

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

Team number: 4

Team name: Team number 105

INTRODUCTION

Intro to the Research paper we will be presenting.

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OVERVIEW OF THE PROBLEM

What problem is this research paper attempting to solve?

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Why this problem is interesting and what challenges it poses?

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SCOPE OF THE PROJECT

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

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What are the specific goals and objectives of our work?

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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 ...

04

TIMELINE

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

05

Identification of any major milestones or deadlines

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INITIAL PROGRESS

Initial progress we have made on the code level

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

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CONCLUSION

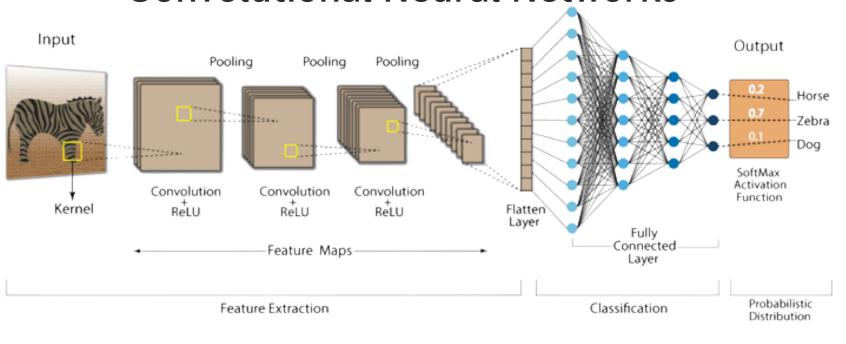
Summarize the key points of the presentation

Explain the potential impact of our work

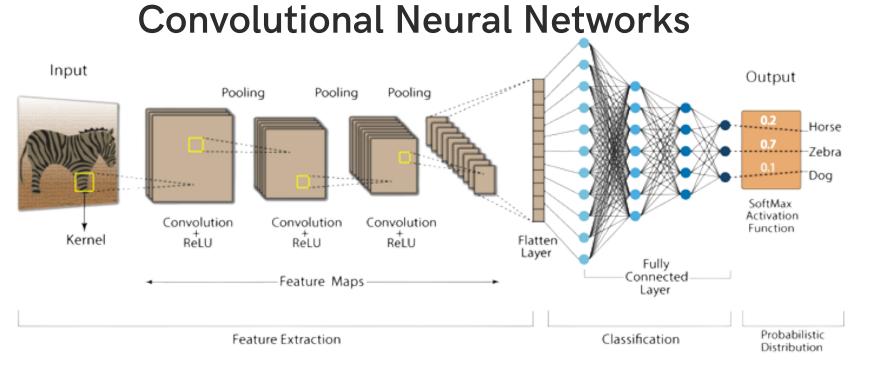
Invite questions and discussion from the audience

07

Strengthening Vision Perception via Convolutional Neural Networks



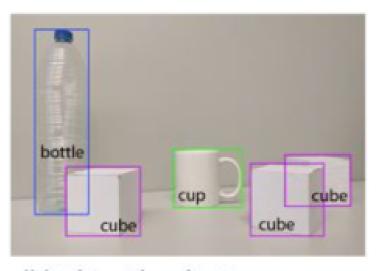
Learning Rich Feature Representations!



