# 101 Food Classification & Calories Identification

#### **Classes & Calories**

- -The calories per gram for each food item:
  - Apple Pie: ~2.5 calories per gram
  - Baby Back Ribs: ~3.5 calories per gram
  - Baklava: ~5 calories per gram
  - Beef Carpaccio: ~2 calories per gram
  - Beef Tartare: ~2.5 calories per gram
  - Beet Salad: ~0.5 calories per gram
  - Beignets: ~3.5 calories per gram
  - Bibimbap: ~1.5 calories per gram
  - Bread Pudding: ~2.5 calories per gram
  - Breakfast Burrito: ~2 calories per gram
  - Bruschetta: ~1 calorie per gram
  - Caesar Salad: ~0.5 calories per gram
  - Cannoli: ~3.5 calories per gram
  - Caprese Salad: ~1 calorie per gram
  - Carrot Cake: ~3.5 calories per gram
  - Ceviche: ~0.5 calories per gram
  - Cheese Plate: ~3.5 calories per gram
  - Cheesecake: ~3.5 calories per gram
  - Chicken Curry: ~1.5 calories per gram
  - Chicken Quesadilla: ~2.5 calories per gram
  - Chicken Wings: ~3 calories per gram
  - Chocolate Cake: ~4 calories per gram
  - Chocolate Mousse: ~3 calories per gram
  - Churros: ~4 calories per gram
  - Clam Chowder: ~1.5 calories per gram
  - Club Sandwich: ~2.5 calories per gram
  - Crab Cakes: ~2 calories per gram
  - Creme Brulee: ~3.5 calories per gram
  - Croque Madame: ~3 calories per gram
  - Cupcakes: ~3.5 calories per gram
  - Deviled Eggs: ~1 calorie per gram
  - Donuts: ~4 calories per gram
  - Dumplings: ~2.5 calories per gram
  - Edamame: ~1 calorie per gram
  - Eggs Benedict: ~2.5 calories per gram
  - Escargots: ~1 calorie per gram
  - Falafel: ~2 calories per gram
  - Filet Mignon: ~2.5 calories per gram
  - Fish and Chips: ~2.5 calories per gram
  - Foie Gras: ~4.5 calories per gram
  - French Fries: ~3.5 calories per gram
  - French Onion Soup: ~1 calorie per gram
  - French Toast: ~2 calories per gram
  - Fried Calamari: ~2.5 calories per gram
  - Fried Rice: ~1.5 calories per gram
  - Frozen Yogurt: ~1 calorie per gram
- Garlic Bread: ~4 calories per gram

- Gnocchi: ~1.5 calories per gram
- Greek Salad: ~0.5 calories per gram
- Grilled Cheese Sandwich: ~3 calories per gram
- Grilled Salmon: ~2 calories per gram
- Guacamole: ~2 calories per gram
- Gyoza: ~2 calories per gram
- Hamburger: ~3.5 calories per gram
- Hot and Sour Soup: ~0.5 calories per gram
- Hot Dog: ~3.5 calories per gram
- Huevos Rancheros: ~2 calories per gram
- Hummus: ~1.5 calories per gram
- Ice Cream: ~2 calories per gram
- Lasagna: ~1.5 calories per gram
- Lobster Bisque: ~1 calorie per gram
- Lobster Roll Sandwich: ~2.5 calories per gram
- Macaroni and Cheese: ~3 calories per gram
- Macarons: ~4 calories per gram
- Miso Soup: ~0.5 calories per gram
- Mussels: ~0.5 calories per gram
- Nachos: ~2.5 calories per gram
- Omelette: ~1.5 calories per gram
- Onion Rings: ~2.5 calories per gram
- Oysters: ~0.5 calories per gram
- Pad Thai: ~2 calories per gram
- Paella: ~1.5 calories per gram
- Pancakes: ~2 calories per gram
- Panna Cotta: ~3.5 calories per gram
- Peking Duck: ~4 calories per gram
- Pho: ~1 calorie per gram
- Pizza: ~2.5 calories per gram
- Pork Chop: ~2.5 calories per gram
- Poutine: ~2.5 calories per gram
- Prime Rib: ~2.5 calories per gram
- Pulled Pork Sandwich: ~2.5 calories per gram
- Ramen: ~1 calorie per gram
- Ravioli: ~1.5 calories per gram
- Red Velvet Cake: ~4 calories per gram
- Risotto: ~1.5 calories per gram
- Samosa: ~2 calories per gram
- Sashimi: ~1 calorie per gram
- Scallops: ~1 calorie per gram
- Seaweed Salad: ~0.5 calories per gram
- Shrimp and Grits: ~2 calories per gram
- Spaghetti Bolognese: ~1.5 calories per gram
- Spaghetti Carbonara: ~2 calories per gram
- Spring Rolls: ~1.5 calories per gram
- Steak: ~2.5 calories per gram
- Strawberry Shortcake: ~3.5 calories per gram
- Sushi: ~1 calorie per gram
- Tacos: ~2 calories per gram
- Takoyaki: ~2.5 calories per gram
- Tiramisu: ~3 calories per gram
- Tuna Tartare: ~1.5 calories per gram
- Waffles: ~2 calories per gram

```
kequirement aiready satisfied: keras==2.15.0 in /opt/conda/lib/python3.10/site-packages (
2.15.0)
In [ ]:
import keras
keras.__version_
Out[]:
'2.15.0'
In [ ]:
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sn
import numpy as np
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import vgg16
from keras.src.layers.pooling.average pooling2d import AvgPool2D
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout
from keras.models import Sequential
from keras.layers import Dense, Input, Flatten
from tensorflow.keras.utils import load img, img to array
from sklearn.metrics import confusion matrix
from keras.preprocessing.image import ImageDataGenerator
from sklearn.model selection import train test split
```

```
import os
print(os.listdir("/kaggle/input/food-101/food-101/food-101/images/"))
```

['macarons', 'french\_toast', 'lobster\_bisque', 'prime\_rib', 'pork\_chop', 'guacamole', 'ba by\_back\_ribs', 'mussels', 'beef\_carpaccio', 'poutine', 'hot\_and\_sour\_soup', 'seaweed\_sala d', 'foie\_gras', 'dumplings', 'peking\_duck', 'takoyaki', 'bibimbap', 'falafel', 'pulled\_p ork\_sandwich', 'lobster\_roll\_sandwich', 'carrot\_cake', 'beet\_salad', 'panna\_cotta', 'donu ts', 'red\_velvet\_cake', 'grilled\_cheese\_sandwich', 'cannoli', 'spring\_rolls', 'shrimp\_and\_grits', 'clam\_chowder', 'omelette', 'fried\_calamari', 'caprese\_salad', 'oysters', 'scall ops', 'ramen', 'grilled\_salmon', 'croque\_madame', 'filet\_mignon', 'hamburger', 'spaghetti\_carbonara', 'miso\_soup', 'bread\_pudding', 'lasagna', 'crab\_cakes', 'cheesecake', 'spaghe tti\_bolognese', 'cup\_cakes', 'creme\_brulee', 'waffles', 'fish\_and\_chips', 'paella', 'maca roni\_and\_cheese', 'chocolate\_mousse', 'ravioli', 'chicken\_curry', 'caesar\_salad', 'nachos', 'tiramisu', 'frozen\_yogurt', 'ice\_cream', 'risotto', 'club\_sandwich', 'strawberry\_shor tcake', 'steak', 'churros', 'garlic\_bread', 'baklava', 'bruschetta', 'hummus', 'chicken\_wings', 'greek\_salad', 'tuna\_tartare', 'chocolate\_cake', 'gyoza', 'eggs\_benedict', 'devile d\_eggs', 'samosa', 'sushi', 'breakfast\_burrito', 'ceviche', 'beef\_tartare', 'apple\_pie', '.DS\_Store', 'huevos\_rancheros', 'beignets', 'pizza', 'edamame', 'french\_onion\_soup', 'ho t\_dog', 'tacos', 'chicken\_quesadilla', 'pho', 'gnocchi', 'pancakes', 'fried\_rice', 'chees e plate', 'onion rings', 'escargots', 'sashimi', 'pad\_thai', 'french\_fries']

#### **Food Classes**

# In [ ]:

```
values = ['macarons', 'french_toast', 'lobster_bisque', 'prime_rib', 'pork_chop', 'guaca
mole', 'baby_back_ribs', 'mussels', 'beef_carpaccio', 'poutine', 'hot_and_sour_soup', 'se
aweed_salad', 'foie_gras', 'dumplings', 'peking_duck', 'takoyaki', 'bibimbap', 'falafel'
, 'pulled_pork_sandwich', 'lobster_roll_sandwich', 'carrot_cake', 'beet_salad', 'panna_co
tta', 'donuts', 'red_velvet_cake', 'grilled_cheese_sandwich', 'cannoli', 'spring_rolls',
'shrimp_and_grits', 'clam_chowder', 'omelette', 'fried_calamari', 'caprese_salad', 'oyste
rs', 'scallops', 'ramen', 'grilled_salmon', 'croque_madame', 'filet_mignon', 'hamburger'
, 'spaghetti_carbonara', 'miso_soup', 'bread_pudding', 'lasagna', 'crab_cakes', 'cheesec
ake', 'spaghetti_bolognese', 'cup_cakes', 'creme_brulee', 'waffles', 'fish_and_chips', '
paella', 'macaroni_and_cheese', 'chocolate_mousse', 'ravioli', 'chicken_curry', 'caesar_s
alad', 'nachos', 'tiramisu', 'frozen_yogurt', 'ice_cream', 'risotto', 'club_sandwich', '
```

```
strawberry_shortcake', 'steak', 'churros', 'garlic_bread', 'baklava', 'bruschetta', 'hum
mus', 'chicken_wings', 'greek_salad', 'tuna_tartare', 'chocolate_cake', 'gyoza', 'eggs_be
nedict', 'deviled_eggs', 'samosa', 'sushi', 'breakfast_burrito', 'ceviche', 'beef_tartare
', 'apple_pie', '.DS_Store', 'huevos_rancheros', 'beignets', 'pizza', 'edamame', 'french
_onion_soup', 'hot_dog', 'tacos', 'chicken_quesadilla', 'pho', 'gnocchi', 'pancakes', 'f
ried_rice', 'cheese_plate', 'onion_rings', 'escargots', 'sashimi', 'pad_thai', 'french_fr
ies']
values.sort()
values = values[1:]
print(values)
```

