# Harnessing AI & CV for Efficient Weed Control in Crop fields.

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Link to youtube video: https://youtu.be/umJs4L_yt-4

# Overview

- Introduction
- Methodology
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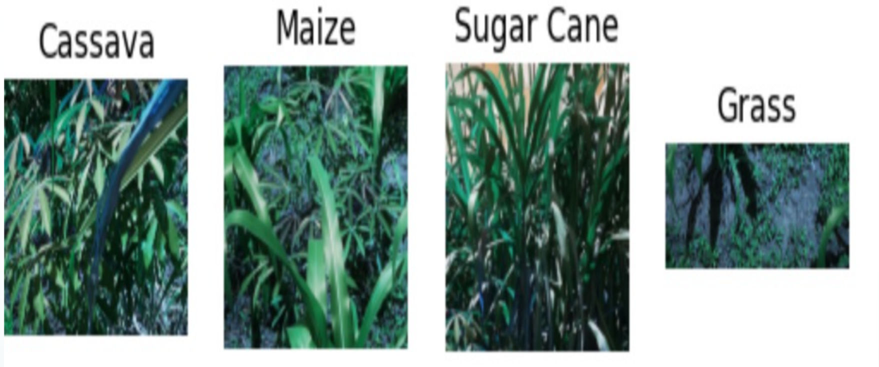
# Introduction & Background

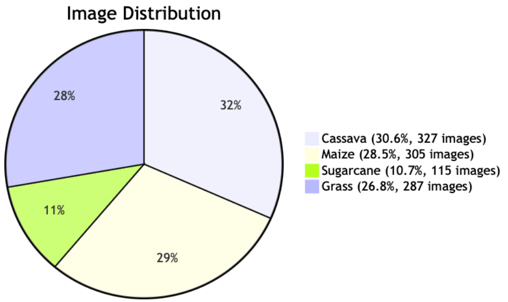
- World population over 8B & projected to hit 9B by 2050.
- Need to put measures that ensure food security and supply.
- Crop fields face a challenge of weed control that cause {sun, nutrients, water} competition and thus low yields.
- CV & AI algorithms(ML & DL) has shown promise in area of weed identification and detection.
- Algorithms such as KNN, NB, SVM, CNNs

- Research focus: build accurate models to properly classify crops(cassava, maize, sugarcane) and grass(weeds) in a crop field.




# Methodology: Data acquisition

1. Dataset acquisition: Images were obtained by passing the garden video in a cv2 package “cv2.VideoCapture” and specifying the framerate(0.5).
2. Saved frames/images were further cropped using snipping tool to boarder out a given crop/grass.
3. Resultant images (apprx. 1034) were saved in crop specific folders to form a dataset.




# Methodology: Data pre-processing

**Image resizing:** For the ML models (Naïve Bayes) this is accomplished by resizing it to 500x500. CNN images were resized to 256x256. For standardization & noise reduction.

**Rescaling**: CNN images were rescaled to fit 1/255.

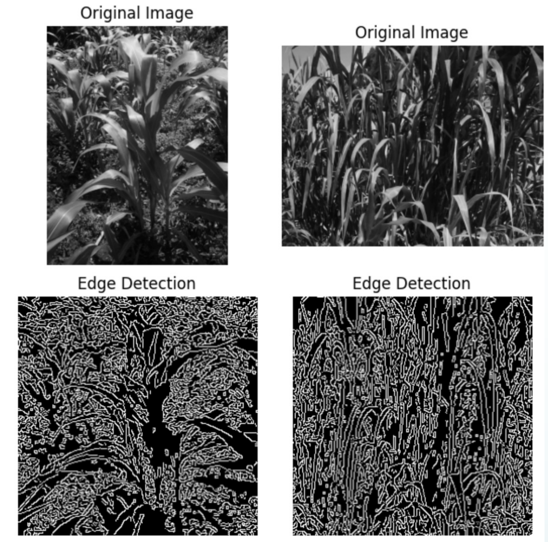
**Data split**: NB (80:20), CNN (75:15:10)

