

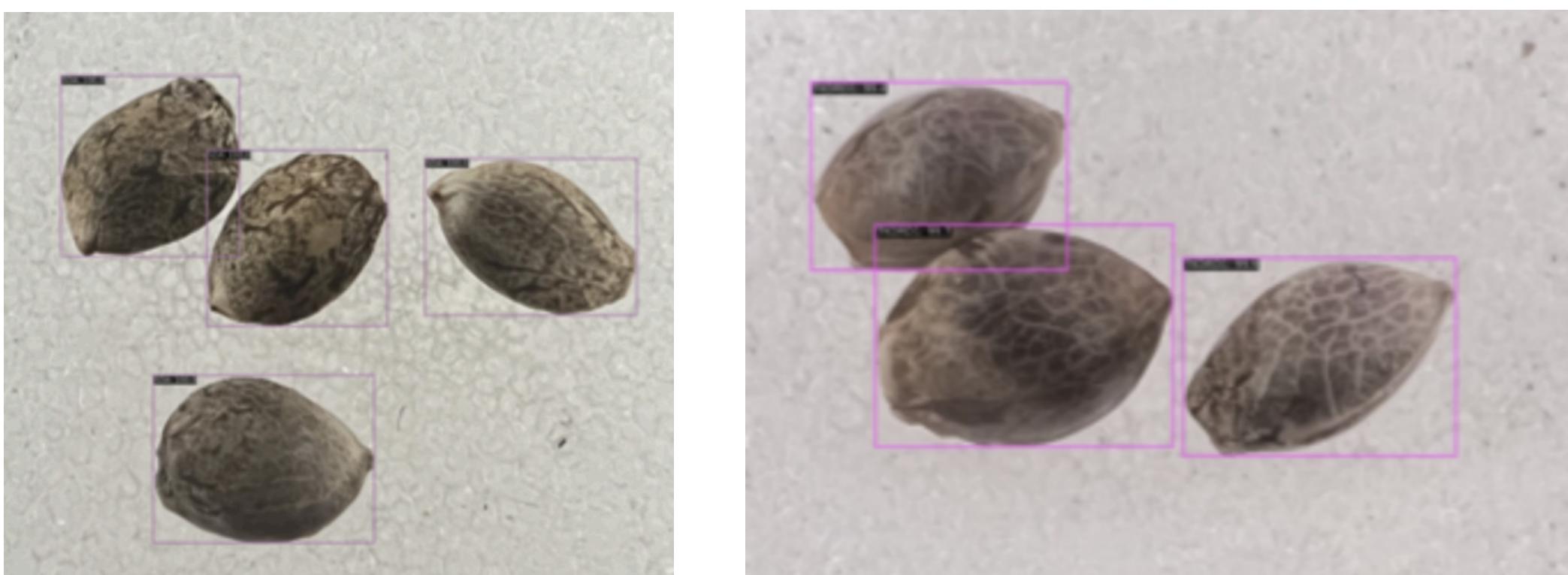
Taminul Islam<sup>a</sup>, Toqi Tahamid Sarker<sup>a</sup>, Khaled R Ahmed<sup>a</sup>, Naoufal Lakhssassi<sup>b</sup>

<sup>a</sup> BASE Lab, School of Computing, Southern Illinois University, Carbondale, IL 62901, United States

<sup>b</sup> Department of Plant, Soil, and Agricultural Systems, Southern Illinois University, Carbondale, IL 62901, United States

