

Food Watch

A CV app for Allergen Detection

Computer Vision Final Project
2026



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Starting point

**ALLERGEN30: DETECTING FOOD ITEMS WITH POSSIBLE ALLERGENS
USING DEEP LEARNING-BASED COMPUTER VISION^[1]**

- By Mishra, M., Sarkar, T., Choudhury, T. et al. 2022
- Food allergies impose a significant health concern on the community
- Presents a new food allergen dataset
- Develops different CV allergen recognition models



The Allergens

The paper pinpoints 6 main allergens

Ovomucoid



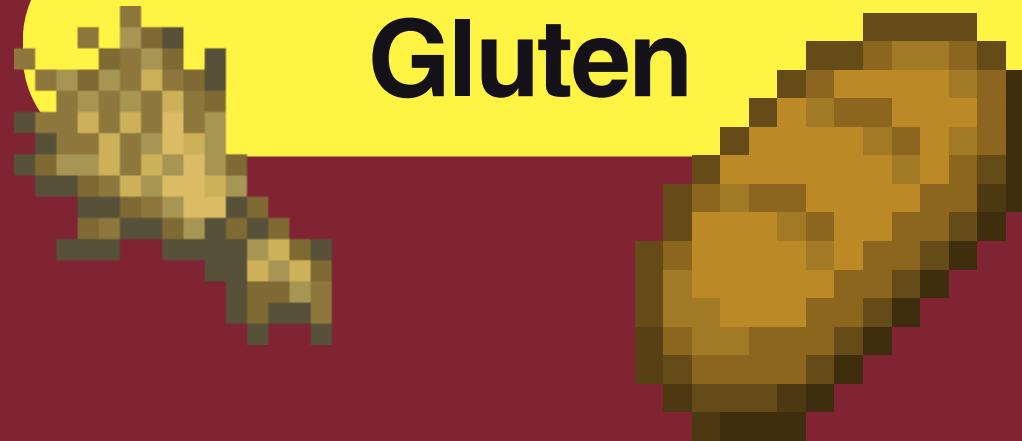
Lactose



Histamine



Gluten



Salicylate



Caffeine





