A REPORT ON
FRUIT DETECTION SYSTEM

SUBMITTED BY

SAKSHI BUDHIA

SHREYA BHONGALE

AKHIL PANDEY

PRATYAKSHA PANDEY

॥वसुधैव कुटुम्बकम्॥

Under the Guidance of

Prof. DEEPALI VORA

SYMBIOSIS INSTITUTE OF TECHNOLOGY

A CONSTITUTENT OF SYMBIOSIS INTERNATIONAL (DEEMED UNIVERSITY)

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1. TOPIC : FRUITS DETECTION SYSTEM

2. INTRODUCTION

Having a high-quality dataset is essential for obtaining a good classifier.
Most of the existing datasets with images contain both the object and the noisy background. This could lead to cases where changing the background will lead to the incorrect classification of the object.
As a second objective we have trained a deep neural network that is capable of identifying fruits from images. This fits the current trend of companies working in the augmented reality field. For eg. Google Lens which will tell the user many useful information about the object toward which the phone camera is pointing. First step in creating such application is to correctly identify the objects.
Such a network would have numerous applications across multiple domains like autonomous navigation, modeling objects, controlling processes or human-robot interactions.
An area in which this research can provide benefits is autonomous fruit harvesting.
While there are several papers on this topic already, from the best of our knowledge, they focus on few species of fruits or vegetables. In this paper we attempt to create a network that can classify a variety of species of fruit, thus making it useful in many more scenarios.As the start of this project we chose the task of identifying fruits for several reasons. On one side, fruits have certain categories that are hard to differentiate, like the citrus genus, that contains oranges and grapefruits.
Thus we want to see how well can an artificial intelligence complete the task of classifying them. Another reason is that fruits are very often found in stores, so they serve as a good starting point for the previously mentioned project.

3. DATASET

The dataset was named Fruits-360

DATASET PROPERTIES:-

- The total number of images: 90483.
- Training set size: 67692 images (one fruit or vegetable per image).
- Test set size: 22688 images (one fruit or vegetable per image).
- The number of classes: 131 (fruits and vegetables).
- Image size: 100x100 pixels

4. DATA VISUALIZATION

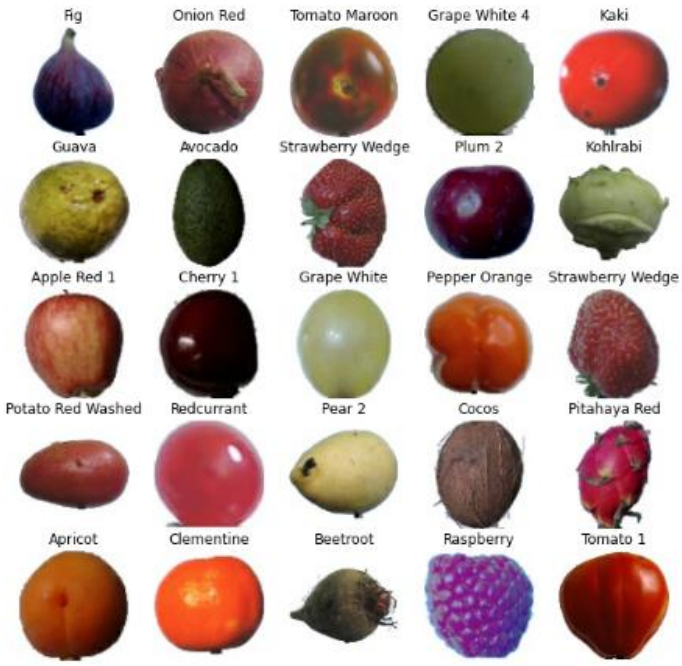
Below are the snapshots of a few specific fruits in the dataset:

The pictures below belong to the class “Apple Braeburn”

