Food Classification with Convolutional Neural Networks and Multi-Class Linear Discernment Analysis

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Abstract
Convolutional neural networks (CNNs) have been successful in representing the fully-connected inferencing ability perceived to be seen in the human brain: they take full advantage of the hierarchy-style patterns commonly seen in complex data and develop more patterns using simple features. Countless implementations of CNNs have shown how strong their ability is to learn these complex patterns, particularly in the realm of image classification. However, the cost of getting a high performance CNN to a so-called "state of the art" level is computationally costly. Even when using transfer learning, which utilize the very deep layers from models such as MobileNetV2, CNNs still take a great amount of time and resources. Linear discriminant analysis (LDA), a generalization of Fisher's linear discriminant, can be implemented in a multi-class classification method to increase separability of class features while not needing a high performance system to do so for image classification. Similarly, we also believe LDA has great promise in performing well. In this paper, we discuss our process of developing a robust CNN for food classification as well as our effective implementation of multi-class LDA and prove that (1) CNN is superior to LDA for image classification and (2) why LDA should not be left out of the races for image classification, particularly for binary cases.

1 Introduction
Machine learning today has accomplished some incredible tasks thanks to the increase in our modern compute capabilities. It has limitless potential in nearly every field, if the mind is creative enough to find the likely hidden optimization problem. A problem we believe that can be solved today with modern machine learning is obesity. Global eating habits continue to get worse, as the world becomes more obese our increased risk to obesity-related conditions such as coronary heat disease and end-stage renal disease.[1] Providing the ability for any person to easily take a picture of their food with their smart phone and identity possible allergies, calories and macromolecules of their food would help sink the ever growing health crisis.

Unfortunately, simply creating a machine learning model capable of accurate food classification won’t solve the health crisis, but it is a start. Which is why we believe the first real step is finding the right algorithm which does not only takes accuracy into account but also speed, size on disk, and the computational workload to do on-device inferencing. On device inferencing, or on device machine learning, is more important than ever today when people are very concerned about their privacy. It is also important due to the possible HIPPA issues one could run into working on such a project.

The CNN created in this paper utilizes several important technologies which lead it to a validation accuracy 95.9%. Transfer learning is certainly the main key to this accuracy, as our CNN was only trained on an Nvidia GTX 1080. Although some level of retraining occurs with transfer learning,
most of the learning is in the lower, added, layers which are focused on learning about our particular data’s features. Utilized as well for the creation of the CNN is image augmentation which allowed us to effectively increase our dataset size by a factor of 10. For our multi-class LDA classifier, we ran into many hurdles that we will discuss later in this paper, namely memory constraints, but we were still able to get an effective test by running LDA on 3 different cakes in the Food-101 dataset. We first performed various preprocessing techniques on our data. Ultimately, our accuracy with LDA ended up being 72.8%.

2 Data Preprocessing

In order to ensure the most ideal performance during training, several image preprocessing techniques were applied on our data. Namely, all images were resized to either 224x224 or 64x64 for the CNN and LDA respectively due to the unique challenges and resource demands they each posed for training. Both our CNN and LDA classifier utilize a version of the Food-101 dataset which has had several techniques applied to it: Principal component analysis (PCA) for dimensionality reduction, noise reduction with a median filter, and contrast enhancement. These 3 techniques were applied to help decrease the size of our data on disk and in memory and to enhance the features in the various images.

2.1 The Food-101 Dataset

Food-101 consists of 101,000 JPEG format RGB images of varying sizes and dimensions. Food-101 is a particularly challenging dataset due to its noisy nature. Prior to any techniques applied such as image augmentation, the data split is at 75% for the train set, 20% for the test set and 5% for the validation set. This leaves 75,750 images for training, 20,200 for testing and 5,050 for validating the model.

Figure 1: The noise in the dataset can easily be seen in the 3 food images above. Although this type of noise does make the task of convergence on a model more difficult, the model will thus tend to generalize more effectively.

2.2 PCA for Dimensionality Reduction

PCA was utilized on our images in order to further reduce the dimensionality of the data. PCA allows, ideally, added improvements to computational speed with minimal loss in important, principal, factors that make our images varied. We selected 400 principal components to capture over 90% of the overall variance found in the dataset. Losing 10% of the variance in the dataset is not ideal, but it is an acceptable loss thanks to the benefits we gain from utilizing PCA, which were discussed earlier. The distribution of 3 classes utilized in the LDA classifier can be seen in the figure below, which show a strong distribution of the variance among the highest variance components remaining high and well distributed.
We reached the conclusion to utilize 400 principal components by experimental testing. We wanted to ensure that the separability of the 3 different cakes remained high due to their similarity, but we also wanted to reduce the components enough to make a difference for our classifiers training time. Through this testing, particularly with the use of Scree Plots and comparing principal components, we arrived to the conclusion of 400 principal components. The Scree plots of the variance and Eigen values can be seen in the figure below.