The Dataset

Allergen30

Dataset Overview

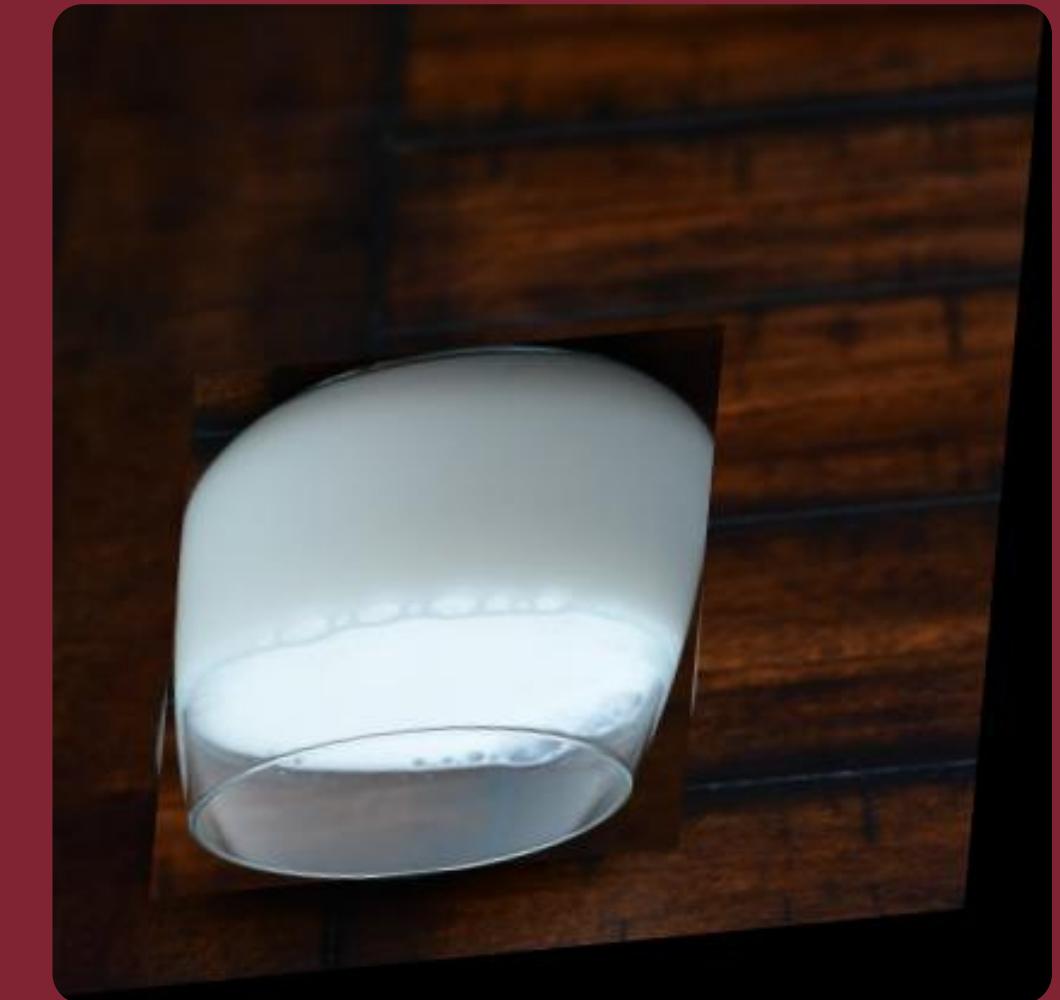
14.5K 416*416 FOOD IMAGES DIVIDED IN 30 CLASSES AND HAND LABELED

Train-Test Split

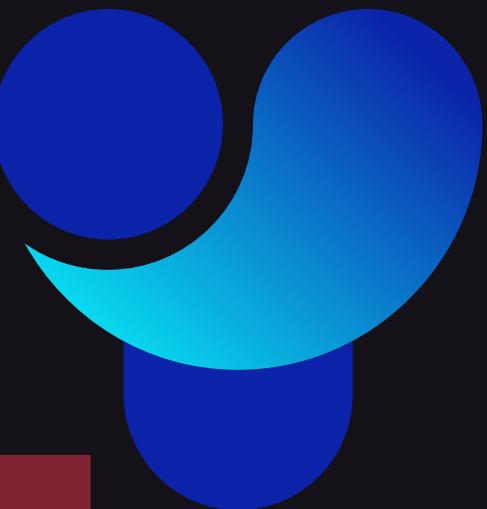
**TRAIN SET 70%
VAL SET 20%
TEST SET 10%**

Augmentation

**RANDOM SHEAR OF $\pm 15^\circ$ HORIZONTALLY AND $\pm 15^\circ$ VERTICALLY
RANDOM 90° ROTATIONS OF THE BOUNDING BOXES**



Sample train image with shear and 180° box rotation



Paper's models

<i>MODEL</i>	<i>PRECISION</i>	<i>RECALL</i>	<i>F1</i>	<i>MAP</i>
YOLOv5s	0.801	0.681	0.7361	0.747
YOLOv5m	0.861	0.679	0.7592	0.749
YOLOv5l	0.845	0.707	0.7698	0.766
YOLOR	0.830	0.741	0.7829	0.811