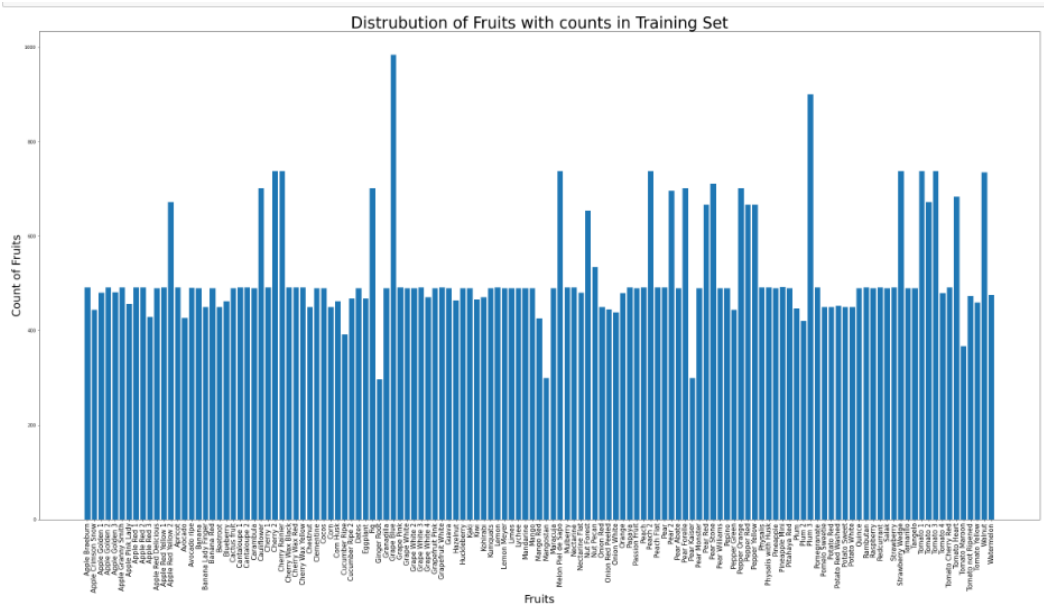
The pictures below belong to the class “Beetroot”

The pictures below belong to the class "Banana Red"

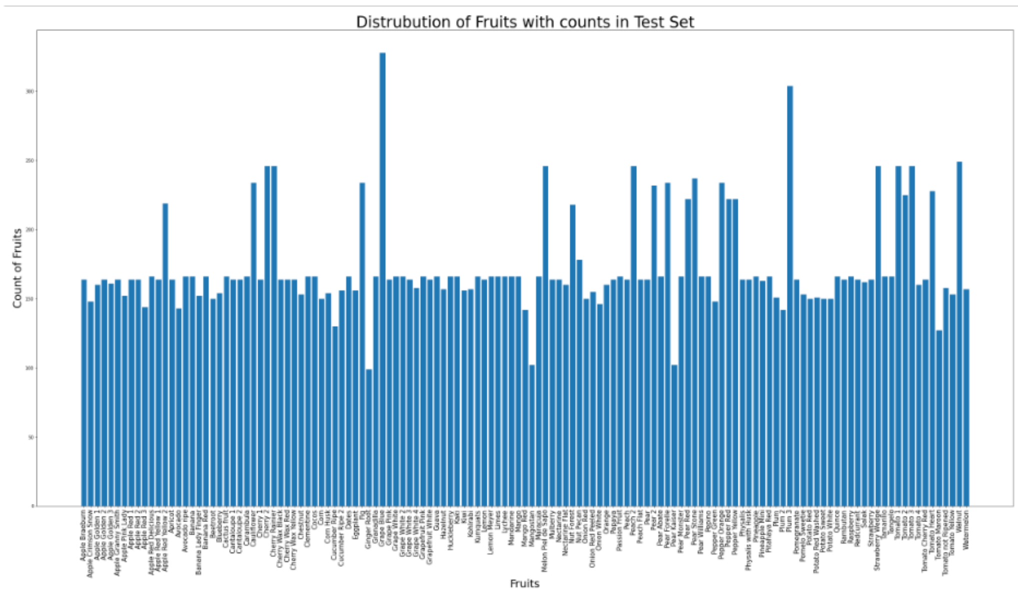
The pictures below belong to various classes in the dataset



Distribution of Fruits with counts in Training Set



Distribution of fruits with counts in Testing Set



5.ALGORITHMS USED

5.1 ALGORITHMS USED

CNN

- By processing data efficiently with a grid-like structure, convolutional neural networks are commonly used to analyze visual images.
- This type of network is also known as a ConvNet. Images are detected and classified according to their contents using convolutional neural networks.

