Food Image Recognition Using Deep Convolutional Network with Pre-training and Fine-tuning

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Introduction: Food & Deep

Food image recognition :

- One of important topics in CEA community
- Helpful for food habit recording.

Deep Convolutional Neural Network:

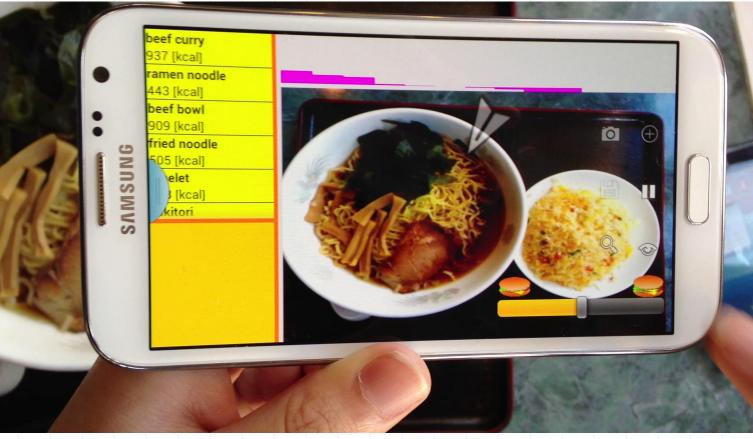
Best image classification method at present
 ILSVRC, Pascal VOC, MIT-SUN, Caltech-101/256,...

How about food datasets such as UEC-Food101/256 and ETH Food-101?

FoodCam: [Kawano et al. MTA13]

http://foodcam.mobi/

Real-time mobile food recognition Android application



Objectives of this work

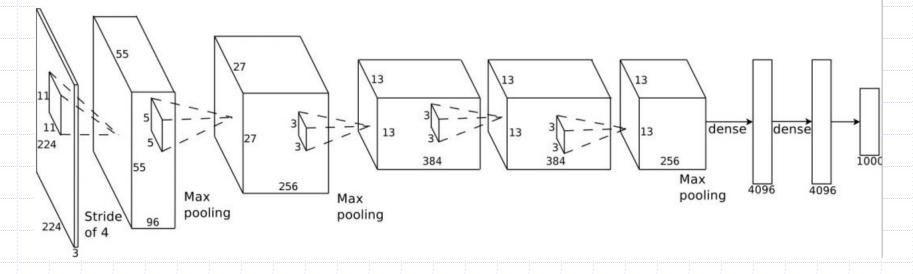
- [Experiments] Introduce deep convolutional neural networks (DCNN) into food image classification task
- Examine its effectiveness
- [Application]
- Apply DCNN-based food classifier to Twitter food photo mining .

Deep Convolutional Neural Network (DCNN)

The most common network architecture for image classification: **AlexNET** proposed by Alex Krizhevsky in ILSVRC2012.

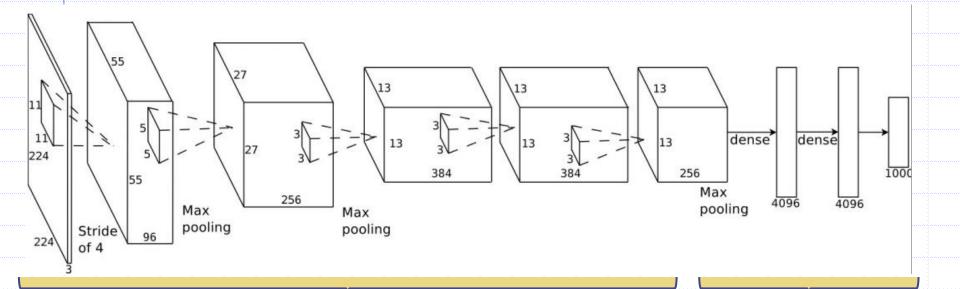
Alex Krizhevsky, I.Sutskever, J. Hinton : ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

We use this in this work.



Deep Convolutional Neural Network

Consists of convolutional layers and full connection layers.

