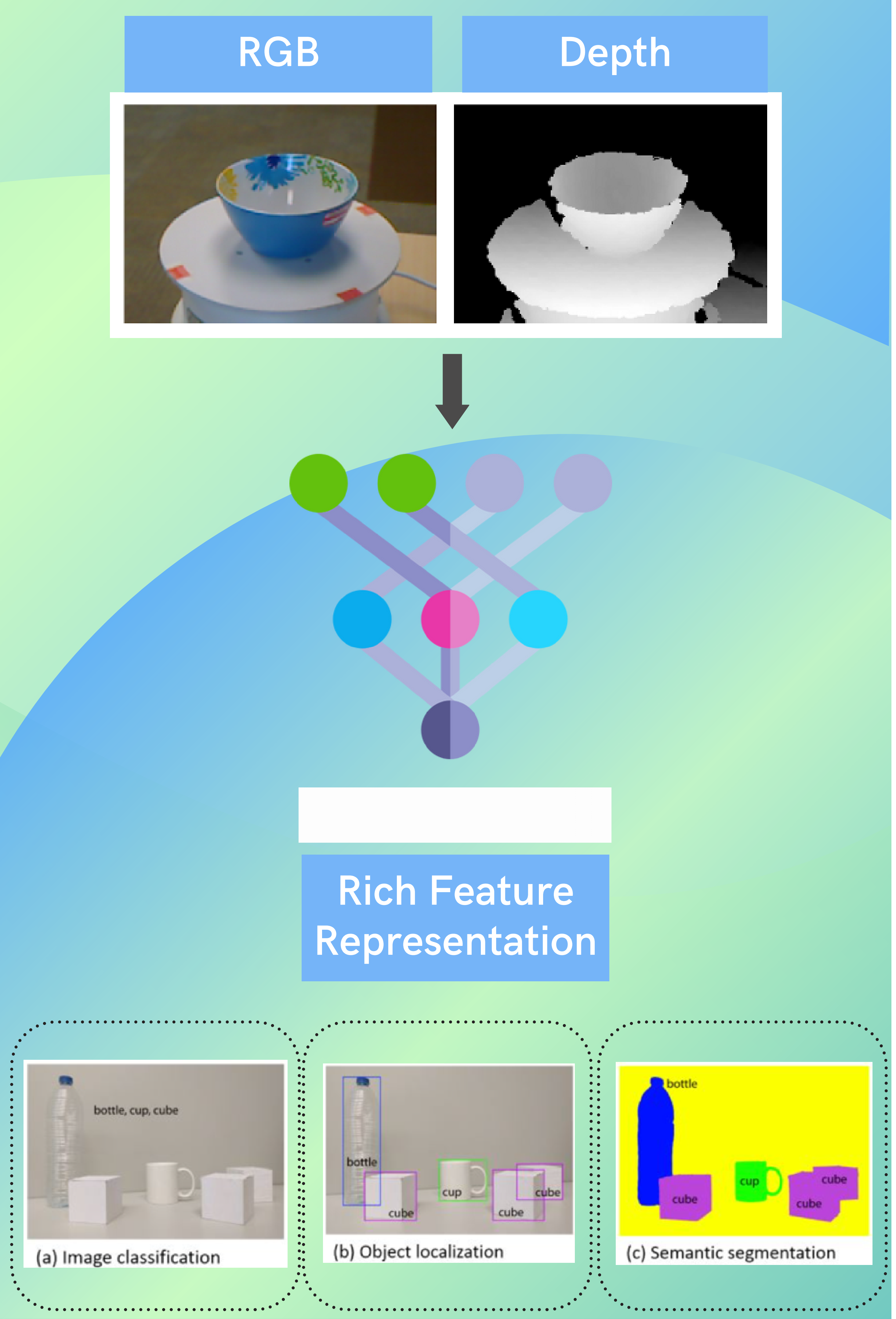


Learning Rich Features from RGB-D Images for Object Detection and Segmentation

Team number: 4
Team name: Team number 105

Agenda →

01

INTRODUCTION

Intro to the Research paper we will be presenting.

Agenda →

01

INTRODUCTION

Intro to the Research paper we will be presenting.

02

OVERVIEW OF THE PROBLEM

What problem is this research paper attempting to solve?

Why this problem is interesting and what challenges it poses?

Agenda →

01

INTRODUCTION

Intro to the Research paper we will be presenting.

02

OVERVIEW OF THE PROBLEM

What problem is this research paper attempting to solve?

Why this problem is interesting and what challenges it poses?

03

SCOPE OF THE PROJECT

Defining the exact scope of what we are attempting as a part of the project.

What are the specific goals and objectives of our work?

Agenda →

01

INTRODUCTION

Intro to the Research paper we will be presenting.

02

OVERVIEW OF THE PROBLEM

What problem is this research paper attempting to solve?

Why this problem is interesting and what challenges it poses?

03

SCOPE OF THE PROJECT

Defining the exact scope of what we are attempting as a part of the project.

What are the specific goals and objectives of our work?

04

METHODOLOGY

How do we plan to accomplish our goals?

The dataset we will be using and how to access it.
The baseline model we will be using.
Experiments, ablations, or comparisons we plan to conduct.
Computing resources we will be using
and other details ...

Agenda →

05

TIMELINE

Outlining a timeline for how we plan to complete the above tasks

Identification of any major milestones or deadlines

Agenda →

05

TIMELINE

Outlining a timeline for how we plan to complete the above tasks

Identification of any major milestones or deadlines

06

INITIAL PROGRESS

Initial progress we have made on the code level

Explain any challenges we have faced and how we have overcome them

Agenda →

05

TIMELINE

Outlining a timeline for how we plan to complete the above tasks

Identification of any major milestones or deadlines

06

INITIAL PROGRESS

Initial progress we have made on the code level

Explain any challenges we have faced and how we have overcome them

07

CONCLUSION

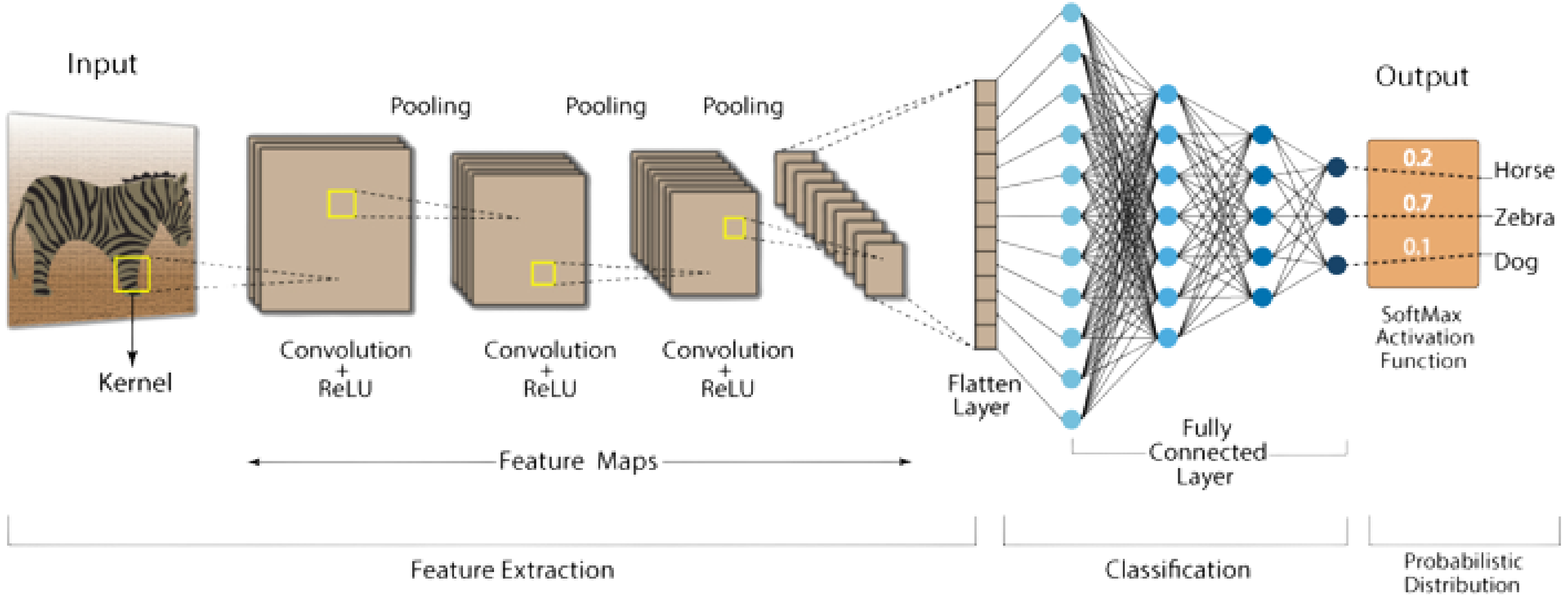
Summarize the key points of the presentation