['apple\_pie', 'baby\_back\_ribs', 'baklava', 'beef\_carpaccio', 'beef\_tartare', 'beet\_salad', 'beignets', 'bibimbap', 'bread\_pudding', 'breakfast\_burrito', 'bruschetta', 'caesar\_sal ad', 'cannoli', 'caprese\_salad', 'carrot\_cake', 'ceviche', 'cheese\_plate', 'cheesecake', 'chicken\_curry', 'chicken\_quesadilla', 'chicken\_wings', 'chocolate\_cake', 'chocolate\_mous se', 'churros', 'clam\_chowder', 'club\_sandwich', 'crab\_cakes', 'creme\_brulee', 'croque\_ma dame', 'cup\_cakes', 'deviled\_eggs', 'donuts', 'dumplings', 'edamame', 'eggs\_benedict', 'e scargots', 'falafel', 'filet\_mignon', 'fish\_and\_chips', 'foie\_gras', 'french\_fries', 'fre nch\_onion\_soup', 'french\_toast', 'fried\_calamari', 'fried\_rice', 'frozen\_yogurt', 'garlic\_bread', 'gnocchi', 'greek\_salad', 'grilled\_cheese\_sandwich', 'grilled\_salmon', 'guacamole', 'gyoza', 'hamburger', 'hot\_and\_sour\_soup', 'hot\_dog', 'huevos\_rancheros', 'hummus', 'ice\_cream', 'lasagna', 'lobster\_bisque', 'lobster\_roll\_sandwich', 'macaroni\_and\_cheese', 'macarons', 'miso\_soup', 'mussels', 'nachos', 'omelette', 'onion\_rings', 'oysters', 'pad\_thai', 'paella', 'pancakes', 'panna\_cotta', 'peking\_duck', 'pho', 'pizza', 'pork\_chop', 'poutine', 'prime\_rib', 'pulled\_pork\_sandwich', 'ramen', 'ravioli', 'red\_velvet\_cake', 'ri sotto', 'samosa', 'sashimi', 'scallops', 'seaweed\_salad', 'shrimp\_and\_grits', 'spaghetti\_bolognese', 'takoyaki', 'tiramisu', 'tuna\_tartare', 'waffles']

#### In [ ]:

```
print("Number of classes:",len(values))
```

Number of classes: 101

#### In [ ]:

```
s = """Apple Pie: ~2.5 calories per gram
Baby Back Ribs: ~3.5 calories per gram
Baklava: ~5 calories per gram
Beef Carpaccio: ~2 calories per gram
Beef Tartare: ~2.5 calories per gram
Beet Salad: ~0.5 calories per gram
Beignets: ~3.5 calories per gram
Bibimbap: ~1.5 calories per gram
Bread Pudding: ~2.5 calories per gram
Breakfast Burrito: ~2 calories per gram
Bruschetta: ~1 calorie per gram
Caesar Salad: ~0.5 calories per gram
Cannoli: ~3.5 calories per gram
Caprese Salad: ~1 calorie per gram
Carrot Cake: ~3.5 calories per gram
Ceviche: ~0.5 calories per gram
Cheese Plate: ~3.5 calories per gram
Cheesecake: ~3.5 calories per gram
Chicken Curry: ~1.5 calories per gram
Chicken Quesadilla: ~2.5 calories per gram
Chicken Wings: ~3 calories per gram
Chocolate Cake: ~4 calories per gram
Chocolate Mousse: ~3 calories per gram
Churros: ~4 calories per gram
Clam Chowder: ~1.5 calories per gram
Club Sandwich: ~2.5 calories per gram
Crab Cakes: ~2 calories per gram
Creme Brulee: ~3.5 calories per gram
Croque Madame: ~3 calories per gram
Cupcakes: ~3.5 calories per gram
Deviled Eggs: ~1 calorie per gram
Donuts: ~4 calories per gram
Dumplings: ~2.5 calories per gram
Edamame: ~1 calorie per gram
Eggs Benedict: ~2.5 calories per gram
```

```
Escargots: ~1 calorie per gram
Falafel: ~2 calories per gram
Filet Mignon: ~2.5 calories per gram
Fish and Chips: ~2.5 calories per gram
Foie Gras: ~4.5 calories per gram
French Fries: ~3.5 calories per gram
French Onion Soup: ~1 calorie per gram
French Toast: ~2 calories per gram
Fried Calamari: ~2.5 calories per gram
Fried Rice: ~1.5 calories per gram
Frozen Yogurt: ~1 calorie per gram
Garlic Bread: ~4 calories per gram
Gnocchi: ~1.5 calories per gram
Greek Salad: ~0.5 calories per gram
Grilled Cheese Sandwich: ~3 calories per gram
Grilled Salmon: ~2 calories per gram
Guacamole: ~2 calories per gram
Gyoza: ~2 calories per gram
Hamburger: ~3.5 calories per gram
Hot and Sour Soup: ~0.5 calories per gram
Hot Dog: ~3.5 calories per gram
Huevos Rancheros: ~2 calories per gram
Hummus: ~1.5 calories per gram
Ice Cream: ~2 calories per gram
Lasagna: ~1.5 calories per gram
Lobster Bisque: ~1 calorie per gram
Lobster Roll Sandwich: ~2.5 calories per gram
Macaroni and Cheese: ~3 calories per gram
Macarons: ~4 calories per gram
Miso Soup: ~0.5 calories per gram
Mussels: ~0.5 calories per gram
Nachos: ~2.5 calories per gram
Omelette: ~1.5 calories per gram
Onion Rings: ~2.5 calories per gram
Oysters: ~0.5 calories per gram
Pad Thai: ~2 calories per gram
Paella: ~1.5 calories per gram
Pancakes: ~2 calories per gram
Panna Cotta: ~3.5 calories per gram
Peking Duck: ~4 calories per gram
Pho: ~1 calorie per gram
Pizza: ~2.5 calories per gram
Pork Chop: ~2.5 calories per gram
Poutine: ~2.5 calories per gram
Prime Rib: ~2.5 calories per gram
Pulled Pork Sandwich: ~2.5 calories per gram
Ramen: ~1 calorie per gram
Ravioli: ~1.5 calories per gram
Red Velvet Cake: ~4 calories per gram
Risotto: ~1.5 calories per gram
Samosa: ~2 calories per gram
Sashimi: ~1 calorie per gram
Scallops: ~1 calorie per gram
Seaweed Salad: ~0.5 calories per gram
Shrimp and Grits: ~2 calories per gram
Spaghetti Bolognese: ~1.5 calories per gram
Spaghetti Carbonara: ~2 calories per gram
Spring Rolls: ~1.5 calories per gram
Steak: ~2.5 calories per gram
Strawberry Shortcake: ~3.5 calories per gram
Sushi: ~1 calorie per gram
Tacos: ~2 calories per gram
Takoyaki: ~2.5 calories per gram
Tiramisu: ~3 calories per gram
Tuna Tartare: ~1.5 calories per gram
Waffles: ~2 calories per gram
calories = s.splitlines()
s = "These values are approximations and can vary based on factors such as ingredients an
d cooking methods."
```

Tn [ ] •

```
len(calories)
Out[]:
101
In [ ]:
calories[0]
Out[]:
'Apple Pie: ~2.5 calories per gram'
In [ ]:
print("First element:", values[0], "\nLast element:", values[-1])
First element: apple pie
Last element: waffles
In [ ]:
train datagen = ImageDataGenerator(rescale=1./255, validation split=0.1)
train data = train datagen.flow from directory('/kaggle/input/food-101/food-101/food-101/
images/',
                                               target size=(224,224),
                                              batch size=100,
                                              class mode='categorical',
                                              shuffle=True,
                                               subset='training')
test data = train datagen.flow from directory('/kaggle/input/food-101/food-101/food-101/i
mages/',
                                               target size=(224,224),
                                              batch size=100,
                                               class mode='categorical',
                                               shuffle=False,
                                              subset='validation')
Found 90900 images belonging to 101 classes.
Found 10100 images belonging to 101 classes.
In [ ]:
print("Images Shape:", train data.image shape)
Images Shape: (224, 224, 3)
In [ ]:
print('\nBatch Size:',100,
     "\nNunmber of Batches in training set:",len(train_data),
     "\nNunmber of Batches in testing set:",len(test data),
     "\nNumber of Samples in training set:",train_data.samples,"Samples",
     "\nNumber of Samples in testing set:", test data.samples, "Samples")
Batch Size: 100
Nunmber of Batches in training set: 909
Nunmber of Batches in testing set: 101
Number of Samples in training set: 90900 Samples
Number of Samples in testing set: 10100 Samples
In [ ]:
print("\nThe 101 Classes numbers:\n", np.unique(train data.labels), "\n",
       ···*30,
       "\nThe 101 classes names:\n",train_data.class_indices,
      sep="")
The 101 Classes numbers:
                             7
 0 1 2 3
                 4 5
                         6
                                 8
                                     9 10 11 12 13 14 15 16 17
  18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35
```

```
37
     38
        39 40 41
                 42
                    43 44 45 46 47
                                    48 49 50 51
36
  55 56
        57
            58 59
                  60 61
                        62 63 64 65 66 67 68 69 70 71
  73 74 75 76
               77 78 79 80 81 82 83 84 85 86 87 88 89
72
90 91 92 93 94 95 96 97 98 99 100]
```

