# Onion Crop Disease Detection & Classification using CNNs

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- Motivation
- Dataset
- Model
- Results & Experiments
- Conclusion

### **Motivation**

- India is the second largest onion-growing country globally, accounting for approximately 20% of the global onion production
- Aim to investigate the performance of different CNN models for onion crop classification and to identify the most accurate model
- Deep learning has shown great potential for crop disease detection, and further research in this area could significantly improve food security and sustainability

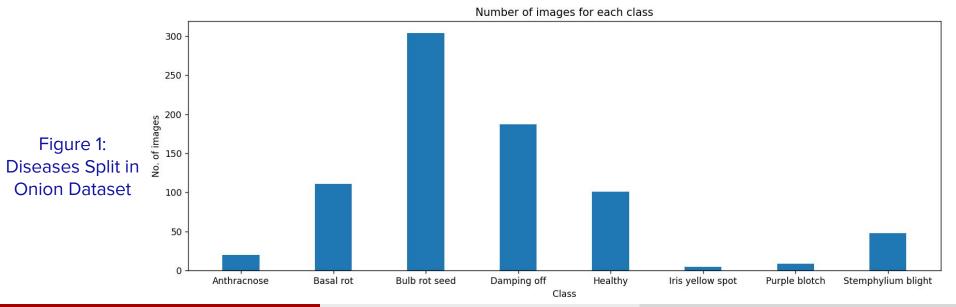
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#### **Onion Dataset**

- Anthracnose disease : 20 images
- Basal rot : 111 images
- Bulb rot seed : 304 images
- Damping off: 187 images

- Healthy: 101 images
- Iris yellow spot virus : 5 images
- Purple blotch disease : 9 images
- Stemphylium blight disease: 48 images

Total 8 classes of onion images in the data



# **Dataset Images**



Stemphylium blight



**Bulb** rot



Healthy



Anthracnose





Damping off



Iris yellow spot

# Plant Village Dataset

- 256 x 256 size images
- 38 Plant leaf classes & 1 background image class
- 54000 total images



Corn Northern Leaf Blight



Grape Leaf blight



Peach Bacterial\_spot

Figure 3: Plant Village Dataset

Source: (https://data.mendeley.com/datasets/tywbtsjrjv/1)

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# Model Training for Binary Classification

- Pre-trained Baseline models trained as feature extractors or fine tuned on the Plant Village Dataset
- The final linear layer of the baseline models is replaced with a **Linear Block** which outputs 39 values corresponding to each class in Plant Village
- Replacing the 39 node linear layer with 2 node layer for Healthy and Diseased onion classification

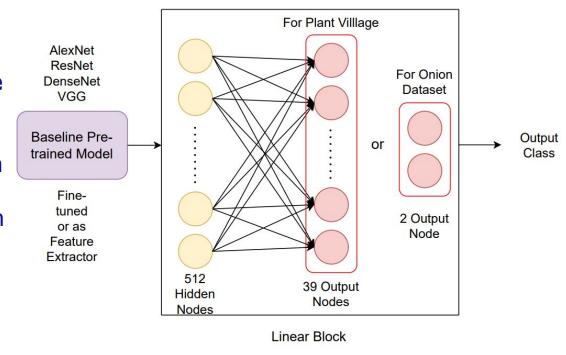
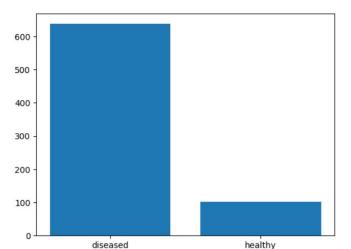


Figure 4: Model

# Train and Test Set of Onion Images

The number of diseased class images in the dataset are significantly larger than that of the healthy class as seen in Figure 4. The onion images are split into a training (70%) and test split (30%) as shown in Figure 5.



|          | Train | Test | Total |
|----------|-------|------|-------|
| Healthy  | 72    | 30   | 102   |
| Diseased | 449   | 195  | 644   |

Table 1: Number of images

Fig 5: Number of Diseased and Healthy images

# Imbalance Dataset Sampler

Sampling different classes differently during training to keep the number of images seen during training for each class similar

