# SeeFood: 10 class dessert classifier

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# Problem Statement

Currently, unmanned supermarkets/ convenience stores are gaining traction in China. Given the current pandemic situation, such a business model is ideal, as it minimizes human contact, and reduces queues.

**Can we create a food classifier to facilitate self checkouts, so as to help retail and F&B businesses save on manpower and productivity costs?**

# METHODOLOGY

## EDA

Exploring files and folders in dataset

Visualise images

Check for imbalanced classes

## Experiment

Created 5 class Japanese food classifier

Transfer Learning on VGG16

Val accuracy 84.8%

## Modelling and Evaluation

Created 10 class desserts dataset

Trained dataset on:
Custom CNN
VGG16
EfficientNetB0

Tuned models for retraining

**Best model: Tuned EfficientNetB0 (Val accuracy: 77.6%)**

## Analysis on misclassified images

Created confusion matrix

Visualised misclassified images

Most commonly misclassified classes:
Tiramisu
Carrot Cake
Cheesecake

## Testing on unseen data

Test on googled images

Created webapp (not deployed yet)

# EDA

# DATASET EXPLORATION

- Food-101 dataset from Kaggle

**Meta**

Files in json, txt format with information about dataset.

**Images**

101 folders of image data ranging from apple pies to waffles.
1000 images per category of food.

**HDF5 files**

Reformatted data in Keras HDF5 Matrix format, e.g.
food*c101*n1000_r384x384x3.h5
(101 categories, 1000 images, 384 x 384 x 3 (RGB, uint8))

# INSIDE THE IMAGE FOLDERS

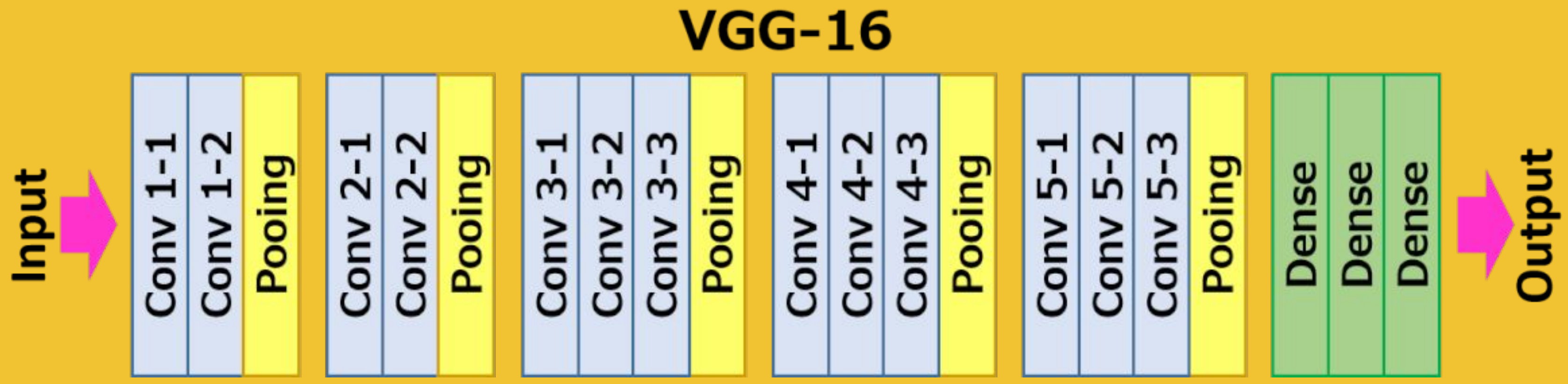
# INSIDE THE IMAGE FOLDERS

# Experiment

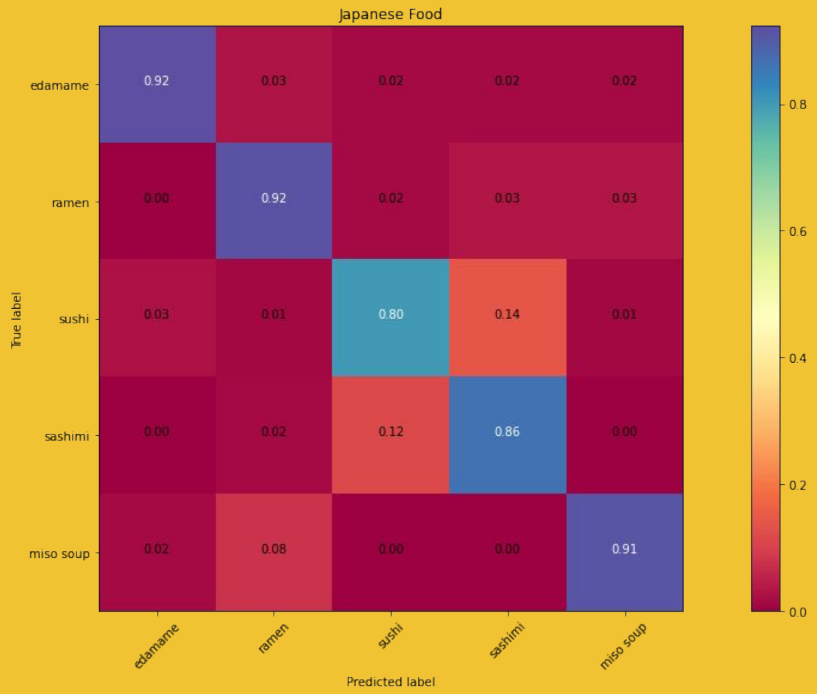
Transfer learning with 5 classes of Japanese Food

# JAPANESE FOOD CLASSIFIER (5 CLASSES)

- Transfer learning with VGG16
- VGG16: pretrained convolutional network model (achieved 92.7% test accuracy in ImageNet)
- 5 classes: Edamame, Ramen, Sushi, Sashimi, Miso Soup
- Freeze all convolutional layers, remove top dense/prediction layers
- Rebuilt top layers with: Global Average Pooling, Dense, Dropout and Prediction



# JAPANESE FOOD CLASSIFIER:
# 84.8% Validation Accuracy




- ❖ Can predict classes with reasonable accuracy
- ❖ Might sometimes misclassify sushi with sashimi and vice versa

```
50/50 [==============================] - 11s 215ms/step - loss: 0.6096 - acc: 0.8487
model accuracy: 0.8487499952316284
```

# JAPANESE FOOD CLASSIFIER:
## Predicting Online Images

sushi

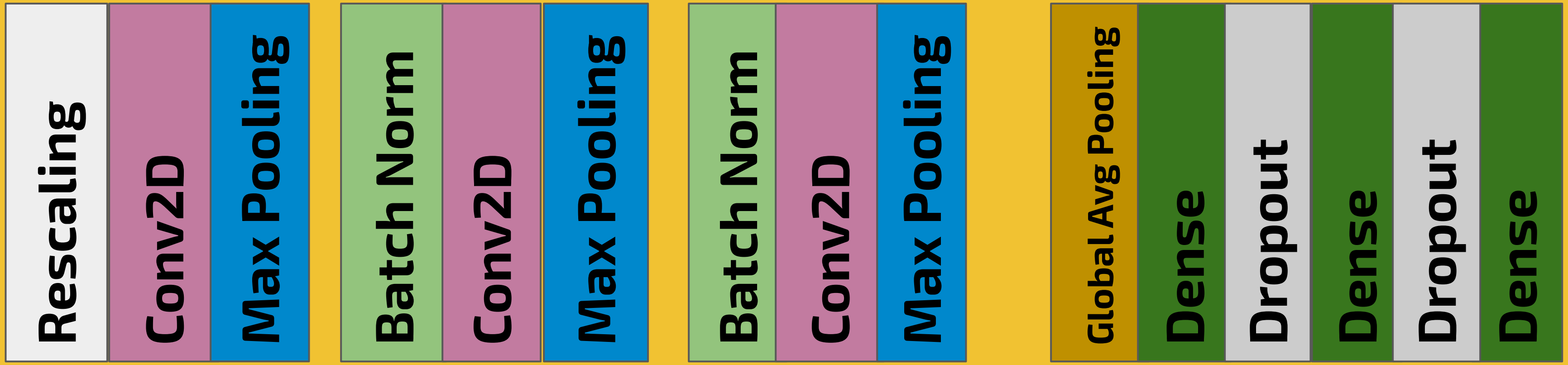
edamame

```
result= np.argmax(pred)
if result==0:
    print("edamame")
elif result==1:
    print("ramen")
elif result==2:
    print("sushi")
elif result==3:
    print("sashimi")
elif result==4:
    print("miso soup")
```