- An image can be extracted from a convolutional neural network by utilizing multiple hidden layers. A CNN consists of four layers:

1. CONVULATION LAYER:-Providing valuable features to an image begins with the convolution layer. This layer contains several filters that perform the convolution process. All images are represented by pixels.
2. ReLU layer:-A negative pixel is set to 0 by the ReLU layer, which performs element-wise operations. The result is a rectified feature map generated by the nonlinearity in the network
3. POOLING:-Pooling operations reduce the dimensionality of feature maps by downsampling them.
4. FLATTENING:- Flattening is a process for converting pooled feature maps from 2D to a single linear vector containing all the feature data.
5. FULLY CONNECTED LAYER:-There are layers that are fully connected if all inputs from one layer are connected to each activation unit in the next layer.

Some Code Snippets of CNN:

Part 2: Building the CNN

Initialising the CNN

```
In [5]: cnn = tf.keras.models.Sequential()

In [6]: # Step 1 - Convolution
        cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu', input_shape=[256,256,3]))

In [7]: # Step 2 - Pooling
        cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

In [8]: # Adding a Second Convolutional Layer
        cnn.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu'))
        cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

In [9]: # Step 3 - Flattening
        cnn.add(tf.keras.layers.Flatten())

In [10]: # Step 4 - Full Connection
         cnn.add(tf.keras.layers.Dense(units=128, activation='relu'))

In [11]: # Step 5 - Output Layer
         cnn.add(tf.keras.layers.Dense(units=131, activation='softmax'))
```


The evaluation parameter used in CNN was the in-built accuracy that the model provides. We got an accuracy of 94.5%.

LSTM

- It is a variety of recurrent neural networks (RNN) capable of learning long-term dependencies, especially when it comes to sequence prediction.

- The LSTM has feedback connections, which means it can process an entire sequence of data, except for a single point of data, such as an image.
- Machine translation, speech recognition, etc. can benefit from this technology.
- In contrast to other RNNs, LSTMs perform exceptionally well on a wide range of problems.
- LSTMs are explicitly designed to avoid the problem of long-term dependencies. They are practically designed to remember information for long periods of time by default.

Some Code Snippets of LSTM:

```
model = build_model(allow_cudnn_kernel=True)

model.compile(
    loss="categorical_crossentropy",
    optimizer=optimizers.RMSprop(lr=0.0001, decay=1e-6),
    metrics=["accuracy"],
)

STEP_SIZE_TRAIN=train.n//train.batch_size
STEP_SIZE_VALID=valid_generator.n//valid_generator.batch_size
STEP_SIZE_TEST=test.n//test.batch_size

model.fit_generator(generator=train,
                    steps_per_epoch=STEP_SIZE_TRAIN,
                    validation_data=valid_generator,
                    validation_steps=STEP_SIZE_VALID,
                    epochs = 5, verbose = 1)
```

```
Epoch 1/5
1587/1587 [==============================] - 1995s 1s/step - loss: 4.8720 - accuracy: 0.0102 - val_loss: 4.8675 - val_accuracy: 0.0146
Epoch 2/5
1587/1587 [==============================] - 2004s 1s/step - loss: 4.8643 - accuracy: 0.0145 - val_loss: 4.8608 - val_accuracy: 0.0146
Epoch 3/5
1587/1587 [==============================] - 2021s 1s/step - loss: 4.8596 - accuracy: 0.0145 - val_loss: 4.8577 - val_accuracy: 0.0146
Epoch 4/5
1587/1587 [==============================] - 2030s 1s/step - loss: 4.8575 - accuracy: 0.0145 - val_loss: 4.8564 - val_accuracy: 0.0146
Epoch 5/5
1587/1587 [==============================] - 2027s 1s/step - loss: 4.8566 - accuracy: 0.0145 - val_loss: 4.8559 - val_accuracy: 0.0146

<tensorflow.python.keras.callbacks.History at 0x7efbc81c78d0>
```

The evaluation parameter used in LSTM was the classification report of all the classes. The overall accuracy was 10%.

