Machine Learning In Agriculture

Fruit Classification and Plant Disease Identification Using One Shot Learning

Group 3

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Content

Introduction

- Machine Learning has proved to be a boon in the recent times. With the advancement in computational power, neural networks are being used to perform variegated tasks. CNNs help us to perform very complex image classification tasks.

- Machine Learning all together has proved to be quite helpful in agriculture, be it yield prediction, crop quality prediction or soil and water management.

- In this study, we aim to develop an approach for 2 tasks-fruit detection based on fruit images and plant disease identification based on leaf images.

- Fruit identification will be useful to reduce the manpower.

- Plant disease detection will be useful in order to detect and prevent the possible diseases among crops.

Fruit Classification-Dataset Description

In this study, the datasets used are Fruits-360 and Plant Village Dataset. Both the datasets are publicly available on Kaggle

Fruit 360 Dataset

- In this dataset, there are 131 classes of fruits and vegetables, with a total of 90483 images.
- These images are divided into 67692 training and 22688 testing images.
- The images are scaled to 100x100 pixels.

Apple Braeburn

Avocado Ripe

Banana

Fruit Classification
Methodology- Deep Convolutional Neural Networks/Transfer Learning

- Mainstream approach is to perform a classification task using deep convolutional neural networks.
- Transfer learning is a technique that makes use of the knowledge gained while solving one problem and applying it to a different but related problem.
- Many pre-trained models (like VGG 16, VGG 19, Dense Net etc) which are trained on a large ImageNet data-set are available as open source and can be used to develop more advanced models by using the pre-trained weights.
- In this study, we propose a deep learning model with the help of transfer learning to perform the image classification tasks on the aforementioned datasets.

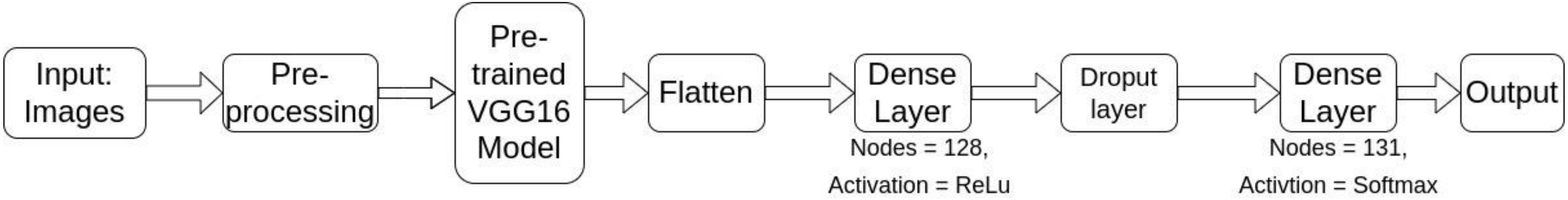


Fig: Deep CNN used in our methodology

Fruit Classification- Results of Transfer Learning Approach

Train-Test Ratio	Testing Accuracy	Testing AUC	Testing Precision	Testing Recall	Testing F1 score
10%-90%	77.46	0.984	0.962	0.655	0.779
50%-50%	90.79	0.9831	0.9335	0.8961	0.912
60%-40%	92.76	0.9864	0.9398	0.9215	0.931
67%-33%	94.13	0.9899	0.9508	0.9375	0.944
70%-30%	94.82	0.9903	0.956	0.9452	0.951
90%-10%	99.75	0.99	0.998	0.996	0.996

Fruit Classification
Methodology - One Shot Learning

1. **Few Shot Learning:**
   In this methodology, we use very less number of images, but more than one image for the training purposes.

2. **One Shot Learning:**
   In this, we only use a single image as our training dataset for the model to classify any test image to a class using that constraint.

3. **Zero Shot Learning:**
   The target in this is to classify images without using a single training example. This can only be done when we have appropriate information about the functionality, appearance etc.

One Shot Learning was first proposed in 2011, in the paper called “One Shot Learning of Simple Visual Concepts”. Later, “Siamese Neural Networks for One-shot Image Recognition” was published which used the Siamese network for the first time.

Fruit Classification
Methodology - One Shot Learning

Figure below gives the proposed methodology that we've used for the implementation.

