

GrubGuru: AI Calorie Predictor

CSCI 413 Advanced Data Science



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Roadmap



1 Data Collection and Preprocessing



2 Exploratory Data Analysis



3 Model Development



4 Results and Evaluation



5 Ethical Considerations



6 Closing Thoughts



Data Collection and Preprocessing



Used the Food101 dataset from ETH Zurich which has 101,000 images of 101 different foods along with FoodData Central API and Nutritionix API for calorie information



Downscaled raw image data to 128x128 using bilinear interpolation and split into training, test, and validation sets



Normalized pixel values to $[0,1]$ for basic CNN and $[-1,1]$ for MobileNetV2 and ViT

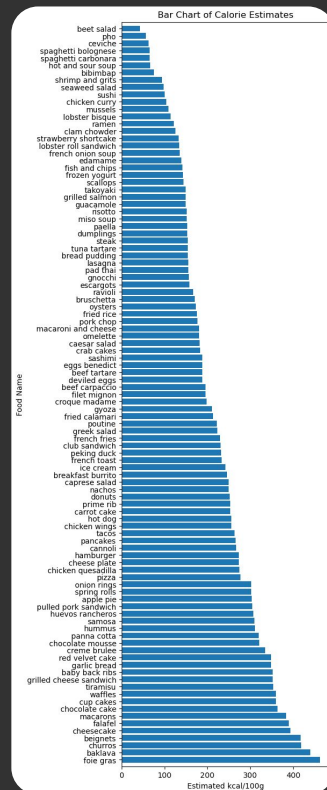
Getting to know the Data

- Visualization of average pixel colors for 8 classes of food
- Chart of the total calories for each of our training food categories gathered from FoodData Central and Nutritionix APIs