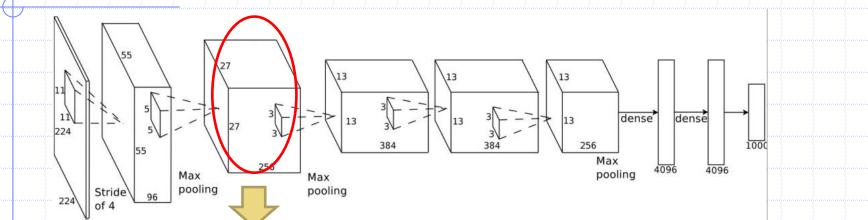


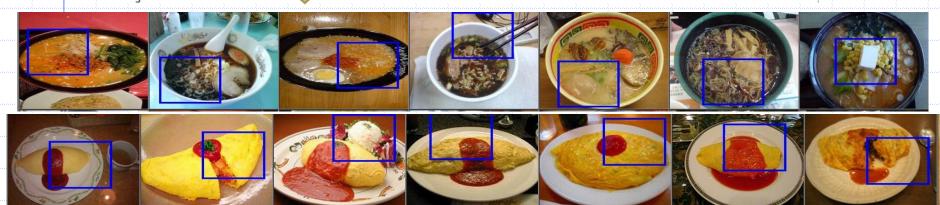
Convolutional layers

Full-connection layers

 \Rightarrow Feature extraction part \Rightarrow classification part

Most activated location on 3rd conv. layer

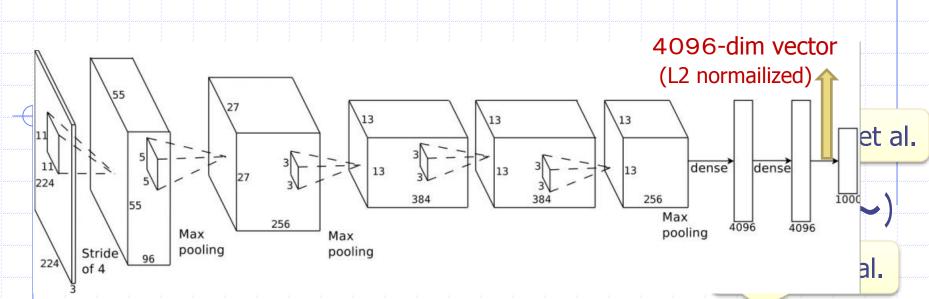






[Exisiting works] DCNN with Food Dataset

- [Kawano et al. CEA2014]
 - DCNN activation features (pre-trained with ILSVRC data)
 - UEC-FOOD100: FV: 65.32%
 - DCNN 57.87%, DCNN+FV: 72.26% (best so far)
- Other work:
 - [Kagaya et al. MM2014] 10 kinds of foods with DCNN trained from scratch
 - [Bossard et al. ECCV2014] ETH-Food101 with AlexNet from scratch



2. Use activation features of pre-trained DCNN

- Extract activation signals from the previous layer of the last one, and use them as visual features
- Easiest among three. (by using Caffe or Overfeat)
- 3. Fine-tune a pre-trained DCNN using non-large-scale dataset

Not explored yet

- Even small data can improve performance over (2)

Introducing pre-training with non-ILSVRC and Fine-tuning

 Existing works: training from scratch or using pre-trained model with ILSVRC

Two kinds of extensions

 Pre-training with food-related ImageNet categories

Fine-tuning

DCNN pre-training Datasets

- **ILSVRC2012**
 - Large Scale Visual Recognition Challenge
 - one thousand training images per category
 - Generic 1000 categories
 - few food categories

DCNN pre-trained with the dataset containing more food-related categories is desirable.

DCNN pre-training Datasets containing more foods

- Select 1000 food-related categories from ImageNet
 - List up all the word under "food" in the ImageNet hierarchy
 - 1526 synsets related to "food"
 - Exclude synsets included in ILSVRC dataset
 - Select the top 1000 synsets in terms of # of images in ImageNet

* ImageNet 2011 Fall release

DCNN pre-training Datasets

- ImageNet2000 categories
 1000 food-related categories from ImageNet
 ImageNet1000 (ILSVRC) categories
 - = 2000 categories

Pre-training with ImageNet2000 DCNN Features with ImageNet 2000 categories

- Using Caffe

- The dimension of full connection layers is modified from 4096 to 6144, since the output dimension is raised from 1000 to 2000.

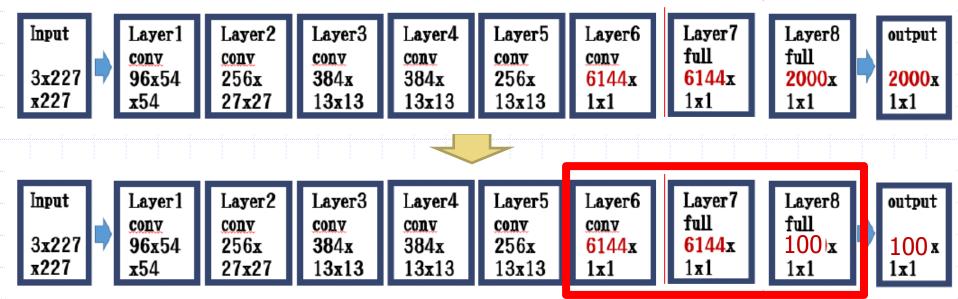
Training time

- About one week (training from scratch)
- GPU, Nvidia Geforce TITAN BLACK, 6GB

Input Layer1 Layer2 Layer3 Layer4 Layer5 Layer6 3x227	full <mark>6144</mark> x	Layer8 full 2000x 1x1	output 2000x 1x1
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Fine-tuning with small dataset

- Modify the size of the last layer (2000⇒100)
- Re-train only weight parameters of full connection layers (L6,7,8)
- Weights from L1-5 are fixed



Fine-tuning

- It enables DCNN to be trained with small data.
- Feature extraction parts are trained with large-scale data such as ImageNet.
- Classification parts are trained with smallscale target data.

