Classification of Food Images Using Convolution Neural Networks

Group 7

Joanne Chung, McLain Wilkinson, Ruonan Jia

Outline

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Introduction

- Services such as yelp contain pictures of menu items relevant to restaurant but do not automatically tag images -
  - rely on self tagging from users, which makes it difficult to find pictures through search
- For a more challenging problem, we wanted to try to build such a classification system that could identify the food item contained in the image
- This problem is difficult by nature - food items themselves can be visually ambiguous, since they may take on a variety of shapes, colors, and textures and an image may contain more than 1 dish

Project Process

Preprocessing

- Normalize image size
- Make HDF5 database
- 12 broad categories

Design Model

- CNN
- Pytorch
- Dropout
- Adam Optimizer

Train CNN

- Mini Batch=30
- Epoch=50
- Time=more than 5 hours

Test Model

- Confusion Matrix
- Accuracy plot
- Loss plot

Update Model

- Analyze loss
- Tune parameters

Conclusion

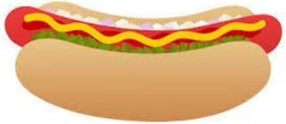
- Reasons for misclassification
- The best and worst classification categories

Data Overview

Data Overview (continued)

- Found dataset on Kaggle (https://www.kaggle.com/kmader/food41)
- Sample datasets use HDF5 database files
- Images folder contains .jpg images (101 categories of 1000 images each)
- Create database using these images
- We want to combine some categories and remove others to increase the number of training examples per class and reduce number of total classes

Data Preprocessing

Is a  a sandwich?

HDF5 database	ResIze Image	Combine classes	New Dataset	Split Data
Create python script convert 101,000 .jpg images to HDF5 database files containing labeled color images of reduced size I/O	Typical .jpg image size ~512x512 pixels - want to reduce to 128x128 with 3 channels for color (clear image without taking too much storage)	Combine classes to create 12 relatively broad classes. Difficult to determine what classes could reasonably be combined	New dataset contains 48,000 total images with ~4,000 images per class	Split into training and testing sets using 80/20 split stratified by class

Data Preprocessing (continued)

Smooth Dessert	Chocolate mousse	Frozen yogurt	Ice cream			
Red Meat	Filet mignon	Pork chop	Prime rib	steak		
Egg	Bibimbap	Deviled eggs	Eggs benedict	Huevos rancheros		
Pasta	Gnocchi	lasagna	Macaroni and cheese	Ravioli	Spaghetti bolognese	Spaghetti carbonara
Soup	French onion soup	Hot and sour soup	Lobster bisque	Miso soup		
Salad	Caesar Salad	Greek salad				
Fried Food	Fish and chips	French fries	Fried calamari	Onion rings	Poutine	
Sandwich	Club sandwich	Grilled cheese sandwich	Hamburger	Hot dog	Lobster roll sandwich	Pulled pork sandwich
Noodles	Pad thai	Pho	Ramen			
Cake	Carrot cake	Chocolate cake	Cup cakes	Red velvet cake	Strawberry shortcake	
Sweet Breakfast	French toast	Pancakes	Waffles			
Shell	Escargots	Mussels	Oysters			

Cupcake

Chocolate Cake

Red Velvet Cake

Carrot Cake

Cake

Strawberry Shortcake

Network / Model Design

- Pytorch Framework
- 6 Convolution/Max Pooling layers & 1 Fully Connected Layer with dropout
- Number of layers & size of kernels limited by input image size
  - Kernel size = 10 for first 4 layers, 4 for 5th layer, 2 for last convolution layer
  - Numbers of kernels (ranging from 64-384 per layer)
- Batch size: 40
- Cross Entropy Loss
- Adam Optimizer
- Experiment with learning parameters & adjust when necessary to improve total accuracy on test set

Parameter Selection

Rules we believe

- # of kernels: Capture enough main features from the original input. (gpu out of memory)
- Small kernel size can capture the details of the images better. (slightly improvement)

