P2P buddy.ai

A Comprehensive Pantry-to-Plate System for
Ingredient Recognition and Recipe Recommendation

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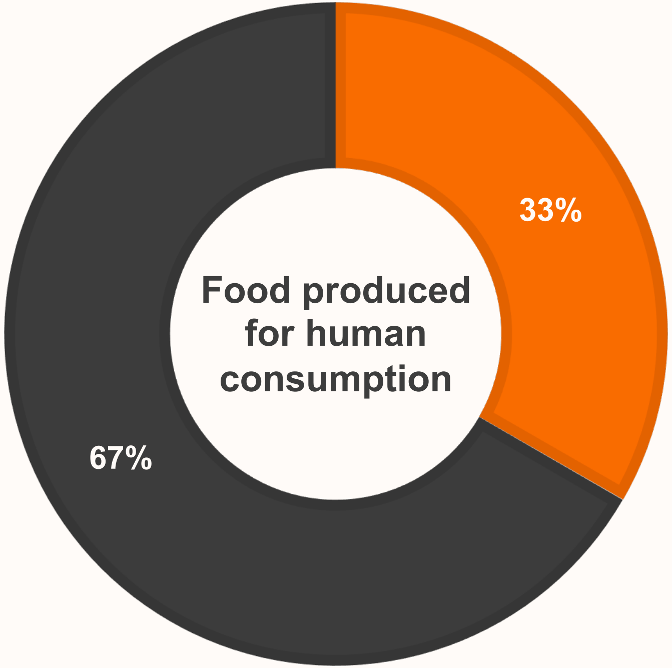
01

Current situation

Food waste is a complex global issue.



$1 trillion

wasted per year globally

Households are the largest contributor

>50%

ECONOMIC

SOCIAL

ENVIRONMENTAL

Source: https://www.wfpusa.org/articles/8-facts-to-know-about-food-waste-and-hunger/

Singapore is no exception.

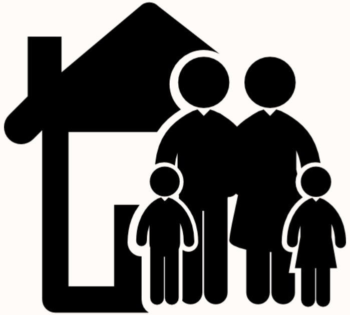
+23%

665mil kg of food thrown away in 2020 → **817mil kg** of food thrown away in 2021

Households contribute about 50%

Source: https://www.towardszerowaste.gov.sg/zero-waste-masterplan/

Singapore is no exception.

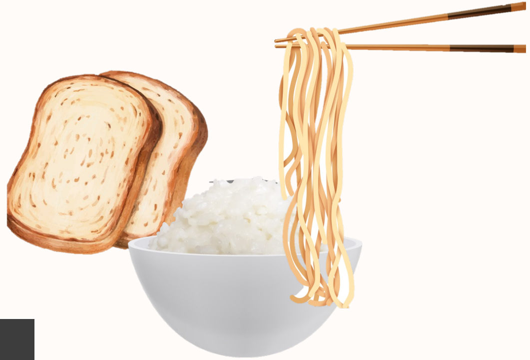


1.4mil
households in Singapore

x

0.75kg
of food waste per household everyday

1.05mil kg
of food wasted at the household level everyday

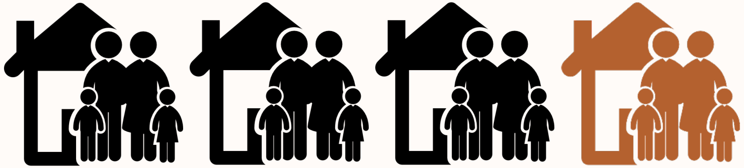


x 365 days

383mil kg
of food wasted at the household level in a year

Source: https://www.towardszerowaste.gov.sg/zero-waste-masterplan/

Why are we wasting food?



1 in 4 households often throw away spoilt or rotten food because they either:

bought too much food or did not realise that they had food hidden at the back of their fridge.

Source: https://www.towardszerowaste.gov.sg/zero-waste-masterplan/

TOWARDS ZERO WASTE

How might we help households deal with excess groceries in their kitchens?

02

Solution aim

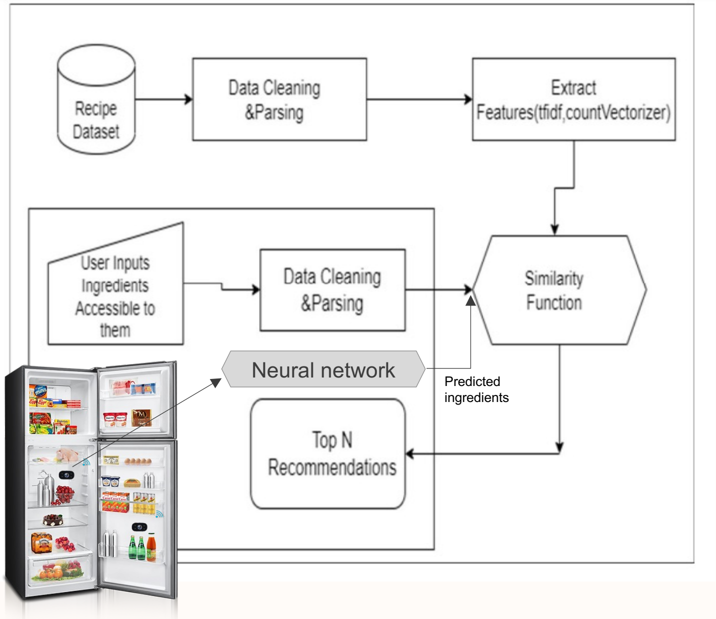
Build an intelligent 2-in-1 tool

- Aim: build a user-friendly and accurate ingredient recognition tool and recipe recommender

- Supervised computer vision machine learning

- Notifies of leftover food and recommends recipes (notifications)

- For a start, we shall start with ingredients laid out on the kitchen countertop/pantry table



Adapted from Chhipa, Shubham, et al. "Recipe Recommendation System Using TF-IDF." ITM Web of Conferences. Vol. 44. EDP Sciences, 2022.