6.RESULTS AND ACCURACY

The following snippet shows the result of the CNN Model with 4 epochs:

```
Epoch 1/4
2116/2116 [==============================] - 8482s 4s/step - loss: 4.1480 - accuracy: 0.8256 - val_loss: 1.4861 - val_accuracy:
0.7838
Epoch 2/4
2116/2116 [==============================] - 6176s 3s/step - loss: 0.6750 - accuracy: 0.8593 - val_loss: 3.1759 - val_accuracy:
0.7038
Epoch 3/4
2116/2116 [==============================] - 5166s 2s/step - loss: 0.3625 - accuracy: 0.9149 - val_loss: 5.1771 - val_accuracy:
0.6088
Epoch 4/4
2116/2116 [==============================] - 5737s 3s/step - loss: 0.2919 - accuracy: 0.9459 - val_loss: 4.6571 - val_accuracy:
0.6634
```

The LSTM model gave 10% accuracy over 5 epochs

··· Output exceeds the size limit. Open the full output data in a text editor

	precision	recall	f1-score	support
Apple Braeburn	0.01	0.01	0.01	164
Apple Crimson Snow	0.01	0.01	0.01	148
Apple Golden 1	0.01	0.01	0.01	160
Apple Golden 2	0.00	0.00	0.00	164
Apple Golden 3	0.01	0.01	0.01	161
Apple Granny Smith	0.03	0.02	0.03	164
Apple Pink Lady	0.00	0.00	0.00	152
Apple Red 1	0.00	0.00	0.00	164
Apple Red 2	0.02	0.02	0.02	164
Apple Red 3	0.00	0.00	0.00	144
Apple Red Delicious	0.02	0.02	0.02	166
Apple Red Yellow 1	0.01	0.01	0.01	164
Apple Red Yellow 2	0.01	0.01	0.01	219
Apricot	0.00	0.00	0.00	164
Avocado	0.01	0.01	0.01	143
Avocado ripe	0.01	0.01	0.01	166
Banana	0.02	0.01	0.01	166
Banana Lady Finger	0.01	0.01	0.01	152
Banana Red	0.01	0.01	0.01	166
Beetroot	0.01	0.01	0.01	150
Blueberry	0.00	0.00	0.00	154
Cactus fruit	0.01	0.01	0.01	166
Cantaloupe 1	0.01	0.01	0.01	164
...				
accuracy			0.01	22688
macro avg	0.01	0.01	0.01	22688
weighted avg	0.01	0.01	0.01	22688

7. CONCLUSION

The model worked well and the CNN model was generated using transfer learning, and thanks to the fast processing time of the CNN, it was able to perform fantastic optimizations that produced very promising training and validation results. Unfortunately, this optimization caused overfitting to the point where the results obtained in the forecasting and classification reports deteriorated to the worst. The model showed good accuracy on training and test images (used for validation). However, it cannot properly classify the new image. I realized there was a flaw in this dataset. All images belonging to a particular class are of the same type (white background and same fruit). Fortunately, the RNN completed the analysis in time, and it turned out that the optimization was not completely in vain. We can ultimately say that CNN was the best choice for this project in terms of model performance.

8. FUTURE WORK

From our point of view, one of the major future challenges is to increase the accuracy of neural networks. This includes further experimentation with network structures. Various settings and changes to any layer, as well as the introduction of new layers can give completely different results. Another option is to turn all the layers into convolutional layers. This has been shown to provide some improvement over networks with fully connected layers in the structure.
In the near future, we plan to create a mobile application that takes pictures of fruits and labels them accordingly.
Another goal is to extend the dataset to include more fruits. This is a more time consuming process because you want to include elements that are not used in most other related articles.

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