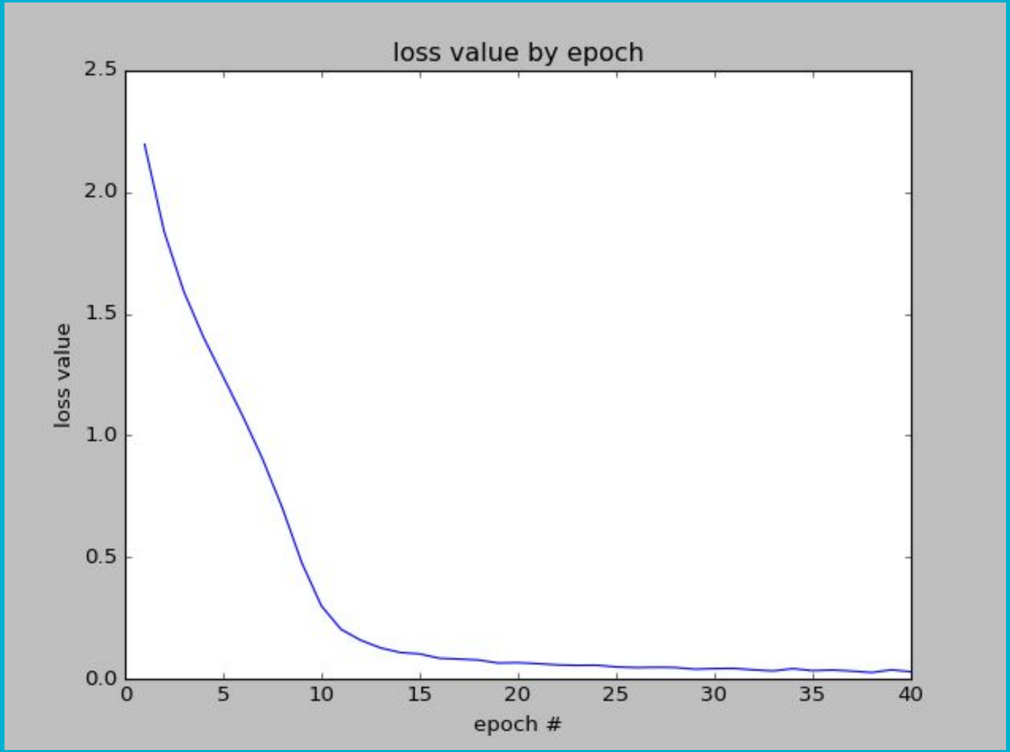
	Model 1	Model 2	Model 3
Kernel size	10 first 4 layers 4 5th layer 2 6th layer	5 first 4 layers 4 5th layer 2 6th layer	10 first 4 layers 4 5th layer 2 6th layer
Number of kernels	128 first 5 layers 64 6th layer	64-128-256-394-256-128	64-128-256-394-256-128
Layers	6	6	6
Accuracy	52%	55%	54%
Time	1523 s	1569 s	1489 s

Epochs=5
Time cost is high

Network / Model Design

- How many epochs is enough?
- Loss value stays roughly constant after ~20 epochs
- 12 epochs VS 20 epochs
- 3% accuracy improvement
  Time Cost Worth it?

Average Training Loss



Our Favorite Equations

- Convolution size equations are helpful to calculate sizes of outputs in convolution layers