Strengthening Vision Perception via

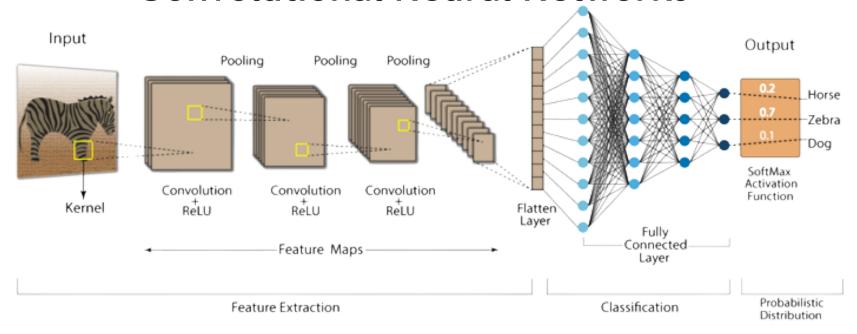


(a) Image classification



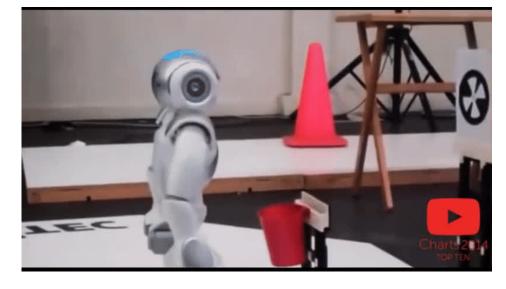
(b) Object localization

Strengthening Vision Perception via Convolutional Neural Networks



Easy for human cognition - difficult for machines

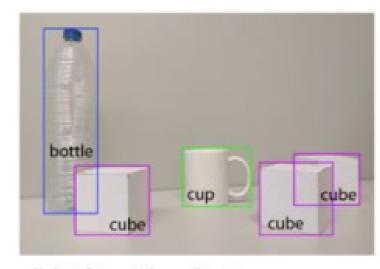




Learning Rich Feature Representations!

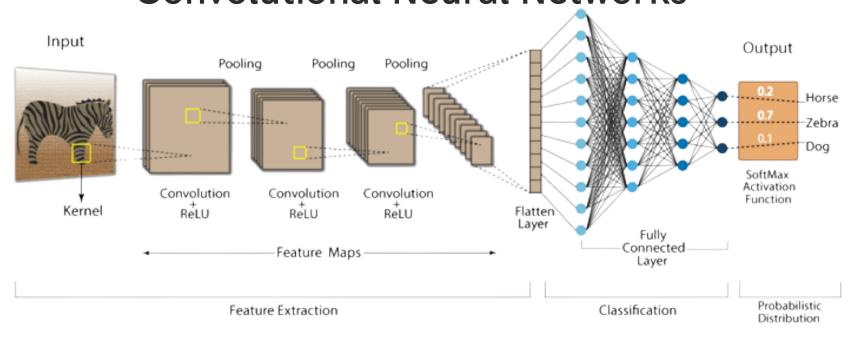


(a) Image classification



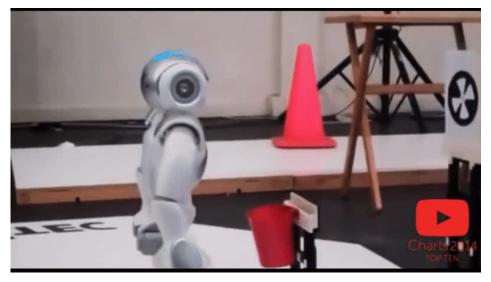
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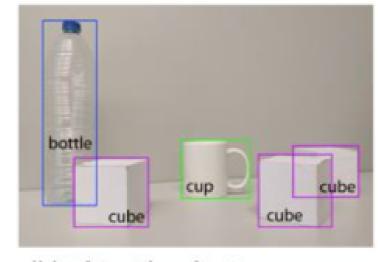




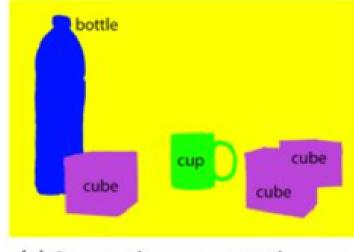
Learning Rich Feature Representations!



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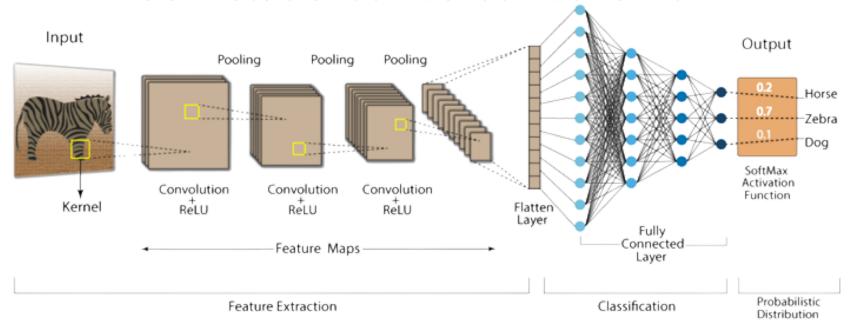


