



# CROP DISEASE DETECTION

GROUP SEVEN





# Problem Statement

Crop diseases are a leading cause of reduced agricultural productivity worldwide, especially in regions where access to expert diagnosis is limited.

Farmers often struggle to identify diseases early, resulting in significant yield loss and increased use of harmful chemicals.

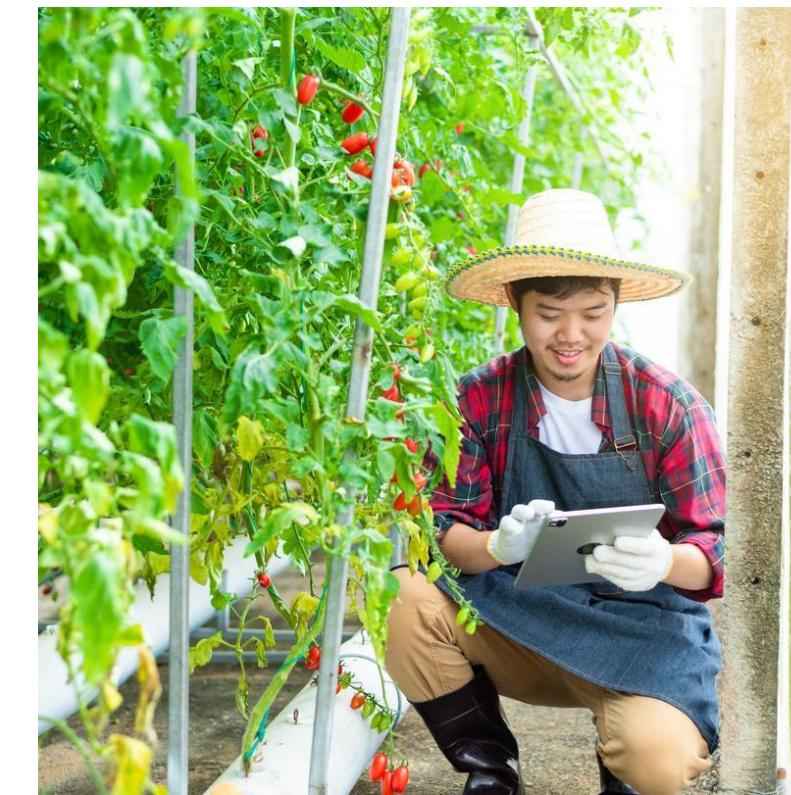
This project proposes a deep learning solution using Convolutional Neural Networks (CNNs) to detect and classify crop diseases from leaf images. The goal is to provide an accessible, image-based diagnostic tool that empowers farmers with timely, accurate disease identification.



# Our Project Objectives

- 01 Build a CNN model to classify crop diseases from leaf images.
- 02 Develop NLP methods to analyze farmers' textual symptom descriptions.
- 03 Integrate CNN and NLP outputs into a single multimodal diagnostic model.
- 04 Compare multimodal performance to image-only and text-only models.
- 05 Create a user-friendly API for farmers to upload photos and symptoms for instant diagnosis.





## What Do You Know About our CNN Data.

- Our data was from:  
<https://www.kaggle.com/datasets/emmarex/plantdiseases>.
- The data contained 15 folders which contained our images classes.
- It had 3 crops:
  - ❖ Bell peppers – had 2 classes
  - ❖ Potato – had 3 classes
  - ❖ Tomato – had 10 classes

## What Do You Know About our NLP Data.

- We had difficulties find a data set that described symptoms of diseased crop so we synthesized our own data using prefix words, adjectives, possible environmental friendly pesticides and descriptions of the actual crop disease we could find from the internet.
- The end result was a data frame containing 1750 rows and 5 columns (description, crop, status of the crop, name of the disease and recommended pesticide)



# Data Cleaning & Preprocessing

01

Since our data was mostly images no cleaning was required for the CNN model

02

For the NLP model we had to remove duplicates. Created new features for target class containing the original 15 classes in our CNN

03

Removed stop words, special characters and numbers, tokenized and lemmatized words to their parent word

04

Vectorized our clean text using TF-IDF then label encoded our target feature.



