

Exp 14

Implement a Pre-trained CNN model as a Feature Extractor using transfer learning.

Aim:

To use a pre-trained CNN model for extracting features and training a new classifier.

Objectives

1. To load a pre-trained model like ResNet50 or VGG16
2. To freeze convolutional layers for feature extraction
3. To add custom dense layers for classification
4. To fine-tune the model for new dataset
5. To evaluate transfer learning performance

Pseudocode

1. Load pre-trained CNN without top layers.
2. Freeze base model weight.
3. Add custom dense and output layers.
4. Compile and train model on new dataset
5. Evaluate and test classification accuracy

~~Permanente~~ VCA16 Architekt

Input 224x224

Conv 3x3 + Relu 64
Conv 3x3 + Relu 64
pool + Max 64

224 to 224

8x8 Gav + Rehu 128.
 3x3 Gav + Rehu 128.
 2x2 Mon Pool 128.

112 x 112

303	Cnv + Reba	2576
303	Cnv + Reba	2546
301	Cnv + Reba	2526
2x2	Conv Pool	2546

~~76 x 56~~ 56 x 56

3x3 conv + ReLu 512
3x3 conv + ReLu 512
3x3 conv + ReLu 512
2x2 Max Pool 512

~~14014~~ 28x28

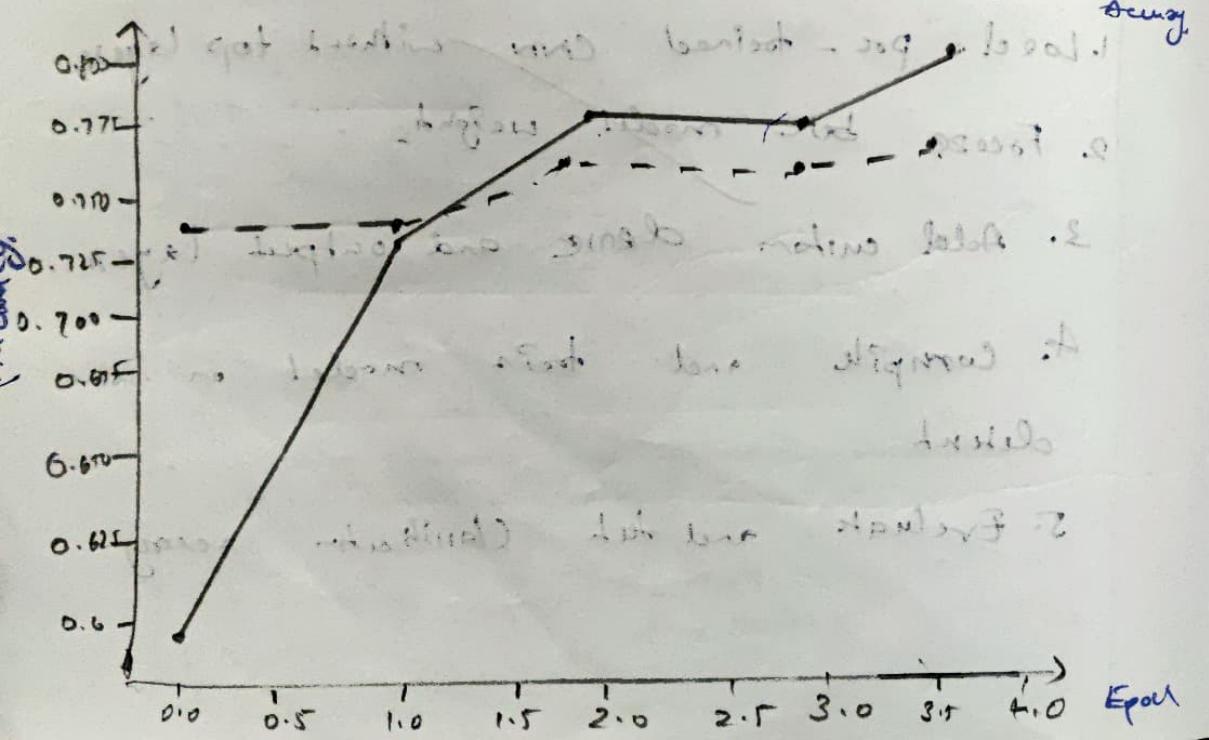
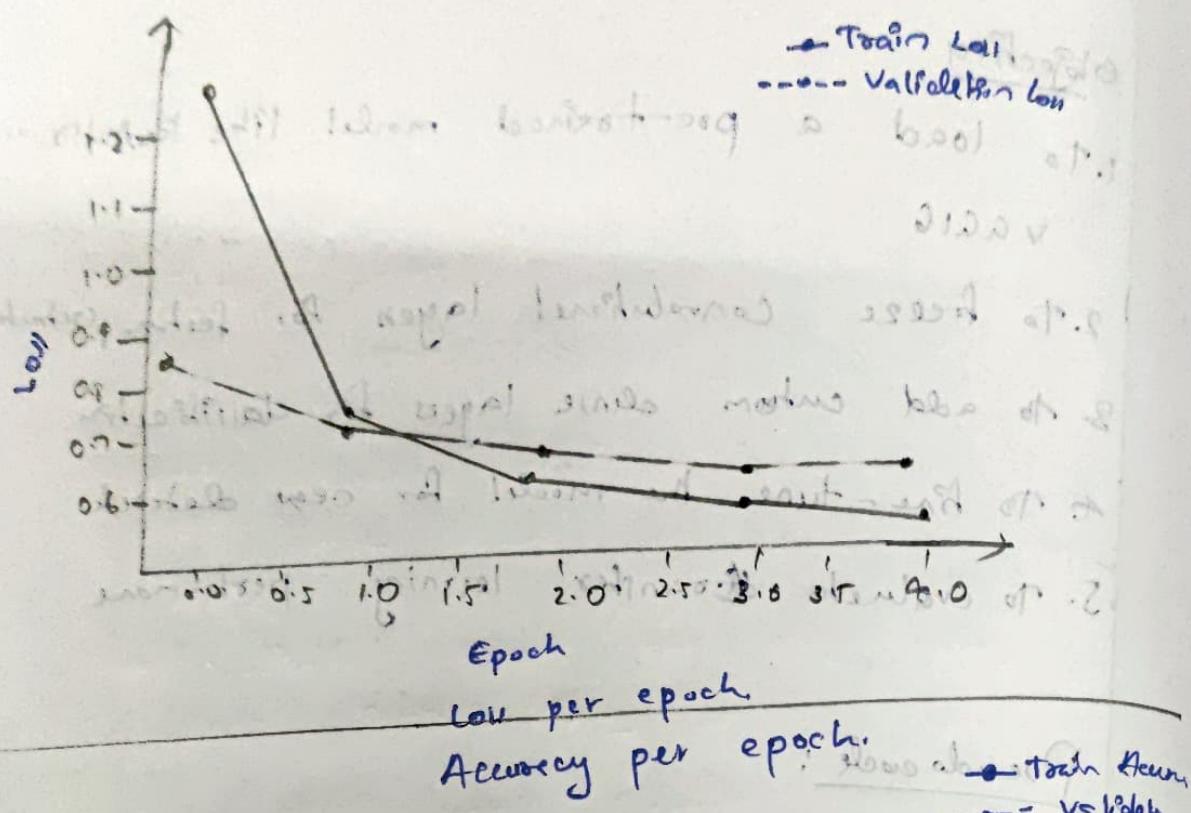
303 Gnr + 12eLm 512
 303 Gnr + 12eLm 512
 303 Gnr + 12eLm 512
 202 - Mex per 512