(b) Object localization

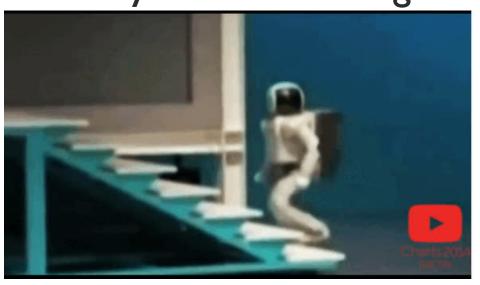


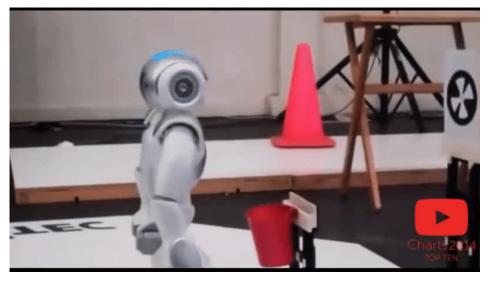
(c) Semantic segmentation

Strengthening Vision Perception via Convolutional Neural Networks



Easy for human cognition - difficult for machines

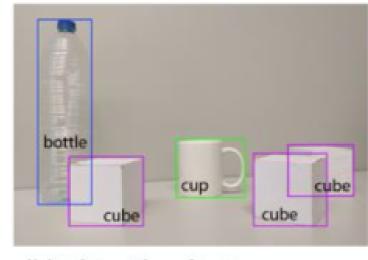




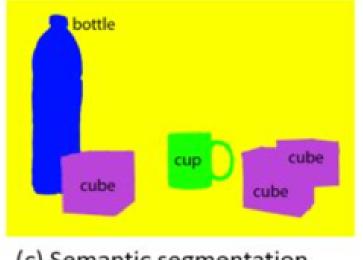
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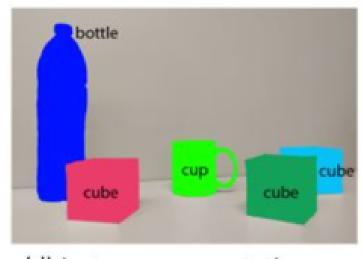
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(b) Object localization

