DSAI SET 3

EURON

1. What is a Perceptron, and how does it work?

A **Perceptron** is the simplest type of artificial neural network and is a fundamental building block of more complex models. It was introduced by **Frank Rosenblatt** in 1958 as a binary classifier.

Components of a Perceptron:

1. **Input layer**: Represents the input features, typically denoted as x1,x2,...,xn.
2. **Weights (w)**: Each input is associated with a weight that determines the importance of that input.
3. **Bias (b)**: A bias term is added to shift the decision boundary.
4. **Summation function**: Computes a weighted sum of the inputs:

$$z = \sum_{i=1}^{n} w_i x_i + b$$

5. **Activation function**: Applies a transformation to decide the final output, commonly a step function

$$y = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$

6. **Working of a Perceptron:**

- It takes the weighted sum of inputs.
- Applies an activation function (often a step function).
- If the weighted sum crosses a threshold, the perceptron outputs **1**, otherwise **0**.

Limitations of a Perceptron:

- It can only solve **linearly separable** problems like AND and OR.
- It **cannot** solve problems like XOR, which requires multiple layers.

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2. What are Activation Functions, and why are they necessary?

An **activation function** introduces non-linearity into a neural network, allowing it to learn complex patterns.

Types of Activation Functions:

1. **Sigmoid**

$$(\sigma(z) = \frac{1}{1+e^{-z}})$$

   - Output range: (0,1)
   - Used in binary classification.
   - **Issues**:
     - Vanishing gradient problem (derivatives become very small for large values of z).
     - Computationally expensive due to exponentiation.
2. **Tanh (tanh)**

$$(\tanh(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}})$$

   - Output range: $(-1,1)$
   - Zero-centered output, which helps in optimization.
   - Suffers from vanishing gradients similar to Sigmoid.
3. **ReLU** (Rectified Linear Unit) **$f(z)=\max(0,z)$)**
   - Output range:$[0,\infty)$
   - Helps avoid vanishing gradient problems.
   - **Issues**:
     - **Dying ReLU problem**: Neurons can become inactive when $z \leq 0$.
4. **Leaky ReLU $f(z)=\max(0.01z,z)$)**
   - Fixes the Dying ReLU problem by allowing a small gradient for $z<0$.
   - Output range: $(-\infty,\infty)$

Why Activation Functions?

- Without an activation function, the entire neural network behaves like a **linear function**, making it ineffective for solving complex tasks.

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3. Explain Forward and Backward Propagation in a Neural Network.

Forward propagation and **backward propagation** are the two fundamental processes used for training a neural network.

Forward Propagation:

- Input data is passed through the network layer by layer.

- Each neuron computes the weighted sum of inputs and applies an activation function.
- The final output is obtained at the output layer.

Mathematically:

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)}$$
$$a^{(l)} = f(z^{(l)})$$

where W is the weight matrix, b is the bias, and f is the activation function.

Backward Propagation:

- The error between the predicted output and the actual output is computed using a loss function.
- Using the **chain rule** of differentiation, gradients of weights are calculated layer by layer from the output layer to the input layer.
- The **weights and biases are updated** using gradient descent.

Gradient update:

$$W^{(l)} = W^{(l)} - \eta \cdot \frac{\partial J}{\partial W^{(l)}}$$

where η is the learning rate, and J is the loss function.

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4. What are Cost Functions in Neural Networks?

A **cost function** measures the difference between predicted and actual outputs.

Common Cost Functions:

1. **Mean Squared Error (MSE)**:

$$J(W, b) = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

Used for regression problems.

2. **Binary Cross-Entropy**:

$$J(W,b) = -\frac{1}{m}\sum_{i=1}^{m} y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)$$

   - Used for binary classification.
3. **Categorical Cross-Entropy**:

$$J(W,b) = -\sum_{i=1}^{m}\sum_{j=1}^{c} y_{ij}\log(\hat{y}_{ij})$$

   - Used for multi-class classification.

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5. What is Dropout Regularization?