The Model YOLOv5

BACKBONE

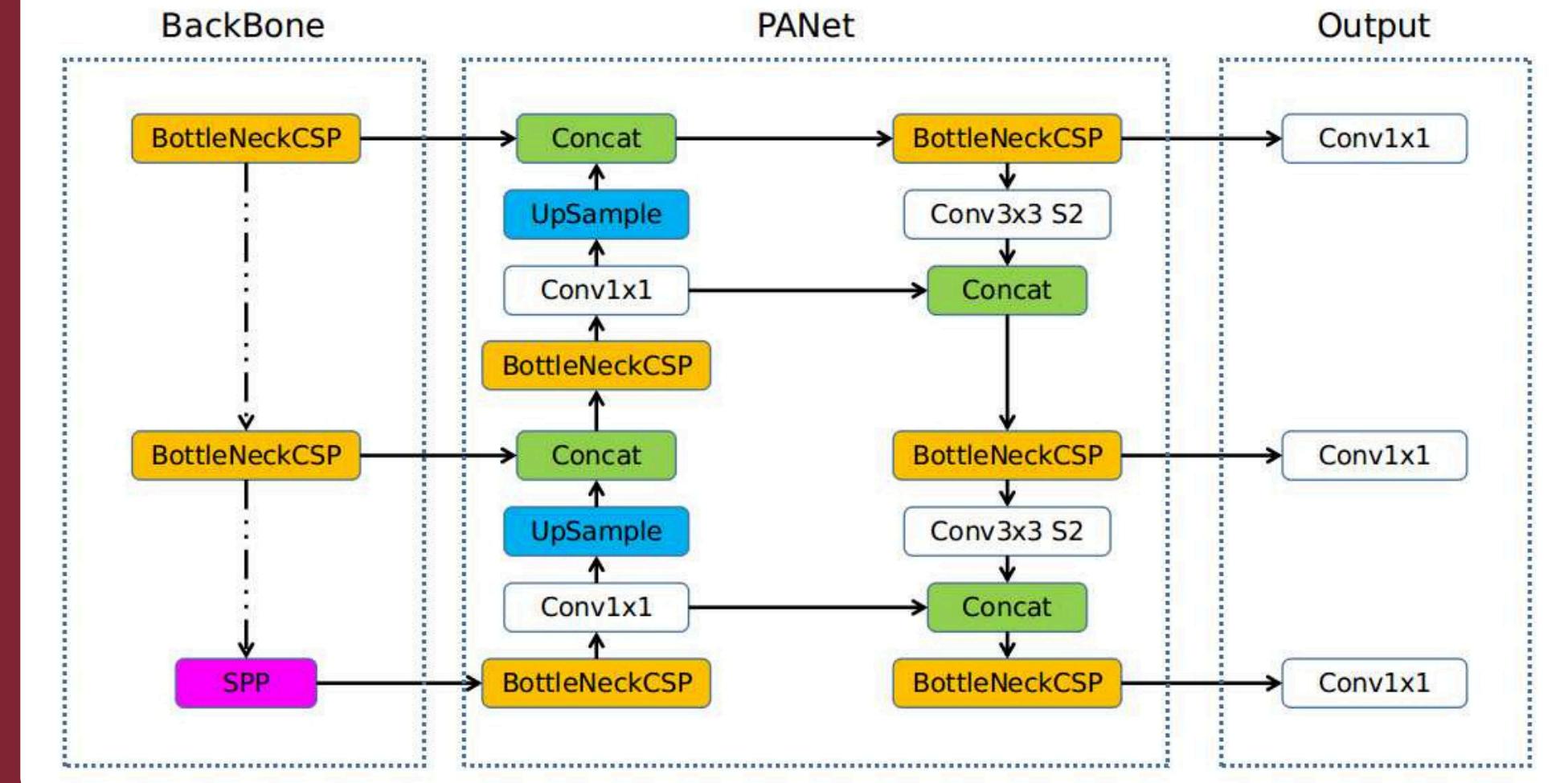
Feature extraction with
BottleNeckCSP and **Spatial
Pyramid Pooling (SPP)** to capture
context at multiple scales

PANet NECK

Feature fusion in two flows:

- one upsamples semantic features then concatenates shallow details.
- the other downsamples and concatenates

