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A Study on Different Evolution in Computer Vision

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Abstract — Computer vision, when a computer and/or machine have sight, can be used in many applications like OCR, Vision Biometrics, Object Recognition, Social Media, Smart Cars etc., Different approach evolved over a period of time in computer vision problems, which can be categorized as, one after the deep learning in computer vision problem and the other before deep learning in computer vision problem. The prior one named as classical approach (HOG & SIFT., etc), could not learn from discrimination features from images and non adoptive for diverse image and doesn't meet human level of accuracy. So there arises a requirement for learning method in computer vision Problems. Machine learning gives computers the ability to learn without being explicitly programmed. Deep learning or machine learning overcomes the drawbacks of classical approach by learning the features in the images and the diversity in the images implicitly and thus meets more accuracy than human vision. In this paper we will study difference methods like Classical & Deep learning for image classification problems , and analyze the draw backs and how the other approach overcome the drawbacks and accuracy levels meet by these approaches over the years.

Keywords—Computer Vision(CV), Convolution; Convolution Neural network(CNN) , Deep Learning ;Gradient , improvement in CV after CNN, Machine Learning, possible improvement in CV.

I. INTRODUCTION

Computer vision is when machine as a sight to it, ten years ago computer vision researcher thought that to say the difference between the cat and the car, almost impossible, now computer vision can identify the object greater than 99.99 accuracy , this is called image classification , given a image classify the images to its category, computer knows 1000's of other categories as well, the significant improvement in the computer vision brought the computer vision to think to beyond the scope of human vision , and brought the current applications like when you just show your phone on the wifi user name and password it knows it's a user name and password it automatically connect to the internet and show your phone on the street where you are standing , computer vision connects to the map know everything where you are and which shop or restaurant you are standing what is their service rating and expecting many more things to come in the future, we start with what is a computer vision & different between computer vision and human vision and different methods evolved, and see as classical approach and Deep Learning in computer vision, and what Deep Learning brought on computer vision before Deep Learning intelligence in computer vision and after Deep learning in computer vision problem and different CNN Architecture which help computer vision problems to meet the accuracy.

Computer Vision Vs Human Vision:

When you look at an image of a mass we can instantaneously figure out who is a known person, who is a stranger, who is a man or a woman, who is a adult or an child, and roughly someone's background. You can also see the cloths people are wearing, who are similar to look and who are not, and what time of day it is or season depending on the background and light. [1]

A computer can look at the same image and see nothing from the image, if we think it so, but with computer vision it can recognize and identify all the faces, tell you the ages of everyone in the picture, and even accurately tell you everyone's background. It may find difficult to determining the season and time of day, due to the shadows, lighting, and shapes [1]

However if we able to make the computer to perceive the image as human do, then with the ability of computer to remember & process trillions and trillions of instruction per unit time, the computer would be a super human with big sight. [1]

1.2 What is Computer Vision?

Computer vision is when a computer and/or machine have sight. [2]

1.3.1 It Seems looking is very Hard?

Is that seeing is just recognizing/classifying it's a bigger sense than just identifying or classifying for instance if we see particular thing our vision system connects to the brain and process the vision and we recollect the things spontaneously and the vision turns to emotions, ideas, decisions etc., however the same can be replicated in computer vision with the help of Machine & Deep Learning [1][2]

1.4 Why is Computer Vision Important?

Computer vision is used for face recognition, identification, emotion analysis, and crowd analysis, without it our business would not be effective so it is extremely important to us. [2][3]

1.5 Application of Computer Vision [2][3]

- **Optical Character Recognition (OCR):** Recognizing and identifying text in documents / image
- **Sports:** In a game when they draw additional lines/graphs on the screen
- **Social Media:** facebook auto friends tagging etc.
- **Vision Biometrics:** Identifying people who have been missing through iris patterns.
- **Object Recognition:** face detection, face recognition, video object co-segmentation, object tracking.
- **3-D Printing and Image Capture:** Used in film making, designing, architectural structures.
- **Smart Cars:** To know the obstacle in front of the car.
- **Medical Imaging:** creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues[29]

II. AN OVERVIEW OF CLASSICAL APPROACH

Now, we know what is computer vision? where it is used or and what impact or significant it could produce if it is inferred in appropriate way.

