Image Recognition for Fruit Stores using Deep Learning

José Luis Rojas Aranda José Ignacio Núñez Varela

UASLP, Facultad de Ingeniería
Fundamentos de Inteligencia Artificial

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Abstract

The purpose of this investigation is to create a intelligent system for a Fruit Store that makes the checkout process easier. For this we propose using a Convolutional Neural Network, and during training we use techniques like transfer learning, fine tuning and data augmentation in order to make the system robust with a small dataset. To test this we introduce a new dataset of fruits images, and explore what will it take to make the system affordable and scalable.

1 Introduction

Whether in a supermarket or in your local store, we all have been there; when the cashier cannot remember what is the code for the fruit or vegetable we are trying to buy, thus making the checkout process inefficient, but what if Deep Learning can help us solve this?. When we hear about Deep Learning we generally think of self driving cars or some high tech industry, but this technologies can help a lot of sectors, for this to happen we need great algorithms and great data. So we propose a deep learning model that is capable through image recognition correctly classify the fruits during the checkout process, the complexity of this is task is big due to all the variations in a single type of fruit that there exit.

To solve this we use Convolutional Neural Networks that are powerful classification models and we use an efficient architecture called MobileNet, that is both light weight and efficient. On the other hand we also consider that for this algorithms to work we need a lot of data, the catch here is that quality really matters, thus making the process of data gathering very expensive. To alleviate this problem we use techniques like transfer learning to improve the accuracy and robustness of the model with small datasets, and tested this by creating our own dataset.

2 Deep Learning

Deep learning is sub field of machine learning, that uses stacks of artificial neural networks to extract features from an input. Deep neural networks are able to outperform other machine

learning algorithms. Since AlexNet[1] vastly outperformed every state of the art algorithm on image recognition in the ImageNet competition back in 2012, this kind of technology has become more accessible

2.1 Convolutional Neural Networks

Convolutional Neural Networks(CNN's) are the way to go when it comes to image recognition, this is because they are very good at pattern recognition and processing bigger input sizes. These kind of neural networks are composed mainly by 3 types of layers: Convolution layers, Pooling layers and Fully Connected layers.

2.1.1 Convolution Layer

Given an input image(tensor more generally) of $n \times n \times n_c$ and a kernel of smaller shape $f \times f \times n_c \times n'_c$ where n'_c is the number of total filters of the layer, the layer is parameterized by the kernel. A convolutional layer convolves the kernel and the input and producing a feature map. Figure 1 shows how a convolution operation is perform.
The 2 purposes of a convulutional layers are:

1. To extract high level features, such as edges or more complex features.
2. Reduce the input size. This is not always the case, it depends on the padding and the stride size.

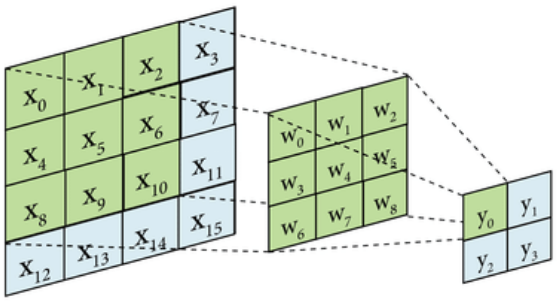


Figure 1: Example of convolution operation in a matrix.

2.1.2 Pooling Layer

A pooling layer has no parameters, its purpose is to reduce the input size. Given a receptive field of size $f \times f$, a pooling layer can perform one of the following operations:

1. Max Pool: Takes the max element of the receptive field.
2. Min Pool: Takes the min element of the receptive field.
3. Average Pool: Takes the average of the receptive field.

2.1.3 Fully Connected Layer

Fully connected layers are the classic neural networks, where each layer l has $n^{[l]}$ neurons, where each neuron is connected to all $n^{[l-1]}$ neurons of the last layer through weights and a bias, with this learnable parameters the neuron computes some activation function.