The 101 classes names: {'apple\_pie': 0, 'baby\_back\_ribs': 1, 'baklava': 2, 'beef\_carpaccio': 3, 'beef\_tartare': 4, 'beet\_salad': 5, 'beignets': 6, 'bibimbap': 7, 'bread\_pudding': 8, 'breakfast\_burrito' : 9, 'bruschetta': 10, 'caesar\_salad': 11, 'cannoli': 12, 'caprese\_salad': 13, 'carrot\_ca ke': 14, 'ceviche': 15, 'cheese\_plate': 16, 'cheesecake': 17, 'chicken\_curry': 18, 'chick en\_quesadilla': 19, 'chicken\_wings': 20, 'chocolate\_cake': 21, 'chocolate\_mousse': 22, 'c hurros': 23, 'clam chowder': 24, 'club sandwich': 25, 'crab cakes': 26, 'creme brulee': 2 7, 'croque madame': 28, 'cup cakes': 29, 'deviled eggs': 30, 'donuts': 31, 'dumplings': 3 2, 'edamame': 33, 'eggs\_benedict': 34, 'escargots': 35, 'falafel': 36, 'filet\_mignon': 37 , 'fish and chips': 38, 'foie gras': 39, 'french fries': 40, 'french onion soup': 41, 'fr ench toast': 42, 'fried calamari': 43, 'fried rice': 44, 'frozen yogurt': 45, 'garlic bre ad': 46, 'gnocchi': 47, 'greek\_salad': 48, 'grilled\_cheese\_sandwich': 49, 'grilled\_salmon': 50, 'guacamole': 51, 'gyoza': 52, 'hamburger': 53, 'hot\_and\_sour\_soup': 54, 'hot\_dog': 55, 'huevos\_rancheros': 56, 'hummus': 57, 'ice\_cream': 58, 'lasagna': 59, 'lobster\_bisque ': 60, 'lobster\_roll\_sandwich': 61, 'macaroni\_and\_cheese': 62, 'macarons': 63, 'miso\_soup ': 64, 'mussels': 65, 'nachos': 66, 'omelette': 67, 'onion\_rings': 68, 'oysters': 69, 'pa d\_thai': 70, 'paella': 71, 'pancakes': 72, 'panna\_cotta': 73, 'peking\_duck': 74, 'pho': 75, 'pizza': 76, 'pork\_chop': 77, 'poutine': 78, 'prime\_rib': 79, 'pulled\_pork\_sandwich': 80, 'ramen': 81, 'ravioli': 82, 'red\_velvet\_cake': 83, 'risotto': 84, 'samosa': 85, 'sash imi': 86, 'scallops': 87, 'seaweed\_salad': 88, 'shrimp\_and\_grits': 89, 'spaghetti\_bologne se': 90, 'spaghetti\_carbonara': 91, 'spring\_rolls': 92, 'steak': 93, 'strawberry\_shortcak e': 94, 'sushi': 95, 'tacos': 96, 'takoyaki': 97, 'tiramisu': 98, 'tuna tartare': 99, 'wa ffles': 100}

# **Model - Inception V3 Architecture**

```
In [ ]:
```

```
from keras.applications.inception_v3 import InceptionV3
from keras.applications.inception_v3 import preprocess_input, decode_predictions
from keras.preprocessing import image
from keras.layers import Input
from keras.models import Sequential, Model
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Convolution2D, MaxPooling2D, ZeroPadding2D, GlobalAveragePooling
2D, AveragePooling2D
from keras.callbacks import ModelCheckpoint, CSVLogger, LearningRateScheduler, ReduceLROn
Plateau
from keras.optimizers import SGD
from keras.regularizers import 12
import keras.backend as K
import math
```

#### In [ ]:

```
base_model3 = InceptionV3(weights='imagenet', include_top=False, input_tensor=Input(shap
e=(224, 224, 3)))

x = base_model3.output
x = AveragePooling2D()(x)
x = Dropout(.5)(x)
x = Flatten()(x)
x = Dense(101, kernel_initializer='glorot_uniform', kernel_regularizer=12(.0005), activa
tion='softmax')(x)
model3 = Model(inputs=base_model3.input, outputs=x)
model3.summary()
```

Model: "model 1"

111F40_10 (111F4014101)		ŭ	LJ
conv2d_1034 (Conv2D)	(None, 111, 111, 32)	864	['input_15[0][0]']
<pre>batch_normalization_1034 ( BatchNormalization)</pre>	(None, 111, 111, 32)	96	['conv2d_1034[0][0]']
<pre>activation_1034 (Activatio n_1034[0][ n)</pre>	(None, 111, 111, 32)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1035 (Conv2D) [0]']	(None, 109, 109, 32)	9216	['activation_1034[0]
<pre>batch_normalization_1035 ( BatchNormalization)</pre>	(None, 109, 109, 32)	96	['conv2d_1035[0][0]']
<pre>activation_1035 (Activatio n_1035[0][ n)</pre>	(None, 109, 109, 32)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1036 (Conv2D) [0]']	(None, 109, 109, 64)	18432	['activation_1035[0]
<pre>batch_normalization_1036 ( BatchNormalization)</pre>	(None, 109, 109, 64)	192	['conv2d_1036[0][0]']
<pre>activation_1036 (Activatio n_1036[0][ n)</pre>	(None, 109, 109, 64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>max_pooling2d_44 (MaxPooli [0]'] ng2D)</pre>	(None, 54, 54, 64)	0	['activation_1036[0]
conv2d_1037 (Conv2D) ][0]']	(None, 54, 54, 80)	5120	['max_pooling2d_44[0
<pre>batch_normalization_1037 ( BatchNormalization)</pre>	(None, 54, 54, 80)	240	['conv2d_1037[0][0]']
<pre>activation_1037 (Activatio n_1037[0][ n)</pre>	(None, 54, 54, 80)	0	<pre>['batch_normalizatio 0]']</pre>

LJ

conv2d_1038 (Conv2D) [0]']	(None, 5	52, 52,	192)	138240	['activation_1037[0]
<pre>batch_normalization_1038 ( BatchNormalization)</pre>	(None, 5	52, 52,	192)	576	['conv2d_1038[0][0]']
<pre>activation_1038 (Activatio n_1038[0][ n)</pre>	(None, 5	52, 52,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>max_pooling2d_45 (MaxPooli [0]'] ng2D)</pre>	(None, 2	25, 25,	192)	0	['activation_1038[0]
conv2d_1042 (Conv2D) ][0]']	(None, 2	25, 25,	64)	12288	['max_pooling2d_45[0
<pre>batch_normalization_1042 ( BatchNormalization)</pre>	(None, 2	25, 25,	64)	192	['conv2d_1042[0][0]']
<pre>activation_1042 (Activatio n_1042[0][ n)</pre>	(None, 2	25, 25,	64)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1040 (Conv2D) ][0]']	(None, 2	25, 25,	48)	9216	['max_pooling2d_45[0
conv2d_1043 (Conv2D) [0]']	(None, 2	25, 25,	96)	55296	['activation_1042[0]
<pre>batch_normalization_1040 ( BatchNormalization)</pre>	(None, 2	25, 25,	48)	144	['conv2d_1040[0][0]']
<pre>batch_normalization_1043 ( BatchNormalization)</pre>	(None, 2	25, 25,	96)	288	['conv2d_1043[0][0]']
<pre>activation_1040 (Activatio n_1040[0][ n)</pre>	(None, 2	25, 25,	48)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1043 (Activatio n_1043[0][ n)</pre>	(None, 2	25, 25,	96)	0	<pre>['batch_normalizatio 0]']</pre>
average pooling2d 109 (Ave	(None. 2	25. 25.	1921	0	['max pooling2d 45[0

][0]'] ragePooling2D)	,,,	Ü	[poozzzzgzwo.; o
conv2d_1039 (Conv2D) ][0]']	(None, 25, 25, 64)	12288	['max_pooling2d_45[0
conv2d_1041 (Conv2D) [0]']	(None, 25, 25, 64)	76800	['activation_1040[0]
conv2d_1044 (Conv2D) [0]']	(None, 25, 25, 96)	82944	['activation_1043[0]
conv2d_1045 (Conv2D) 109[0][0]'	(None, 25, 25, 32)	6144	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1039 ( BatchNormalization)</pre>	(None, 25, 25, 64)	192	['conv2d_1039[0][0]']
<pre>batch_normalization_1041 ( BatchNormalization)</pre>	(None, 25, 25, 64)	192	['conv2d_1041[0][0]']
<pre>batch_normalization_1044 ( BatchNormalization)</pre>	(None, 25, 25, 96)	288	['conv2d_1044[0][0]']
<pre>batch_normalization_1045 ( BatchNormalization)</pre>	(None, 25, 25, 32)	96	['conv2d_1045[0][0]']
<pre>activation_1039 (Activatio n_1039[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1041 (Activatio n_1041[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
activation_1044 (Activatio n_1044[0][ n)	(None, 25, 25, 96)	0	<pre>['batch_normalizatio 0]']</pre>
activation_1045 (Activatio n_1045[0][ n)	(None, 25, 25, 32)	0	<pre>['batch_normalizatio 0]']</pre>
mixedO (Concatenate)	(None. 25. 25. 256)	n	['activation 1039[0]

[0]',		-~,	-~,	,	~	[ 4001.40101005.[0]
][0]',						'activation_1041[0
][0]',						'activation_1044[0
][0]']						'activation_1045[0
conv2d_1049 (Conv2D)	(None, 2	25,	25,	64)	16384	['mixed0[0][0]']
batch_normalization_1049 (	(None, 2	25,	25,	64)	192	['conv2d_1049[0][0]']
BatchNormalization)						
<pre>activation_1049 (Activatio n_1049[0][ n)</pre>	(None, 2	25,	25,	64)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1047 (Conv2D)	(None, 2	25,	25,	48)	12288	['mixed0[0][0]']
conv2d_1050 (Conv2D) [0]']	(None, 2	25,	25,	96)	55296	['activation_1049[0]
batch_normalization_1047 (	(None, 2	25,	25,	48)	144	['conv2d_1047[0][0]']
BatchNormalization)						
<pre>batch_normalization_1050 ( BatchNormalization)</pre>	(None, 2	25,	25,	96)	288	['conv2d_1050[0][0]']
activation_1047 (Activation_1047[0][ n)	(None, 2	25,	25,	48)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1050 (Activatio n_1050[0][ n)</pre>	(None, 2	25,	25,	96)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_110 (Ave ragePooling2D)</pre>	(None, 2	25,	25 <b>,</b>	256)	0	['mixed0[0][0]']
conv2d_1046 (Conv2D)	(None, 2	25,	25,	64)	16384	['mixed0[0][0]']
conv2d_1048 (Conv2D) [0]']	(None, 2	25,	25,	64)	76800	['activation_1047[0]
conv2d 1051 (Conv2D)	(None. 2	2.5.	25.	961	82944	['activation 1050[0]

