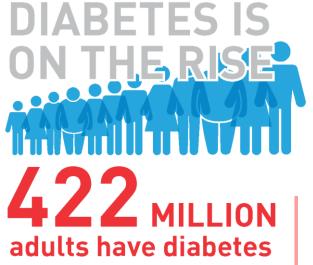


# FOOD IMAGE RECOGNITION with Neural Network

**DSI Capstone Project** 

**Jetnipat Sarawongsuth (Boss)** 

## DIABETES



**3.7 MILLION** deaths due to diabetes and high blood glucose

**1.5 MILLION** deaths caused by diabetes

Second

**82** MILLION in South East Asia

#### Risk factors for type 2 diabetes

Genetics, age and family history of diabetes can increase the likelihood of becoming diabetic and cannot be changed. But some behaviours that increase risk can:



Unhealthy diet



is overweight

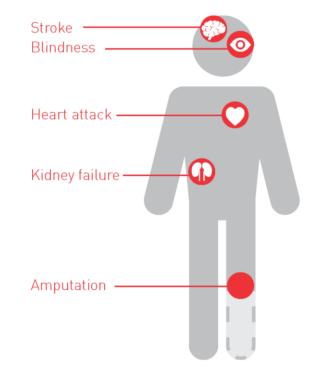


**Physical inactivity** 



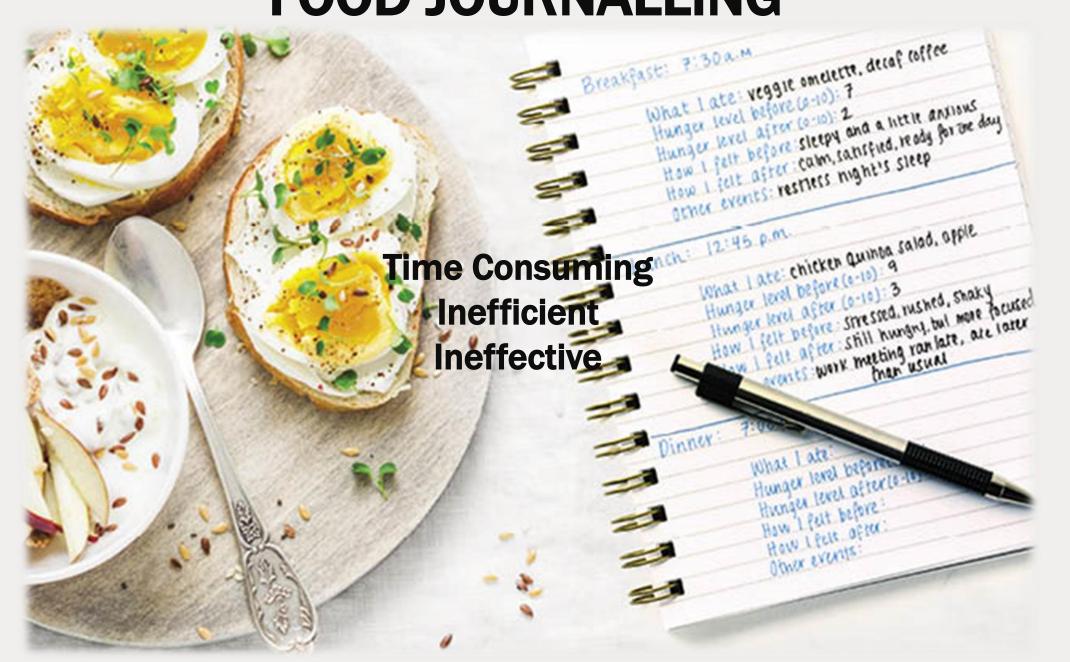
#### Consequences

Diabetes can lead to complications in many parts of the body and increase the risk of dying prematurely.





