







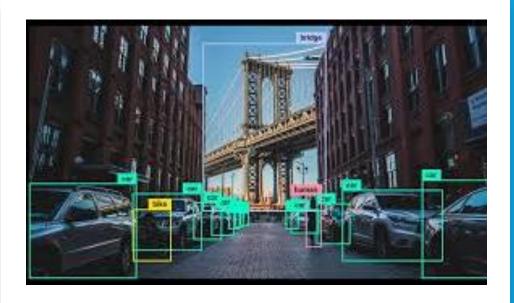
Dent.py: Training Dental Models from Zero to Hero

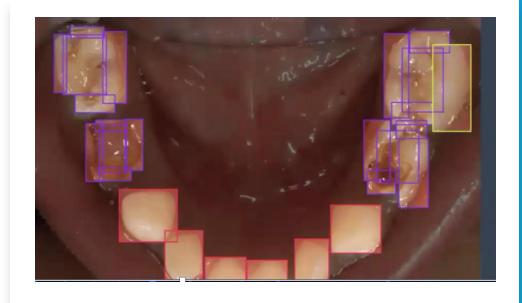
Part 4 of 5

YOLO: You Only Look Once – Deep Dive

### **Object Detection**

- What is object detection?
  - Identifying and locating objects in an image.
  - Used in various applications like autonomous driving, security, retail, etc...