# CNN Architecture

01 Image resizing:  
 $(128 \times 128)$

04

Input shape:  $(128, 128, 3)$

02 Data augmentation:  
• Random flip  
• Rotation  
• Zoom

03 Normalization:  
Pixel values scaled to  
 $[0, 1]$

- 04 Layers:
- Conv2D → ReLU → MaxPooling
  - Conv2D → ReLU → MaxPooling
  - Conv2D → ReLU → MaxPooling
  - Flatten
  - Dense → ReLU
  - Dropout
  - Dense (softmax output)

- 05
- Loss: categorical crossentropy
  - Optimizer: Adam

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_3 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_4 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_4 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_5 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_5 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_2 (Dense)	(None, 128)	3,211,392
dropout_1 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 15)	1,935

Total params: 3,306,575 (12.61 MB)

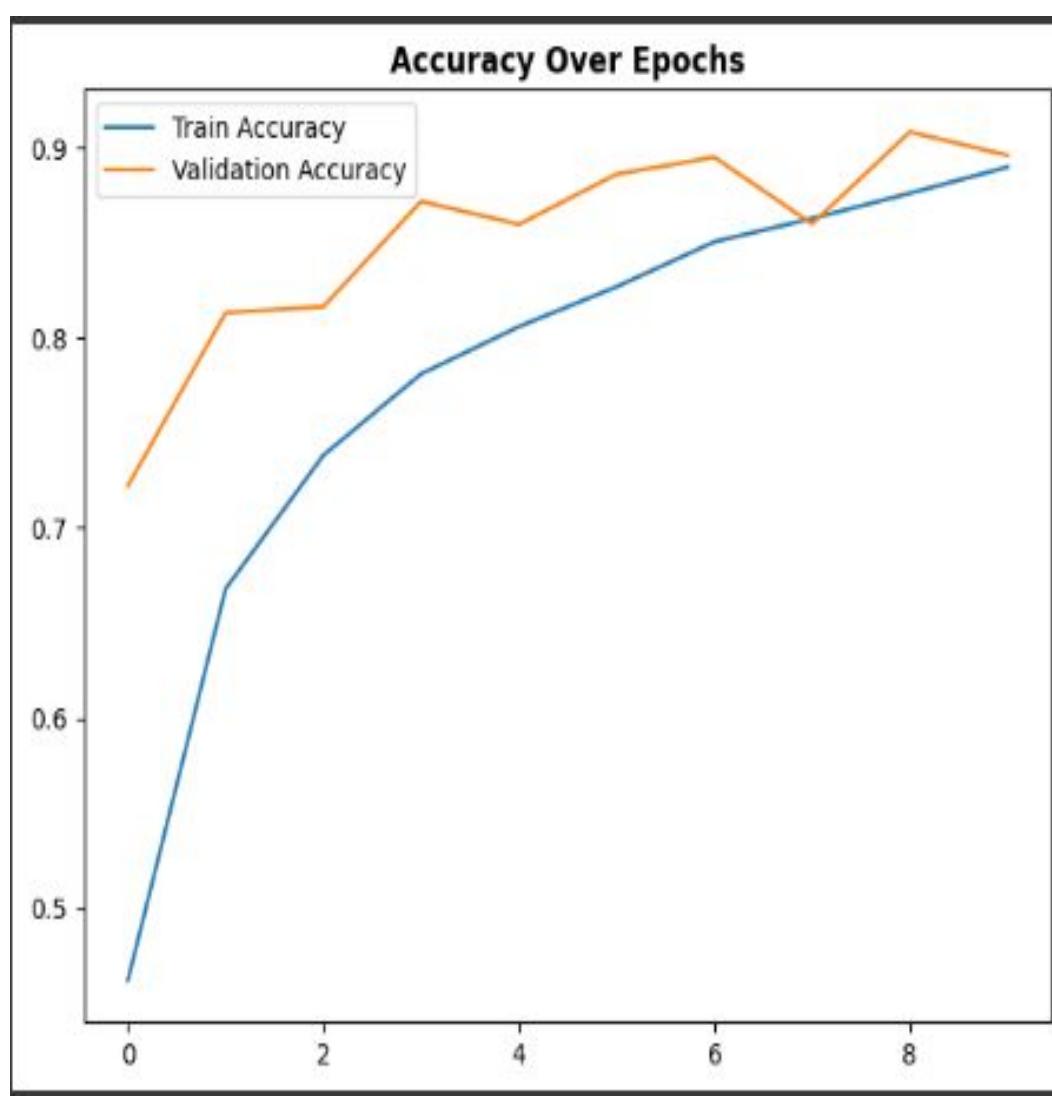
Trainable params: 3,306,575 (12.61 MB)