Also considering improvements in the future, taking the fact improvements is everlasting and learning is a life time process.

2.2 Let us see some of the traditional approaches

Below (Fig .1) Shows the abstract format of the classical approach in computer vision problems

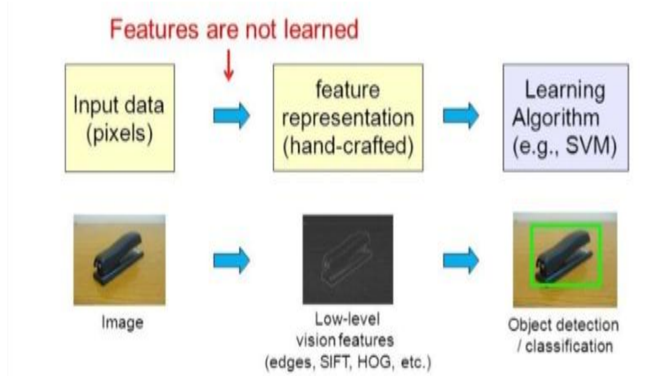

Fig. 1: Example of an image for traditional approach in Computer vision Problems[28]

2.3 What is convolution?

An Operation between every part of image and an operator kernel/filter, output obtained by the convolution is the filtered image. [4][28]

Why Convolution?

- **Parameter Sharing**: A Feature detector(such as vertical edge detector) that's useful in one part of the image is probably useful in another part of the image. [4][28]
- **Sparsity of connection:** In each layer , each output value depends only on a small number of inputs[4][28]

Convolution on grayscale : Grey scale images are the one withthe intensity ranging from 0 to 8 or black & white images (Ref Fig. 2)

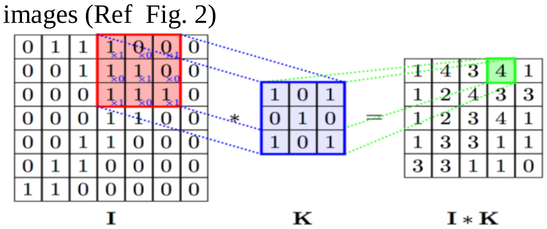

Fig. 2: Example of an image for convolution on grey scale[28]

Convolution on colour image(RGB) : Colour images are the one with three dimensions array for the colour intensityRed , Blue & Green.(Ref.,Fig. 3)

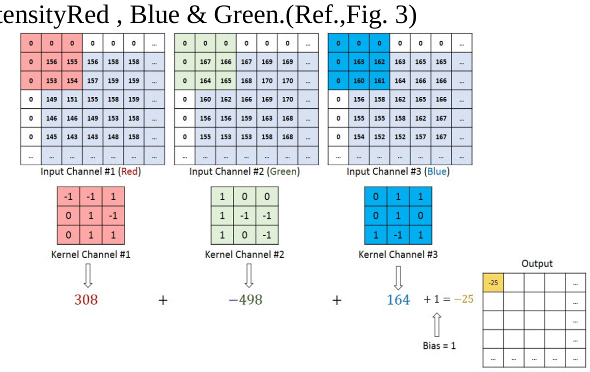

Fig. 3: Example of an image for convolution on colored images[28]

What convolution does?

- Detects edges
- Sharpens/Blurs images
- Extract different features in the images.

It helps to recognize, classify, and detect what is present in the image.