Input 3x227 x227	Layer1 <u>conv</u> 96x54 x54	Layer2 <u>conv</u> 256x 27x27	Layer3 conv 384x 13x13	Layer4 <u>conv</u> 384x 13x13	Layer5 <u>conv</u> 256x 13x13	Layer6 <u>conv</u> 6144x 1x1	Layer7 full <mark>6144</mark> x 1x1	Layer8 full 2000x 1x1	output 2000x 1x1
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Feature extraction part Classification part

Experiments: Food dataset

UEC-FOOD100/256 dataset

- 100 / 256 food categories (Japanese and Asian)
- More than 100 images for each category
- Bounding box information for all the images

• ETH Food-101 [Bossard et al. ECCV2014]

- 101 categories, 1000 images for each category (mainly western and partly Japanese)
- Collecting from http://www.foodspotting.com/
- 20 categories are overlapped with UEC-FOOD100

port cutlet on rice

soba

noodle

oden

sirloin cutlet

stir-fried

beef

curry

ramen

noodle

omelet

nanbanzuke

simmered

pork







pilaf

udon

noodle

potage

tempura

egg roll

eels on rice





sandwiches



vegetable

fish

potato salad





steamed egg hotchpotch



cold tofu











chicken-'n'-

egg on rice

tempura

udon

sausage

fried chicken

Japanese tofu and vegetable soup chowder









chinese soup





rice ball

chicken rice

tensin

noodle

ijaozi

seasoned

beef with

potatoes

sashimi

bowl

sushi

beef noodle

ganmodoki

boiled fish

boiled chicken

and vegetables







dipping noodles

fish-shaped pancake

tempura bowl

spaghetti

teriyaki grilled fish

steak

fried rice

fried

noodle

stew

hambarg steak

sushi bowl

bibimbap

Japanese-style

pancake

fried fish

dried fish

shrimp with chill

toast

takoyaki

grilled

salmon

ginger pork saute

roast chicken



french fries



















burdock







cutlet

curry



















hamburger

sauteed spinach

eggplant

chip butty









raisin bread

roll bread

sauteed

vegetables

sashimi

LLLIT

yakitori

omelet with fried

rice

croissant

gratin

salmon

meuniere

spicy chili-flavored

tofu

steamed

dumpling

meat





sukiyaki

sweet and sour pork

























vegetable tempura

lightly roasted fish

natto











fried

stev

ambarg steak

shi bowl























Japanese tofu and vegetable chowder pork miso soup







pizza toast



goya chanpuru



burdock

mixed rice

sauteed spinach

















chicken rice sushi

fried rice

fried

stew

ambarg steak

shi bowl



bibimbap toast





raisin bread



auteed

eet and

ur pork

egg nny-side up





vegetable tempura



lightly roastec

































mixed rice





dipping noodles

goya chanpuru



fried shrimp















fried rice

fried .oodle

stev

mbarg steak

hi bowl



bibimbap toast





hamburger





vegetable tempura









potato





























mixed rice









rice ball

goya chanpuru burdock





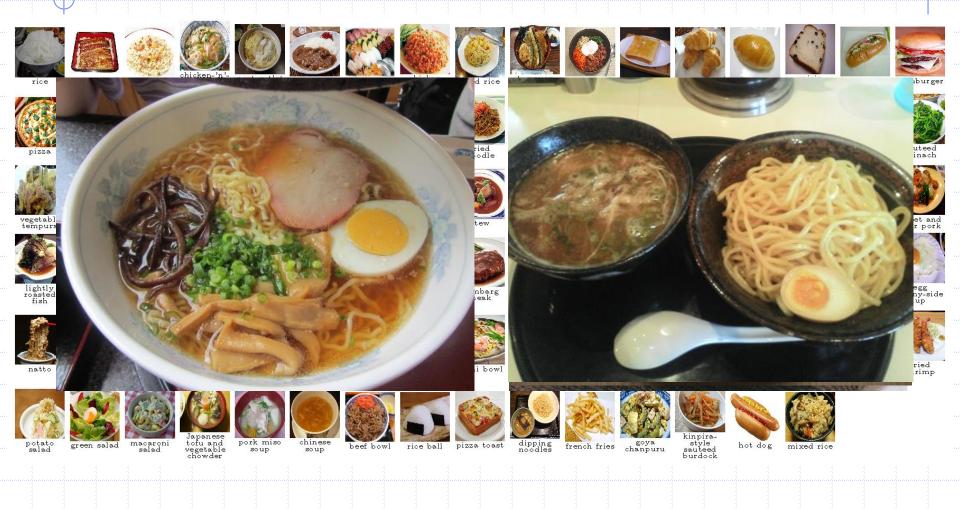


ir pork



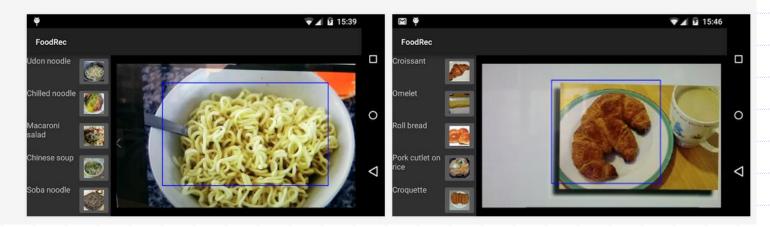


ied rimp



FoodRec: foodrec app with UECFOOD100 by Hamlyn Centre-Imperial College (UK)





