A Report on Image classification and Object detection of Banana and cassava images

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Abstract

Image classification is a pattern recognition technique in computer vision which uses contextual information to classify images.
Object detection is a technique in computer vision and image processing that deals with detecting instances of semantic objects of a certain class in images and videos.
Image classification and object detection utilise machine learning to perform in various applications like face detection, remote sensing of crop gardens among others.
In this report, I performed cropping of cassava and banana plants from images that were taken from a garden with a lot of clutter. I then used SIFT, ORB and color histograms to extract features from the cropped images. The extracted features were then used for image classification using traditional machine learning algorithm of KNN.
I also carried out an object detection task where I first annotated images which I then used on a pre-trained YOLOv5 model to detect images .
Comparing the performance, the YOLOv5 model had average Mean Average Precision (mAP) of .., Precision of .., Recall of ..while the KNN model had accuracy of .., precision of.. and recall of.. The YOLOv5 model proved to be better than K Nearest Neighbor (KNN) due to its pre-training on the coco dataset with 80 classes and about 200,000 labels which makes it faster in training.

1. Introduction

Machine learning and Computer Vision are applications of artificial intelligence which are tremendously being used in various applications of Image classification, object recognition and detection, image analysis, action recognition among others.
The main aim of any image classification based models is to assign labels to captured images and consequently these labels can be used to arrange images in a semantic order. These are then eventually arranged in various domains of digital image processing and computer vision such as image retrieval, object recognition, object detection, image annotation, scene analysis and video analysis.

Plant classification is one of the most experimented applications of image classification and object detection. This has been because of the various challenges in agriculture which affect farmers. These challenges include; pests, weeds, bad weather which when not managed in time lead to reduction in crop yields.
This has therefore triggered many researchers into coming up with solutions that help to combat these challenges.
Machine learning and deep learning algorithms are the state of the art solutions for these challenges. These support in the extraction of features from the crop parts where leaves are especially the main focus for identification of features using the shape, texture, color and veins [1]. Remote sensing technology has been boosted with machine learning algorithms to assist in crop growth monitoring, soil moisture estimation among others.This technology uses less human effort and provides timely information for analysis of crop health [3].

1.1. Related literature

Plant classification from a garden is quite cumbersome due to a lot of challenges like; deformed plant parts like deformed leaves due to pests. Some plants have parts that have similar features with other plants [4].
Plants get covered by other plants which brings about occlusion.

Textual content of the images can potentially provide better results than the other features.
S. Barburiceanu, R. Terebes, and S. Meza [5] proposed a texture feature extraction technique through use of feature vectors and occurrence matrix based methods.
The features that are mostly used in the classification of the plants are leaves as these provide more details for a specific plant.
P. P. Kaur and S. Singh [6] propose an automated system for calculating leaf features like length of the leaf, width, height among others and they use knn and support vector

machine (svm) on model training.
P. Siva Prasad and A. Senthilrajan [1] proposed a deep convolutional neural network to detect leaf images. They the used an Adaboost algorithm to collect classifiers from softmax.
M. D. Fauzi et al. [2] used a DenseNet201 to classify weed and potato plants. The main aim of this model was to help in detection of the potato plants from weeds during pesticide spraying. Since most plants get affected by the pesticides as the farmer is not able to determine which plants are potatoes and which ones are weeds.
Several feature extraction techniques are used to extract features for image classification due to advance in image processing provided by various pre-processing techniques to make images suitable for feature extraction. This involves finding discriminating features which serve as the basis for classification using several machine learning techniques like KNN, Naive Bayes, Support Vector Machines (SVM) among others.
J. A. Villaruz [8] explores use of a pretrained ALexNet to extract features and then later applied a multiclass SVM to classify images of the of the seedlings of the three most important berry trees belonging to the Philippine indigenous plants.
In response to the difficulty in differentiation of various plants from each other, various object detection techniques have been developed to assist in detecting the different plants and classifying them in their respective categories.In addition object detection helps to reduce the adverse effects of diseases that in turn affect the crop yields by classifying the health plants from unhealthy ones.
Various machine learning algorithms like You Only Look Once (YOLOv4) algorithm [10] have been utilised in combating some of these challenges through early detection. J.Wang et al [9] proposed three plant leaf disease detection methods called squeeze-and-excitation SSD (Se-SSD), deep block SSD (DB-SSD) and deep block attention SSD (DBA-SSD) for disease identification and disease degree classification of various plant leaves. From their experiments,DBA-SSD performs better than the rest of the methods. This is then further improved through utilisation of the convolutional layers that were previously trained on the Image Net dataset by the VGG model.

2. Methodology

This section entails the procedures that I followed in performing Image Classification and Object detection tasks.