Non-trainable params: 0 (0.00 B)

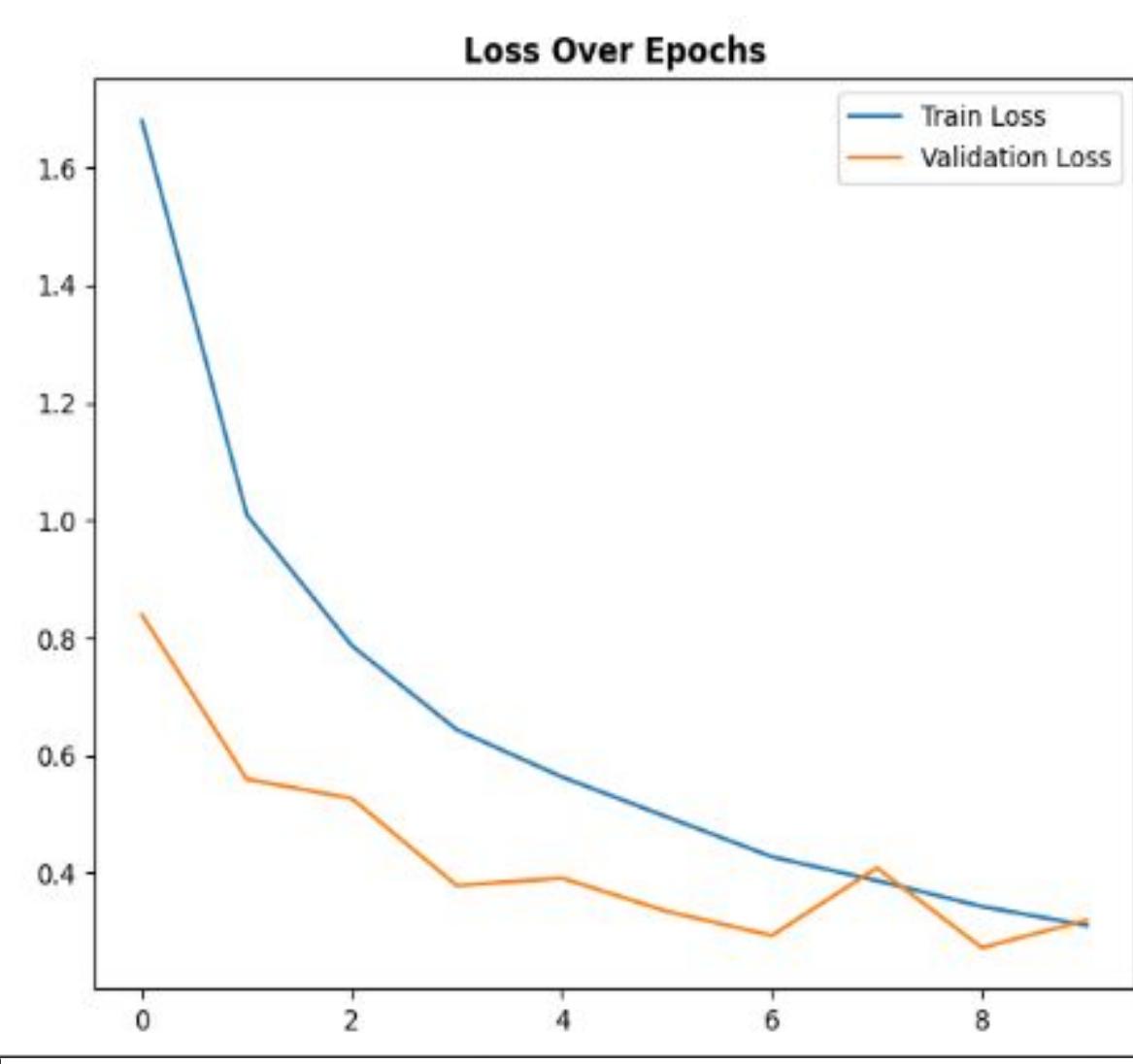


# CNN Performance