Dropout is a regularization technique where randomly selected neurons are ignored during training to prevent overfitting.

- **Why it works?**
  - Forces the network to be robust by preventing reliance on specific neurons.
  - Reduces **co-adaptation** of neurons.

Mathematically, dropout is applied as:

$$a^{(l)} = \text{Dropout}(a^{(l)}, p)$$

where p is the probability of keeping a neuron active.

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6. Explain Batch Normalization and its benefits.

Batch Normalization normalizes the activations of each layer to improve training speed and stability.

- Formula:

$$\hat{x} = \frac{x - \mu}{\sigma}$$

$$y = \gamma \hat{x} + \beta$$

- **Benefits:**

- Reduces internal covariate shift.
- Allows higher learning rates.
- Reduces dependency on weight initialization.

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7. What is Weight Decay and why is it used?

Weight decay (L2 regularization) prevents overfitting by penalizing large weights.

Regularized cost function:

$$J(W) = J_0(W) + \lambda \sum W^2$$

where λ is the regularization parameter.

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8. Explain Xavier and He Initialization Techniques.

1. **Xavier Initialization**:

$$W \sim \mathcal{N}\left(0, \frac{1}{n_{in} + n_{out}}\right)$$

Used for Sigmoid/Tanh activations.

2. **He Initialization**:

$$W \sim \mathcal{N}\left(0, \frac{2}{n_{in}}\right)$$

Used for ReLU activations.

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9. What is a Feedforward Neural Network?

A **Feedforward Neural Network (FNN)** is a type of neural network where information moves in one direction, from input to output, without cycles.

Components:

1. Input layer
2. Hidden layers
3. Output layer

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10. What is the Vanishing Gradient Problem?

In deep networks, gradients become very small, preventing weight updates.

Solution:

- Use **ReLU activation** instead of Sigmoid/Tanh.
- Use **Batch Normalization**.
- Use **He Initialization**.

11. Explain the working of the Adam optimizer. How does it differ from SGD and RMSProp?

The **Adam optimizer (Adaptive Moment Estimation)** is a widely used optimization algorithm in deep learning. It combines the benefits of **Momentum** and **RMSProp**, making it efficient for training deep neural networks.

Differences from SGD and RMSProp:

- **SGD (Stochastic Gradient Descent):**
    - Uses only the gradient to update weights.

    - Susceptible to noisy updates.
    - Converges slowly in deep networks.
- **RMSProp:**
    - Uses the second moment of gradients but **not the first moment**.
    - Helps in controlling the learning rate dynamically.
- **Adam:**
    - Uses **both** first and second moments, making it more adaptive and efficient.
    - Works well in practice across many problems.

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12. What are the key innovations in ResNet, and how does it solve the vanishing gradient problem?

ResNet (**Residual Network**) introduced the concept of **skip (residual) connections**, which allow gradients to flow easily through deep networks.

Key Innovations:

1. **Residual Connections:**
    - ResNet introduces shortcut (identity) connections: $y=f(x)+x$
    - This helps in bypassing the intermediate layers.
2. **Solving the Vanishing Gradient Problem:**
    - Traditional deep networks suffer from **vanishing gradients** because gradients shrink as they propagate backward.
    - The identity connections allow gradients to flow directly through the network, preventing their magnitude from becoming too small.
3. **Deep but Trainable Networks:**
    - Unlike previous architectures, ResNet enabled networks with **hundreds or thousands of layers** without degrading performance.
4. **Batch Normalization + ReLU Activation:**
    - Helps in stabilizing training and accelerating convergence.

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13. How does DenseNet differ from ResNet, and what are its advantages?

DenseNet (**Densely Connected Convolutional Networks**) improves upon ResNet by maximizing feature reuse.