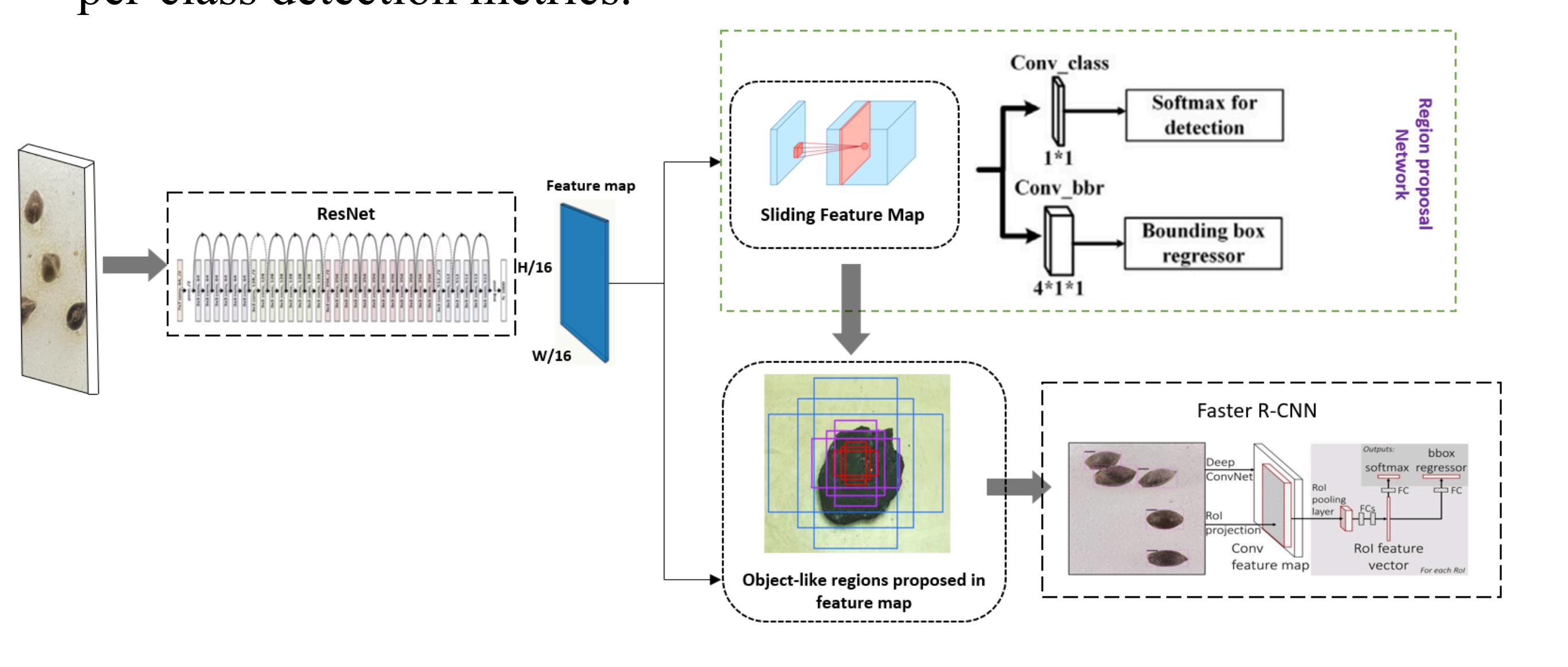
## Motivation

- Address limitations of manual cannabis seed detection methods in terms of accuracy.
- Leverage deep learning models to automate cannabis seed classification.
- Improve efficiency in seed quality control and regulatory compliance using AI technology.