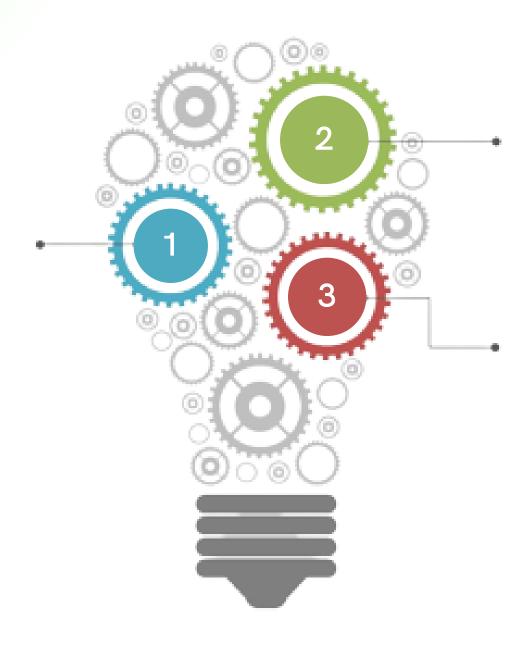


(c) Semantic segmentation

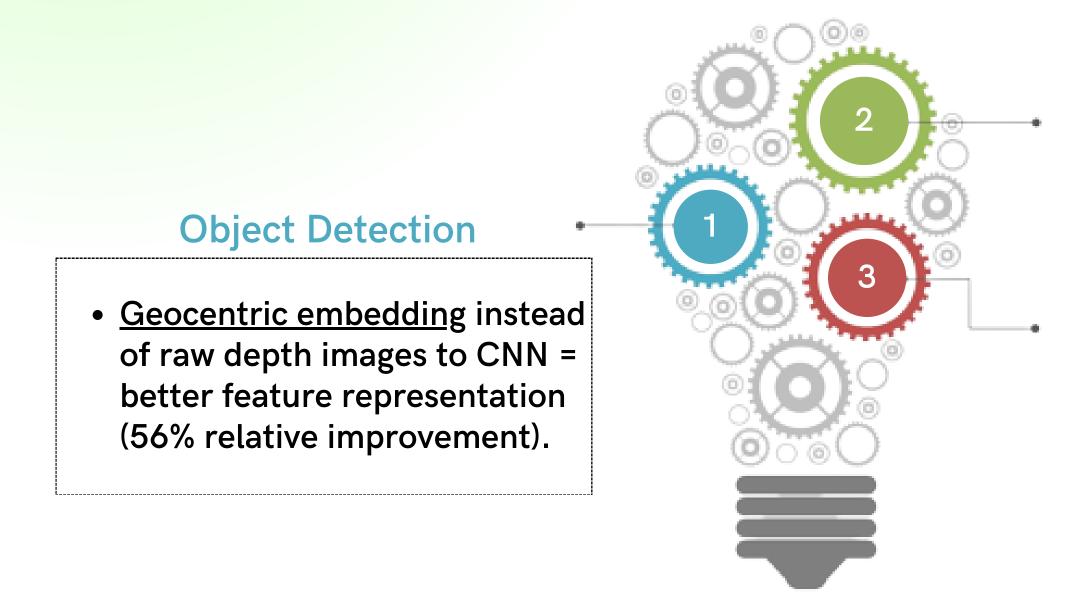


(d) Instance segmentation

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



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



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

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

Object Detection

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

Instance Segmentation

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Object Detection

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

Semantic Segmentation

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

Overview: Proposed Pipeline ->

Architecture of the integrated system

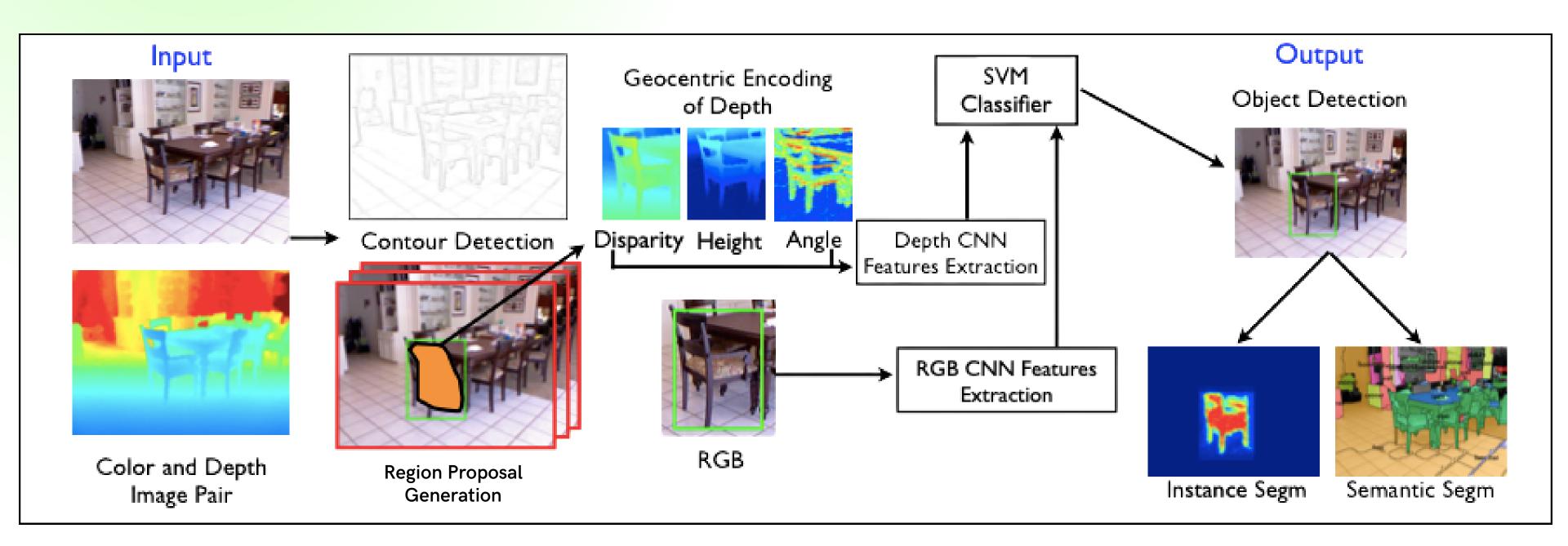
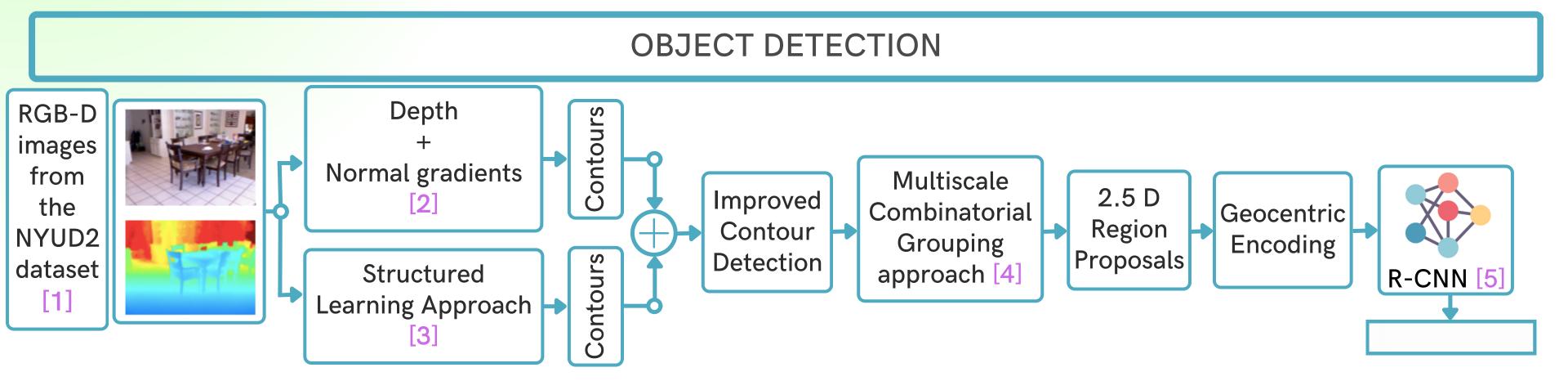
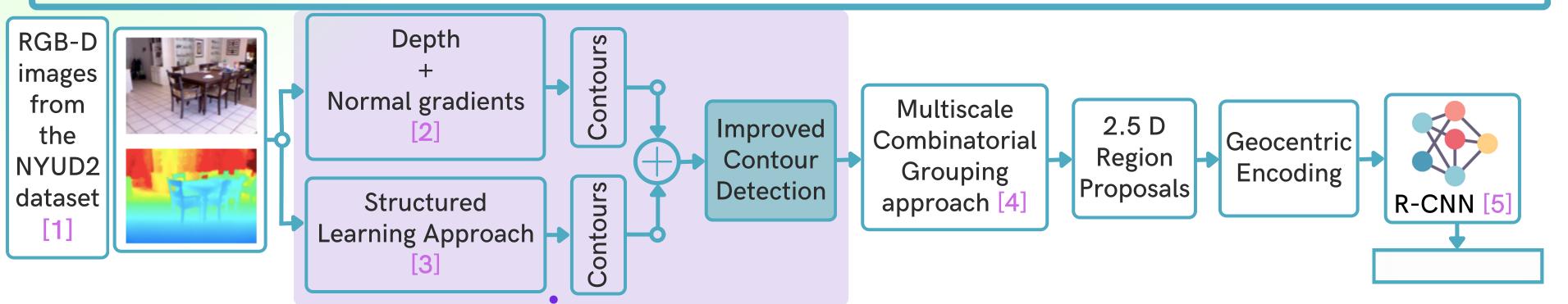