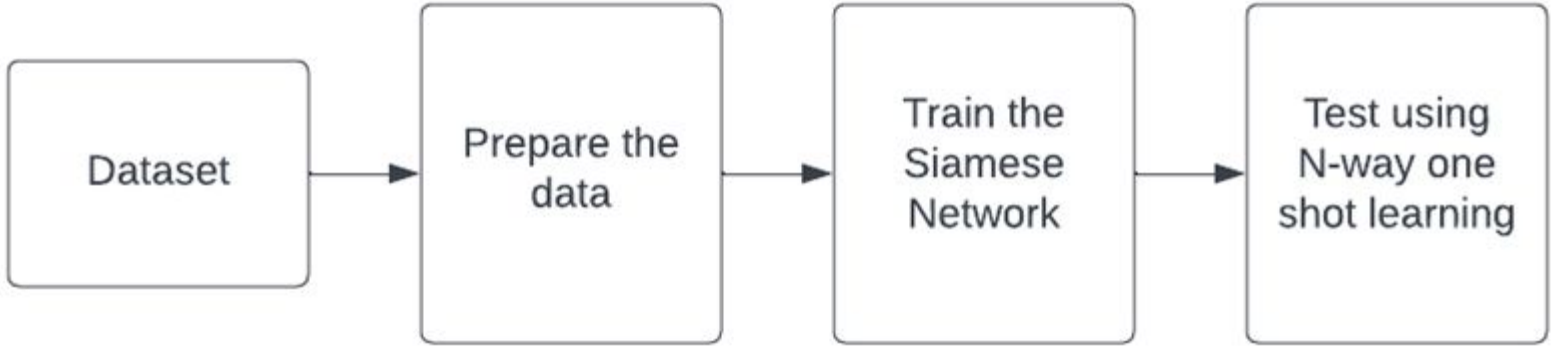


Fig: Proposed Methodology For One Shot Learning

Fruit Classification
One Shot Learning- Siamese Network

A Siamese Network is a type of network architecture that contains two or more identical subnetworks used to generate feature vectors for each input and compare them.

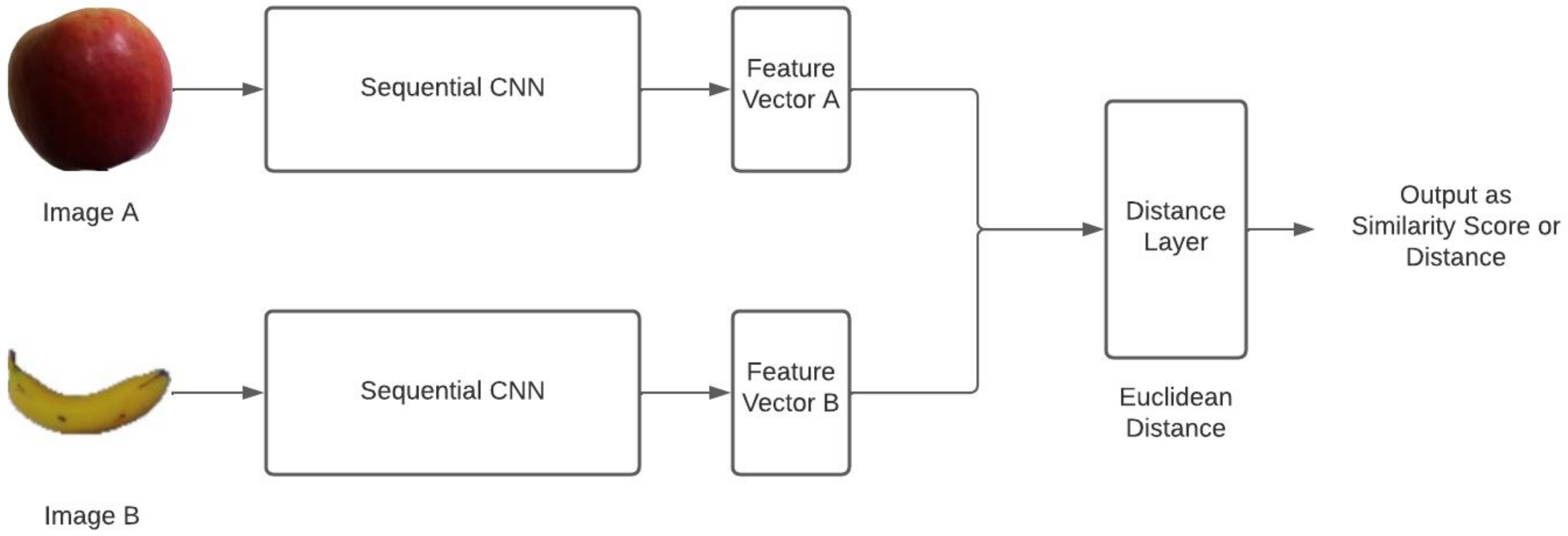


Fig: Siamese Network Used In The Architecture

Fruit Classification
One Shot Learning -Generating Pairs


Genuine Pair

Label- 1


Imposite Pair

Label- 0

Images From Each Class: 20

Total Dataset: 20000 pairs
(10000 genuine + 10000 imposite)

Fruit Classification
One Shot Learning- CNN used in Siamese Network

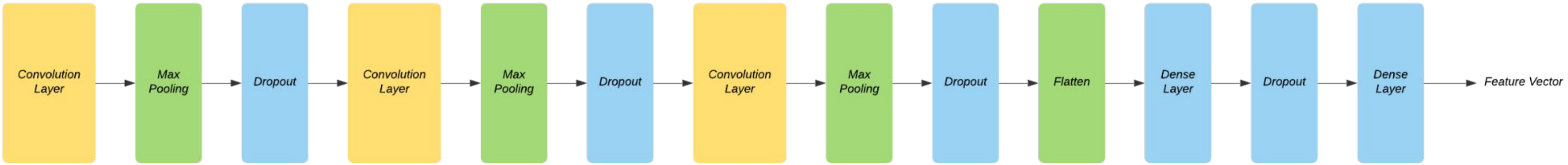


Fig: Sequential CNN used in the architecture.

Optimizer Used - RMS prop

Epochs- 20

Loss : Contrastive Loss

Training Accuracy: 92.94%

Validation Accuracy: 92.97%

Testing Accuracy: 87.5%

Fruit Classification
One Shot Learning- Contrastive Loss

Siamese Networks can be trained using variety of loss functions such as Binary Cross Entropy Loss etc.