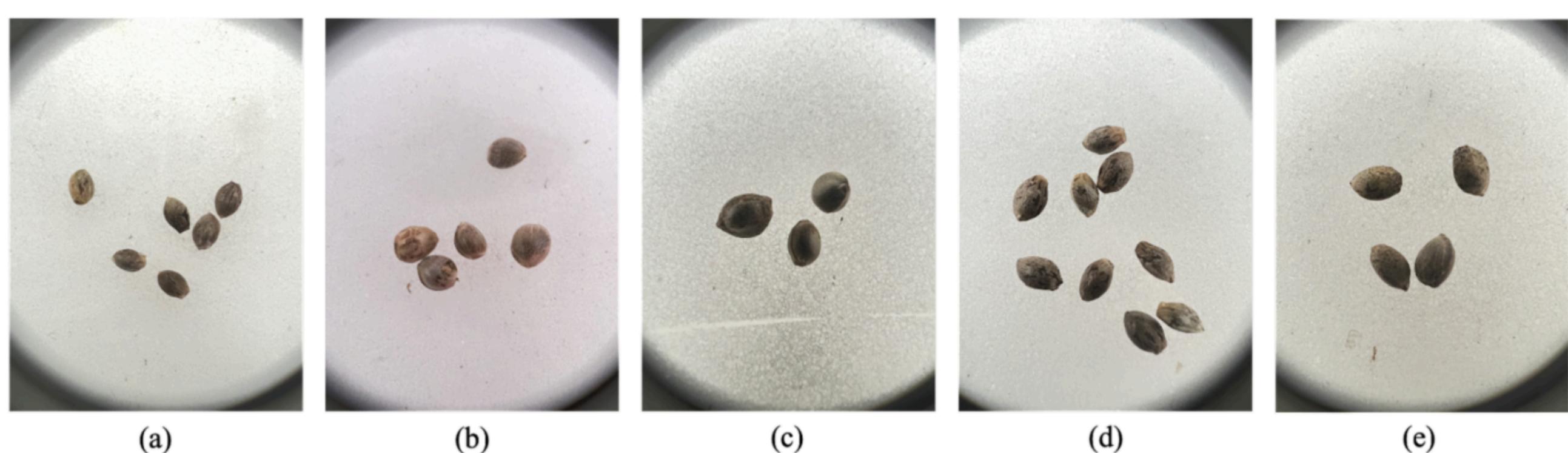
## Contributions

- Enhanced cannabis seed detection by comparing Faster R-CNN with RetinaNet for performance.
- Classified 17 cannabis seed varieties with enhanced accuracy using state-of-the-art models.
- Provided comprehensive evaluation on model performance, speed, and per-class detection metrics.



Architecture of the Faster R-CNN network. The input image undergoes feature extraction via a ResNet backbone, producing a high-dimensional feature map.