Fig 1. Overview: from an RGB and depth image pair, the system detects contours, generates 2.5D region proposals, classifies them into object categories, and then infers segmentation masks for instances of "thing"-like objects, as well as labels for pixels belonging to "stuff"-like categories.



OBJECT DETECTION

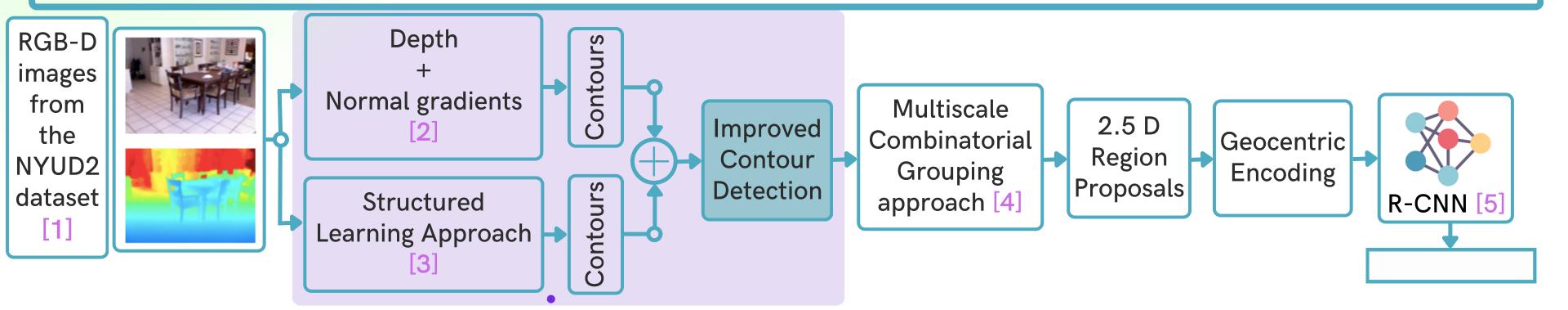


[2] uses gPb_ucm [6] and proposed local geometric gradients dubbed NG-, NG+ and DG to capture convex, concave normal gradients and depth gradients