2.2 CNN Architectures

Since AlexNet[1], there has been a lot of investigation when it comes to designing CNN architectures. Until today the top accuracy on ImageNet uses a ResNet architecture, with a top 5 accuracy of 98%. Which architecture to use depends on the problem you are trying to solve, there isn't one best for all cases, and is still an area with a lot of research.

2.2.1 Going Deeper

One thing that at first seemed to be improving the CNN's was to add more layers, this reached a limit, because it is shown that the deeper the net becomes it makes the optimizer struggle to find an optimal solution due to exponentially increasing weights [2]. One solution to this problem are Residual Blocks that allow to propagate deeper the input signal. For example most of ResNet's models have more than 100 layers!

2.2.2 Computational Complexity

One disadvantage of the big CNN architectures is the computational complexity, for example. A normal convolution has a computational cost of:

$$n \cdot n \cdot n_c \cdot n'_c \cdot f \cdot f$$

This is not a big problem when doing research thanks to GPUs, but when it comes to using this technology in production, we need to consider this limitations.

2.3 MobileNets

MobileNets are CNN models that addresses the computational complexity problem, by making an architecture that is more efficient, that can run on mobile and embedded devices and still achieve top level performance.
They achieve this dividing a normal convolution into two steps[3], first it performs a point wise convolution then a depth wise convolution, with this change the computational complexity of the operation reduces to

$$n \cdot n \cdot n_c \cdot f \cdot f + n_c \cdot n'_c \cdot f \cdot f$$

MobileNetV2[4] uses inverted residual blocks and a bottle neck layers to achieve better performance. Also in the recently MobileNetV3[5] paper was released in which they use novel techniques like Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP) to achieve even better performance with mobile CPUs.

3 Dataset

Machine learning algorithms and the data are married and have a very toxic relationship, this is because they depend way to much in each other to function well. This creates a new paradigm in the computer science world, because in order to create good machine learning models we need to also think in terms of data, as Andrej Karapathy in his great blog post "A Recipe for Training Neural Networks"[11] says, you need to become one with the data, so we expend the time to analize the data and see what patterns will the model learn and in what will it fail, this gives us great answers and can save us time.

3.1 Fruits 360

One dataset in which the model was trained is the Fruits 360 dataset [12] which contains images of 118 fruits and vegetables, we only used images of Apples, Oranges and Bananas. Figure 2 is an example of different images of the training set, and the problem here is obvious, and its that there is not enough variety in the data in order for the model to generalize for the problem we are trying to solve, for this reason we also perform tests on seeing the impact of the dataset size [13], for this we found that quality really matters, in the following Table 1 we see how the model perform trained in subsets of the Fruits360 dataset, and see that it can get high accuracy (> 95) even with a subdataset as little as 18. This means that the general approach of gathering more data to improve the system, matters most if we introduce more variety on the data

Dataset Size	Categorie Size	Test Accuracy
1461	490	0.99
488	164	0.95
43 (custom)	14	0.99
18	6	0.99

Table 1: Model accuracy trained in Fruits360, comparing different sub-dataset sizes

Figure 2: Example of training images of the Fruits360 dataset.

3.2 Creating A Dataset

The Fruits 360 dataset isn't enough to solve the problem this, is why we embark into the task of creating our own dataset, doing this can give us an idea of much data is really needed to solve the problem and how difficult is to gather this data. Generally its said that you need $1,000$ images per categories to make a good classifier, this idea comes from the ImageNet dataset which contains $1,000$ images per category, but this isn't a good answer to the data problem. Because as demonstrated earlier dataset size is relative and more doesn't generally mean better, so we need to ask the following questions: What kind of images will the model see when deployed? and How can we create variety for the model to generalize well?

The advantage here is that we are not trying to make a general purpose fruit detector, rather one for fruit stores. So we need to replicate the environment, to do this the fruits are over a stainless steel sheet and the photos are taken from the top. We selected 3 different fruits per categories for training and other 3 different fruits for testing, and we did combinations of different position, rotation and amount of fruits in the photo. We also need to consider that in the checkout process the fruits are inside a transparent plastic bag, so we also took photos of the fruits inside a bag.