2.1. Image classification

An image can be defined as a two-dimensional function, f (x,y) where x and y are spatial coordinates, and f is the amplitude at any pair of coordinates (x,y)
In this task, I was to build a machine learning model using either KNN or Naive Bayes, which could classify whether a certain image was a cassava or banana plant.
In this task task, I undertook steps like image cropping, image processing, feature detection, feature extraction and so on.

2.1.1 Image processing

During this step, I performed image cropping, where I used the Microsoft office Picture manager to manually crop out banana and cassava plants from the provided images.
The cropped out images were 765 cassava images and 444 banana images.
There was a class imbalance because some images that were provided did not contain any banana plant except had only cassava plants.

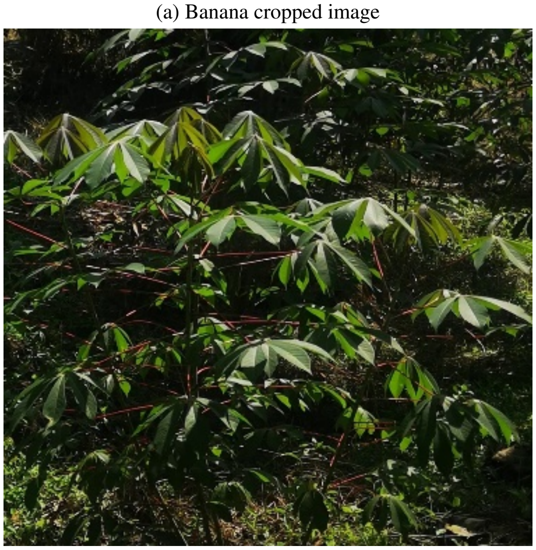
The cropped out images were then resized to a size of 500*500 for uniformity.

Please refer to the author guidelines on the CVPR 2022 web page for a discussion of the policy on dual submissions.

2.1.2 Feature extraction

During this step, I performed feature detection first by use of key points on the cropped images. With the key points, unique features are detected for every image.
I then experimented on the use of colour histograms, SIFT and ORB for the extraction of features to be used for classification.
I also experimented with the key points using SIFT and ORB in the images.
The colour histograms had variations and so were not consistent thus could not rely on them for purpose of classification.
I also used the BF matcher object to find matched features of the images and then computed the sum of the distances of both cassava and banana matches.
I converted the resized images to gray scale and then applied SIFT and ORB for feature extraction.
For image classification, ORB features were preferred since ORB is well known for being rotation invariant and resistant to noise. ORB also executes faster than SIFT.
The ORB features were then applied to the KNN algorithm for classification. The results are visualised in Figure 7 where 0 denotes cassava and 1 denotes banana.

(a) Banana cropped image



(b) Cassava cropped image.

Figure 1. Cropped banana and cassava images

```
# Plot histogram for banana sample
sample = random.sample(ban_imgs_resized, k = 1)[0]
# sample = ban_imgs[34]
print(sample.shape)
plot_hist(sample)
```

```
(200, 200, 3)
```

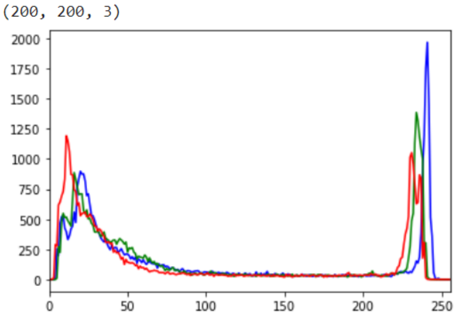


Figure 2. Color histogram for a banana plant

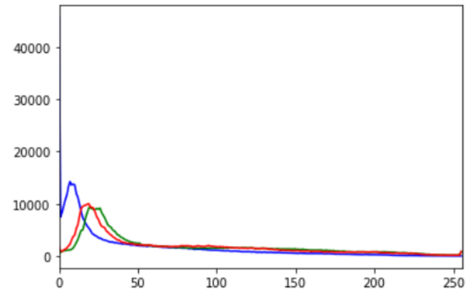
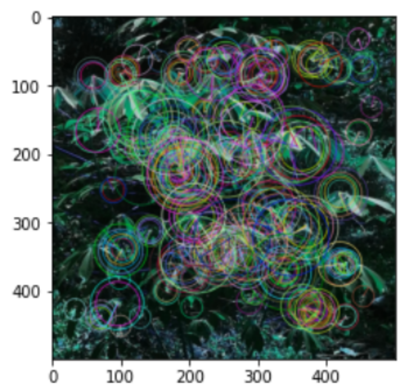
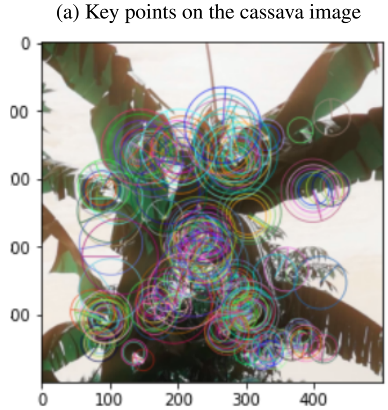