2.4 Gradient Based Method : Other Important way to perceive image is by using the intensity gradient in the image If we say Gradient (Image is two dimension so it is x & y derivatives, are useful because the magnitude of gradient is large around edges & corners as edges and corners group in a lot more information about object shape than flat regions. [5][28]

There are many different approaches to detect features from images using gradient based, let us see few of the common approaches which is important

Histogram of Oriented Gradients [6][7][25][28]

Descriptor Feature used in computer vision mainly for object detection, Distribution of directions of gradients (histograms oriented gradients) is used as features. [6][7][25]

The 5 stages for computing HOG include: [6][7][25]

1. Normalizing the image before to description.
2. Compute gradients in x & y directions
3. Make a histogram by Obtain weighted votes in spatial and orientation cells.
4. Compare normalizing cells.
5. Collect all Histograms of Oriented gradients to form the final feature vector.

Stage1& 2

● A window 64 pixels wide by 128 pixels height is used. [6][7][25] (e.g. Figure4).

● operate on 8*8 pixel cells. [6][7][25] (e.g. Figure4).

● Now compute gradients in each cell [6][7][25]

Fig. 4: Example of an image for HOG Person detection[28]

● place the 64 gradient vectors in 8x8 pixel cell into a 9-bin histogram, 0-180 deg. (e.g. Figure5).

● Reducing 64 vectors with 2 components each losing to just 9 values (the magnitudes of each bin). [6][7][25] (e.g. Figure5).

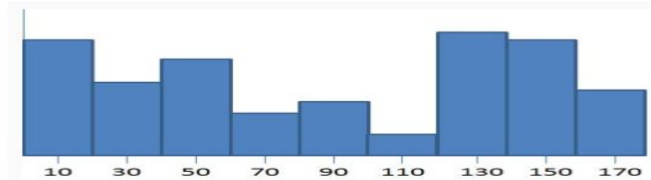

Fig. 5: Example of an image for Gradient Histogram[25][28]

Stage4

● Now normalise the histogram. [6][7][25][28]

● But we won’t do this for each histogram, but for each block. [6][7][25]e.g. Figure6).

● So divide by the 9X4 components (e.g. Figure6).

Fig. 6: Example of an image for Gradient Histogram for each block (4 cells with a 9-bin histogram)[25][28]

Stage 5

Final Descriptor Size[6][7][25][28]

● 64 x 128 window divided into 7 blocks horizontally and 15 blocks vertically, total of 105 blocks. (Fig.7)

● Each block contains 4 cells with a 9-bin histogram for each cell, total of 36 block. (Fig.7)

● Final vector size = 105 blocks x 36 values/block = 3,780 values.

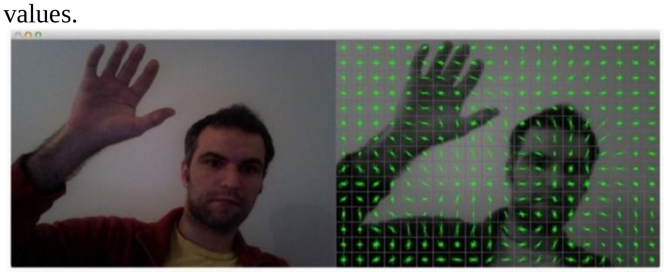

Fig.7: Example of an image for Gradient Histogram – each block contains 9-bin histogram for each 36 per block[6][7][25][28]

2.4.5 Scale Invariant Feature Transform[6][7][26][27][28]

SIFT is a scale invariant feature descriptor which was developed and patented by **D.Lowe.** Computing SIFT features consists of 5 main steps.

Scale-space Extrema Detection [6][7][26][27][28]

● Laplacian of Gaussian (LoG) is found for the image with for different σ values.

● In the **Fig.8** , gaussian kernel with low σ gives high value for small corner while gaussian kernel with high σ fits well for larger corner. hence, we can find the local maxima across the scale and space which gives us a list of (x,y,σ) values which means there is a potential keypoint at (x,y) at scale σ.

●LoG is costly

● SIFT algorithm uses variation of Gaussians which is an approximation of LoG. (Fig.7,9)
● LoG obtained as the variation of Gaussian blurring of an image with gaussians of σ and kσ. (Fig.7,9)
●Images are searched for local extrema regions over scales and space.
● For eg, one pixel in an image is compared with its 8 neighbours as well as 9 pixels in next scale and 9 pixels in previous scales. If it is a local extrema, it is a potential keypoint. It is show (**Fig.11**)

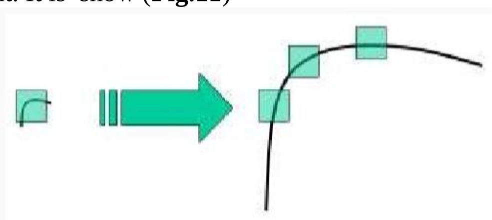

Fig.8: Ex., of Gaussian kernel with low σ gives high value for small corner while Gaussian kernel with high σ fits well for larger corner[27][28]

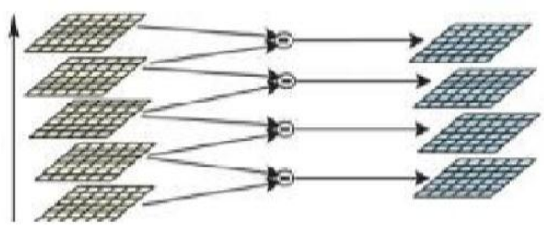

Fig.9: Difference of Gaussian which is an approximation of LOG First Octave[27][28]

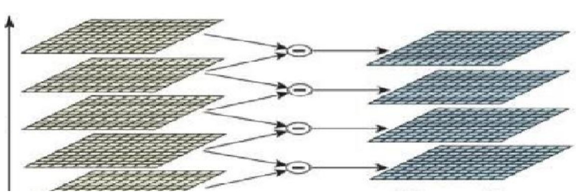

Fig.10: Difference of Gaussian which is an approximation of LOG Next Octave[27][28]

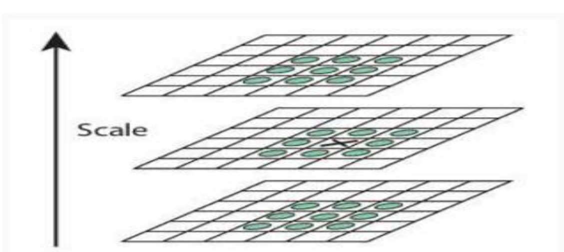

Fig.11: Neighbour 8 pixel & previous , next 9 pixels are examined if is local extrema, it is a potential keypoint[27][28]

Keypoint Localization [6][7][27][28]
● After potential key points /areas locations are found, they are refined.
● The features representing edges, and low contrast points are found and discarded, leaving corners, which convey the most information, with some thresholding.

Orientation [6][7][27][28]
● To obtain invariance in image rotation by assigning orientation to each keypoint. depending on the scale neighborhood is taken around the keypoint location, and the gradient magnitude and direction is calculated in that region.
● An orientation histogram with 36 bins covering 360 degrees is created. Any peak above 80% of it is also considered to calculate the orientation by taking the highest peak in the histogram.

Keypoint Descriptor Creation [6][7][26][27][28]
Feature vectors are created, describing the key points found, which provides better information about the image, rather plain RGB

Keypoint Matching [6][7][26][27][28]
● Keypoints matched by identifying their nearest neighbours.
● In some cases, the second closest-match may be very near to the first, due to noise or some other reasons.
● In that case, ratio of closest-distance to second-closest distance taken. Reject If greater than a threshold (0.8).
● Eliminates around 90% of false matches, discards only 5% correct matches.

III. LIMITATION OF CLASSICAL APPROACH

3.1 All these methods perceive images less accurately then human vision does moreover, discriminatory power is less, For instant to identify man, discriminatory feature would be head, body, shoulder, hands & legs, however it fails to recognize accurately after all identifying the discriminatory feature for example Computer vision system can identify chimpanzee as a man & fails to recognize crippled person to be a man. Other Example, to identify a car, discriminatory feature would be a car wheel, if a car wheel is identified than it's a care, after all identify the wheel it could misinterpret since motorcycles have the wheels, moreover there are different style, type of wheels for a care.

