

# Deep Learning DLIR Assignment Specialist Diploma in applied Generative AI (SDGAI) Apr 2025 Semester

Presented by: Lim Ai Sim Elizabeth (3440680F)

Presented on 09/06/2025



### **Assignment Objectives**

**Main objective:** To design and implement a convolutional neural network (CNN) based model that can accurately classify food images into one of the 10 specified food categories.

#### **Approaches:**

- 1. Customized CNN model ("Build from scratch")
- 2. Use a pretrained model (Apply transfer learning)
- 3. Use the best model on some images taken from the internet.

# **Environment setup**

Work in cloud computing platforms:

- Google Colab
- AWS Sagemaker AI

Run training and analyse in Jupyter Notebook

- TensorFlow / Keras libraries
- matplotlib

## **Data exploration**

**Step 1**: Unzip the image data into a folder, data processing to use the data for training, validation and testing.

**Step 2**: Check the contents and examine images

• Check the number of images provided for training and testing. (750 images per class for training, 250 images per class for validation, 50 images per class set aside for test evaluation.



## **Customized CNN Model Design**

#### 1) Decide on the initial architecture

Sequential model

- 3-4 convolutional + max pooling layers for feature extraction.
- 2-3 fully connected dense layers for classification task.

#### 2) Decide on training and tweaking strategy

- Train the model and monitor progress using accuracy and loss graphs for training and validation.
- Train without augmenting the data. Mitigate overfitting. Perform data augmentation and use that to further improve the model.
- Change one component at a time to observe the effects of the change.

# **Customized CNN Model Training**

#### **Training format:**

• Batch size = 25

• Training epochs = 30-80

• Optimizer: RMSprop

Loss: Categorical cross-entropy

Metric: Accuracy

• Learning rate: 0.0001 (1e-4)

Convolutional 2D, 32

MaxPooling 2D

Convolutional 2D, 64

MaxPooling 2D

Convolutional 2D, 128

MaxPooling 2D

Convolutional 2D, 128

MaxPooling 2D

Flatten

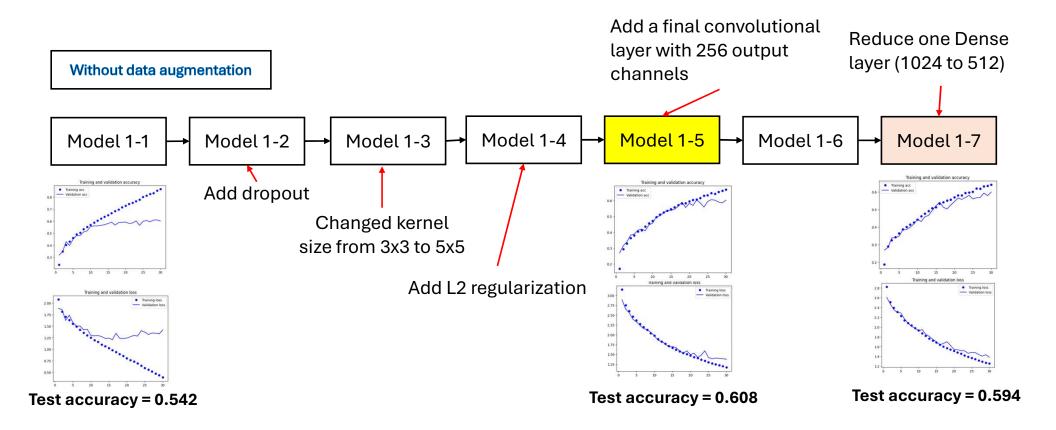
Dense, 1024 [ReLU]

Dense, 512 [ReLU]

Dense, 10 [Softmax]