## **FOOD JOURNALLING**



# **Connectify**.ai







## **Overall Roadmap**

**Target** 

1

**Mobile App** 

User does food journaling by manually entering food they eat into the mobile application



**Target** 

**2**Food
Classification

Instead of entering food manually, user takes a picture of the food and the model identifies the food



**Target** 

**3**Nutrition Data
Retrieval

User is then given the nutrition facts (Calorie, Carb, Fat, Protein) about the food identified in the image



**Target** 

4

**Personalised Meal Recommendation** 

User is provided with personalized healthy meal recommendations



# DATASET Food Images

## **Food Images**

Dataset	# Total Images	# Images per class	Source
Training Set	~26000	~900	Food 101 (Kaggle)
Validation Set	~2900	~100	Food 101 (Kaggle)
Testing Set	580	20	Web Scraping (Google/Bing)

29

**Food Classes** 



## **Image Label Verification**

samosa



Spring\_rolls



Peking\_duck



Chicken curry



Chicken curry



hummus



Spring rolls



Carrot cake



ramemen



pho



Miso soup



Caesar salad



Pad thai



Peking duck

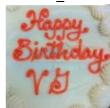


Miso soup





Carrot cake



The dataset contains images irrelevant or ambiguous to the image labels. These images were manually reviewed and removed accordingly.

### **Image Data Augmentation**

Step Random Flip Images are randomly flipped horizontally

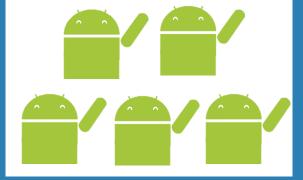
Step Random Rotation Images are randomly rotated clockwise/ anti-clockwise

Step **Random Translation** Images are randomly shifted left/right



#### **More Data**

Model benefits from learning from a larger dataset



#### **More Robust**

Model becomes more robust to the real life images taken at different angles



## **Augmented Images Examples**

















## After Image Data Augmentation...

Dataset	# Total Images	# Images per class	Source
Training Set	~26000	~900	Food 101 (Kaggle)
Validation Set	~2900	~100	Food 101 (Kaggle)
Testing Set	580	20	Web Scraping (Google/Bing)

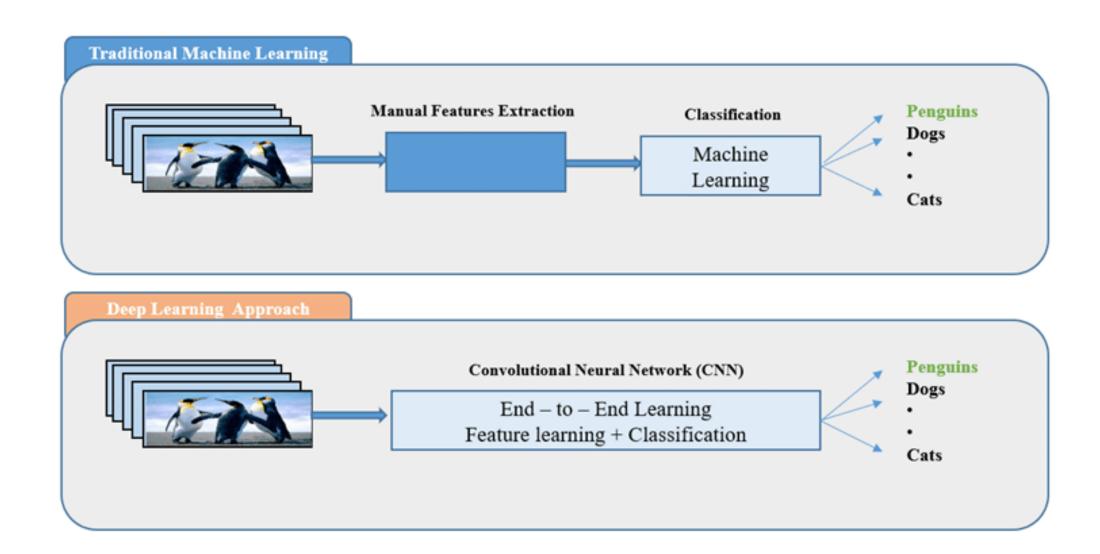


Removing irrelevant Images & Performing Image Data Augmentation (two augmentations per image)

