

```
def __init__(self, data, epochs, mini_batch_size, n_test):
    self.weights = None
    self.biases = None
    self.cost = None
    self.cost_derivative = None
    self.activations = None
    self.zs = None
    self.weights[-1] = None
    self.biases[-1] = None
    self.cost[-1] = None
    self.cost_derivative[-1] = None
    self.activations[-1] = None
    self.zs[-1] = None

    training_data = random.shuffle(data)
    mini_batches = [
        training_data[k:k+mini_batch_size]
        for k in xrange(0, len(training_data), mini_batch_size)
    ]
    for mini_batch in mini_batches:
        if test_data:
            print "Epoch %d: %d" % (epoch, len(mini_batch))
        else:
            print "Epoch %d: %d" % (epoch, len(mini_batch))

        update_mini_batch(mini_batch, n_test)
        nablax_b = [np.zeros(b.shape) for b in self.biases]
        nablax_w = [np.zeros(w.shape) for w in self.weights]
        delta_nabla_b, delta_nabla_w = self.backprop(self, x, y)
        nablax_b = [nb+dnb for nb, dnb in zip(nablax_b, delta_nabla_b)]
        nablax_w = [nw+dnw for nw, dnw in zip(nablax_w, delta_nabla_w)]
        self.weights = [w-(eta*nw) for w, nw in zip(self.weights, nablax_w)]
        self.biases = [b-(eta*nb) for b, nb in zip(self.biases, nablax_b)]

    def backprop(self, x, y):
        nablax_b = [np.zeros(b.shape) for b in self.biases]
        nablax_w = [np.zeros(w.shape) for w in self.weights]
        activations = [x] # list to store all the activations
        zs = [] # list to store all the z values
        for b, w in zip(self.biases, self.weights):
            z = np.dot(w, activation)+b
            zs.append(z)
            activation = sigmoid(z)
            activations.append(activation)
        backward pass
        delta = self.cost_derivative(activations[-1], y)
        sigmoid_prime(zs[-1])
        delta = delta.dot(delta, activations[-1].transpose())
        for l in range(2, self.num_layers):
            delta = delta.dot(delta, activations[l-1].transpose())
            time(z)
```