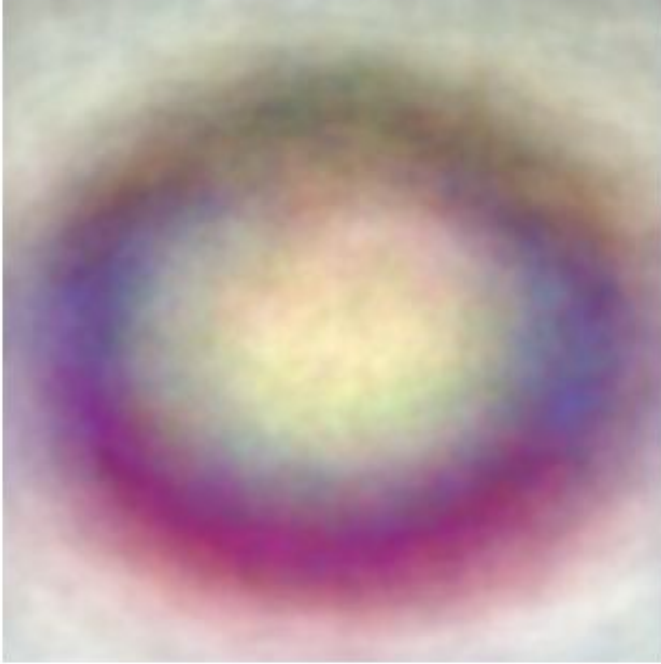
8 Average Foods



Calorie Information



Standard Deviation Across Classes



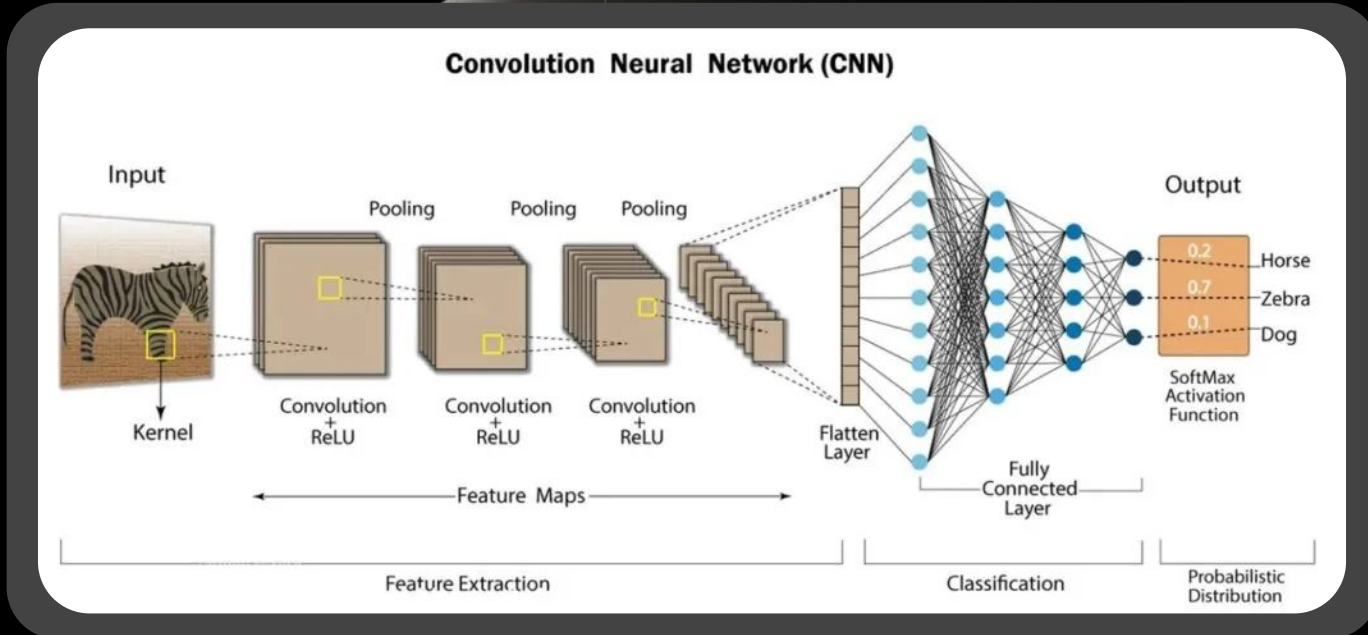
A visualization of the standard deviation in pixel data across 8 classes.

Purple areas are more constant across images, while grey/white are more variable.

CNN Structure



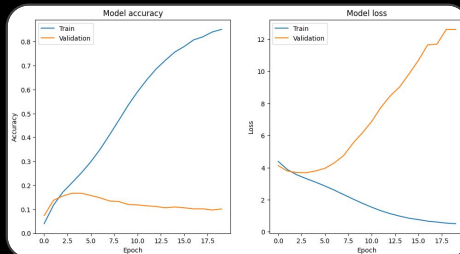
Take an input image, extract features, feed through neural network to output layer where everything gets squished down to get a final best guess for classification



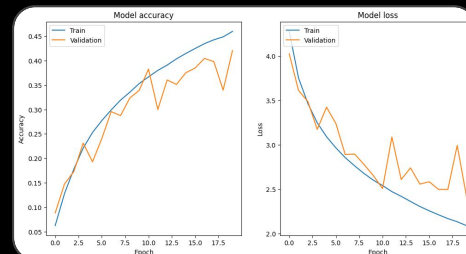
Model Performance Over Time

- Initial Architecture: Used 4 blocks of convolutional layers bundled with max pooling layer. Overfit to the test and only got about **15% accuracy** on Validation Data
- Later Improvements: Switched to VGGNet style architecture, using a global average pooling layer to reduce number of trainable parameters. Helped greatly with overfitting and resulted in **40% accuracy** on Validation Data
- Final Architecture: Switched to using MobileNetV2, an efficient CNN architecture that is focused on images, as the base with our own layers of tuning on top. Achieved **59% accuracy**.