03

Data exploration

Overview:

Recipe dataset

https://themeatmen.sg/all-recipes/

777
recipes

4
features
Text: Directions, Ingredients, Prep time, Difficulty

up to
51 recipes
missing ingredients / missing directions / missing prep time

cleaning and preprocessing recipe dataset

4

features

Text: Directions, Ingredients, Prep time, Difficulty

↓

Clean with Regex, lemmatize, extract ingredient name

No. of ingredients

Clean with Regex, extract prep time in minutes

No. of steps

Map difficulty as ordinal

up to

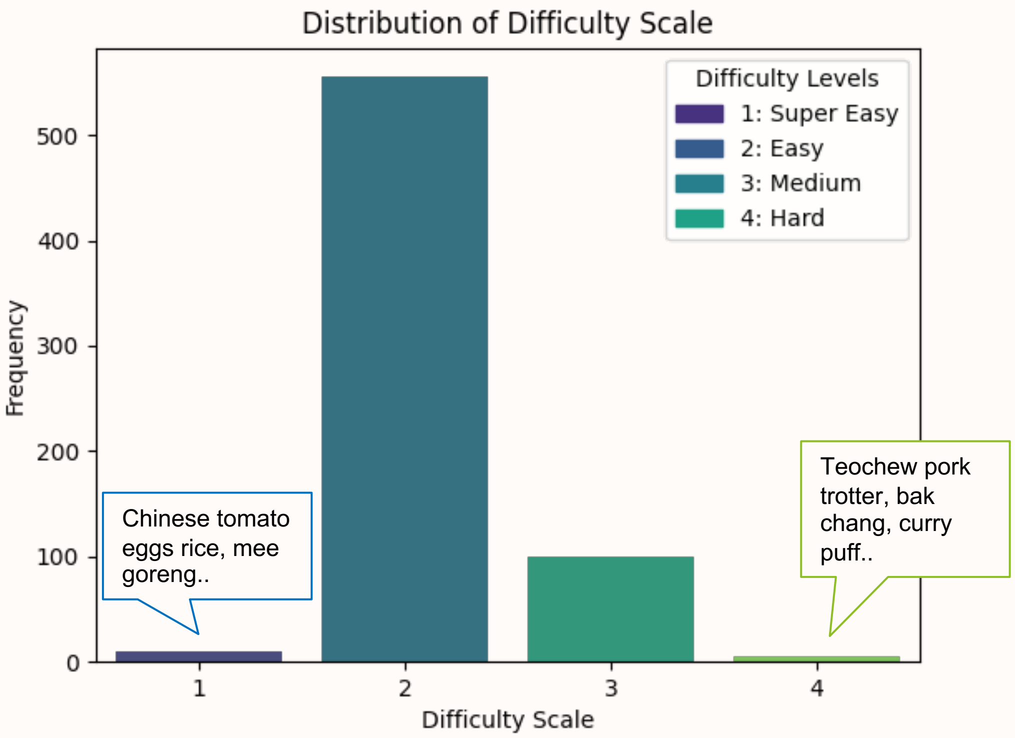
51 recipes

missing ingredients / missing directions / missing prep time

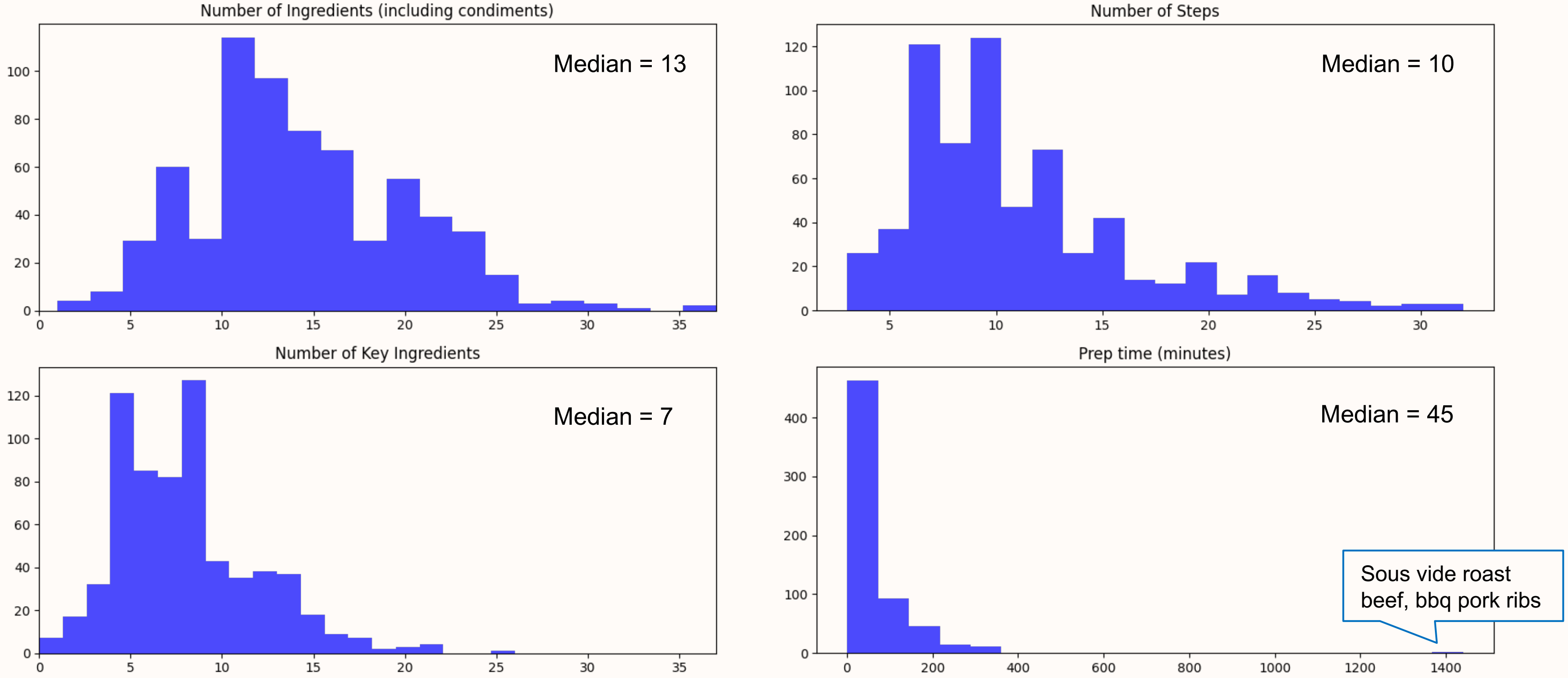
↓

remove recipes with missing ingredients and missing directions – we are unable to recommend these to users