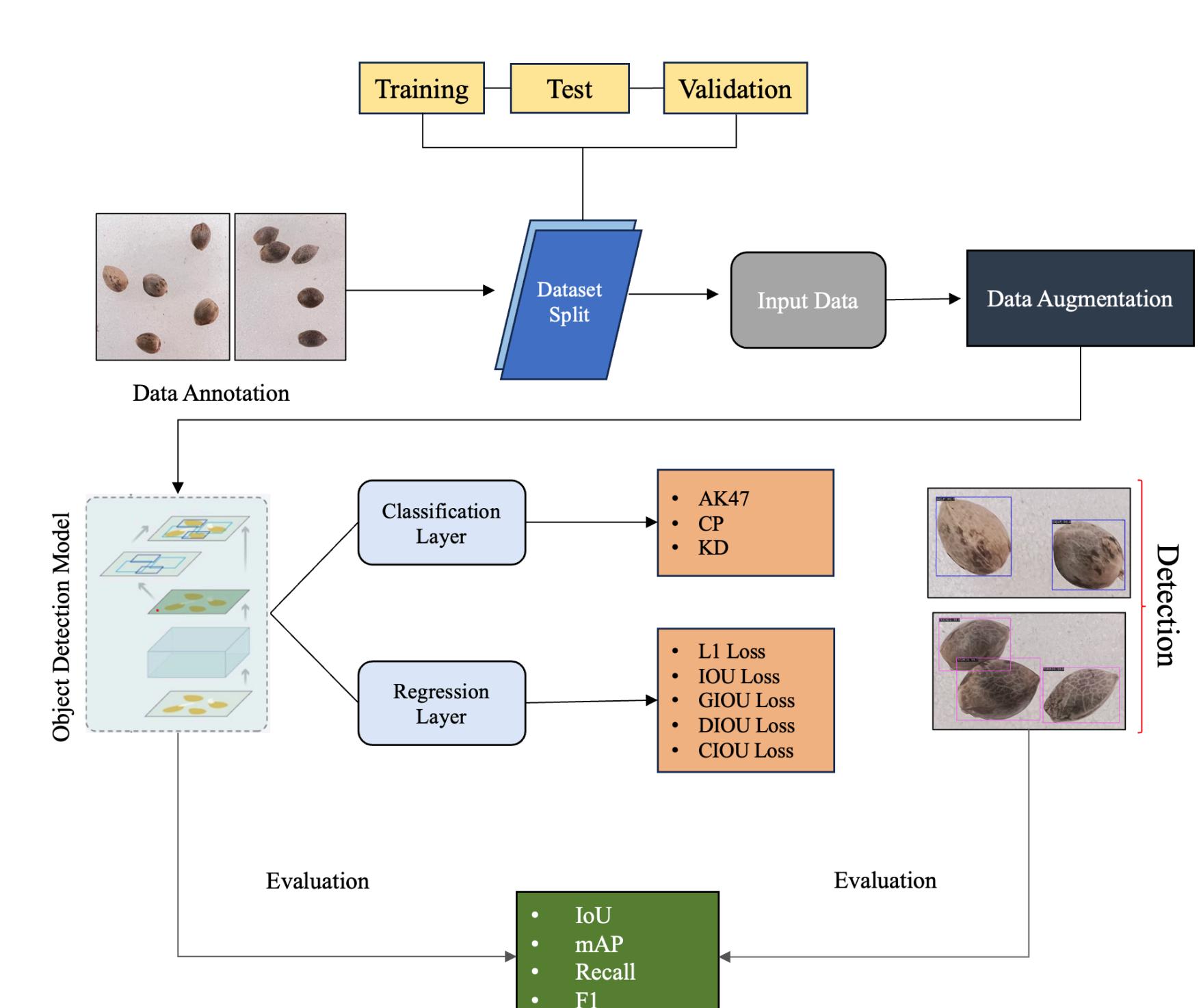
- The original dataset [1] of 3319 high-resolution images representing 17 cannabis seed varieties, captured using an iPhone 13 Pro with dimensions of  $3024 \times 4032$  pixels at 72 dpi resolution.
- Images were taken from multiple angles under varied lighting conditions and annotated using Grounding DINO [2] for precise bounding boxes.



High-resolution images of five different cannabis seed types. The seeds, ranging from 2 to 5 mm in size, include (a) AK47, (b) Gelato, (c) Gorilla Purple, (d) Kd\_kt, and (e) Sour Diesel Auto.