UEC The University of Electro-Communications

UEC-FOOD as a Fine-Grained Image Classification Dataset

arXiv.org > cs > arXiv:1502.07802

Search or Article-i

Computer Science > Computer Vision and Pattern Recognition

Modelling Local Deep Convolutional Neural Network Features to Improve Fine-Grained Image Classification

ZongYuan Ge, Chris McCool, Conrad Sanderson, Peter Corke

(Submitted on 27 Feb 2015)

We propose a local modelling approach using deep convolutional neural networks (CNNs) for finegrained image classification. Recently, deep CNNs trained from large datasets have considerably improved the performance of object recognition. However, to date there has been limited work using these deep CNNs as local feature extractors. This partly stems from CNNs having internal representations which are high dimensional, thereby making such representations difficult to model using stochastic models. To overcome this issue, we propose to reduce the dimensionality of one of the internal fully connected layers, in conjunction with layer-restricted retraining to avoid retraining the entire network. The distribution of low-dimensional features obtained from the modified layer is then modelled using a Gaussian mixture model. Comparative experiments show that considerable performance improvements can be achieved on the challenging Fish and UEC FOOD-100 datasets.









ETH-Food101





Takoyaki







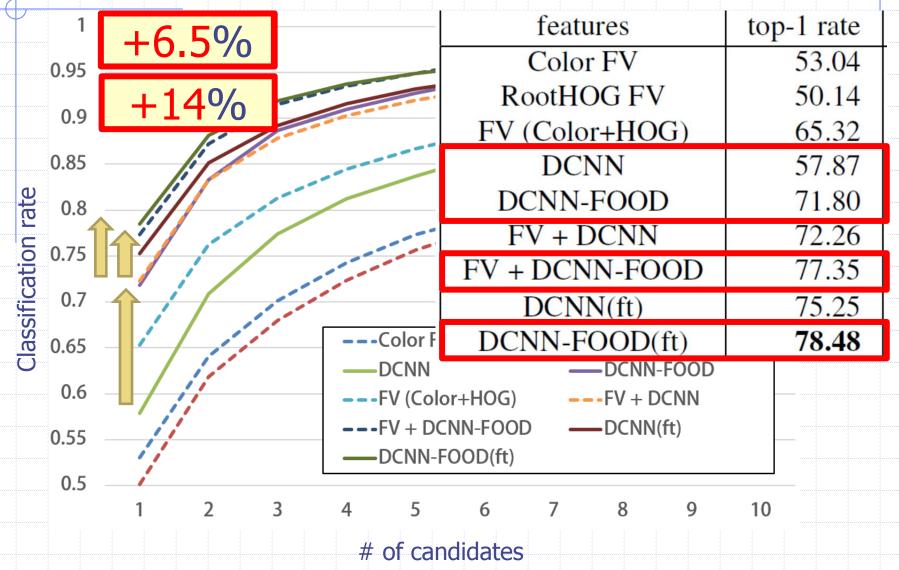




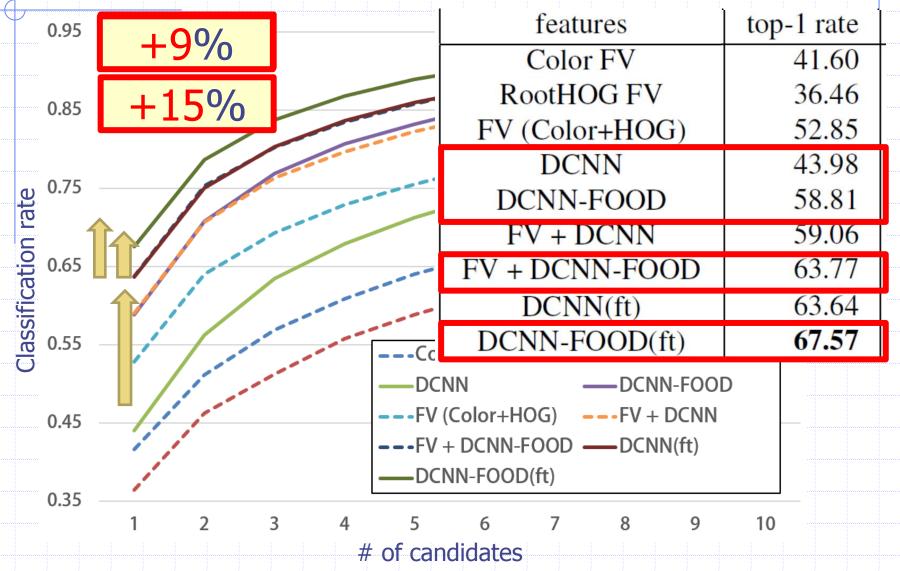
Baseline features & classifiers

- Conventional baseline features
 - Root HOG patch and Color patch
 - Fisher Vector (FV)
 - SPM level2 (1x1+3x1+2x2)
 - 32768-dim RootHOG-FV
 - 24576-dim Color-FV
- Classifiers
 - 1-vs-rest multiclass linear SVM
- Evaluation: 5fold cross-validation

Results: UEC-FOOD100



Results: UEC-F00D256



Results on ETH-Food101

 Table 2. Classification rate on ETH Food-101 dataset [1].