Explain the potential impact of our work

Invite questions and discussion from the audience

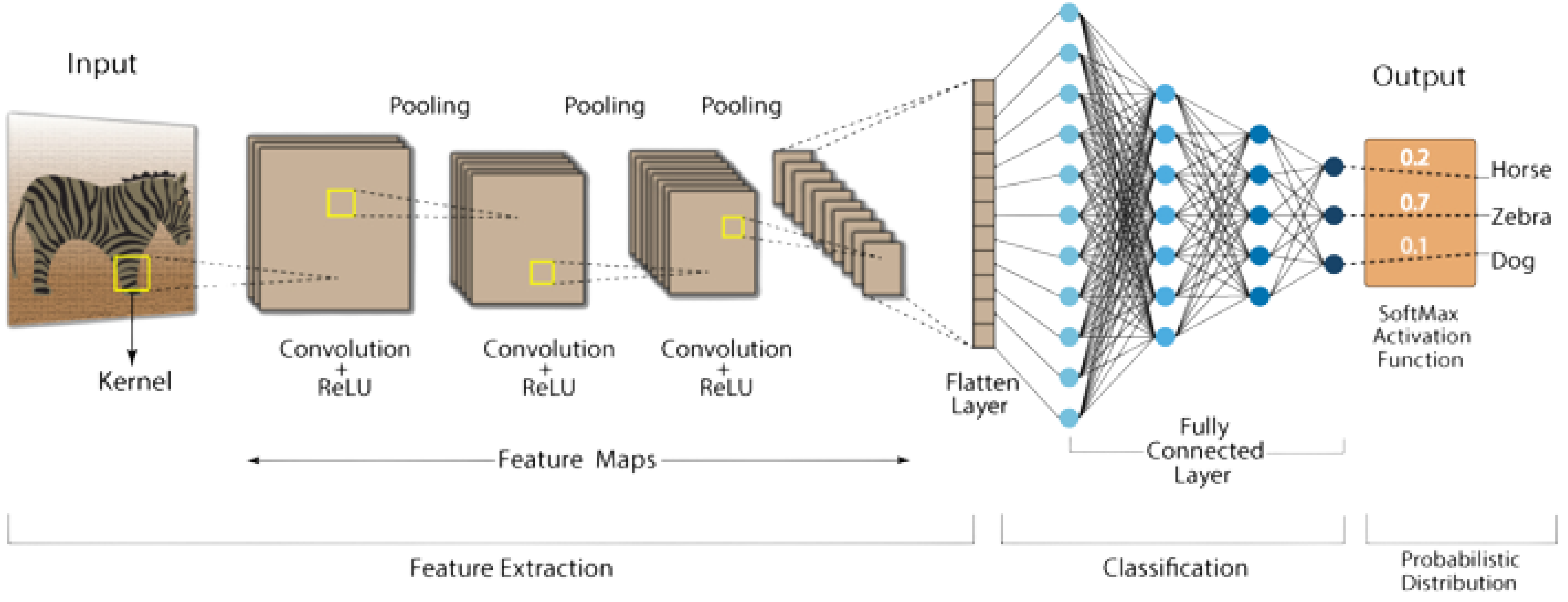
Introduction to Problem Statement

Strengthening Vision Perception via Convolutional Neural Networks

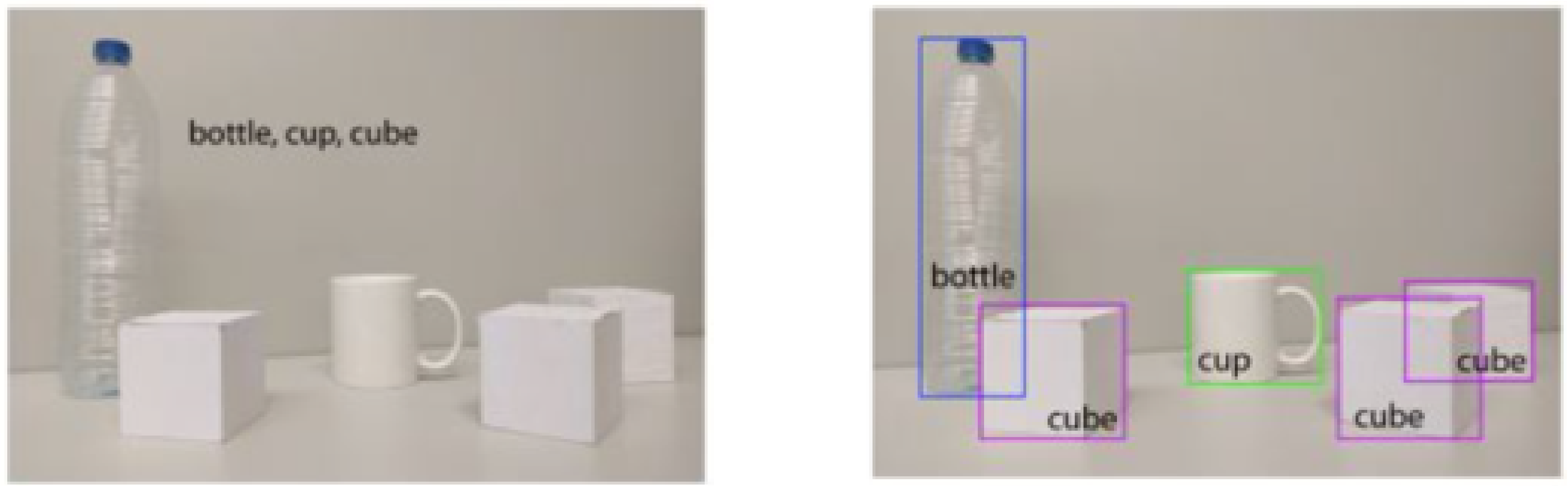


Introduction to Problem Statement →

Strengthening Vision Perception via Convolutional Neural Networks



Learning Rich Feature Representations!

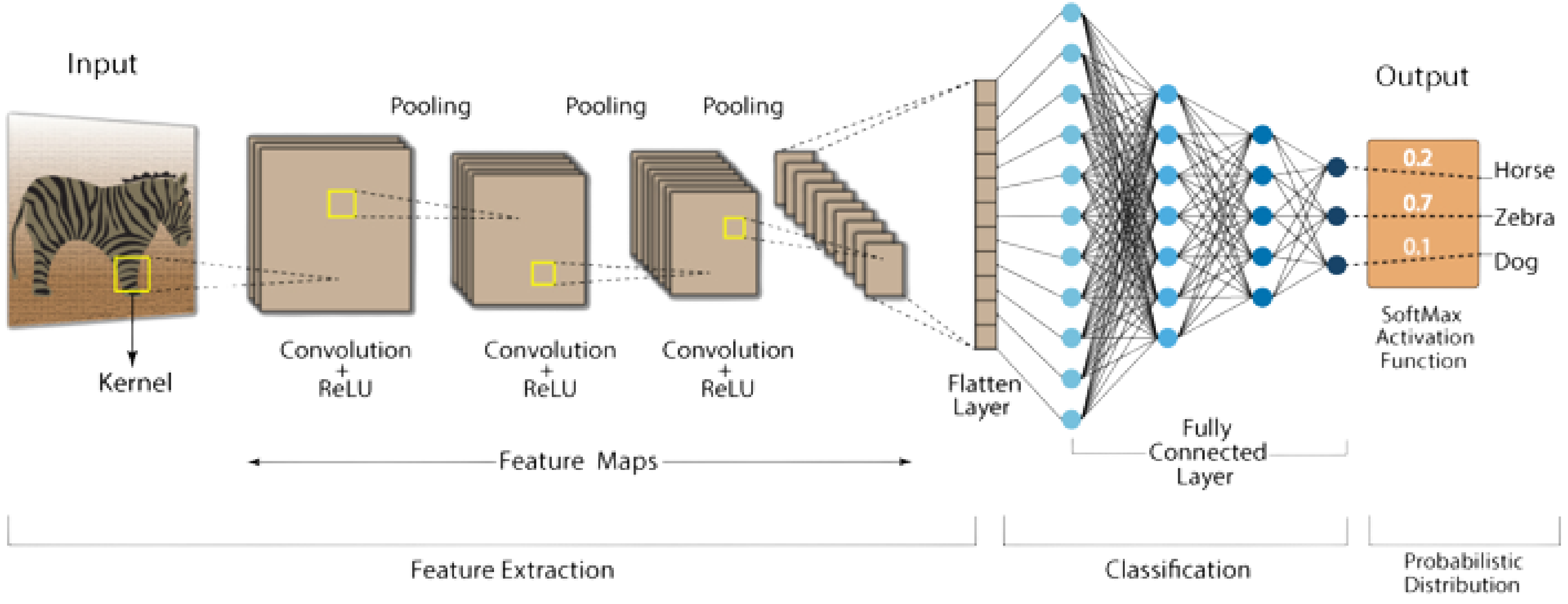


(a) Image classification

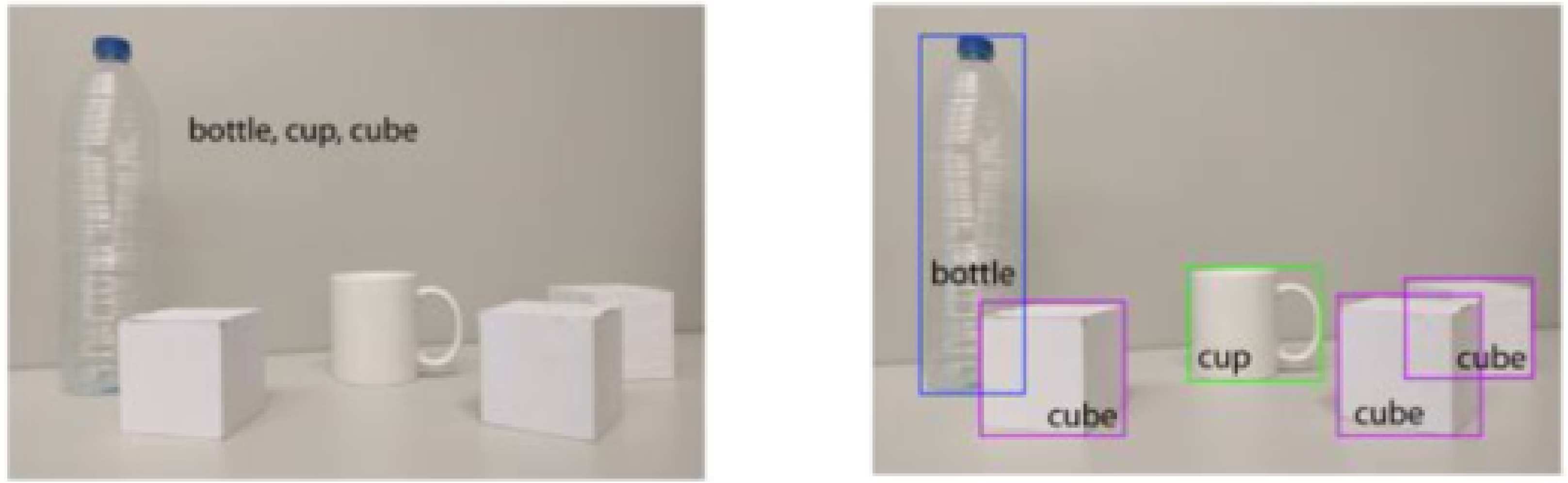
(b) Object localization

Introduction to Problem Statement →

Strengthening Vision Perception via Convolutional Neural Networks



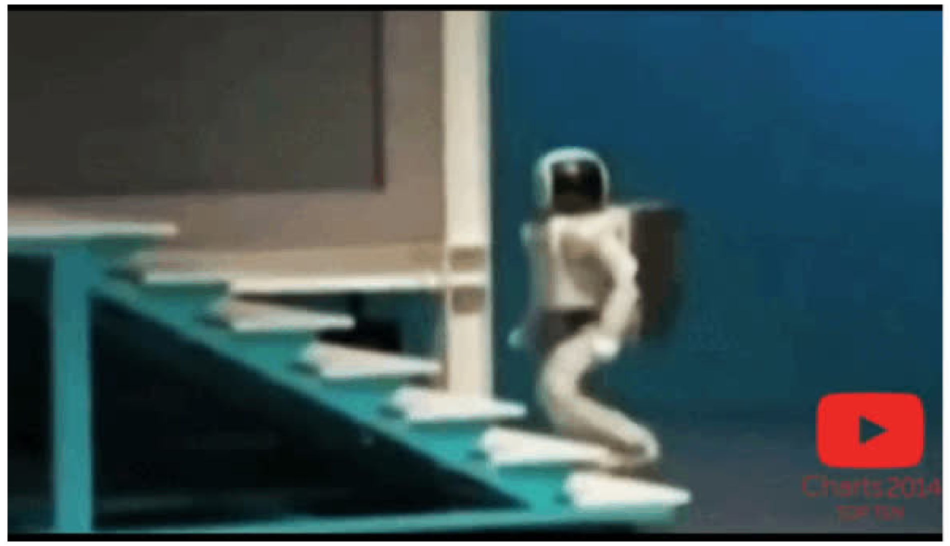
Learning Rich Feature Representations!