However, Contrastive Loss works better for the task of One Shot Learning and to train Siamese Networks

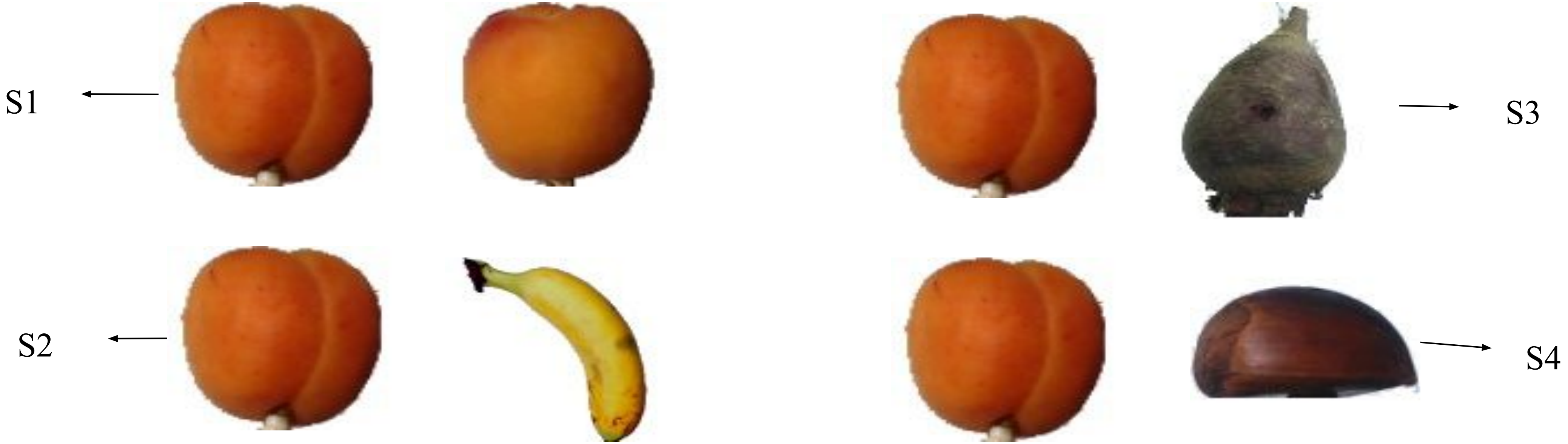
Equation 1 gives the contrastive loss formula:

$$Contrastive\ Loss = \frac{1}{n}\sum_{n}(1 - Y_{true}) * {D_w}^2 + Y_{true} * \{\max(0, margin - D_w)\}^2$$

Where:
N=number of training examples
Y_{true} = Actual label (1 for genuine pair, 0 for imposite)
D_w= Predicted Euclidean Distance between the two feature vectors by the network
Margin=1 (typically)

Fruit Classification
Testing Methodology->N-way One Shot Learning

- Let’s understand the N-Way One Shot Learning through an example.
- Example of 4-Way One Shot Learning is given below.
- Pairs of fruits are generated. Now, for an iteration, out of all the pairs, only one pair is a genuine pair.



Fruit Classification
Testing Methodology->N-way One Shot Learning

- So when the pairs are fed to the trained model, they return a similarity score or the distance for each
- Pair with largest similarity score/least distance is predicted as genuine and is compared with actual label.
- For a correct prediction, the similarity score of the genuine pair should be highest and the distance should be least.
- This process is repeated for a number of iterations. Accuracy is calculated by dividing correct predictions by total iterations.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Iterations} * 100\ \%$$

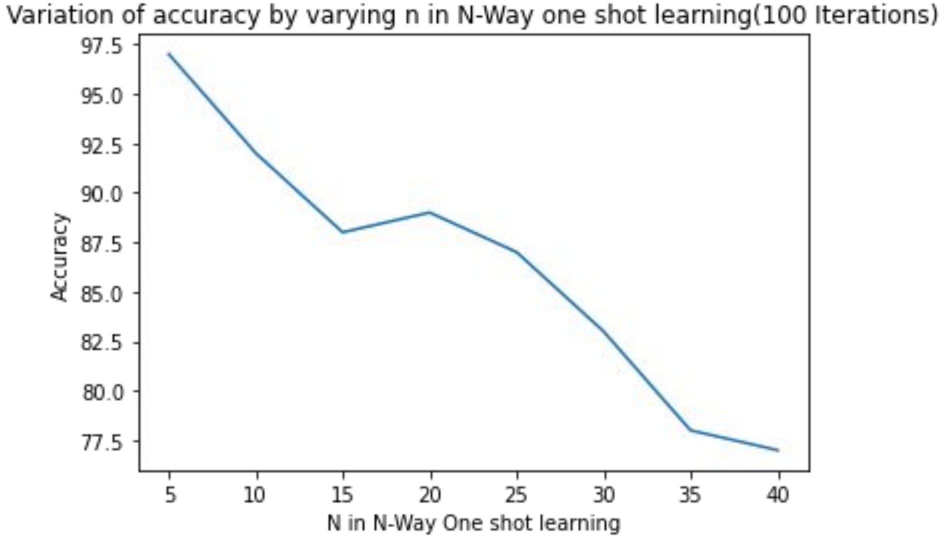
Fruit Classification
Testing Methodology->N-way One Shot Learning
Results