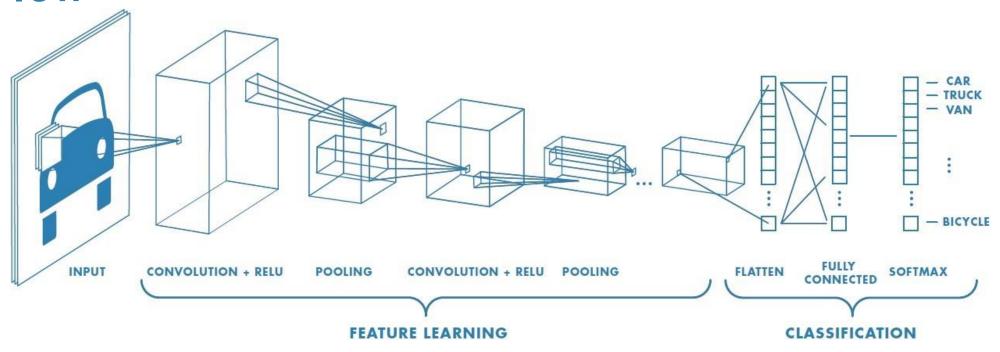
Dataset	# Total Images	# Images per class	Source
Training Set	~76000	~2600	Food 101 (Kaggle)
Validation Set	~8700	~300	Food 101 (Kaggle)
Testing Set	580	20	Web Scraping (Google/Bing)