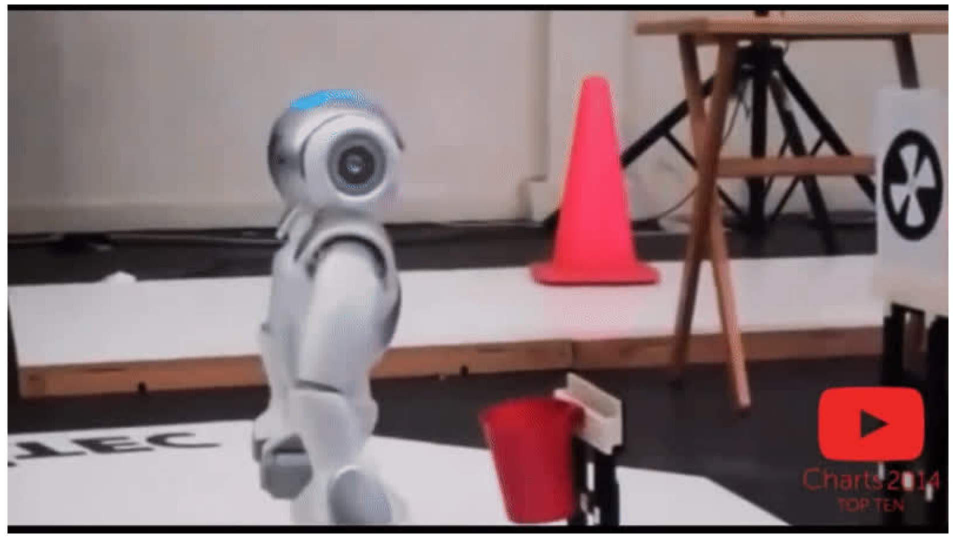


(a) Image classification

(b) Object localization

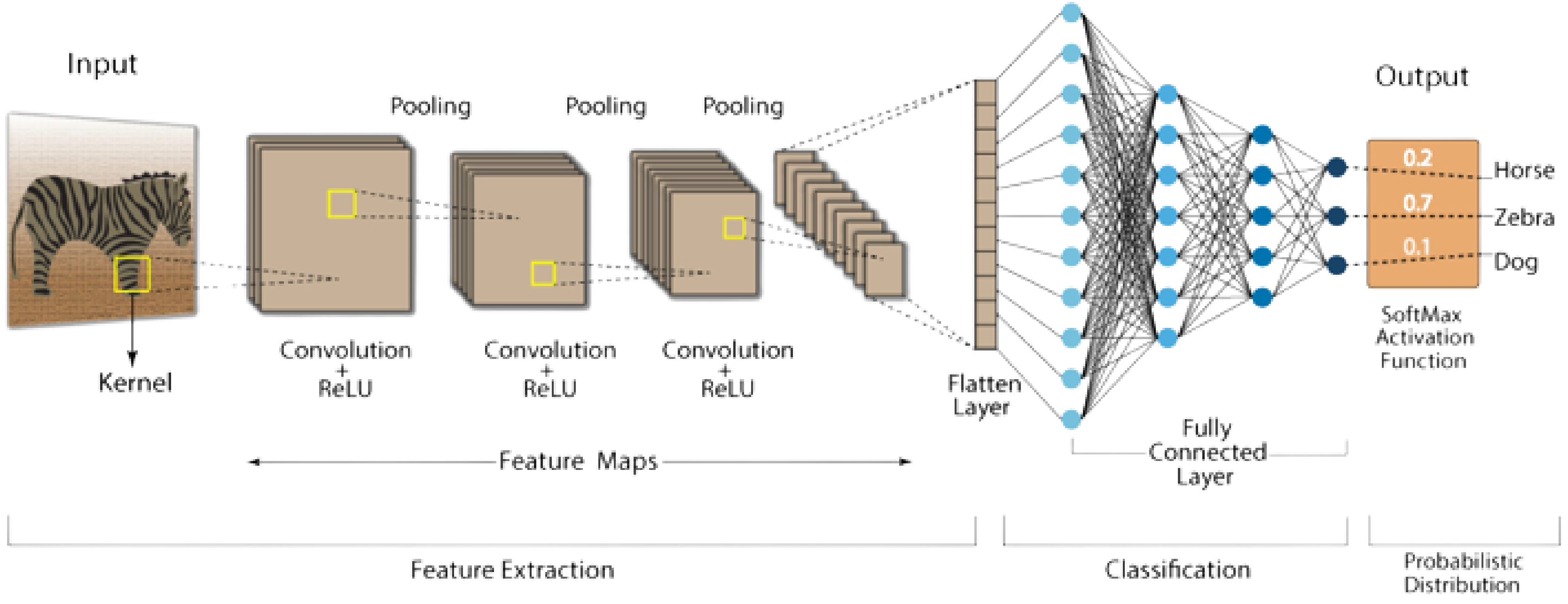
Easy for human cognition - difficult for machines





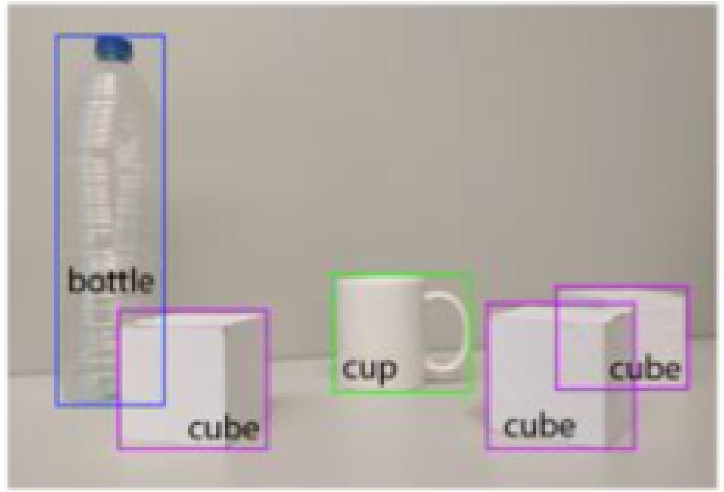
Introduction to Problem Statement →

Strengthening Vision Perception via Convolutional Neural Networks

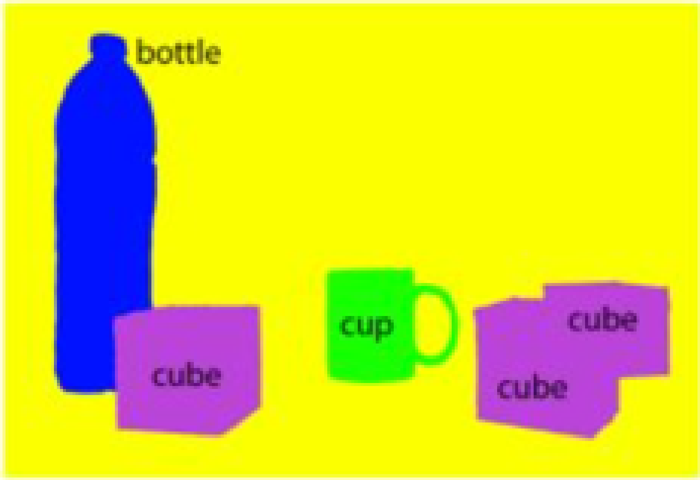


Learning Rich Feature Representations!