Figure 3: The Scree plots of variance[right] and the Eigen value sizes of the first two components[left] show that 400 components is a good choice to maintain a reasonably high variability with the 3 similar labels.

2.3 Image Enhancement with Noise Reduction and Contrast Enhancements

Filtering noise from a dataset has to be a careful balance. Some noise is not a bad attribute for a dataset to have, but we applied a median filter still to remove possible distortion of images. The median filter was chosen particularly for its non-linear behavior due to the nature of a varying image dataset. For this system, a simple first order filter was enough to ensure that we are not removing features while also removing any possible static-like noise. We found some of our images to be particularly dark, possibly not highlighting key features of our data. Due to this, we decided to apply a small contrast enhancement, increasing our sharpness across the entire dataset by a factor of 1. We did so utilizing the R library Magick. Magick does this by enhancing the intensity differences in the image by utilizing a histogram equalization.[6] An example of the outcome of our preprocessing can be seen in the figure below.
Figure 4: The final output of our preprocessing can be seen in this example on the right with the original on the left. Ultimately, we have shrunk the average picture size on disk by 81%, on average.

The outcome of our preprocessing above is ideal for our dataset. We have successfully reduced the size on disk of the dataset, normalized the size of the images and reduced the features of low variability while still maintaining images that look quite similar to their original.

Figure 5: The histograms of the images seen in Figure 4 further highlight that the pixel values of high variance were well maintained despite the reduction of 81% in file size.

### 2.4 Image Augmentation

Augmenting our images allowed us to effectively increase our image data from 101,000 images to 1,010,000; this occurs by applying augments such as rotation, height and width shift, shearing, zooming and horizontal flipping. These augments effectively create 10 more images per original image in our dataset. This allowed us to artificially create a dataset with great variance, ideal for training our model. The augments and their respective parameters can be seen below in table 1.

| Augment      | Parameter          |
|--------------|--------------------|
| Rescale      | $\frac{1}{255}$    |
| Rotation range| 40                 |
| Width shift range | 0.2               |
| Height shift range | 0.2               |
| Shear range  | 0.2                |
| Zoom range   | 0.2                |
| Horizontal flip | True              |
| Fill mode    | Nearest            |

Table 1: Above can be seen the various augmentations applied to the Food-101 dataset as well as their respective values.

These augments were only used in the training, testing and validation of the CNN. They could not be applied to the LDA classifier due to memory limitations.
The image augmentations, applied with the Keras library, are quite handy in increasing the dataset. The various effects chosen are applied randomly with image generators, and thus only generate images on demand during training, testing or validating without the need to ever hold several images in memory or on disk.[4] An example of these augmentations being applied to our example image from Figure 6 can be seen below.

Figure 6: The various augments are applied randomly with Keras. These augmentations are crucial given the likelyhood of the images being processed by our model in deployment may very well look like these.

3 Convolutional Neural Networks for Image Classification

CNN’s are outstanding at understanding and learning from hierarchy-style patterns seen in images. They take these patterns and make new, smaller, patterns from larger feature groups. Much like how the human brain works, CNNs are fully interconnected allowing for the entire network to take advantage of a node’s knowledge of a certain feature. Due to these various features, CNNs are the go-to machine learning practice for large complex image classification tasks. Our CNN utilized transfer learning with MobileNetV2 on ImageNet weights for the top most layers. This allowed us to get state of the art performance without excess needed time and resources to train such a complex network. From those top layers, we added several layers to help reduce dimensionality, optimize regularization as well as tune the dropout to ensure that we are not overfitting, but that we are still learning the important features unique to our dataset.

| Layer (Type)                  | Output Shape   | Param #     |
|-------------------------------|----------------|-------------|
| mobilenetv2_1.0_224 (Model)   | (None, 1, 1280)| 2257904     |
| global_average_pooling_1 (    | (None, 1280)   | 0           |
| activation_1 (Activation)    | (None, 1280)   | 0           |
| dropout_1 (Dropout)          | (None, 1280)   | 0           |
| dense_1 (Dense)              | (None, 101)    | 129301      |
| activation_2 (Activation)    | (None, 101)    | 0           |

Total params: 2,387,365
Trainable params: 2,355,263
Non-trainable params: 34,112

Figure 7: The architecture of our CNN and each layer’s respective parameters and shape.
CNNs require a great deal of computational power, such as a high powered graphics card, to get great performance. In addition, they also require a large amount of data. For this problem, we utilize image augmentation, which was discussed in data preprocessing. Image augmentation effectively allowed us to increase our data 10 fold.