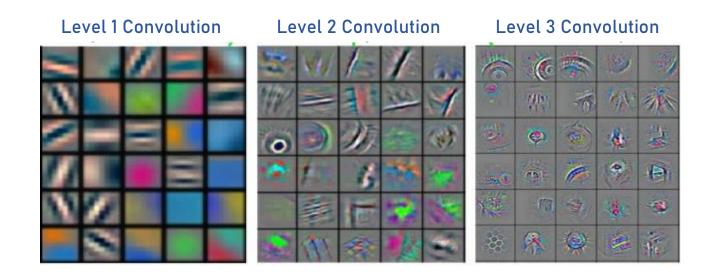
## Modelling

## Why CNN?

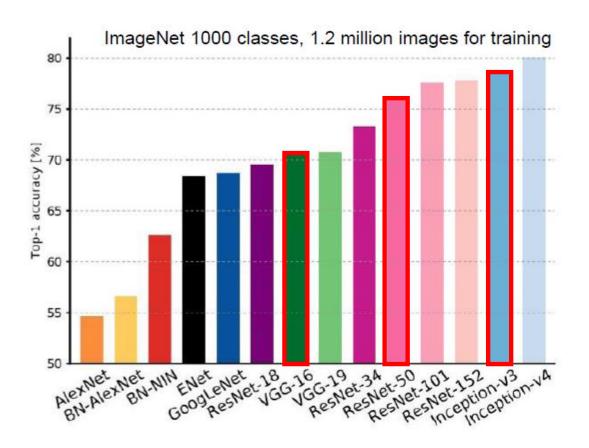


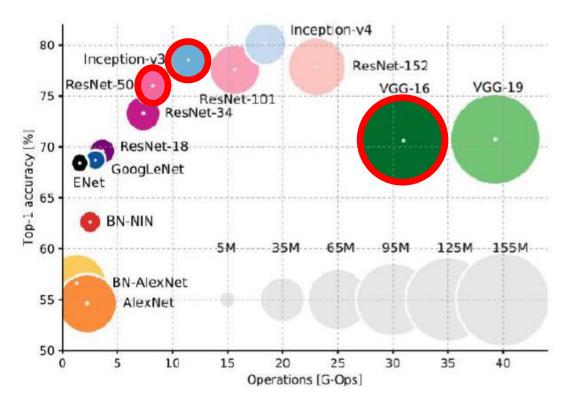
### **CNN Flow**



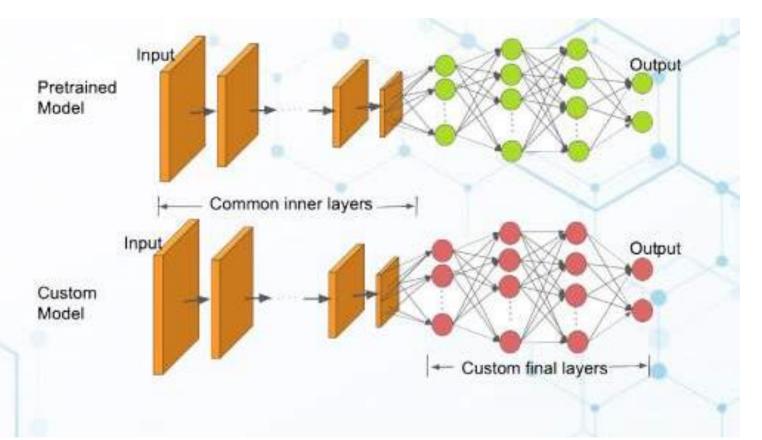


# State of the Art CNN Models





# Transfer Learning



### **Models Setups**

#### **CNN Models**

- Custom Model (From Scratch)
- Inception V3 (Transfer Learning)
- ResNet 50 (Transfer Learning)
- Inception-ResNetV2 (Transfer Learning)
- VGG16 (Transfer Learning)

#### Configuration

- Optimizer: Adam
- Metric: Accuracy

## **Model Specs**

Model	# Layers	# Total Params	# Trainable Params
Custom	15	~5m	~5m
VGG16	16	~134m	~120k
VGG16 Dropout	15	~15m	~555k
InceptionV3 Dropout	49	~24m	~2m
InceptionV3 GAP	48	~22m	~60k
ResNet50	50	~24m	~60k
Inception-ResNetV2	164	~54m	~44k
Inception-ResNetV2 Dropout	165	~56m	~1.6m