[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

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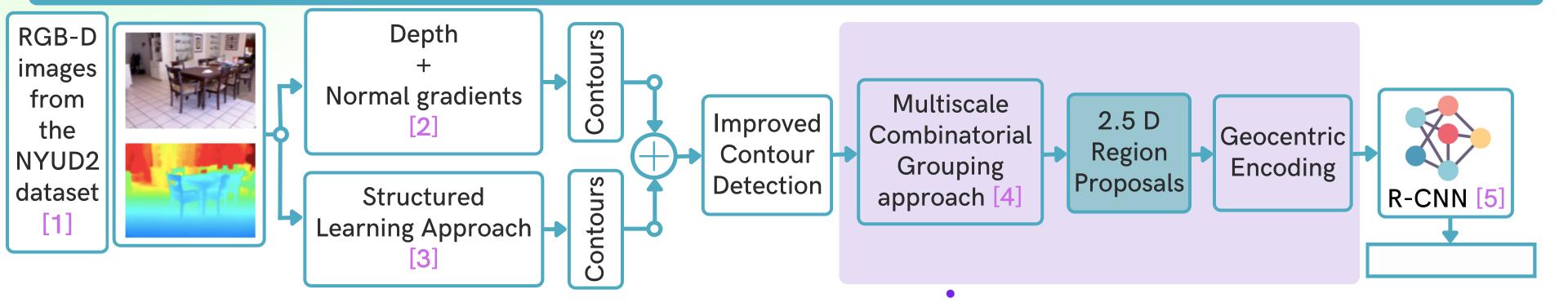




Contours from proposed approach

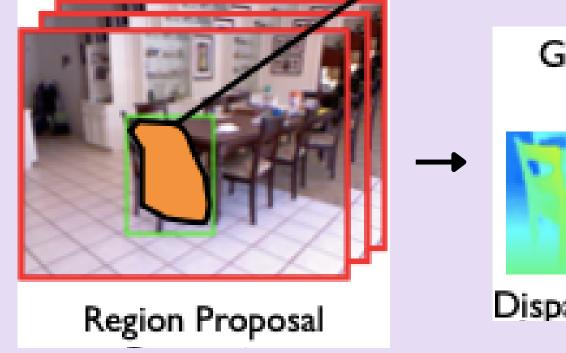
[2]