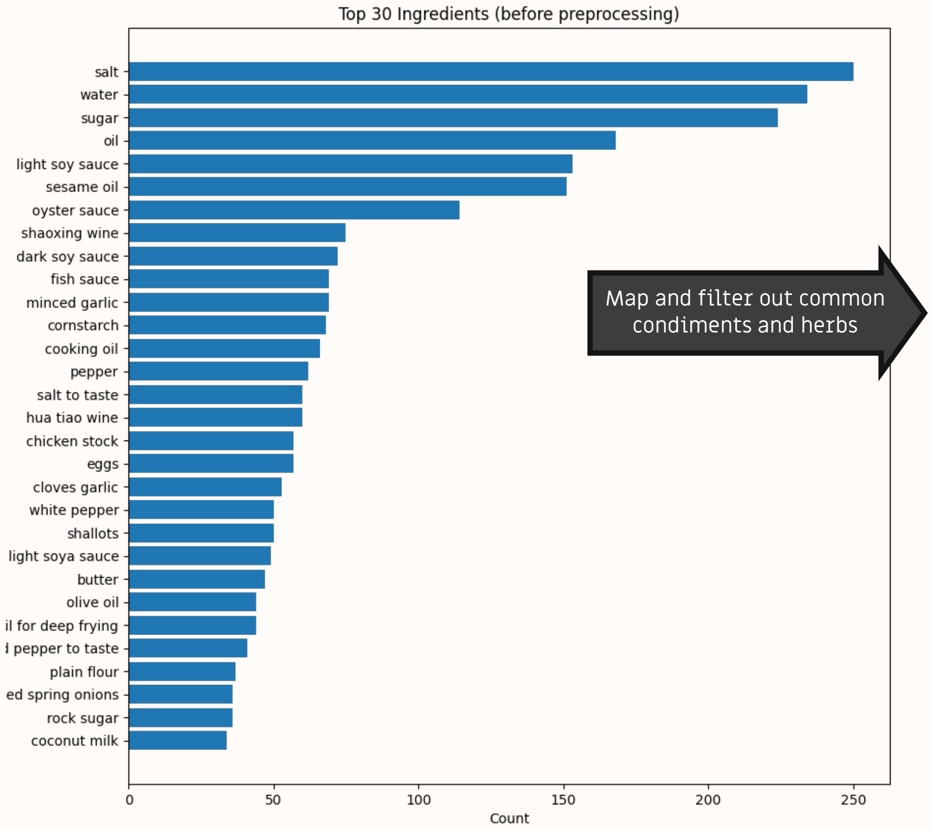
Variety of recipes

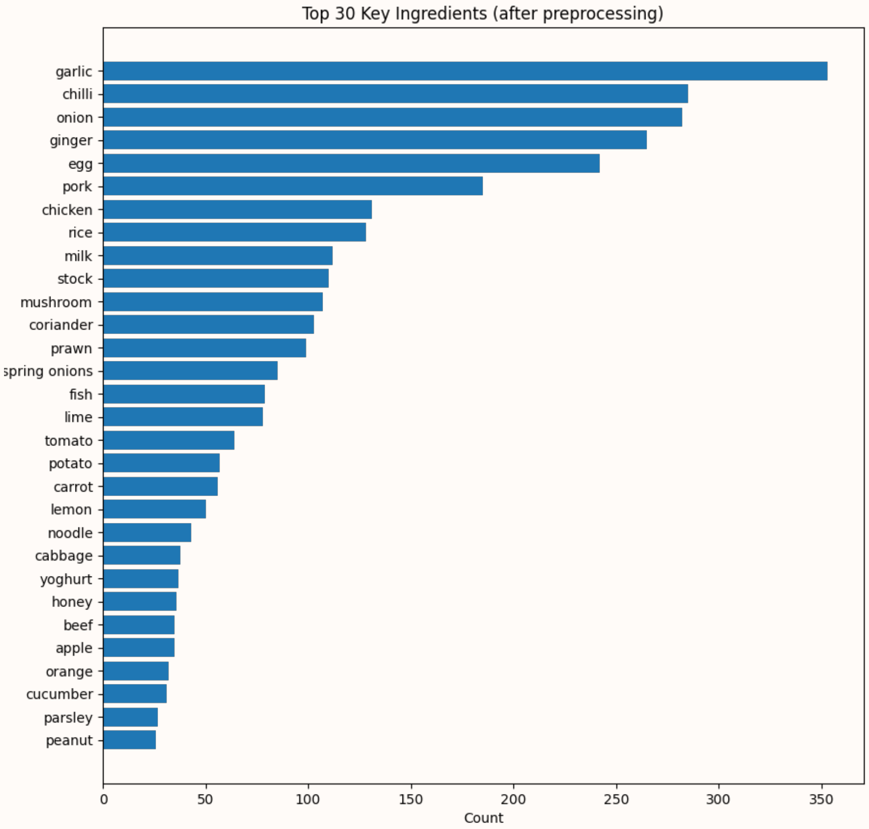


Variety of recipes



Preprocessing is crucial in extracting key ingredients





Overview:

Ingredient images dataset

roboflow

FairPrice

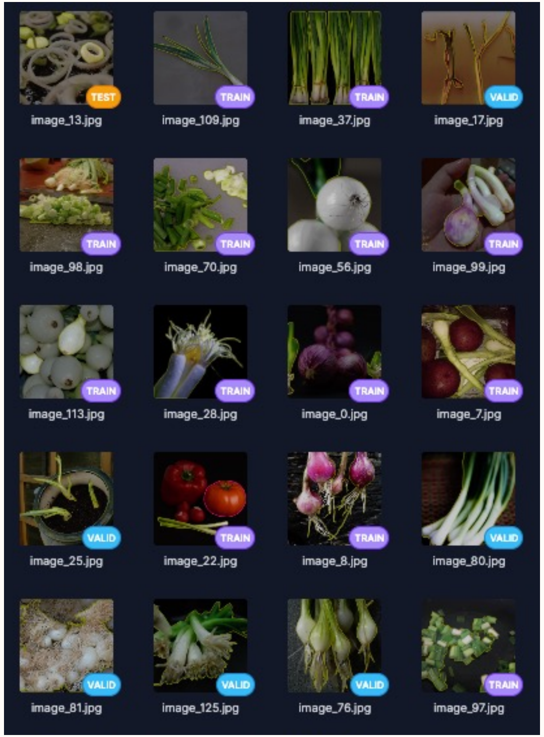
flickr

Visually inspected for relevance

8,942
images

21,810
annotations

30
common
key ingredient classes



04

Modelling

Modelling:
workflow

Preprocess images

Resize

Train Augmentation &
Train-val-test split

Train 85% (6.5k → 13k)
Val 11% (1.6k)
Test 5% (716)

Custom training on Object Detection Models
(pretrained with COCO)