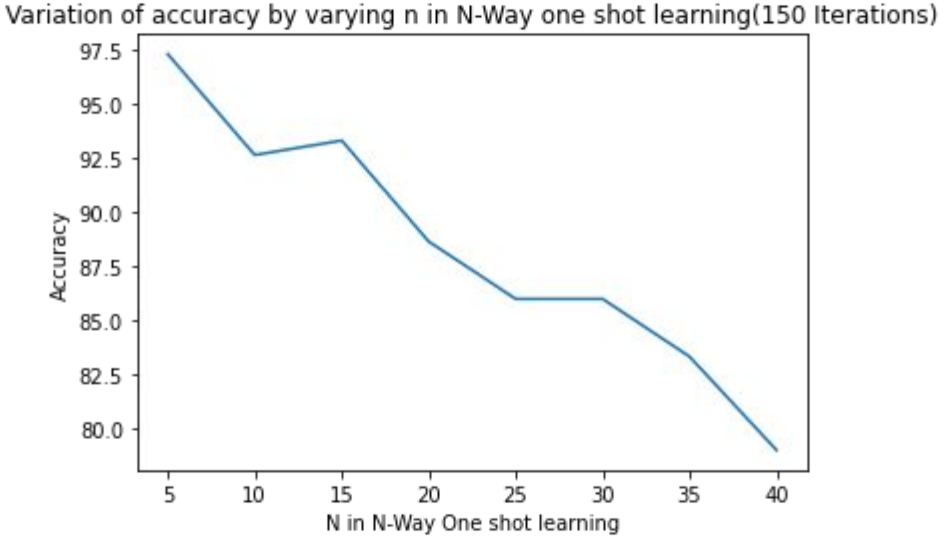
Variables in testing :
1) Number of pairs in the support set (N)
2) Number of iterations
We tested our network for N=1, 40 with a step size of 5.
For each of these, we tested for 100, 150 and 200 iterations.

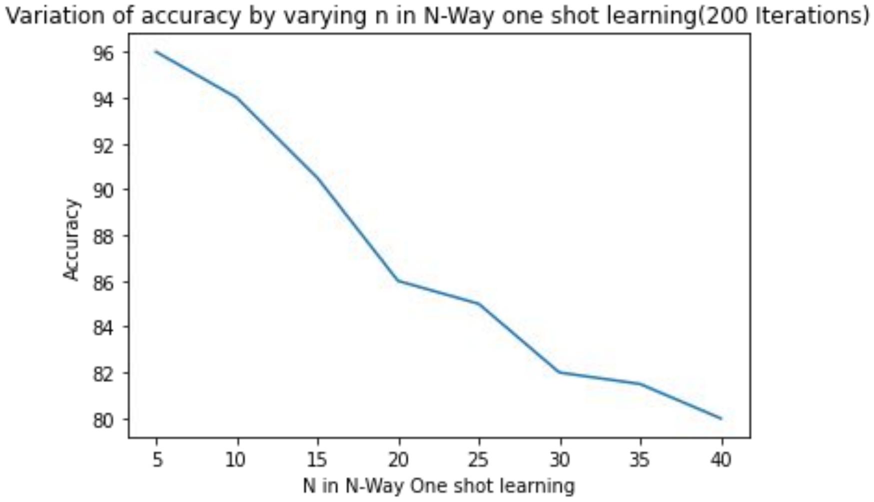
Table: Variation of accuracy(%) with number of pairs and number of iterations

	N=5	N=10	N=15	N=20	N=25	N=30	N=35	N=40
100 Iterations	97%	92%	88%	89%	87%	83%	78%	77%
150 Iterations	97.33%	92.66%	93.33%	88.66%	86%	86%	83.33%	79%
200 Iterations	96%	94%	90.5%	86%	85%	82%	81.5%	80%