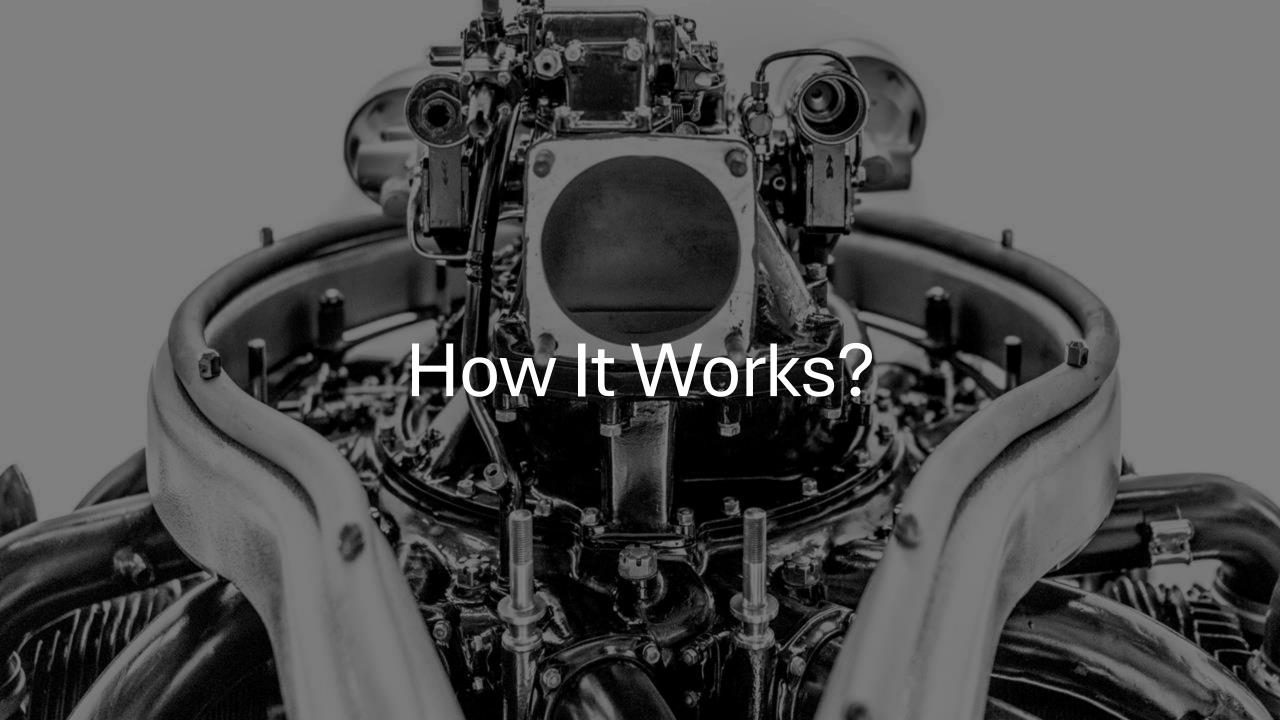




### YOLO

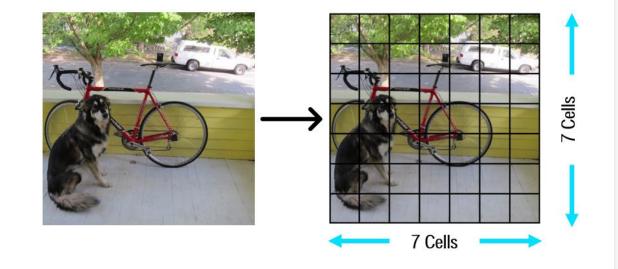
- YOLO
  - You Only Look Once
- Overview
  - A fast and efficient object detection algorithm.
  - Processes an image in a single pass, unlike traditional methods.
- Why YOLO is important
  - Real-time processing capability.
  - High accuracy and efficiency.





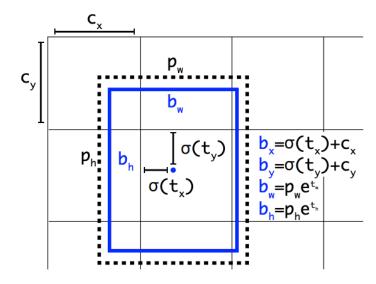
# Grid-based prediction

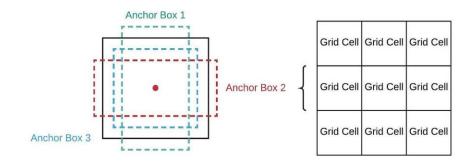
- The image is divided into an S × S grid (e.g., 7×7, 19×19).
- Each grid cell predicts bounding boxes, confidence scores, and class probabilities.
- A grid cell is responsible for detecting objects whose center falls within it.



### Bounding box prediction

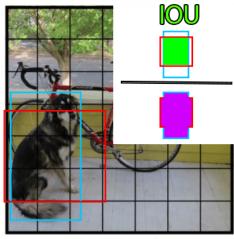
- Each grid cell predicts multiple bounding boxes with (x, y, w, h) coordinates.
- Predefined boxes of different aspect ratios and sizes improve detection.
- Helps in detecting objects of various scales and shapes.
- Each grid cell predicts adjustments to these anchor boxes rather than free-form bounding boxes.



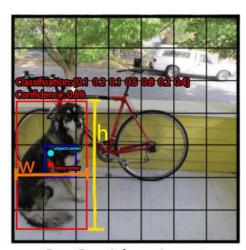


### Confidence Scores

- Represents how likely an object is present and the accuracy of the bounding box.
- Confidence score = Object probability × IoU (Intersection over Union).
- Higher confidence scores indicate more reliable predictions.



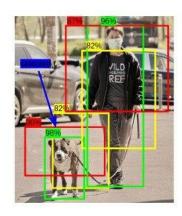
 $S \times S$  grid on input



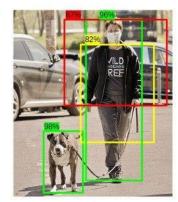
 $S \times S$  grid on input

# Non-Maximum Suppression

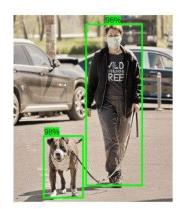
- Removes overlapping boxes to keep only the most relevant detections.
- Ensures that the best bounding box for each object is retained.