Roboflow

Yolov8s

Yolov8m

Model with Highest mAP proceeds

Tuning & Finalising model

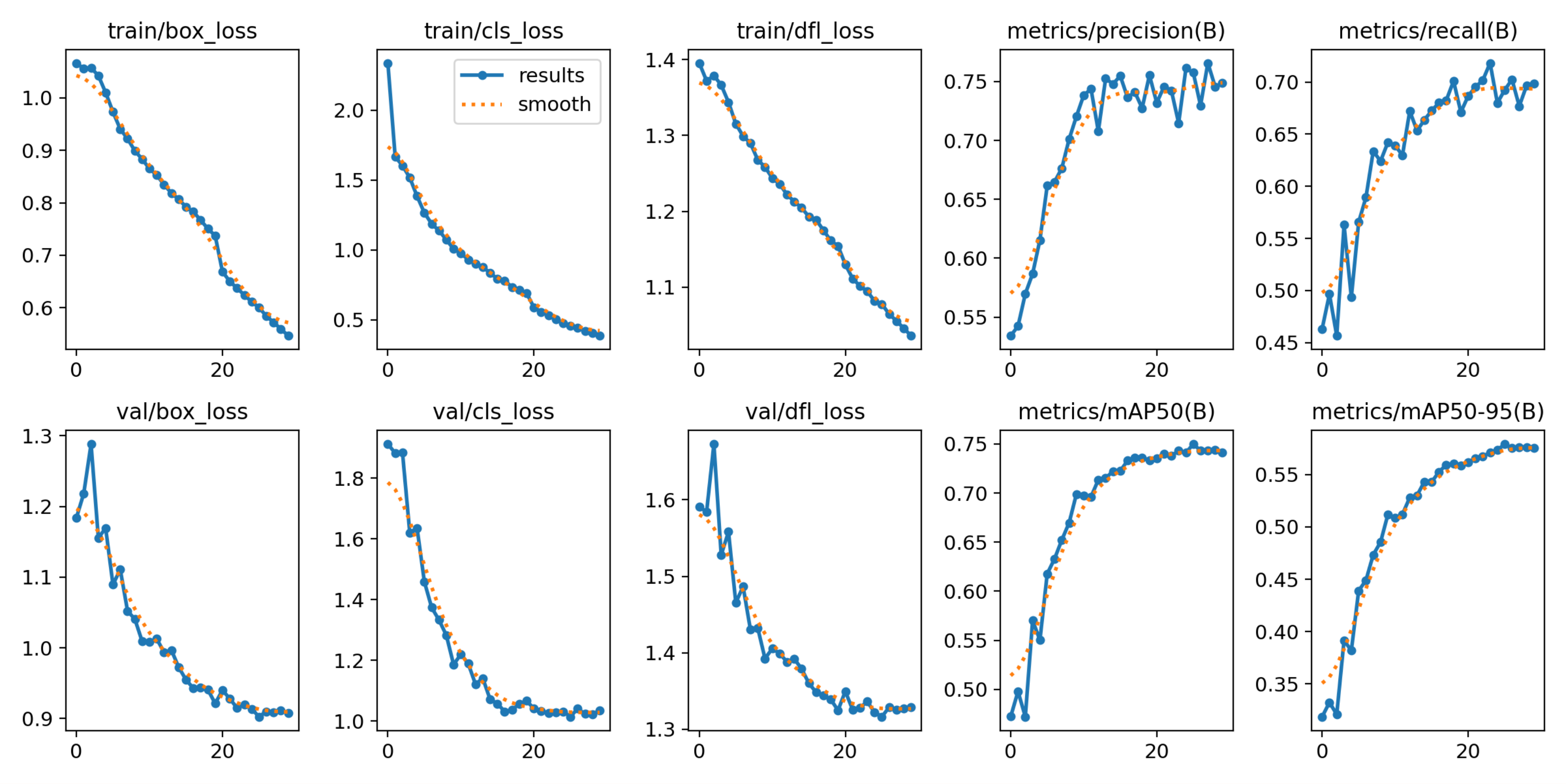
Epochs
Optimiser
Learning rate
Momentum
Weight decay

Modelling:

evaluation summary

	Object detection model	mAP-50
Smaller image dataset (~4k images, 80 classes)	**Roboflow 3.0 (Fast)** 640px	62.9%
	Yolo v8 (small) 800px	50.3% (↓ 12.6pp)
Larger image dataset (~15.5k images, 30 classes)	**Roboflow 3.0 (Fast)** 640px	70.7% (↑ 7.8pp)
	Yolo v8 (small) 800px	72.2% (↑ 9.3pp)
	Yolo v8 (med) 640px	**75.7%** (↑ 12.1pp)

- includes train data augmentation
- Mean Average Precision (mAP) -50 refers to the mean average precision across all classes at Intersection-Over-Union (IOU) threshold of 0.5.

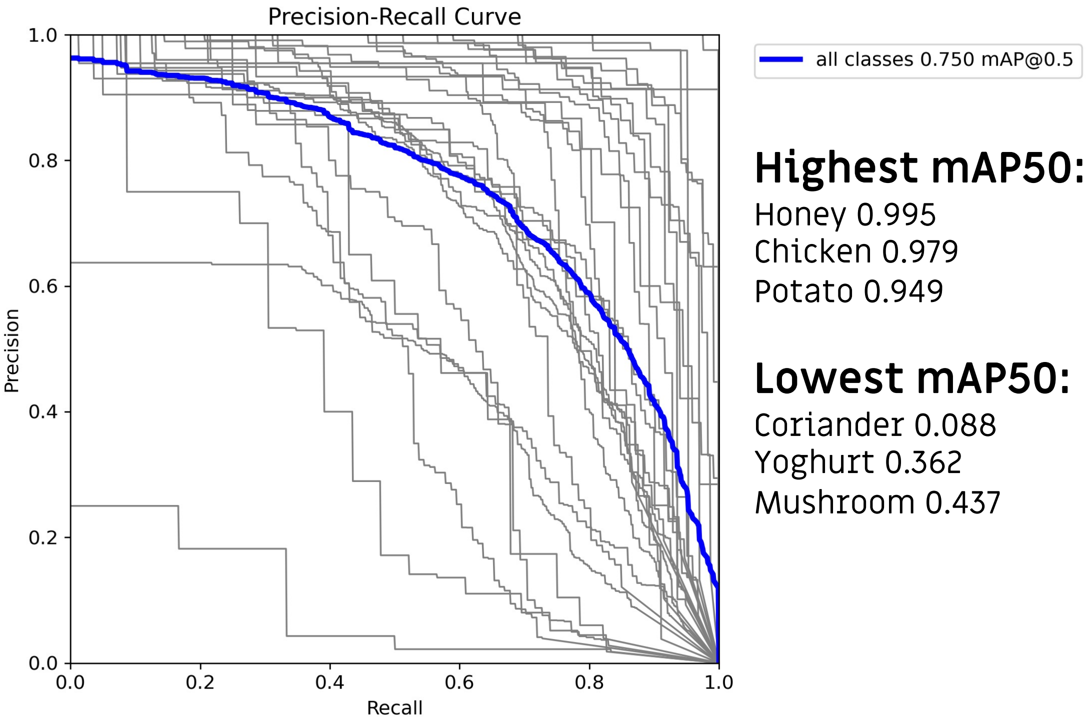


train/box_loss
train/cls_loss
train/dfl_loss
metrics/precision(B)
metrics/recall(B)
results
smooth
val/box_loss
val/cls_loss
val/dfl_loss
metrics/mAP50(B)
metrics/mAP50-95(B)

05

Insights and recommendations

Model is good at correctly identifying and localising most types of ingredients.