RF-based [1]	DCNN [1]	DCNN(ft)	FOOD-DCNN(ft)
50.76	56.40	68.44	70.41

 Fine-tuned DCNN with ImageNet+food1000 pretraining achived the best results.

Summary

- Pre-training with ImageNet + Food1000
 is effective.
- Fine-tuning can improve performance over Pre-training DCNN + FV.

 Fine-tuning the DCNN which was pre-trained with ImageNet1000 + Food1000 is the best.

Comments:

For further improvements

- Using deeper network (VGG16 or GoogLeNet) instead of Alexnet
- Fusing DCNN-FOOD (ft) with FV
- Both are not examined yet.
 (Because the second author graduated…)

Apply DCNN-F00D(ff) to Twitter Real-time Food Photo Mining

Keiji Yanai and Yoshiyuki Kawano: Twitter Food Image Mining and Analysis for One Hundred Kinds of Foods, Pacifit-Rim Conference on Multimedia (PCM), (2014).

Yoshiyuki Kawano and Keiji Yanai, **FoodCam: A Real-time Food Recognition System on a Smartphone**, Multimedia Tools and Applications (2014). (in press) (<u>http://dx.doi.org/10.1007/s11042-014-2000-8</u>)

Twitter Real-time Food Photo Mining System (<u>mm.cs.uec.ac.jp/tw/</u>)

• What kinds of foods are being eaten in Japan ?



Objective

- Twitter Photo Mining for Food Photos
 As a case study of Twitter Photo Mining on specific kinds of photos
 - Food is one of frequent topics of Twitter Photos.
 - Real-time Photo Collection from the stream
- To collect more food photos for training

 Twitter is a good source of food photos.
 Unlike "FoodLog", we have no users who upload their food photos regularly. Twitter is alternative.

Preparation

- Add "non-food" category to the best classifier (FOOD-DCNN (ft)).
- Prepare 10000 non-food samples gathered from Twitter by 100 food names
- Fine-tuning with 101 category.



Food/non-food classification: 98.86%

Approach for food photo mining

[old] Three-step food photo selection



Image-based analysis

[new] Two-step food photo selection

Keywordbased selection



101-foods classification

Experiments

- Collect photo tweets via Twitter Streaming API
 - From 2011/5 to 2013/8
 - About one billion tweets
- Search for the tweets including any of 100food names (in Japanese)
 - 1.7 million ← Apply food image classifier
 - 0.03 image/classification w/GPU (4 hours by 4 GPU machines)



Precision of the top 5 foods

Food	raw	FV-based	DCNN
ramen	275,652	80,021	132,095
	72.0%	99.7%	99.5%
Curry	224,685	59,264	68,091
	75.0%	99.3%	100.0%
sushi	86,509	25,898	224,908
	69.0%	92.7%	99.8%
tsukem	33,165	22,158	22,004
en	88.7%	99.0%	100.0%
omelet	34,125	17,520	20,039
	90.0%	99.0%	99.9%

Only keyword search (Ramen noodle) (72.0%)



After applying 100-class food classifier (final) (99.5%)



Only keyword search (curry) (75.0%)