# **Customized Model Design and Adjustments (I)**

**Strategy**: Adjust and optimize without data augmentation.



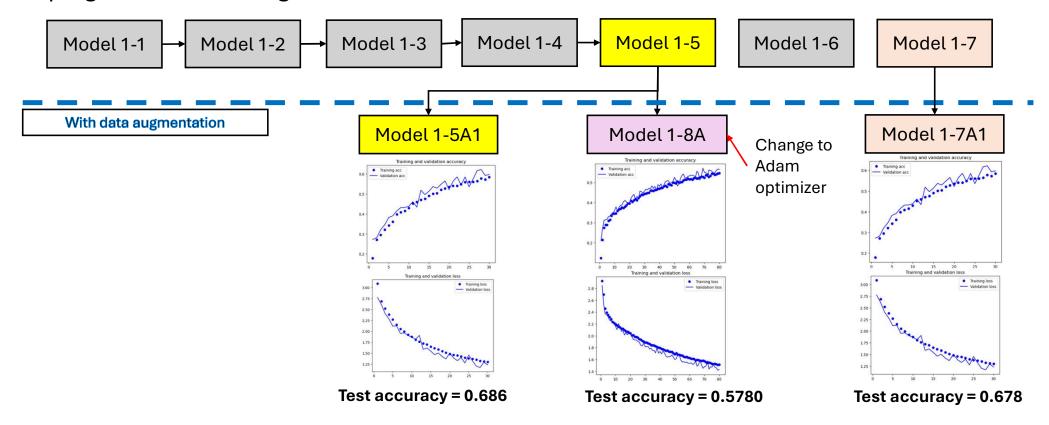
# **Data augmentation**

- Data augmentation increases training data pool by generating variations to existing training data.
- Performed with consideration to realistic variations.

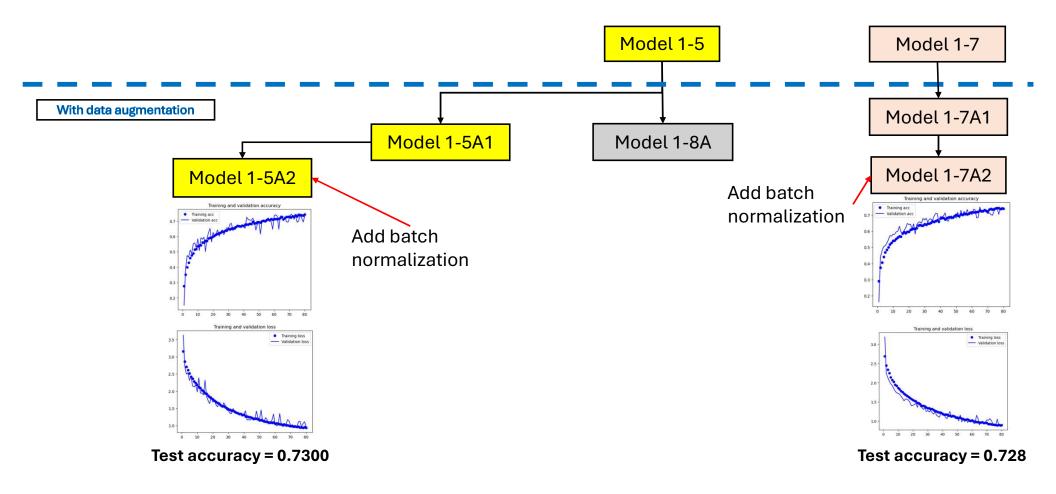
Code	Explanation	
train_datagen = ImageDataGenerator(		
rescale=1./255,	Rotation angle = 40 degrees left or right Shift range is in percentage.0.2 = 20%	
<pre>rotation_range=40, width shift range=0.2,</pre>		
height_shift_range=0.2,	width or height position shift.	
shear_range=0.2,	Shear range is in radians.	
zoom_range=0.3,	<b>Zoom range</b> is in percentage (0.3 = 30%)	
horizontal_flip=True, beightness is in a range 0.8 -1.2		
<pre>brightness_range=[0.8,1.2], fill mode='nearest')</pre>	20% darker to 20% brighter than original	
_	image.	