OBJECT DETECTION



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 of Depth

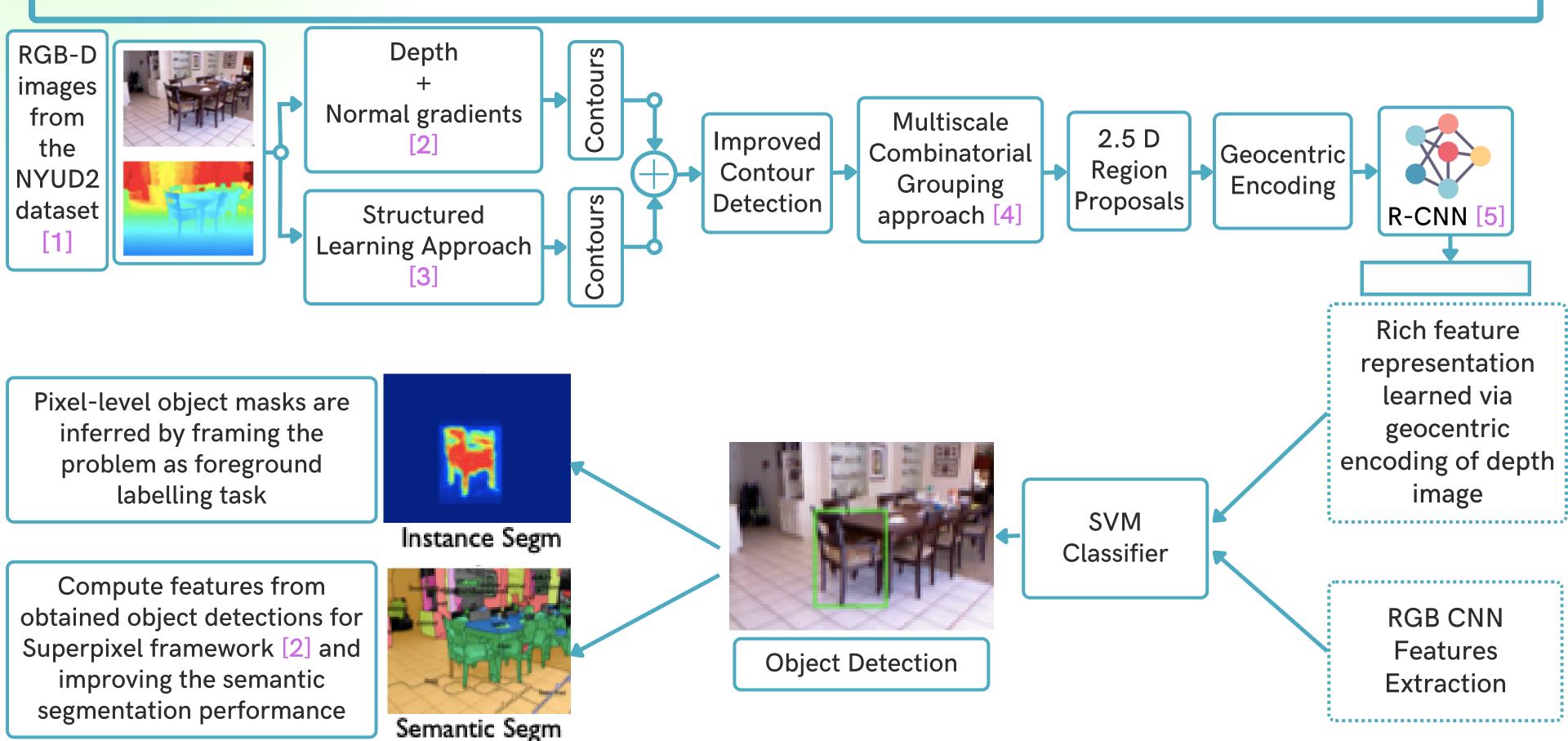
Disparity Height Angle

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

OBJECT DETECTION Depth RGB-D Contours images Normal gradients from Multiscale 2.5 D Improved the Combinatorial Geocentric Region Contour NYUD2 Encoding Grouping Proposals Detection Contours dataset Structured approach [4] **R-CNN** [5] Learning Approach -[3]

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

OBJECT DETECTION + INSTANCE SEGMENTATION + SEMANTIC SEGMENTATION



RESULTS

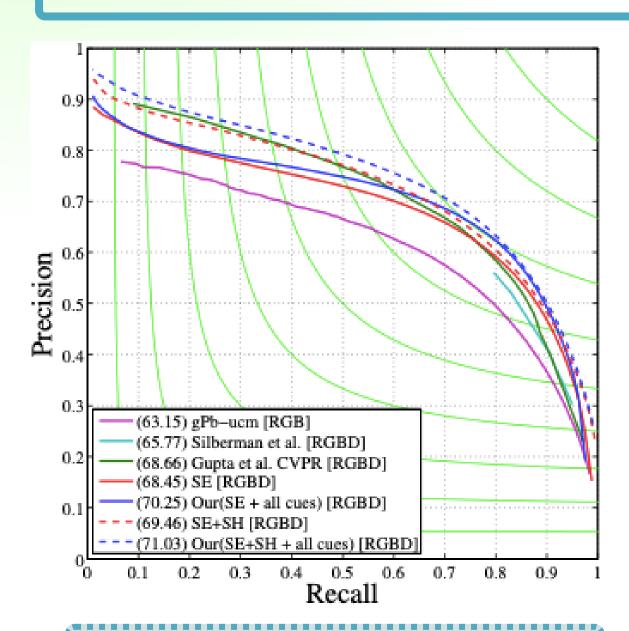


Fig 2: Precision-Recall curve on boundaries on the NYUD2 dataset

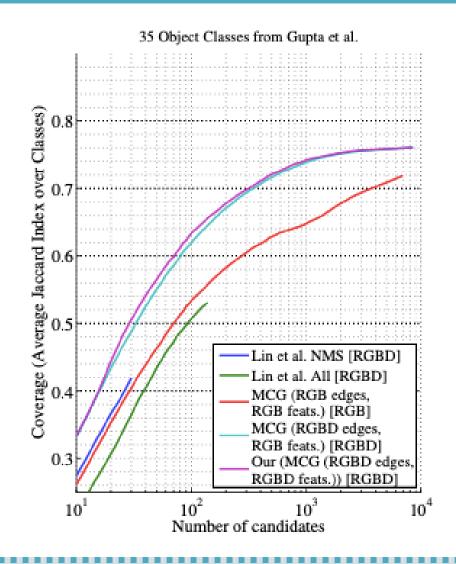


Fig. 4. Region Proposal Quality: Coverage as a function of the number of region proposals per image: Depth-based region proposals using the improved RGB-D contours work better than all past approaches, while at the same time being more general. Note that the X-axis is on a log scale.

