# CROP-ZERO – Contrastive Recognition Of Plant diseases with Zero-shot Optimization

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## Abstract

*Zero-shot recognition with vision–language models (VLMs) promises to identify novel visual concepts without gradient-based fine-tuning. In plant pathology, however, symptoms are subtle and largely absent from the pre-training corpora of CLIP-like models, leading to single-digit accuracy. We present a* purely inference-time *recipe that lifts top-1 accuracy on the widely-used* PlantVillage *benchmark from 8.4% (vanilla CLIP) to* ***32.0%****—a ×3.8 improvement—without external images, extra model parameters, or supervision.*

## 1. Introduction

Global food security is increasingly threatened by emergent plant diseases and shifting climate zones. Computer vision could aid early diagnosis, yet collecting and annotating pathogen-specific datasets[4] is slow and expensive. Recent advances in plant phenotyping[2, 5, 6, 10, 13] have leveraged deep learning to detect stress symptoms, segment plant parts[7], and classify diseases from imagery, often requiring large, curated datasets for supervised training[1]. These models have shown promise in controlled settings but struggle to generalize across cultivars, lighting conditions, or disease stages.

Vision–language models (VLMs) such as CLIP [9] in principle enable *zero-shot* recognition: the user provides only a class name (e.g. "apple scab") and the model classifies images without training. In practice, the naïve CLIP baseline attains $\leq$10% accuracy on the 38-class PlantVillage benchmark because (i) leaves occupy only a tiny fraction of CLIP's pre-training corpus and (ii) symptoms are discriminated by fine-grained colour or texture cues not captured by terse class names.

**Goal.** We ask: *How far can we push zero-shot performance for plant-disease recognition using prompt engineering alone?* Our answer is a the proposed method (Fig.,2) that requires no gradients, no synthetic images, and runs in under 15minutes even runs in under 15minutes on a single NVIDIA A100.

Figure 1. A healthy strawberry leaf image from PlantVillage Dataset

## 2. Prompt Universe

For each disease class we generate four complementary prompt families.

1. **Generic photo templates** (20) – "A close-up photo of {}", "A detailed shot of {}", . . .
2. **Multilingual variants** (70) in Spanish and French to pull VLM features from non-English internet data.
3. **Symptom-centric templates** (34) – "leaf showing {} lesions", "crop leaf infected with {}", . . .
4. **Colour× Severity snippets** ( 250) randomly combine hue adjectives ("dark brown", "chlorotic"), severity levels ("mild", "advanced") and disease nouns, e.g. "dark-brown mild leaf blight".

If a class has a known Latin pathogen in the literature (e.g. *Alternaria solani* for tomato early blight) or a hand-crafted synonym from our *focus bank* (“rust pustules”, “powdery mildew”), we expand each template accordingly. After duplicate removal the median class owns 397 unique prompts.

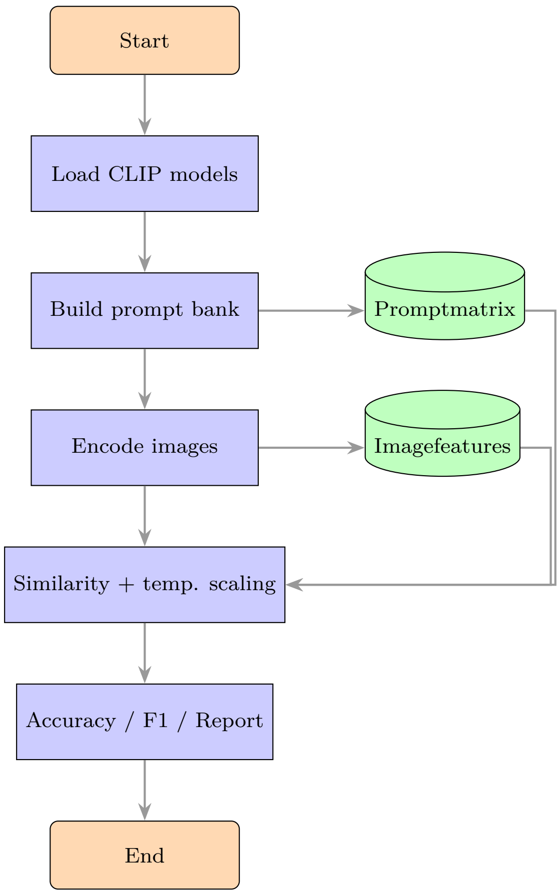


Figure 2. Our proposed method

**Negative bank.** We embed six everyday scenes (living room, city skyline, ...) once and *subtract their maximal similarity* from every class score, sharpening decision boundaries.