$$w = (w + 2*PAD - kernel\ size) / STRIDE + 1$$

$$h = (h + 2*PAD - kernel\ size) / STRIDE + 1$$

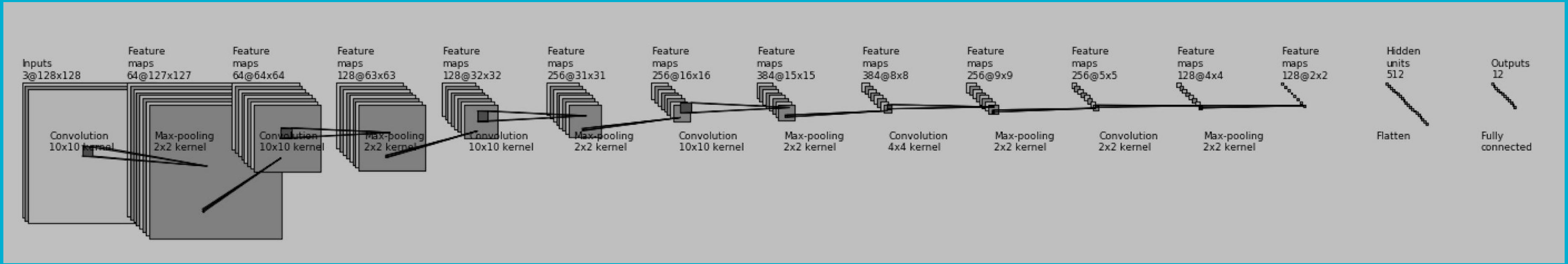
CONV1: kernel size=10 padding=4 stride=1

w=(128+2*4-10)/1+1=127 h=(128+2*4-10)/1+1=127

Pool1: kernel size=2 padding=1 stride=2 (subsampling)

w=(127+1)/2=64 h=(127+1)/2=64

Network Diagram



6 convolution/MAXpooling layers

Kernel Size[10, 2, 10, 2, 10, 2, 10, 2, 4, 2, 2, 2]

Image sizes through the convolution/pooling layers:
128-->127-->64-->63-->32-->31-->16-->15-->8-->9-->5-->4-->2

Results

Output and accuracy of model on 9600 test images after 30 training epochs

training time: 2h 38m

60% overall accuracy

individual class accuracies also listed here

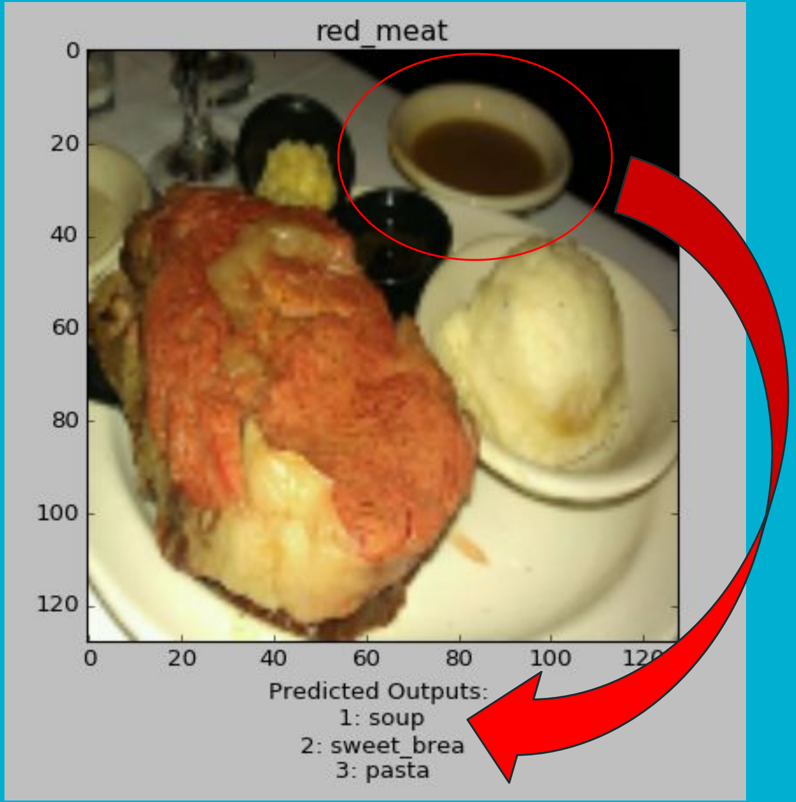
```
Epoch [30/30], Iter [900/960] Loss: 0.0324
training time: 9490.65 seconds
------------------------------------------------------------
Testing...
------------------------------------------------------------
Results
Accuracy of the model on the test images: 60 %

Individual class accuracy:
smooth_des        290 correct / 600 total         =>        48.33 % accuracy
red_meat          533 correct / 800 total         =>        66.62 % accuracy
egg       427 correct / 800 total         =>        53.38 % accuracy
pasta     795 correct / 1200 total        =>        66.25 % accuracy
soup      618 correct / 800 total         =>        77.25 % accuracy
salad     244 correct / 400 total         =>        61.00 % accuracy
fried_food        660 correct / 1000 total        =>        66.00 % accuracy
sandwich          591 correct / 1200 total        =>        49.25 % accuracy
noodles   351 correct / 600 total         =>        58.50 % accuracy
cake      655 correct / 1000 total        =>        65.50 % accuracy
sweet_brea        273 correct / 600 total         =>        45.50 % accuracy
shell     358 correct / 600 total         =>        59.67 % accuracy

class with highest accuracy: soup 77.25 %
class with lowest accuracy: sweet_brea 45.50 %
```