Highest mAP50:

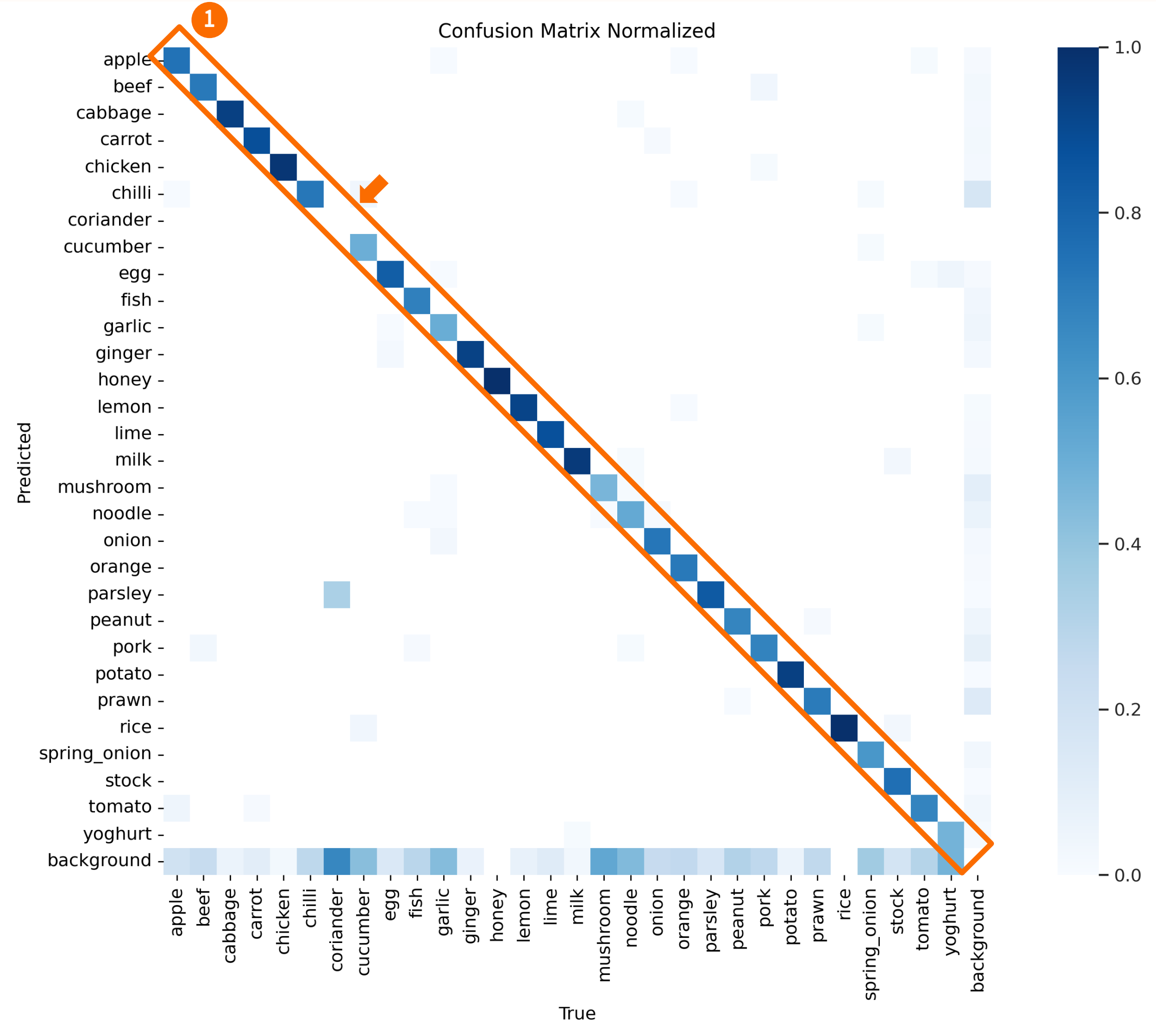
Honey 0.995
Chicken 0.979
Potato 0.949

Lowest mAP50:

Coriander 0.088
Yoghurt 0.362
Mushroom 0.437

Classification accuracy and room for improvement

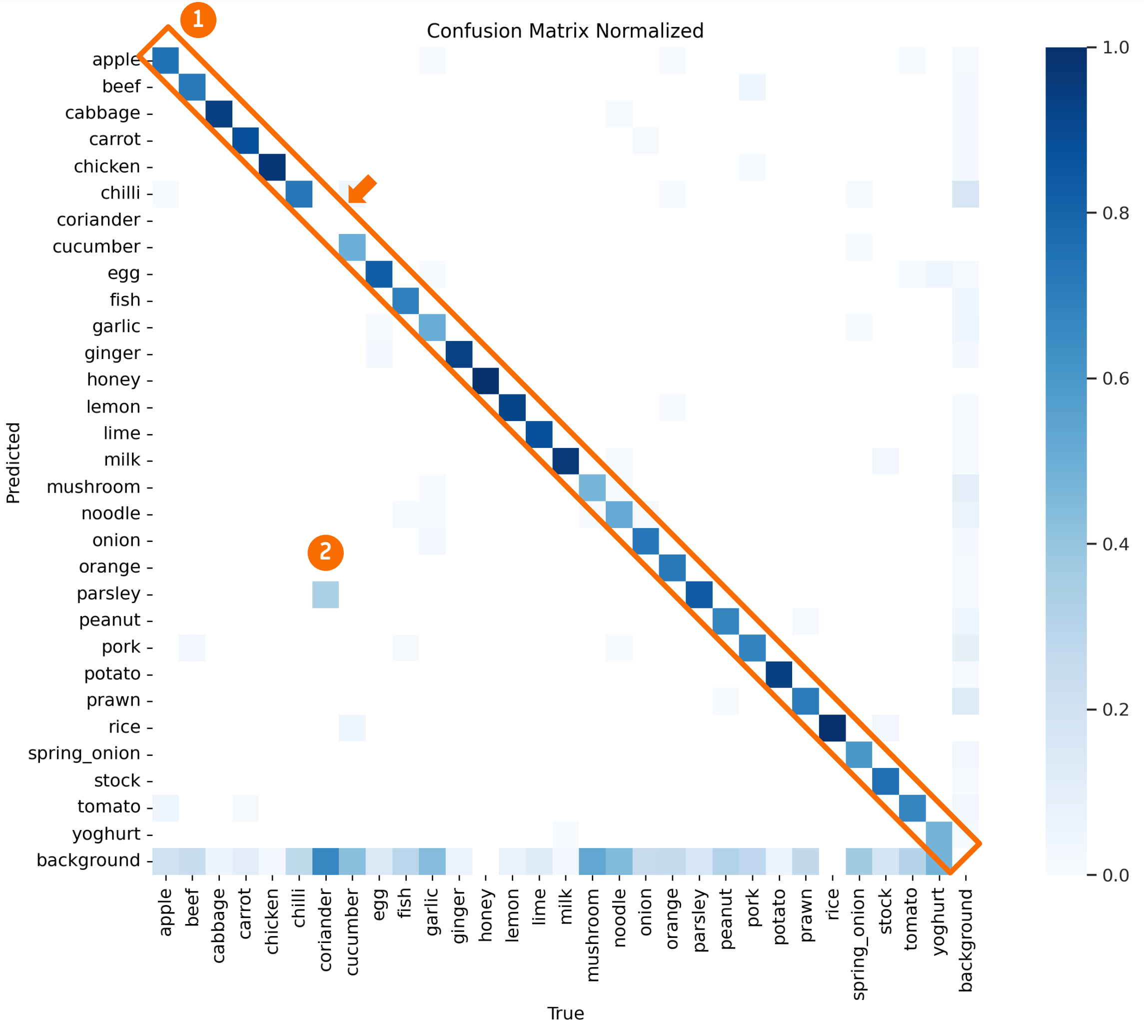
1. **Dark diagonal:** signifies that the model is correctly classifying a large proportion of the instances for each class (except for Coriander)