## Accuracy Over Epochs



## Loss Over Epochs



**Accuracy:** 0.8962  
**Loss:** 0.3202

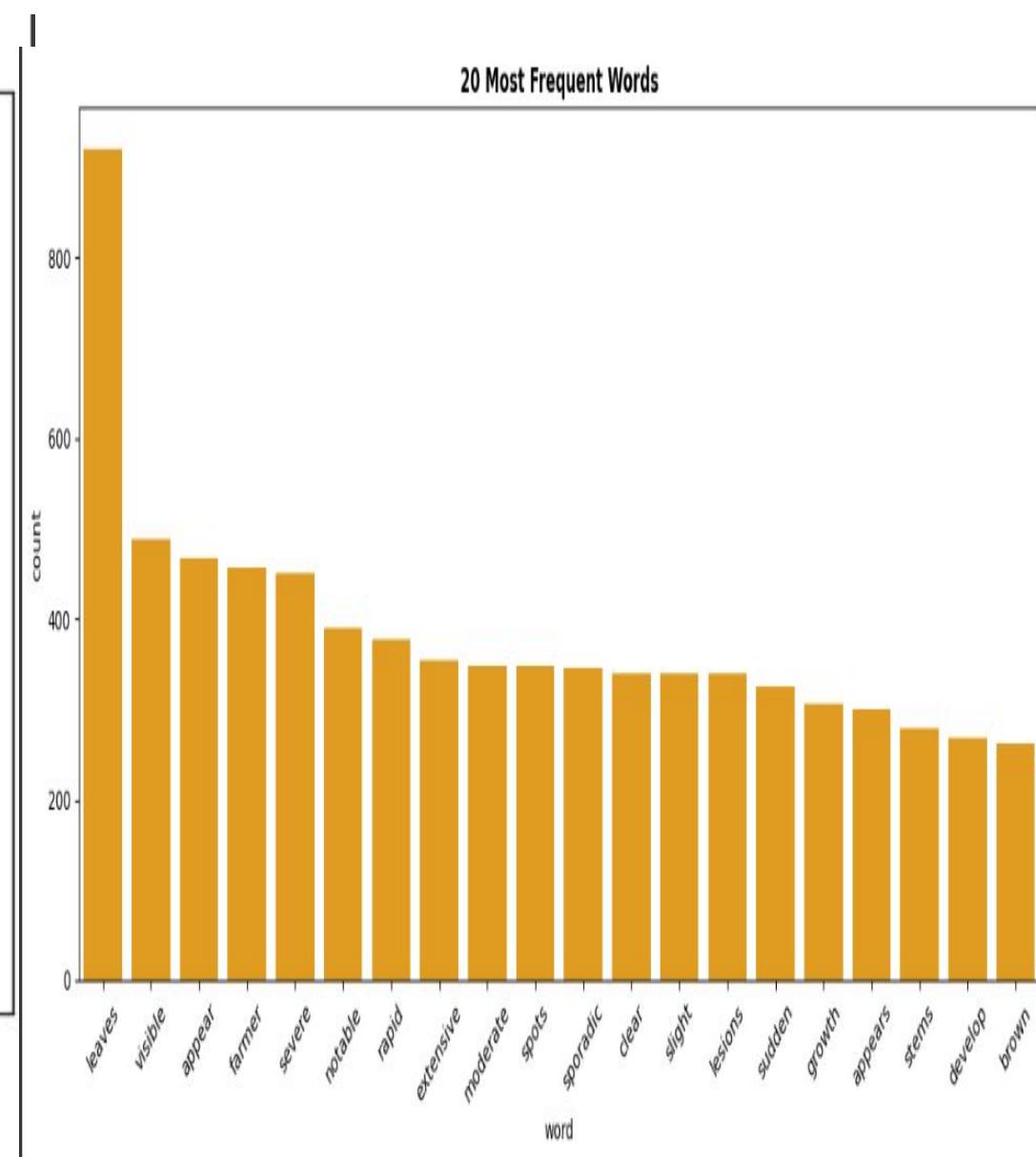
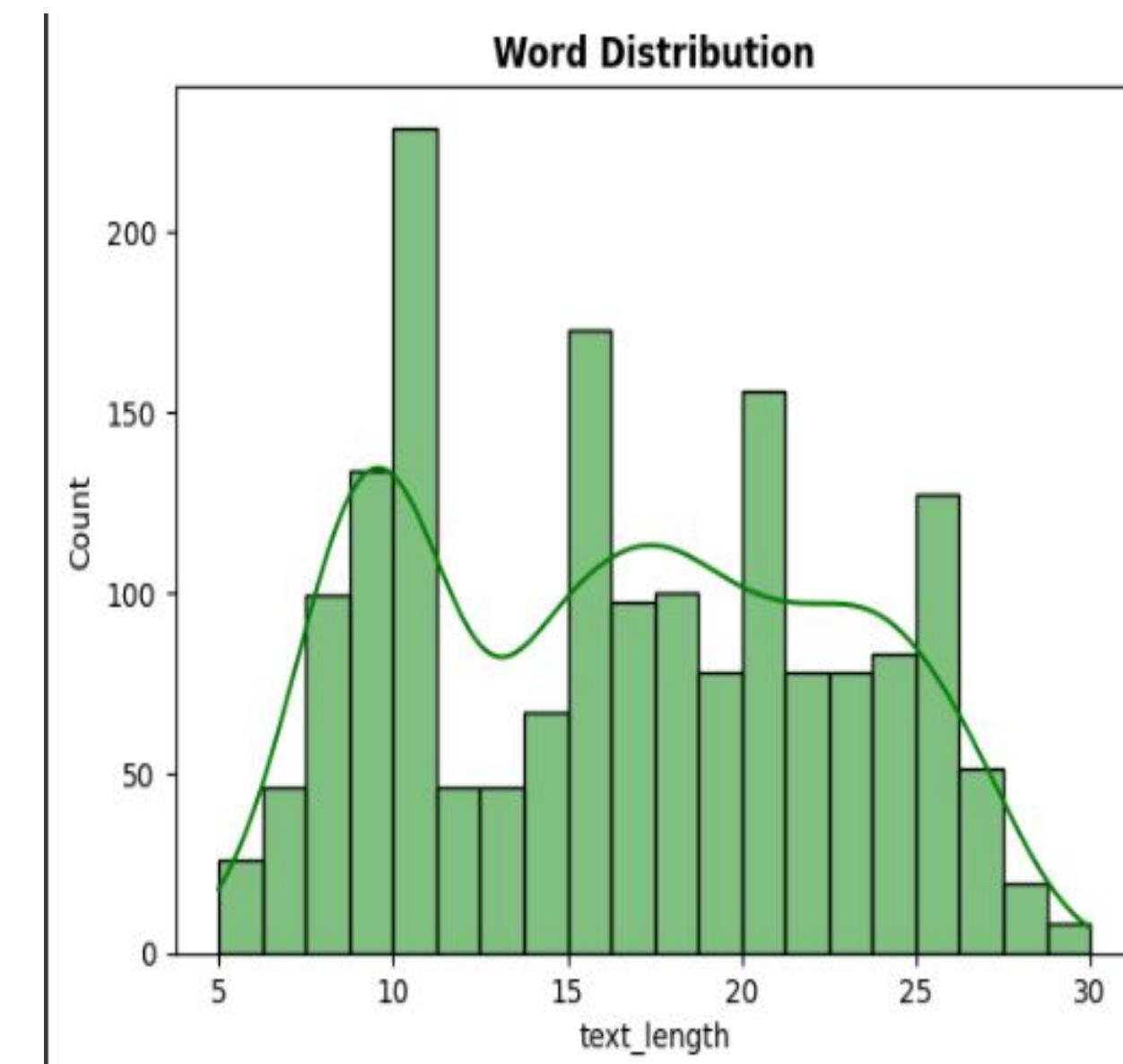
## Confusion matrix