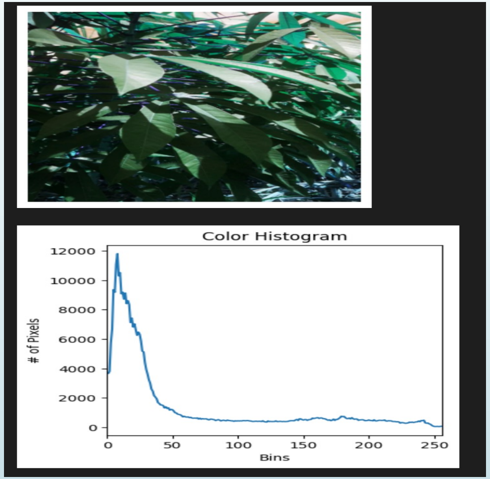
# Methodology: Naïve Bayes Modelling

**Feature selection & Extraction**: Choose edge detection(boundary identification) and color histogram(rep. color distribution efficiently) features for the experiments.

**Experiments**: Created 3 models that used the features separately, and combined and then evaluated.

**Model**: Trained Gaussian NB models on features generated.



# Methodology: CNN Modelling

Keras models built and tuned for efficiency.

Trained for 10 epochs, Batch size 32

**Model Architecture:**

- 3 conv 2d layers(scans the input image with its filters to create feature maps )
- 3 max pool layers(reduces the spatial dimensions of the input (height and width) while preserving the most important features )
- 1 flattening layer(transforms the 2D matrix data into a 1D vector to prepare it for input into the fully connected layers )
- 1 dense layers(interpret the features extracted by the preceding layers)
- 1 dense (softmax) -> Output is 4 probabilities

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_5 (Conv2D)           (None, 254, 254, 32)      896

 max_pooling2d_5 (MaxPooling  (None, 127, 127, 32)     0
 2D)

 conv2d_6 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_6 (MaxPooling  (None, 62, 62, 64)       0
 2D)

 conv2d_7 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_7 (MaxPooling  (None, 30, 30, 128)      0
 2D)