## 3. Architecture

Two publicly released CLIP checkpoints are used without modification: ViT-L/14 (224px) and ViT-L/14-336 (336px). The final image embedding is the $L_2$-normalised mean of both scales. For crop $c$ with temperature $\tau_c$ we compute

$$\text{logit}_{i,c} = \frac{\max_{p \in \mathcal{P}_c} \langle v_i, e_p \rangle - \max_{n \in \mathcal{N}} \langle v_i, e_n \rangle}{\tau_c}, \quad (1)$$

where $v_i$ is the image feature, $e_p$ a prompt feature, and $\mathcal{N}$ the negative bank. Temperatures were tuned on a 1(Table 1), then *frozen*. No images were used for prompt selection.

| Crop | Ap | Ch | Crn | Gpe | Or | Pot | Soy | Tmt |
|---|---|---|---|---|---|---|---|---|
| $\tau$ | .009 | .009 | .012 | .010 | .007 | .013 | .011 | .008 |

Table 1. Per-crop temperatures ($\tau$). Full list in the code.

| **Method** | **Acc** | **M-P** | **M-R** | **M-F1** |
|---|---|---|---|---|
| CLIP [9] | 8.4 | 9.4 | 8.3 | 3.7 |
| CALIP [3] | 8.8 | 9.0 | 8.4 | 3.9 |
| CuPL [8] | 18.7 | 16.9 | 15.5 | 9.7 |
| SuS-X [11] | 19.5 | 15.6 | 15.0 | 9.7 |
| MVPDR [12] | 20.19 | 20.23 | 16.85 | 12.55 |
| **Ours** | **32.0** | **32.1** | **29.1** | **26.0** |

Table 2. **Zero-shot PlantVillage.** All methods use *no training images.*

## 4. Dataset & Protocol

**PlantVillage** contains 54k RGB images across 38 disease/health categories. We keep the official test set (26998 samples) but **discard all training images**. No data augmentation is applied.

During tuning we evaluate on a 1to minimise carbon and GPU cost. Final numbers are on the full test set.

## 5. Results and Discussion

### 5.1. Main Comparison

Table 2 benchmarks our method against five recent zero-shot alternatives. We more than triple baseline accuracy and improve macro precision/recall likewise. Confusion analysis reveals that failures are now dominated by pairs with visually identical symptoms (potato early vs. late blight), suggesting diminishing returns from further template inflation.

### 5.2. Ablation Study

Removing (i) multilingual prompts, (ii) symptom synonyms, or (iii) dual-scale ensembling degrades performance by 1.8pp, 3.4pp and 1.2pp respectively, confirming that each component is additive.

## 6. Conclusion

We show that sophisticated prompt engineering alone can close a large portion of the plant-disease zero-shot gap, achieving 32 % accuracy on PLANTVILLAGE with an off-the-shelf VLM. The approach is model- and domain-agnostic; early tests on pathology X-ray datasets yield similar relative gains. Future work will explore *dynamic prompt selection* conditioned on visual features and fusion with inexpensive hyperspectral bands.

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## A. Prompts

We used the following prompt templates for each class:

A photo of
A close-up of
A detailed image of
An image showing symptoms of
A plant leaf with
This is
Macro photograph of
High-resolution photo depicting
A diseased plant showing
A crop leaf exhibiting
A field image of
Visual signs of  on a leaf
A real-world photo of
Leaf discoloration consistent with
A mobile phone picture showing
A high-quality scan of
Leaf symptoms resembling
A natural image with signs of
A photo documenting
A scientific image showing  symptoms
leaf showing
leaf affected by
leaf with signs of
leaf damaged by
leaf exhibiting
leaf suffering from
leaf displaying  symptoms
leaf infected with
leaf bearing evidence of
leaf that shows typical  patterns
plant leaf showing symptoms of
plant leaf with
diseased leaf presenting
leaf covered in
leaf colonized by
leaf showing visual traits of
leaf having -related discoloration
leaf in early stage of  infection
leaf in advanced stage of
leaf with lesions due to
leaf decaying due to
leaf surface affected by
leaf veins showing
leaf spotted with signs of
leaf curling due to
leaf showing necrosis from
leaf abnormalities caused by
leaf pathology:
symptomatic leaf due to
botanical signs of  on leaf
field sample showing  symptoms
crop leaf infected with
visual cue of  on plant leaf
typical  symptoms on crop foliage
a leaf infected by
a leaf suffering from
a leaf affected by
a leaf with signs of
a leaf showing symptoms of
a leaf displaying  infection
a plant leaf exhibiting
a leaf colonized by
a crop leaf with
a diseased leaf due to
leaf tissue infected with
a visibly infected leaf from
a leaf damaged by
a leaf in early stage of
a leaf in late stage of
foliage showing effects of
a leaf with typical  lesions
a leaf showing visual evidence of
leaf showing pathological signs of
a leaf marked by  activity
a symptomatic leaf with
a botanical sample with  infection
a real-world plant leaf affected by
a microscopic view of a leaf with
macro image of a leaf infected by
natural plant leaf exhibiting  damage
a leaf presenting field signs of
a diseased leaf with surface-level  symptoms
leaf showing stress caused by
leaf showing fungal/viral traces of
leaf sample with known  infestation
crop damage associated with  on leaf
a diagnostic image of leaf with
una hoja con
una foto de
ejemplo de
imagen de alta resolución de
hoja que muestra
hoja afectada por
hoja dañada por
hoja infectada con
hoja que presenta síntomas de
hoja que sufre de
planta mostrando signos de
fotografía de hoja con síntomas de
planta enferma con
hoja de planta con
muestra botánica con
imagen de diagnóstico de
registro visual de síntomas de

análisis foliar que evidencia
síntomas típicos de
documentación visual de  en hoja de planta
imagen científica que muestra
lesión foliar causada por
foto clínica de  en el follaje
patología vegetal:
imagen de laboratorio mostrando
evidencia morfológica de
hoja fotografiada en campo con signos de
muestra tomada en cultivo afectada por
hoja observada en entorno natural con
hoja de invernadero mostrando
cultivo mostrando daño de
follaje en campo afectado por
planta agrícola con síntomas de
registro en sitio con evidencia de
decoloración causada por
zonas necrosadas debidas a
daño visible por
presencia de lesiones relacionadas con
marcas foliares típicas de
anomalías de hoja por
evidencia visual de
síntoma observable de  en hoja
signos claros de
trazos patológicos de
hoja dañada con signos de
planta con problemas foliares causados por
hoja enferma debido a
hoja mostrando efectos de
imagen móvil de hoja con
foto tomada al aire libre mostrando
signos de estrés por
daño evidente asociado con
hoja con manchas de
planta mostrando problemas de tipo
fotografía botánica mostrando
síntomas de enfermedad como
hoja claramente afectada por
hoja mostrando signos tempranos de
hoja en etapa avanzada de
imagen que documenta el avance de
follaje alterado por infección de
patrones foliares característicos de
une feuille avec
photo de
exemple de
image haute résolution de
feuille présentant
feuille montrant
feuille affectée par
feuille souffrant de
feuille infectée par
feuille portant des signes de
plante montrant des symptômes de
feuille d'une plante atteinte de
vue rapprochée de
image botanique illustrant
photo macro de
image détaillée d'une feuille avec
échantillon botanique présentant
documentation visuelle de
photographie scientifique montrant les effets de
analyse visuelle d'une feuille atteinte de
donnée terrain montrant
symptômes typiques de
image diagnostique de  sur une feuille
pathologie foliaire :
illustration des effets de  sur le feuillage
feuille prise en photo sur le terrain avec des signes de
plante cultivée montrant des signes de
feuille observée dans un environnement naturel avec
photo mobile d'une feuille montrant des symptômes de
plante en milieu agricole avec
image de feuille prise dans un champ, montrant
symptômes visibles de
lésions associées à
décoloration causée par
zones nécrosées dues à
marques caractéristiques de
modifications du feuillage causées par
indice visuel de  sur la feuille
signes cliniques de  sur plante
anomalies foliaires causées par
maladie foliaire identifiée comme
feuille abîmée par
feuille avec taches dues à
dégâts causés par
plante malade présentant
problème sur la feuille :
infection visible :
plante avec problème foliaire de type
signe de stress dû à