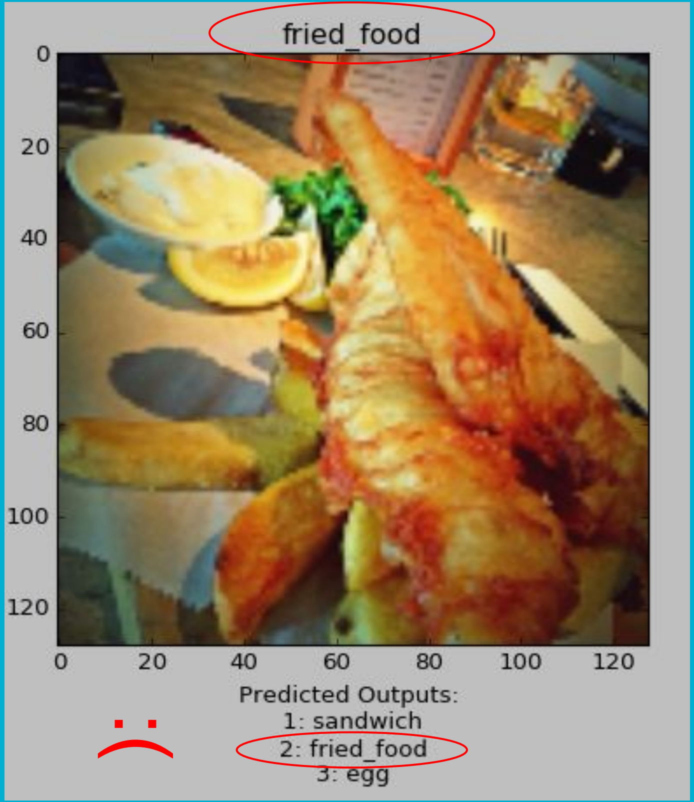
Results (continued)