Figure 3. Color histogram for a Cassava plant



(a) Key points on the cassava image



(b) Key points on the banana image

Figure 4. Extraction of key points on images

```
ban_images_orb
```

```
[array([ 92, 184, 191, ..., 121,  80,  42], dtype=uint8),
 array([201, 180, 188, ..., 243,  70,  33], dtype=uint8),
 array([169, 160, 189, ..., 243,   6,  51], dtype=uint8),
 array([108, 169, 161, ..., 125, 255, 199], dtype=uint8),
 array([205, 118, 250, ..., 223, 218, 245], dtype=uint8),
 array([255, 120, 238, ..., 243, 171,  17], dtype=uint8),
 array([248, 109,  19, ..., 179,  70, 114], dtype=uint8),
 array([ 84,  92, 221, ..., 191,  94, 245], dtype=uint8),
 array([ 38, 165,  33, ..., 204, 181, 249], dtype=uint8),
 array([ 77, 117,  17, ..., 243, 134, 120], dtype=uint8),
 array([100, 120, 211, ..., 243,  70, 114], dtype=uint8),
 array([111, 113, 242, ..., 178, 226,  57], dtype=uint8),
 array([221, 188, 222, ..., 243, 134, 120], dtype=uint8),
 array([197,  92, 215, ..., 121,  80,  42], dtype=uint8),
 array([116,  99, 248, ..., 125, 255, 199], dtype=uint8),
 array([244, 253, 185, ..., 243, 198, 112], dtype=uint8),
 array([ 81,  10, 158, ..., 243, 103, 161], dtype=uint8),
 array([ 95,  28,  23, ..., 251,  80,  34], dtype=uint8),
 array([ 95,  28,  23, ..., 250, 198, 115], dtype=uint8),
 array([237, 253,  57, ..., 121,  80,  42], dtype=uint8),
 array([ 24, 217, 188, ..., 243, 134, 114], dtype=uint8),
 array([248, 250, 234, ..., 243, 198, 114], dtype=uint8),
 array([ 15, 189, 229, ..., 243, 103, 161], dtype=uint8),
```

(a) Banana ORB features

```
cass_images_orb
```

```
[array([248,  34, 250, ..., 241, 136,  49], dtype=uint8),
 array([ 84, 236, 156, ..., 128, 131,  81], dtype=uint8),
 array([224,  80,  89, ..., 180,  11,  93], dtype=uint8),
 array([221, 121, 247, ..., 160,   7, 185], dtype=uint8),
 array([213,  72, 130, ..., 128, 131,  81], dtype=uint8),
 array([ 82, 177, 191, ...,  96, 238, 131], dtype=uint8),
 array([ 61, 181,  29, ..., 129, 203,  35], dtype=uint8),
 array([163, 172, 135, ..., 224,   7, 185], dtype=uint8),
 array([ 41,  92, 113, ..., 129, 219,  35], dtype=uint8),
 array([ 69,  17,  21, ...,  68, 143,  95], dtype=uint8),
 array([  7,  63, 107, ...,  64, 238, 131], dtype=uint8),
 array([233,  16, 213, ..., 211,  17, 120], dtype=uint8),
 array([248, 161,  87, ...,  96, 238, 131], dtype=uint8),
 array([209,  75,  10, ..., 102,  43,  23], dtype=uint8),
 array([ 96,  32, 149, ..., 160,   7, 185], dtype=uint8),
 array([255,  62, 238, ...,  76,  84, 127], dtype=uint8),
 array([224, 160,  57, ...,  59,  86, 115], dtype=uint8),
 array([ 69,  17,  29, ...,  96, 238, 131], dtype=uint8),
 array([119, 126, 129, ..., 133,  14, 117], dtype=uint8),
 array([152, 232,  66, ..., 243,  75,   4], dtype=uint8),
 array([120, 245,  61, ..., 251, 244,  32], dtype=uint8),
```

(b) Cassava ORB features.