Input Layer

Multiple hidden Layers

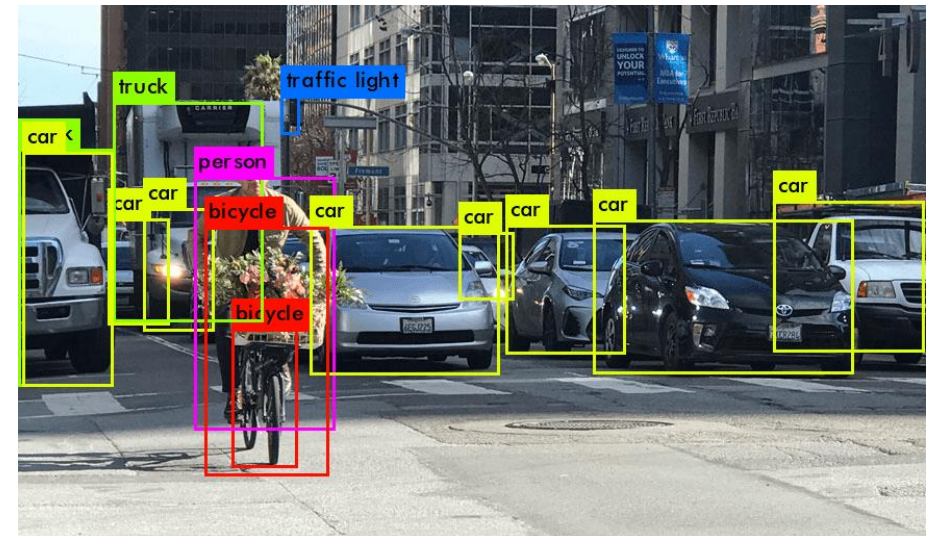
Output Layer

DEEP LEARNING

MINI PROJECT
ID-CARD DETECTION

ID-CARD DETECTION Using YOLOv8

Object Detection on a Custom Dataset



YOLOv8

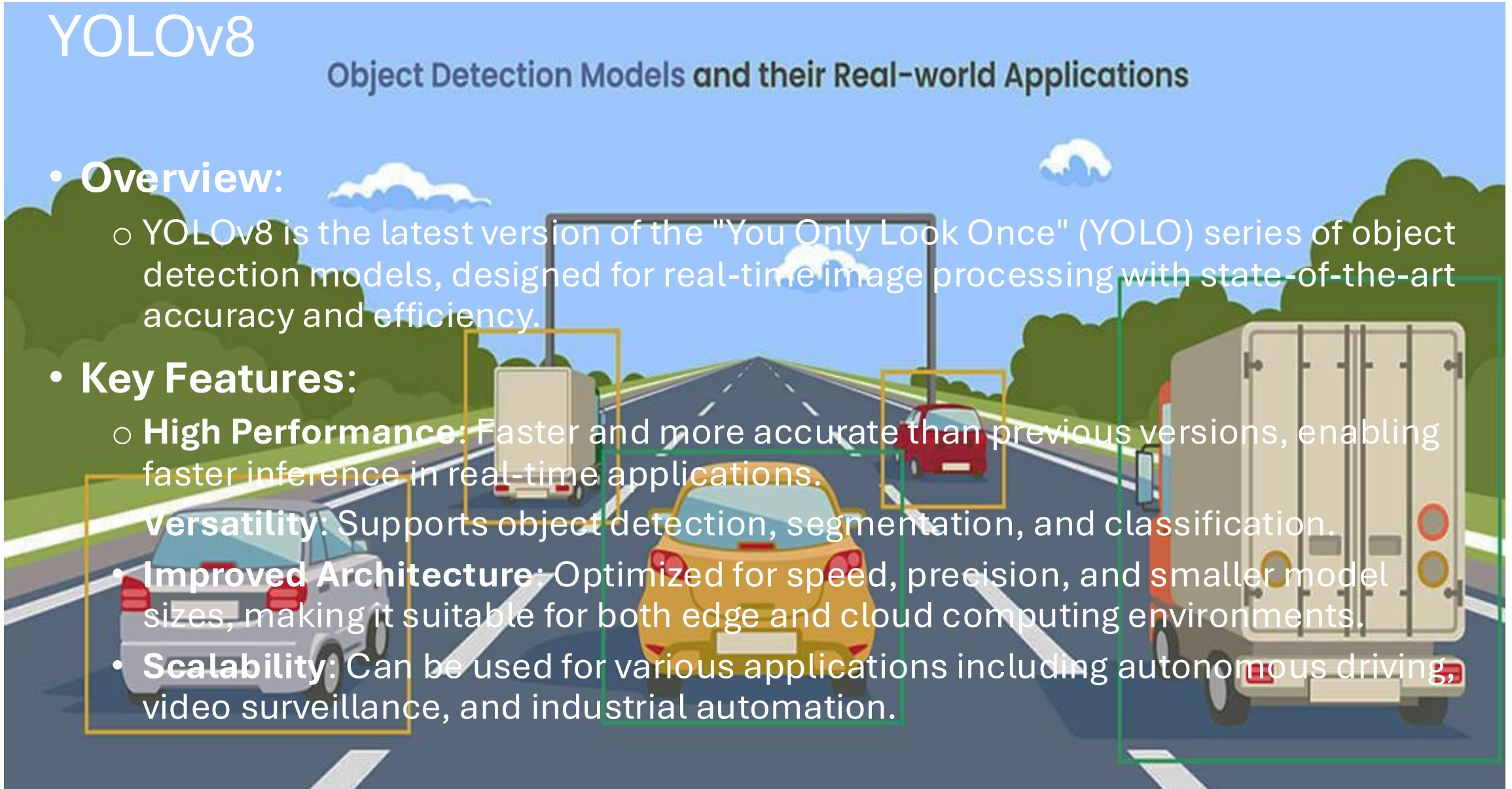
Object Detection Models and their Real-world Applications

- **Overview:**

- YOLOv8 is the latest version of the "You Only Look Once" (YOLO) series of object detection models, designed for real-time image processing with state-of-the-art accuracy and efficiency.