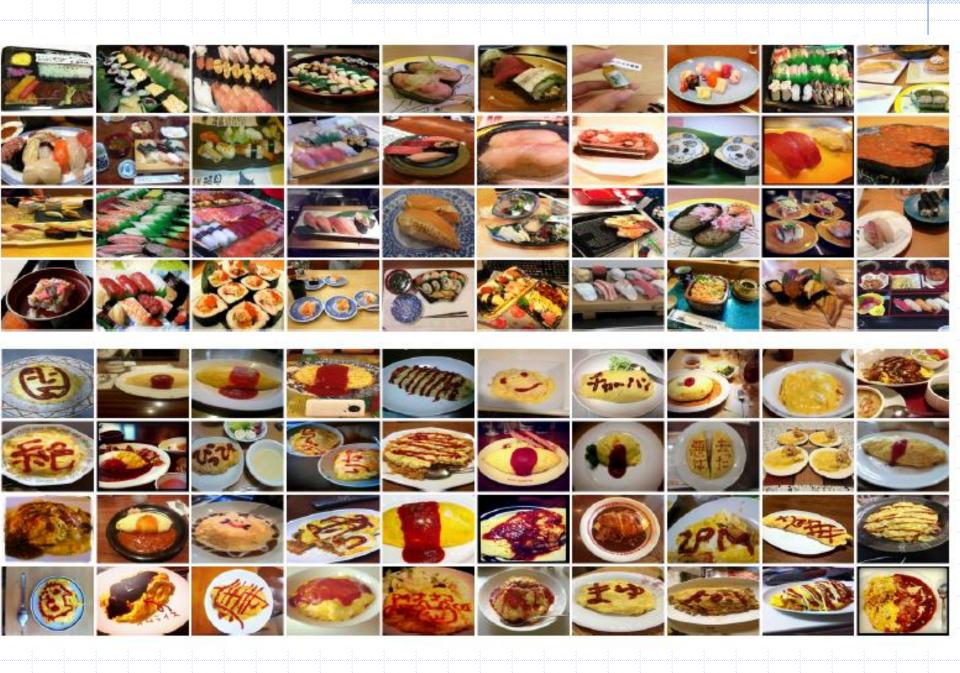


Final results (curry) (100%)



Final results (omelet) (99.9%)





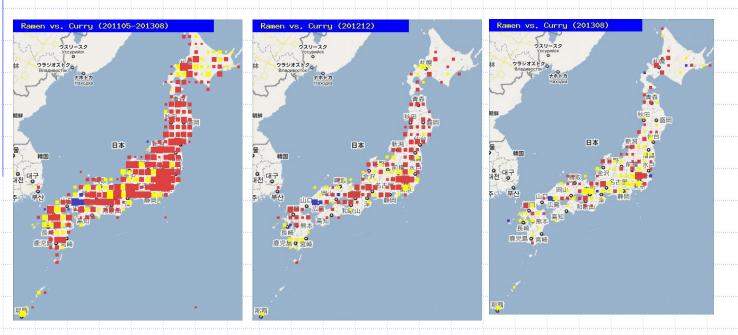
Misclassified photos



Fig. 6. Examples of misclassified Twitter food photos. Eaten ramen bowl (recognized as "ramen"), unopened instant ramen (ramen), a clam (sushi), ice cream (sushi), an eaten plate (omelet) and curry without cutlet (cutlet curry).

Geographical-Temporal analysis on ramen vs curry

12.6% of the obtained food photos have geotag.



Whole year Dec. (winter) Aug. (summer)

Curry

Ramen

Ramen is popular. Curry gets more popular

than ramen in many areas.

Utilization of large number of food photos: Omerice analysis

Omerice-style classification Classification rate: 84.184%



認識結果: 各1000枚で学習.1500枚を分類

分類先⇒	文字	絵	模様	ソース	プレーン
文字	85.6	10.0	3.1	1.1	0.1
絵	9.9	84.2	3.5	1.9	0.5
模様	3.1	5.7	80.7	8.8	1.6
ソース	1.2	1.9	6.9	86.5	3.5
ペープレーン	0.0	2.9	0.0	15.8	81.3

Real-time Food Collection

- Monitor the Twitter stream
 - Photo Tweet
 - Text including any of 100 food names
 - 13 candidate photo tweets / minute on avg.
 - Download: 2~3sec. , recognition: ~1sec.

Single machine is enough !

 Recognize 20,000 photos and find 5,000 food photos from the TW stream everyday in our lab

Demo visualization system

- Map each food photo on an online map with online clustering [Yanai ICMR2012]
 - Geotagged Tweets
 - Non-geotagged Tweets for which GeoNLP can assign locations based on text msg.
- Overlay a food photo on the Streetview
 Finding "ramen noodle shop" game !
 http:/mm.cs.uec.ac.jp/tw/

Twitter Food Image Bots

- Bot who recognize food photos and return results
 @foodimg_bot
- Bot who re-tweets food photo tweets automatically





DeepFoodCam Release soon at http://foodcam.mobi/

DCNN-based food rec. app
 Network-in-network (NIN) instead of AlexNet
 PQ-based weight compression (7MB ⇔ 256MB)



Conclusions

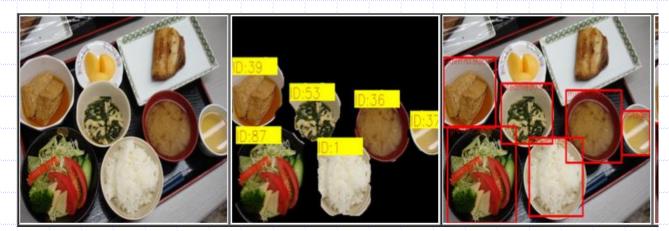
- Food recognition with DCNN features
 - Pre-trained DCNN with ImageNet2000 categories
 - Fine-tuned the pre-trained DCNN with UEC-FOOD

Achieved the best performance so far - UEC FOOD-100: 78.48%
- UEC FOOD-256: 94.85%
We showed the effectiveness for the application, Twitter food photo mining

Future works

CNN-based food region segmentation





Thank you for your attention !



