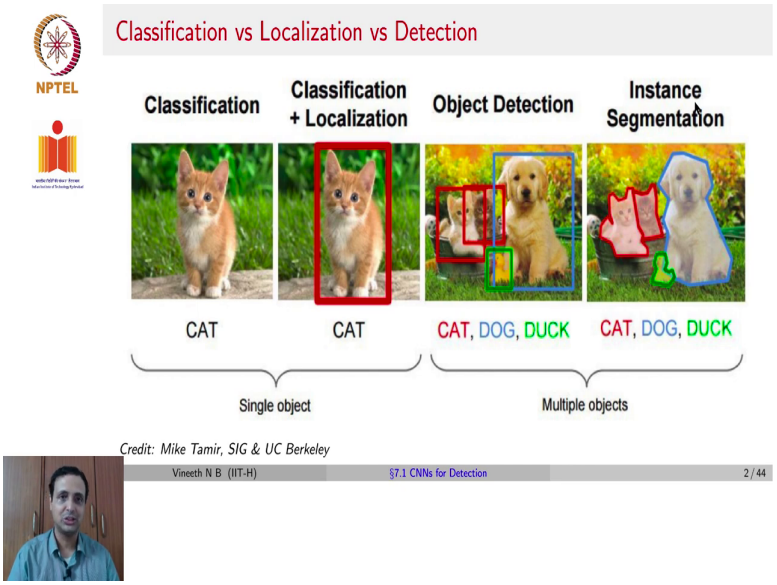

So the difference between classification, localization and detection is as follows. In classification, given a cat in an image, the objective is to say that there is a cat that

corresponds to the image. In localization, in addition to saying that there is a cat you also have a bounding box around the cat to say where in the image the cat was located. In object detection, you go one step further and you detect all possible occurrences of the objects in your set of classes in a given image as well as localize them. In the localization task, there is only one object which you localize whereas in object detection there could be multiple objects, multiple instances of the same object, you could have a cat and a dog or two dogs and one cat all of these possibilities.

The objective here is to recognize each of these objects as well as localize them using these kinds of bounding boxes. Finally, the task of segmentation where the job is to label each pixel as belonging to one of say c classes depending on the number of classes we have. So, we will start this lecture with detection and then move on to segmentation as well as other tasks later this week.

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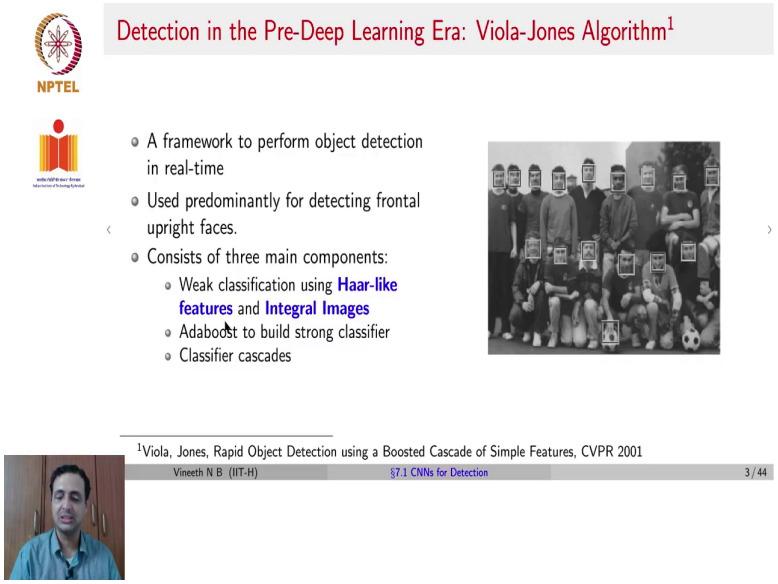

Before deep learning came into the picture, there were other methods that were used to deploy computer vision for object detection on various devices. So, object detection and face detection were even available in say point and shoot cameras 15 years ago when deep learning methods had still not matured. Most of those methods used a variant of what is known as the Viola-Jones Algorithm, this was developed by Viola and Jones and that is the reason for the name and this work was published in CVPR of 2001.

And this is a framework to perform object detection in real time. It was primarily used for detecting frontal upright faces although it was adapted to be able to detect other kinds of objects or even detect parts of objects such as say eye detection on a face. The main contributions of this work was they performed weak classification using what are known as Haar-like features. We will see what these are in the next slide and they also introduced a very powerful idea known as integral images which helps make computations of such haar-like features significantly faster as we will see.

Then they used Adaboost as the classifier of choice but how they used Adaboost was slightly different from the traditional formulation in machine learning and they also used this as a cascade of classifiers as we will see over the next few slides.

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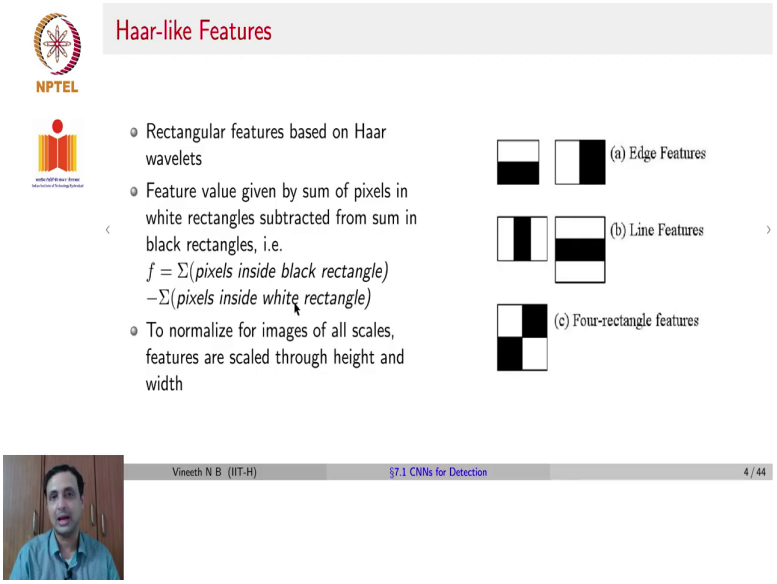

Haar features are rectangular features based on haar wavelets, so these are, this is how the haar features look like. So, you can see here that there are generally a region of black and a region of white but there could be different combinations of those you could have just two regions white and black horizontally aligned vertically arranged or you could have a black sandwiched between a white vertically or horizontally or you could have checkerboard patterns and you can keep going forward you will get various kinds of patterns as you use the same idea.