# Modelling

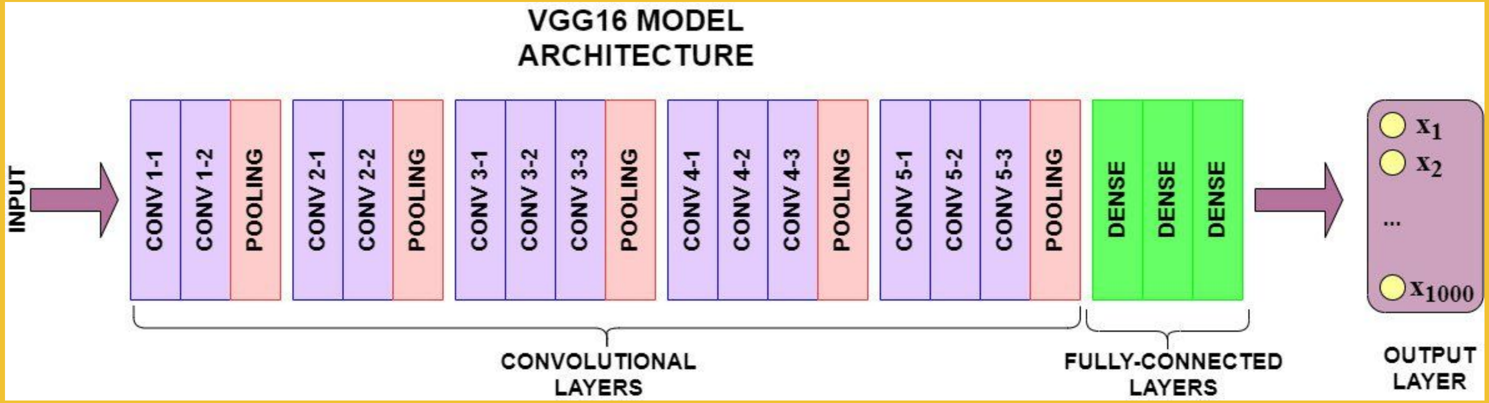
10 class dessert classifier

# CUSTOM CNN




- Retained dimensions for first layer
- Tuned and re-trained using best hyperparameters from Keras Tuner (optimal units in dense layer: 64, optimal learning rate: 0.0001)
- Regularization techniques: Batch Normalization, Dropout, Early Stopping

# VGG16




- ❖ Rebuilt top layers with Global Average Pooling, Batch Normalisation, Dropout, and Dense layers
- ❖ Tuned and re-trained by unfreezing block 5
- ❖ Regularization techniques: Batch Normalization, Dropout, Early Stopping, lowering learning rate

# EfficientNetB0

| Stage $i$ | Operator $\hat{\mathcal{F}}_i$ | Resolution $\hat{H}_i \times \hat{W}_i$ | #Channels $\hat{C}_i$ | #Layers $\hat{L}_i$ |
|---|---|---|---|---|
| 1 | Conv3x3 | $224 \times 224$ | 32 | 1 |
| 2 | MBConv1, k3x3 | $112 \times 112$ | 16 | 1 |
| 3 | MBConv6, k3x3 | $112 \times 112$ | 24 | 2 |
| 4 | MBConv6, k5x5 | $56 \times 56$ | 40 | 2 |
| 5 | MBConv6, k3x3 | $28 \times 28$ | 80 | 3 |
| 6 | MBConv6, k5x5 | $14 \times 14$ | 112 | 3 |
| 7 | MBConv6, k5x5 | $14 \times 14$ | 192 | 4 |
| 8 | MBConv6, k3x3 | $7 \times 7$ | 320 | 1 |
| 9 | Conv1x1 & Pooling & FC | $7 \times 7$ | 1280 | 1 |

- Rebuilt top layers with Global Average Pooling, Batch Normalisation, Dropout, and Dense layers
- Augmented images before training
- Tuned and re-trained by unfreezing block 7a (BatchNormalization layers remain frozen)
- Regularization techniques: Batch Normalization, Dropout, Early Stopping, lowering learning rate