1	ramen noodle	80021	
2	curry	59264	
3	sushi	25898	
4	dipping noodle	22158	
5	omelet with fried rice	17520	
6	pizza	16921	
1 2 3 4 5 6 7 8 9	jiaozi	16014	
8	Japanese-style pancake	15234	
9	steamed rice	14264	
10	sashimi	13927	
11	hambarg steak	11583	
11 12	beef stake	9503	
13	takoyaki	9004	
14	fried rice	8383	
15	fried noodle	7905	
16	oden	7453	
17	toast	6350	
18	cutlet curry	6339	
19	tempura	5905	
20	rice ball	5462	
21	gratin	5223	
22	croquette	4837	
20 21 22 23 24 25 26	stew	4797	
24	sashimi bowl	4730	
25	chicken-'n'-egg on rice	4513	
26	tempura bowl	4464	
27	beef bowl	4285	
27 28	spicy chili-flavored tofu	4081	
29	yakitori	3829	
30	hamburger	3662	
31	chilled noodle	3473	
32	sukiyaki	3408	
33	miso soup	3295	

34	fish-shaped pancake with bean jam	3281
35	pork cutlet on rice	3188
36	omelet with grilled minced meat	2592
37	bibimbap	2368
38	spaghetti	2171
39	lightly roasted fish	2162
40	seasoned beef with potatoes	2129
41	natto	2094
42	spaghetti with meat source	1994
43	steamed egg hotchpotch	1843
44	egg sunny-side up	1635
45	croissant	1579
46	udon noodle	1500
47	simmered pork	1443
48	mixed sushi	1371
49	pork miso soup	1229
50	ginger-fried pork	1158
51	potato salad	1150
52	egg omelet	1146
53	eels on rice	1071
54	egg roll	1058
55	sweet and sour pork	1049
56	fried shrimp	1049
57	sauteed vegetables	1040
58	shrimp with chill source	1003
59	cabbage roll	965
60	mixed rice	901
61	pilaf	891
62	soba noodle	880
63	potage	816
64	hot dog	795
65	chicken rice	736
66	wiener sausage	577

67	dried fish	563	
68	steamed meat dumpling	561	
69	french fries	561	
70	beef ramen noodle	555	
71	sandwiches	551	
72	cold tofu	517	
73	boiled chicken and vegetables	352	
74	sirloin cutlet	331	
75	nanbanzuke	323	
76	fried chicken	314	
77	stir-fried beef and peppers	312	
78	roll bread	288	
79	roast chicken	263	
80	macaroni salad	239	
81	boiled fish	228	
82	kinpira-style sauteed burdock	225	
83	tempura udon	213	
84	raisins bread	205	
85	goya chanpuru	198	
86	green salad	145	
87	chinese soup	141	
88	Japanese tofu and vegetable chowder	137	
89	salmon meuniere	96	
90	grilled pacific saury	84	
91	chip butty	76	
92	fried fish	72	
93	begitable tempura	71	
94	tensin noodle	69	
95	ganmodoki	34	
96	grilled salmon	25	
97 98	sauteed spinach	12	
	teriyaki grilled fish	3	
99	grilled eggplant	34 25 12 3 2 0	
100	pizza toast	0	

noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch
soup	miso soup, pork miso soup, japanese tofu and vegetable chowder
fried	takoyaki, japanese-stype pancake, fried noodle
deep fried	croquette, sirloin cutlet, fried chicken
salad	green salad, sauteed vegetables, vegetable tempra
bread	sandwiches, raisin bread, roll bread
seafood	sashimi, sashimi bowl, sushi
rice	rice, pilaf, fried rice
fish	grilled salmon, grilled pacific saury, dried fish
boiled	sesoned beef with potatoes
and	simmered ganmodoki
seasoned	sesoned beef with potatoes
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
sauce 01	stew, curry, stir-fried shrimp in chili sauce

noodles	udon nooles, dipping noodles, ramen			
vallow color	product potago staamed oos hotobootob ar y c s en samon, grineu paeme sadry, oos hotobootob gill u en samon, grineu paeme sadry, oos hotobootob gill u u			
boiled	sesoned beef with potatoes			
and	simmered ganmodoki			
seasoned	sesoned beef with potatoes			
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock			
sauce 02	stew, curry, stir-fried shrimp in chili sauce			

-		
	noodles	udon nooles, dipping noodles, ramen
	yellow color	omlet, potage, steamed egg hotchpotch
	-	p p p p p p p p p p p p p p p p p p p
	11511	grilled salmon, grilled pacific saury, dried fish
	boiled	sesoned beef with potatoes
	and	simmered ganmodoki
	seasoned	sesoned beef with potatoes
	sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock
	sauce 03	stew, curry, stir-fried shrimp in chili sauce
_		