(a) Image classification

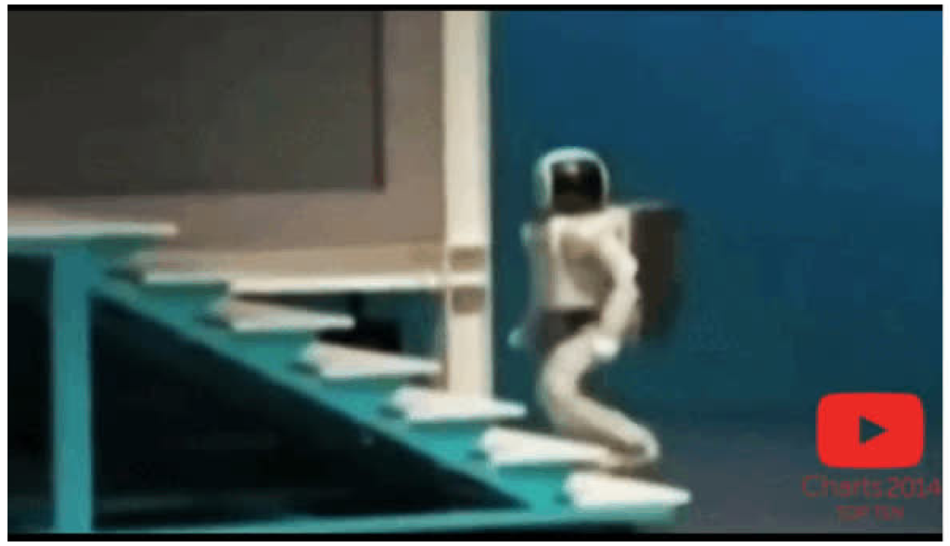


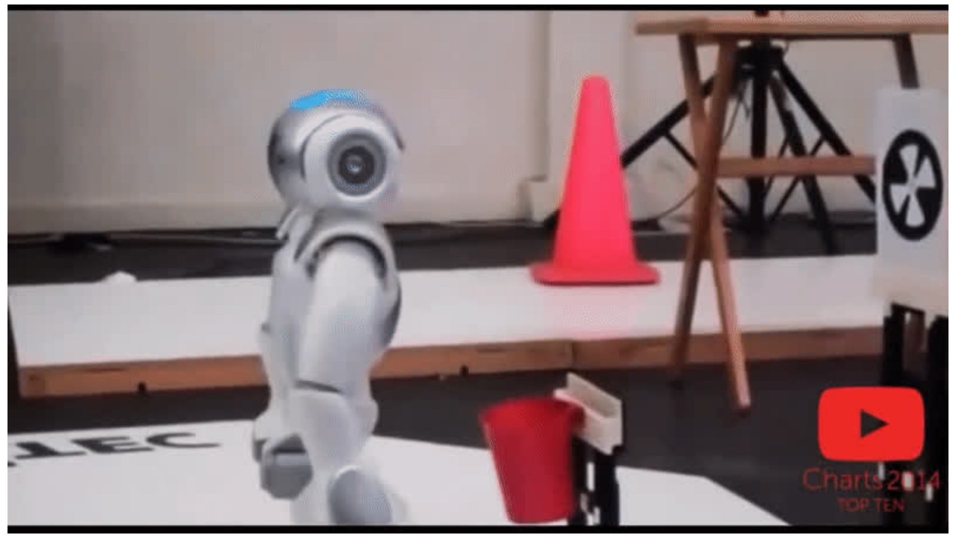
(b) Object localization



(c) Semantic segmentation

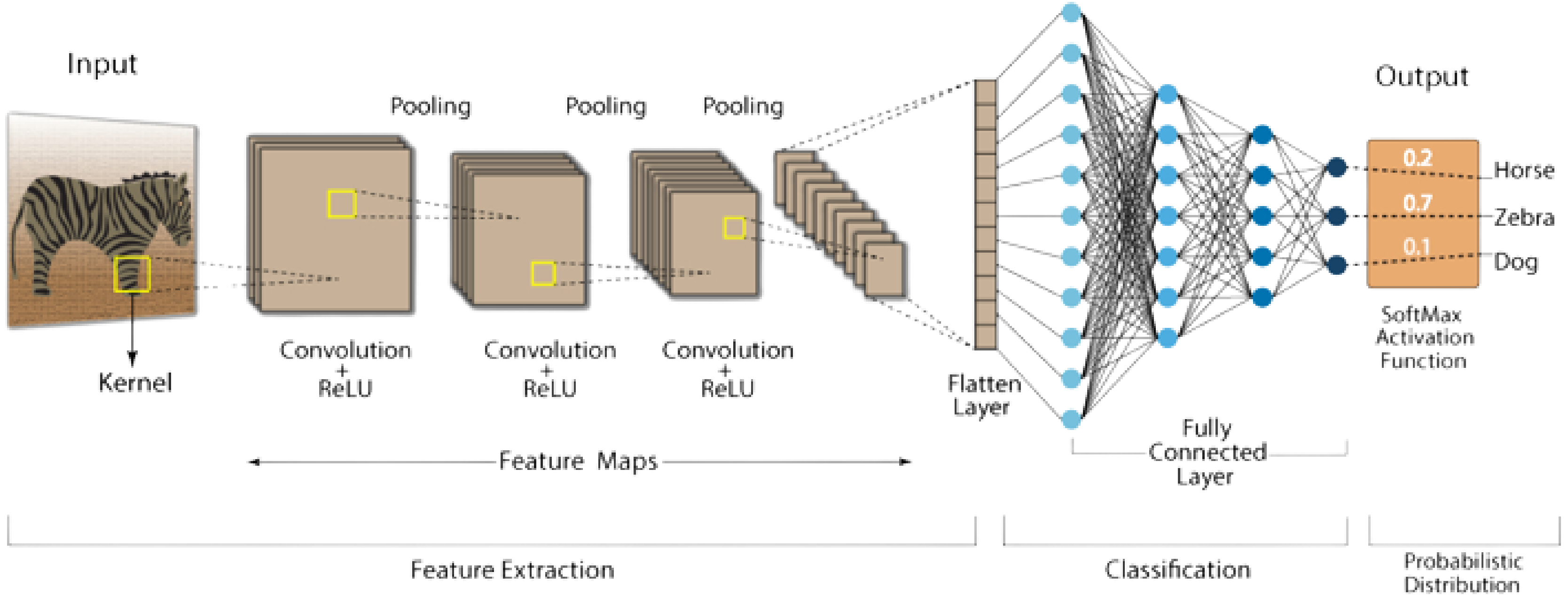
Easy for human cognition - difficult for machines



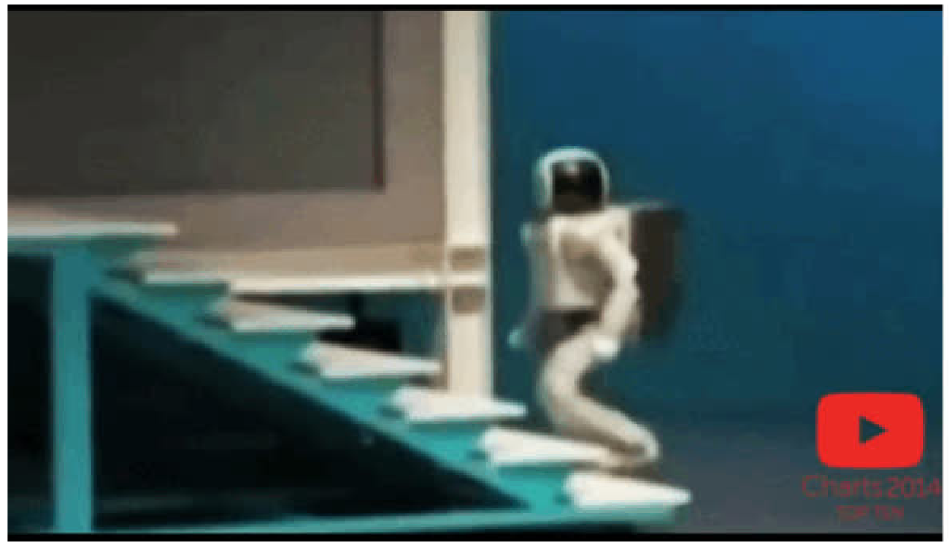


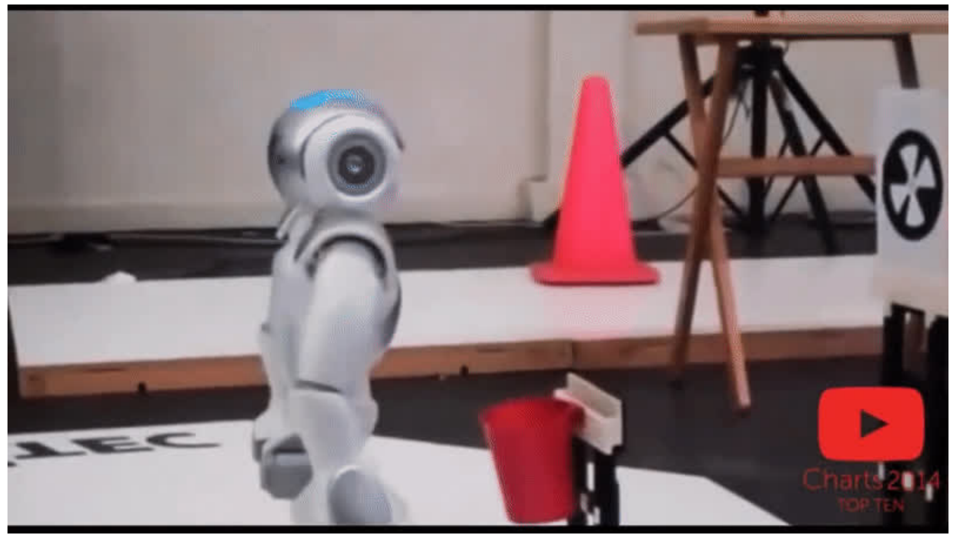
Introduction to Problem Statement →

Strengthening Vision Perception via Convolutional Neural Networks

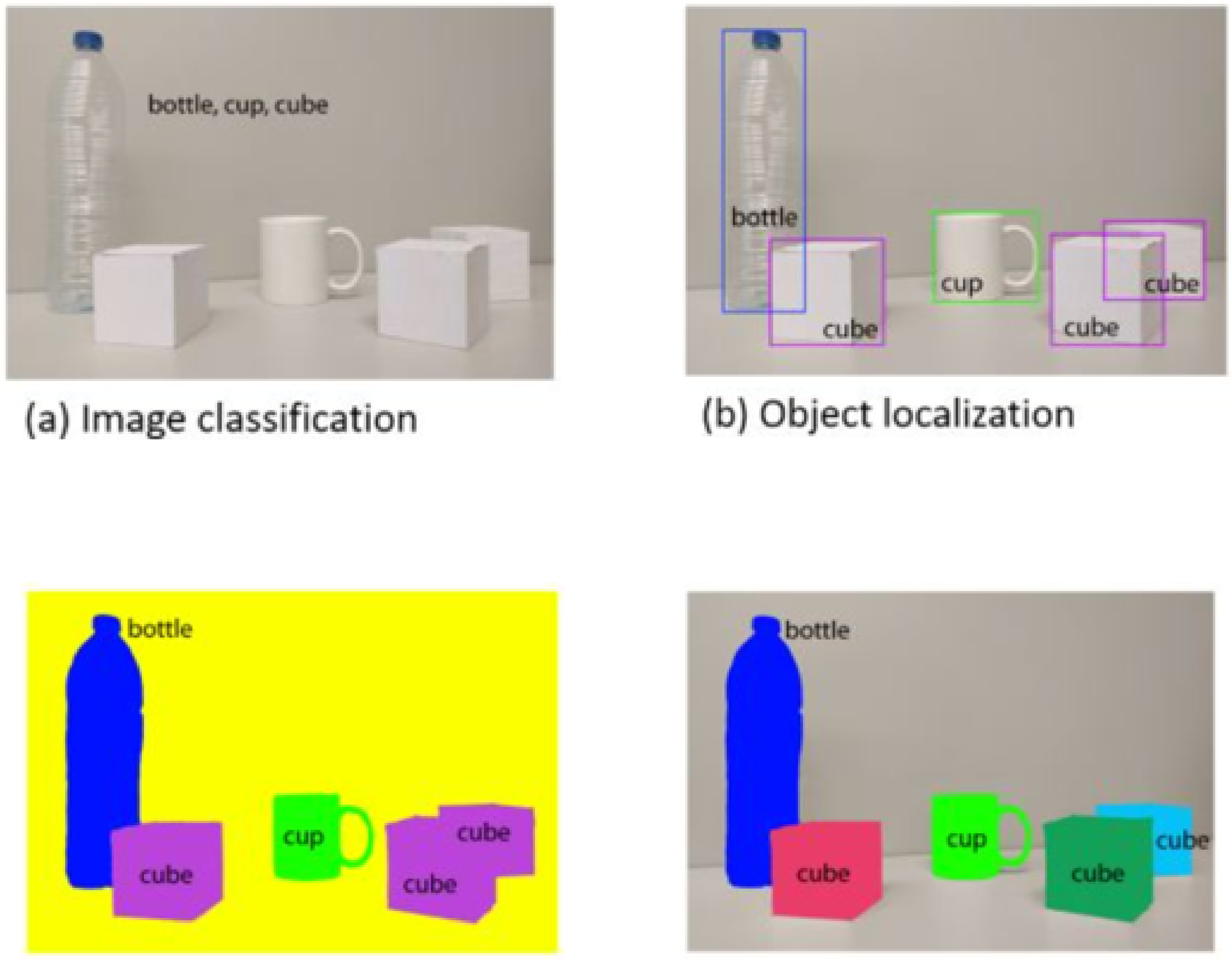


Easy for human cognition - difficult for machines





Learning Rich Feature Representations!