3.2 To address these diversity in a image/object, and understand the image as human do as in the previous examples, Chimpanzee structure looks like a man but not a man, crippled person is still a man however he is crippled or in case of car, car can have different style & type of wheels and motor cycles wheels are different from care (Fig 12), Learning **methods or representation learning is required in computer vision[8][25]**

Fig.12: Depicts diversity in objects

IV. REPRESENTATION LEARNING

What is **Representation Learning** feature learning or feature learning[8] is a set of techniques that allows a system to automatically discover the representations needed for feature detection or classification from raw data. **This replaces manual feature engineering and allows a machine to both learn the features and use them to perform a specific task**[25]

Below (Fig. 13) shows deep learning is a kind of representation learning which is a part of Artificial Intelligence.

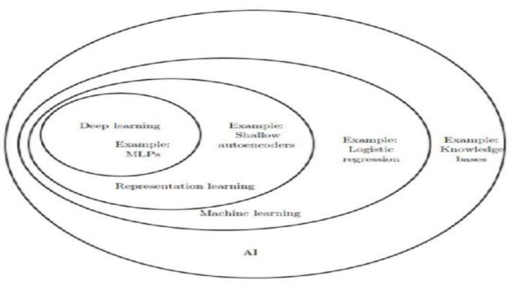

Fig.13: A Venn diagram showing how deep learning is a kind of representation learning, which is in turn a kind of machine learning, which is used for many but not all approaches to AI. Each section of the Venn diagram includes an example of an AI technology[9][25]

Below (Fig. 14) shows how deferent part of AI are related to each other within deferent AI.

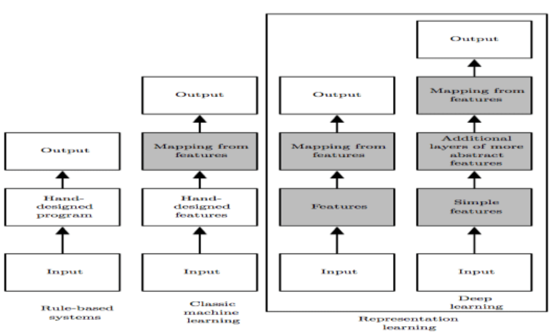

Fig.14: Flowcharts showing how the deferent parts of an AI system relate to each other within deferent AI disciplines. Shaded boxes indicate components that are able to learn from data[9][25]

V. DEEP LEARNING IN COMPUTER VISION PROBLEMS

5.1 What is machine learning?
Machine learning field of study that gives computer the ability to learn without being explicitly programmed. (Fig. 15) [10][11]

5.2 What is Deep Learning?
Evolved by learning the property of human neuron system, structure of sensory organs are connected to neurons and each neurons are interconnected and one learning principal any neurons can learn to see, smell, hear and feel senses. (Fig. 15) [12]

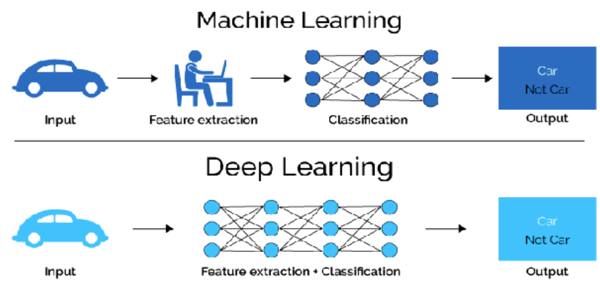

Fig.15: Depicts Machine and deep learning Diagrammatic mapping representation [10][11][12]

VI. CHANGES FAVOURING DEEP LEARNING IN COMPUTER VISION

- When ? Around 2013 post Alexnet is considered the rise of DL

- How?
  ○ GPUs for extremely parallel compute [13]
  ○ Newer techniques in optimization, regularization
  ○ DL frameworks [14]
  ○ Data, lots and lots of Data (kudos IoT, Big Data)[15]