Confusion Matrix

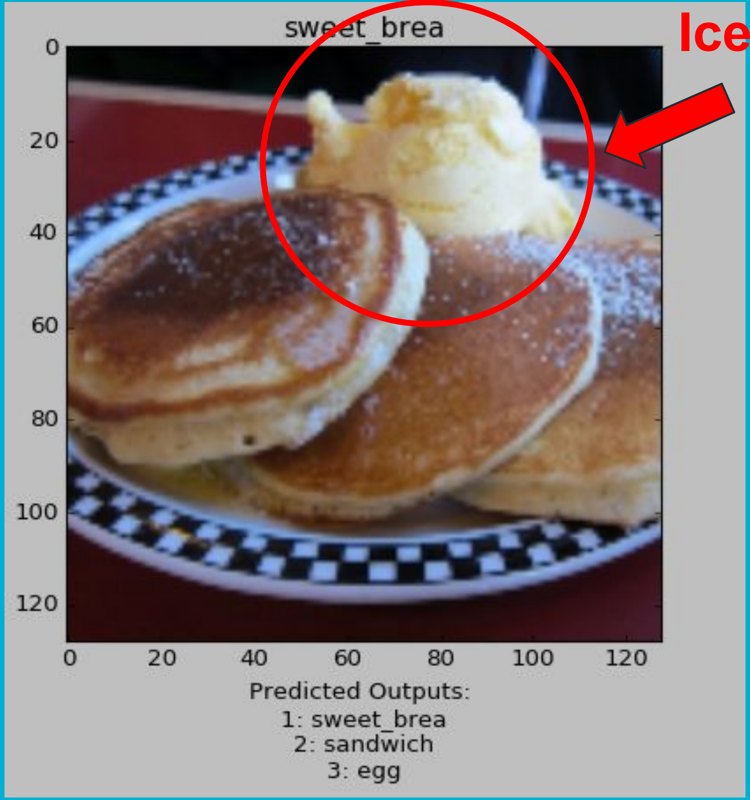
	Smooth Dessert	Red Meat	Egg	Pasta	Soup	Salad	Fried food	Sandwich	Noodles	Cake	Sweet Breakfast	Shell
Smooth Dessert	290	16	20	12	21	3	20	33	10	79	24	10
Red Meat	51	533	45	42	11	10	24	71	19	67	31	59
Egg	19	29	427	54	17	40	25	68	31	23	24	25
Pasta	24	27	90	795	44	33	100	80	78	29	62	35
Soup	15	13	19	67	618	1	9	21	37	12	25	12
Salad	3	8	9	17	1	244	3	13	13	7	2	8
Fried Food	20	27	29	52	14	4	660	135	19	15	46	12
Sandwich	22	38	47	29	11	19	68	591	19	37	36	8
Noodles	7	19	21	48	24	24	11	20	351	1	5	12
Cake	108	48	30	21	12	9	29	68	6	655	52	32
Sweet Breakfast	25	24	48	41	14	3	36	84	7	50	273	29
Shell	16	18	15	22	13	10	15	16	10	25	20	358

Conclusion (continued)