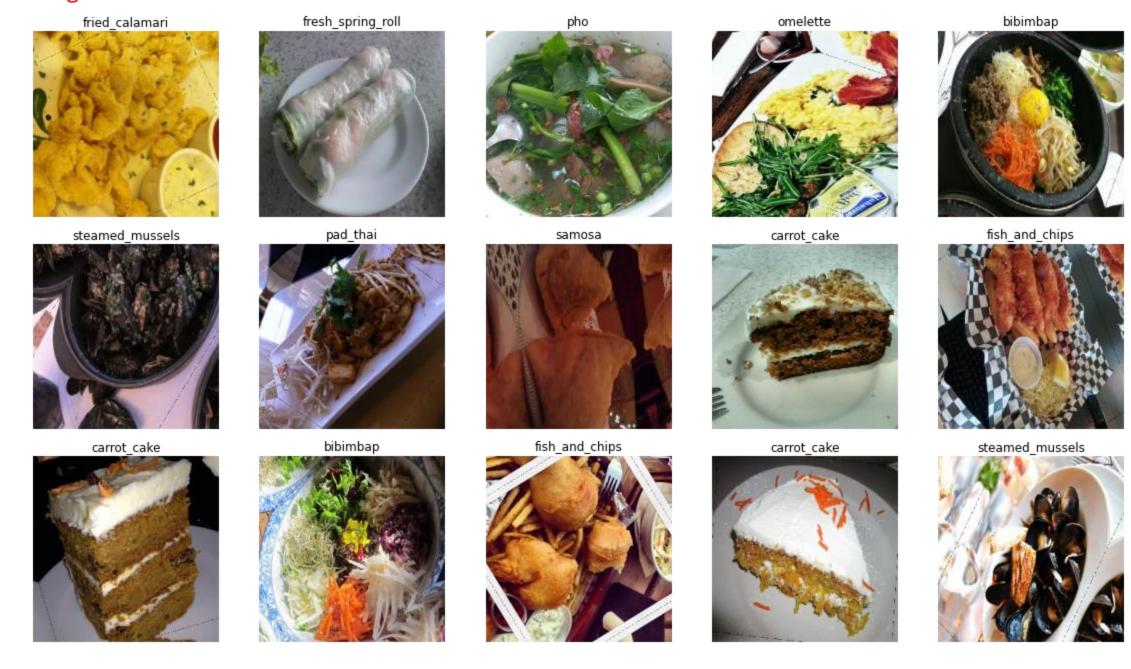
## **Image Preprocessing**

#### **Preprocessing Techniques**

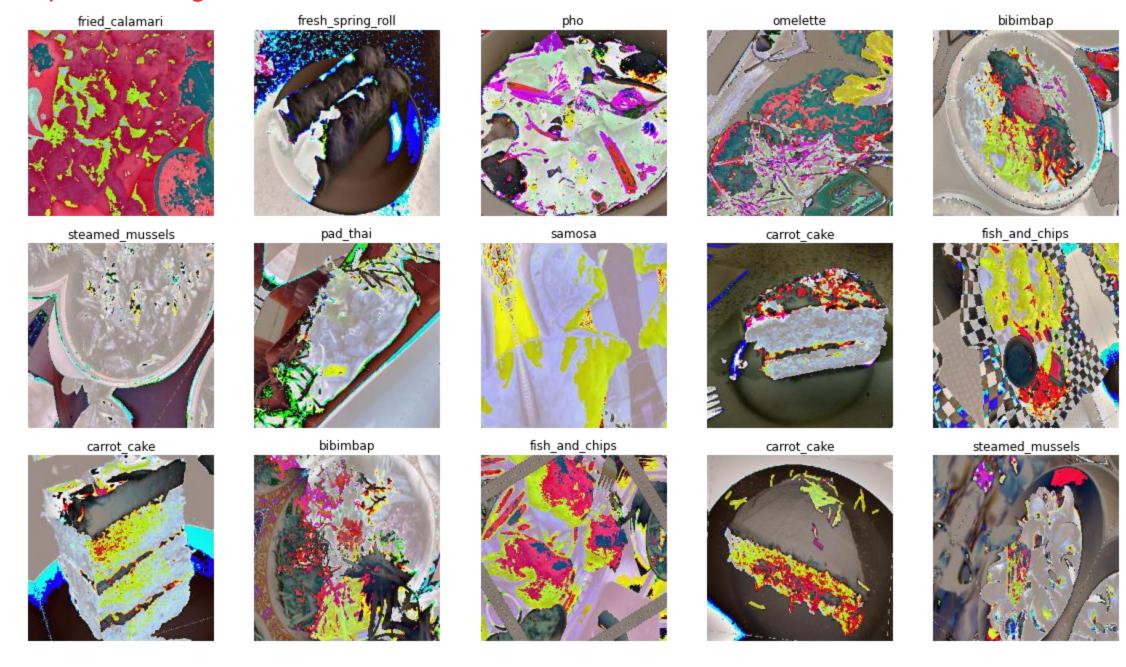
- InceptionV3: Normalize the pixel values between -1 and1
- VGG16: Each color channel is zero-centered with respect to the ImageNet dataset, without scaling.