Figure 3: Example of training images of the Dataset created.

4 Training

For the training process, the dataset is processed and converted to a TFRecord using the TensorFlow Dataset API, which enable us to create an efficient input pipeline for training the model, for example we can use this pipeline to rescale, crop or apply data augmentation to all the dataset.

Training setup, the models are trained using Keras backed by Tensorflow. We use the Adam Optimizer[6] and categorical crossentropy loss, for the hyperparameters choice we choose to use a learning rate of $3e-4$ and the default parameters of the Keras implementation of the optimizer. Learning rate is a very important parameter and recent research has found great progress, for example Super-Convergence that under certain parameters neural networks can be trained an order of magnitude faster using high learning rates[7], but we choose not to try different configurations of hyperparameters because is hard to find and explanation to the results, and instead use default parameters that are known to work well. This way we can focus on making the model reliable.

4.1 Choosing a CNN Architecture

As mentioned earlier in the Deep Learning section, there exist a lot of CNN's architectures, and knowing what to choose depends on the problem at hand, in this section we try to answer that question of what architecture to use, that is able to resolve our problem and at the same time be reliable for daily use.

4.1.1 Smaller VGGNet

The first model we train is a smaller version of VGGNet[8] called SmallerVGGNet[9], which is characterized using only 3×3 convolutional layers, reducing volume size by max pooling and fully-connected layers at the end of the network prior to a softmax classifier.

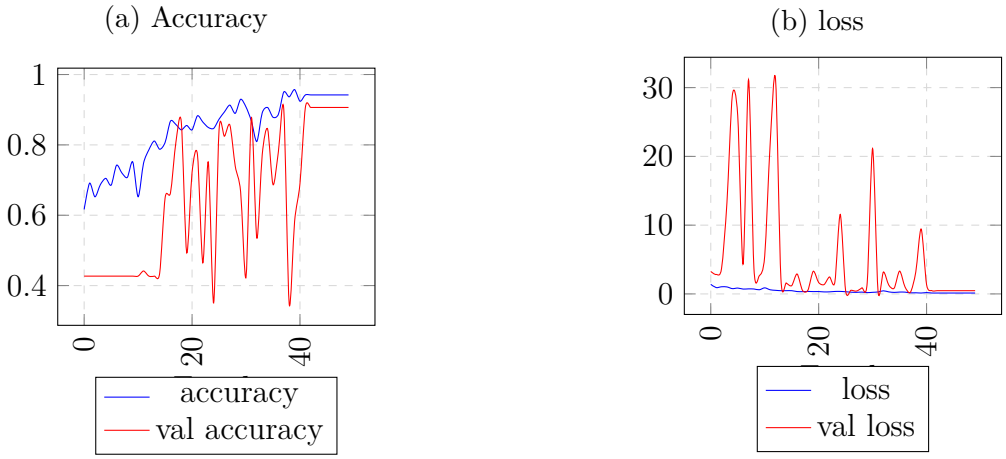


Figure 4: Training logs for SmallerVGGNet

4.1.2 MobileNetV2

For the MobileNetV2 model architecture[4], we are using the Keras implementation, this has several advantages. First it enable us to load trained weights trained in common datasets like ImageNet, and second has flexibility for the input size of the model.