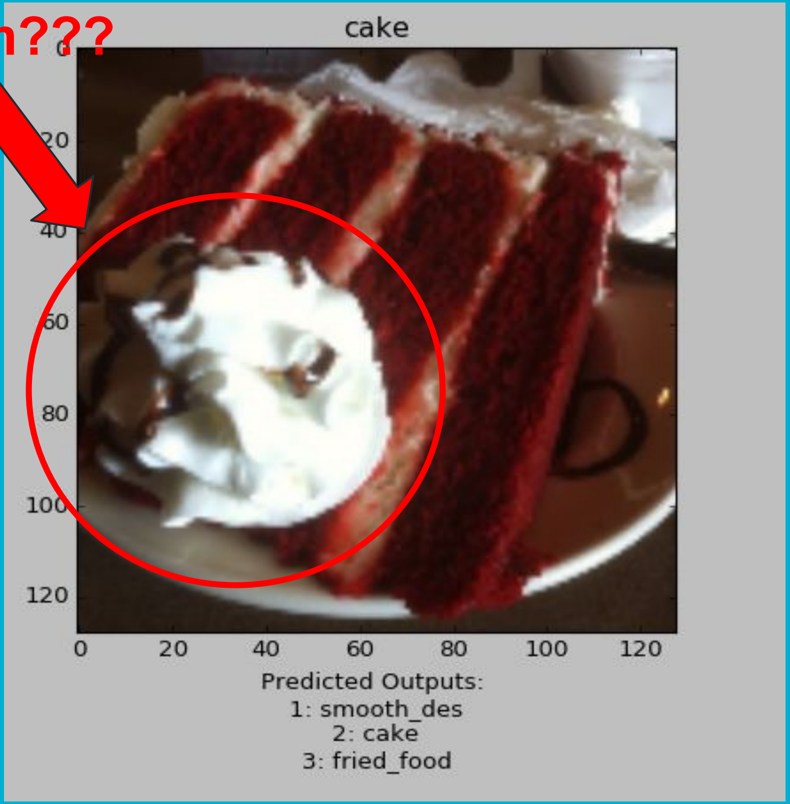




Potentially Confusing Images



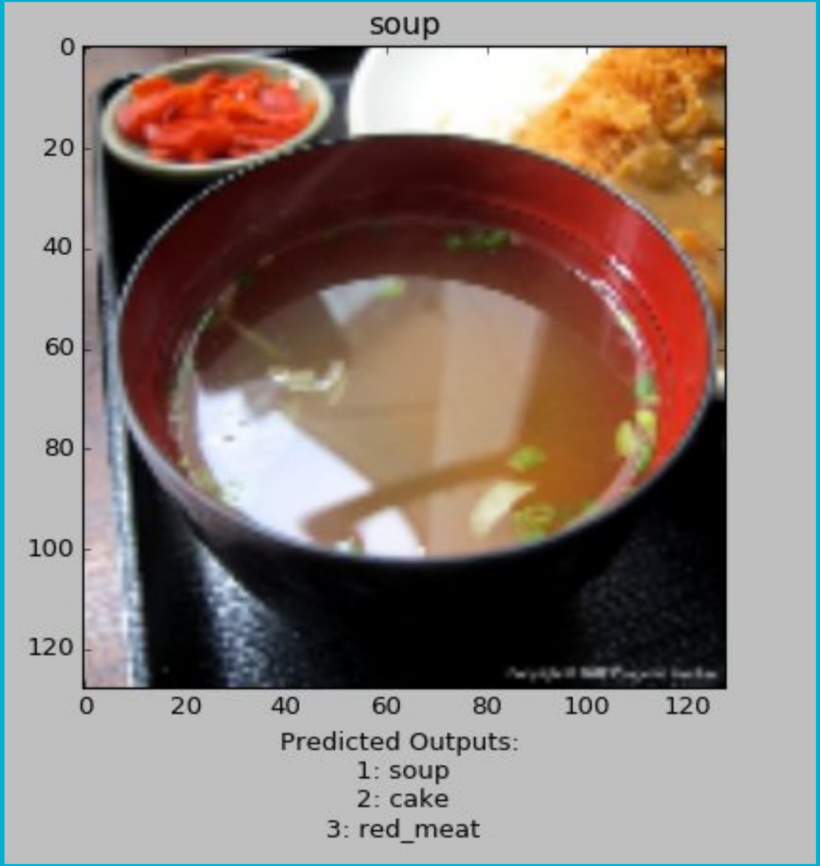
Ice Cream???



Conclusion (continued)

Soup

- 77% accuracy for this category
- Most "uniform" food class in our dataset
    - Typically consists of dark liquid in a circular bowl
- The image pictured clearly displays a bowl of soup centered in the frame



Conclusion (continued)

- Achieving ~60% accuracy significant improvement over ~8-9% (12 classes) with random guess
- Concept of food is such that an item cannot be accurately defined or classified by appearance alone, dooming our approach from the start
- Many images contained more than one menu item, potentially of multiple classifications. (may need preprocessing to instruct the network which object(s) to focus on)
- Some of our target classes (such as pasta) were constructed by combining visually distinct categories (gnocchi, spaghetti, lasagna, macaroni and cheese, etc take on many different shapes and colors), negatively affecting the network's ability to recognize patterns and features within a class

Future Work

- **Images Pre-Processing:**
    - **Food image:** Color; Outline; Texture; Padding before resize keep the shape same proportion; Random cropping and flipping
    - **Tools:** SIFT (Scale-Invariant Feature Transform) / Open CV
    - **Approach:** Outline of the food Color Descriptor; Extract effective information (take out the plate or table in the image)
- **CNN parameters:** Kernel size (smaller like 5 or 3); Number of Kernels(from high to low); Batch Normalization
- **Post-Processing:**
    - **work on the lowest accuracy category (relabel or go)**
    - **More than 1 class in one picture**

Reference

- Python Script for illustrating CNN
  https://github.com/yu4u/convnet-drawer/blob/master/convnet_drawer.py