[0]']		,	· · ,	J_J_1	[ ~~~
conv2d_1052 (Conv2D) 110[0][0]'	(None, 25	, 25,	64)	16384	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1046 ( BatchNormalization)</pre>	(None, 25	, 25,	64)	192	['conv2d_1046[0][0]']
<pre>batch_normalization_1048 ( BatchNormalization)</pre>	(None, 25	, 25,	64)	192	['conv2d_1048[0][0]']
<pre>batch_normalization_1051 ( BatchNormalization)</pre>	(None, 25	, 25,	96)	288	['conv2d_1051[0][0]']
<pre>batch_normalization_1052 ( BatchNormalization)</pre>	(None, 25	, 25,	64)	192	['conv2d_1052[0][0]']
<pre>activation_1046 (Activatio n_1046[0][ n)</pre>	(None, 25	, 25,	64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1048 (Activatio n_1048[0][ n)</pre>	(None, 25)	, 25,	64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1051 (Activatio n_1051[0][ n)</pre>	(None, 25	, 25,	96)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1052 (Activatio n_1052[0][ n)</pre>	(None, 25	, 25,	64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed1 (Concatenate) [0]', ][0]',</pre>	(None, 25	, 25,	288)	0	<pre>['activation_1046[0] 'activation_1048[0</pre>
][0]',					'activation_1051[0
][0]']					'activation_1052[0
conv2d_1056 (Conv2D)	(None, 25	, 25,	64)	18432	['mixed1[0][0]']
batch normalization 1056 (	(None. 25	25.	641	192	['conv2d 1056[01[01']

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BatchNormalization)						
<pre>activation_1056 (Activatio n_1056[0][ n)</pre>	(None, 2	25, 2	25 <b>,</b>	64)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1054 (Conv2D)	(None, 2	25, 2	25,	48)	13824	['mixed1[0][0]']
conv2d_1057 (Conv2D) [0]']	(None, 2	25, 2	25,	96)	55296	['activation_1056[0]
<pre>batch_normalization_1054 ( BatchNormalization)</pre>	(None, 2	25, 2	25,	48)	144	['conv2d_1054[0][0]']
<pre>batch_normalization_1057 ( BatchNormalization)</pre>	(None, 2	25, 2	25 <b>,</b>	96)	288	['conv2d_1057[0][0]']
<pre>activation_1054 (Activatio n_1054[0][ n)</pre>	(None, 2	25, 2	25 <b>,</b>	48)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1057 (Activatio n_1057[0][ n)</pre>	(None, 2	25, 2	25,	96)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_111 (Ave ragePooling2D)</pre>	(None, 2	25, 2	25 <b>,</b>	288)	0	['mixed1[0][0]']
conv2d_1053 (Conv2D)	(None, 2	25, 2	25,	64)	18432	['mixed1[0][0]']
conv2d_1055 (Conv2D) [0]']	(None, 2	25, 2	25 <b>,</b>	64)	76800	['activation_1054[0]
conv2d_1058 (Conv2D) [0]']	(None, 2	25, 2	25,	96)	82944	['activation_1057[0]
conv2d_1059 (Conv2D) 111[0][0]'	(None, 2	25, 2	25,	64)	18432	['average_pooling2d_
<pre>batch_normalization_1053 ( BatchNormalization)</pre>	(None, 2	25, 2	25 <b>,</b>	64)	192	['conv2d_1053[0][0]']

<pre>batch_normalization_1055 ( BatchNormalization)</pre>	(None, 25, 25, 64)	192	['conv2d_1055[0][0]']
<pre>batch_normalization_1058 ( BatchNormalization)</pre>	(None, 25, 25, 96)	288	['conv2d_1058[0][0]']
<pre>batch_normalization_1059 ( BatchNormalization)</pre>	(None, 25, 25, 64)	192	['conv2d_1059[0][0]']
<pre>activation_1053 (Activatio n_1053[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1055 (Activatio n_1055[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1058 (Activatio n_1058[0][ n)</pre>	(None, 25, 25, 96)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1059 (Activatio n_1059[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed2 (Concatenate) [0]', ][0]', ][0]', ][0]']</pre>	(None, 25, 25, 288)	0	<pre>['activation_1053[0]  'activation_1055[0  'activation_1058[0  'activation_1059[0</pre>
conv2d_1061 (Conv2D)	(None, 25, 25, 64)	18432	['mixed2[0][0]']
<pre>batch_normalization_1061 ( BatchNormalization)</pre>	(None, 25, 25, 64)	192	['conv2d_1061[0][0]']
<pre>activation_1061 (Activatio n_1061[0][ n)</pre>	(None, 25, 25, 64)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1062 (Conv2D)	(None, 25, 25, 96)	55296	['activation 1061[0]

<pre>batch_normalization_1062 ( BatchNormalization)</pre>	(None,	25,	25,	96)	288	['conv2d_1062[0][0]']
<pre>activation_1062 (Activatio n_1062[0][ n)</pre>	(None,	25,	25,	96)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1060 (Conv2D)	(None,	12,	12,	384)	995328	['mixed2[0][0]']
conv2d_1063 (Conv2D) [0]']	(None,	12,	12,	96)	82944	['activation_1062[0]
<pre>batch_normalization_1060 ( BatchNormalization)</pre>	(None,	12,	12,	384)	1152	['conv2d_1060[0][0]']
<pre>batch_normalization_1063 ( BatchNormalization)</pre>	(None,	12,	12,	96)	288	['conv2d_1063[0][0]']
<pre>activation_1060 (Activatio n_1060[0][ n)</pre>	(None,	12,	12,	384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1063 (Activatio n_1063[0][ n)</pre>	(None,	12,	12,	96)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>max_pooling2d_46 (MaxPooli ng2D)</pre>	(None,	12,	12,	288)	0	['mixed2[0][0]']
[0]', ][0]',	(None,	12,	12,	768)	0	<pre>['activation_1060[0]  'activation_1063[0  'max_pooling2d_46[</pre>
0][0]'] conv2d_1068 (Conv2D)	(None,	12,	12,	128)	98304	['mixed3[0][0]']
<pre>batch_normalization_1068 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1068[0][0]']
activation_1068 (Activatio n_1068[0][ n)	(None,	12,	12,	128)	0	['batch_normalizatio

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conv2d_1069 (Conv2D) [0]']	(None,	12,	12,	128)	114688	['activation_1068[0]
<pre>batch_normalization_1069 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1069[0][0]']
<pre>activation_1069 (Activatio n_1069[0][ n)</pre>	(None,	12,	12,	128)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1065 (Conv2D)	(None,	12,	12,	128)	98304	['mixed3[0][0]']
conv2d_1070 (Conv2D) [0]']	(None,	12,	12,	128)	114688	['activation_1069[0]
<pre>batch_normalization_1065 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1065[0][0]']
<pre>batch_normalization_1070 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1070[0][0]']
<pre>activation_1065 (Activatio n_1065[0][ n)</pre>	(None,	12,	12,	128)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1070 (Activatio n_1070[0][ n)</pre>	(None,	12,	12,	128)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1066 (Conv2D) [0]']	(None,	12,	12,	128)	114688	['activation_1065[0]
conv2d_1071 (Conv2D) [0]']	(None,	12,	12,	128)	114688	['activation_1070[0]
<pre>batch_normalization_1066 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1066[0][0]']
<pre>batch_normalization_1071 ( BatchNormalization)</pre>	(None,	12,	12,	128)	384	['conv2d_1071[0][0]']

activation 1066 (Activatio (None. 12. 12. 128) 0 ['batch normalization 1066 (Activation 1066 (Activation 1066 (None. 12. 12. 128)]

n_1066[0][ n)		,	,	,	Ü	0]']
<pre>activation_1071 (Activatio n_1071[0][ n)</pre>	(None,	12,	12,	128)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_112 (Ave ragePooling2D)</pre>	(None,	12,	12,	768)	0	['mixed3[0][0]']
conv2d_1064 (Conv2D)	(None,	12,	12,	192)	147456	['mixed3[0][0]']
conv2d_1067 (Conv2D) [0]']	(None,	12,	12,	192)	172032	['activation_1066[0]
conv2d_1072 (Conv2D) [0]']	(None,	12,	12,	192)	172032	['activation_1071[0]
conv2d_1073 (Conv2D) 112[0][0]'	(None,	12,	12,	192)	147456	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1064 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1064[0][0]']
<pre>batch_normalization_1067 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1067[0][0]']
<pre>batch_normalization_1072 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1072[0][0]']
<pre>batch_normalization_1073 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1073[0][0]']
activation_1064 (Activatio n_1064[0][ n)	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
activation_1067 (Activatio n_1067[0][ n)	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
activation 1072 (Activatio	(None.	12.	12.	192)	n	['hatch normalizatio

n 1072[0][	,	,	,	,	~	. ~~~~
<u>n</u> )						0]']
4070 47 41		1.0	10	4.00		
activation_1073 (Activation_1073[0][	(None,	12,	12,	192)	0	['batch_normalizatio
n)						0]']
	(None,	12,	12,	768)	0	['activation_1064[0]
[0]',						'activation_1067[0
][0]',						'activation_1072[0
][0]',						'activation_1073[0
][0]']						
conv2d_1078 (Conv2D)	(None,	12,	12,	160)	122880	['mixed4[0][0]']
batch_normalization_1078 (	(None,	12,	12,	160)	480	['conv2d_1078[0][0]']
BatchNormalization)						
activation_1078 (Activation 1078[0][	(None,	12,	12,	160)	0	['batch_normalizatio
n)						0]']
conv2d_1079 (Conv2D) [0]']	(None,	12,	12,	160)	179200	['activation_1078[0]
<pre>batch_normalization_1079 (</pre>	(None,	12,	12,	160)	480	['conv2d_1079[0][0]']
BatchNormalization)						
4070 47 41	-	10	4.0	1.50		
activation_1079 (Activatio n_1079[0][	(None,	12,	12,	160)	0	['batch_normalizatio
n)						0]']
conv2d_1075 (Conv2D)	(None,	12.	12.	160)	122880	['mixed4[0][0]']
_ , , , , , , , , , , , , , , , , , , ,	,,	,	,	,		
conv2d_1080 (Conv2D)	(None,	12,	12,	160)	179200	['activation_1079[0]
[0]']						_
batch_normalization_1075 (	(None,	12,	12,	160)	480	['conv2d_1075[0][0]']
BatchNormalization)						
batch_normalization_1080 (	(None,	12,	12,	160)	480	['conv2d_1080[0][0]']
BatchNormalization)						