Classification accuracy and room for improvement

1. **Dark diagonal:** signifies that the model is correctly classifying a large proportion of the instances for each class (except for Coriander)

2. **Coriander vs Parsley confusion**



Classification accuracy and room for improvement

1. **Dark diagonal:** signifies that the model is correctly classifying a large proportion of the instances for each class (except for Coriander)

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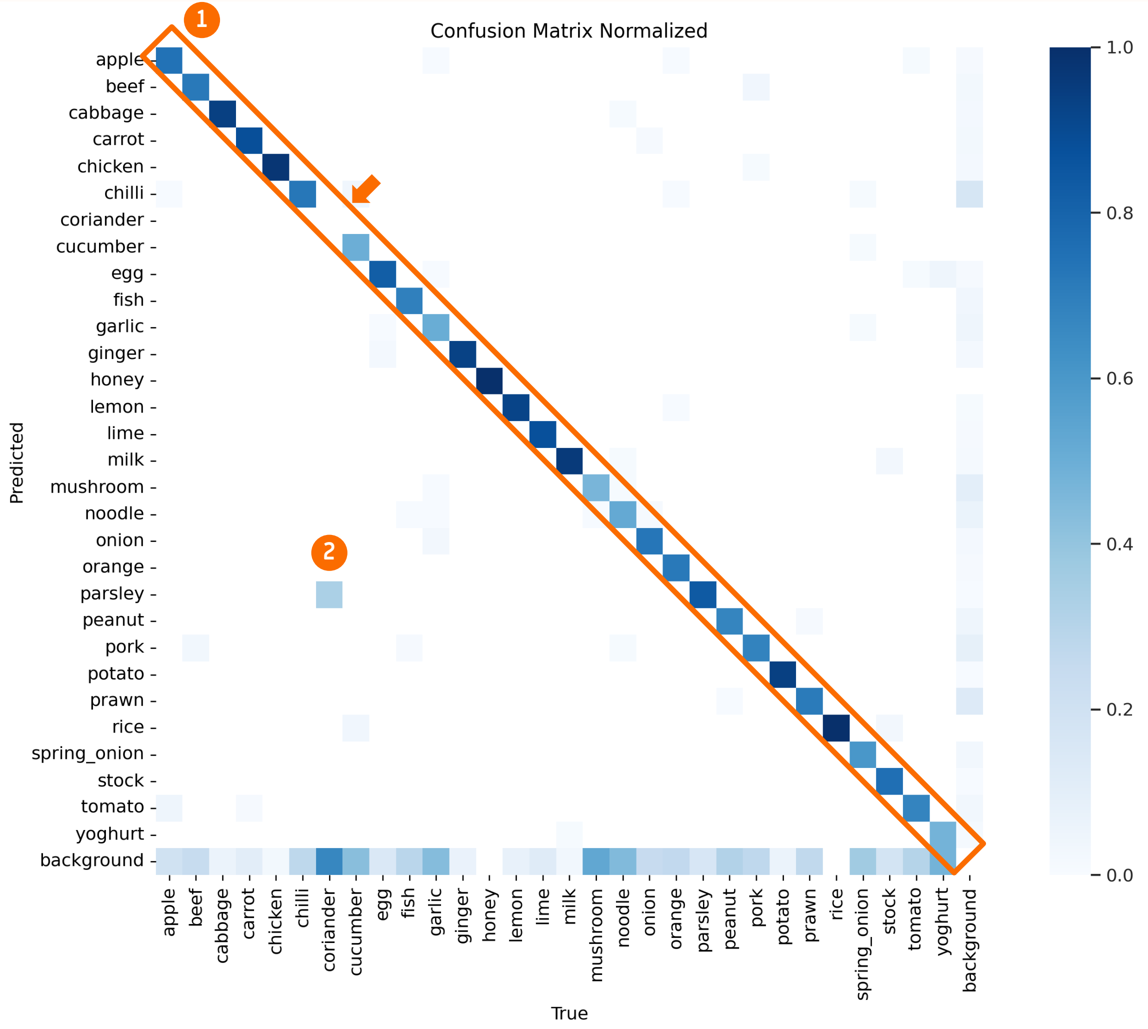
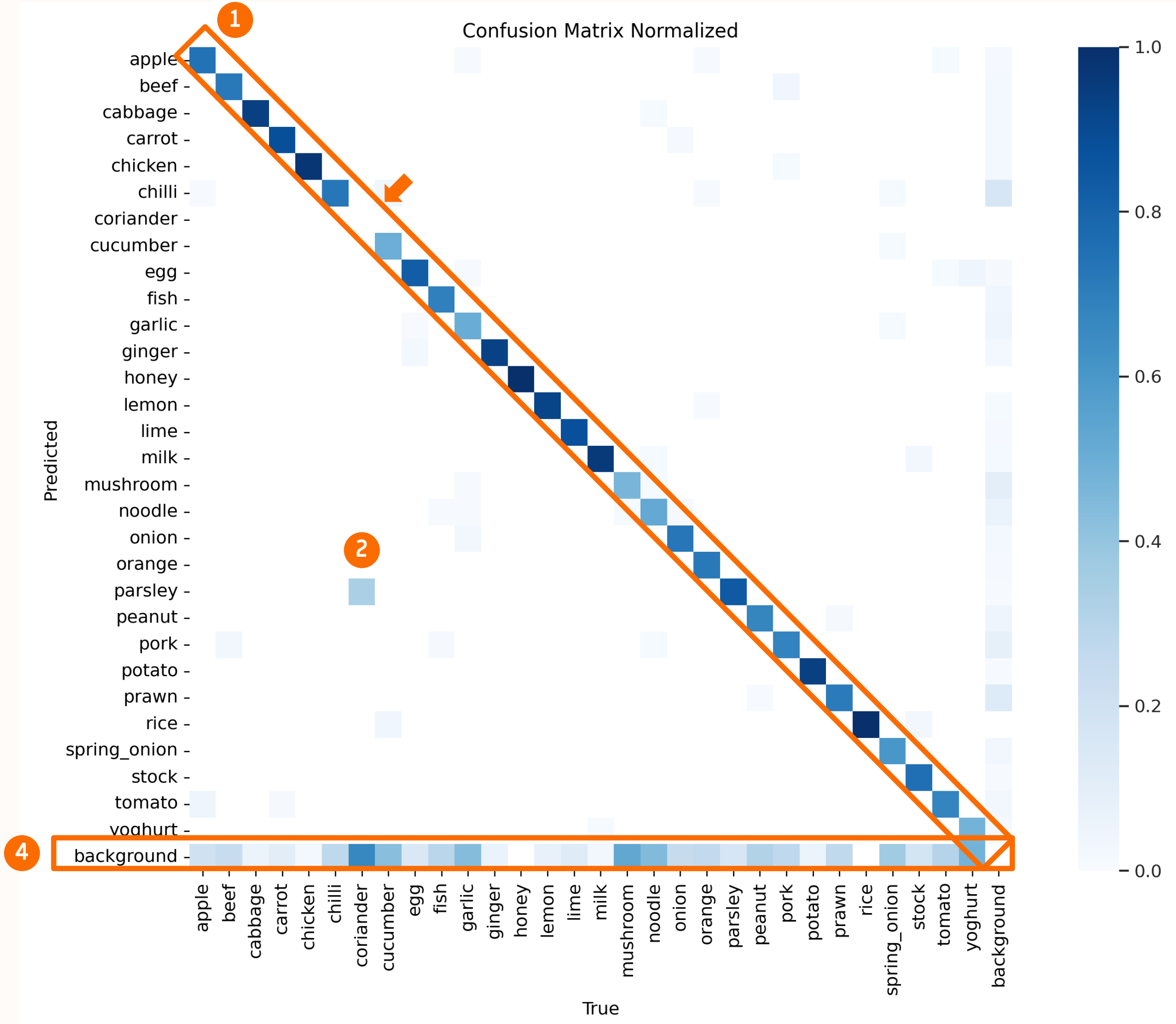
3. **Lightly shaded off-diagonal:** low misclassifications (False Positives and False Negatives)