VII. CNN ARCHITECTURES

7.1 What is convolution & why convolution , what convolution does , convolution on grayscale and color images are explained in the section (2.3)

7.2 Why convolution layers are used before the fully connected layers?
Usually, convolution and pooling layers act as massive filters. imagine about an image 228 x 228 x 3 pixels and FC layer as a direct first hidden layer with 100,000 perceptrons , the total number of connections will be 228*228*3*100000=15,59,5200,000 =>15 billion parameters which is impossible to process with first layer of perceptrons . Convolution and max pooling layers basically help to reduce some features in the image which are may not required to process and train. [16][30]

7.3 Convolution Parameters

In convolution layer, it accepts a volume of size *W* x *H* x *D* and requires four hyper parameters as follows[16]:

- Number of filters → **K**
- Spatial Extent → **Fw, Fh** *(Filter width, Filter height)*
- Stride → **Sw, Sh** *(Stride width, Stride height)*
- Padding → **P**

To calculate receptive field, the formula is as follows,
OutputWidth = (w-Fw+2p)/Sw+1
OutputHeight = (H-Fh+2p)/Sh+1
To calculate pooling layer, the formula is as follows,

- OM = (IM+2p-F)/S+1
- OM → Output Matrix
- IM → Input Matrix
- P → Padding
- F → Filter
- S → Stride

By applying above receptive and pooling calculation formulas, the convolutions, pooling and feature maps outputs are derived.

Below (Fig. 16) Shows the key operations in a CNN,

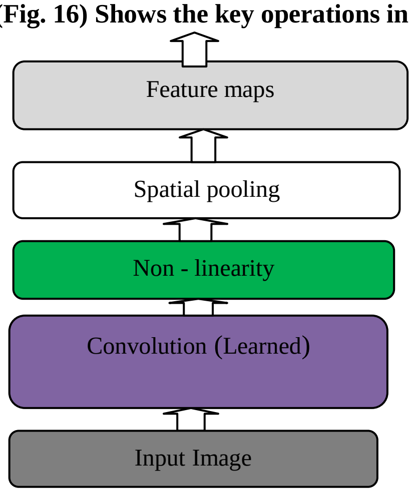

Fig.16: Key operation in an CNN by R. Fergus , Y. LeCun[16][30]

7.4 Below are some popular CNN architecture

- LeNet – 5
- AlexNet
- VGGNet
- GoogleNet
- ResNet

7.4 .1 LeNet-5

In this classical neural network architecture used on handwritten digit recognizer patterns. Below (Fig. 17) is the LeNet-5 architecture model.[17] [30]

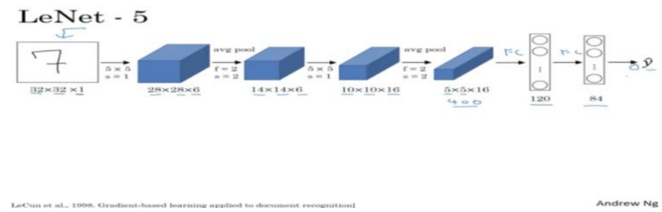

Fig.17: Fig depicts the architecture of LeNet -5 LeCun et., 1988 [17] [30]

In the above figure (Fig.17) LeNet-5 receives an input image (Greyscale image) of 32 x 32 x 1 and aim was to identify handwritten digit patterns. It uses 5 x 5 filter and with stride 1. By applying the above receptive field formula and the output volume result is 28 x 28. The derivation is given below,

- W x H → 32 x 32 (Width x Height)
- F(w x h) → 5 x 5 (Filter)
- S → 1 (Stride)
- P → 0 (Pooling)