<pre>activation_1075 (Activatio n_1075[0][ n)</pre>	(None, 12, 12, 160)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1080 (Activatio n_1080[0][ n)</pre>	(None, 12, 12, 160)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1076 (Conv2D) [0]']	(None, 12, 12, 160)	179200	['activation_1075[0]
conv2d_1081 (Conv2D) [0]']	(None, 12, 12, 160)	179200	['activation_1080[0]
<pre>batch_normalization_1076 ( BatchNormalization)</pre>	(None, 12, 12, 160)	480	['conv2d_1076[0][0]']
<pre>batch_normalization_1081 ( BatchNormalization)</pre>	(None, 12, 12, 160)	480	['conv2d_1081[0][0]']
<pre>activation_1076 (Activatio n_1076[0][ n)</pre>	(None, 12, 12, 160)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1081 (Activatio n_1081[0][ n)</pre>	(None, 12, 12, 160)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_113 (Ave ragePooling2D)</pre>	(None, 12, 12, 768)	0	['mixed4[0][0]']
conv2d_1074 (Conv2D)	(None, 12, 12, 192)	147456	['mixed4[0][0]']
conv2d_1077 (Conv2D) [0]']	(None, 12, 12, 192)	215040	['activation_1076[0]
conv2d_1082 (Conv2D) [0]']	(None, 12, 12, 192)	215040	['activation_1081[0]
conv2d_1083 (Conv2D) 113[0][0]'	(None, 12, 12, 192)	147456	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1074 ( BatchNormalization)</pre>	(None, 12, 12, 192)	576	['conv2d_1074[0][0]']

2000,			
<pre>batch_normalization_1077 ( BatchNormalization)</pre>	(None, 12, 12, 1	192) 576	['conv2d_1077[0][0]']
<pre>batch_normalization_1082 ( BatchNormalization)</pre>	(None, 12, 12, 1	192) 576	['conv2d_1082[0][0]']
<pre>batch_normalization_1083 ( BatchNormalization)</pre>	(None, 12, 12, 1	192) 576	['conv2d_1083[0][0]']
<pre>activation_1074 (Activatio n_1074[0][ n)</pre>	(None, 12, 12, 1	192) 0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1077 (Activatio n_1077[0][ n)</pre>	(None, 12, 12, 1	192) 0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1082 (Activatio n_1082[0][ n)</pre>	(None, 12, 12, 1	192) 0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1083 (Activatio n_1083[0][ n)</pre>	(None, 12, 12, 1	192) 0	<pre>['batch_normalizatio 0]']</pre>
mixed5 (Concatenate) [0]', ][0]', ][0]', ][0]']	(None, 12, 12,	768) 0	<pre>['activation_1074[0]  'activation_1077[0  'activation_1082[0  'activation_1083[0</pre>
	(None, 12, 12, 1	160) 12288	30 ['mixed5[0][0]']
<pre>batch_normalization_1088 ( BatchNormalization)</pre>	(None, 12, 12, 1	160) 480	['conv2d_1088[0][0]']
<pre>activation_1088 (Activatio n_1088[0][ n)</pre>	(None, 12, 12, 1	160) 0	<pre>['batch_normalizatio 0]']</pre>
conv2d 1089 (Conv2D)	(None. 12. 12.	160) 1792(	00 ['activation 1088[0]

[0]']	, 2	, -	,	- · · · ,		[
<pre>batch_normalization_1089 ( BatchNormalization)</pre>	(None, 1	12, 1	2,	160)	480	['conv2d_1089[0][0]']
<pre>activation_1089 (Activatio n_1089[0][ n)</pre>	(None, 1	12, 1	-2 <b>,</b>	160)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1085 (Conv2D)	(None, 1	12, 1	.2 <b>,</b>	160)	122880	['mixed5[0][0]']
conv2d_1090 (Conv2D) [0]']	(None, 1	12, 1	<b>2</b> ,	160)	179200	['activation_1089[0]
<pre>batch_normalization_1085 ( BatchNormalization)</pre>	(None, 1	12, 1	-2 <b>,</b>	160)	480	['conv2d_1085[0][0]']
<pre>batch_normalization_1090 ( BatchNormalization)</pre>	(None, 1	12, 1	<b>-2</b> ,	160)	480	['conv2d_1090[0][0]']
<pre>activation_1085 (Activatio n_1085[0][ n)</pre>	(None, 1	12, 1	-2 <b>,</b>	160)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1090 (Activatio n_1090[0][ n)</pre>	(None, 1	12, 1	2,	160)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1086 (Conv2D) [0]']	(None, 1	12, 1	.2 <b>,</b>	160)	179200	['activation_1085[0]
conv2d_1091 (Conv2D) [0]']	(None, 1	12, 1	2,	160)	179200	['activation_1090[0]
<pre>batch_normalization_1086 ( BatchNormalization)</pre>	(None, 1	12, 1	.2 <b>,</b>	160)	480	['conv2d_1086[0][0]']
<pre>batch_normalization_1091 ( BatchNormalization)</pre>	(None, 1	12, 1	-2 <b>,</b>	160)	480	['conv2d_1091[0][0]']
<pre>activation_1086 (Activatio n_1086[0][ n)</pre>	(None, 1	12, 1	-2 <b>,</b>	160)	0	<pre>['batch_normalizatio 0]']</pre>

<pre>activation_1091 (Activatio n_1091[0][ n)</pre>	(None, 12, 12,	160)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_114 (Ave ragePooling2D)</pre>	(None, 12, 12,	768)	0	['mixed5[0][0]']
conv2d_1084 (Conv2D)	(None, 12, 12,	192)	147456	['mixed5[0][0]']
conv2d_1087 (Conv2D) [0]']	(None, 12, 12,	192)	215040	['activation_1086[0]
conv2d_1092 (Conv2D) [0]']	(None, 12, 12,	192)	215040	['activation_1091[0]
conv2d_1093 (Conv2D) 114[0][0]'	(None, 12, 12,	192)	147456	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1084 ( BatchNormalization)</pre>	(None, 12, 12,	192)	576	['conv2d_1084[0][0]']
<pre>batch_normalization_1087 ( BatchNormalization)</pre>	(None, 12, 12,	192)	576	['conv2d_1087[0][0]']
<pre>batch_normalization_1092 ( BatchNormalization)</pre>	(None, 12, 12,	192)	576	['conv2d_1092[0][0]']
<pre>batch_normalization_1093 ( BatchNormalization)</pre>	(None, 12, 12,	192)	576	['conv2d_1093[0][0]']
<pre>activation_1084 (Activatio n_1084[0][ n)</pre>	(None, 12, 12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1087 (Activatio n_1087[0][ n)</pre>	(None, 12, 12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1092 (Activatio n_1092[0][ n)</pre>	(None, 12, 12,	192)	0	<pre>['batch_normalizatio 0]']</pre>

<pre>activation_1093 (Activatio n_1093[0][ n)</pre>	(None, 12	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed6 (Concatenate) [0]', ][0]', ][0]', ][0]']</pre>	(None, 12	, 12,	768)	0	<pre>['activation_1084[0] 'activation_1087[0 'activation_1092[0 'activation_1093[0</pre>
conv2d_1098 (Conv2D)	(None, 12	12,	192)	147456	['mixed6[0][0]']
<pre>batch_normalization_1098 ( BatchNormalization)</pre>	(None, 12	12,	192)	576	['conv2d_1098[0][0]']
<pre>activation_1098 (Activatio n_1098[0][ n)</pre>	(None, 12	, 12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1099 (Conv2D) [0]']	(None, 12	12,	192)	258048	['activation_1098[0]
<pre>batch_normalization_1099 ( BatchNormalization)</pre>	(None, 12	12,	192)	576	['conv2d_1099[0][0]']
<pre>activation_1099 (Activatio n_1099[0][ n)</pre>	(None, 12	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1095 (Conv2D)	(None, 12	12,	192)	147456	['mixed6[0][0]']
conv2d_1100 (Conv2D) [0]']	(None, 12	12,	192)	258048	['activation_1099[0]
<pre>batch_normalization_1095 ( BatchNormalization)</pre>	(None, 12	12,	192)	576	['conv2d_1095[0][0]']
<pre>batch_normalization_1100 ( BatchNormalization)</pre>	(None, 12	12,	192)	576	['conv2d_1100[0][0]']
<pre>activation_1095 (Activatio n_1095[0][ n)</pre>	(None, 12	, 12,	192)	0	['batch_normalizatio

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<pre>activation_1100 (Activatio n_1100[0][ n)</pre>	(None, 12, 1	12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1096 (Conv2D) [0]']	(None, 12, 1	12, 192)	258048	['activation_1095[0]
conv2d_1101 (Conv2D) [0]']	(None, 12, 1	12, 192)	258048	['activation_1100[0]
<pre>batch_normalization_1096 ( BatchNormalization)</pre>	(None, 12, 1	12, 192)	576	['conv2d_1096[0][0]']
<pre>batch_normalization_1101 ( BatchNormalization)</pre>	(None, 12, 1	12, 192)	576	['conv2d_1101[0][0]']
<pre>activation_1096 (Activatio n_1096[0][ n)</pre>	(None, 12, 1	12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1101 (Activatio n_1101[0][ n)</pre>	(None, 12, 1	12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>average_pooling2d_115 (Ave ragePooling2D)</pre>	(None, 12, 1	12, 768)	0	['mixed6[0][0]']
conv2d_1094 (Conv2D)	(None, 12, 1	12, 192)	147456	['mixed6[0][0]']
conv2d_1097 (Conv2D) [0]']	(None, 12, 1	12, 192)	258048	['activation_1096[0]
conv2d_1102 (Conv2D) [0]']	(None, 12, 1	12, 192)	258048	['activation_1101[0]
conv2d_1103 (Conv2D) 115[0][0]'	(None, 12, 1	12, 192)	147456	['average_pooling2d_
<pre>batch_normalization_1094 ( BatchNormalization)</pre>	(None, 12, 1	12, 192)	576	['conv2d_1094[0][0]']

batch normalization 1097 ( (None. 12. 12. 192) 576 ['conv2d 1097[0][0]']