		True label														
		Pepper_bell_Bacterial_spot	Pepper_bell_healthy	Potato_Early_blight	Potato_Late_blight	Potato_healthy	Tomato_Bacterial_spot	Tomato_Early_blight	Tomato_Late_blight	Tomato_Leaf_Mold	Tomato_Septoria_leaf_spot	Tomato_Spider_mites_Two_spotted_spider_mite	Tomato_Target_Spot	Tomato_Tomato_YellowLeaf_Curl_Virus	Tomato_Tomato_mosaic_virus	Tomato_healthy
Predicted label	Pepper_bell_Bacterial_spot	164	23	0	0	0	1	2	1	1	6	0	0	2	0	0
	Pepper_bell_healthy	2	298	0	0	0	0	0	0	0	2	0	0	0	0	0
Potato_Early_blight	Potato_Early_blight	4	1	179	1	0	0	0	2	0	2	0	0	0	0	0
	Potato_Late_blight	2	2	4	150	2	0	6	20	2	0	0	0	0	0	0
Potato_healthy	Potato_healthy	0	15	0	3	13	0	0	0	0	0	0	0	0	0	0
	Tomato_Bacterial_spot	0	0	0	0	0	408	7	7	0	5	0	0	14	0	0
Tomato_Early_blight	Tomato_Early_blight	2	0	0	1	0	1	169	10	1	4	1	1	1	0	0
	Tomato_Late_blight	4	0	3	5	0	0	31	279	9	7	0	1	1	0	1
Tomato_Leaf_Mold	Tomato_Leaf_Mold	1	1	0	0	0	0	7	4	162	6	1	0	3	0	0
	Tomato_Septoria_leaf_spot	6	7	3	2	0	0	11	6	16	336	0	1	4	0	0
Tomato_Spider_mites_Two_spotted_spider_mite	Tomato_Spider_mites_Two_spotted_spider_mite	0	1	0	0	0	0	9	1	2	2	299	11	5	2	0
	Tomato_Target_Spot	3	3	1	0	0	3	18	2	0	14	19	191	0	2	5
Tomato_Tomato_YellowLeaf_Curl_Virus	Tomato_Tomato_YellowLeaf_Curl_Virus	0	0	0	0	0	2	2	0	0	0	0	530	0	0	0
	Tomato_Tomato_mosaic_virus	0	0	0	0	0	0	0	2	5	5	0	0	0	66	0
Tomato_healthy	Tomato_healthy	0	0	1	0	0	0	0	0	3	0	0	3	0	0	355



# NLP Data Pipeline

- Text pre-processing:
  - Lowercasing
  - Removing punctuation
- Vectorization:
  - CountVectorizer or TF-IDF
- Model:
  - Multinomial Naive Bayes
- Outputs:
  - Crop type
  - Disease/health label
  - Recommended pesticide