Classification accuracy and room for improvement

1. **Dark diagonal:** signifies that the model is correctly classifying a large proportion of the instances for each class (except for Coriander)
2. **Coriander vs Parsley confusion**
3. **Lightly shaded off-diagonal:** low misclassifications (False Positives and False Negatives)
4. **Background confusion**



Examples of correct predictions

Top 3 mAP: Honey, Chicken, Potato (> 0.949)

Examples of incorrect predictions

bottom 3 mAP: Coriander, Yoghurt, Mushroom (<0.43)

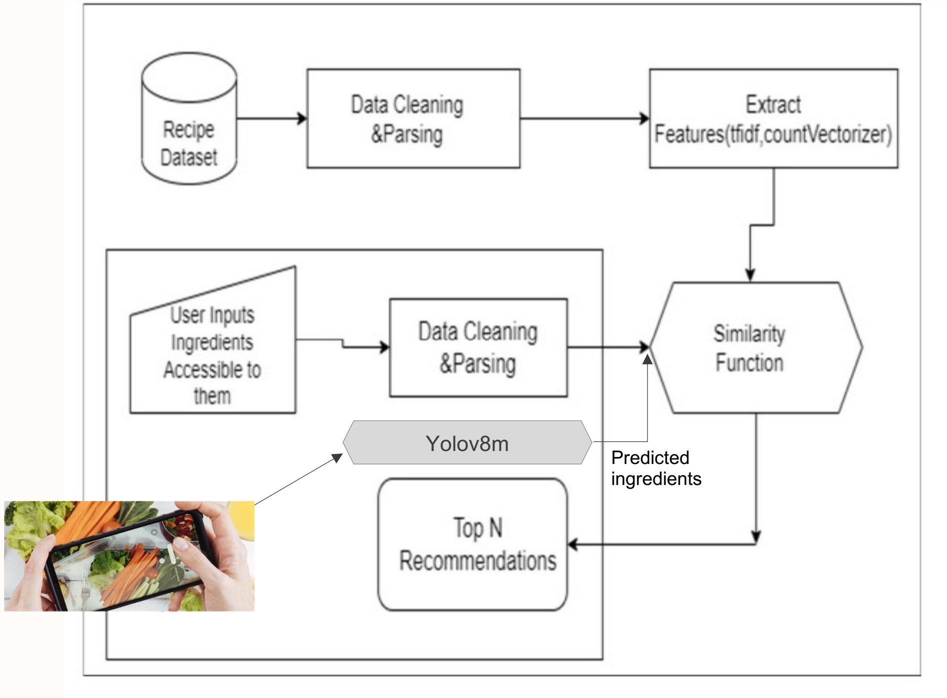
Examples of incorrect predictions

bottom 3 mAP: Coriander, Yoghurt, Mushroom (<0.43)

Coriander-Parsley confusion

Recipe recommender

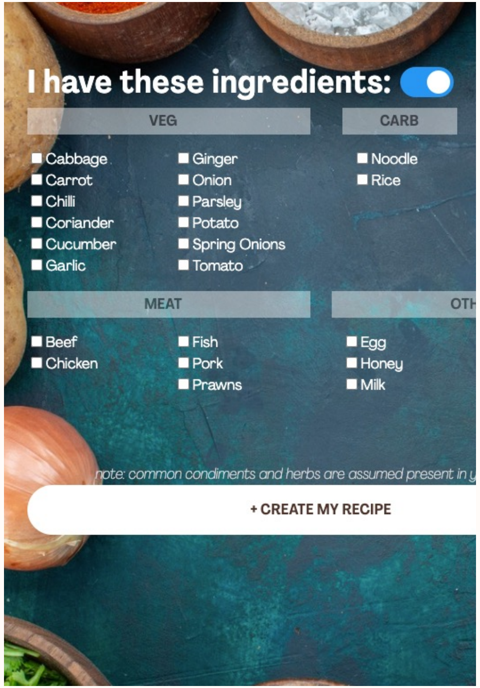
- TF-IDF
- Jaccard similarity score / Cosine similarity score