(a) Image classification

(b) Object localization

(c) Semantic segmentation

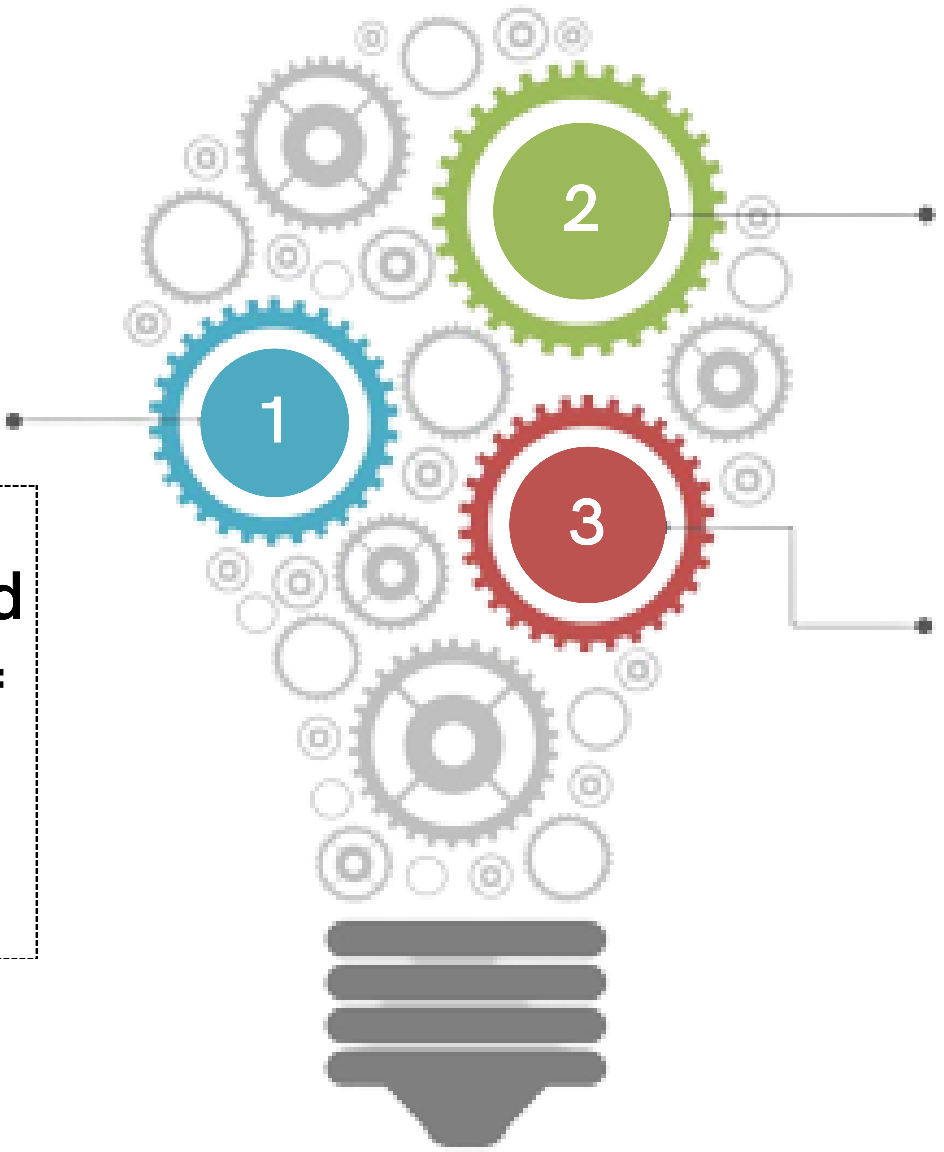
(d) Instance segmentation

Overview: Research Idea →

- Develop an Integrated system for scene understanding from RGB-D images

Overview: Research Idea →

- Develop an Integrated system for scene understanding from RGB-D images



Object Detection

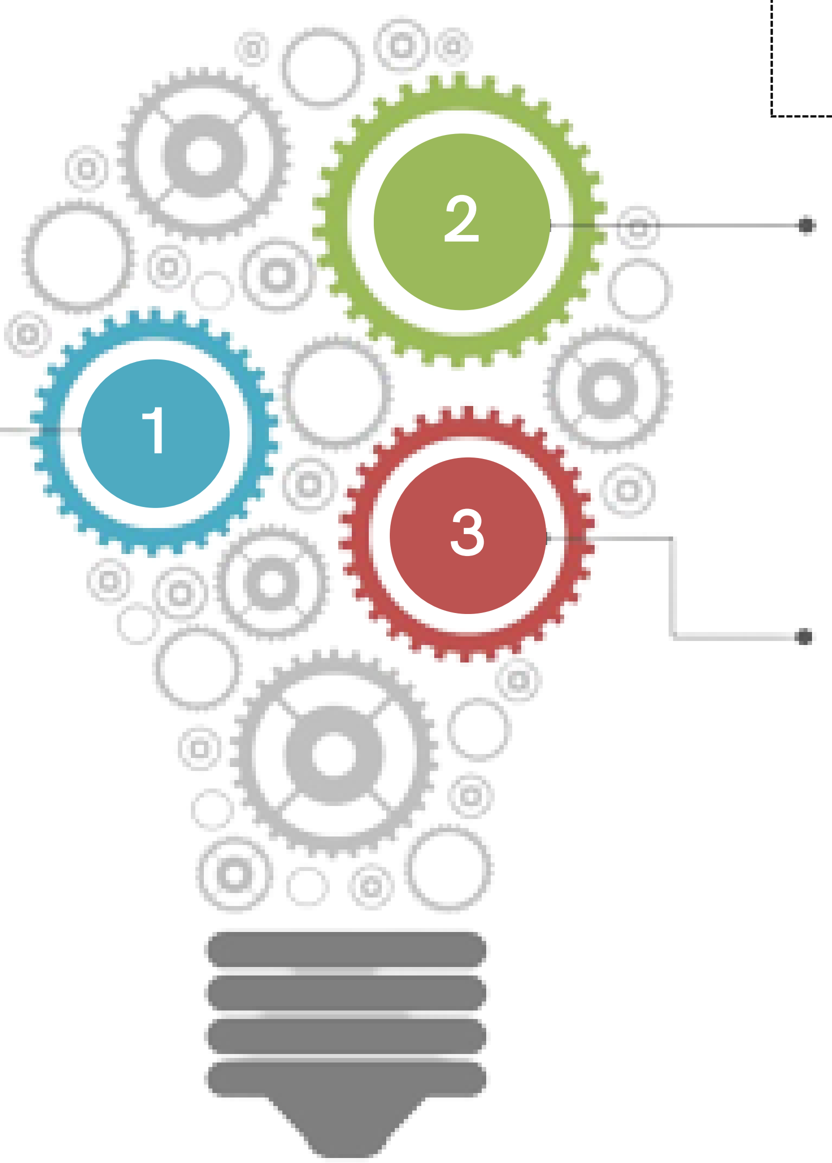
- Geocentric embedding instead of raw depth images to CNN = better feature representation (56% relative improvement).

Overview: Research Idea →

- Develop an Integrated system for scene understanding from RGB-D images

- Decision forest approach that labels pixels of object instances as foreground or background by using the geocentric pose features.

Instance Segmentation



Object Detection

- Geocentric embedding instead of raw depth images to CNN = better feature representation (56% relative improvement).

Overview: Research Idea →

- Develop an Integrated system for scene understanding from RGB-D images

Object Detection

- <u>Geocentric embedding</u> instead of raw depth images to CNN = better feature representation (56% relative improvement).

Instance Segmentation

- <u>Decision forest</u> approach that labels pixels of object instances as foreground or background by using the geocentric pose features.

Semantic Segmentation

- Output of object detectors in a <u>superpixel classification framework</u> for semantic scene segmentation (24% relative improvement).

Overview: Proposed Pipeline →

Architecture of the integrated system

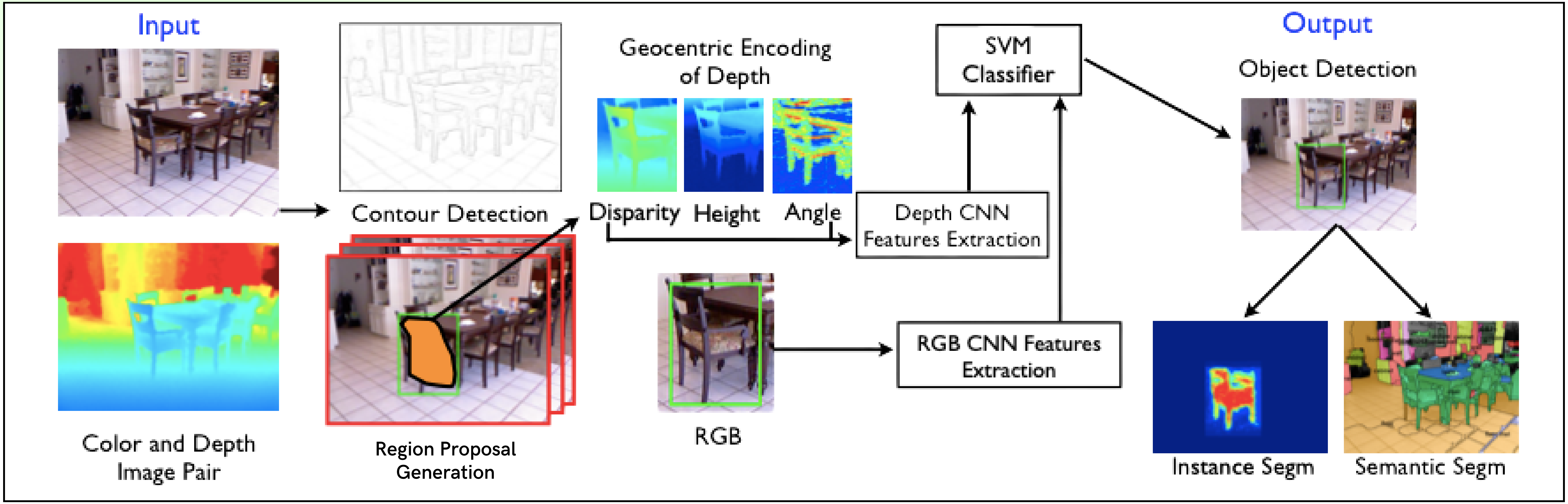
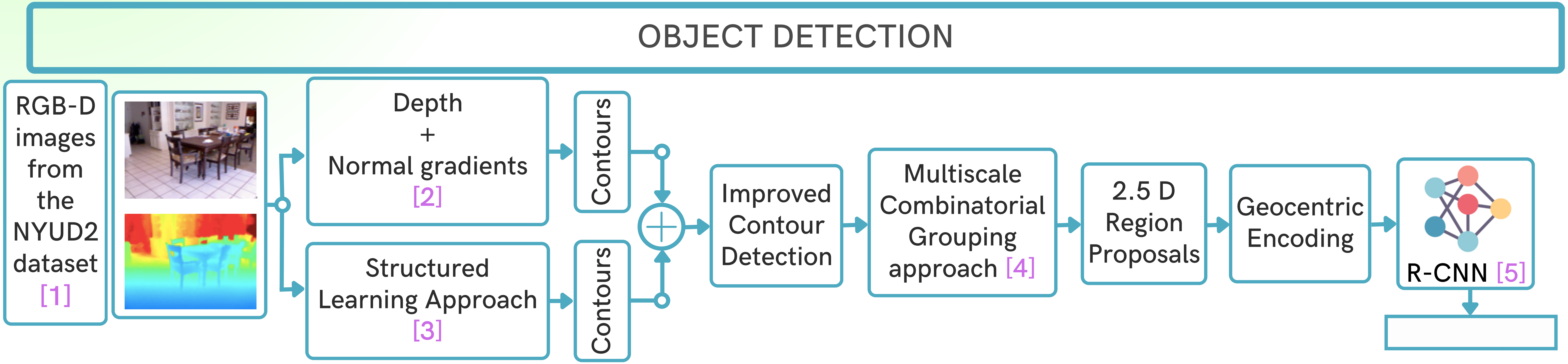
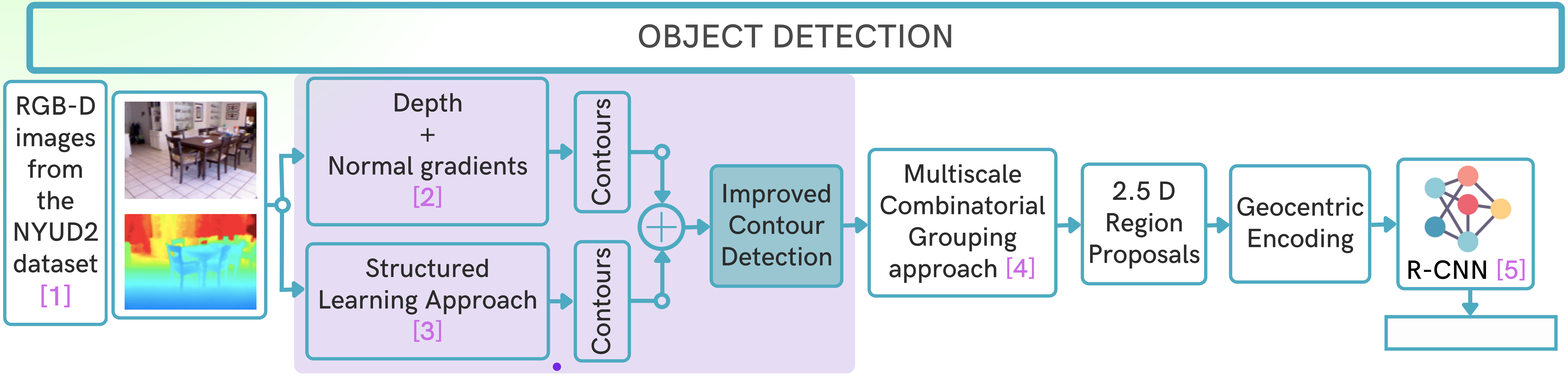