+4 x 14

FC 4096
FC 4096
FC Output 100

\rightarrow output

Epoch	Training Accuracy	Validation Accuracy
1	92.8%	70.9%
5	85.5%	82.8%
10	90.6%	88.9%
15	92.4%	90.5%



Observation

1. Transfer learning reduces computation time
2. Pre-trained layers extract robust features
3. Model performs well with limited data.
4. Fine-tuning improves specific cell recognition
5. High accuracy achieved with fewer epochs

Result:

Transfer learning model achieved strong performance

using a feature extractor and classifier

92.0% test accuracy after 1 epoch

After 5 epochs, best loss and highest accuracy : 89.9%

After 10 epochs accuracy of 89.9%

After 15 epochs, best loss and highest accuracy

If using GPU and more

Exp 11:

Implement a YOLO Model to Detect Objects.

Aim:

To Implement YOLO model for real time object detection

Objectives:-

1. To understand YOLO architecture and working mechanism.
2. To load pre-trained YOLO weights and configuration.
3. To preprocess input image and perform detection.
4. To extract boundary boxes and class labels.
5. To visualize detected objects with confidence score.

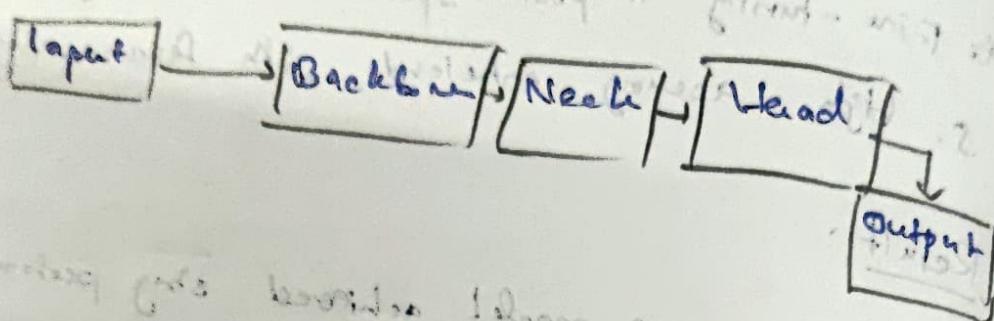
Procedure:

1. Load YOLO config, weights, and class labels.
2. Read Input image and create Image blob.
3. Perform forward pass through YOLO network.
4. Extract and filter detections based on confidence threshold.
5. Draw bounding boxes and display detected objects.

and deeper network don't have

~~BB~~

YOLO vs.