Key Differences:

Feature	ResNet	DenseNet
Connection Type	Residual (skip connections)	Dense (concatenates all previous layers)
Feature Reuse	No	Yes

Feature	ResNet	DenseNet
Computational Cost	Higher	Lower
Gradient Flow	Moderate	Stronger
Number of Parameters	More	Fewer

Advantages of DenseNet:

1. **Feature Reuse:**
   - Each layer receives inputs from **all previous layers**, leading to better gradient flow.
2. **Fewer Parameters:**
   - Since feature maps are reused, fewer parameters are needed.
3. **Stronger Gradient Flow:**
   - Helps in better training of deep networks.

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14. What is transfer learning, and how is fine-tuning different from feature extraction?

Transfer Learning is using a pretrained model on a new task instead of training from scratch.

Feature Extraction vs Fine-Tuning:

1. **Feature Extraction:**
   - The pretrained model's **convolutional layers** are frozen.
   - Only the **final fully connected layers** are trained on new data.
2. **Fine-Tuning:**
   - The pretrained model is **partially unfrozen** (usually deeper layers) and trained on new data.
   - More flexible but requires more data to prevent overfitting.

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15. Why is GPU acceleration necessary for deep learning, and how do TPUs differ from GPUs?

1. **GPU Acceleration:**
   - GPUs speed up deep learning by performing thousands of operations in parallel.
   - Deep learning relies on **matrix multiplications**, which GPUs handle efficiently.
2. **TPUs (Tensor Processing Units):**
   - Developed by Google, TPUs are **specialized for TensorFlow**.
   - **Optimized for tensor operations** (e.g., matrix multiplications).
   - Consumes **less power** than GPUs.

16. What are the key parallelization techniques in deep learning?

1. **Data Parallelism:**
    - Splits data across multiple GPUs while keeping the model the same.
2. **Model Parallelism:**
    - Splits a single model across multiple GPUs.
3. **Pipeline Parallelism:**
    - Breaks the model into sequential stages and runs them in parallel.
4. **Hybrid Parallelism:**
    - Combines data and model parallelism.

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17. Compare PyTorch, TensorFlow, and JAX.

Feature	PyTorch	TensorFlow	JAX
Ease of Use	High	Medium	Low
Dynamic Graphs	Yes	No (but supported with TF 2.0)	Yes
Performance	Good	High	Very High
Hardware Optimization	GPU, TPU	GPU, TPU	TPU (optimized)
Debugging	Easy	Harder	Medium

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18. How does automatic differentiation work in PyTorch?

PyTorch uses **autograd**, which:

1. **Tracks operations** dynamically.
2. **Computes gradients automatically** using backpropagation.
3. **Stores gradients** for each parameter.

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19. How does mixed precision training improve performance?

1. Uses **float16** for faster computation.
2. Uses **float32** for stable gradients.
3. Reduces memory usage.

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20. What are the disadvantages of batch normalization?

1. Adds extra **computation overhead**.
2. Requires **batch size to be large**.
3. **Does not work well with small batch sizes**.

What is transfer learning, and how is it used in deep learning for object detection and segmentation?

Transfer learning is a technique where a pre-trained model (trained on a large dataset like ImageNet) is fine-tuned for a new but related task. Instead of training a model from scratch, transfer learning allows us to leverage learned features from a well-trained network and apply them to a new dataset with fewer computational resources.

In object detection and segmentation, transfer learning is commonly applied by:

1. **Feature Extraction:** Using the convolutional base of a pre-trained model (e.g., ResNet, VGG, MobileNet) and adding custom classification or detection layers on top.
2. **Fine-Tuning:** Unfreezing some of the later layers of the pre-trained network and retraining them with a smaller learning rate to adapt the model to the new task.

This approach improves convergence speed and generalization, making it particularly useful when working with small or medium-sized datasets.

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21. How does data augmentation help in training deep learning models for object detection and segmentation?

Data augmentation artificially increases the size and diversity of training data by applying transformations to existing images. It is crucial for object detection and segmentation because these tasks require models to generalize well across various scales, orientations, and lighting conditions.

Common augmentation techniques:

- **Geometric Transformations:** Rotation, scaling, translation, flipping.
- **Photometric Transformations:** Brightness, contrast, saturation changes.
- **Random Cropping & Padding:** Helps the model detect objects of varying sizes.
- **Cutout & Mixup:** Enhances occlusion robustness.
- **Elastic Transformations:** Useful for medical imaging applications.