Fig 1. Overview: from an RGB and depth image pair, the system detects contours, generates 2.5D region proposals, classifies them into object categories, and then infers segmentation masks for instances of "thing"-like objects, as well as labels for pixels belonging to "stuff"-like categories.

Architecture of the integrated system



Architecture of the integrated system

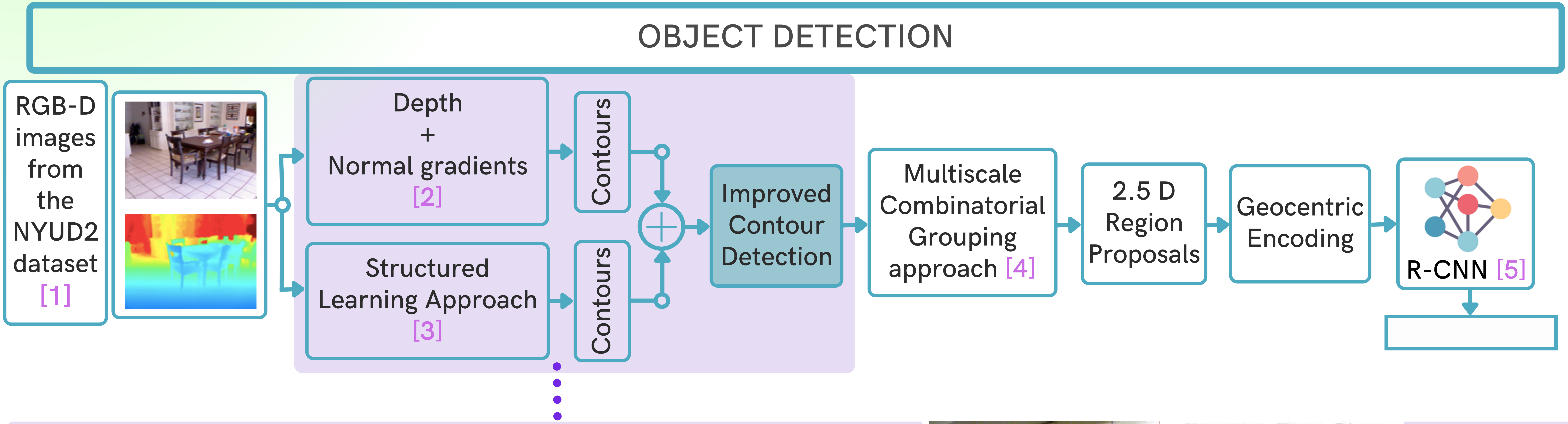


[2] uses **gPb_ucm** [6] and proposed local geometric gradients dubbed NG-, NG+ and DG to capture convex, concave normal gradients and depth gradients

[3] proposed an approach based on structured random forests to directly classify a pixel as being a contour pixel or not

[3] produces better localized contours that capture fine details, but tend to miss normal discontinuities that [2] easily finds

Architecture of the integrated system

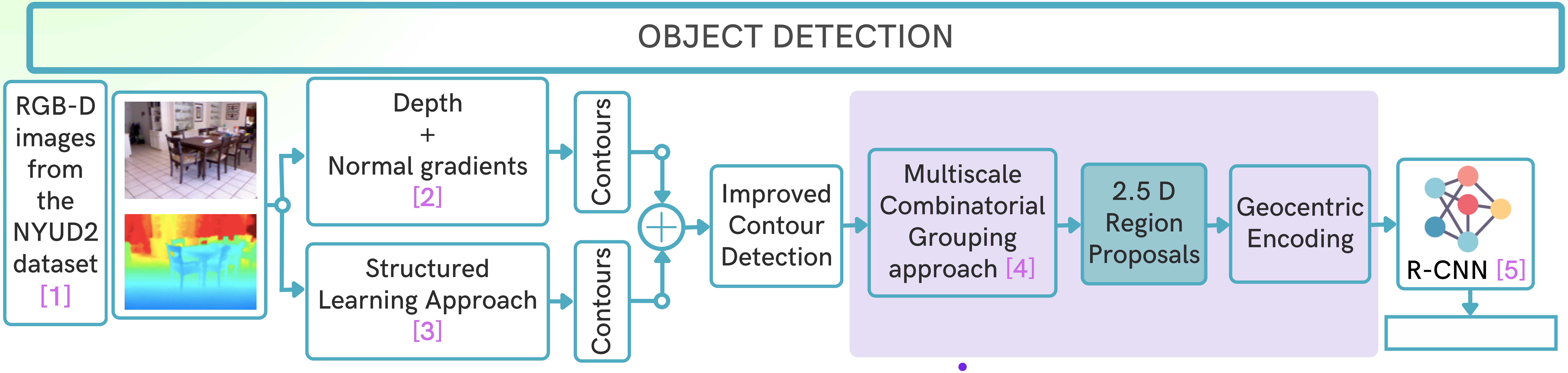


[2] uses gPb_ucm [6] and proposed local geometric gradients dubbed NG-, NG+ and DG to capture convex, concave normal gradients and depth gradients

[3] proposed an approach based on structured random forests to directly classify a pixel as being a contour pixel or not

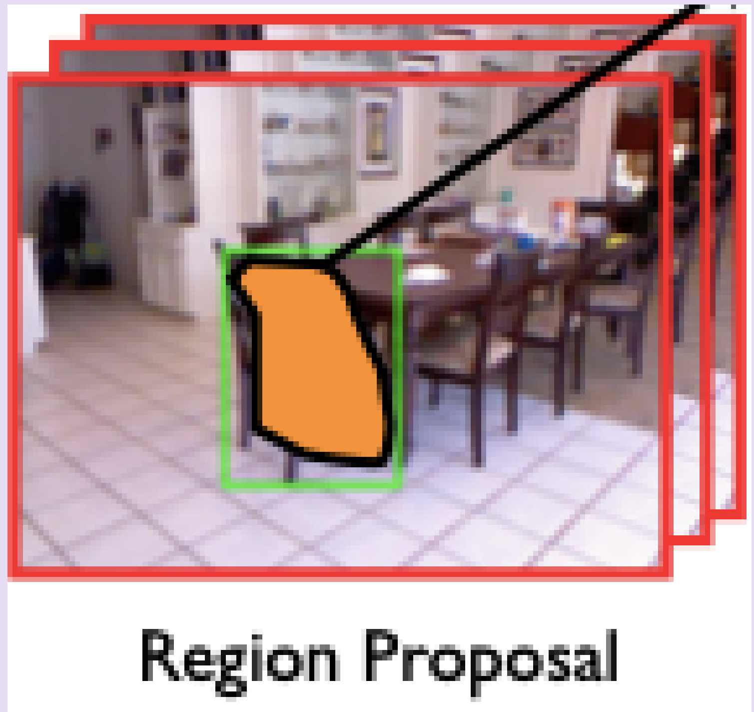
[3] produces better localized contours that capture fine details, but tend to miss normal discontinuities that [2] easily finds

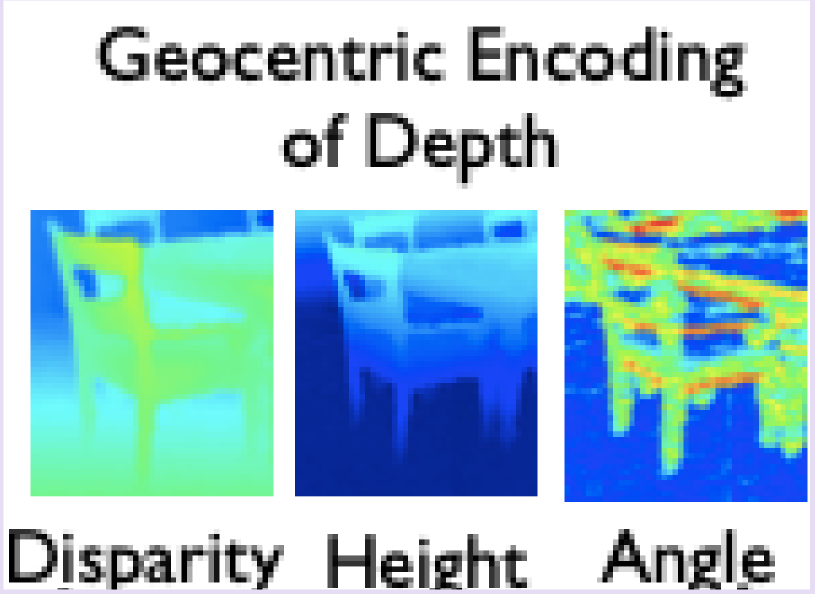
Architecture of the integrated system



MCG is an approach used for object proposal generation.