- Under-sampling the majority class
- Over-sampling the minority class

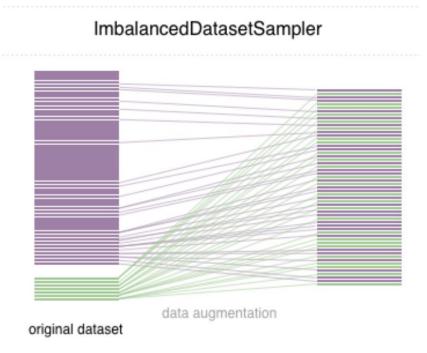


Fig 6: Imbalance Dataset Sampler

# **CutMix Data Augmentation**

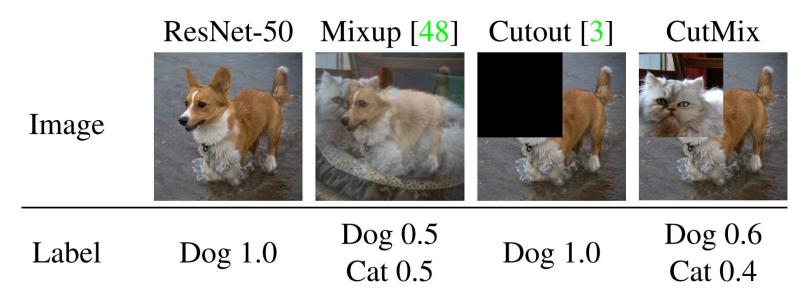


Fig 7: Different Data Augmentations

CutMix augmentation, replaces a patch in the original image with a patch from another image in the training dataset. The label is modified accordingly. This helps in building a more robust model

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### **Parameters**

### Plant Village Pre-training

- Batch Size = 32
- Loss function : Negative Log Likelihood Loss
- Optimizer : Adam
  - Learning Rate
    - For Feature Extracting = 0.01
    - For Fine tuning = 0.0001
  - Decay LR by 0.1 factor every 5 epochs

#### Onion Disease Detection & Classification

- Batch Size = 16
- Loss Function = Negative Log Likelihood Loss
- Optimizer : Adam
  - Learning Rate = 0.001
  - Decay LR by 0.1 factor every 3 epochs

#### **CutMix Parameters**

- Probability of CutMix = 0.5
- Alpha = 0.8

# Baseline Models Trained on Plant Village

Table 2: Results with Plant Village

| Model Name    | odel Name No. of Trainable Parameters | Accuracy on Plant Village (%) |                                    | Model Size<br>(in MB) |
|---------------|---------------------------------------|-------------------------------|------------------------------------|-----------------------|
|               |                                       | Feature<br>Extract            | Fine-tuning<br>(every 20<br>batch) |                       |
| AlexNet       | 62.3 million                          | 92.3                          | 96.4                               | 225                   |
| VGG11         | 133 million                           | 91.45                         | 97.25                              | 500                   |
| DenseNet121   | 8 million                             | 96.1                          | 97.8                               | 29                    |
| ResNet18      | 11 million                            | 94.8                          | 97.2                               | 44                    |
| ResNet50      | 23 million                            | 95                            | 98.1                               | 94                    |
| ResNet152     | 60 million                            | 96.1                          | 98.5                               | 226                   |
| Inception Net | 25 million                            | -                             | 96.3                               | 98                    |

# Binary Classification Results with Onion Dataset

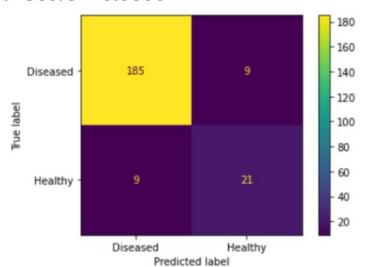
#### Densenet with CutMix

Accuracy = 0.9196

Precision = 0.9536

Recall = 0.9536

F Score = 0.9536



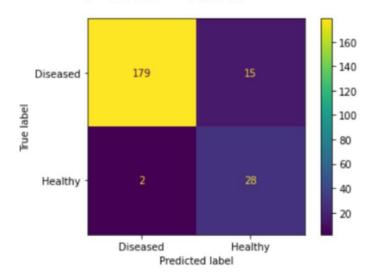
#### DenseNet without CutMix

Accuracy = 0.924

Precision = 0.9889

Recall = 0.922

F Score = 0.9547



# Binary Classification Results with Onion Dataset Contd.

| Model        | Accuracy % | F-Score |
|--------------|------------|---------|
| DenseNet     | 92.4       | 0.9547  |
| ResNet50     | 90         | 0.945   |
| AlexNet      | 91.5       | 0.949   |
| VGG11        | 90         | 0.9448  |
| InceptionNet | 83         | 0.89    |