So, the idea behind the haar filter is, the feature value is given by the sum of the pixels in the white rectangles subtracted from sum of the pixels in black rectangles. Remember this is

convolution, so things would get flipped which is why you have the output of convolving with a Haar filter would be the sum of the pixels inside the black rectangle minus the sum of the pixels inside the white rectangle, remember black is 0 white is 1 but because of the flipping this is what the output would turn out to be.

And to normalize for images of different scales, these features could be scaled through height, through width or even different kinds of patterns as we will see. So, you could have a 6×4filter, a 10×6 filter. You could have a 10×24 filter so on and so forth. You could have them of various sizes depending on what you are applying these haar wavelets for.

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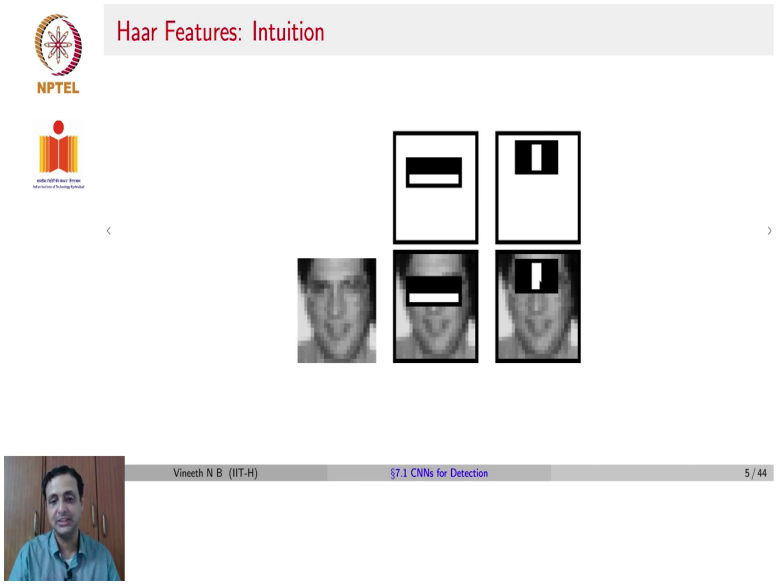

So, the intuition of using haar features for object detection or face detection in particular is that a lot of the features of the human face are about contrast between a certain region and the adjacent region. So, for example, if you looked at the eye region as you can also see here, it is likely to have a black area below and a reasonably brighter intensity area right above that. So, Haar features such as this would capture that difference. You could also look at eyes the other way and represent them and capture eyes using a white block sandwiched by two black blocks in a Haar wavelet. So, these are likely to be good feature detectors of parts of the face.

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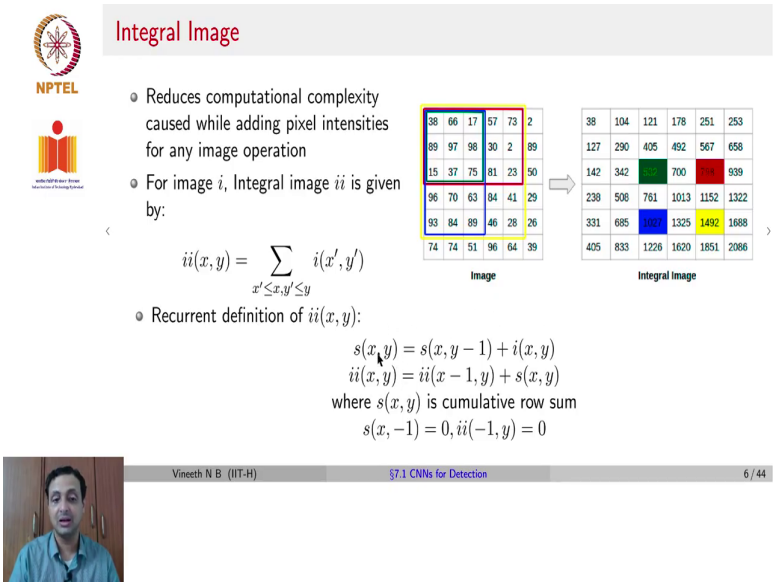

As I just mentioned, this work also introduced the idea of what is known as an integral image this is a fundamental concept not necessarily anything to do with face detection, it is a way of making computations faster especially when you use haar-like features but this was introduced in this particular work by Viola and Jones for doing object detection.

So, let us see what an integral image is? So, the idea is to reduce computational complexity when you are adding pixel intensities for whatever option and the integral image is defined as, for any pixel in the integral image you sum up all the pixel values up till that point starting from the origin on the top left and the summation of all the pixel intensities is what is filled at a particular location.

So mathematically, you could write it as, integral image at x,y location would be the $\sum_{x' \le x, y' \le y} i(x', y')$ where x is the current x location, y being the current y location. So, you add up all the pixel values until that particular pixel that you are looking at and the sum of all of those intensities is what you fill in at that pixel in the integral image. So, given this kind of an image, the integral image would look like this. You can see that for example the 2×2 window 290 is the value given and 290 is given by $38 + 66 + 89 + 97$ and so on and so forth.

So, the recurrent definition for an integral image would be given by $s(x, y) = s(x, y - 1) + i(x, y)$ the above column plus current pixel location and the integral

image at x, y would be $s(x, y) + ii(x - 1, y)$. You can work this out and see that this is correct. And $s(x, y)$ is the cumulative row sum and to make this recurrent definition work you have to define $s(x, -1) = 0$ and $ii(-1, y) = 0$.

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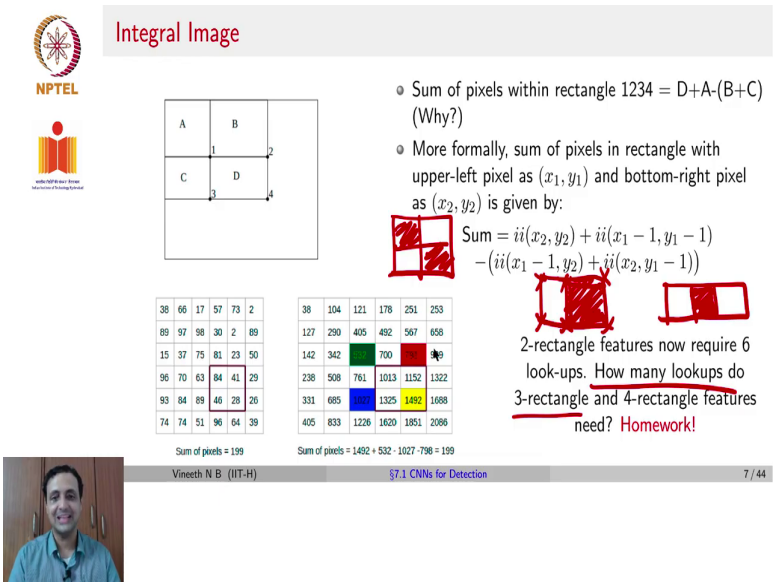

Let us actually now see how the integral image can be used in particular for haar filters. Let us assume now that we want to find the sum of the pixel intensities inside this rectangle defined by 1, 2, 3, 4 A is this top left rectangle B is this entire rectangle including a and including a part of it is A, C is this entire rectangle and D is this full rectangle. So, the sum of the pixels within the rectangle 1, 2, 3, 4 would be given by $D + A - (B + C)$. You can work this out and see that it would be quite true.