### 3.1 Transfer Learning

Transfer learning is one of the most essential practices utilized today. Transfer learning allows one to take a well performing network, "cut" the bottom layers, which are focused on learning the small features and labels of a dataset, and keep the upper layers, which are very good at learning and extracting the big features from a dataset. In our case, we opted for MobileNetV2. We chose this network due to our likely deployment being on a mobile device, and MobileNetV2 is impressively space conscious getting similar accuracy on ImageNet compared to networks multiple times larger with millions of more parameters.

![Figure 8](image.png)

Figure 8: In our case, our generic network would be MobileNetV2 with its dataset being ImageNet. We would then be applying Food-101 through our new model with the top most layers of MobileNetV2 being fed into our lower layers.[3]

### 3.2 Parameter Choices and Tuning

In order to achieve the best performing variant of the CNN, multiple iterations must be created, with their specific parameters, accuracy and loss logged. Our CNN starts with a Linear Sequential model, we then add the MobileNetV2 to the top of our sequential model. Following the MobileNetV2 layers directly, is a global average pooling 2D layer, added to help reduce the dimensionality of the output coming from those upper layers. Next, we then feed into a ReLU activation layer with a rather sharp dropout of 0.7. We discovered although such a large dropout is punishing and can lead to longer training times, it reduces the risk of overfitting greatly. After our dropout, we were ready to feed into a typical dense layer with a dimensionality of 101, or the number of classes in our dataset. We also tuned the L2 regularization, or ridge regression, in this layer to force the weights to be near-zero, but never zero. L2 regularization, along with the following layer of softmax activation, are vital layers in our network as they all but ensure over training does not occur. There is no way to ensure this, but we can implement many preventative measures, which we have done.

| CNN Variation 3 | Learning Rate | Optimizer | Dropout | L2 Regularizer | Accuracy | Loss |
|----------------|---------------|-----------|---------|----------------|-----------|------|
| 0.001          | Adam          | 0.5       | 0.01    | 0.9307         | 0.3213    |
| CNN Variation 13 | 0.0001        | Adam      | 0.7     | 0.01           | 0.9590    | 0.1915|

Table 2: Among the 17 variation of CNNs created, these were ultimately the two highest performing versions. Another feature that could have been tuned for greater generalization is batch size, which was kept constant throughout the all the different CNN iterations.
Seen in Table 2 are the detailed parameters and outcomes of our highest performing variations of our CNNs. We also implemented many callbacks to further ensure the highest quality model and utilization of training time possible. We used early stopping to monitor validation accuracy, checkpoints to save our best performing models and we also utilized a learning rate reduction on plateau callback to monitor out validation loss.

Figure 9: Above are plots from training CNN 13 for. We can see the accuracy of the training and validation set[left] as well as the validation and training loss[right]. These plots appear a bit ‘jittery’ but this can be contributed to the large batch size utilized during training.

From our validation accuracy, we can see that some photos were identified incorrectly. Largely, they share the same characteristics of being a soup or chowder food that does not have a great deal of texture of defining characteristics. Seen in the figure below are several images that were incorrectly classified. Three of the items classified incorrectly in the figure share a very similar appearance but they all in fact are different. Despite this, the top two and bottom right images were all classified as clam chowder even though none of them are. This is related to their bland appearance and lack of defining features. The beet salad was classified as a caprese salad, reasonable given it does have some items commonly found in such a food item.

Figure 10: The images above were all classified incorrectly with near 100% confidence. We can see among the soup-like pictures that they are all quite similar to each other. Further refinement of our model by tuning layers and parameters may have removed such an issue.
4 Multi-class Linear Discriminant Analysis for Image Classification

LDA is certainly a capable technique for multiple-class classification. LDA calculates and picks a new dimension which maximizes the separation between the means of the projected classes while also minimizing the variance within each projected class. This is great for maximizing the component axes for class separation. Although this technique is capable of classification, it was also found to be rather inefficient. When attempting to train our LDA model on our train set of 75,700 images, it quickly filled our RAM and ended up not being a reasonable solution for our computational resources. Due to this, we limited our LDA dataset to three different cakes in the Food-101 dataset in order to still depict the capability of LDA for multi-class image classification. An example image of the three cakes can be seen below.