# MODEL EVALUATION

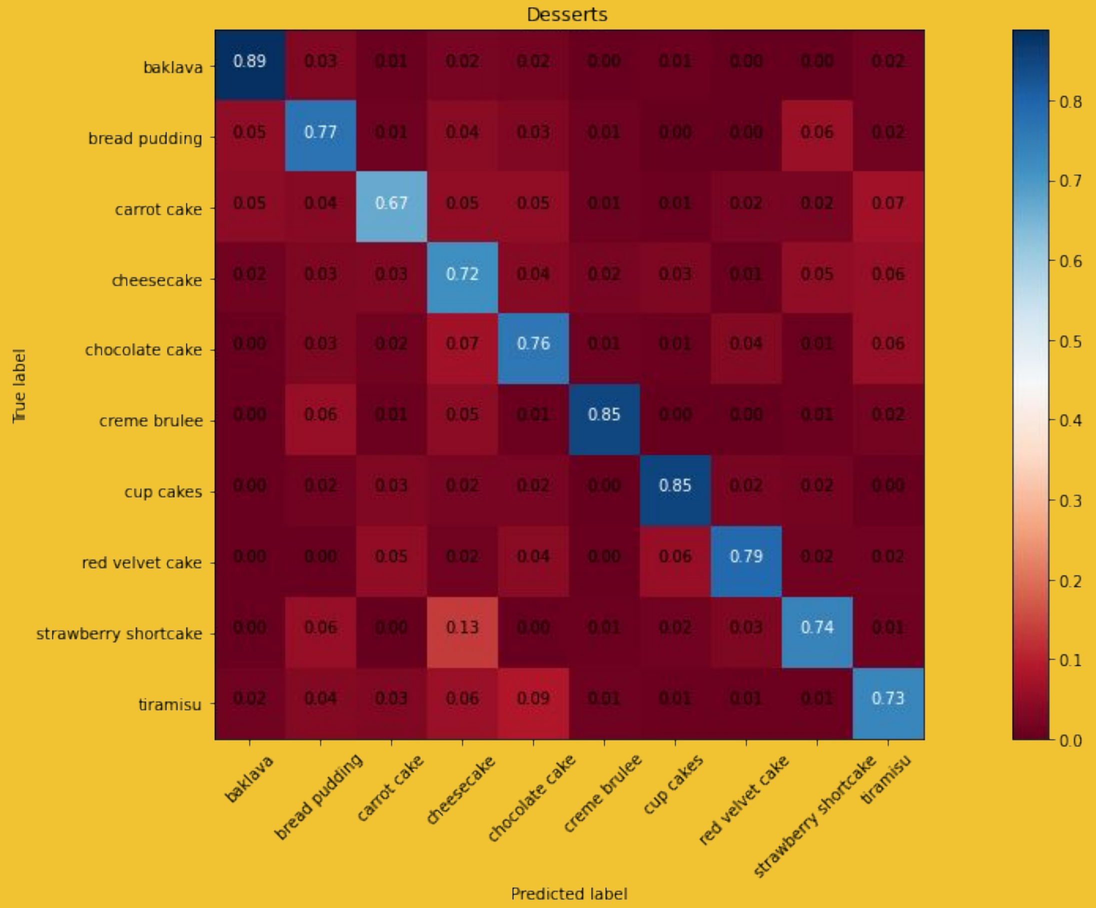
| Model | Val Accuracy (before tuning) | Val Accuracy (after tuning) |
| --- | --- | --- |
| Custom CNN | 46.3% | 56.7% |
| VGG 16 | 59% | 75.6% |
| EfficientNetB0 | 73.2% | 77.6% |

Tuned EfficientNetB0 is our best model, achieving a validation accuracy score of around 77.6%.

# Misclassified Images

10 class dessert classifier

# CONFUSION MATRIX



# MISCLASSIFIED IMAGES


- ❖ Misclassification seems reasonable
- ❖ Lighting and presence of toppings/other ingredients on food might have caused misclassification

# Model Testing

10 class dessert classifier

# WEBAPP DEMO

## 10 Class Desserts Classifier

This is a simple image classification webapp to predict 10 classes of desserts: baklava, bread pudding, carrot cake, cheese cake, cupcakes, chocolate cake, tiramisu, red velvet cake, strawberry shortcake and creme brulee. The model was trained on EfficientNetB0 and has achieved 77% validation accuracy.

Do note that the classifier is not 100% accurate and may tend to misclassify certain images like carrot cake with cheesecake etc.

Please upload an image file

Drag and drop file here

Limit 200MB per file • JPG, PNG

Browse files

carrotcake.jpg 95.5KB

It is carrot cake!

# Conclusion

10 class dessert classifier

# CONCLUSION

- ❖ Managed to build 10 class desserts classifier with val accuracy around 77.6%
- ❖ Room for improvement, as there are still misclassifications

**Next Steps/Room for improvement**

- ❖ Train model with more data of food at different angles and height
- ❖ Train model with more classes of food
- ❖ Try out ensemble models or CutMix to improve accuracy
- ❖ Create object detection model to count items detected

# LEARNINGS

- Retain image dimensions in your first layer, as the machine is learning the edges and features of your data

- Batch Normalization helps improve your accuracy score and allows your model to converge in lesser epochs. It also provides some regularization and reduces generalization error

- Always push your model's (and your own) limits. Keep training, fine tuning and experimenting to improve val accuracy and minimise val loss

# THANK YOU