(W – Fw + 2P)/Sw + 1 => (32 – 5 + 0) / 1 + 1 ➔ 27 + 1 => 28
(W – Fw + 2P)/Sh + 1 => (32 – 5 + 0) / 1 + 1 ➔ 27 + 1 => 28
Output Volume = 28 X 28

Next layer is a pooling layer, to calculate pooling layer in the above LeNet-5 architecture, the derivation as follows in below,

- IM → 28 (Input Matrix → Convolution output volume., Refer above derivation output)
- P → 0 (Pooling)
- S → 1 (Stride)

(IM + 2P – 2)/ S + 1 => (28 +2*0 – 2) / 2 + 1 ➔ (28 – 2) / 2 => 14
Output Volume = 14 X 14
At last, it goes to fully Connected layer which has 120 nodes and followed by one more Fully Connected Layer which has 84 nodes. It uses Sigmoid or Tanh nonlinear functions. The output variable Y with 10 possible values from digits 0 to 9. It is trained on MNIST digit dataset with about 60K parameters to learn. (Fig.16)[17] [30]

7.4 .2 AlexNet

It begin with initial input dimension of 227 x 227 x 3 images and the next convolution layer apply 96 of 11 x 11 filter through stride of 4. The output size reduces its dimension by 55 x 55. subsequently layer is a pooling layer which applies max pool by 3 x 3 filters through stride 2. It goes on and at last reaches FC layer with 9216 parameter and the then two FC layers with 4096 node each. At the end, it uses Softmax function with 1000 output classes. It has 60 million parameters to learn. (Fig. 18)[18]

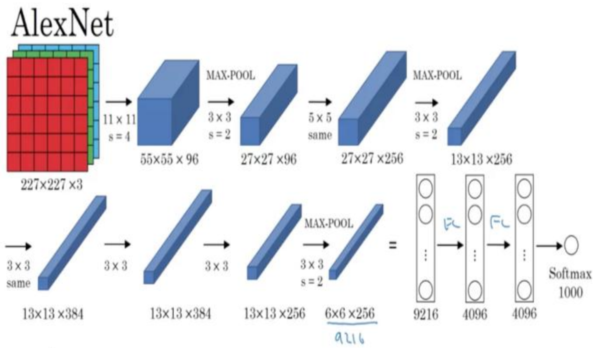

Fig.18: Fig depicts the architecture of AlexNet Krizhevsky et al., 2012 [18] [30]

Some of the things to see in AlexNet Architecture:

- It uses ReLU activation function as a replacement for Sigmoid or Tanh functions. It increased learning speed 5 times faster with same accuracy[18]
- It uses "Dropout" instead of regularisation to deal with overfitting. However the training time is doubled with dropout ratio of 0.5[18]
- More data and bigger model with 7 hidden layers, 650K units and 60Million parameters to learn[18].

7.4.3 VGG-16

- VGG-16 is a simple architecture model, because it's not using a lot hyper parameters. It uses always 3 x 3 filters with stride of 1 in convolution layers and uses SAME padding in pooling layers 2 x 2 with stride of 2. (Ref., Fig. 19)[19] [30]

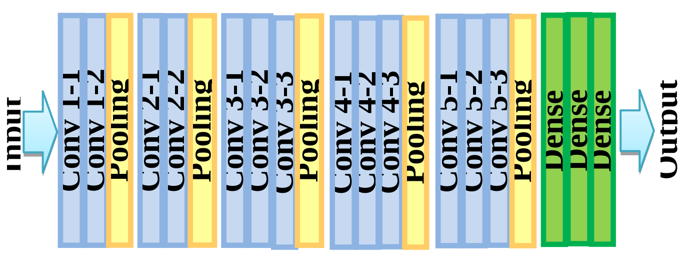

Fig.19: Fig depicts the architecture of VGG – 16 Simonyan & Zisserman , 2015[19] [30]

7.4.4 GoogLeNet

GoogLeNet architecture winner of ILSVRC 2014 is also recognized as Inception Module. It achieved a top-5 error rate with of 6.67% , It goes deeper in parallel paths with different receptive field dimensions [20] [22][23] [30] (Ref., Fig. 20)