For object detection, augmentations should also be applied to bounding boxes, ensuring correct label association. Libraries like **Albumentations, OpenCV, and TensorFlow's tf.image** provide efficient augmentation pipelines.

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22. What are Batch Normalization and Dropout, and how do they impact model training?

- **Batch Normalization (BatchNorm):**
  - Normalizes the input features of each mini-batch to stabilize learning and improve convergence speed.
  - Helps reduce internal covariate shift and allows for higher learning rates.
  - Typically used after convolutional or fully connected layers but before activation functions.
- **Dropout:**
  - A regularization technique where a fraction of neurons is randomly dropped during training, forcing the network to learn more robust and generalized features.
  - Helps prevent overfitting but is rarely used in convolutional layers.

For object detection and segmentation, **BatchNorm is preferred over Dropout** since spatial correlations in convolutional layers make Dropout less effective.

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23. How does Faster R-CNN improve over Fast R-CNN and R-CNN for object detection?

- **R-CNN (Region-based Convolutional Neural Network)**:
  - Uses a **Selective Search** algorithm to generate **Region Proposals**.
  - Each region is independently classified using a CNN.
  - Computationally expensive due to separate CNN forward passes for each region.
- **Fast R-CNN**:
  - Uses a **single shared CNN backbone** for feature extraction.
  - Region proposals are projected onto the feature map instead of processing them separately.
  - Introduces **ROI Pooling** for fixed-size feature extraction.
- **Faster R-CNN** (Improvement over Fast R-CNN):
  - Replaces **Selective Search** with a learnable **Region Proposal Network (RPN)**, reducing the number of proposals and computation time.
  - Fully integrated into a single deep network, making it significantly faster while maintaining high accuracy.

This makes **Faster R-CNN** one of the most widely used object detection models for high-accuracy applications.

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24. What are the key differences between YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector)?

Feature	YOLO (e.g., YOLOv3, v4, v5)	SSD (Single Shot MultiBox Detector)
Architecture	Single neural network with grid-based predictions	Uses multiple feature maps at different scales
Speed	Extremely fast due to single-pass inference	Faster than Faster R-CNN, but slower than YOLO
Accuracy	High-speed but may struggle with small objects	Better handling of small objects due to multi-scale feature maps
Anchor Boxes	Uses predefined anchor boxes with grid cells	Uses different feature maps for object detection
Use Cases	Real-time applications like autonomous driving	Balanced performance for both speed and accuracy

YOLO is often preferred for real-time applications, while SSD provides a good trade-off between speed and accuracy.

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25. What is the difference between Semantic Segmentation and Instance Segmentation?

- **Semantic Segmentation**:
  - Classifies each pixel into a category (e.g., "car", "tree", "road").
  - Does not distinguish between different objects of the same class.
  - Example: DeepLabV3, FCN (Fully Convolutional Networks).
- **Instance Segmentation**:
  - Assigns unique labels to different objects of the same class.
  - Required for applications like medical imaging (tumor detection) and autonomous driving.
  - Example: **Mask R-CNN**, which extends Faster R-CNN with a segmentation head.

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26. How does Mask R-CNN work for instance segmentation?

Mask R-CNN extends Faster R-CNN by adding a **segmentation branch** that predicts a binary mask for each detected object. It consists of:

1. **Backbone (e.g., ResNet + FPN)** for feature extraction.
2. **Region Proposal Network (RPN)** to generate object candidates.
3. **ROIAlign** instead of ROIPool to preserve spatial details.
4. **Two heads**:
   - **Classification & Bounding Box Regression (same as Faster R-CNN)**.
   - **Mask Head**: Predicts a pixel-wise binary mask for each instance.

Mask R-CNN is widely used for **medical imaging, autonomous driving, and robotics**.

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27. What are the key challenges in large-scale image data handling for object detection?