Overview of YOLOv5



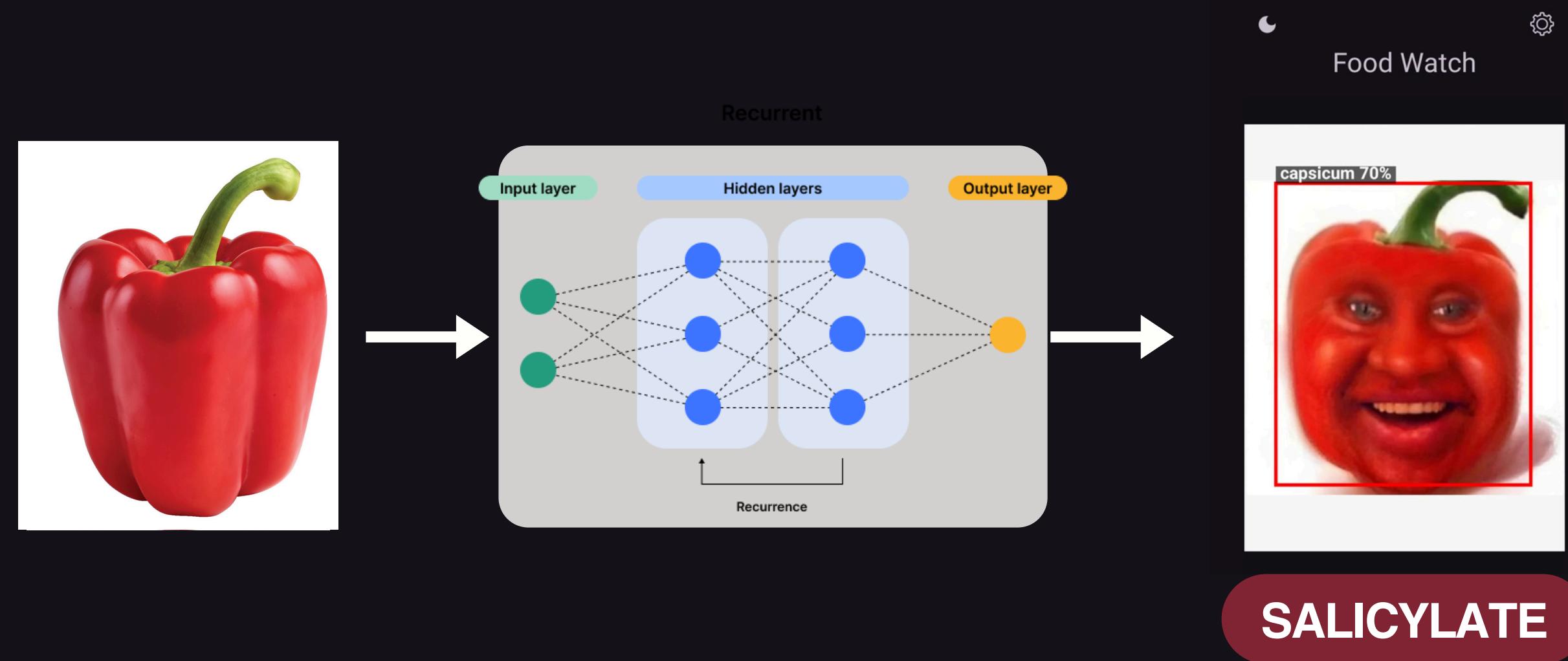
OUTPUT

Three heads to make
predictions on different
scales simultaneously



FOOD WATCH

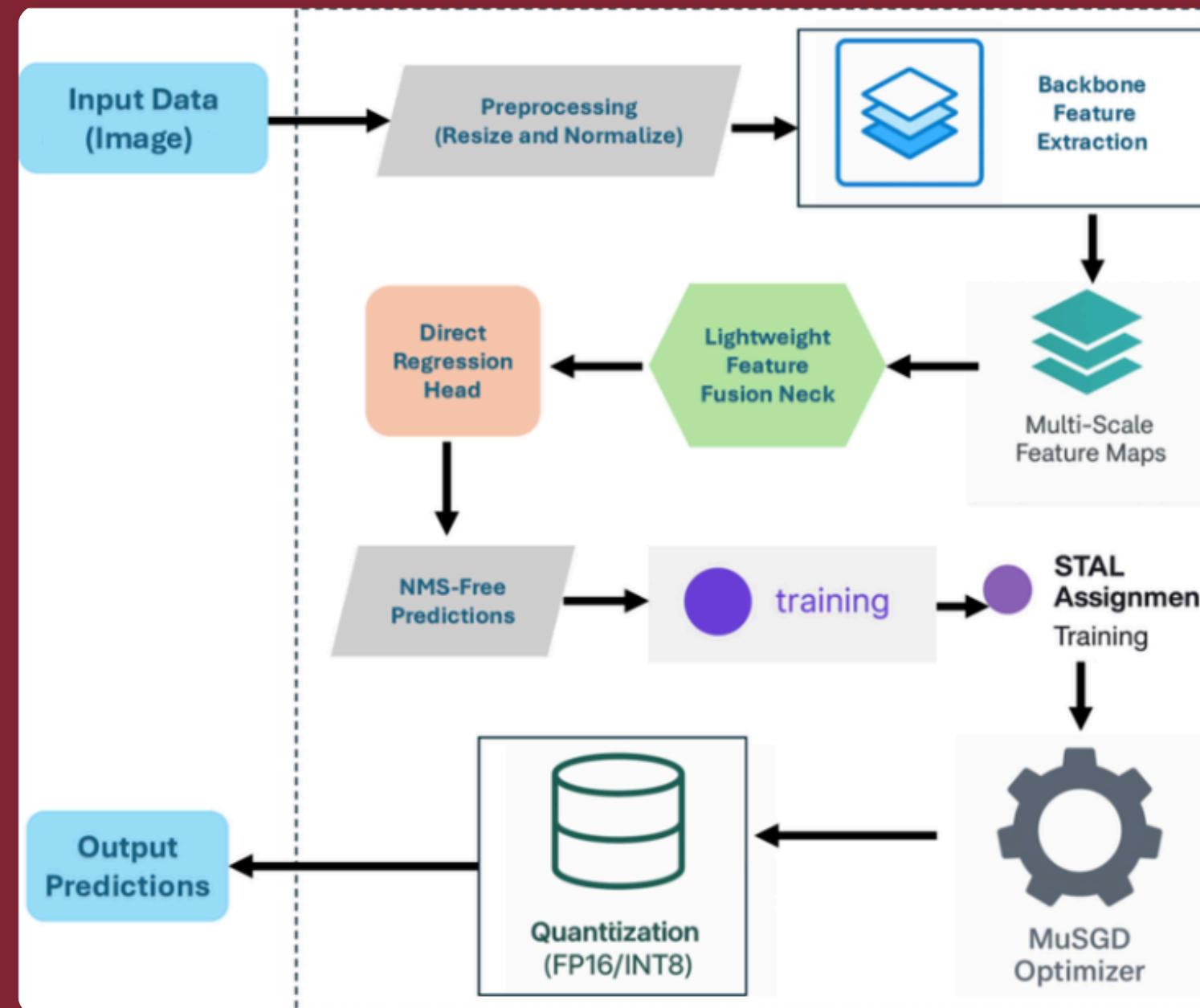
Our Goal



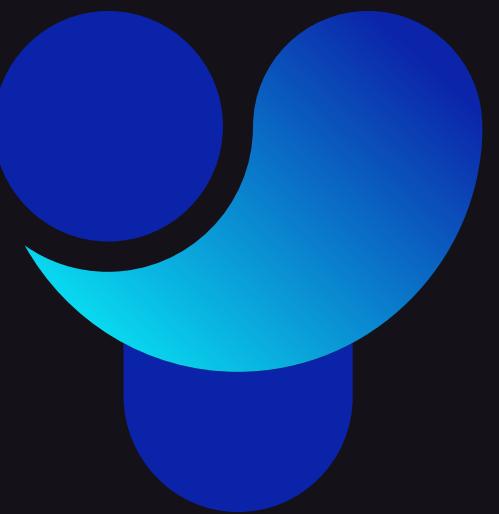
- Develop a fast object detection model for mobile use
- Beat the previous models' performances



The Model YOLO26

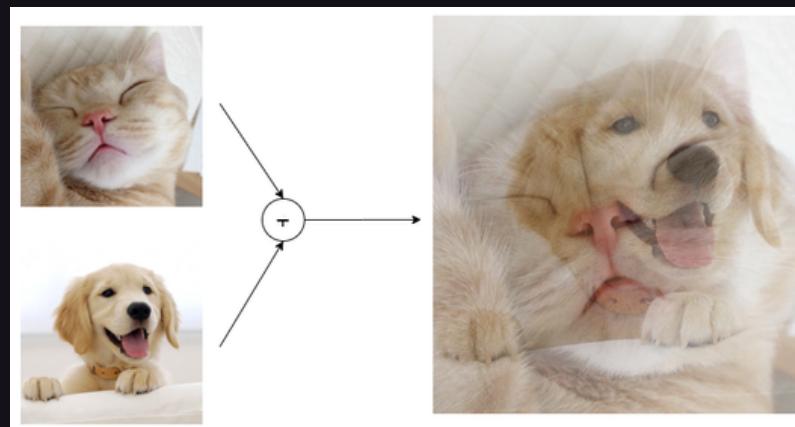


- Using **lightweight backbone** and feature fusion neck enables feature extraction with minimal CPU usage
- It removes **Distribution Focal Loss (DFL)** for faster CPU inference.
- Adopts a native end-to-end **NMS-free** design based on one to one matching
- **Quantization** enables faster computation with simpler types like INT8
- Aims to **directly predict the final box** avoiding complex post processing steps