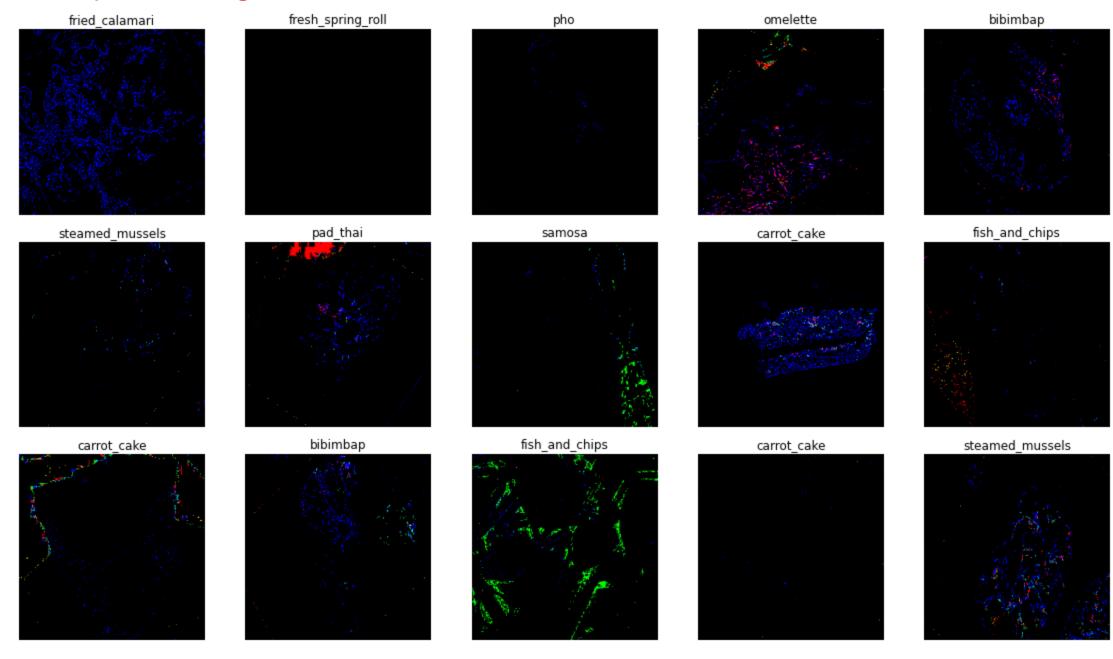
#### **Original Images**



#### **VGG16** Preprocessed Images

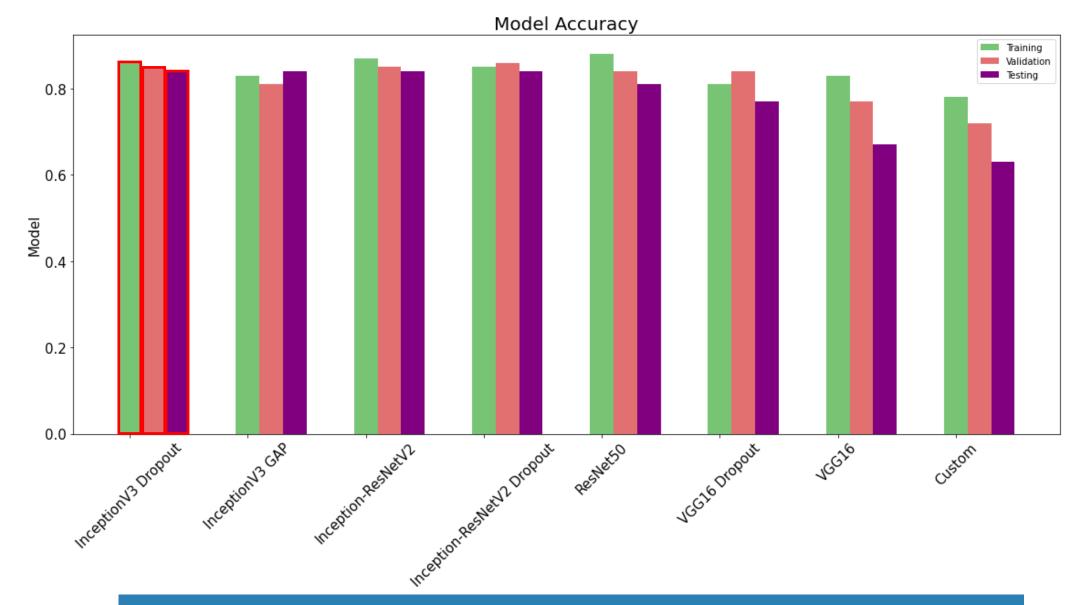


#### **Inception V3 Preprocessed Images**



## **Evaluation**

#### **Model Benchmark**



All models performed better than the baseline accuracy of 3.4%

# Best Performing Model Inception V3 Dropout

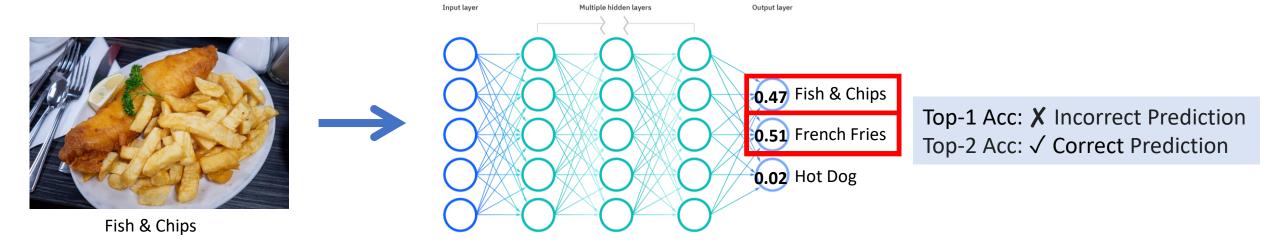