- **Key Features:**

- **High Performance:** Faster and more accurate than previous versions, enabling faster inference in real-time applications.
- **Versatility:** Supports object detection, segmentation, and classification.
- **Improved Architecture:** Optimized for speed, precision, and smaller model sizes, making it suitable for both edge and cloud computing environments.
- **Scalability:** Can be used for various applications including autonomous driving, video surveillance, and industrial automation.



Applications & Advantages

Applications:

- Autonomous vehicles
- Security systems
- Robotics
- Augmented Reality (AR)

Advantages:

- Faster inference times
- Better generalization to unseen data
- Smaller model size for deployment in real-world applications

PROCESS



Data Collection



Data Preprocessing



Annotation



Model Selection



Model Training

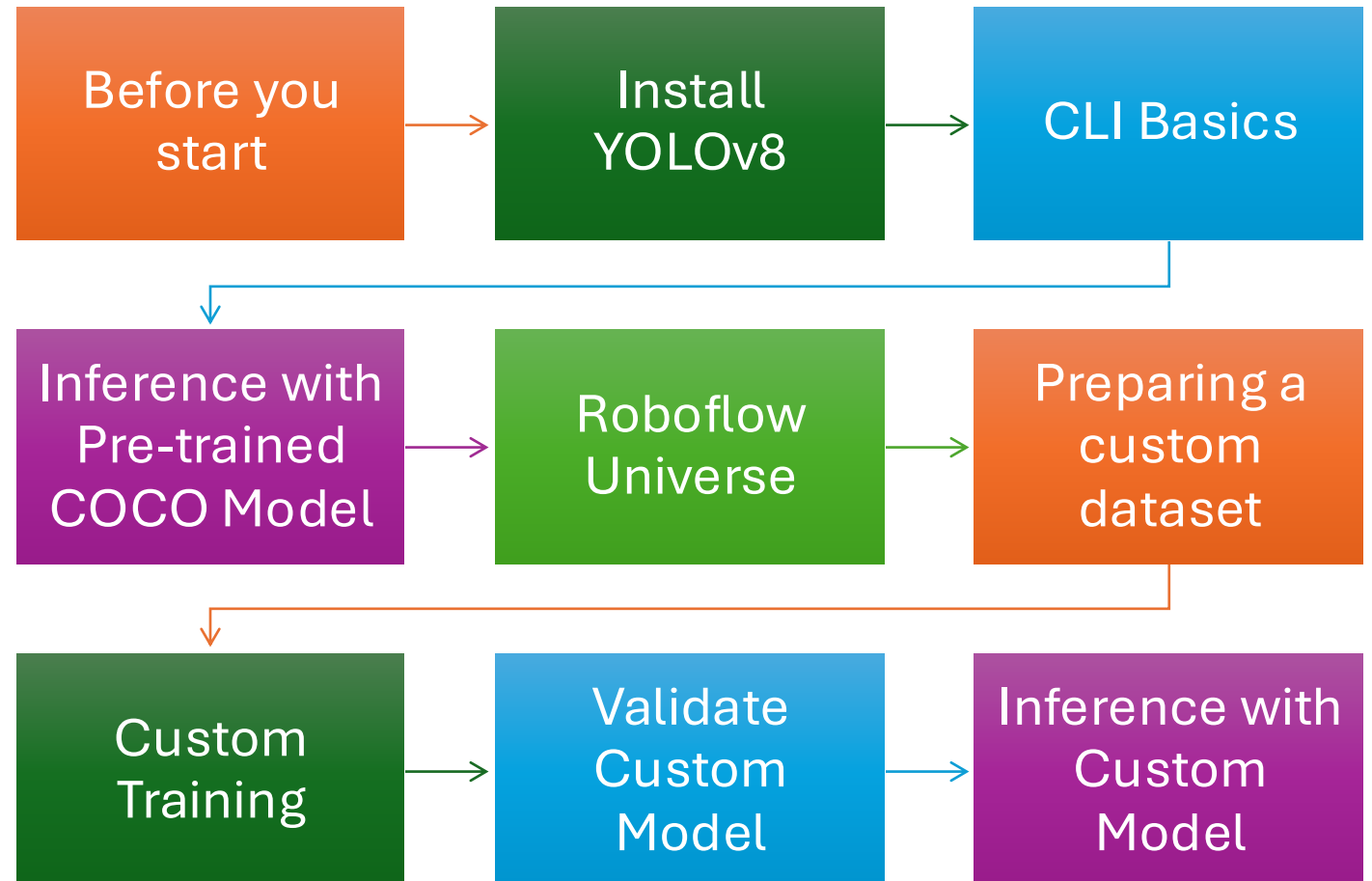


Evaluation



Model Deployment

Steps





Data Collection and Labeling using Roboflow



Data Collection:


- **Upload Images:** Collect and upload your image dataset to Roboflow. Supported file formats include .jpg, .png, .jpeg, etc.
- **Data Diversity:** Ensure that the dataset includes various angles, lighting conditions, and object appearances for better model generalization.

Automatic Data Augmentation:

- **Augmentation Options:** Roboflow allows automatic augmentation of your dataset, including transformations like rotations, flips, color adjustments, and zooming.
- **Increase Dataset Size:** Augmentation increases dataset size and variability without requiring additional manual data collection.



Labeling the Dataset & Formating



Labeling the Dataset:

Manual Labeling: Use the Roboflow interface to manually annotate objects in images by drawing bounding boxes and assigning class labels.

Auto-Labeling: If pre-labeled data is available, Roboflow can auto-label new images based on the existing dataset.

Labeling Tools: Roboflow provides a user-friendly tool to draw bounding boxes around objects and categorize them with predefined classes.

Labeling Formats:

YOLO Format: Bounding boxes are stored as .txt files, where each line contains the class ID and normalized coordinates of the bounding box.

Other Formats: You can also label in other formats like COCO, Pascal VOC, etc., depending on your model's requirements.

Exporting dataset:

```
!mkdir -p {HOME}/datasets
```

```
%cd {HOME}/datasets
```

```
!pip install roboflow
```

```
from roboflow import Roboflow
```

```
rf = Roboflow(api_key="ZtmYcD2C7omgXhd1ovm2")
```

```
project = rf.workspace("nithwin").project("idcard_2_0")
```

```
version = project.version(7)
```

```
dataset = version.download("yolov8")
```

Custom Training

```
%cd {HOME}
```

```
!yolo task=detect mode=train
```

```
model=yolov8s.pt
```

```
data={dataset.location}/data.yaml
```

```
epochs=7 imgsz=500 plots=True save=True
```



task=detect: Specifies that the task is object detection.



mode=train: Initiates the training process.



model=yolov8s.pt: Uses the pre-trained YOLOv8 small model (yolov8s.pt) as a starting point for training.



data={dataset.location}/data.yaml: Specifies the path to the dataset configuration file (data.yaml) that includes details about class names and dataset paths.



epochs=7: Specifies 7 epochs for training (can be adjusted for more/less iterations).



imgsz=500: Sets the image size to 500x500 pixels for input images.



plots=True: Enables the generation of plots during training (e.g., loss curves).



save=True: Saves the model checkpoints after training.

Validate Custom Model

```
%cd {HOME}
```

```
!yolo task=detect mode=val  
model={HOME}/runs/detect/train3/weights  
/best.pt data={dataset.location}/data.yaml
```

This command runs YOLO in validation mode (mode=val) to test a trained object detection model (best.pt).

It uses the dataset specified in the data.yaml file, which contains information about the dataset's images and classes.

The model is located in the {HOME}/runs/detect/train3/weights/ directory.

Deploy model on Roboflow

Inference with Custom Model

```
project.version(dataset.version).deploy(model_type="yolov8",  
model_path=f"{HOME}/runs/detect/train/")
```

The command deploys a YOLOv8 model from the specified directory for the dataset version you're working with.

- **project.version(dataset.version):** This specifies the version of the dataset you are using for the deployment. The version is usually defined in your project to track different stages of the dataset.
- **deploy(model_type="yolov8", model_path=f"{HOME}/runs/detect/train/"):** This part is deploying the model with the specified parameters:
 - **model_type="yolov8":** This indicates you're using the YOLOv8 model version.
 - **model_path=f"{HOME}/runs/detect/train/":** This specifies the directory where the trained YOLOv8 model is stored, using the path {HOME}/runs/detect/train/. In short:

