Identifying Crops from Weeds

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ECM3420 Learning From Data

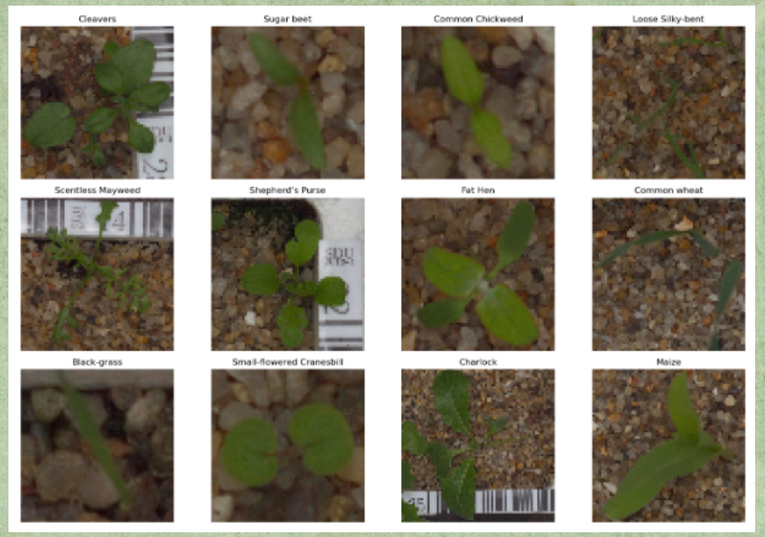
[4]

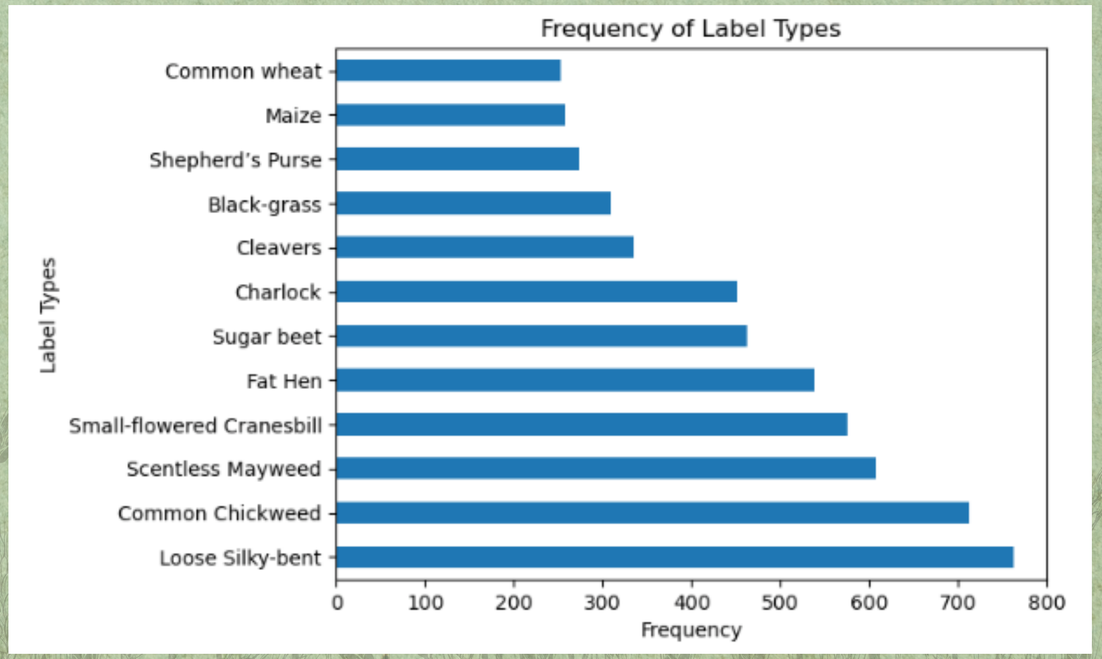
WHY SHOULD WE CARE?

- Importance of distinguishing crops from weeds [2].
- Impacts on agriculture and food supply [1].
- Need for advanced technologies in agriculture.

DATASET USED:

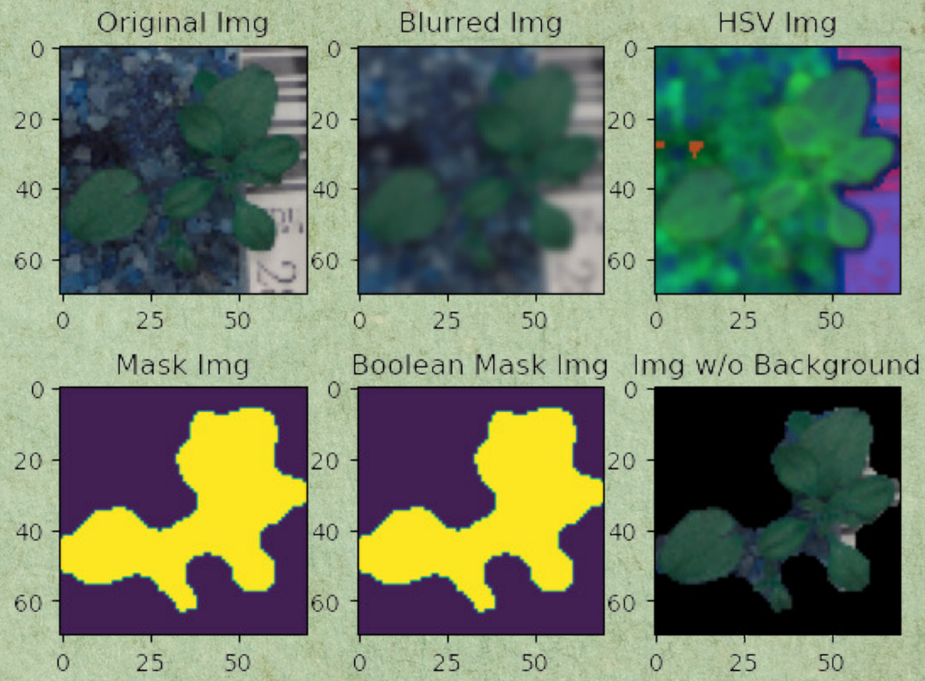
- Plant Seedling Dataset [3]
- 5539 RGB Images
- 12 distinct classes
- Stored in PNG format

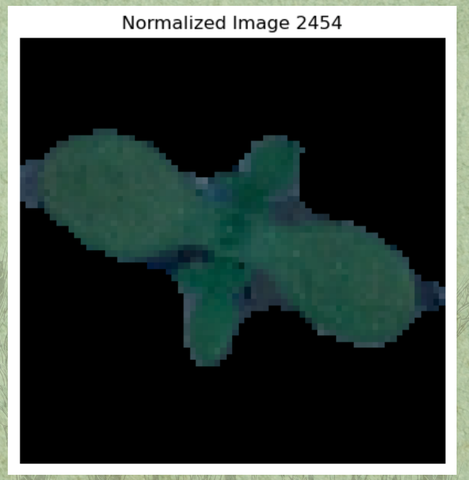




DATA PREPROCESSING:

- Resize to 70x70
- Extract images and labels
- Gaussian blur
- Convert from RGB to HSV
- Isolate plant regions
- Remove background
- Normalise data





MODEL CREATION:

- Dataset is split into a 80, 10, 10 split.
- Data is stratified, random seed is specified.
- Multiple Convolutional layers with batch normalisation, dropout, Max-Pooling and ReLU activation.
- Increasing filters in subsequent convolutional layers.
- Flatten output.
- Dense layers with Batch Normalisation, Dropout. and ReLU activation.
- Final Dense layer with softmax activation.
- Compiled with categorical cross-entropy, Adam optimiser, monitoring accuracy metric during training.

RATIONALE BEHIND CHOICES:

80-10-10 split with random state & stratification:
- External Validation
- Internal Validation
- Reproducibility & preserved distribution

Increasing filter on each subsequent Convolutional Layer
- Capture simple and complex patterns

Max-pooling layer after convolutional layer
- Reduce computational complexity
- Improve feature extraction

Batch Normalisation layers
- Normalise outputs and improve training stability

Dropout Layers

- Prevent overfitting

ReLU activation function

- Faster training

Flatten Layer

- Transition from convolutional to fully connected layers

Dense layers with Batch Normalisation, Dropout. and ReLU activation.

- Responsible for classification task
- Introduces non-linearity to model

Final Dense layer with softmax activation.

- Convert raw scores into probability distribution

Compiled with categorical cross-entropy, Adam optimiser, monitoring accuracy metric during training.

- Measure dissimilarity between true and predicted class
- Adapt learning rates for each parameter during training
- Assess how well model is performing

MODEL TRAINING:

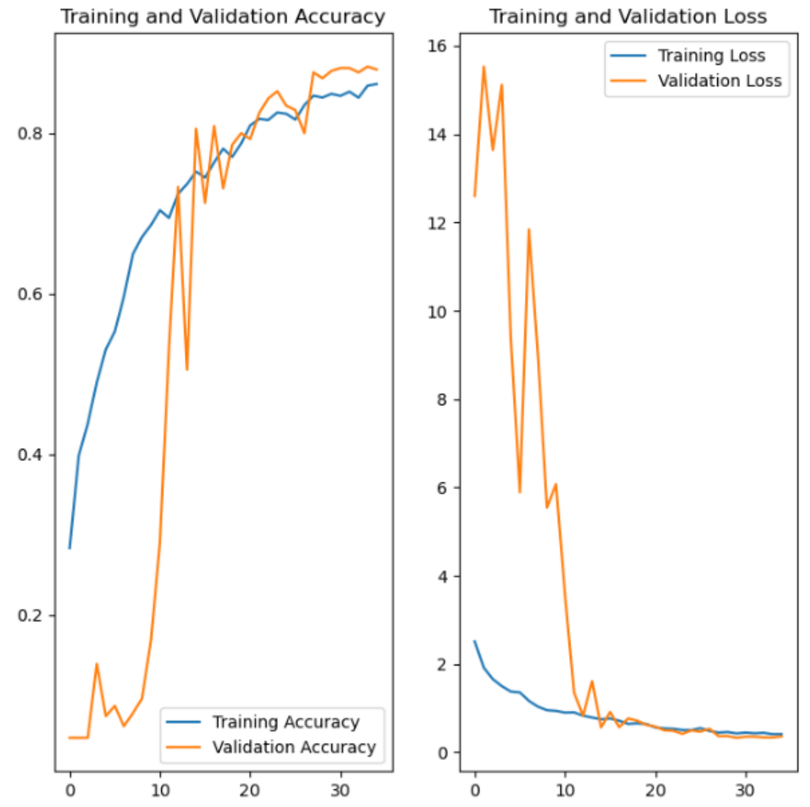
Data Augmentation

- Rotation
- Scaling
- Shifting images
- Flipping images

Callbacks for Model Training

- Best weight
- Latest weight

RESULTS



- Evaluate on Train Set

```
139/139 [==============================] - 21s 150ms/step - loss: 0.269
2   accuracy: 0.9021
[0.26917335391044617, 0.902053713798523]
```

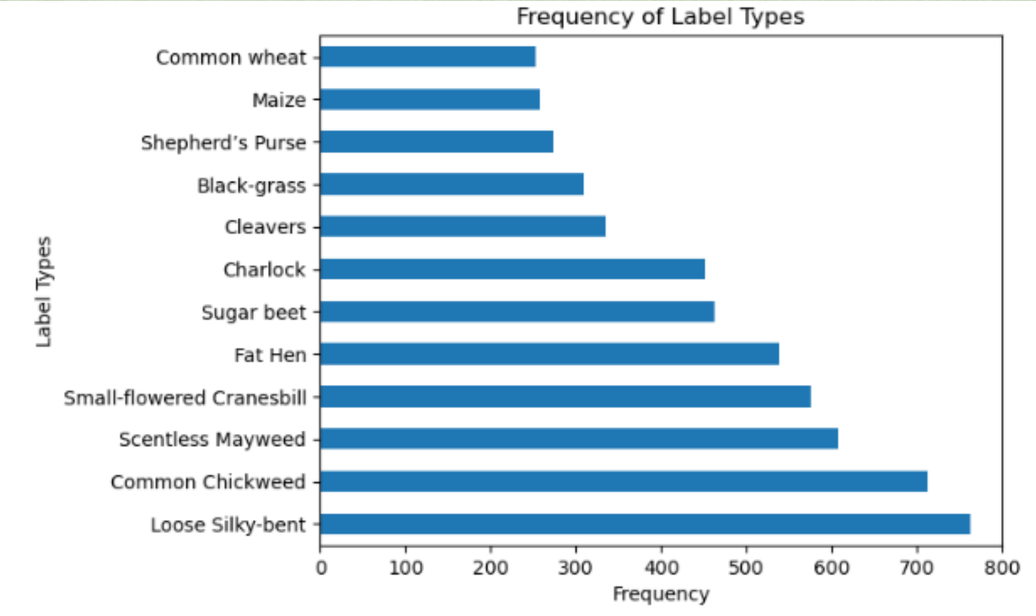
- Evaluate on Validation Set

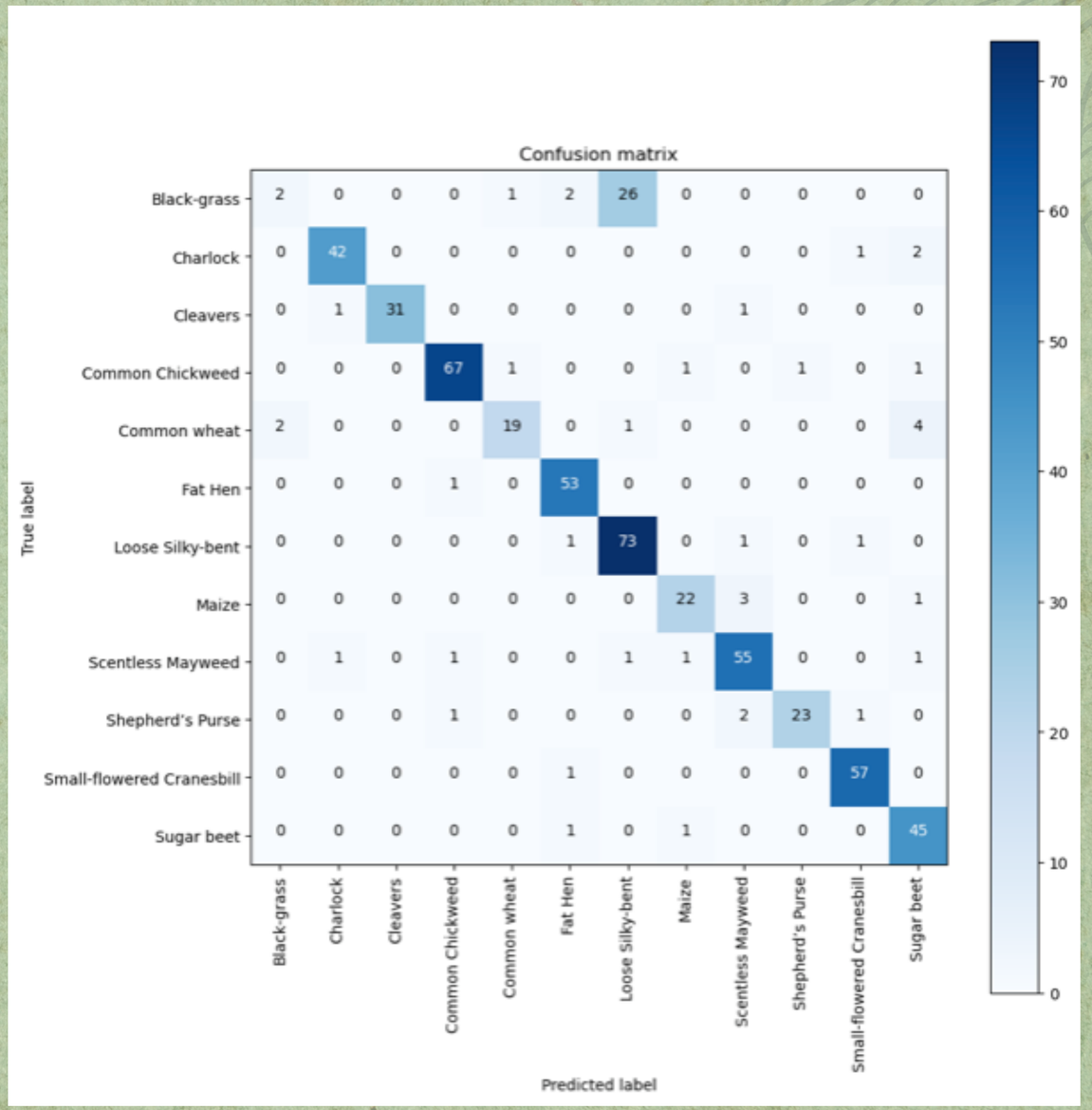
```
18/18 [==============================] - 3s 148ms/step - loss: 0.3359 -
accuracy: 0.8827
[0.3358742892742157, 0.8826714754104614]
```