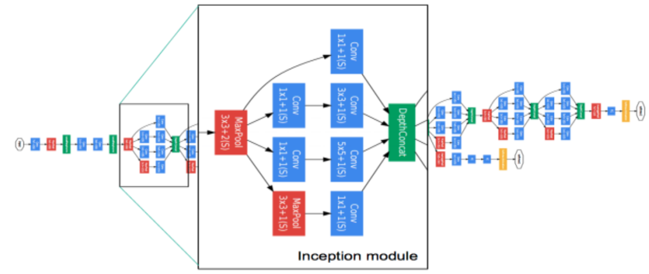

Fig.20: Fig depicts the architecture of GoggLeNet Christian Szegedy et al., 2015 [20][22][23] [30]

This architecture consists of 22 layers in deep. It reduces the number of parameters to learn from 60 million (AlexNet) to 4 million.

7.4.5 ResNet

It's also called as Residual Neural Network (ResNet) by Kaiming. This architecture introduced a idea in CNN called "skip connections". in general, the input matrix calculates in two linear transformation with ReLU activation function. In Residual network, it directly copy the input matrix to the second transformation output and sum the output in final ReLU function, winner of ILSRVC 2015.[21][22][23] [30] (Ref. Fig. 21)

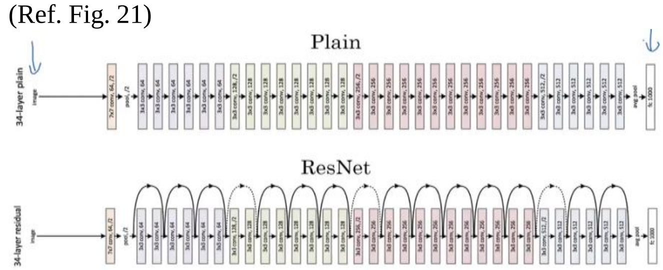

Fig.21: Fig depicts the architecture of ResNet He et al., 2015 [21][22][23] [30]

7.5 The overall summary of various CNN architectures

Table 1: Describes overall summary table of various CNN architecture models with error rates / accuracy level and number of parameters to learn in below [22] [30]

Year	CNN	Developed By	Error rates	No. of parameters
1998	LeNet	Yann LeCunet al		60 thousand
2012	AlexNet	Alex Krizhevsky, Geoffrey Hinton, Ilya Sutskever	15.30%	60 million
2013	ZFNet	Matthew Zeiler Rob Fergus	14.80%	

2014	GoogLeNet	Google	6.67%	4 million
2014	VGGNet	Simonyan, Zisserman	7.30%	138 million
2015	ResNet	Kaiming He	3.60%	

VIII. RECENT IMPROVEMENTS IN COMPUTER VISION

Figure below shows ILSVRC winners for the last 5 years and the accuracy levels meet by the winners [23] [30][31] (Ref., Fig. 22)

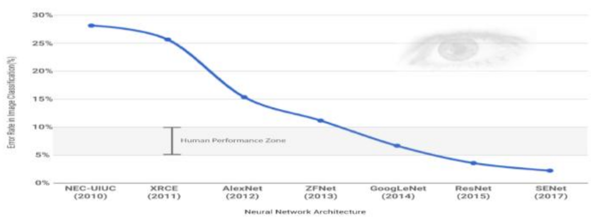

Fig.22: The ILSVRC saw an exponential decline in top 5 error rate for neural network architecture for image classification over past few years [23] **[30][31]**

IX. CONCLUSION

We see remarkable change in accuracy after the convolution neural network competing ILSVRC (2012)[23][30][31], in fact after 2015 accuracy is far more than human performance zone and it is expected to increase in coming years.

CNN took computer vision problem to think in a different way and took computer vision to other level, brought significant improvement and more accuracy than a human vision and expecting lot more things to come in future in motion images(videos).

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