Fruit Classification
Testing Methodology->N-way One Shot Learning
Results







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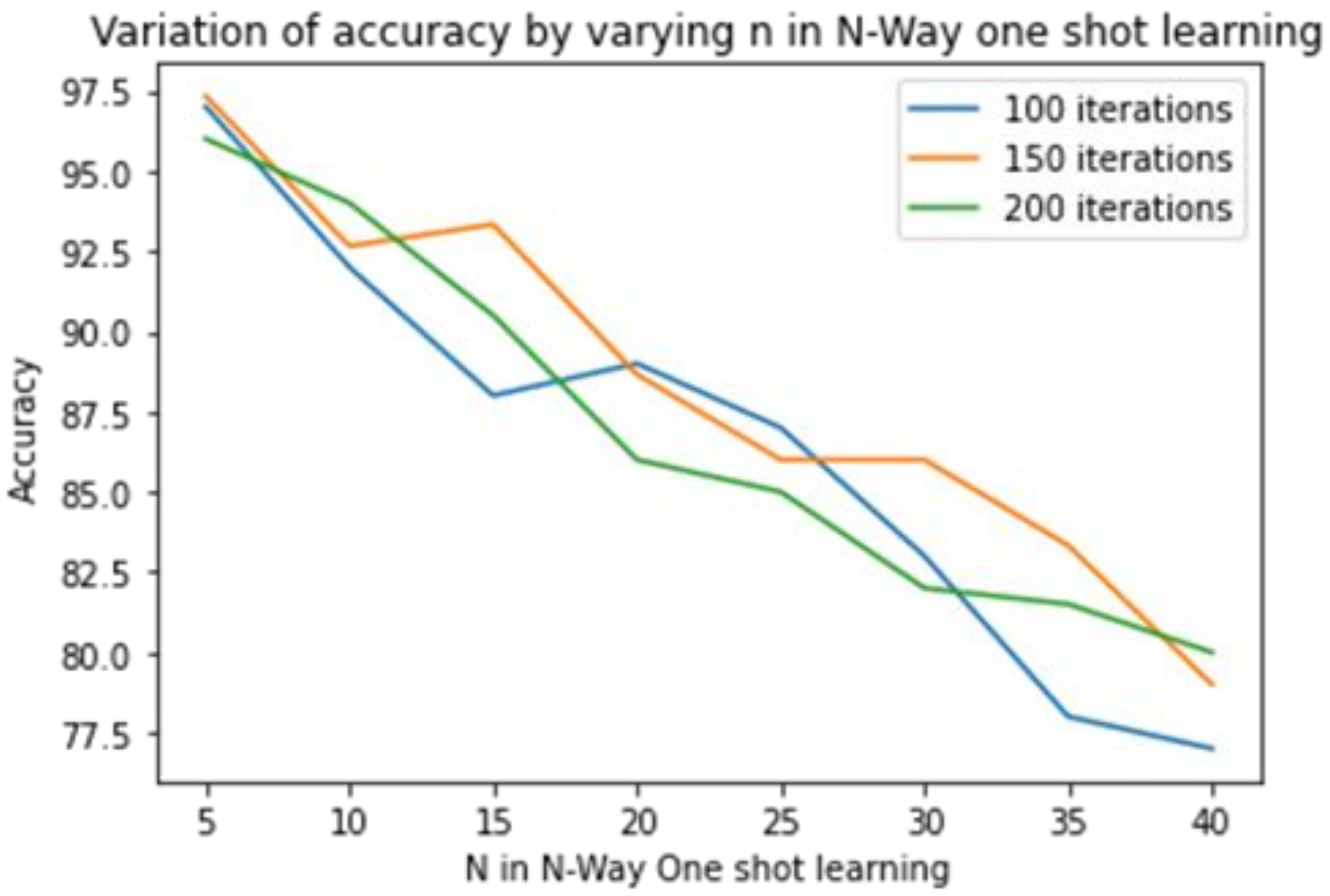

Plant Disease Detection-Dataset Description

In this study, the proposed datasets are Fruits-360 and Plant Village Dataset. Both the datasets are publicly available on Kaggle

PlantVillage Dataset

- In this dataset, there are a total of 54306 images, covering 38 different classes.
- These images are divided into 43445 training and 10861 testing images.
- These images are available in three different formats, namely, RGB, Grayscale and Segmented.

RGB Image

Grayscale Image

Segmented Image

Plant Disease Detection
Methodology - Deep Convolutional Neural Networks/Transfer Learning

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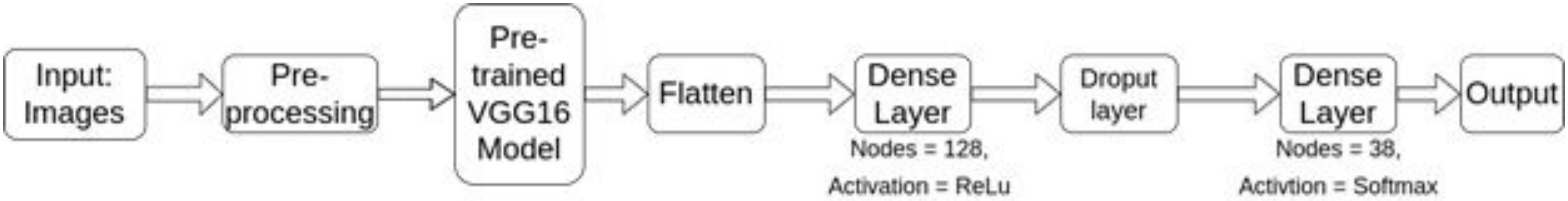

Fig: Deep CNN used in our methodology

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Plant Disease Detection
Proposed Methodology - One Shot Learning

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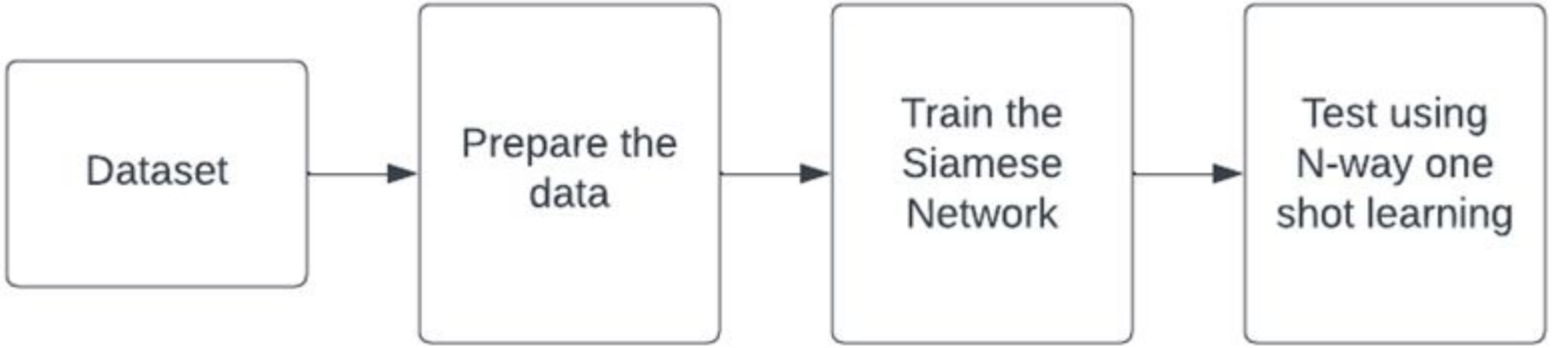