So, more formally you can say that sum of pixels inside a rectangle with an upper left pixel as x1, y1 and bottom right pixel as x2, y2 could be given by the $ii(x_2, y_2) + ii(x_1 - 1, y_1 - 1) - (ii(x_1 - 1, y_2) + ii(x_2, y_1 - 1))$, so you can work this out to see that this is actually true.

So, you would notice now that in this particular case, let us say you wanted to find out the sum of pixel intensities in this particular square block, so then what you could do is you could you already have the integral image computed, so you only have to look up a certain value certain set of values here and say $1492 + 532 - 798 - 1827$. Why is this useful?

When you want to use a convolution such as a Haar filter for these kinds of images, if you had a 2 rectangle feature, what we mean by a 2 rectangle feature is let us assume that you have a Haar filter which is given by just a black region followed by a white region. Remember we said that this is the sum of pixel intensities in the black region minus the sum of pixel intensities in the white region, such a convolution for filter would only need 6 lookups in your integral image, why so?

You would need one lookup for all of these corners, so there are six corners here including the middle ones you will need those 6 lookups and you will be able to compute what would be the output of the haar filter without actually doing any kind of a convolution, you can just look up the integral image and be able to get these values. As an exercise, try to think how many lookups you would need for a 3 rectangle feature. What do we mean by a 3 rectangle feature. Consider a haar filter with say black in the center and white on both sides.

So, this would be a 3 rectangle feature, how many lookups would this need? It is simple but work it out later. Similarly, what if you had a 4 rectangle feature something like a checkerboard something like this. So, then how many lookups do you need? Think about it as homework.

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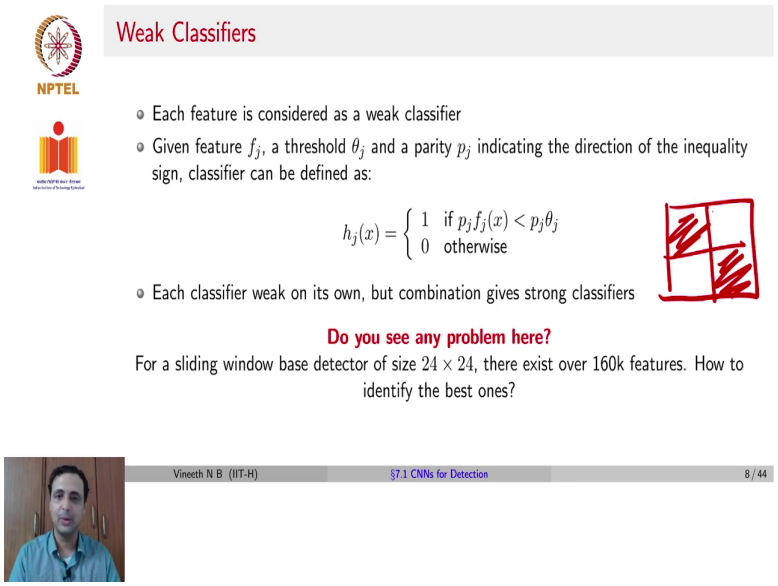

So, once you have the outputs of these Haar filters, the algorithm of Viola and Jones suggested that each feature can be now considered as a weak classifier. Given a feature f_j which is one of those Haar wavelets could be a 2 rectangle feature, a 3 rectangle feature, 4

rectangular feature one of those you can have all possible variants. A threshold θ_j and a parity p_j which only indicates the sign. The classifier is defined as, the weak classifier is defined as $h_j(x) = 1\ if\ p_j f_j(x) < p_j \theta_j$ and 0 otherwise.

So, you are saying that if that feature value is less than a threshold, you are going to call it 1, 0 otherwise, of course you could define the parity to use this otherwise if you like. So now, using this you are going to get one classifier for every Haar feature. We know that a combination of weak classifiers can give strong classifiers but do you see a problem with this approach so far?

If you thought carefully, even if you had a simple sliding window of 24×24 and let us say that is the window you are going to slide across the image and then inside each of those sliding windows you are going to compute various Haar features and use this thresholding to be able to detect whether Haar feature says there is a face or not a face. But the problem is if you had even just a 24×24window there are over 160, 000 features possible. By that we mean, so within a 24×24 window you could have a very large checkerboard then you could imagine all possible combinations of arranging black blocks and white blocks adjacent to each other inside a 24×24 window, you will have a huge number of features.

Now to be able to compute 160, 000 weak classifiers inside each sliding window seems tedious, what do we do?

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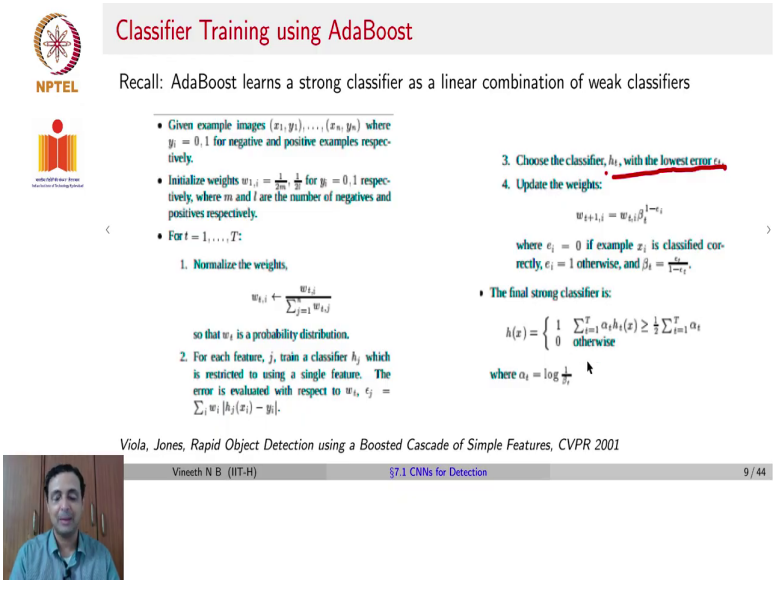

That is where AdaBoost comes into the picture. So, the way Adaboost was used in the Viola Jones algorithm is, the algorithm given here this is from the paper, we will only walk over the salient parts of this, this is the standard Adaboost algorithm where given example images $x_1 y_1$ till $x_n y_n$ you initially start with uniformly weighting all your training samples and you normalize those weights across all of your training samples.