## Methodology

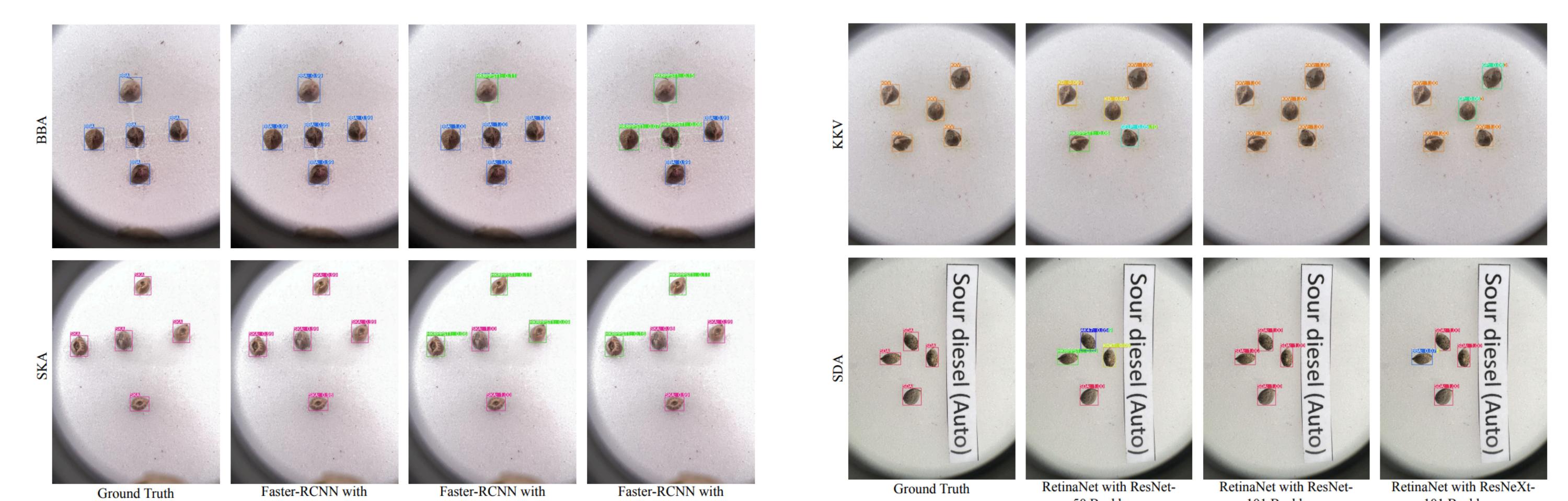
- Applied data augmentation techniques, including flipping, scaling, and color adjustments.
- Trained Faster R-CNN and RetinaNet models using ResNet 50, ResNet101, and ResNeXt101 backbones for seed detection and classification.
- Evaluated model performance using metrics like mAP, recall, F1 score, and inference speed.



## Result

- RetinaNet with ResNet101 achieved the highest mAP of 0.9458, surpassing Faster R-CNN's 0.9408.
- Faster R-CNN with ResNeXt101 demonstrated the fastest inference speed at 17.5 FPS, outperforming other models.

Model	Backbone	mAP@0.5:0.95	mAP@0.5	Avg Recall	F1 Score	FPS
RetinaNet	ResNet50	0.9449	0.9485	0.982	0.9631	16.1
RetinaNet	ResNet101	<b>0.9458</b>	<b>0.9481</b>	<b>0.985</b>	<b>0.9650</b>	15.1
RetinaNet	ResNeXt101	0.9426	0.9448	0.970	0.9561	14.5
Faster R-CNN (Our Previous Work)	ResNet50	0.9408	0.9428	0.973	0.9566	16.8
Faster R-CNN	ResNet101	0.9372	0.9418	0.967	0.9519	14.2
Faster R-CNN	ResNeXt101	0.9352	0.9389	0.961	0.9479	<b>17.5</b>



Qualitative results of Faster R-CNN models with different backbones

Qualitative results of RetinaNet models with different backbones

## Dataset

Seed Variant	Abbreviation	Number of Collected Images
AK47 photo	AK47	106
Blackberry (Auto)	BBA	203
Cherry Pie	CP	50
Gelato	GELP	327
Gorilla Purple	GP	554
Hang Kra Rog Ku	HKRKU	153
Hang Kra Rog Phu Phan ST1	HKRPPST1	249
Hang Suea Sakon Nakhon TT1	HSSNTT1	93
Kd	KD	49
Kd_kt	KDKT	147
Kreng Ka Via	KKV	141
Purple Duck	PD	151
Skunk (Auto)	SKA	233
Sour Diesel (Auto)	SDA	327
Tanaosri Kan Daeng RD1	TKDRD1	157
Tanaosri Kan Kaw WA1	TKKWA1	183
Thastick Foi Thong	TFT	212
Total		3335

## References

[1] Chumchu, P.; Patil, K. Dataset of cannabis seeds for machine learning applications. *Data Brief* 2023, 47, 108954.

[2] Liu, S.; et al. Grounding DINO: Marrying DINO with grounded pre-training for open-set object detection. arXiv 2023, arXiv:2303.05499.