06

Demo of P2P buddy.ai

2-in-1:
Ingredient recognition & recipe recommender



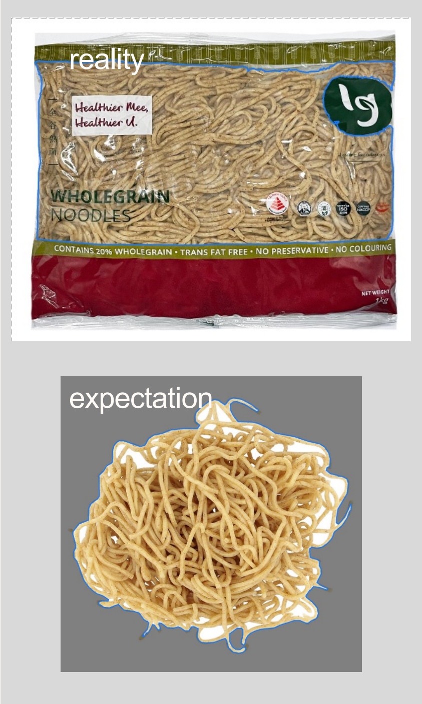
Challenges and Key takeaways

- Data collection and cleaning (images):
  - Mindful of brand and bias
  - Ensure relevance
  - Annotations are time-consuming due to food type

- For a start, focus on fewer but key (common) classes, more images per class

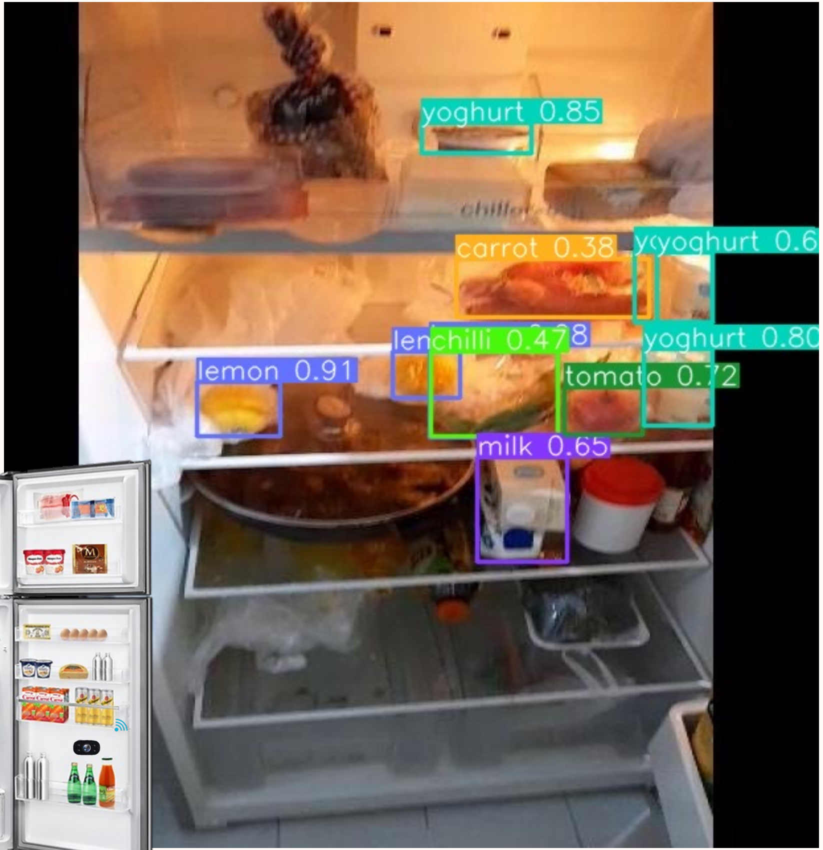
- Text cleaning (recipe) – many interchangeable ingredient terms, some loosely related

- Deep learning requires patience
  - Time
  - A lot of images (the right ones – rubbish in, rubbish out!)



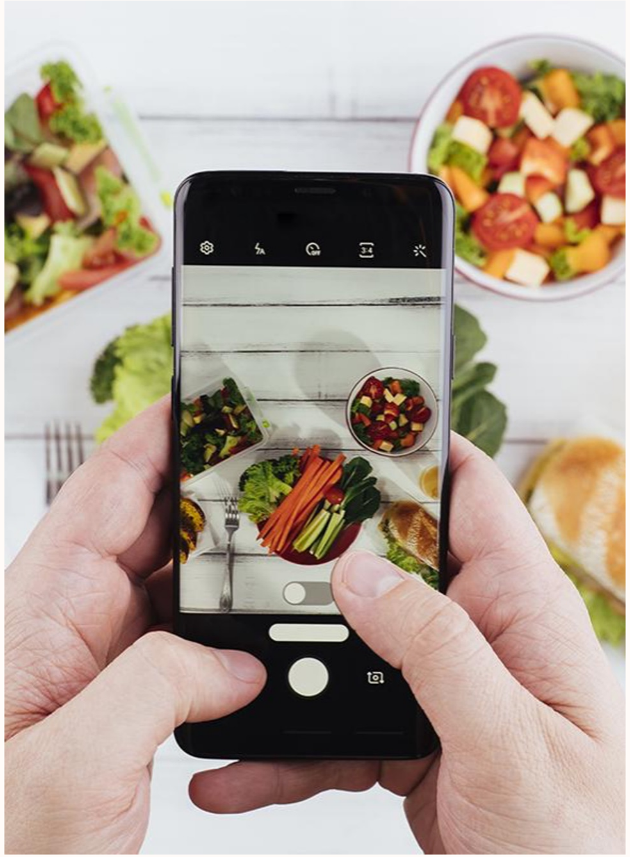
Future possibilities

- Detecting leftovers or neglected ingredients in the fridge
- Predictions seem promising
- Requires a substantial image dataset



Other possibilities

- End-to-end user shopping experience
- Integrate with existing platforms like:
    - Fairprice, Grab, PandaMart, Pricekaki, HealthHub
- In-depth content-based & collaborative filtering (clustering and similarity)
- Price-based recipe recommendations: Live monitoring of food prices
- Direct connection to shopping cart



thank you.

questions?