- **Annotation Cost & Quality**: Manually labeling large datasets is expensive and error-prone.
- **Class Imbalance**: Some classes might be underrepresented, requiring techniques like focal loss.
- **Storage & Computational Cost**: High-resolution images require significant storage and memory.
- **Efficient Loading Pipelines**: Optimized data loading with libraries like TensorFlow Data API or PyTorch Dataloader improves training speed.
- **Data Cleaning & Augmentation**: Removing noisy labels and augmenting data effectively improves model robustness.

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28. How can OpenCV and TensorRT be used for real-time object detection inference?

- **OpenCV (cv2.dnn module)**:
  - Allows running pre-trained models like YOLO, SSD, and Faster R-CNN with OpenCV.
  - Optimized for CPU/GPU inference, making it lightweight for real-time applications.
- **TensorRT (NVIDIA's deep learning optimizer)**:
  - Converts trained models into an optimized format for **low-latency inference**.
  - Uses **precision quantization (FP16, INT8)** for speedup.
  - Works well with **Jetson, NVIDIA GPUs**, and **embedded devices**.

Combining OpenCV for preprocessing and TensorRT for inference ensures **fast, efficient deployment on edge devices**.

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29. What are the challenges and solutions for deploying object detection models on edge devices?

- **Challenges:**
  - Limited compute power (CPU/GPU constraints).
  - Model size & memory footprint.
  - Latency requirements for real-time inference.
- **Solutions:**

- **Quantization** (FP16, INT8) using TensorRT or TFLite.
- **Model pruning & weight sharing** to reduce size.
- **Edge AI hardware** (Jetson Nano, Coral TPU, RKNN).
- **Optimized frameworks** (ONNX Runtime, TensorFlow Lite, OpenVINO).

Deploying object detection models efficiently on edge devices requires balancing **accuracy, speed, and hardware constraints**.

What is an image in computer vision, and how is it represented digitally?

An **image** in computer vision is a **two-dimensional (2D) function** where pixel values represent intensity at different coordinates. Images are stored as matrices in digital form.

- **Grayscale Image (Single Channel)**: Represented as a 2D matrix where each pixel value ranges from **0 (black) to 255 (white)**.
- **Color Image (RGB - 3 Channels)**: Represented as a **3D matrix** where each pixel has **three values (Red, Green, Blue)**.

For an image of size **Height × Width × Channels (H × W × C)**:

- **Grayscale Image**: H×W×1 (single channel)
- **RGB Image**: H×W×3 (three channels)
- **CMYK Image**: H×W×4 (four channels)

In computer vision, images are often **normalized** (values scaled between 0 and 1) to improve model stability.

---

30. What is Convolution in CNNs and how does it work?

Convolution is a mathematical operation that extracts features from an image using a **filter/kernel**.

- A **filter (kernel)** is a small matrix (e.g., **3×3, 5×5**) that slides over the input image.
- At each position, the dot product is computed between the filter and the corresponding part of the image.
- This operation produces a **feature map** (also called an activation map).

Example (3×3 filter on a 5×5 image):

1. Multiply filter values with corresponding image pixels.
2. Sum the multiplied values.
3. Place the result at the center of the receptive field.
4. Slide the filter and repeat.

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31. What is pooling in CNNs and why is it used?

Pooling is a **downsampling operation** that reduces the spatial dimensions of feature maps while retaining important features.

Types of Pooling:

1. **Max Pooling**: Takes the maximum value from each region.
2. **Average Pooling**: Takes the average of all values in the region.

Why is pooling important?

- **Reduces computation** by downsampling.
- **Helps with translation invariance**.
- **Prevents overfitting**.

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32. What is a Fully Connected (FC) Layer in CNNs?

A **Fully Connected (FC) Layer** is the final part of a CNN that **maps extracted features to class scores**.

1. Takes input from the final convolutional layer.
2. Flattens the feature maps into a **1D vector**.
3. Applies **weights & biases** to classify the image.