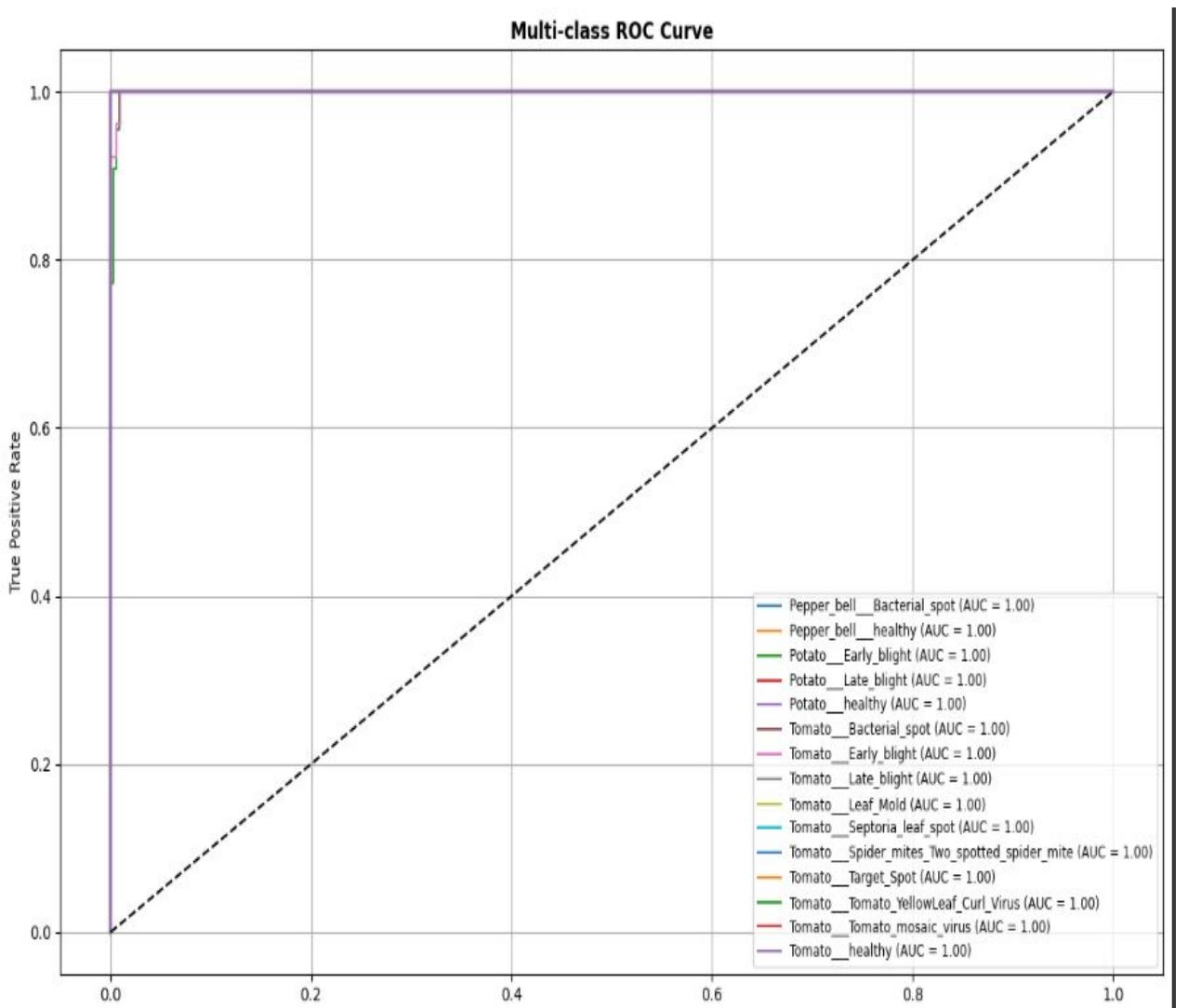


### 20 Most Frequent Words



# NLP Performance

# ROC Curve



**Accuracy:** 0.98  
**Recall:** 0.98  
**Precision:** 0.98  
**F1-Score:** 0.98

## Confusion matrix



## Deployment Approach

- Save trained models:
  - CNN: .keras or .h5
  - NLP pipeline: .pkl (e.g. with joblib)
- Possible deployment:
  - Web app (Flask, FastAPI, Streamlit)
  - Mobile app
- User uploads:
  - Leaf photo → CNN model
  - Text description → NLP mode



# Challenges & Future Work

## Challenges:

- ❖ Similar symptoms between diseases
- ❖ Variability in farmer descriptions

## Future work:

- ❖ Expand dataset
- ❖ Use transfer learning (e.g. EfficientNet)
- ❖ Multilingual NLP models
- ❖ Integration with real-time advisory systems



# Thank You

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