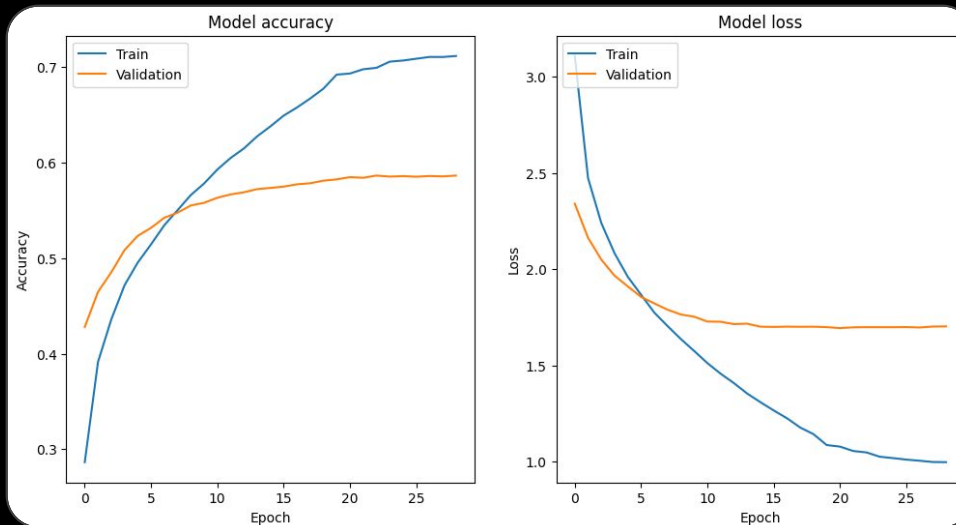
Architecture 1



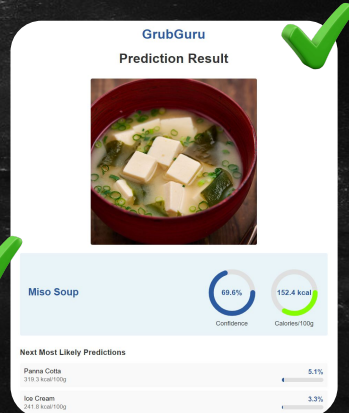
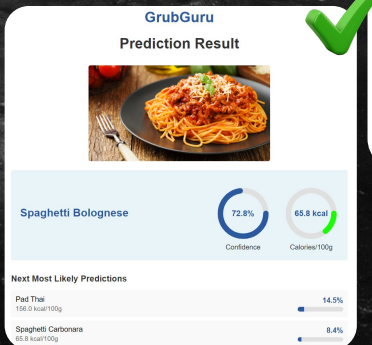
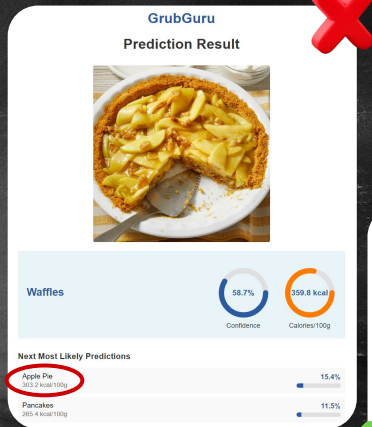
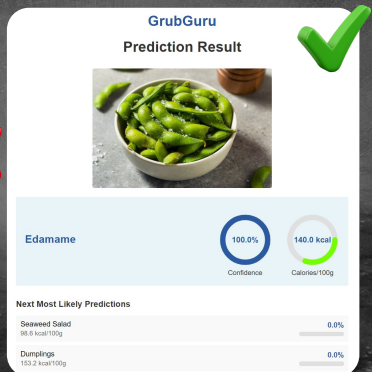
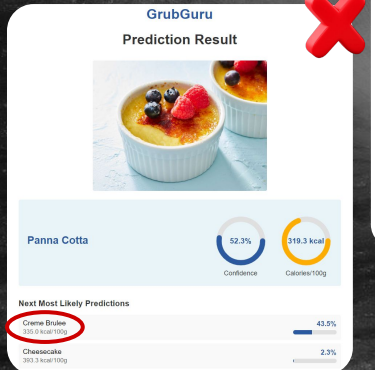
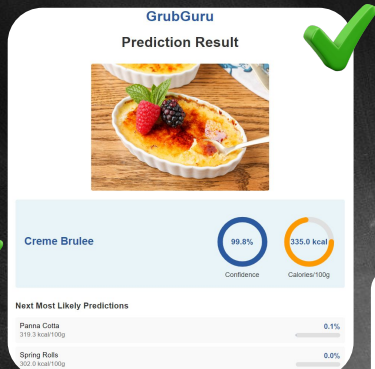
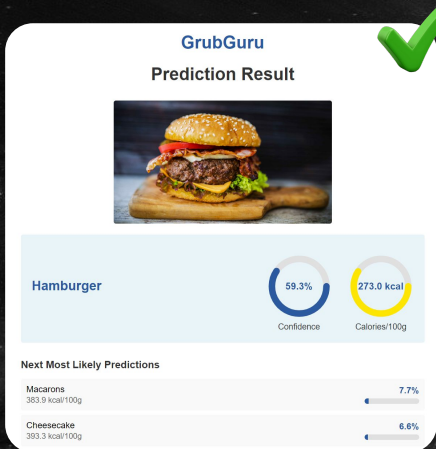
Architecture 5