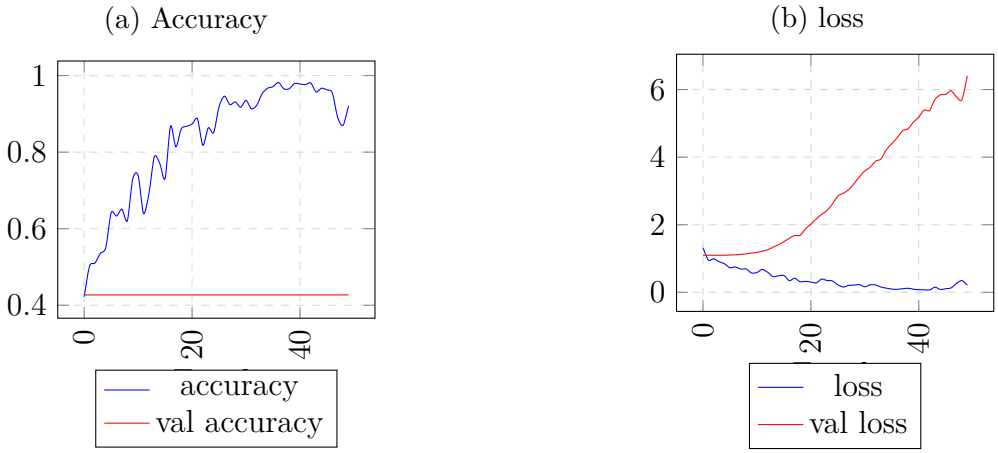


Figure 5: Training logs for MobileNetV2 with weight intialized randomly.

As we can see both architecture are able to learn the training set pretty well, and we clearly see that SmallerVGGNet is a better model because is not overfiting the training set, the disadvantage here becomes obvious if we see the number of parameters in the models.

Model	Num params
SmallerVGGNet	$8,676,227$
MobileNetV2	$2,261,827$

Table 2: Model size comparisons

SmallerVGGNet has more than double the amount of parameters, this means that the model needs more computing power to make a prediction. And because we want the system to work in fruit stores, we need to consider that they may not have very good computer thus making the system useless. One way to solve this is to gather more data but this is expensive, so in the next section we use transfer learning to improve the accuracy of the model.

4.2 Transfer Learning

Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task[10]. This kind of techniques works really well for when our dataset isn't big enough, and it always makes the model converge faster to a solution. We trained MobileNetV2 with transfer learning using weights from a model

trained in the ImageNet dataset. There are several way you can train a model with transfer learning, in this case we trained it two ways:

First we load the trained model and cutoff the last layer, that is a dense layer with 1000 neurons, this serves as a classifier of the previous feature map. Once cut we set the rest of the layers to not trainable, and to the end of the network a dense layer but in this case with the number of classes of fruits we are going to predict. This enable us to keep all the feature extracted with the ImageNet model and repurpose it to the fruit classification problem. Figure 6.

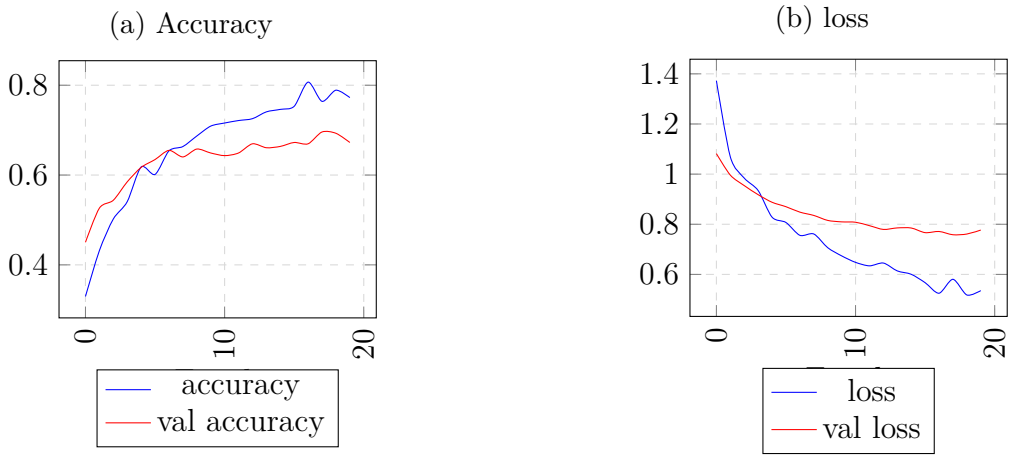


Figure 6: Training logs for MobileNetV2 with ImageNet weights and only training the last fully connected layer.