 flatten_2 (Flatten)         (None, 115200)            0

 dense_4 (Dense)             (None, 128)               14745728

 dense_5 (Dense)             (None, 4)                 516

...
Total params: 14,839,492
Trainable params: 14,839,492
Non-trainable params: 0
```

# Methodology: Model Evaluation

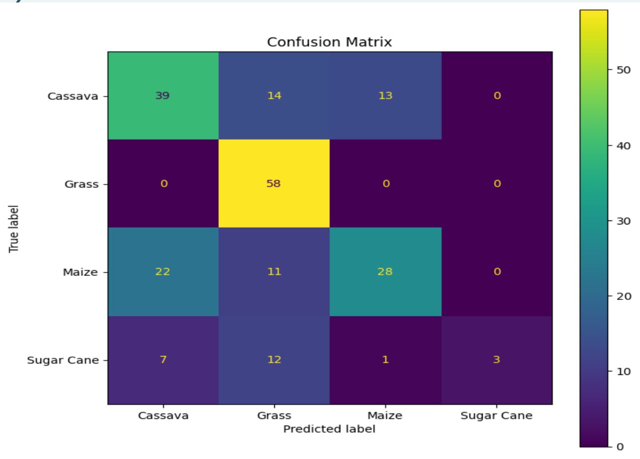
**Used the following evaluation criteria:**

- Accuracy
- Classification Report {precision, recall, f1 score}
- Confusion Matrix

# Results NB: Color Hist vs Edge Detection

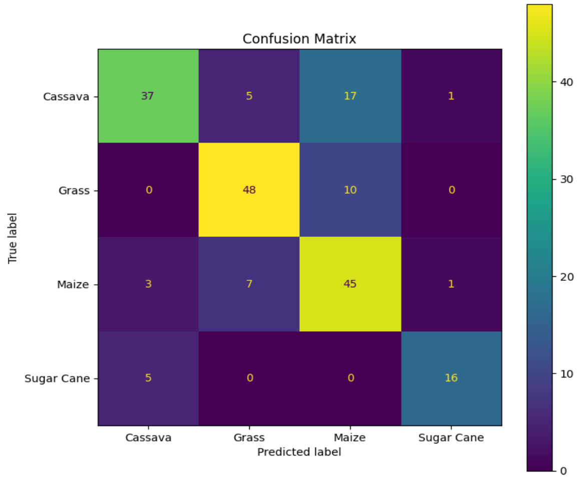
Edge Dect.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.57 | 0.59 | 0.58 | 66 |
| 1 | 0.61 | 1.00 | 0.76 | 58 |
| 2 | 0.67 | 0.46 | 0.54 | 61 |
| 3 | 1.00 | 0.13 | 0.23 | 23 |
| accuracy | | | 0.62 | 208 |
| macro avg | 0.71 | 0.55 | 0.53 | 208 |
| weighted avg | 0.66 | 0.62 | 0.58 | 208 |




Color Hist.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.82 | 0.62 | 0.70 | 60 |
| 1 | 0.80 | 0.83 | 0.81 | 58 |
| 2 | 0.62 | 0.80 | 0.70 | 56 |
| 3 | 0.89 | 0.76 | 0.82 | 21 |
| accuracy | | | 0.75 | 195 |
| macro avg | 0.78 | 0.75 | 0.76 | 195 |
| weighted avg | 0.77 | 0.75 | 0.75 | 195 |

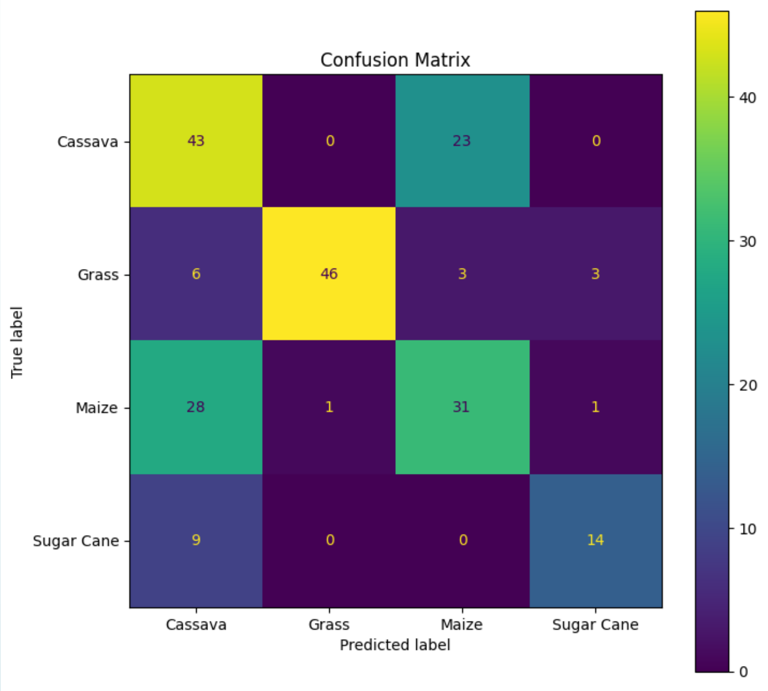


# Results NB: Color Hist plus Edge Detection

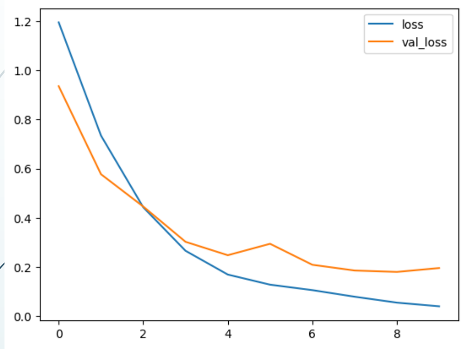
## Classification report

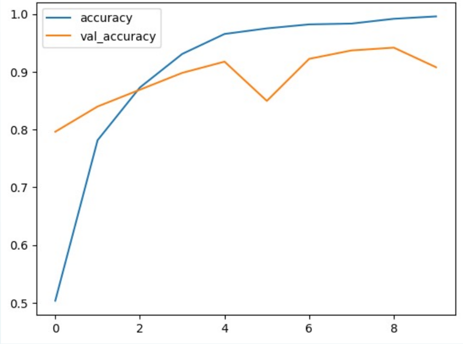
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.50 | 0.65 | 0.57 | 66 |
| 1 | 0.98 | 0.79 | 0.88 | 58 |
| 2 | 0.54 | 0.51 | 0.53 | 61 |
| 3 | 0.78 | 0.61 | 0.68 | 23 |
| accuracy | | | 0.64 | 208 |
| macro avg | 0.70 | 0.64 | 0.66 | 208 |
| weighted avg | 0.68 | 0.64 | 0.65 | 208 |

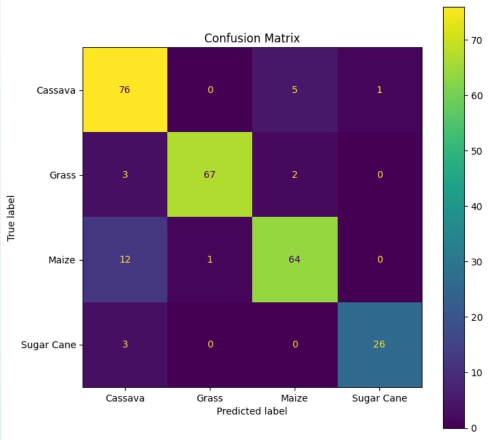
## Confusion Matrix



# Results: CNN




| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.81 | 0.93 | 0.86 | 82 |
| 1 | 0.99 | 0.93 | 0.96 | 72 |
| 2 | 0.90 | 0.83 | 0.86 | 77 |
| 3 | 0.96 | 0.90 | 0.93 | 29 |
| accuracy | | | 0.90 | 260 |
| macro avg | 0.91 | 0.90 | 0.90 | 260 |
| weighted avg | 0.90 | 0.90 | 0.90 | 260 |