Architecture 7



Our Flask Web Application



Live DEMO!!!

Full Classification Report

A-G

Class	Precision	Recall	F1-score	Support
apple_pie	0.33	0.31	0.32	150
baby_back_ribs	0.63	0.69	0.66	150
baklava	0.62	0.65	0.63	150
beef_carpaccio	0.60	0.62	0.61	150
beef_tartare	0.47	0.45	0.46	150
beet_salad	0.50	0.55	0.53	150
beignets	0.73	0.82	0.77	150
bibimbap	0.73	0.77	0.75	150
bread_pudding	0.34	0.38	0.36	150
breakfast_burrito	0.43	0.44	0.44	150
bruschetta	0.45	0.39	0.42	150
caesar_salad	0.59	0.67	0.63	150
cannoli	0.62	0.64	0.63	150
caprese_salad	0.51	0.49	0.50	150
carrot_cake	0.68	0.56	0.61	150
ceviche	0.39	0.36	0.38	150
cheese_plate	0.51	0.49	0.50	150
cheesecake	0.42	0.37	0.39	150
chicken_curry	0.47	0.39	0.42	150
chicken_quesadilla	0.60	0.56	0.58	150
chicken_wings	0.62	0.72	0.67	150
chocolate_cake	0.48	0.53	0.50	150
chocolate_mousse	0.34	0.42	0.38	150
churros	0.70	0.74	0.72	150
clam_chowder	0.72	0.74	0.73	150
club_sandwich	0.69	0.63	0.66	150
crab_cakes	0.43	0.38	0.40	150
creme_brulee	0.71	0.71	0.71	150
croque_madame	0.70	0.75	0.72	150
cup_cakes	0.69	0.71	0.70	150
deviled_eggs	0.75	0.75	0.75	150
donuts	0.58	0.55	0.57	150
dumplings	0.80	0.77	0.79	150
edamame	0.95	0.94	0.94	150
eggs_benedict	0.74	0.71	0.72	150
escargots	0.64	0.59	0.62	150
falafel	0.51	0.45	0.48	150
filet_mignon	0.46	0.37	0.41	150
fish_and_chips	0.64	0.67	0.65	150
foie_gras	0.30	0.30	0.30	150
french_fries	0.78	0.82	0.80	150
french_onion_soup	0.71	0.57	0.63	150
french_toast	0.50	0.51	0.50	150
fried_calamari	0.58	0.60	0.59	150
fried_rice	0.64	0.69	0.66	150
frozen_yogurt	0.76	0.72	0.74	150
garlic_bread	0.51	0.49	0.50	150
gnocchi	0.44	0.49	0.47	150
greek_salad	0.56	0.58	0.57	150
grilled_cheese_sandwich	0.53	0.41	0.46	150
grilled_salmon	0.42	0.34	0.38	150
guacamole	0.71	0.71	0.71	150
gyoza	0.58	0.65	0.62	150