Training YOLO26

- 100 Epochs, 32 Batch size with Patience of 25 to enable Early Stopping
- AdamW optimizer with a Starting Learning Rate of 0.001 and a Cosine Scheduler for smooth convergence
- Label Smoothing to prevent overfitting
- To be more robust on smaller objects we combined Mixup and Mosaic



MIXUP



MOSAIC



Evaluation

3 models

<i>MODEL</i>	<i>PRECISION</i>	<i>RECALL</i>	<i>F1</i>	<i>MAP</i>
YOLO26n	0.823	0.636	0.717	0.730
YOLO26s	0.835	0.664	0.740	0.769
YOLO26m	0.838	0.640	0.726	0.746
YOLOv5s	0.801	0.681	0.736	0.747

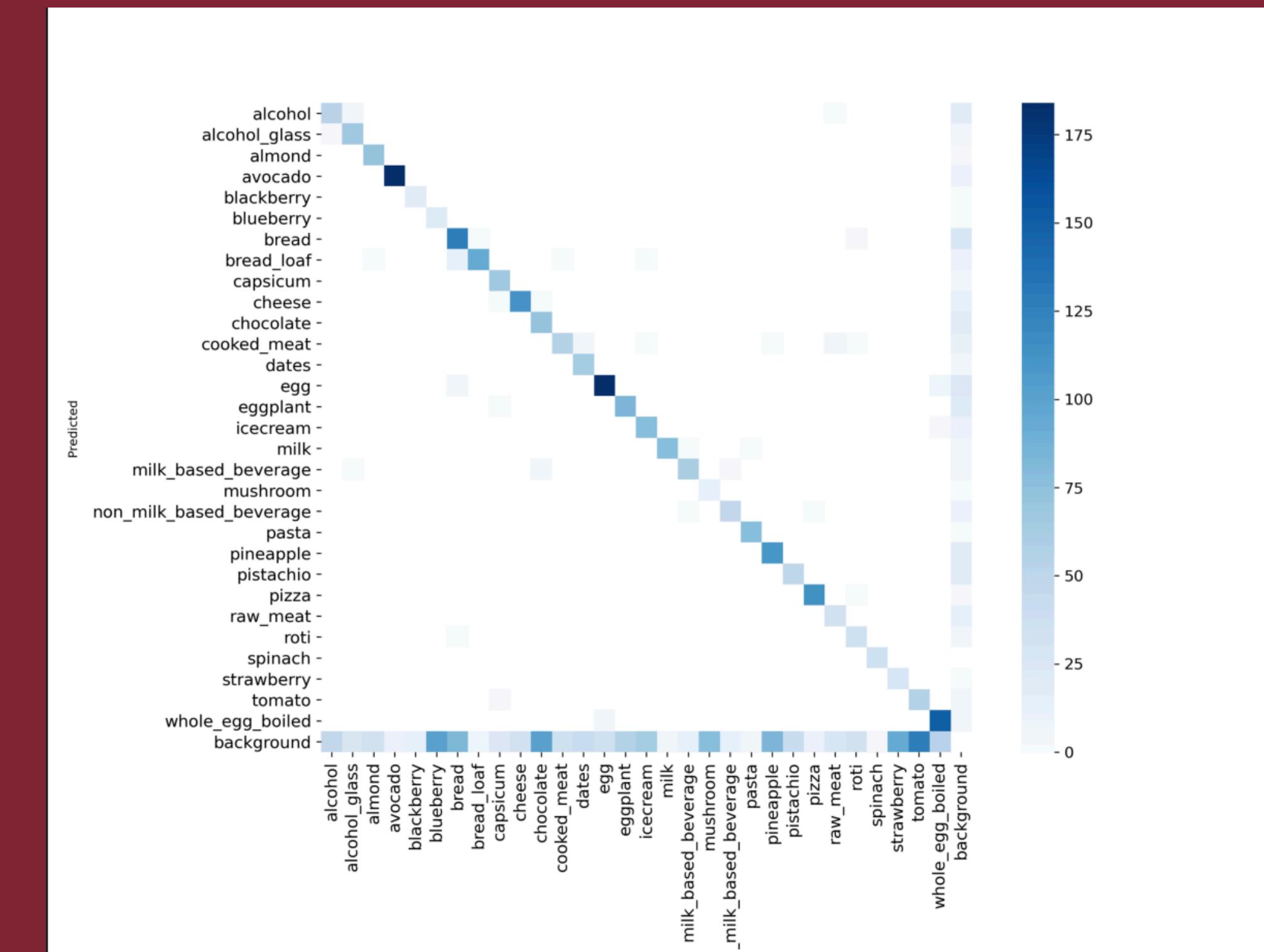


Evaluation

Confusion matrix



- Mushrooms are problematic due to intra-class variance





The App Logic

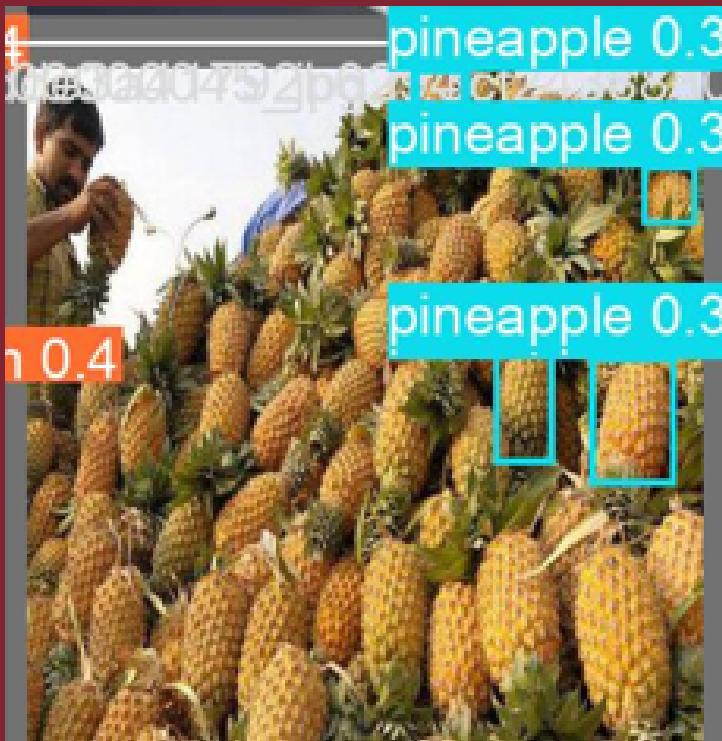
**INITIALLY THE SYSTEM DETECTED LOW CONFIDENCE PREDICTIONS
FOR VARIOUS BACKGROUND TEXTURES**

- We couldn't rely on a global threshold because it would cut out smaller objects
- We implemented a post processing layer directly in Kotlin
- We applied a Hybrid Filtering composed of **Confidence Thresholds** and **Aspect Ratio Physics**



Conclusions *And further developments*

- Our YOLO26s performance is **slightly better** than the paper's results
- We suggest using the small model for mobile production



- Smaller models tend to have low recall on images with multiple instances

EXPAND THE DATASET

- Real scenario images
- Align with EU regulations on allergens^[2]



FOOD WATCH

Thank you for
your attention!

Questions?

[1] Mishra, M., Sarkar, T., Choudhury, T. et al. Allergen30: Detecting Food Items with Possible Allergens Using Deep Learning-Based Computer Vision. *Food Anal. Methods* 15, 3045–3078 (2022); doi: [10.1007/s12161-022-02353-9](https://doi.org/10.1007/s12161-022-02353-9)

[2] EFSA NDA Panel (EFSA Panel on Dietetic Products, Nutrition and Allergies), 2014. Scientific Opinion on the evaluation of allergenic foods and food ingredients for labelling purposes. *EFSA Journal* 2014; doi: [10.2903/j.efsa.2014.3894](https://doi.org/10.2903/j.efsa.2014.3894)