Accuracy & F-Score of different baseline models

### **GradCam Observations**

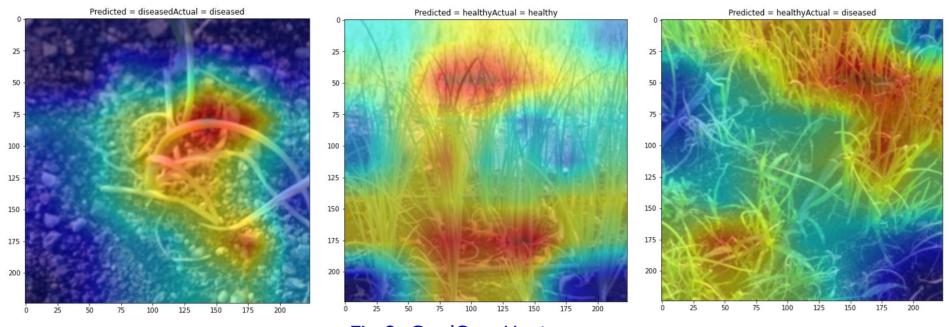


Fig 8: GradCam Heatmaps

- Specifies the areas of the image which led to the predictions seen
- The GradCam heatmaps shows that the model is able to look at the crop part of the image selectively, and ignore the ground and other background regions

### Multi-Class Classification of Onion Dataset

We aim to classify the four classes: Basal Rot, Bulb rot Seed, Healthy and Damping off disease using the Densenet baseline mode.

The overall classification accuracy achieved is **78%** 



# Few-shot classification of Onion Images

#### N-way-K-shot Classification:

N classes are chosen in each episode during training/testing, and in each episode K support images are used to learn an embedding function.

#### TRAIN set:

- Basal rot : 111 images
- Bulb rot seed : 304 images
- Damping off: 187 images
- Healthy: 101 images

#### **NOVEL** set:

- Iris yellow spot virus : 5 images
- Purple blotch disease: 9 images
- Anthracnose disease : 20 images
- Stemphylium blight: 48 images

```
Accuracy on new classes: 46 %
```

```
Training:
N = 4
# of Support Set images per episodes (K) = 5
# of query set images per episodes = 5

Test:
N = 4
# of Support Set images per episodes (K) = 3
# of query set images per episode = 2
```

Conclusion: Poor few-shot performance using prototypical networks for few-shot learning

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### Conclusion

- Baseline CNN models give good accuracy numbers for Binary Onion Crop classification into healthy and diseased classes
- DenseNet121 model proves to be one of the best-performing models for binary classification achieving an accuracy of 92.4% and occupying a memory size of only 29 MB
- The cut mix data augmentation helps bring the classification's recall and precision to the same level, making the model robust to classifying both classes correctly without compromising on accuracy
- We achieve a multi-classification accuracy of around 74% to classify between three types of onion diseases and healthy onion images.
- Few-shot classification fails to generalize an embedding function for multi-class classification of different onion diseases

# Summary

Aim: To classify healthy and diseased onion images taken from the field. Also to try a few-shot learning approach for multi-class classification of these diseases.

Method: Pre-trained baseline models tuned on Plant Village Dataset, then trained and tested on Onion image dataset.

Model

#### For Plant Village AlexNet ResNet For Onion DenseNet Dataset VGG Baseline Pre-Output trained Model Class Finetuned 2 Output or as Node Feature Extractor 39 Output Hidden Nodes

**Results:** 

| Model     | Accuracy on          |         | Model   |
|-----------|----------------------|---------|---------|
| Name      | Plant Village<br>(%) |         | Size    |
|           |                      |         | (in MB) |
|           | Featur               | Fine-tu |         |
|           | е                    | ning    |         |
|           | Extract              |         |         |
| AlexNet   | 92.3                 | 96.4    | 225     |
| VGG11     | 91.45                | 97.25   | 500     |
| DenseNet  | 96.1                 | 97.8    | 29      |
| ResNet18  | 94.8                 | 97.2    | 44      |
| ResNet50  | 95                   | 98.1    | 94      |
| ResNet152 | 96.1                 | 98.9    | 226     |

Onion Dataset

| Accuracy  | 0.924     |
|-----------|-----------|
| Precision | 0.65      |
| Recall    | 0.93      |
| F-score   | 0.767     |
|           | - N 1 - 1 |

DenseNet

| Accuracy  | 0.90   |
|-----------|--------|
| Precision | 0.59   |
| Recall    | 0.833  |
| F-score   | 0.6944 |

ResNet 152