Mathematical Representation:

$y=Wx+b$

Where:

- x= Input feature vector
- W = Weight matrix
- b= Bias vector
- y = Output prediction

FC layers allow CNNs to **learn complex decision boundaries**.

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33. Explain the architecture of LeNet-5 and its significance.

LeNet-5 (1998) was one of the earliest CNNs, designed for **handwritten digit recognition (MNIST dataset)**.

Architecture:

1. **Conv1 (C1):** 6 filters (5×5), output **28×28×6**
2. **Pooling (S2):** 2×2 avg pooling, output **14×14×6**
3. **Conv2 (C3):** 16 filters (5×5), output **10×10×16**
4. **Pooling (S4):** 2×2 avg pooling, output **5×5×16**
5. **Fully Connected (F5):** 120 neurons
6. **Fully Connected (F6):** 84 neurons
7. **Output Layer:** Softmax (10 classes)

Key Features:

- First CNN with hierarchical feature extraction.
- Used **Tanh activation**.
- Inspired modern deep learning architectures.

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34. How does AlexNet improve upon LeNet?

AlexNet (2012) introduced **deep CNNs** and won the **ImageNet Challenge**.

Improvements over LeNet:

- **More layers** (8 vs. 5).
- **Larger kernels** (11×11, 5×5).
- **ReLU activation** instead of Tanh.
- **Dropout for regularization**.
- **GPU parallelization**.

Architecture:

1. **Conv1:** 96 filters (11×11)
2. **Max Pooling (3×3)**
3. **Conv2:** 256 filters (5×5)
4. **Max Pooling**
5. **Conv3, Conv4, Conv5:** 384, 384, 256 filters
6. **FC Layers:** 4096, 4096, 1000 (Softmax)

Impact: AlexNet **revolutionized deep learning**, showing CNNs can scale to large datasets.

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35. What is the key innovation in VGG networks?

VGG (2014) introduced **small 3×3 filters** and deep architectures.

VGG-16:

- **13 convolutional layers**
- **Max Pooling after every 2-3 conv layers**
- **Fully connected layers at the end**

Advantages:

- **Uniform small kernels (3×3)** improve feature extraction.
- **Increased depth** (up to 19 layers) helps learn hierarchical features.

Limitations:

- **High computational cost**.
- **Large model size (~500MB)**.

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36. What is the Inception architecture, and how does it improve efficiency?

Inception (GoogLeNet, 2014) introduced **Inception modules** that apply different convolutional filters **in parallel**.

Key Innovations:

- Uses **1×1 convolutions** for dimensionality reduction.
- Uses **multiple filter sizes (1×1, 3×3, 5×5) in parallel**.
- Introduces **global average pooling** to reduce FC layers.

Impact:

- Reduced parameters from **60M (AlexNet) to 5M**.
- Improved **computational efficiency**.

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37. What is ResNet and why is it important?

ResNet (2015) introduced **Residual Learning** to solve the **vanishing gradient problem** in deep networks.

Key Idea:

- **Skip connections** allow gradients to bypass some layers.
- Uses **"identity mapping"**: y=x+f(x).

ResNet-50 Architecture:

1. **Conv Layer**
2. **4 Residual Blocks**
3. **Global Average Pooling**
4. **Fully Connected Layer**

Impact:

- Allowed training **very deep networks** (152+ layers).
- Improved accuracy in ImageNet.

38.What is Transfer Learning and why is it useful in deep learning?

Transfer Learning is a deep learning technique where a **pre-trained model** (trained on a large dataset) is fine-tuned for a new task.

- **Reduces training time**: Instead of training from scratch, we use a model pre-trained on large datasets like **ImageNet**.
- **Requires less labeled data**: Pre-trained models have learned general features, so we need fewer labeled examples.
- **Improves performance**: Leveraging **deep features** from powerful models like **ResNet, VGG, or EfficientNet** helps in better accuracy.

Approaches to Transfer Learning:

1. **Feature Extraction**: Use pre-trained model layers as **feature extractors** and add a new classifier on top.
2. **Fine-Tuning**: Unfreeze the last few layers of the pre-trained model and train on the new dataset.