Now, for each feature j which is one of your Haar features among the all possible combinations that you could have, you train a classifier j which is a h_j which is a weak classifier which is restricted to using a single feature and the error with respect to this weak classifier is given by ϵ_j which is given by $w_i \times \left|h_j(x_i) - y_i\right|$, rather $h_j(x_i)$is the output of this weak classifier y_i was the expected output, so how close this weak classifier was to the expected output multiplied by the weight of that sample that we are evaluating, that is the standard Adaboost approach to weight more erroneous samples a little higher and less erroneous samples a little lower.

But now, the Viola Jones approach to using Adaboost says, among all those possible features which would have given you several different classifiers, choose the classifier ht which with the lowest error epsilon t is among all your possible classifiers choose the one that gives you the least error. Based on the error of this classifier you re-weight all your samples as you see here, this is again the standard reweighting step in AdaBoost and you repeat this over and over again and your final strong classifier after a certain number of iterations, remember now you would not be using all features you are only using the T number of features where capital T is a parameter that you can give.

In each iteration you pick one of the features that is really strongest and at the end you only use a weighted combination of capital T different features. And once again this final strong classifier rule is the standard AdaBoost algorithm.

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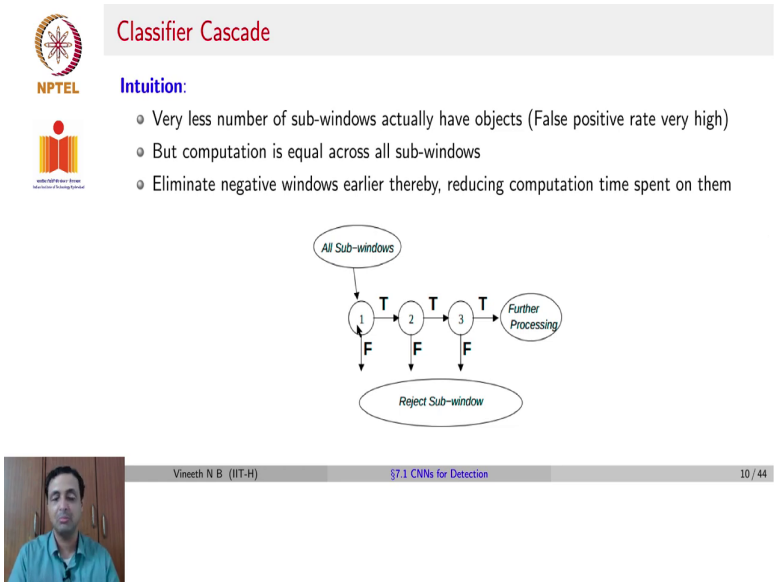

A third component of the Viola Jones algorithm was known as a classifier cascade, so this came from the motivation that very few sub windows of an image actually have objects or faces. Remember you could have 100s of 1000s of sub windows in a given image but you are not going to have that many faces in a given image, so there it is very likely that the false positive rate may be very high if you evaluate every possible window. So, how do we overcome this issue?

So, what this classifier cascade idea suggests is eliminate negative windows earlier therefore reducing computation time spent on them, so if there is a sub window that is negative ignore it and never include any further sub windows inside that sub window for any further processing. Speaking at a very high level, so you have all possible sub windows that goes to the first stage and you rule out a certain number of them and assume that they will never have a face at all then only those sub windows where a face is likely it goes to a next stage in the classifier which again checks for faces again and if there are sub windows rejected at that stage, that again comes out. Only the remaining sub windows go through the next stage so on and so forth.

And in each of these stages, you have a set of weak classifiers. You can constrain that using the number in capital T, but now you can ensure that you can use a stage of different classifiers to keep refining your performance over time.

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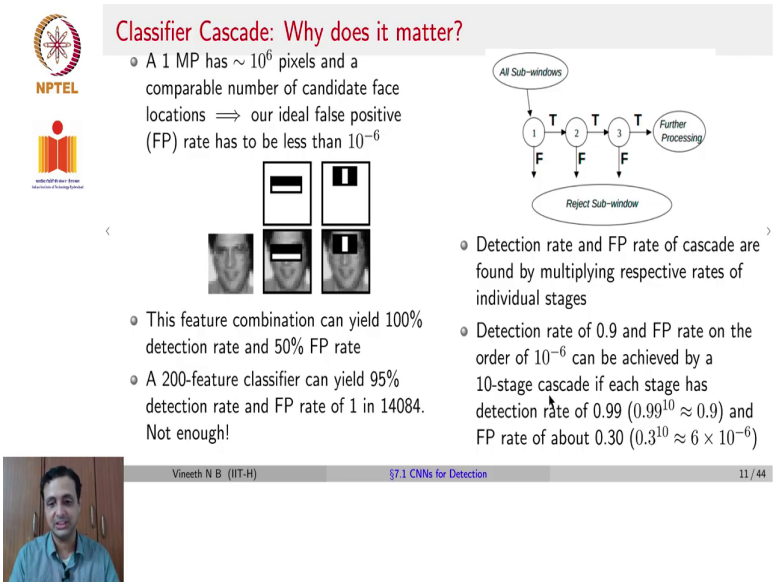

Why does this classifier cascade matter? We just mentioned that for a problem like phase detection or object detection, false positive rate is very important. So, if you had a one megapixel image, remember you are dealing with 10^6 pixels and at least a comparable number of candidate phase locations, even as if you assumed that a face could be at each of these locations you are at least looking at 10^6 probabilities. Once again, you could have different sized faces which would even further expand the possible candidate phase regions but for the moment, let us assume that you have at least 10^6 candidate locations.

So, your ideal false positive rate has to be less than 10^{-6} assuming there is only 1 face or of the order of a few faces. So, you want your false positive rate to be about 10^{-6}. If you took these basic Haar filters that we spoke about a few slides ago, this combination would yield 100 percent detection rate would give you a 50 percent false positive rate and it gives you a lot of possibilities of faces. Not all of them would actually turn out to be faces.