# **Customized Model Design and Adjustments (II)**

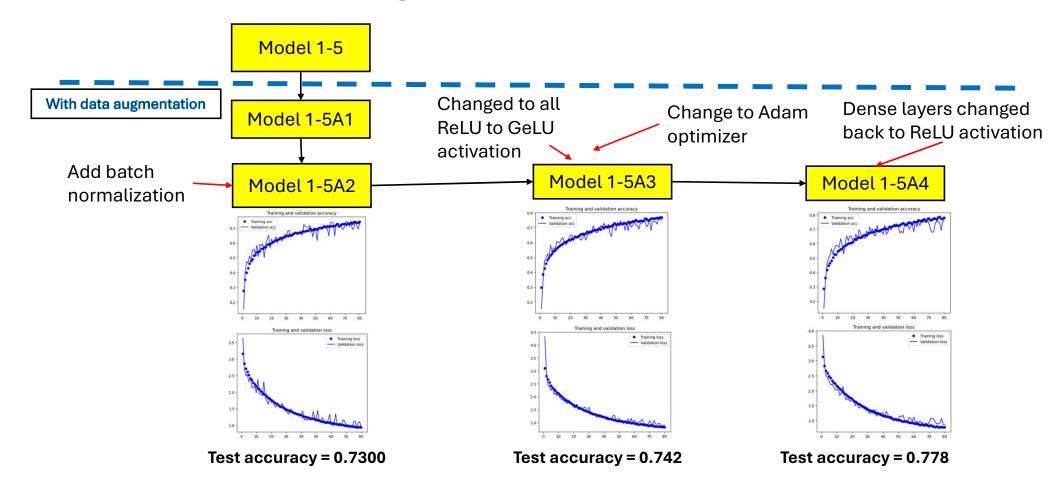
**Strategy**: Adjusting best models from previous round. (Subsequent slides show the progression of training and model selection.



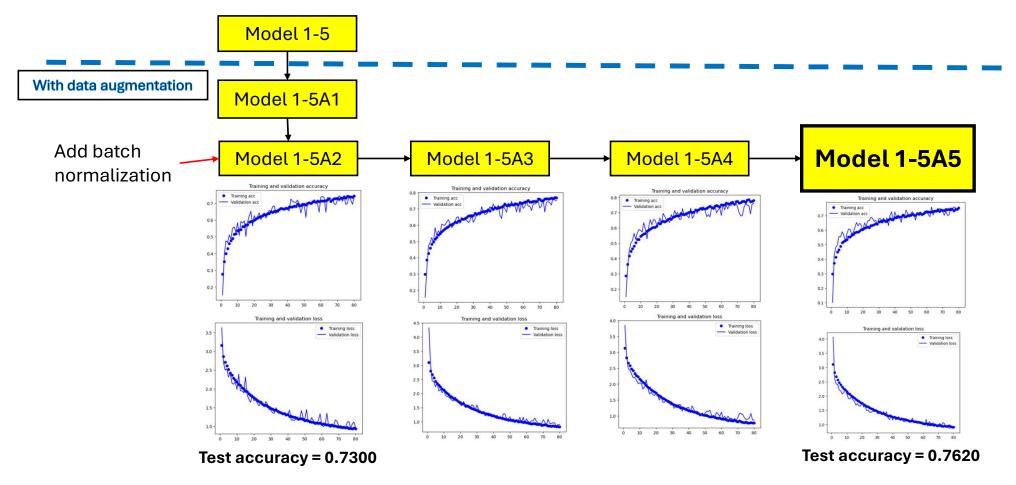
# **Customized Model Design and Adjustments (III)**



# **Customized Model Design and Adjustments (IV)**



# **Customized Model Design and Adjustments (V)**



# Summary of adjustments to Custom CNN Model Design

- Changing number of units in the Dense layers
- Adding a dropout layer and L2 regularization
- Adjusting the kernel size in the convo2D layer from 3x3 to 5x5
- Adding convo2D and MaxPooling2D blocks
- Adding batch normalization layers
- Changing the activation function from ReLU to GeLU
- Adjusting learning rate (1e-4 to 2e-5)
- Using different optimizers (RMSprop vs Adam)

# Customized CNN Model Design – The Final Built Model 1-5A5

Convolutional 2D, 32

MaxPooling 2D

Convolutional 2D, 64

MaxPooling 2D

Convolutional 2D, 128

MaxPooling 2D

Convolutional 2D, 128

MaxPooling 2D

Flatten

Dense, 1024 [ReLU]

Dense, 512 [ReLU]

Dense, 10 [Softmax]

Initial Build
Test accuracy = 0.542

Convolutional 2D, 32 [GeLU]

Batch Normalization

MaxPooling 2D

Convolutional 2D, 64 [GeLU]

Batch Normalization

MaxPooling 2D

Convolutional 2D, 128 [GeLU]

Batch Normalization

MaxPooling 2D

Convolutional 2D, 128 [GeLU]

Batch Normalization

MaxPooling 2D

Convolutional 2D, 256 [GeLU]

Batch Normalization

MaxPooling 2D

Flatten

Dropout

Dense, 1024 [ReLU]

Dense, 512 [ReLU]

Dense, 10 [Softmax]

Final Build: Model 1-5A5 Test accuracy = 0.7620

## **Transfer Learning with Pretrained Model**

- Deciding on which pretrained model to use:
- 1) Resnet-50
- 2) InceptionV3

Both models have been used for food classification, but have different internal convolutional structures.

- Resnet models have skipped connections to overcome vanishing gradients.
- **Inception models** have convolutional blocks arranged in parallel to capture various features and patterns and to achieve computation efficiency.

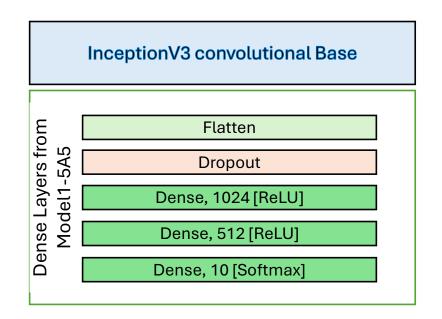
Selected **InceptionV3** as its architecture is very different from own custom CNN model and its convolutional modules suitable for capturing the image details of food.

## Transfer Learning with Pretrained Model

Structure: InceptionV3 convolutional base + classification layers from Model 1-5A5.

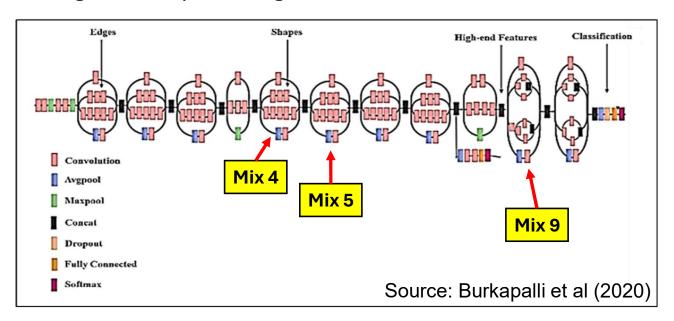
Training and adaptation strategy:

- Integrate pretrained model and custom model layers.
- Train our classifier with augmented training data.
- Finetune the model by unfreezing parts of the convolutional base.



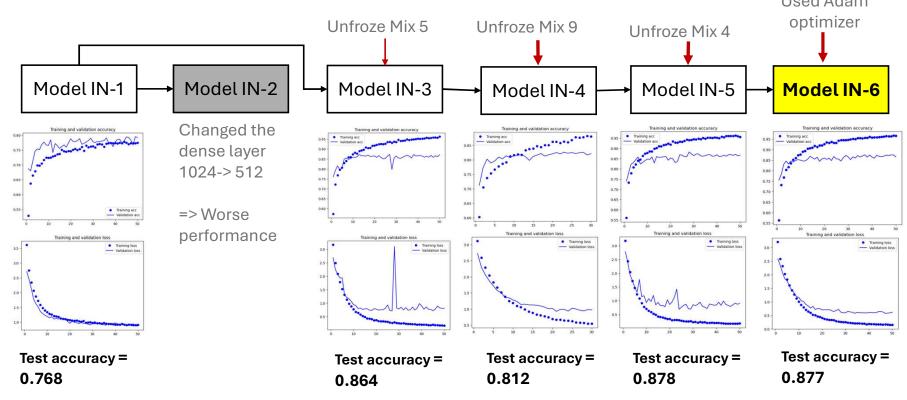
# Finetuning – Unfreezing the convolutional modules in InceptionV3

There are **11 inception blocks** (or 'mix' numbered 0 to 10). Each progressive module in the model is learning more and more complex features (Burkapalli *et al* (2020)), from edges to shapes to higher features.



# **Transfer Learning Model Design and Adjustments**

**Strategy**: finetuning by unfreezing each Inception module and see its effect on accuracy and loss graphs and test accuracy scores.