Fig: Proposed Methodology For One Shot Learning

Plant Disease Detection
One Shot Learning- Siamese Network

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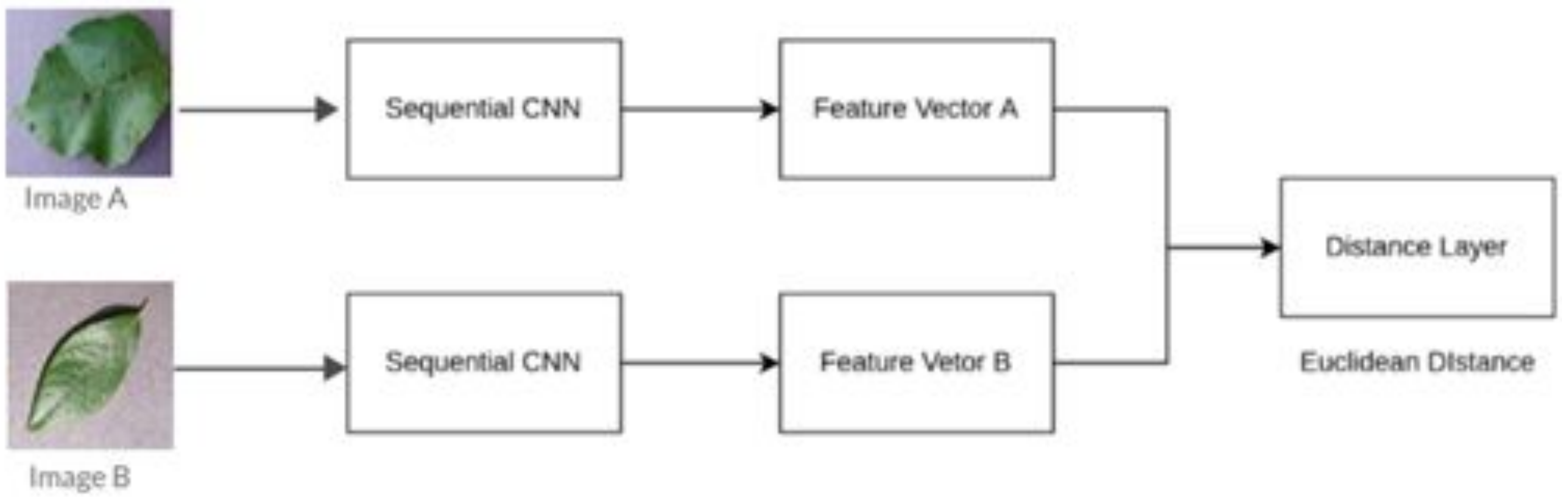
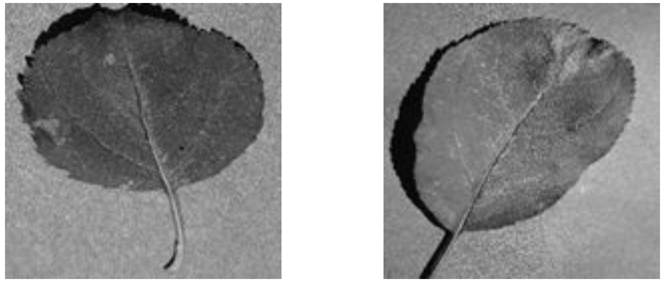


Fig: Siamese Network Used In The Architecture

Plant Disease Detection
One Shot Learning -Generating Pairs

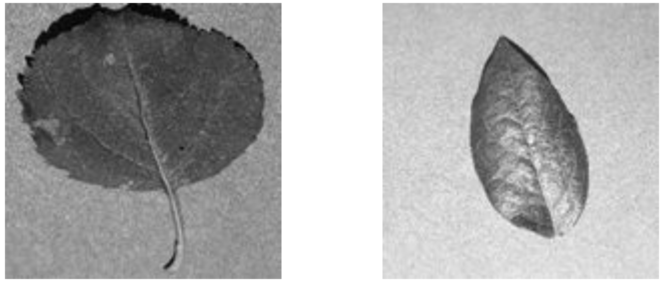
RGB- Genuine Pair



Grayscale- Genuine Pair

Segmented- Genuine Pair

RGB- Imposite Pair



Grayscale- Imposite Pair

Segmented- Imposite Pair

Plant Disease Detection
One Shot Learning- CNN used in Siamese Network

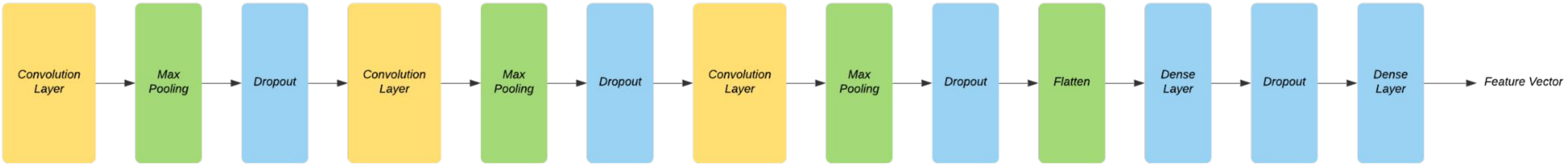


Fig: Sequential CNN used in the architecture.