If you went a little further and included 200 features, remember the above example we had only two kinds of Haar filters, if you included 200 kinds of Haar filters, when we say 200 kinds you arrange those black rectangles and white rectangles in several ways you could have them as a checkerboard 2×2 checker board, a 5×5 checker board, you could have 3 rectangles you could have 5 rectangles 7 rectangles all those possibilities are open. You have 200 features that yields a 95 percent detection rate and a false positive rate of 1 in roughly

about 14, 000. It is better but it is still not enough to what we want which is 10^{-6} false positive rate.

What do we do? The classifier cascade comes to our rescue. So remember, that when you have a cascade the final detection rate and the false positive rate are found by multiplying the false positive rate and reduction rate of each of these stages. So, if each of these stages was say a 200 feature classifier which means your capital T was 200, then you may have a detection rate of say approximately 0.9. You could then achieve a false positive rate of 10 power minus 6 across a 10 stage cascade if each stage had a deduction rate of 0.99 and a false positive rate of 0.3.

Because if you had a false positive rate of 0.3 in each stage of the cascade, you would then have 0.3^{10}because you are talking about 10 stage cascade so $0.3 \times 0.3 \times 0.3$ and so on, we will have 0.3^{10} which is roughly about the order of 10^{-6}. So the idea of classifier cascade allows us for each stage in the cascade to have a reasonable detection rate of 0.99 and a false positive rate of 0.3 which as we saw is possible with just a few features and we just keep refining these over stages of the cascade and obtain the false positive rate we ideally wanted.

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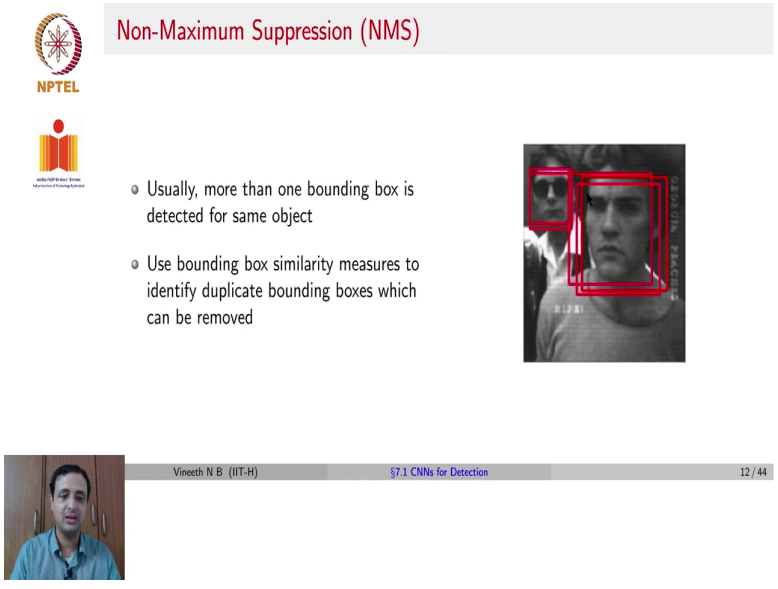

Another aspect of this method, for that matter any detection method, is the notion of non-maximum suppression. So, it is likely that many windows around an object may be classified as containing an object. So, how do you choose which one of them is the right object?

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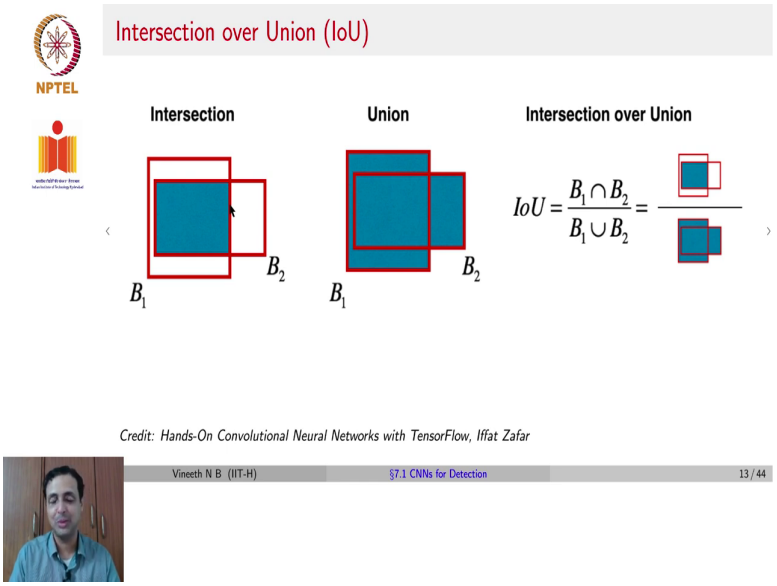

So, we have to use some kind of bounding box similarity measures and the most popular one is known as intersection over union. Intersection over union states that if you have two bounding boxes B1 and B2 you take their intersection and you take their union. The ratio of the intersection to the union gives you a sense of how close these bounding boxes are. If the ratio is 1 which means the bounding boxes B1 and B2 are exactly the same or as they get close to 1 you are going to have that these bounding boxes are fairly overlapping with each other. How do we use this IoU?

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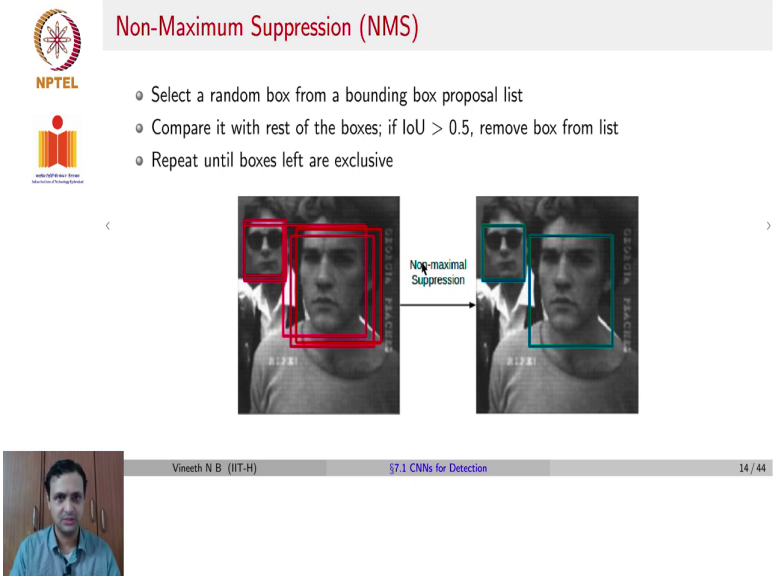

We can now use it for non-maximum suppression. So, if you had a set of possible bounding boxes which contain an object you can select a random box from them. Then you compare that box with the rest of the boxes. If IoU is greater than 0.5, you remove that box from the list. So, you are ensuring that if there are multiple boxes that have a 50 percent overlap with each other, you retain only one of them.