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BatchNormalization)						
<pre>batch_normalization_1102 (</pre>	(None,	12,	12,	192)	576	['conv2d_1102[0][0]']
BatchNormalization)						
<pre>batch_normalization_1103 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1103[0][0]']
<pre>activation_1094 (Activatio n_1094[0][ n)</pre>	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1097 (Activatio n_1097[0][ n)</pre>	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1102 (Activatio n_1102[0][ n)</pre>	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1103 (Activatio n_1103[0][ n)</pre>	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed7 (Concatenate) [0]',</pre>	(None,	12,	12,	768)	0	['activation_1094[0]
][0]',						<pre>'activation_1097[0 'activation 1102[0</pre>
][0]',						'activation_1103[0
][0][]						_
conv2d_1106 (Conv2D)	(None,	12,	12,	192)	147456	['mixed7[0][0]']
<pre>batch_normalization_1106 ( BatchNormalization)</pre>	(None,	12,	12,	192)	576	['conv2d_1106[0][0]']
<pre>activation_1106 (Activatio n_1106[0][ n)</pre>	(None,	12,	12,	192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1107 (Conv2D) [0]']	(None,	12,	12,	192)	258048	['activation_1106[0]
batch normalization 1107 (	(None.	12.	12.	192)	576	['conv2d 1107[0][0]']

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BatchNormalization)			
<pre>activation_1107 (Activatio n_1107[0][ n)</pre>	(None, 12, 12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1104 (Conv2D)	(None, 12, 12, 192)	147456	['mixed7[0][0]']
conv2d_1108 (Conv2D) [0]']	(None, 12, 12, 192)	258048	['activation_1107[0]
<pre>batch_normalization_1104 ( BatchNormalization)</pre>	(None, 12, 12, 192)	576	['conv2d_1104[0][0]']
<pre>batch_normalization_1108 ( BatchNormalization)</pre>	(None, 12, 12, 192)	576	['conv2d_1108[0][0]']
<pre>activation_1104 (Activatio n_1104[0][ n)</pre>	(None, 12, 12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1108 (Activatio n_1108[0][ n)</pre>	(None, 12, 12, 192)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1105 (Conv2D) [0]']	(None, 5, 5, 320)	552960	['activation_1104[0]
conv2d_1109 (Conv2D) [0]']	(None, 5, 5, 192)	331776	['activation_1108[0]
<pre>batch_normalization_1105 ( BatchNormalization)</pre>	(None, 5, 5, 320)	960	['conv2d_1105[0][0]']
<pre>batch_normalization_1109 ( BatchNormalization)</pre>	(None, 5, 5, 192)	576	['conv2d_1109[0][0]']
<pre>activation_1105 (Activatio n_1105[0][ n)</pre>	(None, 5, 5, 320)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1109 (Activatio n_1109[0][ n)</pre>	(None, 5, 5, 192)	0	['batch_normalizatio

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<pre>max_pooling2d_47 (MaxPooli ng2D)</pre>	(None, 5, 5, 768)	0	['mixed7[0][0]']
<pre>mixed8 (Concatenate) [0]', ][0]', 0][0]']</pre>	(None, 5, 5, 1280)	0	<pre>['activation_1105[0] 'activation_1109[0 'max_pooling2d_47[</pre>
conv2d_1114 (Conv2D)	(None, 5, 5, 448)	573440	['mixed8[0][0]']
<pre>batch_normalization_1114 ( BatchNormalization)</pre>	(None, 5, 5, 448)	1344	['conv2d_1114[0][0]']
<pre>activation_1114 (Activatio n_1114[0][ n)</pre>	(None, 5, 5, 448)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1111 (Conv2D)	(None, 5, 5, 384)	491520	['mixed8[0][0]']
conv2d_1115 (Conv2D)	(None, 5, 5, 384)	1548288	['activation_1114[0][
<pre>batch_normalization_1111 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1111[0][0]']
<pre>batch_normalization_1115 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1115[0][0]']
<pre>activation_1111 (Activatio n_1111[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1115 (Activatio n_1115[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1112 (Conv2D) [0]']	(None, 5, 5, 384)	442368	['activation_1111[0]
conv2d_1113 (Conv2D) [0]']	(None, 5, 5, 384)	442368	['activation_1111[0]

conv2d_1116 (Conv2D) [0]']	(None, 5, 5, 384)	442368	['activation_1115[0]
conv2d_1117 (Conv2D) [0]']	(None, 5, 5, 384)	442368	['activation_1115[0]
<pre>average_pooling2d_116 (Ave ragePooling2D)</pre>	(None, 5, 5, 1280)	0	['mixed8[0][0]']
conv2d_1110 (Conv2D)	(None, 5, 5, 320)	409600	['mixed8[0][0]']
<pre>batch_normalization_1112 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1112[0][0]']
<pre>batch_normalization_1113 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1113[0][0]']
<pre>batch_normalization_1116 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1116[0][0]']
<pre>batch_normalization_1117 ( BatchNormalization)</pre>	(None, 5, 5, 384)	1152	['conv2d_1117[0][0]']
conv2d_1118 (Conv2D) 116[0][0]'	(None, 5, 5, 192)	245760	['average_pooling2d_
<pre>batch_normalization_1110 ( BatchNormalization)</pre>	(None, 5, 5, 320)	960	['conv2d_1110[0][0]']
<pre>activation_1112 (Activatio n_1112[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1113 (Activatio n_1113[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1116 (Activatio n_1116[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>

<pre>activation_1117 (Activatio n_1117[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>batch_normalization_1118 ( BatchNormalization)</pre>	(None, 5, 5, 192)	576	['conv2d_1118[0][0]']
<pre>activation_1110 (Activatio n_1110[0][ n)</pre>	(None, 5, 5, 320)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed9_0 (Concatenate) [0]', ][0]']</pre>	(None, 5, 5, 768)	0	['activation_1112[0] 'activation_1113[0
<pre>concatenate_22 (Concatenat [0]', e) ][0]']</pre>	(None, 5, 5, 768)	0	['activation_1116[0] 'activation_1117[0
<pre>activation_1118 (Activatio n_1118[0][ n)</pre>	(None, 5, 5, 192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed9 (Concatenate) [0]',</pre>	(None, 5, 5, 2048)	0	<pre>['activation_1110[0]  'mixed9_0[0][0]',  'concatenate_22[0]</pre>
[0]', ][0]']			'activation_1118[0
	(None, 5, 5, 448)	917504	['mixed9[0][0]']
<pre>batch_normalization_1123 ( BatchNormalization)</pre>	(None, 5, 5, 448)	1344	['conv2d_1123[0][0]']
<pre>activation_1123 (Activatio n_1123[0][ n)</pre>	(None, 5, 5, 448)	0	<pre>['batch_normalizatio 0]']</pre>
conv2d_1120 (Conv2D)	(None, 5, 5, 384)	786432	['mixed9[0][0]']
conv2d_1124 (Conv2D) 0]']	(None, 5, 5, 384)	1548288	['activation_1123[0][
batch normalization 1120 (	(None. 5. 5. 384)	1152	['conv2d 1120[0][0]]

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BatchNormalization)					
<pre>batch_normalization_1124 (</pre>	(None. 5.	5.	384)	1152	['conv2d_1124[0][0]']
BatchNormalization)	(Holle) o,	٠,	331,	1102	[ 0011124_1121[0][0] ]
Batchnormallzation)					
<pre>activation_1120 (Activatio n 1120[0][</pre>	(None, 5,	5,	384)	0	['batch_normalizatio
n)					0]']
activation_1124 (Activatio	(None, 5,	5,	384)	0	['batch_normalizatio
n_1124[0][ n)					0]']
con-2d 1121 (Con-2D)	(None, 5,	E	2041	112260	[lastimation 1120[0]
conv2d_1121 (Conv2D) [0]']	(None, 3,	٠,	304)	442368	['activation_1120[0]
conv2d_1122 (Conv2D) [0]']	(None, 5,	5,	384)	442368	['activation_1120[0]
<del>_</del>	(None, 5,	5,	384)	442368	['activation_1124[0]
[0]']					
conv2d_1126 (Conv2D)	(None, 5,	5,	384)	442368	['activation_1124[0]
[0]']					
average pooling2d 117 (Ave	(None 5	5	2048)	0	['mixed9[0][0]']
	(10110) 3)	٥,	2010)	Ü	[ mixeds[0][0] ]
ragePooling2D)					
conv2d_1119 (Conv2D)	(None, 5,	5,	320)	655360	['mixed9[0][0]']
<pre>batch_normalization_1121 (</pre>	(None, 5,	5,	384)	1152	['conv2d_1121[0][0]']
BatchNormalization)					
<pre>batch_normalization_1122 (</pre>	(None, 5,	5,	384)	1152	['conv2d_1122[0][0]']
BatchNormalization)					_
2.22					
hatah ali sa	/NT ==	_	204)	1150	[]01 11055015015
batch_normalization_1125 (	(None, 5,	٥,	384)	1152	['conv2d_1125[0][0]']
BatchNormalization)					
<pre>batch_normalization_1126 (</pre>	(None, 5,	5,	384)	1152	['conv2d_1126[0][0]']
BatchNormalization)					