Optimizer Used - RMS prop

Epochs- 25

Loss : Contrastive Loss

Fruit Classification
Testing Methodology->N-way One Shot Learning

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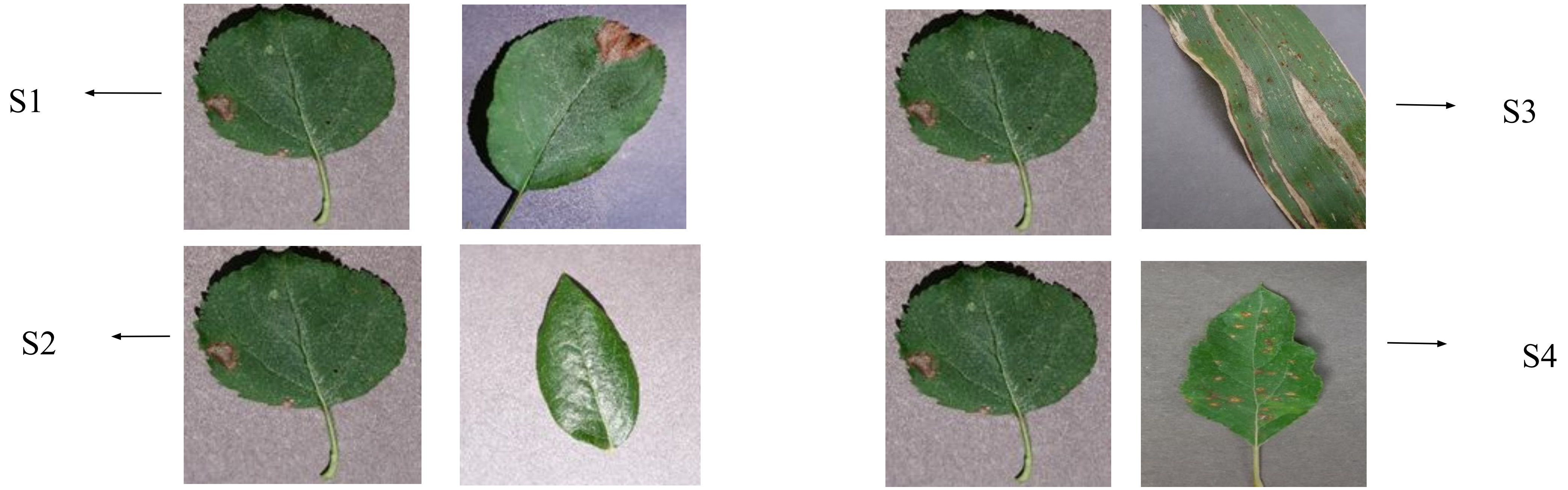


Fruit Classification
Testing Methodology->N-way One Shot Learning

- So when the pairs are fed to the trained model, they return a similarity score or the distance for each
- Pair with largest similarity score/least distance is predicted as genuine and is compared with actual label. .
- This process is repeated for a number of iterations. Accuracy is calculated by dividing correct predictions by total iterations.
- The process is repeated for each of the 3 trained Siamese networks of each of the 3 datasets, i.e. grayscale, color and segmented.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Iterations} * 100\ \%$$

S1

S2

S3

S4

Plant Disease Detection
Testing Accuracy for different values of N(100 iterations)

	N=3	N=6	N=9	N=12	N=15	N=18	N=21
Color	90.5%	88.33%	85%	83.5%	81%	78.5%	77.5%
Grayscale	88%	87.5%	84%	81%	77.5%	74.66%	71%
Segmented	93%	90%	91%	86.5%	81%	78%	76%

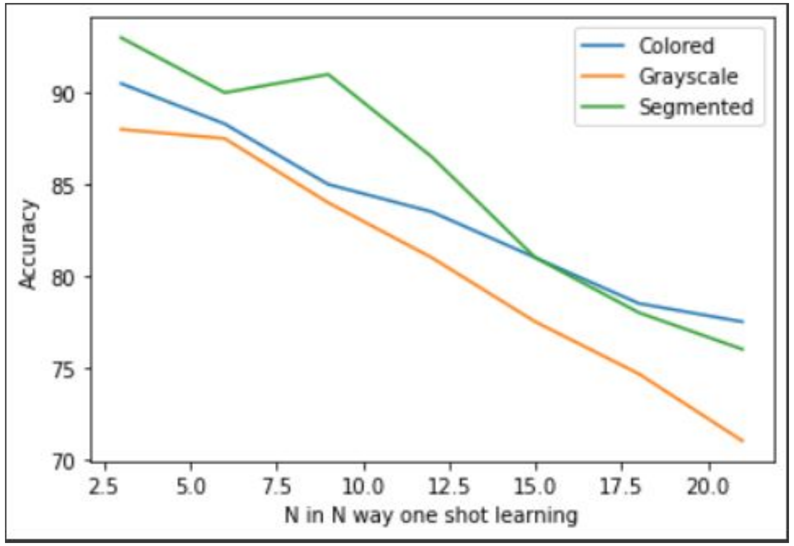
Plant Disease Detection
Testing Accuracy for different values of N(150 iterations)