- Evaluate on Test Set

```
18/18 [==============================] - 3s 149ms/step - loss: 0.3393 -
accuracy: 0.8827
[0.3392665386199951, 0.8826714754104614]
```

RESULTS


Frequency of Label Types
Label Types
Common wheat
Maize
Shepherd's Purse
Black-grass
Cleavers
Charlock
Sugar beet
Fat Hen
Small-flowered Cranesbill
Scentless Mayweed
Common Chickweed
Loose Silky-bent
0
100
200
300
400
500
600
700
800
Frequency


Confusion matrix
True label
Black-grass 2 0 0 0 1 2 26 0 0 0 0 0
Charlock 0 42 0 0 0 0 0 0 0 0 1 2
Cleavers 0 1 31 0 0 0 0 0 1 0 0 0
Common Chickweed 0 0 0 67 1 0 0 1 0 1 0 1
Common wheat 2 0 0 0 19 0 1 0 0 0 0 4
Fat Hen 0 0 0 1 0 53 0 0 0 0 0 0
Loose Silky-bent 0 0 0 0 0 1 73 0 1 0 1 0
Maize 0 0 0 0 0 0 0 22 3 0 0 1
Scentless Mayweed 0 1 0 1 0 0 1 1 55 0 0 1
Shepherd's Purse 0 0 0 1 0 0 0 0 2 23 1 0
Small-flowered Cranesbill 0 0 0 0 0 1 0 0 0 0 57 0
Sugar beet 0 0 0 0 0 1 0 1 0 0 0 45
Black-grass
Charlock
Cleavers
Common Chickweed
Common wheat
Fat Hen
Loose Silky-bent
Maize
Scentless Mayweed
Shepherd's Purse
Small-flowered Cranesbill
Sugar beet
Predicted label
70
60
50
40
30
20
10
0

RESULTS

	precision	recall	f1-score	support
Black-grass	0.50	0.06	0.11	31
Charlock	0.95	0.93	0.94	45
Cleavers	1.00	0.94	0.97	33
Common Chickweed	0.96	0.94	0.95	71
Common wheat	0.90	0.73	0.81	26
Fat Hen	0.91	0.98	0.95	54
Loose Silky-bent	0.72	0.96	0.82	76
Maize	0.88	0.85	0.86	26
Scentless Mayweed	0.89	0.92	0.90	60
Shepherd's Purse	0.96	0.85	0.90	27
Small-flowered Cranesbill	0.95	0.98	0.97	58
Sugar beet	0.83	0.96	0.89	47
accuracy			0.88	554
macro avg	0.87	0.84	0.84	554
weighted avg	0.87	0.88	0.86	554

CONCLUSION:

- CNN is a good approach to the problem
- A balanced dataset is very important!

THANK YOU

References

[1] R. T. Hewson and H. A. Roberts. Some effects of weed competition on the growth of onions. Journal of Horticultural Science, 48(1):51–57, 1973. Accessed: November 29, 2023

[2] United Nations News. Plants, the ‘core basis for life on earth’, under increasing threat, warns un food agency, 2019. Accessed: November 29, 2023

[3] VBookshelf. V2 plant seedlings dataset, 2023. https://www.kaggle.com/datasets/vbookshelf/v2-plant-seedlings-dataset/data?select=Sugar+beet Accessed: November 29, 2023

[4] Dmitry Dreyer. "Woman Planting Plant During Daytime," https://unsplash.com/photos/woman-planting-plant-during-daytime-gHho4FE4Ga0, Accessed: December 5, 2023.

[5] Ryan Searle. "Bird's Eye Photography of Trees," https://unsplash.com/photos/birds-eye-photography-of-trees-7Ku54ZgKEcs, Accessed on December 5, 2023.