We will see a little later that we would not just follow this, we will also follow trying to find which of these boxes has the highest confidence on the object being in the box, we will see that in a few slides from now. So, this process is known as non-maximal suppression NMS, which is extensively used in detection today as we will see.

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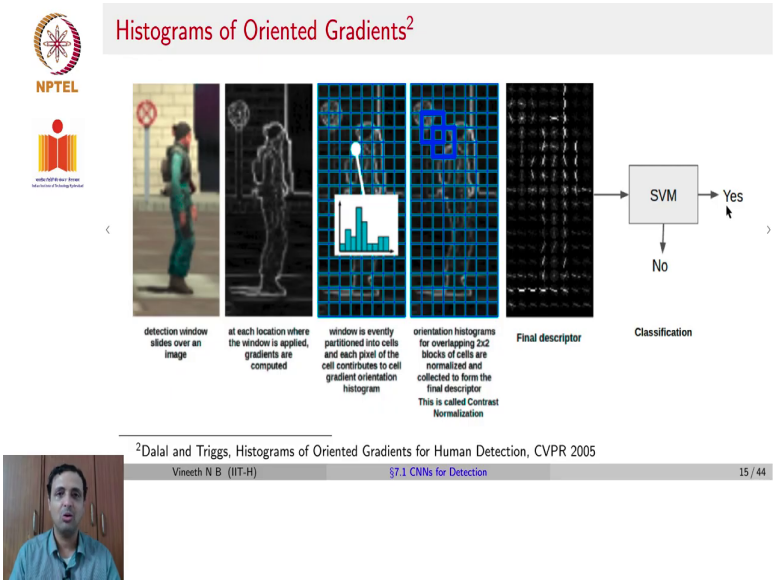

That was the Viola Jones algorithm for phase detection. Very popular. Was used in several technologies. Another popular approach at that time was known as the Histogram of Oriented Gradients. We have seen this when we talked about extracting handcrafted features from images. But we will now talk about it as to how they are used for the task of pedestrian detection.

So, if you have say a pedestrian given in an image, you have a detection window that slides over an image and gets all your gradients. Could be a sobel filter, an elegy filter so on, so you have all of your gradients. Now you divide the entire image into cells and in each cell you draw out a histogram of orientations of gradients. We have done this before with sift so you

perhaps know how to do it. Once you get these histograms of oriented gradients in each of these cells, then you consider overlapping 2×2 blocks of cells.

So you see here that you have 4 different 2×2 cells. So they could be overlapping. But you take a set of 2×2 cells, normalize the histograms in all of those 4 blocks and that is what you define as the final histogram for the center pixel. When you do this for all the cells in your image, you would get a final descriptor which looks like this where you have a set of histograms of oriented gradients across different locations in the image. How do you use this? Once you get this final descriptor you then train a support vector machine to say whether this is a pedestrian or not a pedestrian. So, this was introduced in this work in 2005 by Dalal and Triggs.

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So, you can also visualize as to how the weights of the support vectors look in this particular scenario. So, if you took the average gradient image over all your training examples, you can visualize what are the positive and negative SVM weights. Remember these are your different dimensions here because the cells are your dimensions of your entire descriptor vector. So, you can now imagine positive and negative SVM weights after you learn a support vector machine.

Given a test image and its corresponding histogram of oriented gradient descriptor, you can multiply these descriptors by the positive and negative weights and you would get something

like this and you notice here that looking at the positive weights it would be easy for the SVM to classify this as a pedestrian being in an image.

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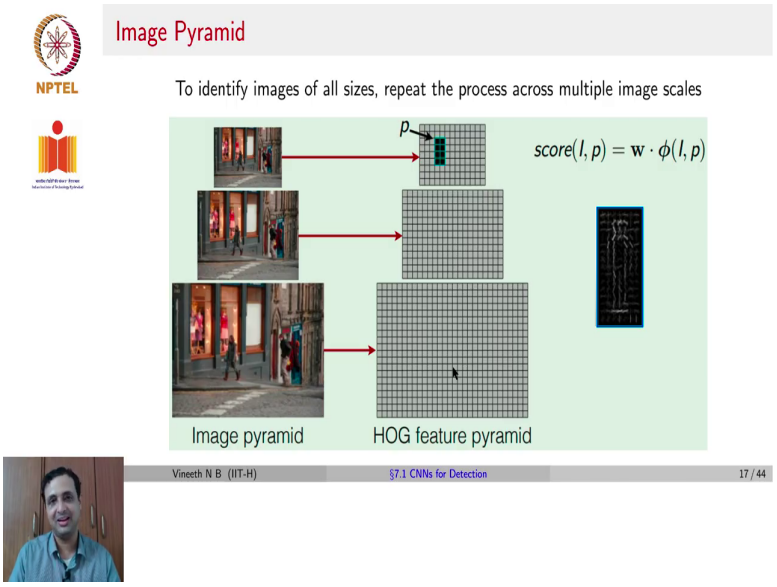

This was also extended to be done at a multi-resolution level, where you have an image pyramid and you perform the same approach at each stage of the pyramid. So, for example, at the lowest resolution you have one specific block and you would get a score using a support vector machine for that particular window in the lowest resolution image. You get a certain score for a pedestrian being there. You would do this similarly for the higher resolution and the highest resolution images and then you can use various techniques to integrate the scores. You could integrate the scores the way we did it for pyramid matching by giving a high score for the highest resolution and a low score for the lowest resolution.

Or you could take a vote or you could use other kinds of heuristics to combine these scores to find out whether a person was in an image. These were the different approaches that were used for detection before deep learning came into the picture.