	N=3	N=6	N=9	N=12	N=15	N=18	N=21
Color	90.5%	86.5%	86.5%	84.66%	80.33%	77%	75.5%
Grayscale	88.5%	86.66%	83.33%	81%	77.66%	75.5%	73%
Segmented	92.33%	89.33%	87.66%	83%	83%	80.5%	78.6%

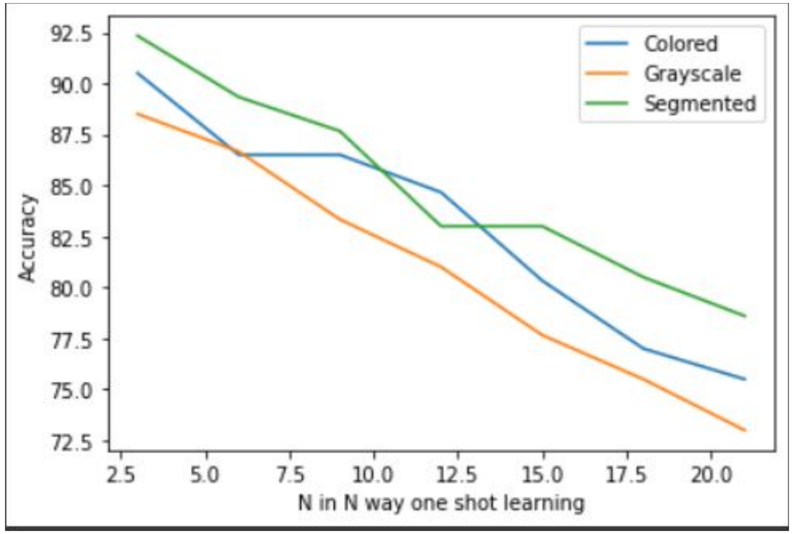
Plant Disease Detection
Testing Accuracy for different values of N(200 iterations)

	N=3	N=6	N=9	N=12	N=15	N=18	N=21
Color	90.5%	91%	89%	85.33%	81%	77.5%	76%
Grayscale	87%	85.66%	82.5%	79.66%	77.5%	76%	75.5%
Segmented	92%	89%	85.5%	83%	80%`	77.33%	77.5%

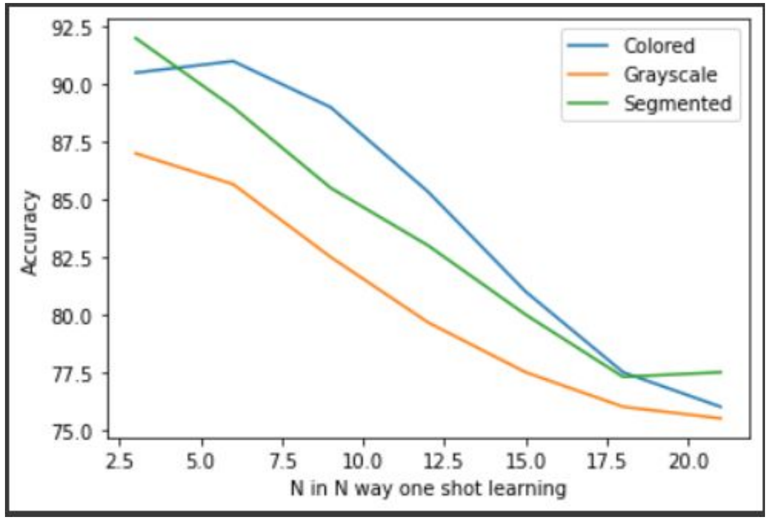
Plant Disease Detection
Testing Methodology->N-way One Shot Learning
Results



100 iterations



150 iterations



200 iterations

Conclusion

- With the advances in machine learning algorithms and techniques, various attempts have been made to address the problem of scarcity of data in the field of agriculture.
- In this study, one such attempt was made by employing the technique of one shot learning for fruit classification task and plant disease identification.
- For fruit classification, a mini dataset was prepared and a siamese network was trained on the prepared dataset. Siamese network takes a pair of images as an input and outputs a similarity score. The trained model was evaluated using N-Way one shot learning. N was varied from 5 to 40 with a step size of 5.
- Each time, the process was repeated for 100, 150 and 200 iterations. There was a gradual decrease in accuracy with increase in N. However, even for 40- Way classification, the model was able to generate accuracy of 80%.
- For the task of plant disease identification, as there were 3 types of available datasets; colored, segmented and grayscale, hence 3 mini datasets were prepared for each of the image type available. Siamese networks were trained on each of the dataset. Further N-Way one shot learning was performed for each of the trained networks, and N was varied from 3 to 21 with a step size of 3.
- Each of it was repeated for 100,150 and 200 iterations. For 21 Way classification, dataset prepared from segmented images was able to generate accuracy of 77.5%.

Future Work

1. In the future, we aim to extend this project to more domains of agriculture.
2. We aim to improve the accuracy obtained by combining the transfer learning approach with one shot learning.
3. The accuracy and robustness of the model can also be improved by trying different architectures and hyperparameters.
4. We aim to develop a research paper for plant disease detection just like we did for fruit classification.

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THANK YOU!

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