conv2d_1127 (Conv2D) 117[0][0]'	(None, 5, 5, 192)	393216	<pre>['average_pooling2d_</pre> ]
<pre>batch_normalization_1119 ( BatchNormalization)</pre>	(None, 5, 5, 320)	960	['conv2d_1119[0][0]']
<pre>activation_1121 (Activatio n_1121[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1122 (Activatio n_1122[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>activation_1125 (Activatio n_1125[0][ n)</pre>	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
activation_1126 (Activatio n_1126[0][ n)	(None, 5, 5, 384)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>batch_normalization_1127 ( BatchNormalization)</pre>	(None, 5, 5, 192)	576	['conv2d_1127[0][0]']
<pre>activation_1119 (Activatio n_1119[0][ n)</pre>	(None, 5, 5, 320)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed9_1 (Concatenate) [0]', ][0]']</pre>	(None, 5, 5, 768)	0	<pre>['activation_1121[0] 'activation_1122[0</pre>
<pre>concatenate_23 (Concatenat [0]', e) ][0]']</pre>	(None, 5, 5, 768)	0	['activation_1125[0] 'activation_1126[0
<pre>activation_1127 (Activatio n_1127[0][ n)</pre>	(None, 5, 5, 192)	0	<pre>['batch_normalizatio 0]']</pre>
<pre>mixed10 (Concatenate) [0]',</pre>	(None, 5, 5, 2048)	0	['activation_1119[0] 'mixed9_1[0][0]', 'concatenate 23[0]

```
[0]',
                                                             'activation 1127[0
][0]']
average_pooling2d_118 (Ave (None, 2, 2, 2048)
                                                          ['mixed10[0][0]']
ragePooling2D)
dropout 11 (Dropout) (None, 2, 2, 2048)
                                                 0
                                                          ['average pooling2d
118[0][0]'
flatten 12 (Flatten)
                        (None, 8192)
                                                  0
                                                           ['dropout 11[0][0]']
                         (None, 101)
                                                 827493
dense 12 (Dense)
                                                          ['flatten 12[0][0]']
Total params: 22630277 (86.33 MB)
Trainable params: 22595845 (86.20 MB)
Non-trainable params: 34432 (134.50 KB)
In [ ]:
opt = SGD(lr=.1, momentum=.9)
model3.compile(optimizer=opt, loss='categorical crossentropy', metrics=['accuracy'])
In [ ]:
from keras.models import load model
model3 = load model("/kaggle/input/food-101-model/tensorflow2/food-101/1/model food 101.h
5")
In [ ]:
from tensorflow.keras.callbacks import EarlyStopping
results3 = model3.fit(train data, epochs=10, validation data=test data,
               steps per epoch=len(train data), validation steps=len(test data),
               callbacks = EarlyStopping(patience=2, monitor='val accuracy', restore b
est weights=True)
Epoch 1/10
2024-03-14 23:31:53.916425: E tensorflow/core/grappler/optimizers/meta optimizer.cc:961]
layout failed: INVALID ARGUMENT: Size of values 0 does not match size of permutation 4 @
fanin shape inmodel 1/dropout 11/dropout/SelectV2-2-TransposeNHWCToNCHW-LayoutOptimizer
WARNING: All log messages before absl::InitializeLog() is called are written to STDERR
I0000 00:00:1710459118.259536 186 device compiler.h:186] Compiled cluster using XLA!
This line is logged at most once for the lifetime of the process.
4 - val loss: 1.6280 - val accuracy: 0.7065
Epoch 2/10
909/909 [=========== ] - 829s 912ms/step - loss: 0.0646 - accuracy: 0.9
962 - val loss: 1.4801 - val accuracy: 0.7417
Epoch 3/10
909/909 [============ ] - 830s 913ms/step - loss: 0.0562 - accuracy: 0.9
970 - val loss: 1.4059 - val accuracy: 0.7487
Epoch 4/10
```

```
986 - val loss: 1.3613 - val accuracy: 0.7535
Epoch 5/10
909/909 [============ ] - 828s 911ms/step - loss: 0.0379 - accuracy: 0.9
995 - val loss: 1.2399 - val accuracy: 0.7697
Epoch 6/10
909/909 [============= ] - 828s 911ms/step - loss: 0.0325 - accuracy: 0.9
997 - val loss: 1.2145 - val accuracy: 0.7693
Epoch 7/10
997 - val loss: 1.1774 - val accuracy: 0.7716
Epoch 8/10
909/909 [================= ] - 828s 911ms/step - loss: 0.0245 - accuracy: 0.9
999 - val loss: 1.1357 - val accuracy: 0.7722
Epoch 9/10
909/909 [================= ] - 828s 910ms/step - loss: 0.0216 - accuracy: 0.9
999 - val loss: 1.1133 - val accuracy: 0.7721
Epoch 10/\overline{10}
909/909 [============= ] - 827s 910ms/step - loss: 0.0191 - accuracy: 1.0
000 - val loss: 1.0886 - val accuracy: 0.7736
In [ ]:
loss, acc = model3.evaluate(test data)
In [ ]:
print("Test Accuracy:",round(acc*100,2),"%","\nTest Loss:",loss)
Test Accuracy: 77.36 %
Test Loss: 1.0886189937591553
In [ ]:
model = model3
Training again
In [ ]:
from tensorflow.keras.callbacks import EarlyStopping
results3 = model3.fit(train data, epochs=10, validation data=test data,
              steps_per_epoch=len(train data), validation steps=len(test data),
              callbacks = EarlyStopping(patience=2, monitor='val accuracy', restore b
est weights=True)
Epoch 1/10
909/909 [============= ] - 829s 912ms/step - loss: 0.0173 - accuracy: 0.9
999 - val loss: 1.0805 - val_accuracy: 0.7749
Epoch 2/10
000 - val loss: 1.0645 - val accuracy: 0.7743
Epoch 3/10
909/909 [============ ] - 828s 910ms/step - loss: 0.0145 - accuracy: 1.0
000 - val_loss: 1.0611 - val_accuracy: 0.7733
In [ ]:
loss, acc = model3.evaluate(test data)
49
In [ ]:
print("Test Accuracy:",round(acc*100,2),"%","\nTest Loss:",round(loss,4))
```

Test Accuracy: 77.49 %

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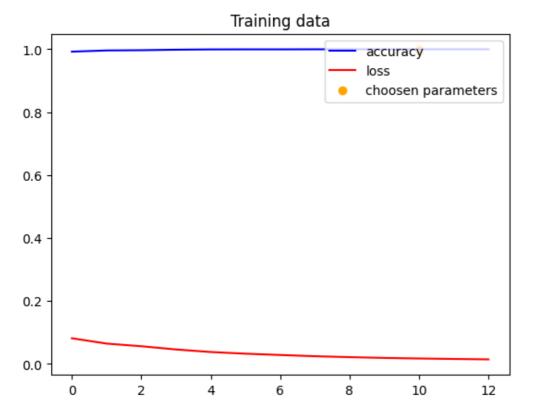
```
Test Loss: 1.0805
In [ ]:
results3 = {"accuracy": [0.9924,0.9962,0.9970,0.9986,0.9995,0.9997,0.9997,0.9999,0.99
99,1.0000,0.9999,1.0000,1.0000],
                            [0.0816, 0.0646, 0.0562, 0.0460, 0.0379, 0.0325, 0.0284, 0.0245, 0.02
            "loss":
16,0.0191,0.0173,0.0158,0.0145],
            "val accuracy": [0.7065,0.7417,0.7487,0.7535,0.7697,0.7693,0.7716,0.7722,0.77
21,0.7736,0.7749,0.7743,0.7733],
                           [1.6280,1.4801,1.4059,1.3613,1.2399,1.2145,1.1774,1.1357,1.11
            "val loss":
33,1.0886,1.0805,1.0645,1.0611]}
In [ ]:
model3.save("model food 1012.h5")
/opt/conda/lib/python3.10/site-packages/keras/src/engine/training.py:3103: UserWarning: Y
ou are saving your model as an HDF5 file via `model.save()`. This file format is consider
ed legacy. We recommend using instead the native Keras format, e.g. `model.save('my model
.keras')`.
 saving_api.save_model(
In [ ]:
results3['val accuracy']
Out[]:
[0.7065,
 0.7417,
 0.7487,
 0.7535,
 0.7697,
 0.7693,
 0.7716,
 0.7722,
 0.7721,
 0.7736,
 0.7749,
 0.7743,
 0.7733]
In [ ]:
results3['val loss']
Out[]:
[1.628,
 1.4801,
 1.4059,
 1.3613,
 1.2399,
 1.2145,
 1.1774,
 1.1357,
 1.1133.
 1.0886,
 1.0805,
 1.0645,
 1.0611]
In [ ]:
i = results3['val loss'].index(round(loss, 4))
Out[]:
10
```

```
In []:
results3['val_accuracy'][i]
Out[]:
0.7749
```

## Visualize training history

```
In [ ]:
```

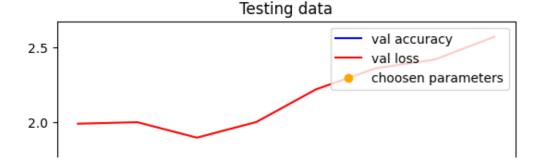
```
fig = plt.figure()
plt.plot(results3['accuracy'], c='blue', label='accuracy')
plt.plot(results3['loss'], c='red', label='loss')
plt.scatter(i,results3['accuracy'][i], c='orange', marker='o', label='choosen parameters
')
plt.title('Training data')
plt.legend(loc='upper right')
plt.show()
```



# **Visualize testing history**

```
In [ ]:
```

```
fig = plt.figure()
plt.plot(results3.history['val_accuracy'], c='blue', label='val accuracy')
plt.plot(results3.history['val_loss'], c='red', label='val loss')
plt.scatter(i,results3.history['val_accuracy'][i], c='orange', marker='o', label='choose
n parameters')
plt.title('Testing data')
plt.legend(loc='upper right')
plt.show()
```



```
1.5 -
```

```
In [ ]:
```

# Out[]:

```
Predicted 0 1 2 3 4 5 6 7 8 9 ... 91 92 93 94 95 96 97 98 99 100
```

## Actual

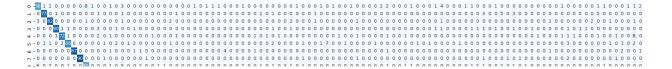
```
0
                                                                       2
                                       0
                                                     0
                                                                       0
                                                  0
                                                                       0
                        0
                           0
                              0
                                 0 ...
                                       1
                                           0
                                                 0
                                                     0
                                                               0
                                                                   0
                                                                       0
        0
              80
                     1
                                              O
                                                        0
                                                            O
                        0
                          0
                              0
                                 0 ...
                                       0
                                           0
                                                                       0
                     0
                       0
                          0
                              1 0 ...
                                       0
                                           0
                                              0
                                                 0
                                                     0
                                                          91
                                                               0
                                                        0
                                                                       0
98
           0
                     0
                        0
                           0
                              2
                                 0 ...
                                       1
                                           0
                                              0
                                                 0
                                                     0
                                                              78
                                                                       1
                                                                       0
                           0 1 0 ... 0
                                           0
                                              0
                                                 0
100
                  0 0 0 0 0 0 ... 0 0
                                                 2
                                                     0
```