Backbone: extract essential visual features from input using convolutional and CSP layers

Neck: connect backbone and head combining multi-scale features using structure like PAN or FPN

Head: predict boundary boxes, object class, and confidence scores from other process F.L

Observation:

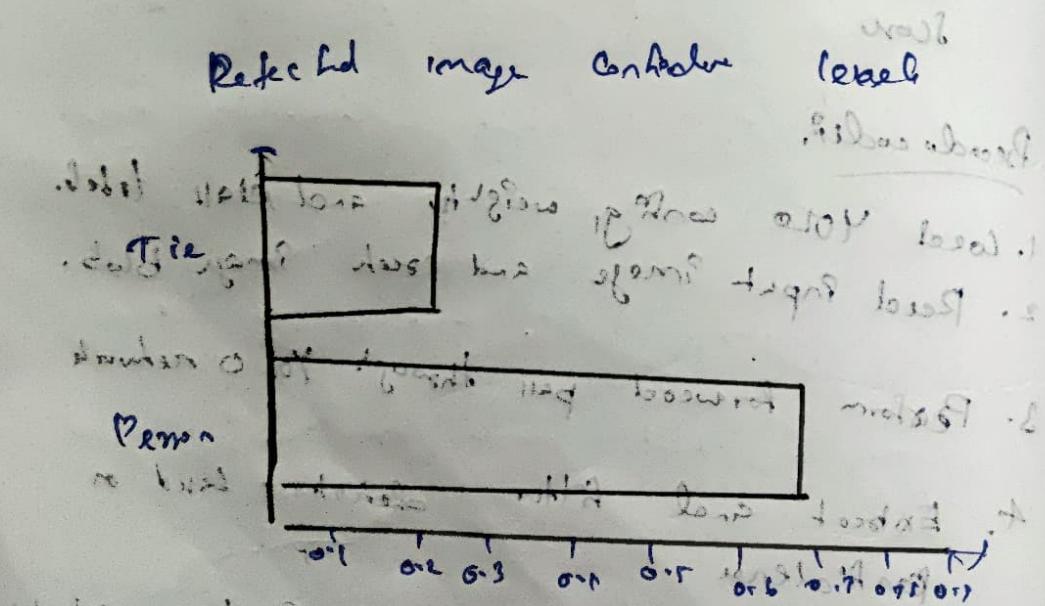
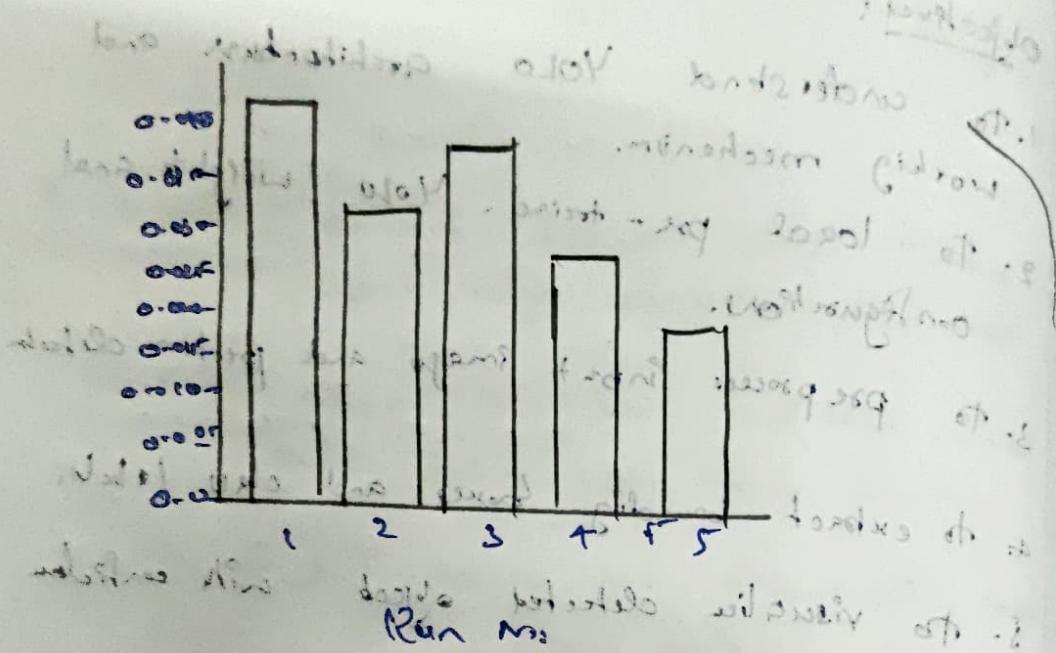
1. YOLO detects multiple objects in real-time
2. Accuray depends on chosen confidence threshold.
3. Detection is faster with GPU support
4. Bounding boxes accurately track objects.
5. Works effectively across across different object classes

Result

YOLO model successfully & successfully
detected and labeled multiple objects with
high accuracy in images and video streams

~~CS~~ 11

Object	Contrast (%)	Bous Dig box (cm) (320, 180, 100, 120)
Person	94	
Car	88	0.10V
Dog.	91	(450, 200, 120, 100)



Notes: Chair has most contrast and was at 0.1 cm.