---

39. What is Data Augmentation, and how does it help in deep learning?

Data Augmentation artificially expands the training dataset by applying transformations like:

- **Geometric transformations**: Rotation, flipping, cropping.
- **Color transformations**: Brightness, contrast, hue changes.
- **Noise injection**: Adding random noise to improve robustness.

Why is it important?

- **Prevents overfitting** by creating variations of the dataset.
- **Improves generalization** by exposing the model to different perspectives.
- **Reduces dependency on large datasets**.

40. What is Batch Normalization, and how does it work?

Batch Normalization (BatchNorm) normalizes activations in a neural network to stabilize and accelerate training.

Formula:

$$\hat{x} = \frac{x - \mu}{\sigma}$$

$$y = \gamma \hat{x} + \beta$$

- μ, σ = Mean and standard deviation of activations per batch.
- γ, β = Learnable parameters.

Benefits:

- **Reduces internal covariate shift**.
- **Allows higher learning rates**.
- **Acts as a regularizer**, reducing the need for dropout.

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41. What is Dropout, and how does it prevent overfitting?

Dropout randomly drops neurons during training, forcing the network to learn more robust features.

42. Explain the difference between R-CNN, Fast R-CNN, and Faster R-CNN.

1. **R-CNN (2014)**:
    - Uses **Selective Search** to generate **2,000 region proposals**.
    - Classifies each region using a CNN.

    - **Slow (~47 seconds per image).**
2. **Fast R-CNN (2015)**:
    - **Extracts features first** from the entire image.
    - Uses **RoI Pooling** to extract region features.
    - Faster than R-CNN.
3. **Faster R-CNN (2016)**:
    - Replaces Selective Search with a **Region Proposal Network (RPN)**.
    - **Real-time (5 FPS).**

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43. What is YOLO, and how does it differ from R-CNN?

YOLO (You Only Look Once) predicts bounding boxes in a **single forward pass**.

Differences:

Feature	YOLO	R-CNN (Faster)
Approach	Single Shot	Two-stage detection
Speed	Fast (45 FPS)	Slow (5 FPS)
Accuracy	Lower (more localization errors)	Higher

YOLO Architecture:

- Splits image into an **S×S grid**.
- Predicts **bounding box + class** for each grid cell.

---

44. What is SSD (Single Shot MultiBox Detector) and how does it work?

SSD predicts bounding boxes **at multiple scales** using **default anchor boxes**.

Key Features:

- Uses **multi-scale feature maps**.
- Faster than Faster R-CNN but slightly less accurate.
- Uses **6 different feature maps** for detection.

---

45. What is the difference between Semantic Segmentation and Instance Segmentation?

Type	Description	Example
Semantic Segmentation	Assigns a **class label to each pixel**.	Every car is labeled as "car".
Instance Segmentation	Assigns unique labels to **each object instance**.	Different cars have different labels.

Example Models:

- **Semantic Segmentation**: U-Net, DeepLabV3.
- **Instance Segmentation**: Mask R-CNN.

Practical Considerations

46. How is large-scale image annotation handled for object detection?

- **Manual Annotation**: Using tools like **LabelImg** or **CVAT**.
- **Semi-Automated Annotation**: Using pre-trained models to assist in labeling.
- **Crowdsourcing**: Amazon Mechanical Turk for labeling.

File Formats:

- **COCO JSON**
- **Pascal VOC XML**
- **YOLO TXT Format**

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47. How can object detection models be deployed on edge devices?

Edge deployment requires **optimized models** due to hardware constraints.

Optimization Techniques:

1. **Model Quantization** (reduces size, e.g., INT8 precision).
2. **TensorRT acceleration** (for NVIDIA GPUs).
3. **ONNX Runtime** (cross-platform inference).
4. **Edge AI Hardware**: Jetson Nano, Coral TPU.

Example: TensorRT Optimization

```
python
CopyEdit
import tensorrt as trt
```

```
trt_model = trt.Builder().build_cuda_engine(onnx_model)
```