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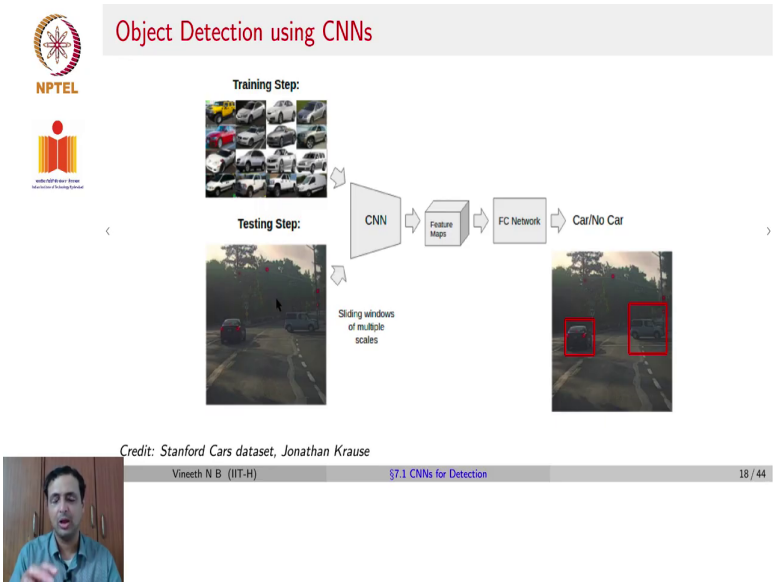

Now let us try to see how one would do object detection using CNNs in the simplest possible manner. If you had say images of cars during training, you would train a CNN on various images of cars to learn a car classifier. So you would use a standard cross entropy loss. CNN, a simple CNN. At test time, when you get an image where a car could be located anywhere in the image, you take different sliding windows of multiple scales.

So, you may have to take say 100, 000 sliding windows potentially from this image and each of those sliding windows you give as input to the CNN assuming that they all are of the same size or you can bring them to the same size. You give that as input to the CNN and that CNN now classifies each window in the original image as belonging to a car or not a car. So, based on that you would detect a car here and here.

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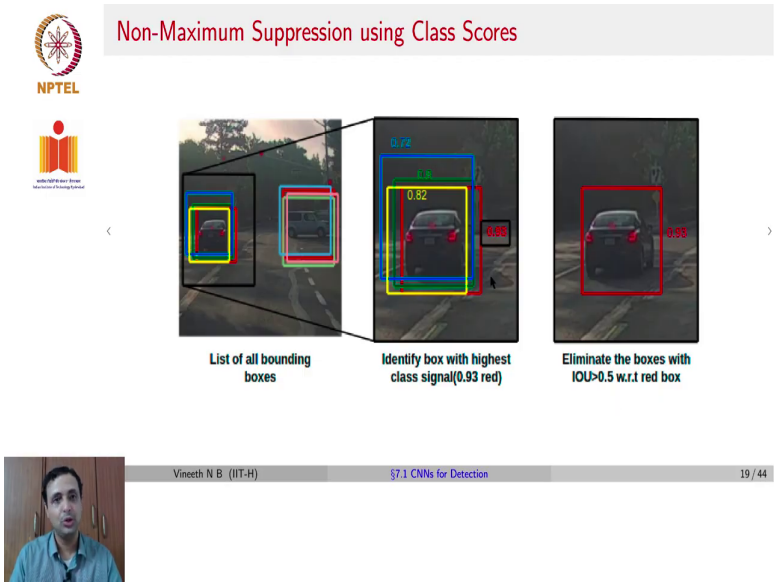

Once again in this approach you can include non-maximum suppression to improve the performance but here as we said before once you get the list of all possible bounding boxes where a car could be present, you consider a bounding box with the highest class signal. So, in this case, the red box would be the box with the highest class signal 0.93. Now you take the IoU of all the other bounding boxes with respect to this bounding box, this red bounding box. If any of them have a high overlap or a high IoU, with this red bounding box, you eliminate them and retain only the red bounding box because it had the highest confidence of a car present in that bounding box.

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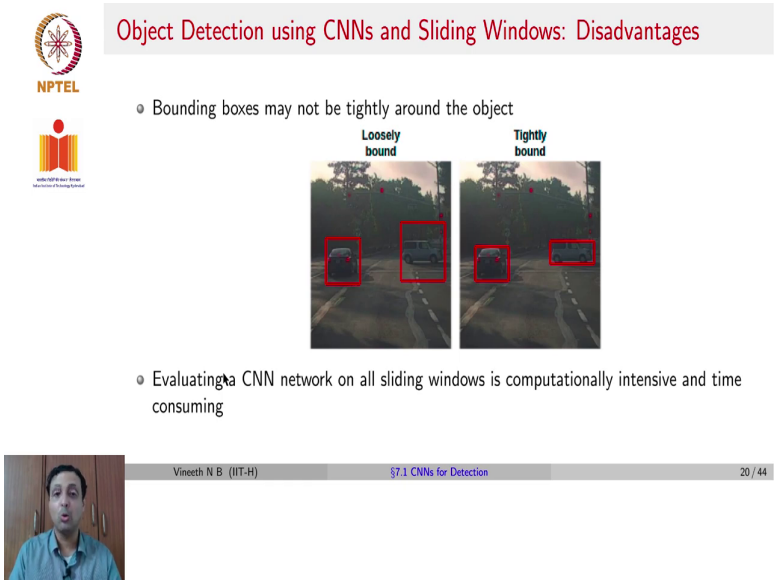

Do you see problems with this approach? This is the simplest way of adapting CNNs for object detection but do you see any issues? There are actually a few of them. Firstly, the bounding boxes may not be tightly around the object. You can see here that some of these bounding boxes are fairly loose. We ideally want a tight bounding box so that we exactly focus on only that part of the object, that part of the image that contains the object. That could happen in this kind of an approach.

The other problem here is obviously that you have to evaluate thousands of sliding windows through the CNN to be able to find which of them contain your object of choice. We are going to talk about methods that overcome this issue.

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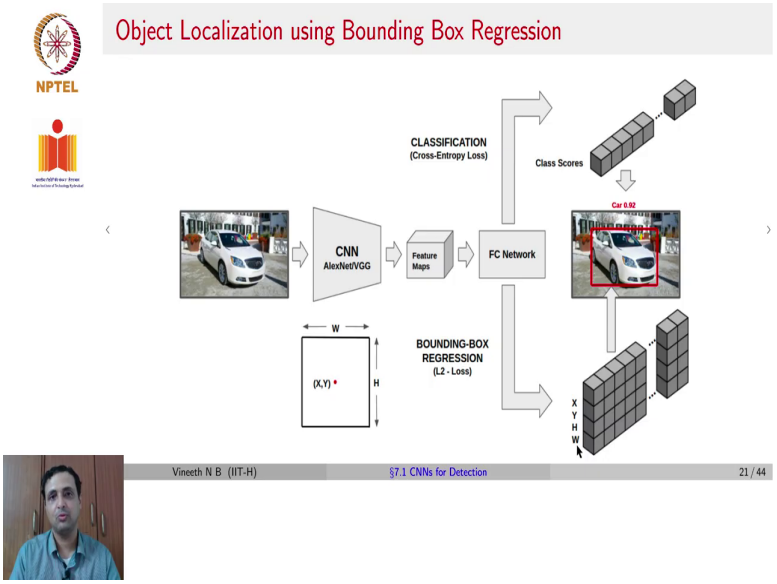

But before we go there, we will talk about object localization which as we said was a precursor to detection. So, object localization can be achieved by, if you had only a single object in an image, you can then give that as input to a CNN, you get your feature maps, you get your fully connected network. Now, you branch out your CNN into two parts, one part that gives you a classification score which can be learnt using a cross entropy loss, that is the standard CNN for classification that we have spoken about so far, but we could also do a bounding box regression.