The second approach is to also cut the last layer and add a classifier with the number of classes we are going to classify, but instead of setting the layers to not trainable, we let the optimizer retrain the full network. This makes the model start training at some point and not with random values, thus making the convergence to a solution way faster and to not overfit the training dataset. Figure 7.

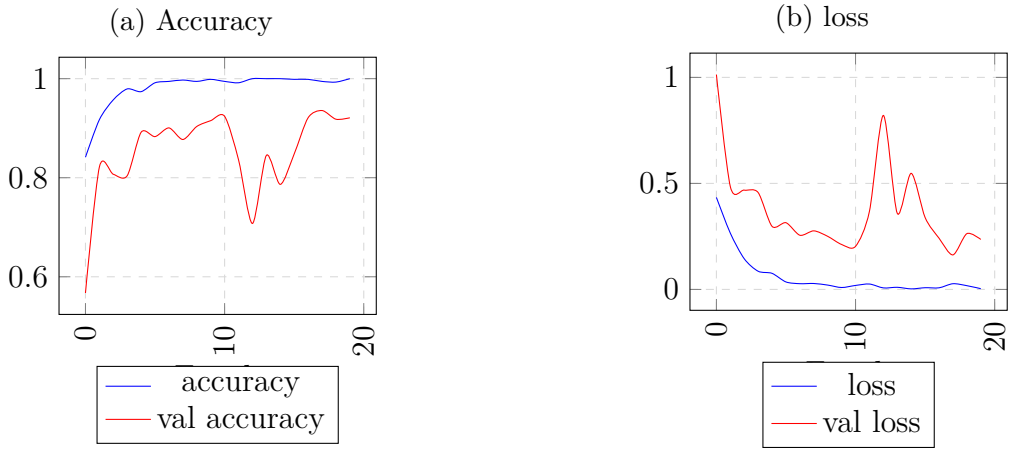


Figure 7: Training logs for MobileNetV2 with ImageNet weights and traning all network.

For the first approach we get better results on the test dataset and the model is able to

generalize better. Another big advantage is the training times, due that we only train the last layer of the model each epoch is trained way faster. In the second approach training isn't as stable and it's doing a little overfiting, but we get +0.9 accuracy and we do not need as much epochs.

4.3 Comparisons

4.3.1 Training with Fruits 360

At the start of the project the model was trained using the Fruits360 dataset, and the result weren't good in images of our problem, but in the test and train set of the Fruits360 it performed well. This is because our problem images aren't of the same distribution of the Fruits360, and is naive of us to expect that it will perform well, it's accuracy was of 0.33 that means that is clearly overfiting the dataset.

4.3.2 Data Augmentation

Also we trained the model using data augmentation, with random changes in hue, saturation and illumination. But didn't obtain better results, this is because the model detects very good the patterns of the image, but we are not promoting the model to put more attention to the color of the image, so the data augmentation we are applying is not improving the accuracy.

4.3.3 Final Results

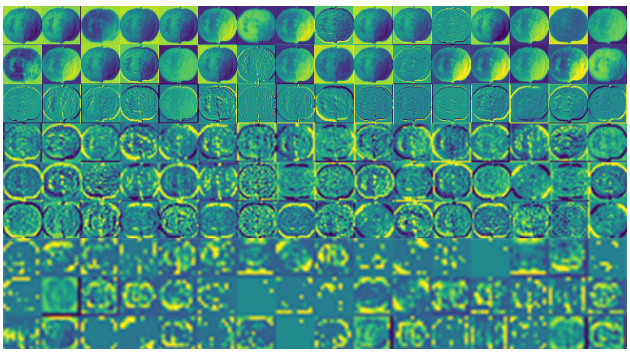
In table 3 we compare the trained models, the results tell us that transfer learning makes the model perform better due to the small dataset we are dealing, SmallerVGGNet also isn't bad but, as mentioned earlier the disadvantage is the model size. Also we compare how the model performs when we remove the images of the fruits inside the plastic bag, and see that it gets better results, but the difference isn't as big as we expected.