Step 1: Selecting Bounding box with highest score



Step 3: Delete Bounding box with high overlap



Step 5: Final Output

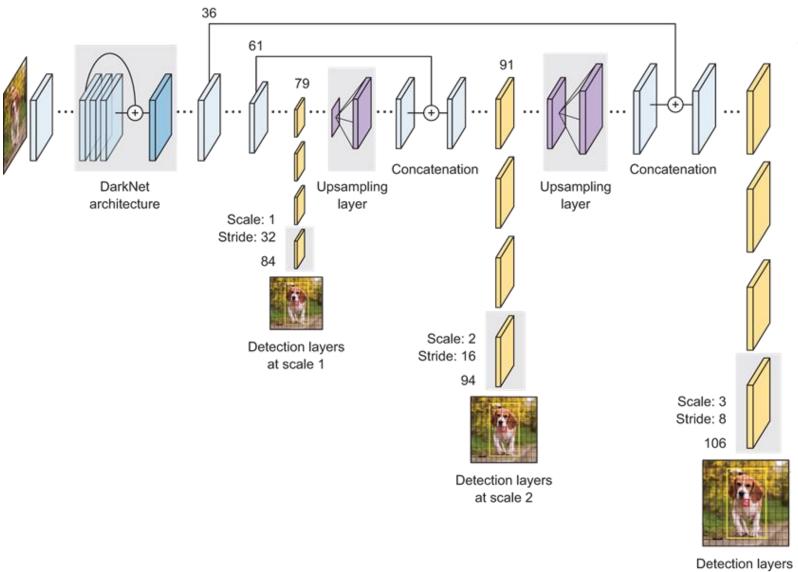


### Overview

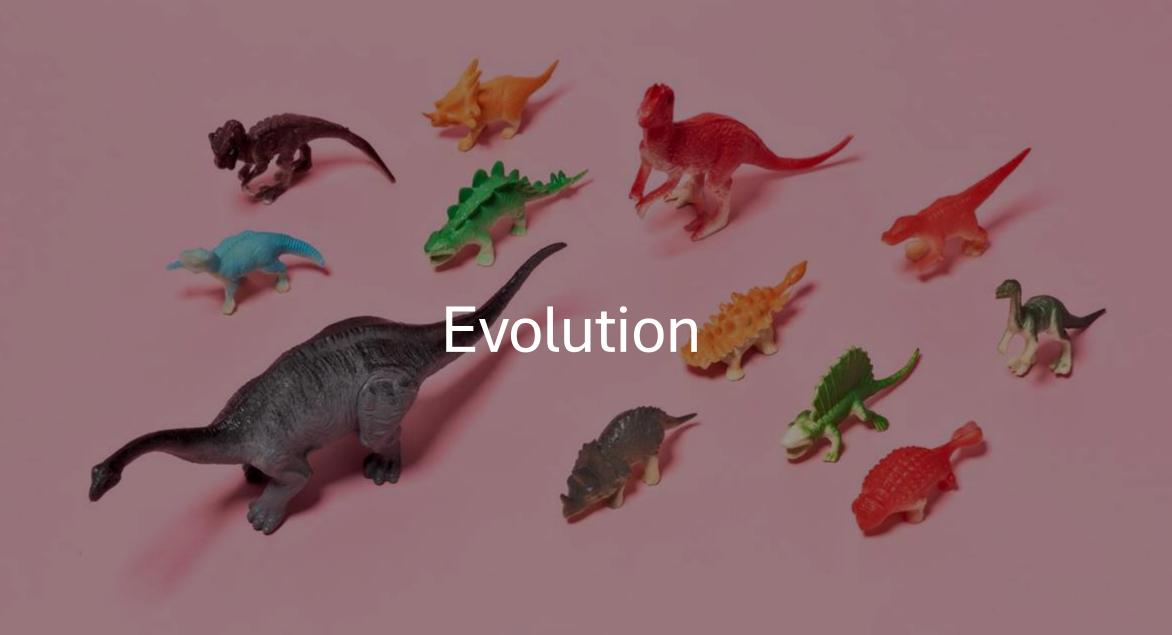
- Input and Feature Extraction
  - Uses a CNN backbone (e.g., Darknet-53 in YOLOv3) to extract hierarchical features.
  - Processes input images through convolutional layers with increasing depth.
- Detection Head
  - Splits into multiple scales for multi-scale detection (FPN-like structure in YOLOv3).
  - Outputs bounding box coordinates, objectness score, and class probabilities.