H-Z

Class	Precision	Recall	F1-score	Support
hamburger	0.60	0.57	0.59	150
hot_and_sour_soup	0.82	0.85	0.83	150
hot_dog	0.64	0.67	0.66	150
huevos_rancheros	0.35	0.31	0.33	150
hummus	0.41	0.39	0.40	150
ice_cream	0.49	0.58	0.53	150
lasagna	0.55	0.48	0.51	150
lobster_bisque	0.68	0.74	0.71	150
lobster_roll_sandwich	0.67	0.63	0.65	150
macaroni_and_cheese	0.49	0.55	0.52	150
macarons	0.78	0.80	0.79	150
miso_soup	0.88	0.81	0.85	150
mussels	0.72	0.83	0.77	150
nachos	0.51	0.56	0.53	150
omelette	0.41	0.36	0.38	150
onion_rings	0.68	0.82	0.75	150
oysters	0.81	0.77	0.79	150
pad_thai	0.70	0.67	0.68	150
paella	0.61	0.67	0.64	150
pancakes	0.60	0.61	0.60	150
panna_cotta	0.45	0.52	0.48	150
peking_duck	0.60	0.67	0.63	150
pho	0.86	0.84	0.85	150
pizza	0.70	0.81	0.75	150
pork_chop	0.31	0.30	0.30	150
poutine	0.73	0.69	0.71	150
prime_rib	0.65	0.62	0.64	150
pulled_pork_sandwich	0.56	0.55	0.56	150
ramen	0.68	0.63	0.66	150
ravioli	0.45	0.30	0.36	150
red_velvet_cake	0.68	0.75	0.72	150
risotto	0.48	0.46	0.47	150
samosa	0.60	0.58	0.59	150
sashimi	0.74	0.74	0.74	150
scallops	0.44	0.43	0.43	150
seaweed_salad	0.74	0.79	0.77	150
shrimp_and_grits	0.46	0.49	0.48	150
spaghetti_bolognese	0.73	0.75	0.74	150
spaghetti_carbonara	0.79	0.87	0.83	150
spring_rolls	0.65	0.63	0.64	150
steak	0.34	0.31	0.32	150
strawberry_shortcake	0.53	0.57	0.55	150
sushi	0.53	0.53	0.53	150
tacos	0.36	0.36	0.36	150
takoyaki	0.57	0.63	0.60	150
tiramisu	0.55	0.47	0.51	150
tuna_tartare	0.37	0.34	0.35	150
waffles	0.61	0.61	0.61	150

Final Architecture Results



GrubGuru AI
Results on Unseen Data

59%

Average Overall Accuracy

#1 category

Edamame (95% Accuracy)

Average Results

59%

Precision

59%

Recall

59%

F1-Score

"The best to ever do it."

- Charles

Trusted Reviews



Data Privacy

User Image Data

- Our application deals with user uploaded images so it is important to ensure that user privacy is respected
- Images will be processed anonymously and purely for the purpose of classifying the food and will not be stored after that
- Users will be clearly informed of what happens to their uploaded images

[Learn more](#)



Bias

Training Data

- The Food101 Dataset is heavily skewed towards Western (American/Western European Foods)
- 68% of the dataset is Western foods, 8% is Japanese, 5% is Mexican/Latin American, 5% is Chinese/East Asian, 2% is Thai/Vietnamese, 2% is Indian, 2% is Middle Eastern, and remaining 8% is everything else
- Means our model will be much better at identifying Western foods and almost useless in other contexts.
- For an actual production model we would want a much more diverse dataset of food

[Learn more](#)



Future Improvements

1



Increase Resolution

Right now we are downscaling images to 128x128. Scaling to 224x224 would yield significant improvements in accuracy but would 3x the amount of pixels to process which would significantly increase training time.

2



Switch Model

Switch to Vision Transformer (ViT) which is cutting edge compared to CNN's but also more compute intensive. Or keep CNN but switch to EfficientNetV2 which is more memory and compute intensive than MobileNetV2 but also results in better performance.

3



Ensemble Method

Keep current model but add additional models and take average results to make final prediction. Similar to idea of random forests, this often yields better results.

4



Data Augmentation

Add more random adjustment to training images to improve performance in real world settings. Images won't always be in the same lighting, angle, etc. So make sure our model doesn't get fine tuned for small details in the specific training images.

5



Portion Estimates

Train new model to estimate portion sizes to give custom calorie estimates

6



More Images

Increase the amount of training images and food classes.