![Image of three cakes]

Figure 11: Above are images from the three classes we used in the training of our LDA classifier: chocolate cake[left], strawberry short cake[right] and carrot cake[bottom].

Our three classes, now chocolate cake, strawberry short cake, and carrot cake, each have 1000 images. Our data split as 75% or 2250 training images and 25% or 750 test images. Additionally, to further limit memory, we down sampled our images again to a resolution of 64x64.

![Scatter plot of LDA]

Figure 12: The images above were all classified incorrectly with near 100% confidence. We can see among the soup-like pictures that they are all quite similar to each other. Further refinement of our model by tuning layers and parameters may have removed such an issue.

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2Our system was equipped with 48GB of RAM.
Plotting the first two linear discriminants shows that our classes share many values, as expected, but it also shows that they are also separable with the use of our multi-class LDA classifier. When now classifying our data, we found that we had an accuracy of 72.8%, with the 95% CI at 69.46% and 75.96% respectively. We also found that our P-value was very small, less than 2e-16 which is very good and proves that our accuracy is well founded and statistically relevant. We particularly found that chocolate cake struggled the most at being predicted correctly, with the lowest sensitivity of the 3 classes at only 65.60%. This could potentially be improved if we were able to run the LDA classifier on a system with more memory and therefore not have to down sample the images so much. Further statistics can be seen below in Table 3.

| LDA Statistics | Accuracy | P-Value | Kappa |
|----------------|----------|---------|-------|
|                | 0.728    | <2e-16  | 0.592 |

Table 3: Our small P-Value shows that our classification accuracy does in fact have some statistical importance.

5 Conclusion

In this paper we discussed our approach to image classification of food with a CNN and multi-class LDA classifier. The CNN performance was very good, with a 95.9% accuracy on the validation set, along with a small file size and highly deployable format, it is easy to see why it is the technology to use for a large image classification task. Our multi-class LDA classifier struggled with only a 72.8% accuracy. Our LDA could have been tested on a larger set of data if it ran on a system with greater computational power and significantly more RAM. We would like to revisit LDA on a system with more memory and a higher resolution dataset to see if the accuracy will improve. For the situation of binary cases with LDA, we believe there is great potential here. On the other hand, with a large dataset like Food-101, LDA is not the ideal approach. The CNN is the best performer and has given us the result we want for easy and fast food classification.

6 Discussion and Future Work

We anticipated the CNN to be the best performer compared to LDA, which was proven correct. However, we think LDA can perform better if it had more features to work with. We would like to approach this again with more principal components, greater than the 400 used. It is possible that PCA threw away some features that LDA would have found meaningful. With the conclusion of the CNN being the best performing model between itself and LDA, we would like to expand and refine it more by collecting and refining our data further. Our data is largely based on western dishes which is something that we would greatly like to expand. Our current code and model can be accessed on our github under "Food101-CNN".

We have deployed our current CNN to an iOS application, currently available for download on the Apple App Store under the name "Obviously Food". It is a simple application which allows the user to either upload or take a picture of their food. The app then returns the top three probabilities to the user with their respective labels. We would like to expand on this application and build a database which lists each food's possible allergens and calories. The app would then fetch this information and make it available for the users consideration.

Broader Impact

We would like to help combat the crisis of obesity-related diseases which have been on the rapid rise.[1] Our application has great potential to become something powerful and healthy for those with smart phones, enabling them to make healthier choices and be more conscious of what they put into their bodies. There certainly may be those who can suffer from this, however. Those who are easily obsessed with their weight, or have unhealthy tendencies with regards to weight loss may weaponize

3 The code and model can be accessed here: github.com/JBall1/Food101-CNN
4 Obviously Food can be downloaded here: apps.apple.com/app/id1534447041
the future version of this system and use it to indulge in their unhealthy lifestyles further. The possibility of an incorrect classification is also possible by our models which can result in someone choosing not to eat something that is otherwise fine for them.

There also lies the question of bias in our models. Although our models were trained on a high variance dataset, it was limited to only 101 different types of food which does not come close to the amount of dishes in the world. Furthermore, our dataset was heavily weighed on western dishes, leaving out a majority of the world’s population. To solve such a bias correctly would require a large undertaking to acquire adequate images of food from around the world. This solution would also require a massive amount of computing power to get through such a proposed dataset.

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