OBJECT DETECTION

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

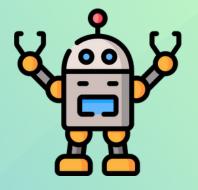
Why is this Problem → Interesting

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

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

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

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

Data Quality

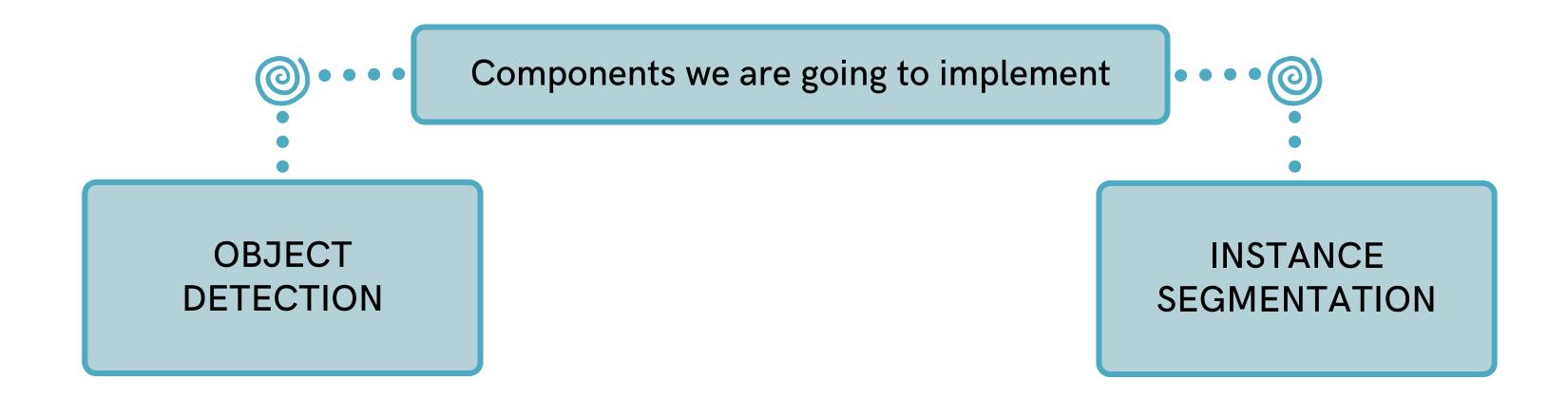
Computational Complexity

Variability in object appearance

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 faster R-CNN

Using v2 of NYUD dataset

Replace SVM classifier with a Deep Learning base method

Timeline ->



4 Apr

Write code for 2.5 D region proposal.



8 Apr

Implement geocentric encoding of depth information



10 Apr

Fine tune R-CNN for geocentric encoding.



12 Apr

Random forest for instance segmentation.

Timeline ->



14 Apr

Implement Semantic Segmentation.



16 Apr

Replace SVM classifier for object detection.



18 Apr

Replace R-CNN with faster R-CNN.



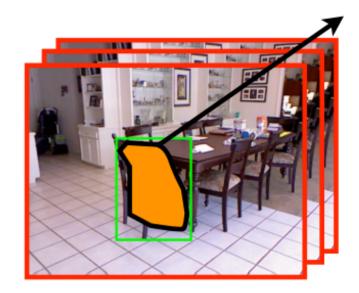
21 Apr

Final presentation.

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)

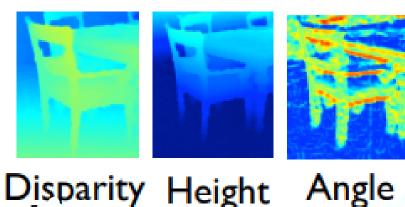


Region Proposal Generation

Encoding Depth Images for Feature Learning

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





Team ->



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Roll No: 2019115005

Work Distribution ->

Feature Representation

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

Segmentation Pipeline

- SVM Classifier
 Deepti, Mihir
- Instance Segmentation Rishabh, Kshitijaa
- Semantic Segmentation
 Deepti, Mihir

Proposed Changes

- Faster R-CNN
 Mihir, Kshitijaa
- Objective of the control of the c
- Instance Segmentation
 Deepti, Rishabh

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)