Figure 5. Extracted features

```
cass_images_sift
```

```
[array([1., 0., 1., ..., 0., 0., 0.], dtype=float32),
 array([0., 0., 0., ..., 0., 0., 0.], dtype=float32),
 array([107.,  56.,  35., ...,   0.,   0.,   0.], dtype=float32),
 array([2., 0., 1., ..., 0., 3., 1.], dtype=float32),
 array([0., 0., 0., ..., 6., 1., 5.], dtype=float32),
 array([0., 0., 0., ..., 0., 0., 0.], dtype=float32),
 array([ 0.,  0.,  0., ..., 44.,  2.,  5.], dtype=float32),
 array([12., 13., 13., ...,  4.,  2.,  6.], dtype=float32),
 array([11., 16.,  2., ..., 69.,  4.,  9.], dtype=float32),
 array([121.,  57.,  16., ...,   0.,   0.,   0.], dtype=float32),
 array([12.,  4.,  7., ...,  0.,  0.,  0.], dtype=float32),
 array([ 0.,  1., 10., ...,  0.,  0.,  0.], dtype=float32),
 array([60.,  2.,  3., ...,  0.,  0.,  0.], dtype=float32),
 array([128.,  92.,  22., ...,   0.,   0.,  19.], dtype=float32),
 array([36., 66., 43., ..., 34.,  5.,  2.], dtype=float32),
 array([6., 2., 2., ..., 0., 0., 0.], dtype=float32),
 array([26., 25., 21., ...,  0.,  0.,  0.], dtype=float32),
```

Figure 6. Cassava SIFT features

```
print(classification_report(y_orb_test, preds))
```

	precision	recall	f1-score	support
0	1.00	0.89	0.94	199
1	0.83	1.00	0.91	102
accuracy			0.93	301
macro avg	0.91	0.95	0.93	301
weighted avg	0.94	0.93	0.93	301

Figure 7. KNN Classification Report on ORB features

3. Object detection

Object detection is a computer vision field, which involves detection of instances of an object from the image. In this task, I carried data annotation using the LabelImg tool.

I annotated banana and cassava plants from the images while using the bounding boxes, which help to determine the target plant by extracting the x and y coordinates for the image's borders.

I split the data into training, testing and validation with the use of the roboflow tool. I used transfer learning of YOLOv5 to train the model. I considered this because it was trained on a famous COCO dataset of 80 classes with about 200,000 image labels. With this transfer learning, it helps to attain better accuracy since the model is already trained on a larger dataset with better weights.

Figure 8. Detected annotated images

3.1. Experimental results

In this subsection, I visualise the results obtained from the model training.

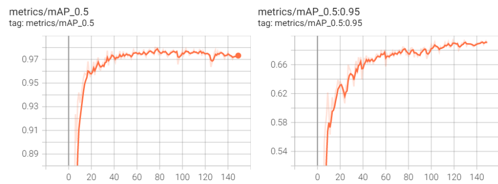


Figure 9. Mean Average Precision curve

Figure 10. Precision and Recall curve

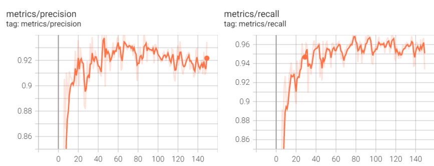


Figure 11. Visualisation of the training loss

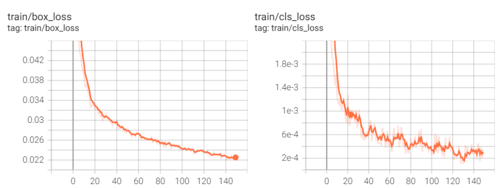


Figure 12. Visualisation of training loss

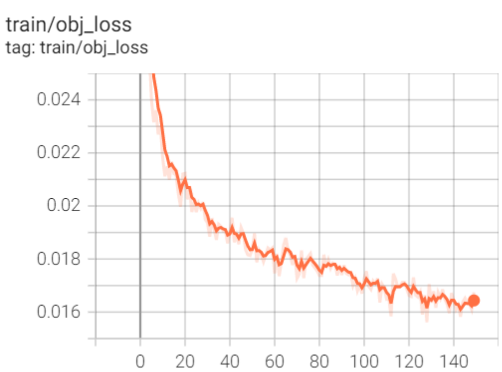
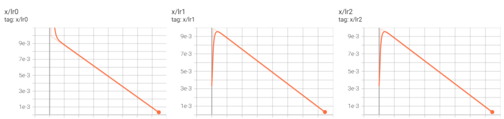


Figure 13. Visualisation of the learning rate



4. Results

Figure 14. Results from the model weights

```
150 epochs completed in 0.774 hours.
Optimizer stripped from runs/train/exp/weights/last.pt, 14.3MB
Optimizer stripped from runs/train/exp/weights/best.pt, 14.3MB

Validating runs/train/exp/weights/best.pt...
Fusing layers...
Model summary: 157 layers, 7015519 parameters, 0 gradients, 15.8 GFLOPs
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 25/25 [00:02<00:00,  9.44it/s]
                   all        195        393      0.924      0.956      0.978      0.694
                banana        195        140      0.967      0.993      0.995      0.789
               cassava        195        253      0.882       0.92      0.961      0.598
Results saved to runs/train/exp
```

Figure 15. Predictions from the unknown images

References

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