# Results Discussion: Comparative Analysis of Model Performance

**Model 1 (Naive Bayes with Edge Detection):** Achieved an accuracy of 62%, suggesting edge detection alone may not be sufficient for accurate classification.
**Model 2 (Naive Bayes with Color Histogram)**: Achieved higher accuracy of 75%, indicating the color histogram approach provides more discriminative information for classification.
**Model 3 (Naive Bayes with Combined Edge Detection and Color Histogram):** Accuracy went to 64%, suggesting the combination of these techniques may not be complementary or may introduce noise.
**Model 4 (Convolutional Neural Network):** Achieved the highest accuracy of 90%, indicating superior capabilities for feature extraction and classification.

NOTES: Non maximum suppression and image size affect accuracy.

**Recommendations**:

- Focus on **optimizing the color histogram feature** extraction technique due to its promising results plus **image size matters**.
- Given the high accuracy of the CNN model, **further investigation into deep learning** approaches is recommended.

# Conclusion

- Machine learning and deep learning models show potential in crop and weed classification.
- Feature extraction technique choice significantly impacts model performance.
- Color histogram technique yielded better results with Naive Bayes classifier than edge detection.
- Combining edge detection and color histogram did not enhance performance as expected.
- Convolutional Neural Network (CNN) model achieved highest accuracy, highlighting the power of deep learning.

Future Directions

- Optimize parameters of the color histogram technique and explore its variations.
- Given the superior performance of the CNN model, further research into deep learning approaches is recommended.
- Aim to develop more accurate and efficient models for crop and weed classification, crucial for precision agriculture.

# References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# GITHUB LINK

https://github.com/MutegekiHenry/cv-weed-classification