$i \in \mathbf{V} \mathbf{V}$ $i = i = i$	$(x_1, x_2, x_3, x_4, x_4, x_4, x_4, x_4, x_4, x_4, x_4$
noodles	udon nooles, dipping noodles, ramen
yellow color	omlet, potage, steamed egg hotchpotch
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noodles	udon nooles, dipping noodles, ramen
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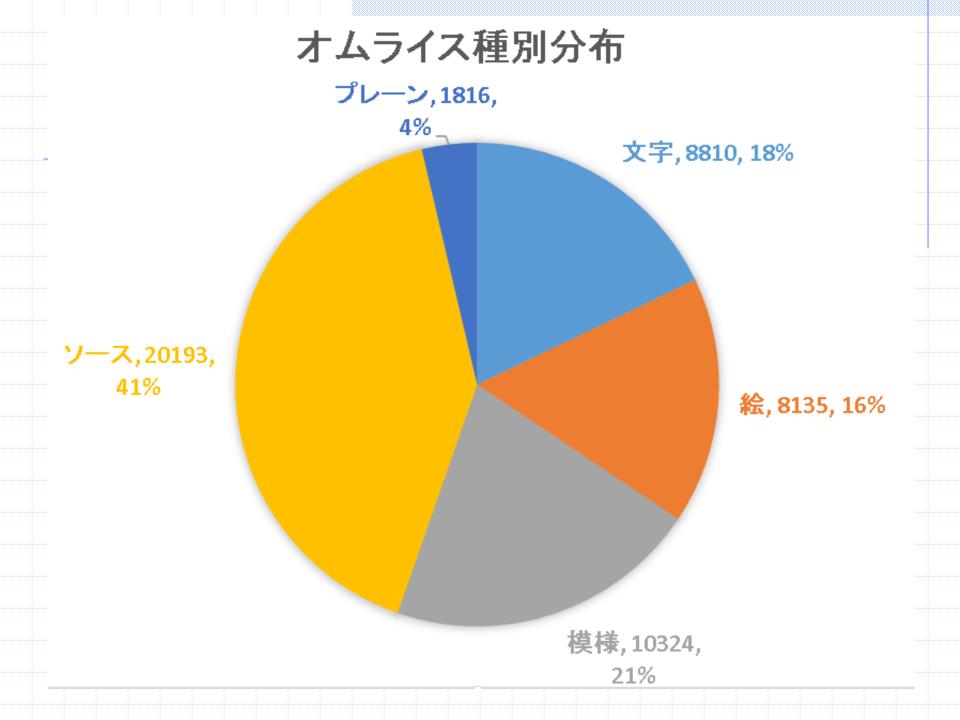
boiled	sesoned beef with potatoes	
and	simmered ganmodoki	
seasoned	sesoned beef with potatoes	
sauteed	sauteed vegetables, goya chanpuru, kinpira-style sauteed burdock	-
sauce 05	stew, curry, stir-fried shrimp in chili sauce	_

クラウドソーシング体験課題

【復習】



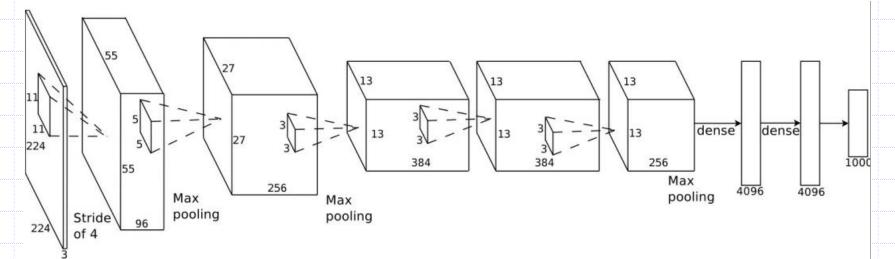




大規模画像認識のための 標準ネットワーク構成: Alex Net ILSVRC 2012 で, Alex Krizhevskyらが用い たネットワーク構成.

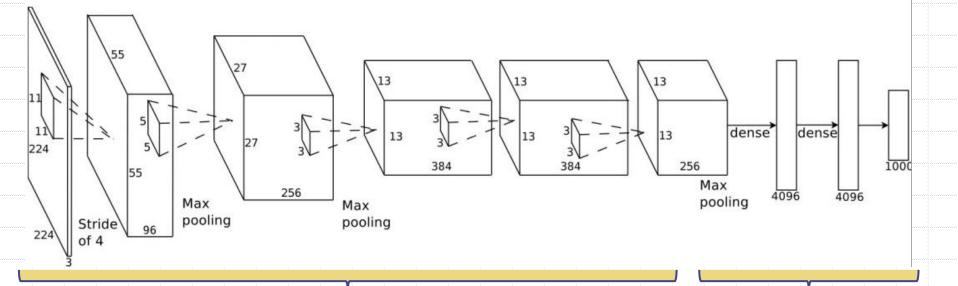
 Alex Krizhevsky, I.Sutskever, J. Hinton : ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

2013, 2014はどのチームもこれをベースに改良, 拡張.
 ⇒ 事実上の標準ネットワーク.



Convolutional network

・前半が畳み込み層(convolutional layer), 後半が昔と同じ全結合層(full



Convolutional layer

109

Full-connection layer