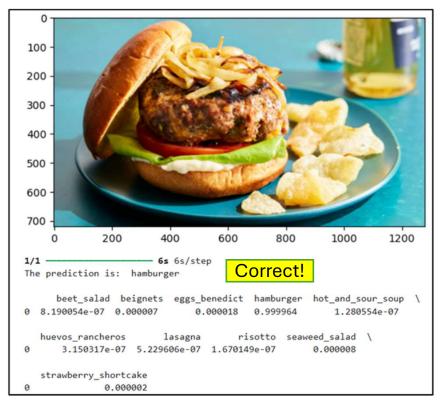


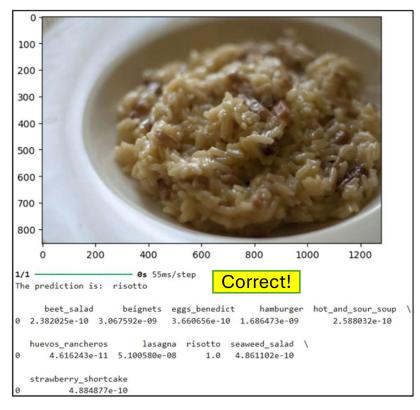
#### **Final Test Evaluation**

From the final test evaluation accuracy and loss scores, Model 'Food\_IN6' is the better model.

Model	Test accuracy	Test Loss score
1-5A5 [Built-from-scratch CNN	0.7659	0.8871
model]		
Model Food_IN6 [InceptionV3	0.8750	0.5881
convolutional base +		
customized Dense layers]		

# Testing with images from the internet



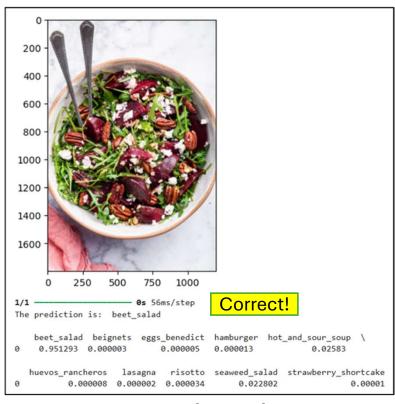


Hamburger (0.999)

Risotto (1.0)

# Testing with images from the internet (II)

200



400 1000 200 400 600 Correct! The prediction is: seaweed\_salad beet salad beignets eggs\_benedict hamburger hot\_and\_sour\_soup \ 0 8.635825e-07 5.498294e-08 1.211709e-09 2.164986e-08 huevos\_rancheros lasagna risotto seaweed\_salad \ 0.000031 1.941014e-08 0.000016 strawberry\_shortcake 1.055280e-10

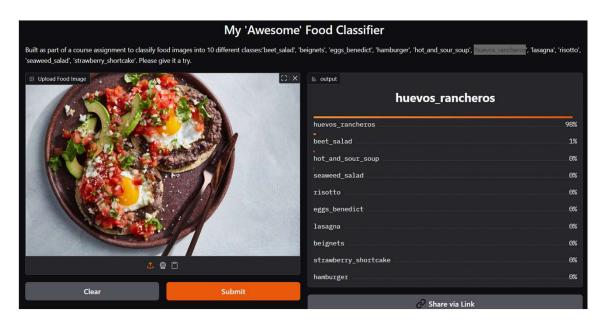
↑ ↓ **♦** © 国

**Beet Salad (0.951)** 

Seaweed Salad (0.937)