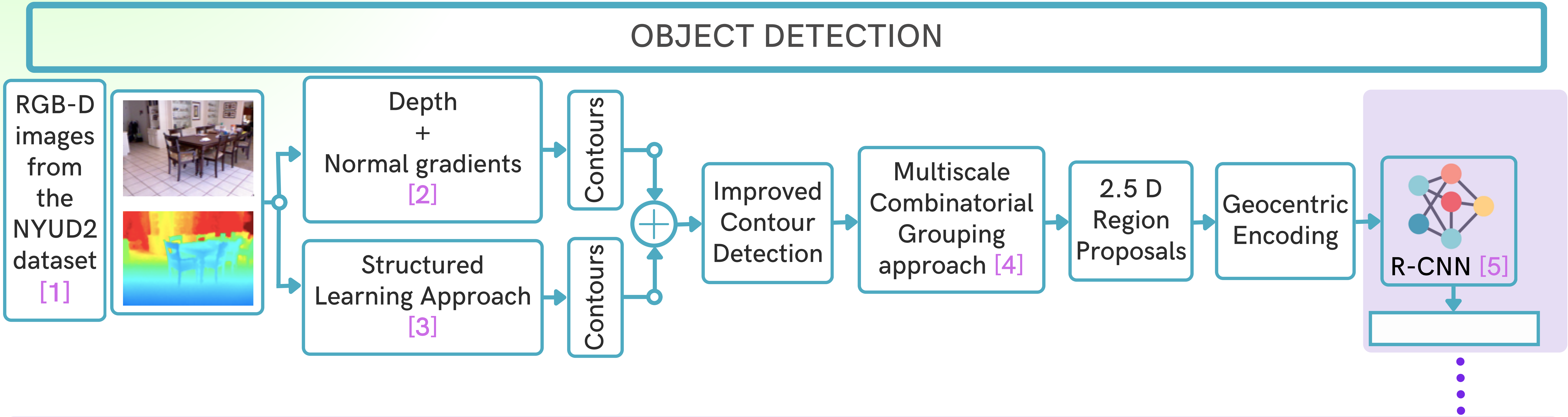
From improved contour, we obtain object proposals by generalizing MCG to RGB-D images





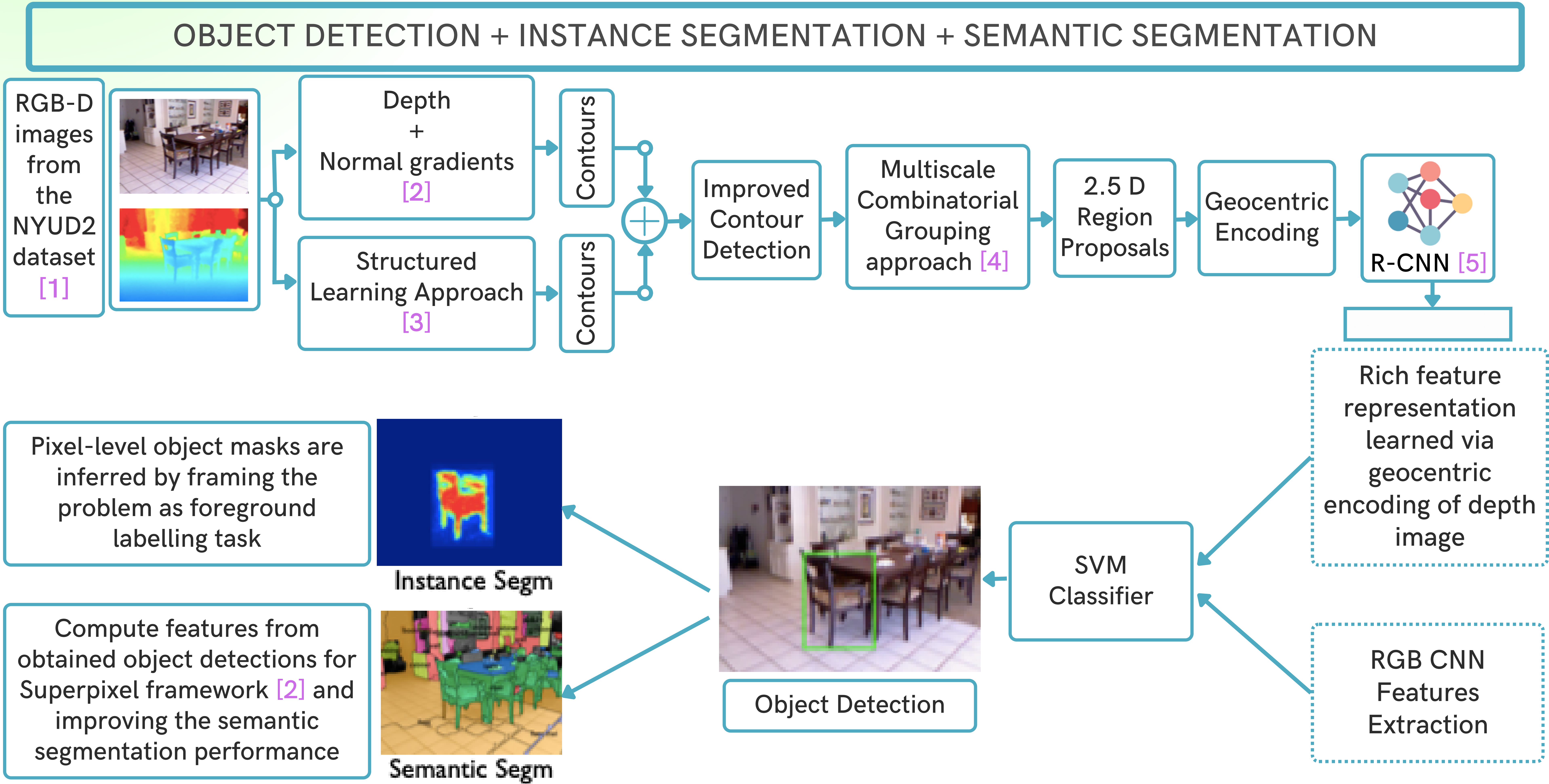
Geocentric encoding allows CNN to learn strong features than by using disparity alone

Architecture of the integrated system



A large R-CNN pre-trained on RGB images, can be adapted to generate rich features from this representation of depth images.

Architecture of the integrated system



Architecture of the integrated system

RESULTS

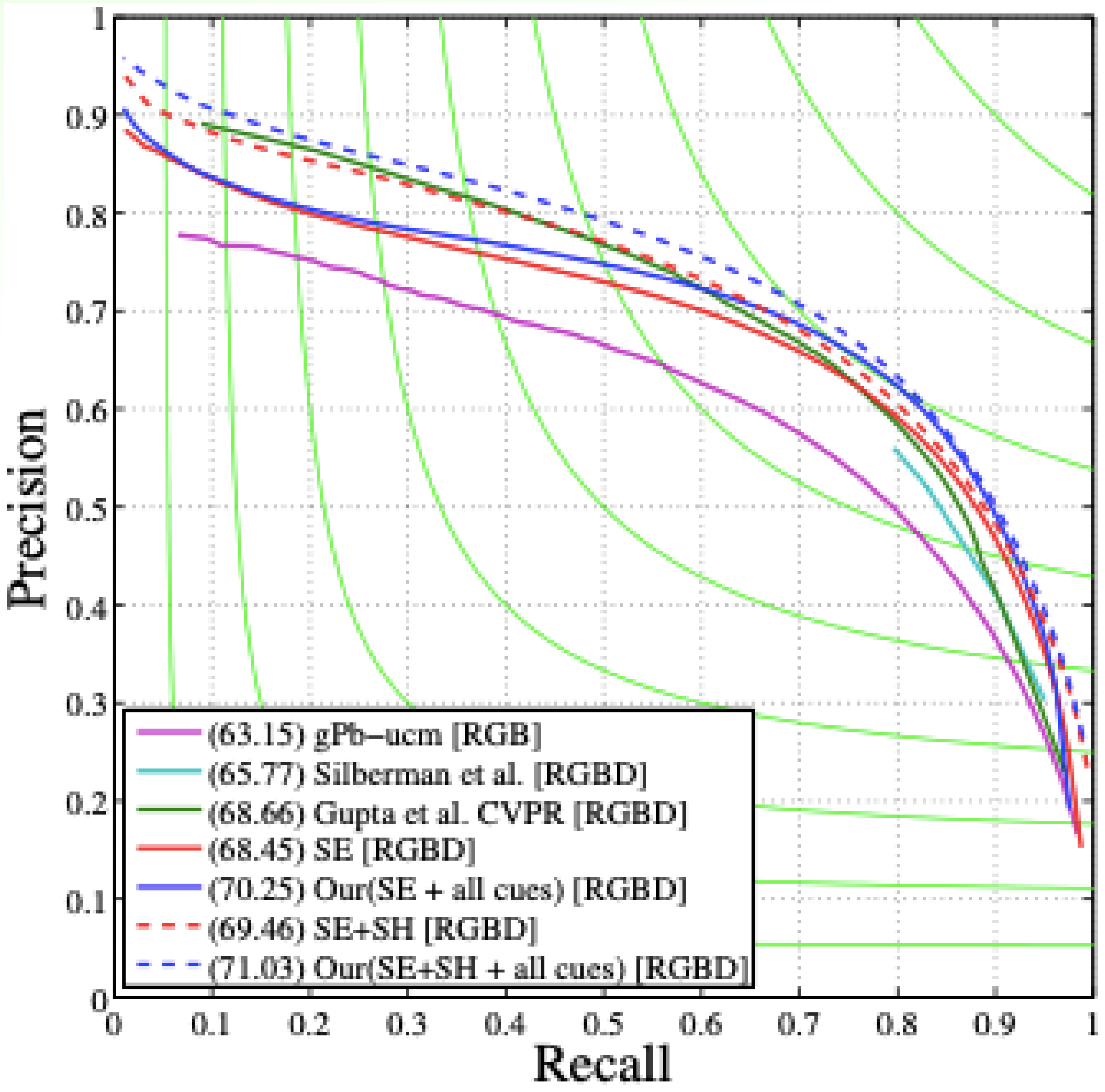


Fig 2: Precision-Recall curve on boundaries on the NYUD2 dataset

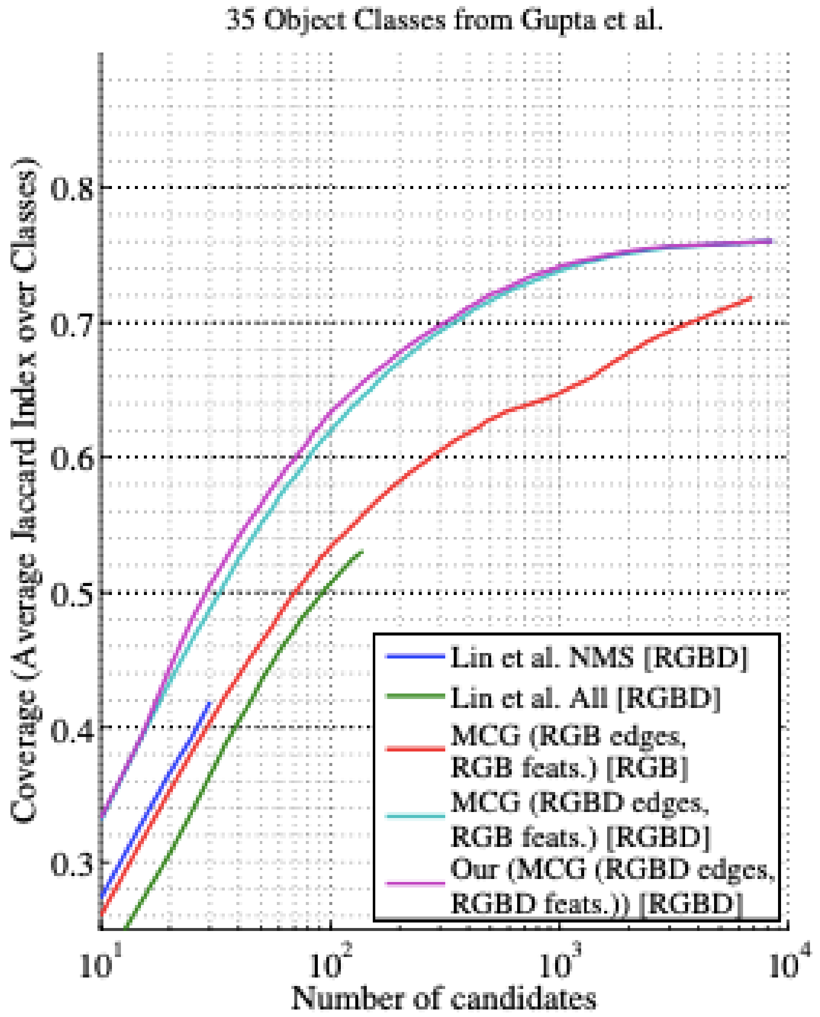


Fig. 4. Region Proposal Quality: Coverage as a function of the number of region proposals per image: Depth-based region proposals using the improved RGB-D contours work better than all past approaches, while at the same time being more general. Note that the X-axis is on a log scale.