So, you could now try to see what are the exact coordinates of the bounding box say with respect to the entire image or with respect to any other box in the image. You could see what is the offset and you also learn that as part of your learning procedure. So, your fully

connected network at the end would have two heads, a classification head and a regression head. The classification head would require clock cross entropy loss, the regression head which will learn in x, y the top left corner of the box, a height and the width. 4 coordinates, 4 values.

And these values can be learnt using a normal L2 or mean square loss, so the entire network would be trained by the sum of these two losses to not only classify the image but also localize the image.

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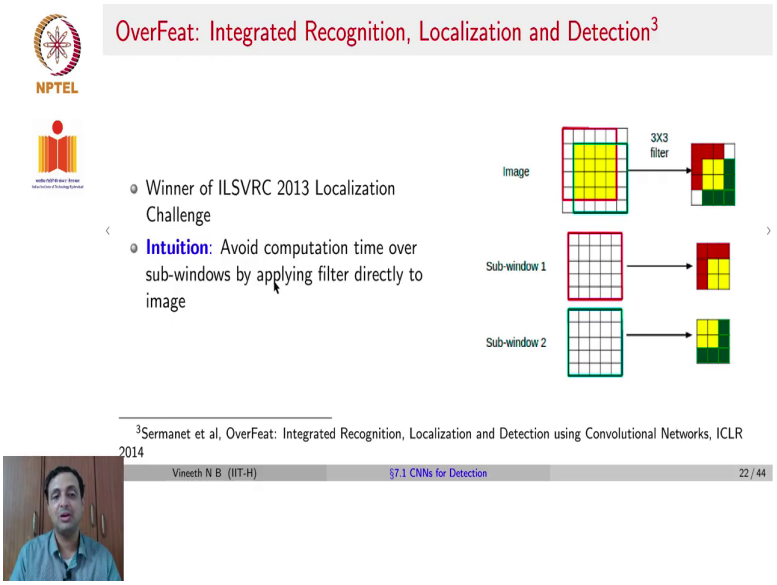

One of the first successes of a good localizer in CNN was OverFeat. OverFeat was the winner of the ImageNet localization challenge. Every year, ImageNet, in addition to having the classification challenge also had a localization challenge and OverFeat was the winner of this challenge in 2013 and the way OverFeat did localization was to ensure that your entire network is convolutional instead of having fully connected layers. So, this avoids computation time over sub windows by applying filter directly to the image, let us see how.

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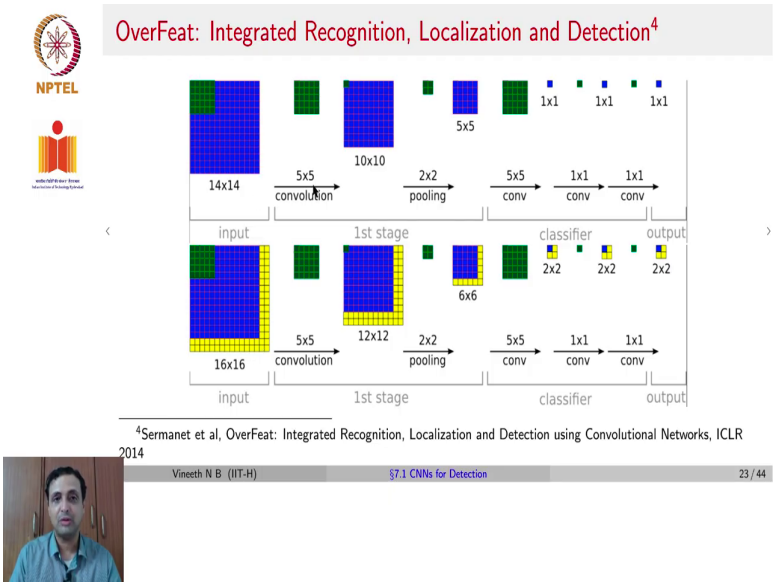

So, given an input which is say 14×14 or you pad and make it 16×16 you perform 5×5convolution this is only an example for visualization you get a 10×10 output assume if you did not do padding and if you do 2 pixel padding it becomes 12×12 then a 2×2 pooling makes it 5×5. A 5×5 convolution makes it 1×1 and now using multiple one cross one convolutions you can get an output directly without having to perform any fully connected layer operations.

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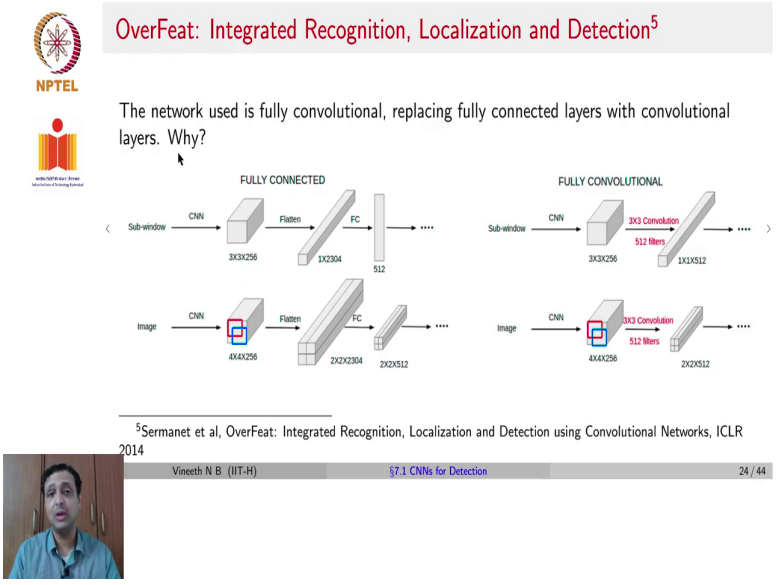

So, this idea of OverFeat made computations significantly faster as you can see now, instead of using a fully connected layer OverFeat replaces it with a fully convolutional layer which

finally has 1×1 convolution similar to what we saw with InceptionNet if you recall or GoogleNet and the this OverFeat approach uses that to get your final performance. Why is this useful? Because we remember we said that fully connected layers use up a lot of parameters. That is what we said and using a fully convolutional approach overcomes this and hence can speed up performance.