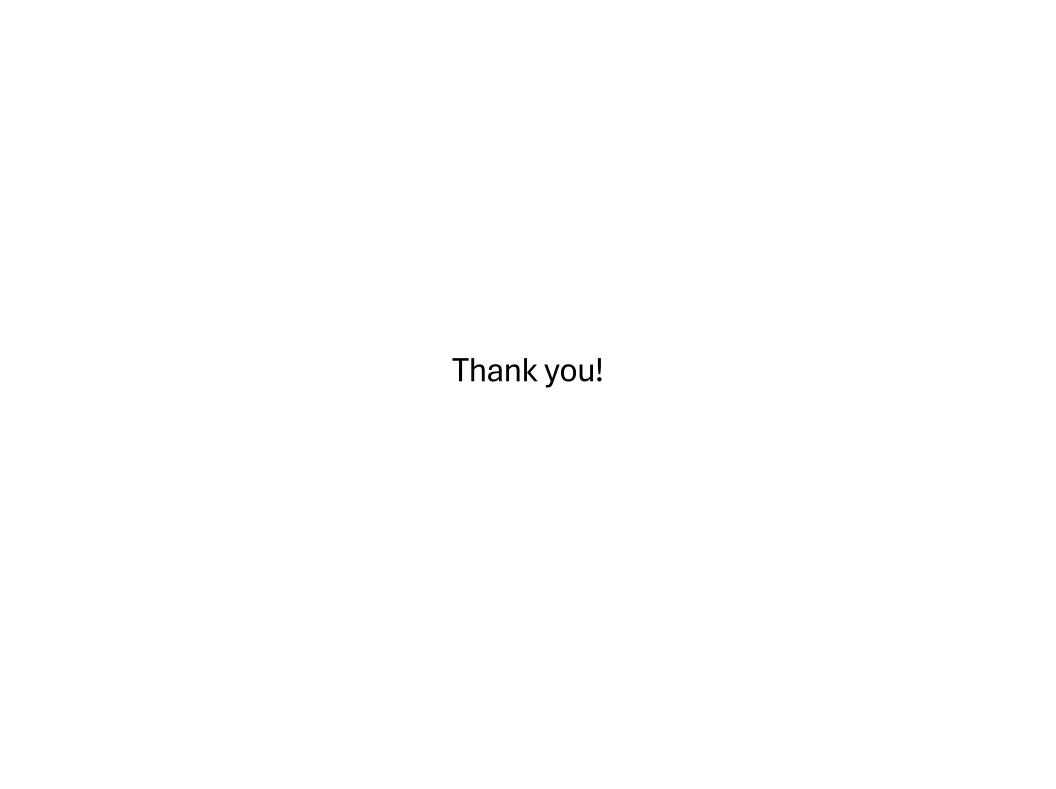
#### **Model Demo**

• The model is available for testing on Hugging Face's Spaces: <a href="https://huggingface.co/spaces/Ravenblack7575/DLIRfood">https://huggingface.co/spaces/Ravenblack7575/DLIRfood</a>

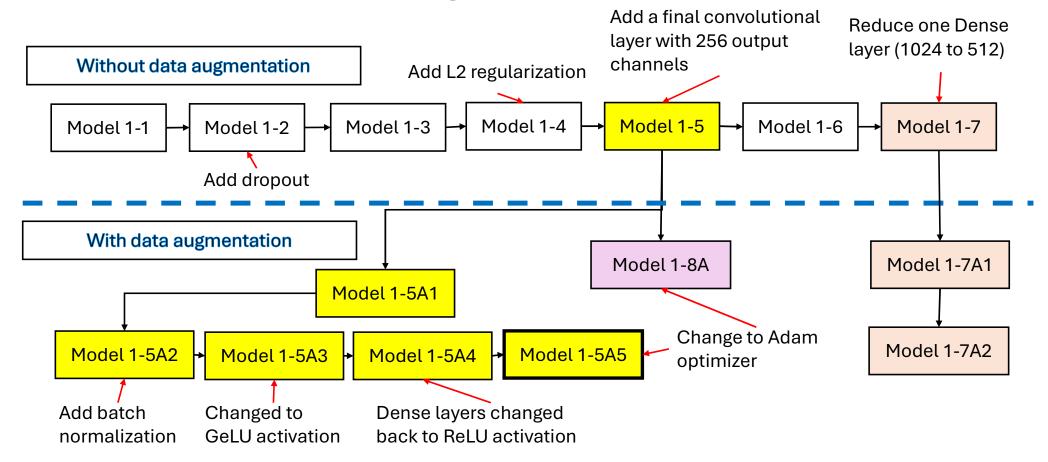


#### **Limitations and recommendations**

- Currently, if the model was given an image that doesn't fall into any one of these categories, it would still give a prediction based on these ten classes.
   One way to mitigate this is to implement prediction threshold score where if an image scores are low for this score, then the result could be 'unclassifiable'.
- Functions could be written so that the codes used for model training could be neater and more organized, which may translate to easier execution.
- In future model training, data augmentation will be performed before training commences.



# **Customized Model Design and Adjustments**



# **Customized Model Design and Adjustments**