#### 101 rows × 101 columns

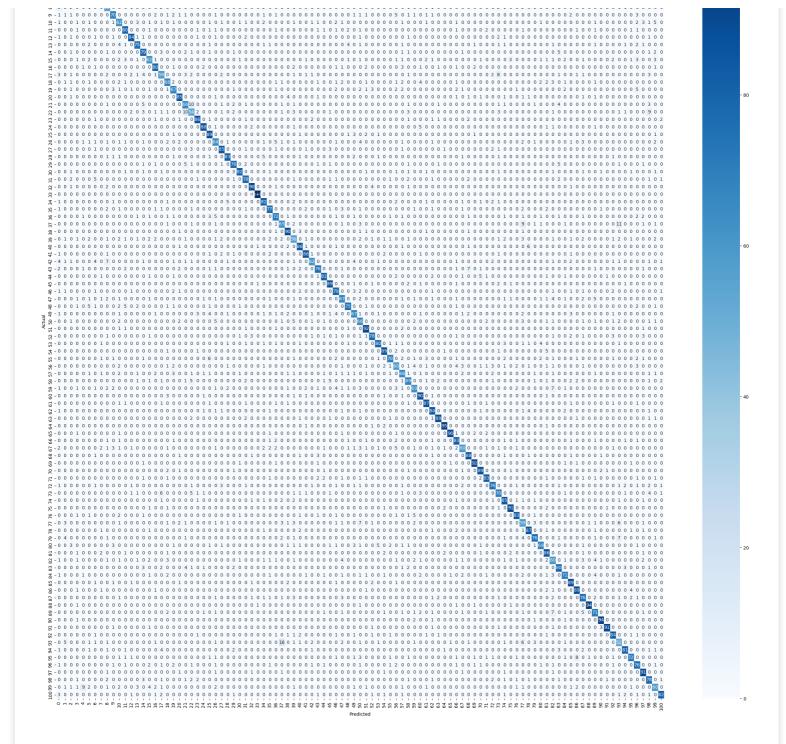
# In [ ]:

```
print("Heatmap\n")
plt.figure(figsize=(30, 30))
sn.heatmap(m,annot=True, cmap='Blues')
plt.show()
```

Heatmap







# **Testing Samples**

In [ ]:

print(os.listdir("/kaggle/input/food-101/food-101/food-101/images/"))

['macarons', 'french\_toast', 'lobster\_bisque', 'prime\_rib', 'pork\_chop', 'guacamole', 'ba by\_back\_ribs', 'mussels', 'beef\_carpaccio', 'poutine', 'hot\_and\_sour\_soup', 'seaweed\_sala d', 'foie\_gras', 'dumplings', 'peking\_duck', 'takoyaki', 'bibimbap', 'falafel', 'pulled\_p ork\_sandwich', 'lobster\_roll\_sandwich', 'carrot\_cake', 'beet\_salad', 'panna\_cotta', 'donu ts', 'red\_velvet\_cake', 'grilled\_cheese\_sandwich', 'cannoli', 'spring\_rolls', 'shrimp\_and\_grits', 'clam\_chowder', 'omelette', 'fried\_calamari', 'caprese\_salad', 'oysters', 'scall ops', 'ramen', 'grilled\_salmon', 'croque\_madame', 'filet\_mignon', 'hamburger', 'spaghetti\_carbonara', 'miso\_soup', 'bread\_pudding', 'lasagna', 'crab\_cakes', 'cheesecake', 'spaghetti\_bolognese', 'cup\_cakes', 'creme\_brulee', 'waffles', 'fish\_and\_chips', 'paella', 'maca roni\_and\_cheese', 'chocolate\_mousse', 'ravioli', 'chicken\_curry', 'caesar\_salad', 'nachos', 'tiramisu', 'frozen\_yogurt', 'ice\_cream', 'risotto', 'club\_sandwich', 'strawberry\_shor tcake', 'steak', 'churros', 'garlic\_bread', 'baklava', 'bruschetta', 'hummus', 'chicken\_w ings', 'greek\_salad', 'tuna\_tartare', 'chocolate\_cake', 'gyoza', 'eggs\_benedict', 'deviled\_eggs', 'samosa', 'sushi', 'breakfast\_burrito', 'ceviche', 'beef\_tartare', 'apple\_pie', '.DS\_Store', 'huevos\_rancheros', 'beignets', 'pizza', 'edamame', 'french\_onion\_soup', 'hot\_dog', 'tacos', 'chicken\_quesadilla', 'pho', 'gnocchi', 'pancakes', 'fried\_rice', 'cheese\_plate', 'onion\_rings', 'escargots', 'sashimi', 'pad\_thai', 'french\_fries']

```
print("Macarons Sample")
macarons = load_img("/kaggle/input/food-101/food-101/food-101/images/macarons/2428554.jpg
",target_size=(224,224))
macarons
```

## Macarons Sample

## Out[]:



#### In [ ]:

```
print("Pizza Sample")
pizza = load_img("/kaggle/input/food-101/food-101/food-101/images/pizza/768276.jpg",targe
t_size=(224,224,3))
pizza
```

# Pizza Sample

## Out[]:



#### In [ ]:

```
print("Donuts Sample")
donuts = load_img("/kaggle/input/food-101/food-101/food-101/images/donuts/2563686.jpg",ta
rget_size=(224,224,3))
donuts
```

## Donuts Sample

## Out[]:





```
print("Frensh Toast Sample")
toast = load_img("/kaggle/input/food-101/food-101/food-101/images/french_toast/2769309.jp
g",target_size=(224,224,3))
toast
```

Frensh Toast Sample

## Out[]:



#### In [ ]:

```
print("French_fries Sample")
fries = load_img("/kaggle/input/food-101/food-101/food-101/images/french_fries/2246621.jp
g",target_size=(224,224))
fries
```

French\_fries Sample

#### Out[]:



## In [ ]:

```
print("Ice Cream Sample")
ice = load_img("/kaggle/input/food-101/food-101/food-101/images/ice_cream/579407.jpg",tar
get_size=(224,224))
ice
```

Ice Cream Sample

## Out[]:





```
fig = plt.figure(figsize=(14,7))
# plt.grid=False
fig.add subplot(1, 6, 1)
plt.axis('off')
plt.imshow(macarons)
plt.title("Macarons")
fig.add subplot(1, 6, 2)
plt.axis('off')
plt.imshow(fries)
plt.title("Frensh Fries")
fig.add subplot(1, 6, 3)
plt.axis('off')
plt.imshow(ice)
plt.title("Ice Cream")
fig.add subplot(1, 6, 4)
plt.axis('off')
plt.imshow(toast)
plt.title("Frensh Toast")
fig.add subplot(1, 6, 5)
plt.axis('off')
plt.imshow(pizza)
plt.title("Pizza")
fig.add subplot(1, 6, 6)
plt.axis('off')
plt.imshow(donuts)
plt.title("Donuts")
```

## Out[]:

Text(0.5, 1.0, 'Donuts')













## In [ ]:

```
macarons = img to array(macarons)
fries = img to array(fries)
ice = img to array(ice)
pizza = img_to_array(pizza)
donuts = img_to_array(donuts)
toast = img to array(toast)
macarons = macarons/255
fries = fries/255
ice = ice/255
pizza = pizza/255
donuts = donuts/255
toast = toast/255
macarons = macarons.reshape(1,224,224,3)
fries = fries.reshape(1,224,224,3)
ice = ice.reshape(1,224,224,3)
pizza = pizza.reshape(1,224,224,3)
donuts = donuts.reshape(1,224,224,3)
```

```
toast = toast.reshape(1,224,224,3)
macarons.shape

Out[]:
(1, 224, 224, 3)
```

# Samples Predicting

```
In [ ]:
p1 = (model.predict(macarons)).argmax()
print("Class ",p1,": ",values[p1],sep='')
print(calories[p1],'\nNote:',s)
1/1 [======= ] - 3s 3s/step
Class 63: macarons
Macarons: ~4 calories per gram
Note: These values are approximations and can vary based on factors such as ingredients a
nd cooking methods.
In [ ]:
p2 = (model.predict(fries)).argmax()
print("Class ",p2,": ",values[p2],sep='')
print(calories[p2], '\nNote:',s)
1/1 [=======] - Os 28ms/step
Class 40: french fries
French Fries: ~3.5 calories per gram
Note: These values are approximations and can vary based on factors such as ingredients a
nd cooking methods.
In [ ]:
p3 = (model.predict(ice)).argmax()
print("Class ",p3,": ",values[p3],sep='')
print(calories[p3], '\nNote:',s)
1/1 [======= ] - Os 24ms/step
Class 58: ice cream
Ice Cream: ~2 calories per gram
Note: These values are approximations and can vary based on factors such as ingredients a
nd cooking methods.
In [ ]:
p4 = (model.predict(pizza)).argmax()
print("Class ",p4,": ",values[p4],sep='')
print(calories[p4], '\nNote:',s)
1/1 [=======] - 0s 29ms/step
Class 76: pizza
Pizza: ~2.5 calories per gram
Note: These values are approximations and can vary based on factors such as ingredients a
nd cooking methods.
In [ ]:
p5 = (model.predict(donuts)).argmax()
print("Class ",p5,": ",values[p5],sep='')
print(calories[p5], '\nNote:',s)
```

1/1 [======] - Os 28ms/step

Class 31: donuts

- - - - - - - - - - -

Donuts: ~4 calories per gram

Note: These values are approximations and can vary based on factors such as ingredients a nd cooking methods.

## In [ ]:

```
p6 = (model.predict(toast)).argmax()
print("Class ",p6,": ",values[p6],sep='')
print(calories[p6],'\nNote:',s)
```

1/1 [======] - 0s 28ms/step

Class 42: french\_toast

French Toast: ~2 calories per gram

Note: These values are approximations and can vary based on factors such as ingredients a nd cooking methods.