Model	Plastic Bag	Train accuracy	Test accuracy
SmallerVGGNet	Yes	0.91	0.82
MobileNetV2	Yes	0.97	0.436
MobileNetV2 + ImageNet weights (only head classifier)	Yes	0.77	0.70
MobileNetV2 + ImageNet weights	Yes	0.99	0.92
MobileNetV2 + ImageNet weights	No	0.99	0.98

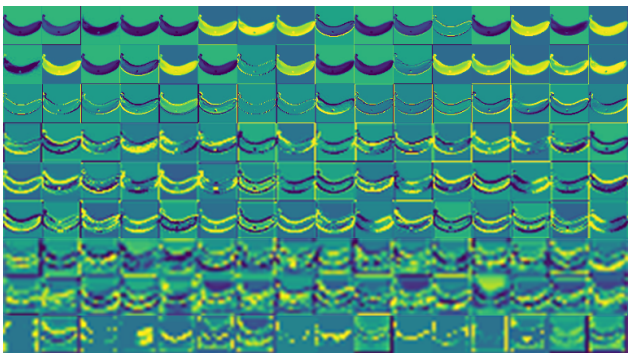
Table 3: Trained model comparisons

5 Visualizing Activations

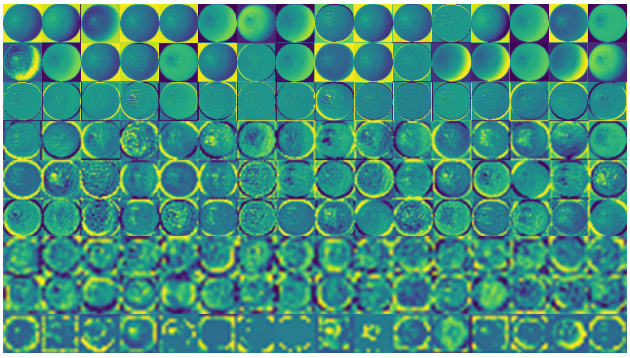
One disadvantage of using deep neural networks for machine learning models is that we don't have a good way of telling what is the model really learning, this imposes a lot of problems in the deep learning world. One technique to visualize what CNN's are learning is to graph the activations of the convolution layers, by doing this we can see what information is being retained by the layers



(a) Activations of a apple image.



(b) Activations of a banana image.



(c) Activations of a orange image.

Figure 8: Visualizing activation of MobileNetV2, layers 1, 7, 16, 27, 42, 57. The model is trained in the Fruits360 dataset

When we see the activations of our model with images of apple Figure 8(a), banana Figure 8(b) and orange Figure 8(c). We can see that our model is retaining mainly the form of the fruit and the texture.

With this in mind, we can say that if we want to improve the accuracy of our model in the real world. We need the following:

1. More photos of the fruit at different positions and different size, so the model can learn different shapes of the same fruit.

2. Variety in the texture of the same fruit.

6 Future Work

There is deficiency in the model, and is that a CNN is very good a pattern recognition and extracting features, but the problem is that is not giving as much weight as it should to the colors of the image. Causing confusion to the model with apples and oranges, because the have a very similar shape.

On possible way to address this problem is to create a multi-input model, this means that the models do not only takes as input only the whole image, rather the image and some extra information about the colors of the image, and in the last fully connected layer of the neural network, the feature map and the color data is concatenated to produce the final prediction. To obtain the color data we can do it by hand, using a K-Means machine learning algorithm or the information of the histogram.

7 Conclusion

We saw that Convolutional Neural Networks are powerful image classification models, but for them to work well we need a lot of data, and we also saw that more is not always better, we are rather looking for variety. But if we use techniques like transfer learning and fine tuning, we can achieve good performance if we have a representative dataset.

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