#### **Description:**

Uses Transfer Learning on the architecture of Inception V3 CNN Model with weights from ImageNet dataset.

- Inception V3 image preprocessing (normalized between -1 and 1)
- Classification Layers:
  - 2 Dense layers (1024 and 29 filters)
  - Dropout layer (0.5)
- 49 layers and 2 million parameters to finetune.

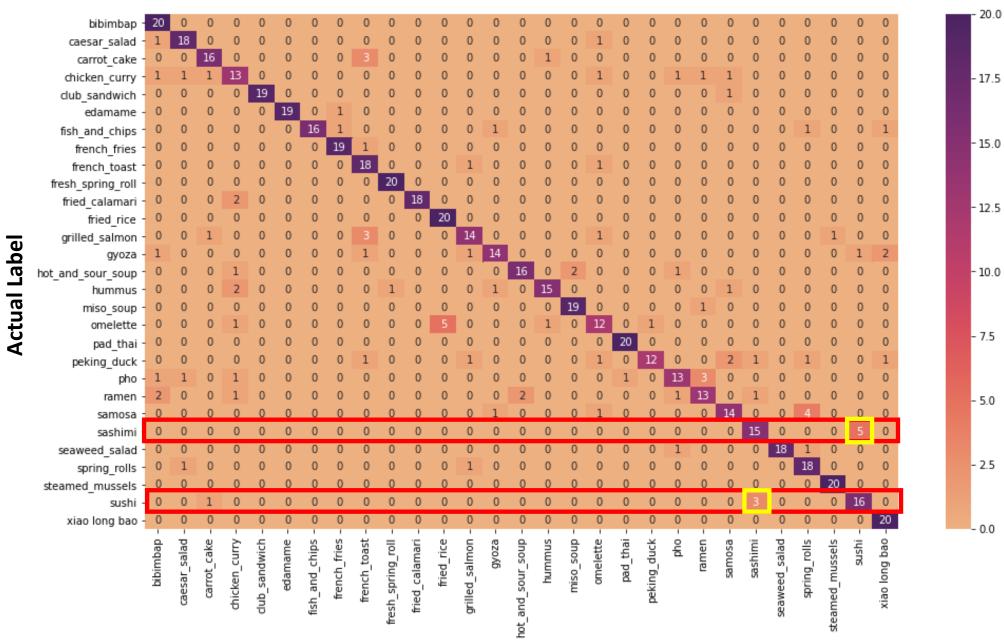
# Top-N Accuracy Testing Set

Model	Top-1 Accuracy	Top-3 Accuracy	Top-5 Accuracy
Inception V3 Dropout	0.84	0.95	0.97