OBJECT DETECTION

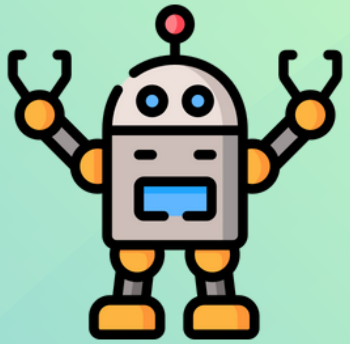
Final object detection system achieves an average precision of 37.3%, which is a 56% relative improvement over existing methods

Why is this Problem Interesting →

FACILITATE THE USE OF PERCEPTION IN FIELDS LIKE SMART TRAFFIC MONITORING, SUPPLY-CHAIN MONITORING, MEDICAL ASSISTANCE

- Advanced human-machine interfaces (gesture recognition, motion tracking, etc.)
- Crowd monitoring
- Self-driving cars
- Navigation systems for unmanned robotic vehicles, and much more

Virtual Reality



Robot Navigation

Augmented Reality

Challenges →

Depth images may contain noise due to sensor limitations or environmental factors such as reflections or interference from other devices. This can lead to inaccurate depth measurements, which can affect the accuracy of object detection and segmentation

➢ Data Quality

Processing both RGB and depth information requires more computational resources than traditional 2D image-based methods. This can lead to slower detection and segmentation times, which may be a problem in real-time applications

➢ Computational Complexity

Objects can vary in shape, size, color, and texture, which can make it difficult to create accurate models for object detection and segmentation. This can lead to false positives or false negatives

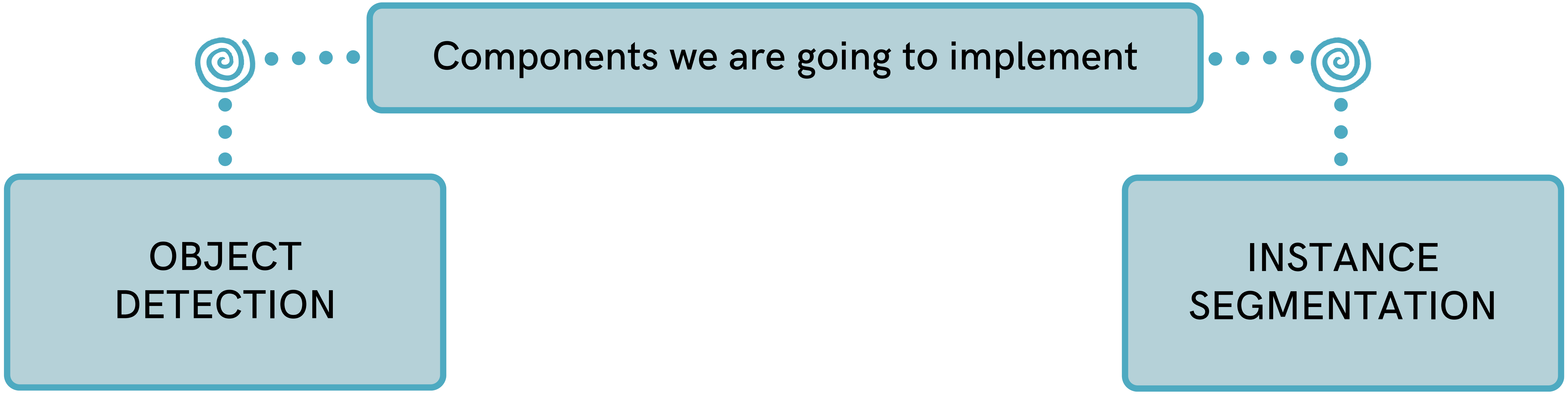
➢ Variability in object appearance

Training deep learning models for RGB-D object detection and instance segmentation requires large amounts of annotated data. However, there are currently only a limited number of publicly available annotated datasets for this task

➢ Limited availability of annotated dataset

Scope of the Project →

What are we attempting as a part of the project



Exact details regarding the implementation of all the sub-components - Timeline Slide

Methodology →

1 Datasets

What and how to access?

Dataset name

NYU Depth Dataset v2

Access

Open Source

2 Computing Resources

What and how much?

Specifications

GPU: RTX 2080Ti
CPU: Intel Xeon E5-2640 v4

Estimated Time

Finetuning: 90 hrs (100 epochs)

3 Baseline models

The requirements

- 2.5D region proposal
- Geocentric encoding of depth information (HHA)
- Random forest for **Instance Segmentation**
- Finetune R-CNN for HHA
- Implement **Semantic Segmentation**

4 Improvements

The extras

- Replace R-CNN with YOLO v5
- Using v2 of NYUD dataset
- Replace SVM classifier with a Deep Learning base method

Dataset

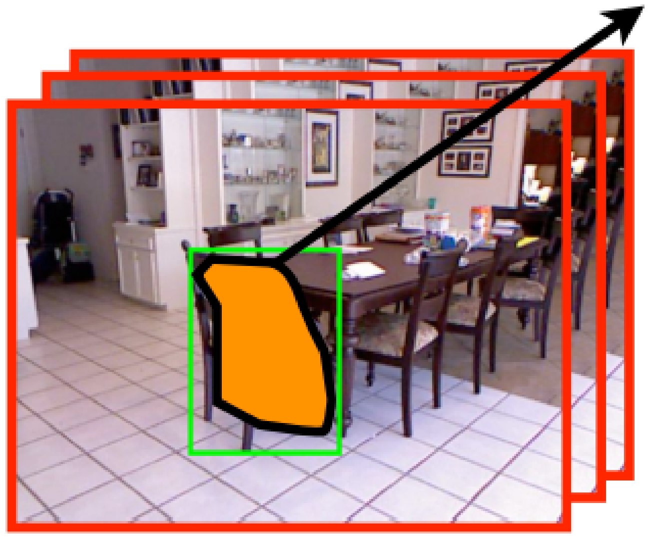
Table 1

Dataset Name	Source	Dataset Preparation	Class Labels	
NYUD2 dataset	https://cs.nyu.edu/~silberman/datasets/	Custom code to extract the following files from the available mat file. • 1449 RGB images • 1449 Depth images • 1449 Raw Depth maps • 1449 Instance maps • 1449 Label maps	bathtub	lamp
			bed	monitor
			bookshelf	night-stand
			box	pillow
			chair	sink
			counter	sofa
			desk	table
			door	television
			dresser	toilet
			garbage-bin	

Initial Progress →

Implementation of 2.5D region proposal

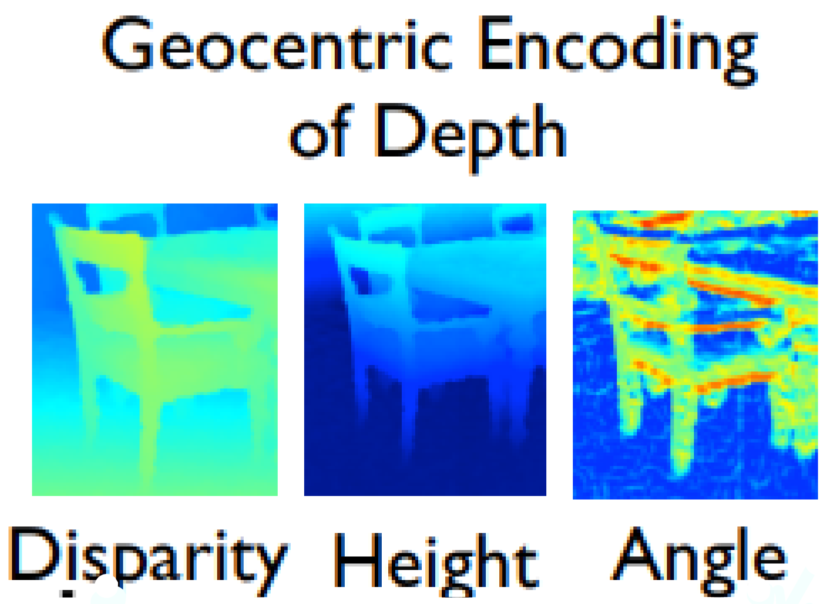
[4] Arbela ́ez, P., Pont-Tuset, J., Barron, J., Marques, F., Malik, J.: Multiscale combinatorial grouping. In: CVPR (2014)



Region Proposal Generation

Encoding Depth Images for Feature Learning

[18] Gupta, S., Arbel ́ aez, P., Malik, J.: Perceptual organization and recognition of indoor scenes from RGB-D images. In: CVPR (2013)



Team →

Deepti Rawat
deepti.rawat@research.iiit.ac.in
Roll No: 2022801016

Rishabh Khanna
rishabh.khanna@research.iiit.ac.in
Roll No: 2019113025

Mihir Rawat
mihir.r@research.iiit.ac.in
Roll No: 2020113005

Kshitijaa Jaglan
kshitijaa.jaglan@research.iiit.ac.in
Roll No: 2019115005

Work Distribution →

Feature Representation

- 2.5D Region Proposal
  Kshitijaa, Mihir
- Geocentric Encoding
  Deepti
- Fine Tuning R-CNN
  Rishabh
- RGB R-CNN
  Rishabh

Segmentation Pipeline

- SVM Classifier
  Kshitijaa
- Instance Segmentation
- Semantic Segmentation

Proposed Changes

- YOLO v5
  Deepti
- DL Classifier
  Rishabh
- Instance Segmentation

References

- [1] https://cs.nyu.edu/~silberman/datasets/nyu_depth_v2.html
- [2] Gupta, S., Arbela´ez, P., Malik, J.: Perceptual organization and recognition of indoor scenes from RGB-D images. In: CVPR (2013)
- [3] Dolla´r, P., Zitnick, C.L.: Structured forests for fast edge detection. In: ICCV (2013)
- [4] Arbela´ez, P., Pont-Tuset, J., Barron, J., Marques, F., Malik, J.: Multiscale combinatorial grouping. In: CVPR (2014)
- [5] Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. In: CVPR (2014)
- [6] Arbela´ez, P., Maire, M., Fowlkes, C., Malik, J.: Contour detection and hierarchical image segmentation. TPAMI (2011)