# **Building Blocks**

- Convolutional Layers
  - Extract spatial features from images.
- Batch Normalization
  - Speeds up training and stabilizes learning.
- Residual Connections
  - Help gradient flow and improve learning efficiency.
- Leaky ReLU Activation
  - Prevents vanishing gradients and speeds up training.



at scale 3



# **YOU** Greatest Hits

#### **YOLO-NAS** Scaled-YOLOv4 YOLOv6 YOLOv3 Shay Aharon et al / Deci **YOLO 11** Chuyi Li, Alexey Bochkovskiy et al Joseph Redmon et al / UW Chuvi Li et al / Meituan YOLO-NAS: A Next-Generation, Object Scaled-YOLOv4: Scaling Cross Stage Partial Glenn Jocher et al / Ultralytics YOLOv6: A Single-Stage Object Detection Detection Foundational Model generated by YOLOv3: An Incremental Improvement Network Deci's Neural Architecture Search Technology YOLOv11 GitHub Framework for Industrial Applications YOLO is introduced **YOLOS** YOLOv9 Joseph Redmon et al / UW YOLOv5 YOLOv8 Yuxin Fang et al / HUST Chien-Yao Wang et al You Only Look Once: Unified, Real-Time Object You Only Look at One Sequence: Rethinking Glenn Jocher et al / Ultralytics Glenn Jocher et al / Ultralytics Detection YOLOv9: Learning What You Want to Learn Transformer in Vision through Object Detection YOLOv5 GitHub YOLOv8 GitHub Apr 23, 2020 Jul 23, 2020\* May 10, 2021 Jul 18, 2021\* Jul 6, 2022 Jan 30, 2024\* Jan 13, 2023 May 23, 2024 Dec 25, 2016 Jun 1, 2021 Jun 2022+ Jun 8, 2015 Apr 8, 2018 Jun 9, 2020+ Feb 21, 2024\* Sep 30, 2024+ Nov 16, 2020\* Jan 10, 2023+ May 2, 2023+ **YOLOv6 3.0** YOLOv10 YOLOX PP-YOLO YOLOv2 aka YOLO9000 Zheng Ge et al / Megvii Chuyi Li et al / Meituan X Long et al / Baidu Ao Wang et al / Tsinghua Univ Joseph Redmon et al / UW YOLOv6 v3.0: A Full-Scale Reloading YOLOX: Exceeding YOLO Series in 2021 YOLOv10: Real-Time End-to-End Object An Effective and Efficient Implementation of YOLO9000: Better, Faster, Stronger Detection **Object Detector YOLOR YOLO-World** YOLOv4 YOLOv7 Chien-Yao Wang et al Alexev Bochkovskiv et al Chien-Yao Wang, Alexey Bochkovskiy et al Tianheng Cheng et al / Tencent

You Only Learn One Representation: Unified

**Network for Multiple Tasks** 

YOLOv4: Optimal Speed and Accuracy of

**Object Detection** 

YOLOv7: Trainable bag-of-freebies sets new

state-of-the-art for real-time object detectors

YOLO-World: Real-Time Open-Vocabulary Object

Detection

<sup>\*</sup>Denotes paper updated after first publication date

<sup>\*</sup>Denotes repository predates paper publication date

## YOLOv12

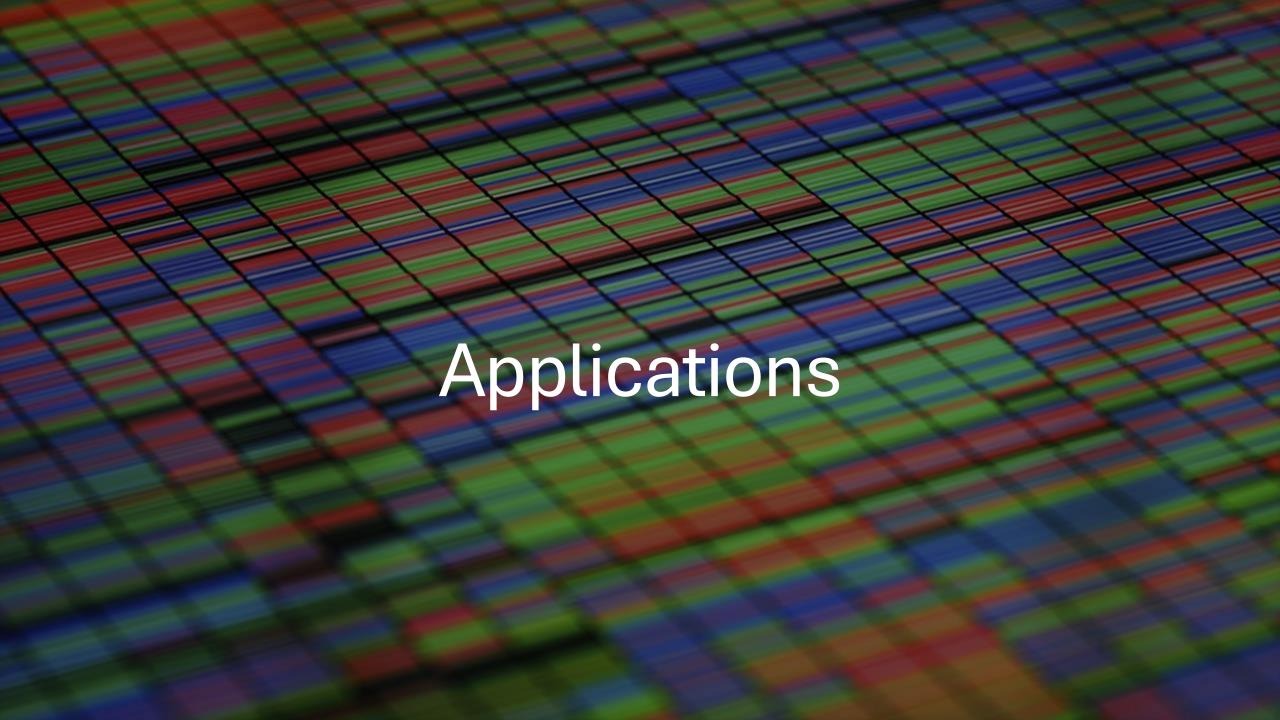
- Released on February 18, 2025
- Introduced in the paper "YOLOv12: Attention-Centric Real-Time Object Detectors."

#### Key Features

- Incorporates advanced attention mechanisms for improved detection accuracy.
- Optimized for real-time applications with lower latency.
- Open-source implementation available for fine-tuning and customization.

#### Performance

- Benchmarked on the Microsoft COCO dataset.
- Achieves higher mean Average Precision (mAP) while reducing computational overhead.



### General



#### **Autonomous Vehicles**

Detects pedestrians, vehicles, traffic signs in real-time.



### **Security & Surveillance**

Identifies objects in CCTV footage.



### **Medical Imaging**

Used for detecting tumors, anomalies in medical scans.



### **Retail & Logistics**

Automated checkout systems, inventory tracking.

# Dentistry



#### **Tooth Segmentation**

Identifying individual teeth for orthodontic planning.



#### **Caries and Cavity Detection**

Detecting early-stage cavities in dental X-rays.



#### **Root Canal Detection**

Assisting endodontists in visualizing canal morphology.



### IAN (Inferior Alveolar Nerve) Localization

Preventing nerve damage during surgeries.



### Pros

- Fast and efficient, capable of real-time detection.
- Single-stage processing, end-to-end learning.
- Works well in real-world applications.

### Cons

- Struggles with detecting small objects.
- May not be as accurate as two-stage methods like Faster R-CNN.
- Limited interpretability due to end-to-end learning.

# Questions?

# Workshop Activity

- Notebooks Link
  - <a href="https://github.com/KnightsLab/EMRA-Workshop">https://github.com/KnightsLab/EMRA-Workshop</a>