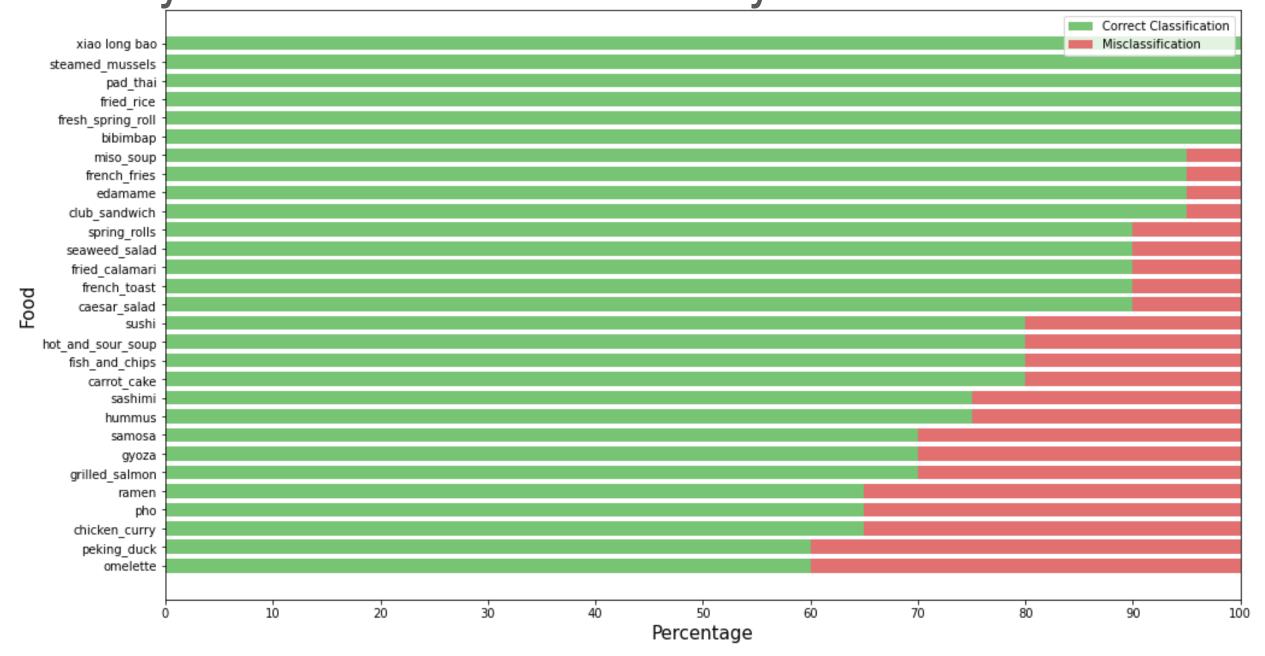
## Web App Demo

#### **Confusion Matrix**



**Predicted Label** 

#### Accuracy and Misclassification Rate by Food Class



### **Misclassified Food Examples**

True: miso\_soup Pred:ramen



True: omelette Pred:fried rice



True: peking\_duck Pred:samosa



True: omelette Pred:fried\_rice



True: omelette Pred:peking\_duck



True: peking\_duck Pred:xiao long bao



True: omelette Pred:chicken\_curry



True: omelette Pred:fried rice



True: peking\_duck Pred:samosa



True: omelette Pred:fried rice



True: omelette Pred:fried\_rice



True: peking\_duck Pred:grilled\_salmon



True: omelette Pred:hummus



True: peking\_duck Pred:spring\_rolls



True: peking\_duck Pred:omelette



### **Limitations & Improvements**

## 1

#### Multiple Food Types

Food Images can often contain multiple food classes (eg. Fish&Chips vs French Fries)

#### **Possible Solution**

Assign class\_weight when training to prioritise certain classes over others

2

## Large intra-class diversity

Food Images belonging to same class might be diverse in how they look (eg. Peking ducks – whole, sliced, duck rolls)

#### **Possible Solution**

Acquire more training data and/or
Split classes that have large diversity

3

## Large inter-class similarity

Food Images of different classes might look very similar (eg. Sushi vs Sashimi)

#### **Possible Solution**

Acquire more training data and/or
Group very similar classes together